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Knowledge Spillovers From Superstar Tech-Firms: The Case of Nokia

by Jyrki Ali-Yrkkö, Reda Cherif, Fuad Hasanov, Natalia Kuosmanen, Mika Pajarinen

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Knowledge Spillovers From Superstar Tech-Firms: The Case of Nokia

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I. Abstract

Do workers hired from superstar tech-firms contribute to better firm performance? To address this question, we analyze the effects of tacit knowledge spillovers from Nokia in the context of a quasi-natural experiment in Finland, the closure of Nokia's mobile device division in 2014 and the massive labor movement it implied. We apply a two-stage difference-in-differences approach with heterogeneous treatment to estimate the causal effects of hiring former Nokia employees. Our results provide new evidence supporting the positive causal role of former Nokia workers on firm performance. The evidence of the positive spillovers on firms is particularly strong in terms of employment and value added.

JEL Classification Numbers: J24, J62, O30, D83

Keywords: human capital, employment, value added, Nokia, difference-in-differences, heterogeneous treatment, knowledge spillovers, superstar firms.

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II. INTRODUCTION

Knowledge is an important driver of innovation and economic growth (e.g. Keller 2021, Saito and Gopinath 2011, Romer 1990). The most useful forms of knowledge for firms are by nature *tacit* and they cannot be easily acquired (Polanyi 1958). It is the type of knowledge that skilled workers have and cannot be easily codified. It can be generated internally by firms through the accumulation of experience and passed on through internal training and apprenticeship, but it can also be obtained externally through labor mobility or the observation of and interaction with other workers/firms. Knowledge spillovers are typically understood as a flow of knowledge from one entity to another (Ramadani et al. 2017). It is a process of the transmission of knowledge to others beyond the intended boundaries (Fallah and Ibrahim 2004) and represents the external benefits from the creation of knowledge, accruing to parties other than the creator (Agarwal et al. 2010, Hur 2017).

In this study we examine knowledge spillovers of former Nokia employees that were hired by other Finnish firms. We argue that Nokia, formerly the world's largest mobile phone manufacturer and the flagship of the Finnish technology industry, provides not only a fascinating empirical case, but in fact, an ideal setting to study knowledge spillovers in the context of a superstar tech-firm. Comparing firms that hire former Nokia workers vs. firms that hire other workers allows us to identify Nokia-specific spillovers. During the past decades, Nokia invested heavily in R&D. For instance, its R&D activities conducted in Finland in 2008 were approximately 49 percent of total business sector R&D expenditure and 37 percent of the total R&D expenditure in Finland (Ali-Yrkkö 2010, Ali-Yrkkö et al. 2021a). Although Nokia funded the majority of its R&D efforts, it also received considerable R&D funding from the Finnish government (Business Finland). As other global firms introduced smartphones, Nokia's crisis started in 2008, and thousands of its employees left the company and found new employment in other firms (Ali-Yrkkö et al. 2021b for an update of former Nokia workers' employment status). From the perspective of hiring firms, the company's demise, leading many highly educated and skilled workers who gained an experience in a unique environment to enter the labor market, can be seen as a positive exogenous shock and constitutes a quasi-natural experiment we exploit as most exits happened when the company was in decline.

This study has three major contributions. *First*, it contributes to the literature by exploiting a quasi-experiment to identify the causal impact of knowledge spillovers on firm performance via labour mobility from a superstar technology firm. This quasi-experiment resulted from the closure of Nokia's mobile unit when most worker departures happened. This shock, mitigating potential reverse causality problems, provides us with clearer identification to identify knowledge spillovers. In addition, we use job tenure as a new measure of the spillover, which, to our knowledge, has not been considered before in the literature. This measure allows us to mitigate the endogeneity problem resulting from Nokia's employees being potentially more skilled upon their initial hiring by Nokia. *Second*, using a unique and comprehensive dataset that practically covers all companies operating in Finland and being able to track Nokia employees, we provide new empirical evidence of knowledge spillovers from Nokia, the former global market leader in mobile devices. This is the first study that evaluates the impact of spillovers from Nokia, the archetype of a superstar tech-firm or champion, via its former employees. More important, being able to track employees directly potentially gives us better identification of knowledge spillovers in the labor markets. *Third*, our empirical results demonstrate the positive implications of public R&D funding policy with its large support for Nokia, in which the social return of R&D is higher than the private return (Ali-Yrkkö 2004), suggesting a knowledge spillover channel as another externality that drives the return wedge.

An extensive literature focuses on knowledge spillovers and their effects on economic growth and productivity. In general, the spillover literature can be divided into theoretical, qualitative, and quantitative studies (see, e.g., Cristo-Andrade and Ferreira 2020 for a review). More specifically, the empirical quantitative literature includes certain central themes, which can be generalized into the following categories: evidence and impact of knowledge spillovers (Fritsch and Franke 2004, Ornaghi 2006, Ibrahim et al. 2009, Isaksson et al. 2016, Keller 2021), spatial dimension and geography of knowledge spillovers (Jaffe et al. 1993, Audretsch and Feldman 2004, Döring and Schnellenbach 2006, Ponds et al. 2009), different channels and mechanisms (Filatotchev et al. 2011, Lee 2006, Qian 2018, Serrano-Domingo and Cabrer-Borrás 2017, Keller 2021), and levels of knowledge spillovers (Fallah and Ibrahim 2004, Niosi and Zhegu 2005, Fischer et al. 2009, Bournakis et al. 2018).

The present study relates to two of the above-mentioned themes, the channels and the effects of knowledge spillovers in the context of a "superstar" firm. Focusing on the spillover channels, labor mobility is closely linked to knowledge spillovers, and can be seen as one of the key mechanisms that generates the transmission of knowledge among organizations and firms (Arrow 1962, Møen 2005). By recruiting an employee, a firm obtains tacit knowledge and experience that the employee has obtained in his or her former positions in other organizations, which can contribute to the future performance of a recruiting firm. This effect could be magnified if the employee is hired from a large and high-performing firm or superstar firm. Regarding the impact of knowledge spillovers, there are a handful of studies focusing specifically on identifying labour mobility spillovers and their impact on the economic performance of hiring firms, finding positive effects (Cardoza et al. 2020, Maliranta et al. 2009, Stoyanov and Zubanov 2012).[2] In the context of superstar firms, the opening of "Million Dollar Plants" in a region has positive effects on the total factor productivity of incumbent plants in the same region (Greenstone et al 2010). In contrast, the demise of Kodak has resulted in the shrinkage of the Rochester, New York, high-tech cluster, which in turn has negatively affected the productivity of non-Kodak inventors in Rochester (Moretti 2021). Indeed, it is plausible that a large firm focused on technology and innovation and exposed to fierce international competition, such as Kodak or Nokia, could create an environment that is conducive to acquiring unique skills as well as creating knowledge (Romer 2018).[3] In the words of Bradford DeLong, it creates a community of excellence in engineering.

As the previous research reveals, the empirical identification of spillover effects remains challenging. Identification of spillovers and their effects involves at least the following two issues. The first issue concerns the direction of causality: does the knowledge spillover improve firm performance, or is it the selection of more skilled workers into high-performing firms? Second, when identifying the impact of spillovers, an appropriate spillover measure is needed. Current literature often relies on proxy information on "knowledge carriers" such as the cumulative sum of R&D workers or other specialists, their ratio to total workers, and their current or former workplace characteristics (see e.g., Møen 2005, Maliranta et al. 2009, Chang et al. 2016, Stoyanov and Zubanov 2012, and Serafinelli 2019).

We address the first issue by utilizing a quasi-experimental research design and causal inference techniques to analyze knowledge spillovers from a large high-tech firm through its departing employees. The empirical analysis is divided into a two-stage procedure, which combines the coarsened exact matching (henceforth CEM) approach developed by Iacus et al. (2011, 2012) with the difference-in-difference (diff-in-diff) estimation (Card and Krueger 1994 for the pioneering

[2] Cardoza et al. (2020) find that about 20 percent of workers move along the supply chain, creating considerable gains for hiring firms such as higher worker wages and productivity growth.

[3] This could be different in large firms that extract a monopoly rent thanks to a network effect (Aghion et al. 2021).

implementation of diff-in-diff).[4] CEM is used to match a group of treated firms with a group of non-treated firms with similar characteristic in order to minimize the selection bias. Causal inference rests on a quasi-experimental diff-in-diff methodology and heterogeneity in treatment intensity proxied by the exogenous spillovers from Nokia that determine firms' exposure to treatment.

To address the second issue about the spillover measurement, in the spirit of the Mincer approach (Mincer 1974) to the measurement of human capital accumulation and his concept of the returns to schooling, we operationalize the spillover measure by using a similar concept of the returns to experience. More specifically, in addition to a commonly used measure such as knowledge carriers, we use job tenure at an R&D-intensive firm (i.e., years of experience) as a measure of spillover. We thus study knowledge diffusion by modelling spillovers based on the returns to experience. Taking explicitly into account the intensity of treatment (e.g., years of job tenure at Nokia) helps us examine the impact of spillovers in greater detail and mitigate the endogeneity problem stemming from Nokia's workers being potentially more skilled in the first place.[5] While the diff-in-diff and CEM methods are widely used in economics, a few studies have used these approaches to explicitly account for the heterogeneous treatment intensity in the context of knowledge spillover effects.[6]

The rest of paper is structured as follows. In Section 2, we present the empirical motivation for this study. Section 3 presents an identification strategy and econometric specification used to estimate causal spillover effects. Section 4 describes our data sources. The main empirical results are presented in Section 5. Section 6 presents our concluding remarks.

III. EMPIRICAL BACKGROUND

The purpose of this section is to provide key stylized facts motivating the use of Nokia as a quasi-ideal case to study knowledge spillovers. Nokia, the flagship firm of the Finnish industry, has not only played a critical role in transforming the Finnish ICT industry, but has also influenced the society and Finland as a country (Ali-Yrkkö et al. 2000, Ali-Yrkkö and Hermans 2004). Following a meteoric rise, it went through a dramatic, and well documented, collapse with deep implications for the Finnish economy (Ali-Yrkkö et al. 2021a).

In the 1990s and early 2000s, Nokia was one of the world's largest mobile phone companies in terms of sales, volume, and market share (Pajarinen and Rouvinen 2013). One reason for Nokia's success is that it invested heavily in R&D activities during the past decades (Ali-Yrkkö and Hermans 2002, Ali-Yrkkö 2010, Ali-Yrkkö et al. 2021a).[7] For instance, annual R&D expenditure increased considerably from 1.8 billion euros in 1999 up to about 6 billion euros in 2008. However, the difficulties of Nokia started around 2008, when Google's operating system Android and Apple's

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[4] A few studies have employed a similar two-stage approach. For example, a study by Aghion et al. (2018) used conditional diff-in-diff approach to provide evidence on income spillovers from invention within the inventing firm.

[5] Nokia may hire more skilled workers and spillovers from Nokia may thus reflect their initial skills. The intensity of treatment such as years of job tenure at Nokia allows us to differentiate the learning at Nokia and thus knowledge spillovers from Nokia.

[6] For instance, a recent work of Fornaro et al. (2020) used a similar conditional diff-in-diff with a CEM weight-generation process to measure indirect effects of R&D subsidies. In addition to modelling treatment with a treatment dummy, as in the standard average treatment effect models, they also consider a specification in the spirit of a diff-in-diff analysis with heterogeneous treatment intensity.

[7] The total expenditure on R&D by Nokia during the period 1999–2014 is presented in Appendix A (Figure A.1).

iPhone attracted an increasing number of customers away from Nokia, which affected Nokia's net sales.[8] This contributed to a large number of workers leaving Nokia (see, Pajarinen and Rouvinen 2013, Ali-Yrkkö et al. 2021b). Approximately 25 thousand of Nokia employees left the company in Finland during the period 2008-2017, from which a bit more than fifty percent left to ICT and other companies in Finland and the rest found jobs in the public sector or elsewhere (Ali-Yrkkö et al. 2021b). In 2012 Nokia lost its status as the world's largest mobile phone manufacturer, and in 2014 Nokia exited the mobile device market by selling its mobile device operations to Microsoft.

To illustrate the demise of Nokia, the two leftmost columns of Table 1 present the stock of Nokia employees in Finland and the share of departing Nokia workers to the number of Nokia employees in 2004-2016, respectively. Other columns show the number of workers that left Nokia, and the breakdown of the number of departing workers between specialist and other positions.[9] The group of specialist positions includes senior officials and employees in research and planning. As can be seen from the table since 2010 the number of specialist workers leaving Nokia exceeded other departing workers. In 2010, the share of specialist to the total number of workers leaving the company constituted 88 percent, while in 2004 the share was only 28 percent. In total in 2004-2016, approximately 30 thousand employees left the company, from which 57 percent was workers from senior positions, in a relatively small economy where all other firms are dwarfed by Nokia.

Table 1. Worker Exits from Nokia (2004-2016)

Year	**Total Nokia employment**	**Share of departing workers in total nr of employees, %**	**Nr of departing workers**	**Nr of departing specialist workers**	**Nr of departing other workers**
2004	23,938	5.4	1,274	362	912
2005	24,452	5.9	1,427	528	899
2006	25,044	4.9	1,207	439	768
2007	24,661	8.6	2,147	944	1,203
2008	25,265	6.4	1,598	725	873
2009	22,763	12.5	3,000	1,340	1,660
2010	20,810	12.6	2,752	1,520	1,232
2011	18,178	15.9	3,108	1,878	1,230
2012	12,961	35.0	5,454	2,866	2,588
2013	10,967	21.9	2,630	1,819	811
2014	6,955	48.9	4,386	3,862	524
2015	6,705	7.6	521	385	136
2016	5,872	14.6	917	564	353

Having a unique dataset that allows us to track the former Nokia employees over time and link this information with the information on their new employers, we are able to study their role in the performance of recruiting firms and explore knowledge spillovers from Nokia.

[8] The net sales of Nokia in period 1999-2014 are reported in Appendix A (Figure A.2).

[9] Specialist workers are determined based on the classification of socio-economic groups. More specifically, specialist position refers to category 3 *Upper-level employees with administrative, managerial, professional, and related occupations*. Note, that this category includes a sub-category of R&D workers specified as *Senior officials and employees in research and planning*. (Statistics Finland, retrieved from: https://www.stat.fi/en/luokitukset/sosioekon_asema/sosioekon_asema_1_19890101/).

IV. IDENTIFICATION STRATEGY AND THE ECONOMETRIC SPECIFICATION

A. Identification strategy

The case of Nokia provides an optimal setting to study knowledge spillovers and their effects on the performance of firms that recruited former Nokia employees. However, certain issues must be considered. The first issue relates to the direction of causality. Putting it in the context of the present study, is it the former Nokia employees that contributed to the performance of hiring firms, or is it that the productive firms hired ex-Nokia employees? To estimate causal spillover effects, we resort to causal inference and treatment effect models. In contrast to the standard average treatment effect models that compare treatments or interventions in randomized experiments, the assignment to treatment in our case is far from random. In labor markets, hiring decisions involve matching between hiring firms and workers. It is not the case that former Nokia employees were randomly distributed among the hiring firms; rather, the process was based on a form of selection.[10]

To address this issue, the present study mimics an experimental research design in the context of a quasi-natural experiment using observational study data. Similar to a classic clinical experiment, a treatment is applied to a group of units, and the outcomes of the treatment intervention are observed. To determine the causal treatment effect, the outcomes for the treated units (i.e., the treated group) are compared to the outcomes for the non-treated units (i.e., the control group). In the context of the present study, a *treated unit* is a firm that hired former Nokia employees, among others, and a *non-treated unit* is a similar firm, which did not hire former Nokia workers. The term *treatment* denotes an exposure to the Nokia spillover through its former employees, and a *treatment effect* is an impact of the Nokia spillover. More specifically, the treatment group consists of firms that hired their first former Nokia employee during the treatment period 2004-2015. The years 2000-2003 are included in our analysis as the pre-treatment period, and the years 2016-2017 are the post-treatment period.

The second issue relates to the lack of a clearly defined measure for knowledge spillovers. To address this issue, we build on the well-established stream of human capital theory literature (see Mincer 1958, 1974, Becker 1962, 1964, 1967) to examine the impact of knowledge spillovers. Based on the insights of the Mincer approach to the measurement of human capital accumulation and his concept of the returns to schooling, we use a similar concept of the returns to experience and introduce a new measure of spillovers. More specifically, to measure knowledge accumulation, we use the years of experience at a high-tech firm (i.e., the years of job tenure at Nokia) as the years of schooling are used in Mincer's approach to capture the accumulation of human capital (see also Romer 2018).

In the standard treatment effect models all units in the treatment group receive exactly the same "amount" of treatment. In contrast, in this paper causal inference rests on a heterogeneous treatment intensity.[11] The intensity of treatment varies across the treated units: e.g., the number of former

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[10] However, this problem may have been mitigated in the context of a massive and sudden arrival of ex-Nokia employees on the job market.

[11] There is a large literature on heterogeneous treatment effects (see e.g., Heckman 2000; Heckman and Vytlacil 2007a, 2007b), but there is also an emerging stream of literature on heterogeneous treatment intensity (see e.g., Florens et al. 2008, Lopes da Fonseca 2017).

Nokia employees and their job tenure at Nokia differ considerably across hiring firms. Therefore, to control for the intensity of the treatment and for robustness purposes, we consider the following three alternative specifications/measures of the treatment intensity:

(i) Number of hired former Nokia employees,

(ii) Years of job tenure at Nokia (1990-2017)

(iii) Years of job tenure at Nokia during its growth (1990-2008) and decline (2009-2017) periods.

In specification (i), the intensity of Nokia treatment is represented by the number of former Nokia employees hired by treated firms. In specifications (ii) and (iii), intensity is modeled by job tenure at Nokia, measured as the total years of accumulated Nokia experience summed over the hired former Nokia employees.[12] We believe this would provide a more precise measure of human capital and knowledge spillovers from Nokia to the hiring firms. In specification (iii), we consider job tenure separately for two periods: the growth period in 1990-2008 and the decline period in 2009-2017. If workers are hired during the decline period, their job tenure is split into growth and decline periods. These periods are justified by the rise and fall of Nokia's net sales (see Appendix A): the purpose of this distinction is to test if spillover effects through hired former Nokia employees differ between the growth and decline phases of Nokia. Our conjecture is that working at Nokia during its golden years must have been a very different experience than working there during the most challenging times.

B. Econometric approach

Our estimation strategy employs a two-stage conditional difference-in-difference approach augmented by the intensity of treatment.[13] In the first stage, we implement the coarsened exact matching (CEM) procedure by Iacus et al. (2011, 2012), where each treated unit is matched with a control unit in order to minimize the selection bias. The main idea of matching is to find control units that are similar or close to treated ones with respect to their background characteristics. The matching is done without replacement on an annual basis for each cohort (i.e., years 2004-2015) one year prior to the treatment. At the matching stage, the data were temporarily coarsened into discrete strata within which exact matching was performed. The variables used to form the strata are firm size (net sales and employment), firm age, capital intensity (fixed assets/employment), human capital in firms (the average education level of workers), and industry. In addition, we performed matching on the dependent variables that appear in the second stage of the analysis and added a one-year proportional change of the dependent variable to account for its pre-treatment development. The matching was performed separately for two treated groups defined as *All hires* and *Specialist hires* (see the next section for details). In the sample *All hires*, treated units are the firms that hired any type of former Nokia employees. In the sample *Specialist hires*, treated units are the firms that recruited former Nokia employees to specialist positions. CEM produces weights that are utilized in the second stage of the analysis.

[12] Our measures of treatment intensity take into account the possibility that the treatment group (i.e., firms that hired their first former Nokia employee in 2004-2015) can hire more former Nokia employees during the post-treatment period 2016-2017. We start accumulating job tenure in 1990 due to the start date of our dataset.

[13] A similar model is used by Aghion et al. (2018) and Jaravel et al. (2018), but without a time-varying treatment. In our econometric specification, treatment intensity is modeled in similar fashion as in Fornaro et al. (2020).

In the second stage, the identification strategy relies on a quasi-experimental diff-in-diff methodology and heterogeneity in treatment intensity proxied by specifications (i)-(iii) described in the previous section. Diff-in-diff is a standard technique to estimate causal effects from observational data. Suppose we have a treatment (i.e., based on a spillover from Nokia) and we are investigating a particular outcome of this treatment, y_{it} for unit i in year t (e.g., labor productivity or net sales). Let D_i be a dummy indicating treatment status: it receives a value of one if i is in the treatment group, that is, it hired at least one former Nokia employee over a certain period, and zero otherwise. The treatment effect δ depends on the treatment intensity denoted by TI_{it}, which is measured by (i)-(iii) above. In the following diff-in-diff regression model, the intensity of the treatment is interacted with the treatment such that:

$$(1) \qquad \ln y_{it} = \alpha_i + \delta D_i \ln TI_{it} + \sum_{t=2000}^{2017} \alpha_t D_t + \sum_{j=1}^{k} \beta_j C_{itj} + \varepsilon_{it} .$$

The parameter δ, the diff-in-diff estimator, can be interpreted as the elasticity of the treatment effect (i.e., a one percent increase in the treatment intensity increases outcome y by δ percent). D_t is a yearly dummy variable and C_{itj} stands for other control variables that capture heterogeneity in units' characteristics.[14] The parameters $\alpha_i, \delta, \alpha_\tau, \alpha_t, \beta_j$ are the coefficients to be estimated.

To capture treatment effects by year, we also estimate the intensity effect by treatment year using:

$$(2) \qquad \ln y_{it} = \alpha_i + \sum_{\tau=-15}^{13} \delta_\tau D_{i\tau} \ln TI_{i\tau} + \sum_{t=2000}^{2017} \alpha_t D_t + \sum_{j=1}^{k} \beta_j C_{itj} + \varepsilon_{it} .$$

In contrast to equation (1) where parameter δ is a constant, in equation (2) the elasticity of the treatment effect depends on the treatment time, represented by the dummy variable $D_{i\tau}$, which is constructed separately for each firm i. Index τ spans all the possibilities in terms of the duration of treatment in years, while $D_{i\tau}$ is constructed such that for each firm i, value $\tau = 0$ corresponds to the first year of treatment during the period 2004-2015, and the negative values refer to the pre-treatment period. For example, for a treated firm i that hires its first former Nokia employee in year 2007, $D_{i\tau}$ is equal to zero for years 2004-2006 ($\tau = -3,-2,-1$), and $D_{i\tau}$ is equal to one during years 2007-2017 ($\tau = 0,1,\ldots,10$). Note if the treatment begins in 2015, the pre-treatment period is 15 years. Further, the treatment can continue until 2017, and thus the maximum duration of treatment is 13 years. For the firms in the control group, $D_{i\tau}$ is equal to zero in all years.

Note that δ estimated by equation (1) for different specifications (i)-(iii) (introduced in Section 3.1) of treatment intensity TI_{it} are not directly comparable across these specifications. To be able to compare the effects of different treatment intensities in terms of their magnitude, we compare the effects of different treatment intensities at the level of an average treatment, $\overline{TI}$, similar to the marginal effects in probit and logit models. We propose to measure the average spillover effect (ASE) as the percentage change in output due to the average intensity of treatment:

[14] Since CEM matching rarely identifies perfectly identical counterparts to the treated units, a number of control variables are included in the analysis in order to control for the remaining heterogeneity in the sample. The full set of the control variables is presented in Appendix B.

$$(3) \qquad ASE = 100\% \cdot \left[\left(F(C_{itj}, \varepsilon_{it}) \cdot \overline{TI}^{\delta} - F(C_{itj}, \varepsilon_{it}) \right) \Big/ F(C_{itj}, \varepsilon_{it}) \right] = 100\% \cdot \left[\overline{TI}^{\delta} - 1 \right], \text{ where}$$

$F(C_{itj}, \varepsilon_{it}) = \exp(\alpha_i + \sum_{t=2000}^{2017} \alpha_t D_t + \sum_{j=1}^{k} \beta_j C_{itj} + \varepsilon_{it})$ captures the impacts of control variables and the random error term. Evaluating $F(C_{itj}, \varepsilon_{it})$ at the mean implies that the average spillover effect only depends on the average intensity of treatment $\overline{TI}$ and the elasticity δ.

V. DATA

The analysis of this study is based on various population- and nationwide administrative datasets gathered by Statistics Finland. A key benefit of our register-based data is that it covers practically all working population and operating companies in Finland. Using unique workers' and firms' identifiers, we are able to link every worker with his or her employer at every observation-year. This feature of the data is crucial for identifying and analyzing workers' cross-firm mobility. In addition, Nokia has granted us permission to identify all its business units in the data, which allows us to trace all former Nokia employees.

The data includes information on characteristics of individuals and firms. Information on individuals' characteristics originates from tax and other administrative registers and is extracted from several Statistics Finland's FOLK panel data modules. It includes information on individuals' characteristics such as occupation, employer, education, gender, and age as recorded during the last week of each year. To construct a panel dataset on firms' characteristics and scale of business operations, we link the business register data with the financial statement data. The total sample covers 2000-2017. However, we limit our estimation sample to 2004-2015 to be able to observe firms' performance four years prior and two years after the recruitment of Nokia ex-employees (i.e., treatment). Thus, we dropped from the samples those firms that recruited former Nokia employees (971 firms that hired 3,282 employees) in 2000-2003 to account for the sufficient number of pre-treatment observation years.

To estimate the causal effect of Nokia treatment, we use samples of treated firms that received Nokia treatment by hiring former Nokia employees, among others, and control (or non-treated) firms that did not hire former Nokia employees. In our estimations we consider two samples of treated and control groups of firms. In a less restrictive setting, we use linked employer-employee data to compare treated and non-treated firms (henceforth *All hires* sample). Thus, there is no restrictions on the type of employees or their position. We also consider a more restrictive setting, where the treated group consists of firms that hired former Nokia employees to specialist positions only, and the control group includes firms that recruited workers to similar specialist positions (henceforth *Specialist hires* sample). To illustrate, Table 2 provides the summary statistics for some selected variables.[15] It reports average characteristics of treated and control firms in *All hires* sample before and after the CEM matching, and average characteristics of employees. All monetary values are deflated to the base year 2010.

Examining the average characteristics of *All hires* sample before CEM (the left side of the table), Nokia-treated firms are on average larger in size compared to the control firms (124.3 versus 14.7 employees). Note that this gap is much smaller after CEM: while the average treated firm has about 55 workers, the average control firm has about 33 workers. A treated firm has on average higher

[15] See Appendix B for definitions of the control variables used in the estimations.

values of net sales, value added, labor productivity, and operating profit compared to those of an average control firm. The composition of industries in the "after matching" sample shows that both treated and control firms are more likely to be in *Other services* (38 and 51 percent, respectively). In addition to *Other services*, the treated firms are in *ICT services* (21 percent), *Non-ICT business services* (17 percent), and *Non-ICT manufacturing* (17 percent). While there is a reasonable match found in groups of treated and control firms in *Non-ICT manufacturing* and *Non-ICT business services*, there are some differences between the shares of treated and control firms in *ICT services* (21 percent treated firms versus 5 percent of control firms) and *Other services* (38 percent of treated firms versus 51 percent of control firms).

Turning to workers' composition in the hiring firms, the characteristics between the treated and control groups of firms are rather similar, especially workers' age, years of education, and gender composition. The one characteristic where a slight difference exists is the share of highly educated workers, which is somewhat lower within the control firms. It seems that the treated firms are more likely to have higher educated workers: about 16 percent of workers in the treated group of firms have an academic degree compared to 12 percent in the control group of firms. Other interesting observation in Table 2 is that about 90 percent of the treated firms is located in the same region as Nokia compared to the share of 67 percent of the control firms.

VI. EMPIRICAL RESULTS

In this section, we present our main empirical findings on causal effects of spillovers from Nokia.[16] We begin with the estimated treatment effects that describe the marginal impact from treatment intensities (i)-(iii) on the performance of treated firms. To examine the impact of the intervention, the empirical analysis focuses on five outcome variables related to firm performance such as employment, value added, labor productivity, net sales, and operating profit of firms (EBIT). In order to compare the effects from different specifications, we then show the average spillover effects, which represent a percentage change in firm performance associated with average treatment intensity. Lastly, we examine the estimated spillover effects by treatment year.

A. Marginal or partial spillover effects

Table 3 shows the results estimated using the sample of *All hires* for the five outcome variables. In the estimations based on *All hires* sample we compare treated firms that recruited former Nokia employees to non-treated firms that recruited non-Nokia employees. The table provides coefficient estimates for different specifications of treatment intensity (i)-(iii), described in Section 3.[17] In specification (i), treatment intensity is measured by the number of ex-Nokia employees, while in specifications (ii) and (iii) by the years of job tenure. The estimated coefficients in Table 3 represent

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[16] The parallel trends in both treatment and control groups in the period prior to the treatment is an essential assumption for the diff-in-diff method. Appendix C includes the figures of common trends that illustrate the averages of the outcome variables up to three years before the treatment time in the treated and control groups. The trends of the group averages before the treatment period do not substantially deviate from each other. While there are some differences in absolute values, they are controlled for in the diff-in-diff regressions.

[17] Having five outcome variables and three specifications of treatment intensity, we estimate fifteen specifications of equation (1) for each sample.

Table 2. Means and standard deviations for the treated and control groups before and after CEM, calculated either one year prior to the recruitment of the first former Nokia employee or being in the control group.

	Before CEM				After CEM			
	Treated group		Control group		Treated group		Control group	
	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
Average firm's characteristics								
Nr of workers	124.33	(376.62)	14.70	(46.52)	55.23	(97.48)	32.46	(95.10)
Net sales, mill. €	38.76	(214.43)	3.10	(17.14)	13.56	(45.34)	7.95	(36.09)
Value added, mill. €	9.51	(36.78)	0.84	(3.37)	3.98	(7.99)	1.98	(5.94)
Labor productivity, 10^3 €	88.30	(346.25)	56.24	(116.67)	85.99	(363.71)	67.21	(96.51)
Operating profit, 10^3 €	2,347	(20,532)	164.81	(1,393)	784.13	(3,439)	285.7	(2,022)
Fixed assets per workers, 10^3 €	187.55	(1,467)	99.05	(1,608)	93.62	(817.16)	105.88	(670.38)
Share of firms operating in the same region as Nokia:	0.90	(0.30)	0.61	(0.49)	0.90	(0.30)	0.67	(0.47)
Share of firms according to ownership (scale 0-1):								
Foreign-owned firms	0.18	(0.38)	0.03	(0.16)	0.16	(0.37)	0.07	(0.25)
State-owned firms	0.03	(0.18)	0.01	(0.10)	0.02	(0.14)	0.02	(0.15)
Share of innovators:	0.12	(0.20)	0.04	(0.12)	0.13	(0.21)	0.10	(0.21)
Share of firms from industries (scale 0-1):								
ICT manufacturing	0.01	(0.11)	0.00	(0.05)	0.01	(0.12)	0.00	(0.04)
Non-ICT manufacturing	0.18	(0.39)	0.14	(0.34)	0.17	(0.37)	0.13	(0.34)
ICT services	0.18	(0.39)	0.02	(0.16)	0.21	(0.40)	0.05	(0.22)
Non-ICT business services	0.16	(0.37)	0.09	(0.29)	0.17	(0.38)	0.19	(0.39)
Other services	0.39	(0.49)	0.55	(0.50)	0.38	(0.49)	0.51	(0.50)
Other industries	0.07	(0.25)	0.20	(0.40)	0.06	(0.24)	0.12	(0.32)
Age of firm, years	15.32	(15.18)	11.07	(10.90)	13.8	(11.8)	13.4	(11.5)
Average worker's characteristics								
Average education, years	13.55	(1.74)	12.10	(1.57)	13.6	(1.8)	13.4	(1.7)
Average age, years	38.11	(6.02)	37.48	(6.98)	37.7	(6.1)	38.9	(6.8)
Share of females	0.36	(0.27)	0.34	(0.34)	0.35	(0.27)	0.39	(0.34)
Education shares:								
Academic	0.16	(0.21)	0.05	(0.13)	0.16	(0.21)	0.12	(0.20)
College	0.70	(0.19)	0.71	(0.23)	0.70	(0.20)	0.76	(0.22)
Lower	0.13	(0.14)	0.24	(0.23)	0.13	(0.15)	0.12	(0.16)
Age shares:								
16-24	0.11	(0.15)	0.17	(0.20)	0.11	(0.15)	0.11	(0.16)
25-34	0.33	(0.21)	0.27	(0.22)	0.34	(0.22)	0.29	(0.24)
35-44	0.27	(0.16)	0.25	(0.20)	0.27	(0.16)	0.26	(0.21)
45-54	0.19	(0.14)	0.20	(0.19)	0.19	(0.15)	0.22	(0.20)
55-70	0.10	(0.12)	0.10	(0.15)	0.10	(0.12)	0.12	(0.16)
Number of observations	1,403		51,698		1,214		40,197	

the estimated percentage change in output variable for a percentage change in treatment intensity variable.

We find empirical evidence supporting the existence of positive spillovers from Nokia on firm performance. More than half of the results are statistically significant. For most of the specifications, there are significant positive effects on employment (except for negative effect from job tenure in the growth period), value added, net sales, and operating profit. In all specification, the spillover effect is the highest on operating profit and net sales. However, the coefficient estimates on labor productivity are insignificant.

Table 3. Treatment effects estimated on the sample of *All hires*.

Treatment intensity	Employment	Value added	Labor prod.	Net sales	Oper. profit
(i) Nr of Nokia ex-employees	0.020	0.071**	0.019	0.077	0.110**
	(0.014)	(0.030)	(0.024)	(0.053)	(0.044)
(ii) Job tenure, total	0.009*	0.035***	0.012	0.043**	0.046***
	(0.005)	(0.011)	(0.009)	(0.019)	(0.016)
(iii) Job tenure, growth period	-0.019***	-0.004	0.004	0.013	0.015
	(0.006)	(0.014)	(0.011)	(0.024)	(0.023)
Job tenure, decline period	0.071***	0.101***	0.022	0.078*	0.085**
	(0.011)	(0.024)	(0.019)	(0.041)	(0.039)

Notes: Diff-in-diff regression results from the estimation of equation (1) using the sample of *All hires*. The left column lists different measures for the treatment intensity (i)-(iii). The estimated coefficients represent the elasticity of dependent variable (i.e., employment, value added, labor productivity, net sales, and operating profit) with respect to the treatment intensity variable (i)-(iii). Thus, each cell provides the estimate from a different regression. Asterisks *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parenthesis below the estimated coefficients.

For specification (i), we find that a one percentage change in the number of hired ex-Nokia employees on average causes about 0.08 percent and 0.11 percentage change in net sales and operating profit, respectively. There is also a positive spillover impact on value added and employment. A one percentage change in treatment intensity causes 0.02 and 0.07 percent change in employment and value added, respectively. The estimated coefficients for specification (ii) also reveal larger spillover effects on net sales and operating profit, followed by the impact on value added. In this case, a one percentage change in treatment intensity results in 0.05, 0.04, 0.04, and about 0.01 percentage change in operating profit, net sales, value added, and employment, respectively. In both specifications (i) and (ii), we do not find significant empirical evidence of spillovers on labor productivity.

In specification (iii), where job tenure at Nokia is considered separately for periods of Nokia's growth and decline, we find some differences in the estimated spillover effects. We consistently observe that tenure at declining Nokia has positive and higher spillover impact on the outcomes of interest compared to the impact of tenure at growing Nokia. For instance, a one percent change in intensity of "tenure at declining Nokia" results in 0.07 percent change in employment, whereas a one percent change in intensity "tenure at growing Nokia" results in 0.02 percentage decrease of employment. The largest significant positive spillover effect during the decline period is on value added – a one percentage change in job tenure of Nokia workers during its decline period causes a 0.1 percentage change in value added. These results suggest that Nokia spillovers from employees who have worked at Nokia during its challenging years are larger than the experience obtained during Nokia's growth times. These results potentially capture the fact that the majority of workers left Nokia during the decline period, helping identify a much larger spillover effect on other firms.

Table 4 provides the regression results for an alternative sample of *Specialist hires*. In this sample, the groups of treated and non-treated firms include only those firms that recruited former Nokia employees and non-Nokia employees for specialist positions. Thus, firms that hired ex-Nokia/non-Nokia employees for other than specialist positions are not included in this sample. Similar to the results presented above, Table 4 shows the results for the same five outcome variables and specifications (i)-(iii) using the *Specialist hires* sample.

Table 4. Treatment effects estimated on the sample of *Specialist hires*.

Treatment intensity	Employment	Value added	Labor prod.	Net sales	Oper. profit
(i) Nr of Nokia ex-employees	0.014	0.066**	-0.000	-0.005	0.019
	(0.017)	(0.032)	(0.022)	(0.068)	(0.047)
(ii) Job tenure, total	0.001	0.026**	0.001	0.012	0.001
	(0.006)	(0.012)	(0.009)	(0.024)	(0.019)
(iii) Job tenure, growth period	-0.037***	-0.012	-0.006	-0.008	-0.032
	(0.008)	(0.016)	(0.012)	(0.030)	(0.026)
Job tenure, decline period	0.092***	0.095***	0.016	0.043	0.083*
	(0.014)	(0.027)	(0.020)	(0.052)	(0.044)

Notes: Diff-in-diff regression results from the estimation of equation (1) using the sample of *Specialist hires*. The left column lists different measures for the treatment intensity (i)-(iii). The estimated coefficients represent the elasticity of dependent variable (i.e., employment, value added, labor productivity, net sales, and operating profit) with respect to the treatment intensity variable (i)-(iii). Thus, each cell provides the estimate from a different regression. Asterisks *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are reported in parenthesis below the estimated coefficients.

The results of the average partial effects estimated on *Specialist hires* sample are less statistically significant for labor productivity, net sales and operating profit regressions. However, the results suggest evidence of positive spillovers on some of the outcomes of interest. Statistically significant positive spillovers are still observed on employment and value added. Further, for employment and value-added regressions, coefficient estimates are of a similar magnitude as the results obtained using the sample of *All hires*.

More specifically, in specification (i), a one percent change in treatment intensity accounts for about 0.07 percent change in value added. Regarding specification (ii), a one percent change translates into about 0.03 percent change in value added. Finally, in specification (iii), the results are in line with the results estimated using the sample *All hires* supporting the differential impact of Nokia spillovers between the expansion years and the contraction ones.

Taken together, comparing the estimated partial effects obtained using both samples and different specifications for the intensity of treatment, the findings are particularly consistent for spillovers on employment and value added of hiring firms. However, there is little evidence on the existence of spillover effects on labor productivity, while the evidence of statistically significant spillovers on net sales and operating profits of firms is somewhat less conclusive and is only evident in the sample of *All hires*. Even though we do not observe a direct spillover impact on labor productivity, it could be due to positive impact on both employment and value added, potentially offsetting the impact of spillovers on labor productivity.

B. Average spillover effects

From the results presented above, the impact of spillovers from Nokia on hiring firms' performance is found to be generally positive. However, the marginal or partial treatment effects presented in the previous section are not directly comparable across different specifications of the treatment intensity. In the following, we compute ASE using equation (3) that represents the magnitude of knowledge spillovers from Nokia on the performance of firms that hired former Nokia employees. More specifically, we use the average treatment intensities of specifications (i)-(iii) reported in Appendix D and the coefficient estimates reported in Tables 3 and 4. The figures in Tables 5 and 6 are the average spillover effects obtained using the samples of *All hires* and *Specialist hires*, respectively. The estimates indicate the percentage change in employment, value added, labor productivity, net sales, and operating profits due to the average intensity of the treatment. In other words, each value in the table indicates the average magnitude of spillovers on firm performance.

In the sample of *All hires* (Table 5), regardless of whether the treatment is modeled by the number of former Nokia employees or the years of job tenure, the largest spillover impact is on operating profit. For example, the average treatment represented by the number of former Nokia employees (2 former Nokia employees) implies an increase in operating profit by about 8 percent while the effect is 14 percent if measured by the years of job tenure at Nokia (17 years of Nokia experience). We find that the spillover effects are almost two times larger when modelling knowledge spillovers by the years of job tenure. In specification (ii), the average treatment of job tenure, which varies between about 17 and 20 years of Nokia experience, suggests an increase in employment, value added, net sales, and operating profit by about 3, 10, 13, and 14 percent, respectively. In specification (iii), the average spillover effects from Nokia modeled by job tenure during Nokia's decline period are positive and have the largest effects on the performance of hiring firms compared to other specifications. For instance, the average treatment represented by the years of job tenure during the decline period (about 6 years of work experience at Nokia in 2009-2014) implies a 20 percent increase in value added of a treated firm that received the average treatment.

Table 5. The average spillover effects from Nokia on firm performance for the sample of *All hires* (in percent).

Treatment intensity	Employment	Value added	Labor prod.	Net sales	Oper. profit
(i) Nr. of Nokia ex-employees	1.59	**5.21**	1.37	5.12	**8.00**
(ii) Job tenure, total	**2.61**	**10.43**	3.47	**12.79**	**14.05**
(iii) Job tenure, growth period	**-5.26**	-1.02	1.02	3.37	4.01
Job tenure, decline period	**15.19**	**20.40**	4.04	**14.53**	**17.28**

Notes: The results obtained with equation (3) using the sample of *All hires*. The left column lists different measures for the treatment intensity (i)-(iii). Estimated values represent a percent change in dependent variable (i.e., employment, value added, labor productivity, net sales, and operating profit) caused by an average treatment intensity in the treated group of firms in comparison to the control group of firms. The cell values based on statistically significant estimated coefficients in Table 3 are shown in bold.

In the restricted sample of *Specialist hires* (Table 6), the largest spillover effect is on value added. The average treatment intensity in terms of number of ex-Nokia employees (about 3 hired former Nokia employees) implies an increase in employment by almost 7 percent, whereas an average treatment intensity measured by the years of Nokia tenure (about 25 years of work experience at

Nokia in 1990-2008) contributes to an increase in employment by about 9 percent. The spillovers on value added are of similar magnitude for specifications (i) and (ii). Similar to the results of *All hires* (Table 5), in specification (iii), the average treatment intensity represented by job tenure at Nokia during its decline period has positive spillover effects on performance of hiring firms. The largest spillovers are observed in employment (21 percent), value added (22 percent), and operating profit of firms (18 percent).

Table 6. The average spillover effects from Nokia on firm performance for the sample of *Specialist hires* (in percent).

Treatment intensity	Employment	Value added	Labor prod.	Net sales	Oper. profit
(i) Nr. of ex-Nokia employees	1.30	**6.69**	-0.03	-0.47	1.65
(ii) Job tenure, total	0.37	**8.62**	0.40	3.78	0.45
(iii) Job tenure, growth period	**-10.35**	-3.45	-1.74	-2.34	-8.79
Job tenure, decline period	**20.79**	**22.26**	3.57	9.29	**17.92**

Notes: The results obtained with equation (3) using the sample of *Specialist hires*. The left column lists different measures for the treatment intensity (i)-(iii). Estimated values represent a percent change in dependent variable (i.e., employment, value added, labor productivity, net sales, and operating profit) caused by an average treatment intensity in the treated group of firms in comparison to the control group of firms. The cell values based on statistically significant estimated coefficients in Table 4 are shown in bold.

The results of the average spillover effects show that the magnitude of the spillover varies depending on the specification of the treatment. Various specifications and samples broadly show important Nokia spillovers. However, there are also some differences. For instance, using the less restrictive sample *All hires* and modeling treatment by the number of former Nokia employees and the total job tenure at Nokia, the results reveal that regardless of the treatment specification the highest spillover impact from Nokia is on operating profit of firms. In a more restrictive sample *Specialist hires*, the results suggest positive spillovers of similar magnitude from the same treatment specifications on value added.

C. Marginal spillover effects over time

To capture spillover effects by treatment year on the same five outcome variables, we estimate the treatment intensity effects using equation (2). Figure 1 illustrates the estimated effects of the treatment represented by job tenure (specification (ii)) using the sample of *All hires*. The results for the specification (ii) on the sample of *Specialist hires* and the results for the specification (i), where the treatment intensity is represented by the number of former Nokia employees, on both samples are presented in Appendix E. In Figure 1, the horizontal axis represents the duration of the treatment in years (i.e., the years after the first former Nokia employee was hired). The maximum duration of the treatment is 13 years and year 0 is the first treatment year. The vertical axis indicates the spillover effects that depend on the treatment time. The solid lines are the estimated elasticities of the treatment effect and the dotted lines are the 95 percent confidence intervals. As expected, the confidence intervals are wider with an additional treatment year. For example, in the treatment year 13, there are less observations compared to the first year after the treatment. Only those treated firms that recruited former Nokia employees in year 2004 are present in the 13th year of the treatment.

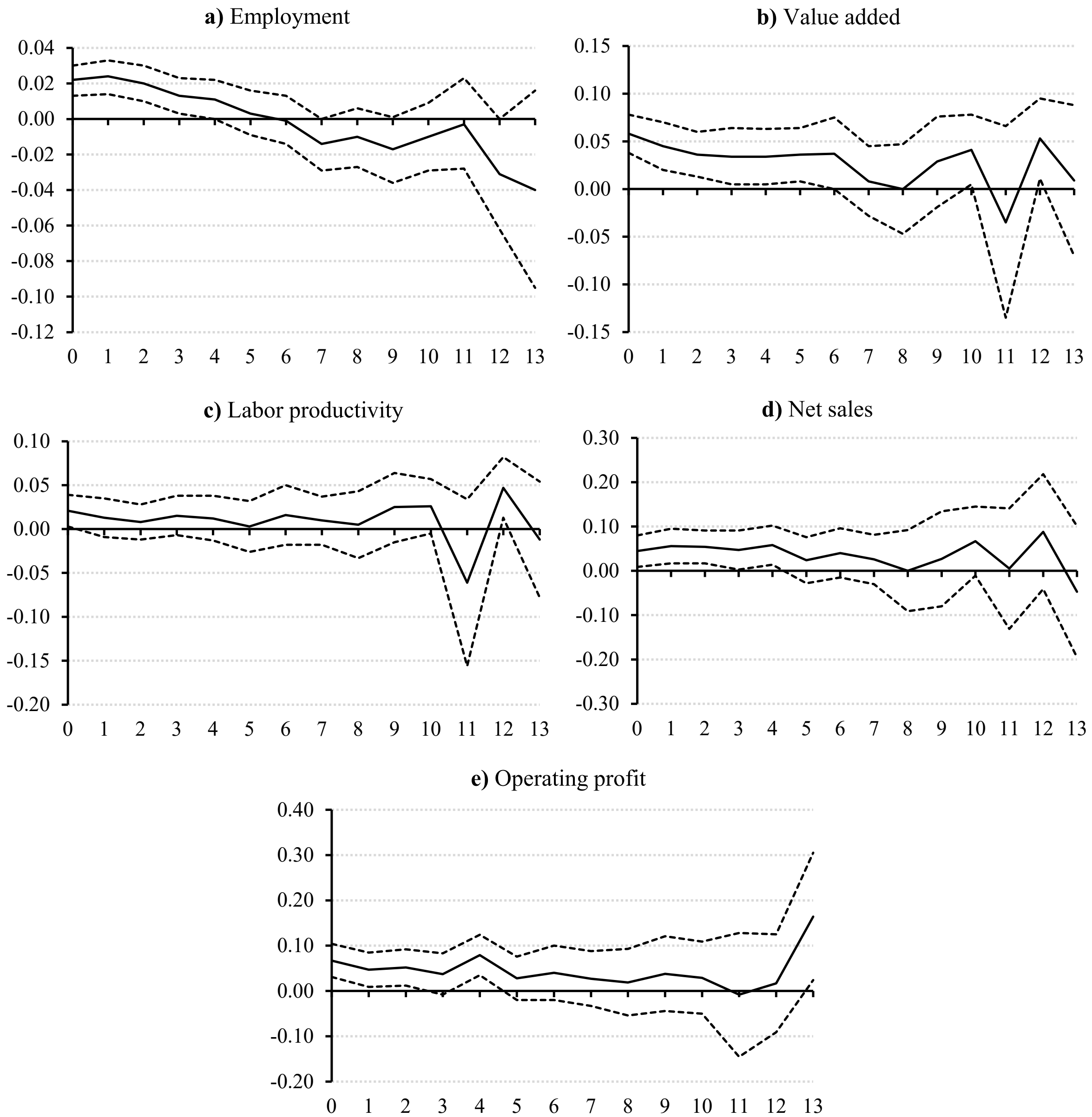

Figure 1 Spillover Effects by Treatment Year Estimated on the Sample of All Hires.

The regression results from the estimation of equation (2) using job tenure as a measure of treatment intensity (specification (ii)). The treatment effects are estimated on five outcome variables: a) employment, b) value added, c) labor productivity, d) net sales, and e) operating profit.

Figure 1(a) shows that the spillover effect on employment is immediate and is the highest one year after the treatment (a one percentage change in treatment intensity results in about 0.02 percent change in employment in the treatment year 1). However, the treatment effect decreases over time and become statistically insignificant about four years after the treatment. The spillover effects on value added fluctuate but stay positive and statistically significant for about 6 years. The largest treatment effect on value added is observed immediately after the treatment (0.06 percent in treatment year 0). The treatment effect on labor productivity is at its peak in the 12th treatment year: a one percent change in intensity of "tenure at Nokia" results in 0.05 percent change in labor productivity at the 1% significance level. Statistically significant positive spillover on net sales is observed until the 4^{th} treatment year. Regarding operating profits of hiring firms, the spillover effect from treatment becomes statistically significant again 13 years after firms initially hire former Nokia employees (0.31 at the 5% significance level). The results presented in Figure 1 suggest that the duration of spillovers from Nokia may have a lasting impact on firm performance long after the treatment took place (up to 13 years after the treatment).

VII. Conclusion

The literature on knowledge spillovers is vast but the present study uses a unique database of the mobility of former Nokia employees in Finland to estimate the impact of knowledge spillovers. Using matched employer to employee data set that includes the information on former Nokia employees and information on their employment, we estimate causal spillover effects on the performance of firms that hired former Nokia employees. The identification strategy rests on a quasi-experimental difference-in-differences methodology and heterogeneity in treatment intensity. Knowledge spillovers in this study are captured as a treatment administered to treated firms and assessed on key outcomes of firm performance.

The empirical analysis in this study contributes to the existing literature as follows: (i) It is the first study that identifies knowledge spillovers from Nokia – a superstar high-tech firm – in Finland by utilising a unique data set that allows us to link the individual information of employees and employers and, more importantly, to track the former Nokia employees over time; and (ii) while similar studies on spillovers via labour mobility usually rely on the number of workers as a measure of knowledge spillovers, we also model it more explicitly by the years of Nokia experience (i.e. job tenure), further mitigating potential endogeneity problems related to capturing the effect of a potential initial skills' premium among Nokia workers rather than spillovers from working at Nokia for a certain time (that is, the effect of more skilled workers being hired by Nokia in the first place, who then move onto other firms).

Our findings have an important policy implication. Knowledge spillovers are widely used as an argument for public R&D funding for private companies (Arrow 1962, Griliches 1998). In parallel, there is a "romantic" view of SMEs, which are supposed to be more vibrant and innovative, but the discussion as to the need for some of these SMEs to grow and become larger enterprises is often overlooked. In contrast, our study suggests that large tech firms, at least those operating in a highly competitive global market, may create a skill and learning agglomeration effect, which is transmitted through labor mobility spillovers. In other words, a relatively large and inter-disciplinary community at the nexus of innovation and industrial production creates a unique learning environment for workers that can then be transferred to other firms. Due to these knowledge spillovers, the social return of R&D is likely to exceed the private return even more. Without public R&D funding, some R&D projects with positive impact on society would not be carried out because they would be unprofitable. Notwithstanding that Nokia financed the great majority of its R&D, the company also received substantial public R&D funding. Our results suggest that society benefits from Nokia's former employees even though they may not work at Nokia any longer.

To conclude, our results suggest that there is significant impact of knowledge spillovers from Nokia on the growth performance of the firms hiring former Nokia employees (in terms of employment, values added, sales and net operating profits). The positive spillover effect is especially evident when we consider the experience of employees that were employed at Nokia during its decline period, essentially when many workers left the firm. This could be interpreted as a sign that the fall of Nokia was perhaps not necessarily related to a degradation of its learning environment and knowledge accumulation in comparison with other factors, such as the strategic decisions taken and the appetite for risk and innovation by managers.

In terms of the spillover magnitude, we find that the average spillover effect varies depending on the chosen measure of spillover. The estimations using the less restrictive sample indicate the largest spillovers from Nokia on net sales and operating profit of hiring firms, while the estimations using the more restrictive sample indicate that Nokia spillovers have largest impact on firms' employment and value added. Finally, our results demonstrate that identification of the impact of knowledge spillovers and their magnitude vary depending on the choice of the control group of firms and the choice of the specification for the treatment. By considering different specifications for Nokia treatment and estimating treatment effects in two samples, we obtain broadly robust positive estimates of Nokia spillovers on firm performance.

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Appendix A. Nokia's expenditure on R&D and the net sales in 1999–2014.

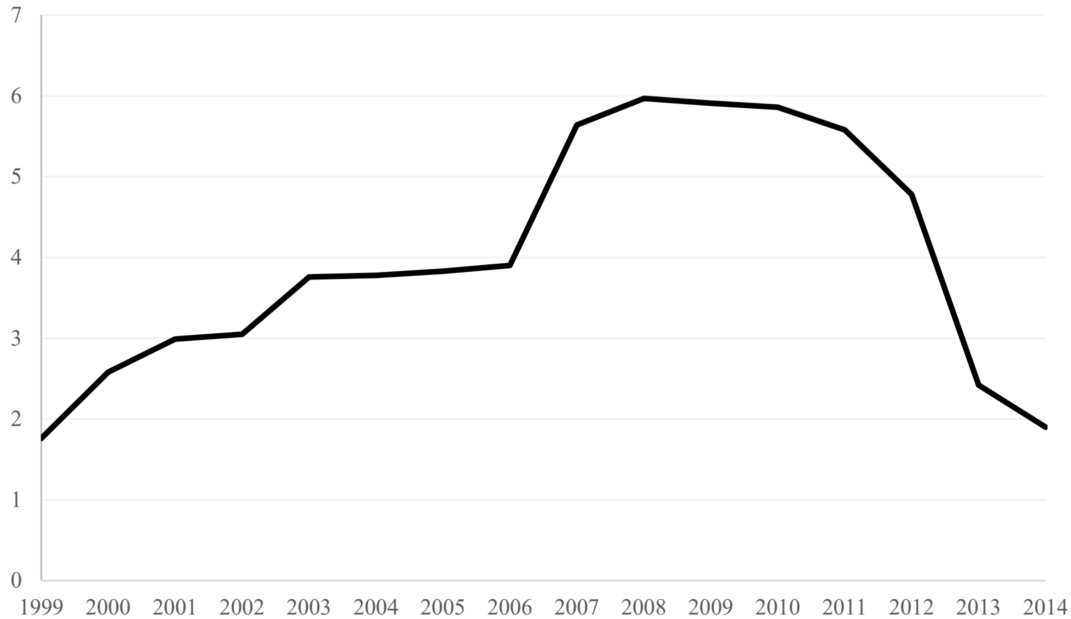


Figure 2 The Total Expenditure on R&D by Nokia in 1999–2014, in Billion Euros (in Current Prices).

Source: authors' calculations based on Nokia's annual reports.

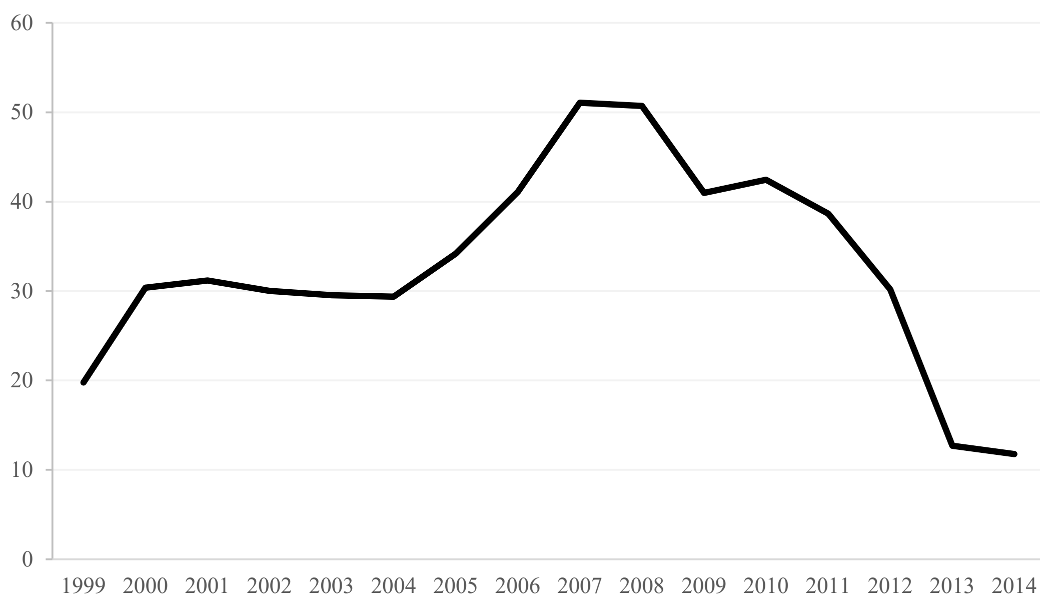


Figure 3 The Net Sales of Nokia in 1999-2014, in Billion Euros (in Current Prices).

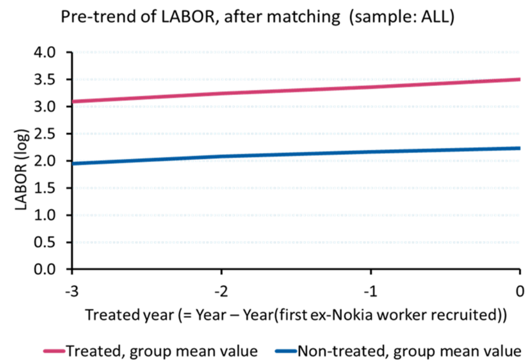
Source: authors' calculations based on Nokia's annual reports.

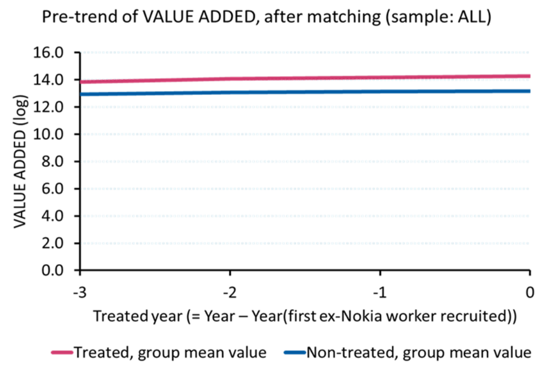
Appendix B. The control variables included in the analysis.

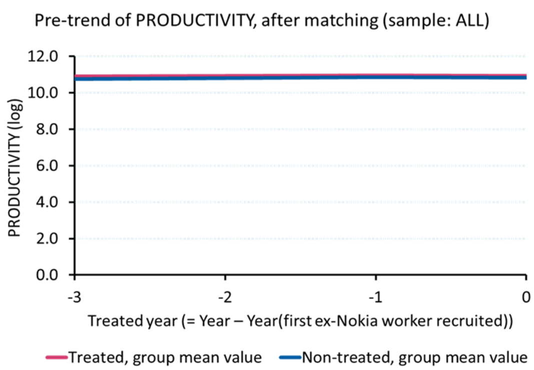
Variable	Description
Other hires	The logarithm of the cumulative sum of hired non-Nokia workers
Other specialist hires	The logarithm of the cumulative sum of non-Nokia workers hired for specialist positions[18]
Capital to labor ratio	Logarithm of the ratio of fixed assets to employment
Firm age	Logarithm of firm's age, years
Firm size dummies:	
EMP_FIRM_10_49	Dummy: firm has 10-49 workers (omitted group is size class 0-9 workers)
EMP_FIRM_50_249	Dummy: firm has 50-249 workers
EMP_FIRM_250_+	Dummy: firm has 250+ workers
Education level of employees:	
Academic	Share of academic-level educated workers, (scale 0-1, omitted group is the share of less than college-level educates workers)
College	Share of college-level educated workers, (scale 0-1)
Age of employees:	
AGE_EMP25_34	Share of 25-34 years old workers, (scale 0-1, omitted group is the share of 16-24 years old workers)
AGE_EMP35_44	Share of 35-44 years old workers, (scale 0-1)
AGE_EMP45_54	Share of 45-54 years old workers, (scale 0-1)
AGE_EMP55_70	Share of 55-70 years old workers, (scale 0-1)
Share of R&D-workers	Share of R&D-workers based of socio-economic classification (class 32 Senior officials and employees in research and planning), scale 0-1
Share of females	Share of females, scale 0-1
FOREIGN_OWNED	Dummy for foreign-owned firms
GOV_OWNED	Dummy for state-owned firms
Same region	Dummy: receives a value of one if a firm is in the same geographical region as Nokia's business unit
Industry	Industry dummy based on NACE Rev. 2 (at the 2-digit level of industry classification)
Region	Dummy for the region (21 regions)

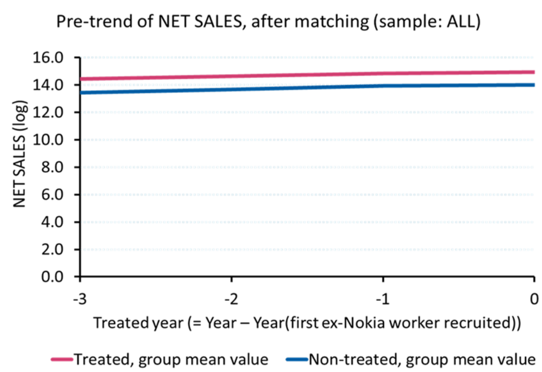
[18] Specialist position refers to Category 3 in the Classification of Socio-economic Groups 1989 (Statistics Finland). This category includes upper-level employees with administrative, managerial, professional, and related occupations. For further information on the Classification of Socio-economic Groups 1989 see: https://www.stat.fi/en/luokitukset/sosioekon_asema/sosioekon_asema_1_19890101/.

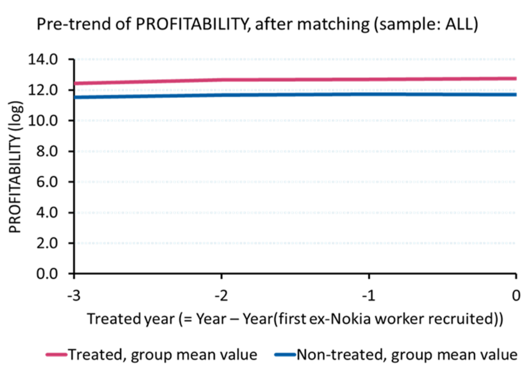
Appendix C. Pre-trends of outcome variables prior to the treatment time.











Appendix D. Average treatment intensities for specifications (i)-(iii) for *All hires* and *Specialist hires* samples (in units).

Treatment	Employment	Value added	Labor prod.	Net sales	Oper. profit
All hires					
i) Nr. of Nokia ex-employees	2.21	2.04	2.02	1.91	2.01
ii) Job tenure, total	19.59	17.37	17.16	16.48	17.14
iii) Job tenure, growth period	15.95	14.39	14.18	13.77	14.27
Job tenure, decline period	7.32	6.29	6.29	5.68	6.54
Specialist hires					
i) Nr. of Nokia ex-employees	2.57	2.67	2.71	2.59	2.40
ii) Job tenure, total	23.69	24.79	25.18	24.22	21.75
iii) Job tenure, growth period	19.39	20.26	20.57	19.82	18.12
Job tenure, decline period	7.82	8.38	8.54	8.06	7.28

Appendix E. Spillover effects over time.

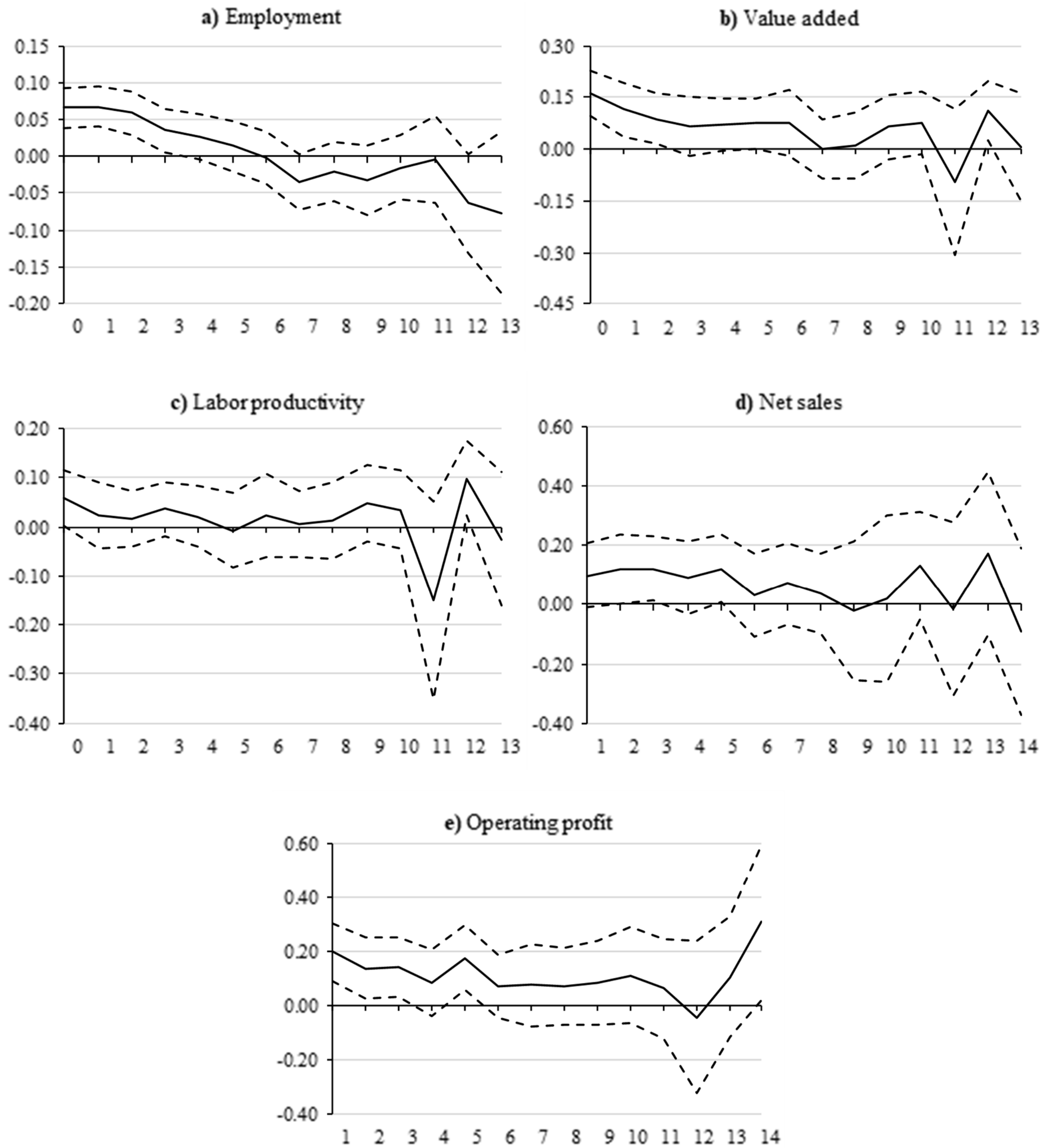


Figure 4 Spillover Effects by Treatment Year Estimated on the Sample of All Hires.

The regression results from the estimation of equation (2) using the number of former Nokia employees hired by treated firms as a measure of treatment intensity (specification (i)). The elasticities of the treatment effects are estimated on five outcome variables: a) employment, b) value added, c) labor productivity, d) net sales, and e) operating profit.

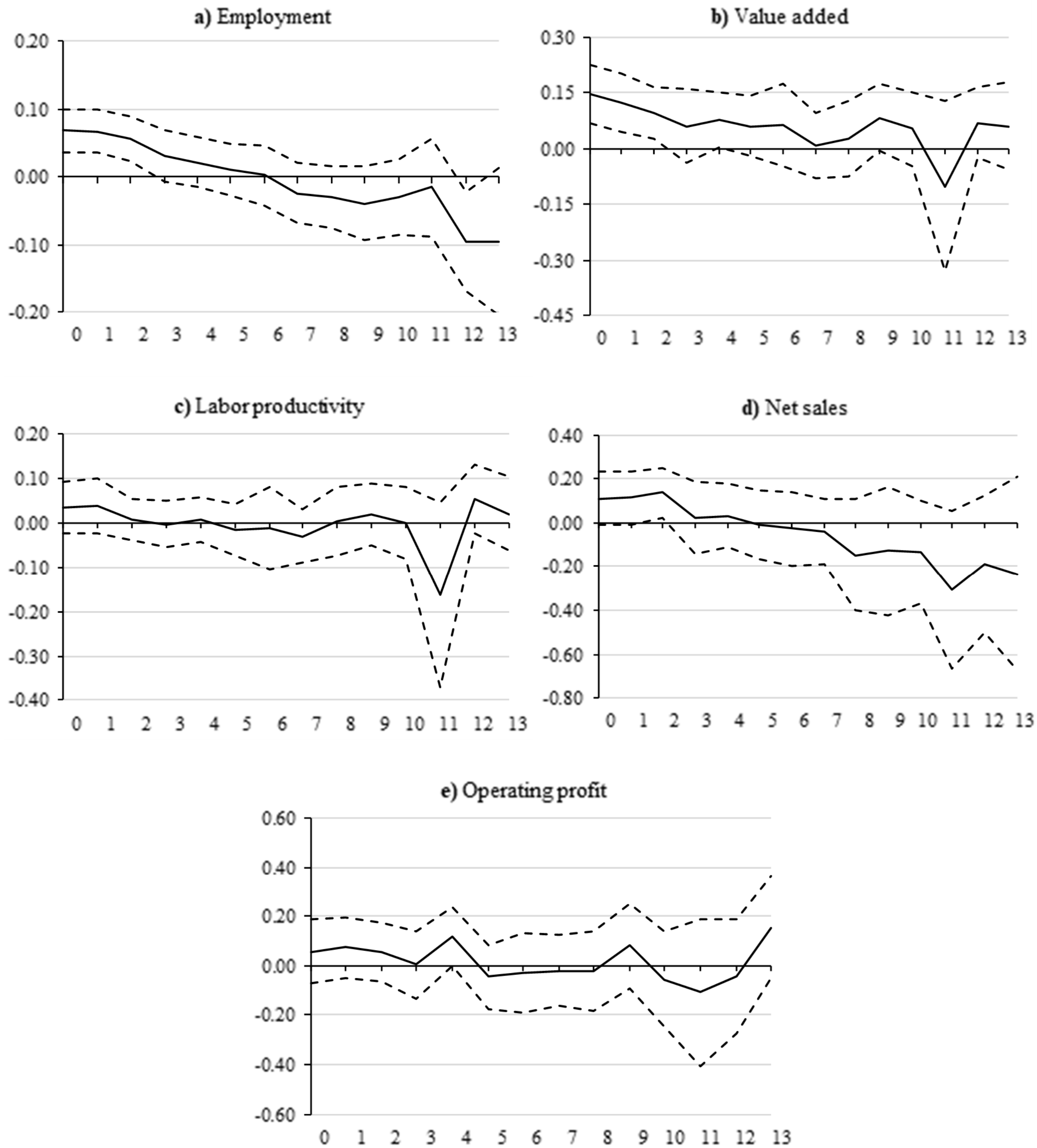


Figure 5 Spillover effects by treatment year estimated on the sample of Specialist hires.

The regression results from the estimation of equation (2) using the number of former Nokia employees hired by treated firms as a measure of treatment intensity (specification (i)). The elasticities of the treatment effects are estimated on five outcome variables: a) employment, b) value added, c) labor productivity, d) net sales, and e) operating profit.

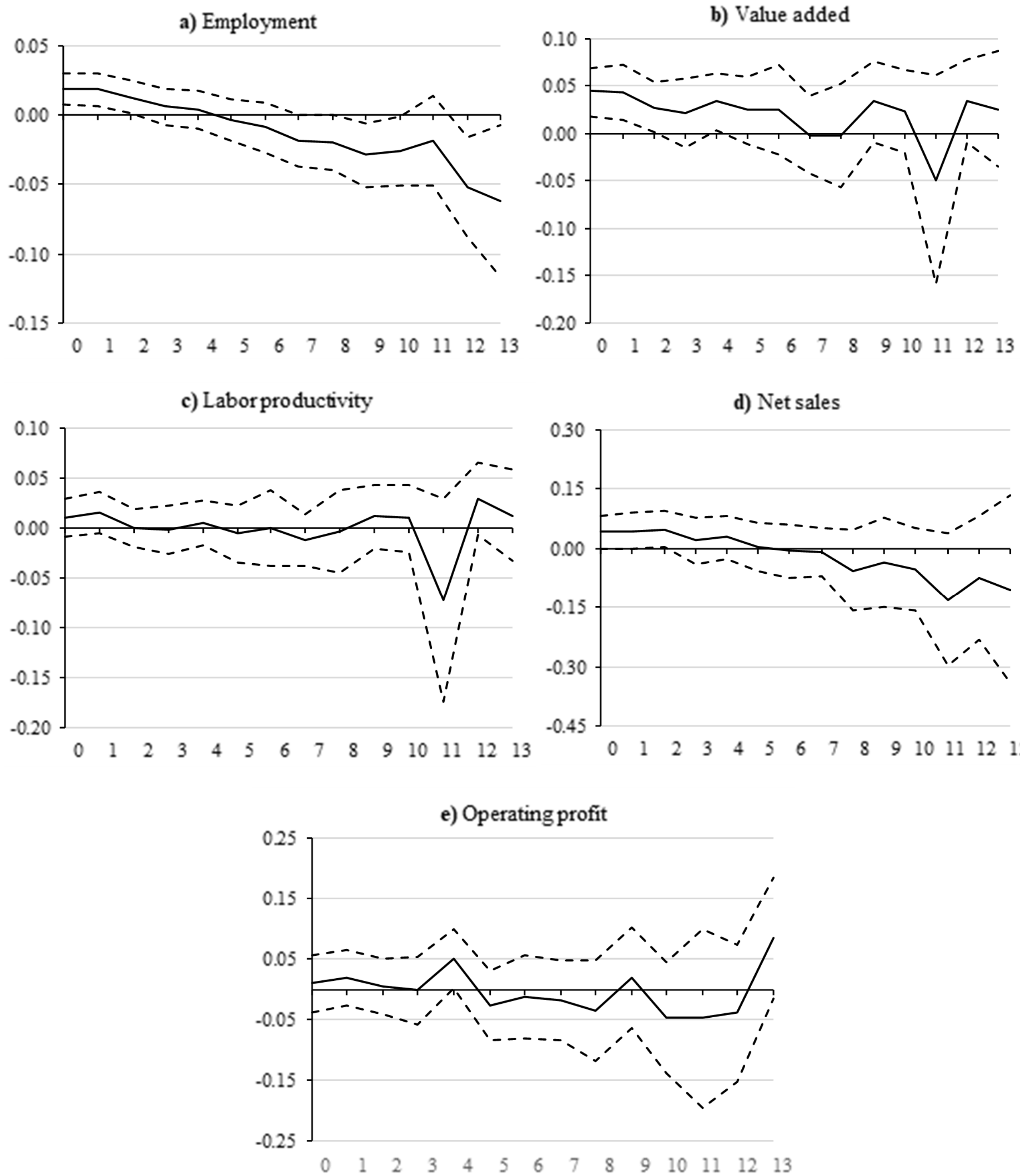


Figure 6 Spillover effects by treatment year estimated on the sample of Specialist hires.

The regression results from the estimation of equation (2) using job tenure as a measure of treatment intensity (specification (ii)). The elasticities of the treatment effects are estimated on five outcome variables: **a)** employment, **b)** value added, **c)** labor productivity, **d)** net sales, and **e)** operating profit.