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HOW DOES INWARD FDI AFFECT WAGES IN ESTONIA?

Master's Thesis

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Name and signature of supervisor……………………………….

Allowed for defense on …………….

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I have written this master’s thesis independently. All viewpoints of other authors, literary sources, and data from elsewhere used for writing this paper have been referenced.

(Signature of the author) ......

Abstract

This thesis estimates how wages at Estonian firms are affected by foreign acquisition. Using Estonian firm-level data spanning from 1995-2018, I utilize propensity score matching and standard fixed effects to complete this treatment analysis. By separating the data into three distinct eras, I estimate that the foreign wage premium has decreased by approximately 5%. Compared to domestically owned firms, Estonian firms acquired by a foreign entity between 2010-2018 have a wage difference of approximately 9% after two years. This wage disparity is largely seen in those firms specializing in knowledge-intensive services, an industry seldom examined for wage gap disparity until this thesis; this thesis seeks to improve upon the existent literature on this wage difference and contribute further analysis regarding foreign acquired versus domestic Estonian firms in the services industries.

Keywords: foreign direct investment, treatment analysis, propensity score matching

JEL Classification: F23, J31

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1. Introduction

Foreign direct investment (FDI) continues to receive persistent attention with its decline due to the global pandemic and protectionist policies. With less FDI, workers will likely bear a burden of wages not rising to the same extent as before. The standard narrative is that foreign-owned firms pay their workers higher wages due to higher productivity (Aitken et al., 1996; Hale & Long, 2011). This paper estimates the relationship between foreign ownership and wages using Estonian establishment-level data.

The complication of studying the firm's effects of inward FDI stems from the problem of endogeneity (Hale & Long, 2011). Since this study cannot randomly assign the treatment of being a foreign-owned firm, I am forced to create a research design to address the selection bias of foreign investors. One way to address this problem is to utilize instrumental variables. The categorical variable determining foreign ownership is instrumented with variables correlated with FDI but not the error term (Hale & Long, 2011). In practice, the instrumental variables approach is difficult due to the complexity of finding adequate instruments that do not correlate with the error term. I attempt to address endogeneity to some extent by using propensity score matching (PSM) and standard fixed effects. Using this combination, I can estimate the average treatment effect on the treated (ATT). Therefore, I estimate what the wages of foreign firms would have been without receiving FDI and take the difference between the actual and counterfactual to obtain the ATT.

The Estonian Business Registry provides firm characteristics, such as wages, location, sector, and capital intensity, between 1995-2018. A benefit of using Estonian data is that I include the services sector in my analysis. The importance of FDI in the services sector has grown in recent years, especially in transition economies because they have underdeveloped non-tradable sectors (Köllő et al., 2021). According to Varblane et al. (2020), the type of FDI inflow into Estonia has changed over the years. To capture the change in inward FDI targeting, I will split the study into multiple subperiods based on two key developments in the Estonian economy: the accession of Estonia to the European Union and the global financial crisis. I present estimations of the foreign ownership's effect on wages for the periods 1995-2018, 1995-2003, 2004-2009, and 2010-2018. Additionally, I use the Statistical Classification of Economic Activities in the European Community (NACE Rev.2) to segregate the firms into four groups based on their technological intensity for the manufacturing sector and their knowledge intensity for the services sector. These four groups are low-technology, high-technology, less knowledge-intensive, and knowledge-intensive.

After controlling for the covariates to make the treatment assignment relatively arbitrary through nearest-neighbor matching, I find that one year after a firm becomes majority foreign-owned, the firm pays approximately 14% higher wages during the entire period of 1995-2018 without breaking the study into different eras. This difference is seen predominately in the foreign low-technology manufacturers and less knowledge-intensive services. By contrast, separating the analysis into three distinct eras shows that the smallest wage premium for being acquired by a foreign firm is the last era of 2010-2018, approximately 7.3% for one year after acquisition. This difference is driven by the foreign wage premium in the knowledge-intensive services.

This study is presented as follows: Section 2 presents key literature in the area of FDI and wages; Section 3 describes the methodology; Section 4 presents a short data overview; Section 5 reports the results of the standard fixed effects and PSM; Section 6 discusses the implications of the study; Section 7 concludes the study.

2. Literature Review

This paper focuses on FDI's effect of foreign investment on employee wages in foreign-owned firms. Since foreign firms lack knowledge of the local market, the advantages of the multinational enterprises (MNEs) must outweigh their "foreignness" relative to the local enterprises (Dunning, 1977). The MNEs will invest conditional on ownership, location, and internalization (Dunning, 1979). If the MNE possesses an intangible asset like a patent or work culture, the foreign firm can overcome that disadvantage. For example, Coca-Cola utilizes horizontal foreign direct investment to produce its soft drinks in Estonia to sell to the Estonian market. By opting for this FDI, Coca-Cola protects the quality and recipe while saving on costly shipping costs. The same advantages that enabled the MNE to enter the market led to measurable benefits over the local firms (Girma & Görg, 2007; Taylor & Driffield, 2005). Theoretically, the influx of capital results in higher wages due to the increase in labor productivity. Therefore, the foreign-owned firms who perform better than the domestic-owned firms will also pay higher relative wages, *ceteris paribus* (Aitken et al., 1996; Feliciano & Lipsey, 2006; Girma et al., 2001; Lipsey & Sjöholm, 2004).

According to Malchow-Møller et al. (2013), theories explaining the wage premium in foreign firms can be grouped into three categories: worker heterogeneity, firm heterogeneity, and heterogeneity in the learning opportunities. Worker heterogeneity means that the higher wages at the MNE relative to the domestic firm stem from the selection bias of the foreign firm to "cherry-pick" the more productive workers. Similarly, the unique characteristics of the foreign firm, such as working conditions, could also result in the wage premium; meanwhile, worker preferences for local firms could also force foreign firms to pay a premium (Lipsey, 2004; Lipsey & Sjöholm, 2004). Lastly, workers who have access to better training in foreign firms will become more productive (Görg et al., 2007). As they become more productive, foreign firms will increase their workers' wages to prevent domestic firms from poaching workers who have increased their human capital.

Studies often draw an important distinction between developed and developing economies because the host country's labor market structure usually alters the findings. Using an empirical macro approach, Figini and Görg (2011) demonstrate that without segregating the countries into different levels of development, the results are biased (Blonigen & Wang, 2005). Hence, the division of countries into OECD and non-OECD proposed by Figini and Görg (2011) is well-founded. This division supports the approach of this paper's separation of the period of 1995-2018 into different eras in Estonia because Estonia went from a non-OECD member to an OECD member in 2010 (OECD, 2012). Furthermore, Estonia's accession to the European Union saw a greater inflow of FDI (Durán, 2019). Therefore, I separate the time period studied into three subperiods of 1995-2003, 2004-2009, and 2010-2018, which coincide with these two important developments in the Estonian economy.

To better understand the methods of analyzing the effects of FDI, it is imperative to focus on case studies spanning over three decades. Using cross-sectional analysis, Aitken et al. (1996) research the wage differentials between foreign firms and domestic firms for Mexico, Venezuela, and the United States in the manufacturing sector. According to these findings, MNEs in all three countries pay higher wages on average than their domestic counterparts. Yet, Aitken et al. (1996) find that the host countries' different characteristics play a role in the effects of inward FDI since the United States also experienced higher domestic wages on average after a foreign firm entered the market. Howenstine and Zeile (1994) assert that the wage differentials for this 1987 U.S. data, which Aitken et al. (1996) use, arise from the larger average size and higher productivity of the foreign-owned firms. Doms and Jensen (1998) contribute to this area of study by realizing that the more productive foreign-owned plants pay higher wages while being relatively capital intensive than the domestic firms of the United States in 1987. Additionally, Doms and Jensen (1998) distinguish that the MNEs originating from the United States have the highest productivity compared to any MNE originating outside of the country.

In contrast to Aitken et al. (1996), Feliciano and Lipsey (2006) use 1987 and 1992 U.S. data for both manufacturing and non-manufacturing sectors. Feliciano and Lipsey (2006) find that the low-skill industries, such as manufacturing and retail trade, pay a significant foreign wage premium of 4-6%. According to Köllő et al. (2021), former state-socialist countries have underdeveloped non-tradable sectors. Therefore, I utilize this knowledge to assume that the services sector will be critical in analyzing FDI's effect on Estonian wages because the inward FDI may be attracted to this sector. Additionally, Köllő et al. (2021) estimate that the wage gap between foreign and domestic firms is largest in the Hungarian services sector, 2003-2011. While Köllő et al. (2021) add depth to the study of foreign wage premiums, they do not estimate the effects of FDI based on different aggregations of services and manufacturing like Feliciano and Lipsey (2006). To address this gap to some extent, I allocate firms based on NACE Rev. 2 at the 2-digit level for compiling aggregates into low-technology manufacturers, high-technology manufacturers, less knowledge-intensive services, and knowledge-intensive services. With this segregation, I attempt to capture the effect of FDI on wages in different industries.

An issue of studying FDI's effect on wages is the problem of endogeneity, which means that FDI is not randomly assigned (Hale & Long, 2011). While studying Chinese firm-level data, Hale and Long (2011) utilize instrumental variables to address the endogeneity of FDI. The identification of "good instruments" is often elusive because the instruments must be correlated with the endogenous regressor for verifiable reasons (Angrist & Krueger, 2001). Therefore, Hale and Long (2011) reason that FDI is export-oriented companies in China. Another possible way to make an effort to control endogeneity is matching treated units with untreated control units and estimating the effect of the treatment. Peluffo (2015) and Girma and Görg (2007) use this method as an attempt to remove the selection bias of FDI by matching firms that were acquired by a foreign entity with firms that remained domestically owned over the same time span.

The use of fixed effects is another common method to mitigate endogeneity. By controlling for each firm's individual characteristics, Sjöholm and Lipsey (2006) estimate that the foreign wage premium reduces by 23% for production-worker wages and 31% for non-production-worker wages. This same logic can also be applied to the individual characteristics of workers. Therefore, firm-level fixed effects control for firm heterogeneity, and worker-level fixed effects control for worker heterogeneity. After combining these fixed-effects models with propensity score matching, Heyman et al. (2007) estimate that the foreign wage premium for foreign takeovers of Swedish firms to be nonexistent. Heyman et al. (2007) also suggest that greenfield investments, which are firms originally established as foreign, may have a higher foreign wage premium than foreign acquisitions. This assertion may be an interesting notion to investigate, considering the number of greenfield investments has declined since the global financial crisis (Durán, 2019).

According to Dunning (1993), investment motivation is the distinguishing characteristic of FDI types. The four categories are natural resource-seeking, market-seeking, efficiency-seeking, and strategic asset-seeking (Dunning 1993). An example of natural resource-seeking is an MNE investing in a country for its natural resources like raw materials. Market-seeking FDI means that the MNEs are trying to enter a new market by investing in the host country (Tomohara & Yokota, 2011). When an investor invests for efficiency, the MNE wants to utilize the host country's competitive advantage (Tomohara & Yokota, 2011). Lastly, strategic asset-seeking FDI usually takes place via mergers and is motivated by common ownership advantages. Besides the type of FDI, the origin of foreign investment can alter the effects of inward FDI. According to Tomohara and Yokota (2011), these two aspects of FDI work in tandem. While examining establishment-level panel data from 1998-2002 for Thailand, Tomohara & Yokota (2011) find that Japanese and Taiwanese FDI into Thailand did not cause wage inequality because this FDI increased unskilled labor demand. Since Japan and Taiwan already had access to Thailand's market before this period, this inward FDI is motivated by the comparative advantage of the host country, which in Thailand was the relatively cheap unskilled labor compared to the home countries. This logic means that this efficiency-seeking FDI increased unskilled workers' wages due to the increased labor demand. Similarly, Girma and Görg (2007) discover that FDI's origins also matter for wages of unskilled and skilled labor when studying U.K. firms from 1980 to 1994. According to Girma and Görg (2007), the wages of both types of workers increase when a U.S. firm acquires the U.K. firm; yet, no significant wage increase occurs when an E.U. firm did the same. Since my study investigates twenty-three years of Estonian firms, there is a possibility that the country's comparative advantage has changed. Therefore, inward FDI seeking to utilize Estonia's comparative advantage may have shifted from manufacturing to services or to more skill-intensive industries. According to Varblane et al. (2021), the rising wages of Estonian workers have reduced the profits of certain manufacturing industries, such as textiles. Therefore, I hope to capture this change by investigating the three subperiods coupled with firms' technological intensity and knowledge intensity.

Since Estonia will be the focus of this case study, the past literature regarding the effects of FDI in Estonia must be covered. Using the whole population of Estonian firms, Vahter and Masso (2007) attempt to discern how inward and outward FDI affect Estonian firms. Vahter and Masso (2007) find that the firm receiving or financing the FDI sees related positive productivity. Conversely, the spillover effects of inward and outward FDI are inconclusive and likely depend on FDI type. Vahter (2011) uses the entire population of Estonia's manufacturing firms while also implementing Estonian firms' sample surveys. With this data, Vahter (2011) discovers that domestic innovation is associated with increased FDI. Vahter and Masso (2019) employ linked Estonian employer-employee data for the entire population of firms from 2006 to 2014. Using these plentiful data, Vahter and Masso (2019) examines the gender pay gap in MNEs and find that FDI is associated with higher wages at the firm, on average. Many of the facets discussed about FDI analysis are included in this work, including observing FDI origin.

When conducting the current study, I plan to build upon these past works of literature. According to Dunne et al. (2004), the between-firm component, especially within the same industry, is the most prominent aspect affecting wages. Using the latest data on Estonian firms at the establishment level, I can estimate the direct effects of inward FDI on wages. Additionally, I approximate how the FDI affects different sectors based on the period studied.

3. Methods

I attempt to estimate the relationship of a domestic firm becoming a foreign firm in Estonia for the period 1995-2018. The economy of Estonia in the late 1990s is different than the Estonian economy of the late 2010s (Varblane, 2020). In the 1990s, Estonia received inward FDI as a transitioning country (Varblane, 2001). By 2010, the country became a member of the OECD (OECD, 2012). Suppose I do not account for the fact that the Estonian economy has changed over the period of 1995-2018. In that case, the estimation of FDI's effect on wages may fail to provide useful information. To this end, my estimations are divided into the following four eras: 1995-2018, 1995-2003, 2004-2009, and 2010-2018. By completing this split, I expect that the estimated effect of FDI on wages to be the largest in the first era where Estonian firms' relatively low labor costs attracted foreign firms in labor-intensive sectors, such as the textile industry (Varblane et al., 2008). By the last era, I expect that the industries that require high human capital, skilled workers, will see the largest effect of foreign acquisition in sectors like ICT (Durán, 2019). Since I plan to estimate this relationship and hypothesize that different sectors receive different kinds of FDI, I use NACE Rev. 2 to indicate two levels of technology intensity and two levels of knowledge intensity for the manufacturing and services sectors, respectively. This division of firms and periods allows me to explore how the estimated effect of FDI on wages changes based on time and sector intensity.

I use the propensity score matching (PSM) and standard fixed effects to estimate the relationship between foreign direct investment (FDI) and the real wages of laborers in the period from 1995-2018 for Estonian firms. Using standard fixed effects, I control for time-invariant firm effects. Adapting the standard fixed effects equation of Wooldridge (2012), I estimate Equation (1), where i is the firm, t is the year, λ_t represents the combined time effects, α_i represents the unobserved time-invariant firm effects, $Wage_{it+1}$ and $Wage_{it+2}$ represent the natural logarithm of real wages of a firm per employee for the one-period lead and two-period lead after t, $Foreign_{it}$ represents if a firm is majority foreign-owned, Age_{it} represents the natural logarithm of a firm's age, $Size_{it}$ represents the natural logarithm of a firm's number of employees, $Capital\ Intensity_{it}$ represents the natural logarithm of a firm's capital per employee, $Wage_{it-1}$ represents the natural logarithm of real wages of a firm per employee from the previous year, $Industry$ represents the dummy variable for each industry at the 2-digit NACE Rev. 2 level, $Region$ represents the dummy variable for Northern, Central, North-Eastern, Western and Southern Estonia, u_{it} is the error term.

$$\begin{gathered} Wage_{it+1}, Wage_{it+2} = \lambda_t + \alpha_i + Foreign_{it}\beta + Age_{it}\beta + Size_{it}\beta + Capital\ Intensity_{it}\beta + Wage_{it-1}\beta + \\ Industry_i + Region_i + u_{it}, \\ i = 1, \dots, N \end{gathered} \tag{1}$$

The specification in Equation (1) stems from the interest of studying the effect of foreign ownership on wages. According to Doms and Jensen (1998), the potential difference between foreign-owned and domestically owned firms may be the result of industry, size, age, and location. By controlling for these four covariates, I hope to estimate a closer relationship between wages and foreign ownership. Additionally, I control for the capital intensity of a firm using the notion that multinationals tend to be the most capital intensive (Doms & Jensen, 1998; Heyman et al., 2007). The last specification of the standard fixed effects equation is my choice to incorporate the lagged wage of the firm and observe the one and two-period leads.

To conduct my treatment analysis, I match foreign firms with firms that have not received foreign investment. I utilize PSM developed by Rosenbaum and Rubin (1983). According to PSM, the probability of receiving FDI, which is the treatment, is based on the specified covariates. Therefore, the likelihood of receiving FDI for all firms is first calculated by using a probit model. A firm belonging to the control group with the closest propensity score to a treated firm is the counterfactual. Since my current study is not randomized, the propensity score enables me to create a pseudo-randomized control group because these controls all have particular characteristics relevant to my study. This form of matching is quite common for impact evaluation studies as these findings are not done with participants like traditional studies that assign treatments themselves. For example, testing the effectiveness of a drug would be carried out by having some participants take a placebo to act as the control group. Unfortunately, impact evaluation studies do not have this opportunity because I estimate what would have happened in the absence of the treatment, but I cannot assign the treatment randomly. Therefore, the treatment assignment is based on whether a firm is foreign-owned or not, and the outcome variable is the real wages of the firm.

Before thoroughly covering the steps of PSM, the two key assumptions of matching ought to be understood and accounted for. The assumption of conditional independence states that the potential outcomes are independent of treatment assignment after controlling for the confounding factors. Rosenbaum and Rubin (1983) represent this assumption with Equation (2), where d is treatment status, X is the set of covariates that have been controlled for, and y is the outcome variable.

$$E[y_1 \mid X, d = 1] = E[y_0 \mid X, d = 0] \tag{2}$$

The conditional independence assumption implies that the untreated observations can be used as an unbiased counterfactual for the treatment group. Additionally, the common support assumption states that the probability of receiving treatment is strictly between 0 and 1 after controlling for the covariates, which Rosenbaum and Rubin (1983) represent as Equation (3). If this assumption is satisfied, the characteristics of treated and untreated are close enough for matches.

$$0 < P(d = 1 \mid X) < 1 \tag{3}$$

I will now go step-by-step on how to formulate the propensity scores and evaluate them. The first step I take is to use a probit regression with foreign ownership, which is classified as 0 for domestic-owned firms and 1 for foreign-owned firms, as the dependent variable and the confounders as the independent variables. Therefore, the selection of these explanatory variables is crucial for the validity of the study. According to prior literature, the covariates chosen should be those variables that affect the treatment and/or the related to the outcome variable (Brookhart et al. 2006). In my case, I ought to include variables that could influence the fact that a firm is foreign-owned and possibly those that affect employees' wages. According to Barrowman et al. (2019), a confounder that is not accounted for will likely bias the treatment effect in the impact evaluation study. An important caveat is that including irrelevant explanatory variables can reduce bias (Imbens, 2004). If a researcher includes a covariate that influences the treatment but fails to affect the outcome, he or she does not reduce bias because this variable does not need to be controlled for (Brookhart et al., 2006). According to Imbens (2004), explanatory variables affected by the treatment should be excluded from the analysis. If these variables were included, the treatment effect that would be estimated in accordance with the propensity score would be biased. Additionally, Abadie and Imbens (2002) assert that confounders with perfect collinearity with the treatment cannot be used because this covariate cannot produce a control group of the untreated. Lastly, I may be forced to omit independent variables if they are perfectly collinear with other covariates. Therefore, carefully choosing the correct covariates is crucial for estimating the propensity scores in order to reduce bias and estimate the accurate treatment effect. The selected covariates are based on prior literature and the readily available data provided to me.

My data source for the panel of all firms operating in Estonia is the Estonian Business Registry, which includes data from 1995 until 2018. I will emphasize the importance of particular variables because these play a crucial role in the study of FDI on wages. Similar to Feliciano and Lipsey (2006), I will differentiate the manufacturing and services sectors. To further build upon this concept, I have further segregated firms based on how intensive the sector uses technology or knowledge for manufacturing and services sectors. Using NACE Rev.2, I indicate two levels of technology intensity and two levels of knowledge intensity. Therefore, special importance is placed on the specific sectors when matching the treated to their controls because the sector-specific characteristics have been seen to largely affect where the FDI is invested (Hoi & Pomfret, 2010; Pittiglio et al., 2015). Hale and Long (2011) acknowledge the importance of sector characteristics when creating their instruments, but they also consider firms' location. As suggested by prior literature, the regional location of firms tends to also play a role in a firm receiving FDI, which is likely to do with other factors that are correlated with location (Girma & Görg, 2007; Vahter & Masso, 2007). Additionally, I utilize lags of variables to account for the possibility of foreign investors "cherry-picking" the most productive firms (Lipsey & Sjöholm, 2004). The naturals logarithms of lagged variables that are employed are age, size, labor productivity, and capital intensity. The firm's size is considered because the bigger firms may appear more attractive to foreign investors (Girma & Görg, 2007; Görg et al., 2007; Vahter & Masso, 2007). While including age and size, I include the squared lags to account for the likelihood that the relationship between these variables and foreign acquisition is non-linear. Additionally, the more productive firms and more capitally intensive firms may also attract these foreign investors (Görg et al., 2007; Peluffo, 2015). Labor productivity is measured as value-added per employee. Capital intensity is measured by the amount of capital relative to the number of laborers. By including these variables from the previous period, I eliminate the influence of the treatment. I specify Equation (4) to estimate the probit regressions for all periods, where the variables are the same as Equation (1) with the addition of $Foreign\ Acquired_{it}$ which indicates if the firm became foreign in period t and $Productivity_{it-1}$ which represents the natural logarithm of value-added per employee at period

$t-1$. These probit regressions enable me to create an artificial propensity score that accounts for the probability of a foreign takeover.

$$Foreign\ Acquired_{it} = \Phi(Constant + \lambda_t + Age_{it-1} + Age^2{}_{it-1} + Size_{it-1} + Size^2{}_{it-1} + Capital\ Intensity_{it-1} + Productivity_{it-1} + Wage_{it-1} + Industry_i + Region_i), \quad i = 1, \dots, N \tag{4}$$

After selecting the covariates and calculating the propensity scores, the assumption of common support must be checked to determine if the propensity scores are able to match for both groups, treated and untreated. According to Imbens (2004), the propensity scores should also balance between the treated and control groups. The standardized difference compares the mean of continuous and binary variables between the two groups (Austin, 2009). The standardized difference for a continuous variable is shown in Equation (5), where $\bar{x}_{\text{treatment}}$ and $\bar{x}_{\text{control}}$ are the sample mean of the covariate in treated and untreated, $s^2_{\text{treatment}}$ and s^2_{control} are the sample variance of the covariate in each group.

$$d = \frac{(\bar{x}_{\text{treatment}} - \bar{x}_{\text{control}})}{\sqrt{\frac{s^2_{\text{treatment}} + s^2_{\text{control}}}{2}}}, \tag{5}$$

For categorical variables, the standardized difference is given by Equation (6), where $\hat{p}_{\text{treatment}}$ and $\hat{p}_{\text{control}}$ are the prevalence of the covariate in the two groups.

$$d = \frac{(\hat{p}_{\text{treatment}} - \hat{p}_{\text{control}})}{\sqrt{\frac{\hat{p}_{\text{treatment}}(1-\hat{p}_{\text{treatment}}) + \hat{p}_{\text{control}}(1-\hat{p}_{\text{control}})}{2}}}, \tag{6}$$

According to Austin (2009), a standard difference less than 0.1 has been considered negligible between the two means. Therefore, the accounted for covariates would reasonably represent the treated and untreated groups and allowing the researcher to estimate the treatment effect.

In addition to determining that covariates are balanced between treated and untreated groups after matching by a propensity score, I will describe the process of finding the actual matches of treated to untreated subjects. I utilize nearest-neighbor matching, which matches the treated observation to the untreated observation with the closest propensity score (Rosenbaum & Rubin, 1985). According to Rosenbaum and Rubin (1985), nearest-neighbor matching does not automatically limit the acceptable difference between treated and control; instead, they describe nearest-neighbor matching with a maximum permitted difference between the two matched subjects called the caliper. This caliper prevents unfit matching from reducing bias. There has been little direction on the correct value of caliper. According to Raynor (1983), the relationship between the treatment and outcome variable reflects the restrictiveness of the caliper. If the treatment is highly linked with the outcome variable, the caliper ought to be smaller. Additionally, the caliper can be made too small and force an inadequate number of matches, resulting in inefficiency and selection bias. For my matching procedure, I utilize a caliper of 0.05 to ensure that firms of the same sector and year are matched together in my 5-nearest neighbor matching.

After I am confident in my selection of covariates and matching method, I complete the average treatment effect on the treated (ATT). According to Ho et al. (2007), the ATT is of great interest because this represents the effect of treatment when the treatment is applied. As shown in Equation (7), the ATT is the average wage of the foreign-owned firms subtracted by the average wage of foreign-owned firms if they had not been foreign-owned, where Y_{1i} represents the wage of the foreign-owned firm, Y_{0i} represents the wage of the domestic-owned firm, D_i denotes the treatment assignment for a firm with 1 being a foreign-owned firm and 0 being a domestic-owned firm, and X_i denotes the controlled covariates for the firm.

$$ATT = E[Y_{1i} - Y_{0i} \mid D_i = 1] = E[\{E[Y_{1i} \mid X_i, D_i = 1] - E[Y_{0i} \mid X_i, D_i = 0]\} \mid D_i = 1] \quad (7)$$

I estimate the ATT for the firm's wages after one year of becoming a foreign-owned firm, and I also do the same for two years after the treatment occurs.

After describing, in detail, the necessary steps to complete this study, I will discuss the software and commands used to complete my analysis. I use Stata to complete my standard fixed effects, matching, and ATT. Using the package -psmatch2-, I create matched pairs between the treated and control groups based on the propensity scores resulting from the probit regression that used the foreign ownership as the dependent variable with all the aforementioned covariates (Leuven & Sianesi, 2003). While this command is quite useful for performing this task of matching, there is a problem with an assumption in its code for calculating the standard errors. According to Leuven and Sianesi (2003), the -psmatch2- command assumes homoskedasticity of the outcome variable within both the treated and control groups. Abadie and Imbens (2006) demonstrate that this assumption for nearest-neighbor matching estimators creates a bias in the errors. Instead, the standard errors need to be calculated with the Abadie-Imbens (A.I.) method matching two or more continuous covariates (Abadie & Imbens, 2006). Therefore, I include the necessary option on the -psmatch2- command to correct for this bias, which would affect the ATT.

The next necessary step is to use the standardized difference to check that the covariates have a reasonably close mean regardless of treatment assignment. I use the -pstest- command to conduct this balancing test, which calculates the standardized percentage bias (Leuven &

Sianesi, 2003). Additionally, the -pstest- command enables me to see the reduction in the bias of each covariate.

4. Data

As previously mentioned, I use the Estonian Business Registry, which includes data from 1995 until 2018 of 73,777 unique firms after removing missing data and outliers. The outliers were excluded based on the observation containing at least one key variable that is the lowest 1% or highest 1%, which excludes approximately 31,000 of approximately 430,000 observations. This firm-level data includes an indicator that shows whether each firm is majority foreign-owned or not. In addition to this foreign ownership indicator, the data includes characteristics of each firm, such as size, sector, and real wages, based on the firms' balance sheets. I use the natural logarithms of all the GDP deflated variables throughout this study, except for categorical variables like foreign ownership.

Table 1 describes the means of some of the important variables that I will be working with. Wage is the natural logarithm of real wages that the firm paid. Age is the natural logarithm of the number of years that the firm existed. Size is the natural logarithm of the number of employees at the firm. Capital intensity is the deflated stock of capital relative to the number of employees. By including these descriptive statistics, I can view the basic characteristics of the sample. In addition to providing the means for each variable, I segregate the means of each observation based on the sector of the firm. According to Table 1, the mean of foreign-owned firms in each variable is higher relative to domestic-owned firms for each sector. Additionally, I observe that the highest mean wages are paid to workers at a foreign-owned firm operating in the services sector of the economy.

These descriptive statics enable me to perceive the possibility that heterogeneity exists among the foreign-owned and domestically owned firms. To discern if the distribution of wages is the same for these two groups, the two-sample Kolmogorov-Smirnov test is conducted. According to this test, the distributions of wages are significantly different based on foreign ownership of the firm. This observation is also seen by the kernel density graph displayed in Figure 1. According to Figure 1, the peaks of the foreign-owned firms show that they have a denser concentration of higher real wages relative to the domestic-owned firms in each respective sector. This higher concentration gives reason to investigate the relationship between foreign ownership and higher wages.

Table 1

Descriptive statistics of the entire sample period 1995-2018

1995-2018 Sector Intensities	Foreign Firms				Domestic Firms			
	Manufacturing		Services		Manufacturing		Services	
	Low	High	Low	High	Low	High	Low	High
Wage	9.29 (0.666)	9.52 (0.544)	9.47 (0.864)	9.57 (0.875)	8.73 (0.745)	9.07 (0.788)	8.82 (0.859)	8.95 (0.859)
Age	2.05 (0.748)	2.07 (0.759)	1.92 (0.781)	1.81 (0.820)	2.00 (0.782)	2.11 (0.767)	2.02 (0.775)	1.93 (0.778)
Size	2.76 (1.218)	2.95 (1.259)	1.62 (1.231)	1.61 (1.310)	1.55 (1.244)	1.75 (1.323)	1.23 (1.049)	0.78 (0.953)
Capital Intensity	8.82 (1.698)	8.76 (1.578)	8.81 (1.888)	8.14 (1.884)	8.47 (1.602)	8.64 (1.570)	8.65 (1.822)	8.25 (1.672)
Number of obs.	3937	1233	15970	5230	40003	4602	229981	88162
Number of firms	777	214	3783	1510	7602	940	41484	18312

Note: Data from Estonian Business Registry, 1995-2018.
[a]Mean coefficients reported with standard deviations in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity

Source: author's calculations using Estonian Business Registry 1995-2018

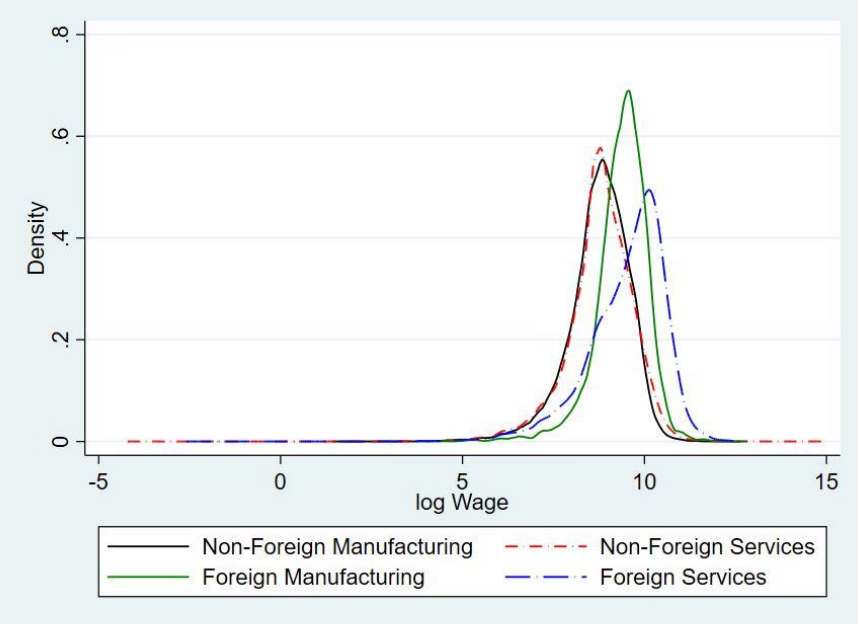

Figure 1. Kernel density graphs with domestic-owned firms versus foreign-owned firms
Source: author's calculations using Estonian Business Registry 1995-2018

Using this data from the Estonian Business Registry, I estimate if foreign ownership results in higher wages. According to the aforementioned descriptive statistics, I expect foreign ownership to positively affect wages after controlling for confounding factors.

5. Results

To estimate the relationship between foreign ownership and wages for Estonian firms, I utilize standard fixed effects and PSM for the unbalanced panel data provided to me by the

Estonian Business Registry for 1995-2018. As mentioned earlier, the treatment is a foreign acquisition of a domestic, which is defined as a domestic firm becoming majority foreign-owned. Additionally, I split the data into three eras of 1995-2003, 2004-2009, and 2010-2018 since the type of FDI coming into Estonia may change. This section provides the estimations of all periods according to three different models, ordinary least squares (OLS), fixed effects (FE), propensity score matching (PSM).

5.1 OLS model

The OLS model is likely biased due to endogeneity, but this regression still gives an idea of the potential relationship between foreign firms and wages. For this model, I estimate the relationship between foreign ownership and wages rather than foreign acquisition, which will be estimated with the standard fixed-effects model and PSM. To correctly interpret the relationship between a dummy variable like foreign ownership and a natural logarithm like real wages, I utilize the method of Halvorsen and Palmquist (1980). According to Table 2, a foreign firm pays approximately 70% higher wages on average, holding everything else constant when observing the entire sample from 1995-2018. Additionally, foreign-owned firms paying higher wages holds across all four types of industries. The narrative of a foreign wage premium also holds for all four eras covered, which are 1995-2018, 1995-2003, 2004-2009, and 2010-2018 (Table 2; Appendix A). For Indonesian manufacturers, Sjöholm and Lipsey (2006) estimate a similar wage equation and approximate a foreign wage premium of 34% and 54% for production-worker and non-production-worker wages, respectively. Therefore, we estimate a larger foreign wage premium, but this may be a consequence of estimating the manufacturing and services sectors in this model. According to Table 2 and Appendix A, the services sector has the largest foreign wage premium in every era. The largest estimated gap between wages for foreign-owned and domestically owned firms is estimated to be the less knowledge-intensive services from 1995-2003, during which foreign-owned companies pay about 110% higher wages than domestic firms. An important distinction of this OLS estimation is that it captures the approximate wage difference between all foreign firms and all domestic firms. Therefore, foreign firms that result from greenfield investments, which result from MNE creating subsidiaries in a host country, and foreign firms stemming from acquisitions are considered in this estimation. According to Heyman et al. (2007), the foreign wage premium is estimated to be larger for greenfield investments than the wage premium for foreign-owned firms arising from acquisitions. While useful, this OLS model tells a biased narrative because the model does not address the endogeneity problem of FDI. Since FDI is not randomly assigned to firms, the results of these regressions are biased and lead me to consider the next method of estimating the relationship of foreign acquisition of a firm and wages in Estonia.

Table 2

OLS model for 1995-2018

1995-2018 OLS	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.533***	0.349***	0.207***	0.591***	0.552***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
Age	0.036***	−0.004	0.002	0.053***	0.044
	(0.000)	(0.675)	(0.947)	(0.000)	(0.366)
Size	0.218***	0.189***	0.162***	0.212***	0.313***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	0.080***	0.112***	0.119***	0.083***	0.081***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	401330	45745	6342	252672	96571
Number of firms	73777	8261	1122	44593	19801
R^2	0.197	0.329	0.308	0.203	0.178

Note: Data from Estonian Business Registry, 1995-2018.
[a]OLS model with standard errors corrected for heteroscedasticity. $p - values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author's calculations using Estonian Business Registry 1995-2018

5.2 Fixed effects model

The standard fixed effects model controlling for time-invariant firm fixed effects enables me to estimate the relationship between foreign ownership and real wages within a firm. This model allows me to control for the fact that something within the firm may bias the results. Therefore, I estimate the effect of the foreign acquisition on wages while considering the firm's characteristics. In this model, I control for the firm's age, size, capital intensity, and previous year's wage while estimating the firm's wage for a one-period lead and a two-period lead. According to Table 3, I estimate that, for a given firm, foreign ownership significantly increases the real wages by 2.74% after a one-period lead for the overall sample of 1995-2018. Specifically, the less knowledge-intensive services appear to be the driving force of this wage premium because foreign ownership significantly increases the real wages by 3.56% after one-period. This fixed effect estimation may be supported by the results from the OLS estimation, which estimated that the less knowledge-intensive services had the largest magnitude for all three eras except 2010-2018. To investigate this further, I estimate the same fixed effects model for the eras 1995-2003, 2004-2009, and 2010-2018. As Table 3 shows, the period of 2010-2018 appears to be a driving force in this foreign wage premium because the model estimates a statistically significant increase of wages by 4.29% after one year of a foreign acquisition. Additionally, foreign firms that are less knowledge-intensive services pay a wage 4.71% higher after one year of being acquired. Meanwhile, the estimations for 1995-2003 and 2004-2009 describe a different narrative, which is in Appendix B. According to the fixed effects estimations, these two eras lack a significant difference in wages for foreign and domestic firms. A possible explanation for these results stems from the nature of my data. Using firm-level data prevents me from controlling for individual-level characteristics of workers. Linked employer-employee data could be used to control for the possibility of worker heterogeneity (Malchow-Møller et al., 2013; Vahter & Masso, 2019). This worker heterogeneity does seem to be prevalent in the Estonian workforce, as demonstrated by the Estonian gender pay gap (Vahter & Masso, 2019). According to the results in Table 3 and Appendix B, I estimate that the changes in average wages after acquisition have increased in recent years. Sjöholm and Lipsey (2006) estimate a similar sector level study by approximating the fixed effects of five Indonesian manufacturing industries since they claim that acquisitions are concentrated by sector. The progression of my analysis is to utilize treatment analysis with PSM to estimate the effect of foreign acquisitions on average wages at the firm level.

Table 3

Fixed effects model for 1995-2018 and 2010-2018

1995-2018 Fixed Effects One Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.027**	0.012	0.053	0.035**	0.020
	(0.014)	(0.566)	(0.230)	(0.016)	(0.460)
Age	−0.066***	−0.042**	−0.072	−0.064***	−0.045**
	(0.000)	(0.027)	(0.141)	(0.000)	(0.019)
Size	0.017***	−0.007	−0.032	0.006	0.052***
	(0.000)	(0.526)	(0.171)	(0.192)	(0.000)
Capital Intensity	0.021***	0.024***	0.013	0.020***	0.015***
	(0.000)	(0.000)	(0.196)	(0.000)	(0.000)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	246424	29636	4068	157370	55350
Number of firms	47409	5589	772	28734	12314
Within-group R^2	0.103	0.204	0.210	0.099	0.056

Note: Data from Estonian Business Registry, 1995-2018.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

1995-2018 Fixed Effects Two Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.230*	0.012	0.027	0.017	0.038
	(0.061)	(0.608)	(0.539)	(0.315)	(0.192)
Age	−0.064***	−0.061***	−0.071	−0.061***	−0.044**
	(0.000)	(0.003)	(0.165)	(0.000)	(0.041)
Size	0.030***	0.004	−0.025	0.022***	0.071***
	(0.000)	(0.739)	(0.297)	(0.000)	(0.000)
Capital Intensity	0.014***	0.010**	0.017*	0.013***	0.012***
	(0.000)	(0.017)	(0.089)	(0.000)	(0.001)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	211738	26048	3615	135404	46671
Number of firms	41733	5053	699	25411	10570
Within-group R^2	0.071	0.186	0.196	0.099	0.035

Note: Data from Estonian Business Registry, 1995-2018.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2010-2018 Fixed Effects One Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.042***	0.041	0.153**	0.046***	0.040
	(0.003)	(0.242)	(0.032)	(0.008)	(0.319)
Age	−0.038***	0.002	−0.048	−0.032**	−0.012
	(0.001)	(0.955)	(0.506)	(0.021)	(0.654)
Size	0.110***	0.097***	0.045	0.102***	0.114***
	(0.000)	(0.000)	(0.230)	(0.000)	(0.000)
Capital Intensity	0.011***	0.013**	−0.004	0.011***	0.006
	(0.000)	(0.026)	(0.764)	(0.000)	(0.104)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	143219	15146	2106	89590	36377
Number of firms	34782	3587	487	20822	9886
Within-group R^2	0.057	0.132	0.116	0.060	0.027

Note: Data from Estonian Business Registry, 2010-2018.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2010-2018 Fixed Effects Two Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.046***	0.063**	0.147***	0.036*	0.055
	(0.004)	(0.049)	(0.007)	(0.078)	(0.295)
Age	−0.014	0.036	0.029	−0.018	0.011
	(0.271)	(0.214)	(0.740)	(0.238)	(0.710)
Size	0.097***	0.076***	0.045	0.096***	0.095***
	(0.000)	(0.000)	(0.336)	(0.000)	(0.000)
Capital Intensity	0.007***	0.012*	0.008	0.006***	0.004
	(0.000)	(0.054)	(0.517)	(0.002)	(0.316)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	116226	12607	1775	72773	29071
Number of firms	30459	3220	444	18388	8407
Within-group R^2	0.050	0.129	0.128	0.058	0.020

Note: Data from Estonian Business Registry, 2010-2018.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author’s calculations using Estonian Business Registry 1995-2018

5.3 Treatment analysis with PSM

To study the effect of foreign acquisition, I implement PSM for 1995-2018, 1995-2003, 2004-2009, and 2010-2018. Using 5-nearest-neighbor matching with a caliper, I match untreated firms, those not acquired by a foreign firm, with treated firms, those that we acquired. Table 4 shows the probability of a firm becoming foreign by estimating Equation (4) using a probit model. These estimated probit models enable me to complete my treatment analysis because the foreign-acquired firms are matched to the five nearest domestic firms in the same sector and year, which is ensured by creating an artificial propensity score that emphasizes sector and year.

Table 4

Probit estimation of the probability of a firm becoming foreign-owned

Probit Model For Matching	1995-2018	1995-2003	2004-2009	2010-2018
Productivity	−0.024	−0.028	−0.058*	−0.016
	(0.117)	(0.398)	(0.059)	(0.447)
Age	−0.071	0.162	−0.075	−0.055
	(0.182)	(0.191)	(0.551)	(0.501)
Age^2	−0.025	−0.137***	−0.032	−0.021
	(0.124)	(0.004)	(0.419)	(0.361)
Size	0.044	0.136**	0.112*	−0.003
	(0.133)	(0.039)	(0.092)	(0.946)
Size^2	0.013*	−0.012	0.009	0.028***
	(0.054)	(0.393)	(0.556)	(0.005)
Capital Intensity	0.016**	0.040**	0.006	0.006
	(0.030)	(0.012)	(0.697)	(0.558)
Lagged Wage	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Number of obs.	211516	39029	62431	114101
Pseudo R^2	0.116	0.175	0.112	0.084

Note: Data from Estonian Business Registry, 1995-2018.
[a]Probit model with $p - values$ reported in parentheses
[b]All variables are the natural logarithms lagged by one period for matching before the treatment occurs
[c]Productivity is the natural logarithm of value added per employee.
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author's calculations using Estonian Business Registry 1995-2018

Table 5 presents the estimated average treatment effect on the firms that were acquired by foreign firms for all four time periods; an example of the standardized percent bias across covariates is presented in Appendix C. Additionally, I estimate this same effect for the subcategories of firms based on their technological intensity and knowledge intensity. According to Table 5, foreign acquisition of an Estonian firm significantly increases the overall average wages of workers between 1995-2018 and for every subperiod studied. When observing the sample over the entire period of 1995-2018, I approximate that the foreign wage premium increases from about 14% to approximately 16% after one and two years of being acquired, respectively. During this period, the two firm types that experience this foreign wage premium are low-technology manufacturers and less knowledge-intensive services. By observing the subperiods of the sample, I estimate that the less knowledge-intensive firms are also paying this wage premium between 1995-2003 and 2004-2009. Meanwhile, the latest subperiod of 2010-2018 sees knowledge-intensive firms paying a wage premium of 18% and

21% after one- and two-years post-acquisition. Notably, the overall ATT of all types of firms is lowest between 2010-2018.

Table 5

PSM model for 1995-2018, 1995-2003, 2004-2009, 2010-2018

1995-2018 ATT using PSM	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Unmatched Sample Difference (Lead 1)	0.378***	0.252***	0.091	0.417***	0.539***
	(0.024)	(0.055)	(0.109)	(0.031)	(0.073)
ATT After Matching (Lead 1)	0.141***	0.175*	0.032	0.115***	0.199
	(0.030)	(0.104)	(0.829)	(0.030)	(0.242)
Unmatched Sample Difference (Lead 2)	0.409***	0.307***	0.096	0.435***	0.589***
	(0.025)	(0.056)	(0.112)	(0.031)	(0.076)
ATT After Matching (Lead 2)	0.162***	0.212**	0.044	0.134***	0.268
	(0.030)	(0.105)	(0.833)	(0.032)	(0.240)
Treated On Support	704	133	33	443	95
Treated Off Support	1	0	1	0	0
Untreated On Support	164930	21122	2444	109191	32173
Untreated Off Support	0	0	0	0	0
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	165635	21255	2478	109634	32268

Note: Data from Estonian Business Registry, 1995-2018.
[a]Propensity score matching with standard errors corrected for heteroscedasticity. Standard errors are reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

1995-2003 ATT using PSM	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Unmatched Sample Difference (Lead 1)	0.506***	0.476***	0.390**	0.594***	0.491***
	(0.040)	(0.075)	(0.170)	(0.051)	(0.162)
ATT After Matching (Lead 1)	0.118*	0.203	0.015	0.144***	0.062
	(0.066)	(0.211)	(1.525)	(0.045)	(0.852)
Unmatched Sample Difference (Lead 2)	0.525***	0.508***	0.392**	0.584***	0.595***
	(0.042)	(0.078)	(0.179)	(0.053)	(0.168)
ATT After Matching (Lead 2)	0.142**	0.228	0.023	0.138***	0.178
	(0.067)	(0.215)	(1.556)	(0.050)	(0.842)
Treated On Support	294	69	12	189	24
Treated Off Support	6	1	4	1	0
Untreated On Support	30264	4598	539	21037	4090
Untreated Off Support	0	0	0	0	0
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	30564	4668	555	21227	4114

Note: Data from Estonian Business Registry, 1995-2003.
[a]Propensity score matching with standard errors corrected for heteroscedasticity. Standard errors are reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2004-2009 ATT using PSM	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Unmatched Sample Difference (Lead 1)	0.577***	0.288***	0.218	0.663***	0.786***
	(0.055)	(0.110)	(0.202)	(0.071)	(0.153)
ATT After Matching (Lead 1)	0.189**	0.031	−0.044	0.269***	0.301
	(0.086)	(0.374)	(1.728)	(0.070)	(0.604)
Unmatched Sample Difference (Lead 2)	0.598***	0.347***	0.176	0.669***	0.807***
	(0.056)	(0.111)	(0.209)	(0.072)	(0.157)
ATT After Matching (Lead 2)	0.172**	0.078	−0.058	0.211***	0.355
	(0.085)	(0.358)	(1.721)	(0.067)	(0.598)
Treated On Support	137	28	9	78	22
Treated Off Support	0	0	0	0	0
Untreated On Support	45334	6435	756	31389	6754
Untreated Off Support	0	0	0	0	0
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	45471	6463	765	31467	6776

Note: Data from Estonian Business Registry, 2004-2009.
[a]Propensity score matching with standard errors corrected for heteroscedasticity. Standard errors are reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2010-2018 ATT using PSM	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Unmatched Sample Difference (Lead 1)	0.348***	0.348***	−0.149	0.300***	0.512***
	(0.036)	(0.096)	(0.194)	(0.044)	(0.096)
ATT After Matching (Lead 1)	0.073*	0.231	−0.309	0.000	0.181*
	(0.039)	(0.233)	(1.330)	(0.051)	(0.099)
Unmatched Sample Difference (Lead 2)	0.371***	0.395***	−0.121	0.320***	0.539***
	(0.038)	(0.098)	(0.199)	(0.046)	(0.100)
ATT After Matching (Lead 2)	0.090**	0.268	−0.293	0.018	0.211**
	(0.040)	(0.232)	(1.363)	(0.053)	(0.100)
Treated On Support	277	37	9	179	52
Treated Off Support	0	0	0	0	0
Untreated On Support	93175	10584	1254	60749	20588
Untreated Off Support	0	0	0	0	0
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	93452	10621	1263	60928	20640

Note: Data from Estonian Business Registry, 2010-2018.
[a]Propensity score matching with standard errors corrected for heteroscedasticity. Standard errors are reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author’s calculations using Estonian Business Registry 1995-2018

5.4 Implications for the area of study

I cautiously interpret the results of Table 5 as a signal that the inward FDI into Estonia has changed over time. According to Varblane et al. (2020), the productivity advantage of foreign-owned firms in manufacturing has lessened over the years. This productivity is thought to be the source of foreign wage premium (Aitken et al., 1996; Hale & Long, 2011). Therefore, reducing the productivity advantages of foreign-owned manufacturers might result in lessening any foreign wage premium. Additionally, past literature has focused heavily on the manufacturing sector while neglecting the services sector, which may be more critical in former-socialist countries with undeveloped non-tradeable sectors (Köllő et al., 2021). According to the results in Table 5, I estimate that the less knowledge-intensive firms have a significant average wage premium for the two first eras of 1995-2003 and 2004-2009. Then, the knowledge-intensive firms have a significant average wage premium for the last subperiod of 2011-2018. These results potentially support the notion that the productivity gains in the knowledge-intensive sectors, such as financial and insurance activities, have become the focus of FDI. These findings also demonstrate that the literature on FDI's effect on average firm wages should include the services sector. Furthermore, studies like Köllő et al. (2021) that group all services together without considering the knowledge intensity of the sectors potentially lose a critical facet to research.

The current study is based on firm-level data, so I attempt to control for firm heterogeneity to some extent while examining the effects of FDI on the different types of manufacturing and services firms. A limitation of this study stems from the inability to control for the possibility of worker heterogeneity. Studies with linked employer-employee data, such as Malchow-Møller et al. (2013), can use worker fixed effects coupled with firm fixed effects to address endogeneity to some extent. As a possible future research design, I propose investigating how FDI affects wages throughout different sectors and intensities while also controlling for worker heterogeneity to some degree.

6. Conclusions

According to this research, I estimate that the foreign wage premium varies by firm type and era. Using the notion that the three subperiods of this study capture different stages of the Estonian economy, I construct a study to compare the effects of the foreign acquisition on the manufacturing and services sectors. The OLS estimations capture the possible effects of foreign wage premiums of greenfield investments and foreign acquisitions. I attempt to address the problem of endogeneity to an extent with standard fixed effects and PSM. Therefore, I expect the estimated foreign premium to decrease when utilizing these methods. Additionally, I solely focus on foreign acquisitions when estimating the fixed effects and PSM models. According to Heyman et al. (2007), greenfield investments contain the largest foreign wage premium. Yet, greenfield investments have steadily decreased in Estonia since the global financial crisis; meanwhile, the number of mergers and acquisitions has increased (Durán, 2019). Focusing on these acquisitions enables me to estimate how sector aggregations of technology-intensive and knowledge-intensive firms react to FDI. According to my results, I approximate that during 1995-2003 and 2004-2009, acquired firms experienced a foreign wage premium associated with less knowledge-intensive services. This finding can be associated with the wholesale and retail trade surge during these periods (Köllő et al., 2021). Additionally, the foreign wage premium in knowledge-intensive services between 2010-2018 may indicate that Estonia is attracting less foreign investment in manufacturing and less knowledge-intensive sectors because the level of development has increased since joining the OECD in 2010 (OECD, 2012).

For further investigation into the relationship of FDI and wages in Estonia, I propose that the sector intensities be considered with employer-employee linked data. Having the ability to utilize worker fixed effects to some extent will be useful for this future study.

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References

1. Abadie, A., & Imbens, G. W. (2002). Simple and bias-corrected matching estimators for average treatment effects. Technical Working Paper T0283, NBER.

2. Abadie A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica, 74*(1), 235-267. doi:10.2307/3598929

3. Aitken, B., Harrison, A., & Lipsey, R. E. (1996). Wages and foreign ownership: a comparative study of Mexico, Venezuela, and United States. *Journal of International Economics, 40*(3–4), 345–71. doi:10.1016/0022-1996(95)01410-1

4. Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: from supply and demand to natural experiments. *Journal of Economic Perspectives, 15*(4), 69–85. doi:10.1257/jep.15.4.69

5. Austin, P. C. (2009). Using the standardized difference to compare the prevalence of a binary variable between two groups in observational research. *Communications in Statistics—Simulation and Computation, 38*(6), 1228-1234. doi:10.1080/03610910902859574.

6. Barrowman, M. A., Peek, N., Lambie, M., Martin, G. P., & Sperrin, M. (2019). How unmeasured confounding in a competing risks setting can affect treatment effect estimates in observational studies. *BMC Medical Research Methodology, 19*(1), 166. doi:10.1186/s12874-019-0808-7

7. Blonigen, B. A., & Wang, M. G. (2005). Inappropriate pooling of wealthy and poor countries in empirical FDI studies. In T. H. Moran, E. M. Graham, & M. Blomström (eds.), *Does foreign direct investment promote development?* (pp. 221-243). Washington D.C.: Institute for International Economics and Center for Global Development.

8. Brookhart M. A., Schneewiess S., Rothman K.J., Glynn R.J., Avorn J., & Stürmer T. (2006) Variable selection for propensity score models. *American Journal of Epidemiology,163*(12):1149–56. doi:10.1093/aje/kwj149

9. Doms, M. E., & Jensen, J. B. (1998). Comparing wages, skills, and productivity between domestically and foreign-owned manufacturing establishments in the United States. In R. E. Baldwin, R. E. Lipsey, & J. D. Richardson (eds.), *Geography and ownership as bases for economic accounting* (pp. 235–58). Vol. 59 of *Studies in income and wealth*. Chicago: University of Chicago Press.

10. Dunne, T., Foster, L., Haltiwanger, J., & Troske, K. R. (2004). Wage and productivity dispersion in United States manufacturing: the role of computer investment. *Journal of Labor Economics, 22*(2), 397-429. doi:10.1086/381255

11. Dunning, J. H. (1977). Trade, location of economic activity and the MNE: a search for an eclectic approach. In B. Ohlin, P.-O. Hesselborn, & P. M. Wijkman (eds.), *The international allocation of economic activity*. New York: Macmillan.

12. Dunning, J. H. (1979). Toward an eclectic theory of international production: some empirical tests. *Journal of International Business Studies, 11*(1), 9–31. doi:10.1057/palgrave.jibs.8490593

13. Dunning, J. H. (1993). *Multinational enterprises and the global economy*. Wokingham: Addison-Wesley Publishing Company.

14. Durán, J. (2019). *FDI and investment uncertainty in the Baltics*. European Commission Economic Brief No. 043, Luxembourg: Publications Office of the European Union.

15. Feliciano, Z. M., & Lipsey, R. E. (2006). Foreign ownership, wages, and wage changes in U.S. industries, 1987-92. *Contemporary Economic Policy, 24*(1), 74-91. doi:10.1093/cep/byj003

16. Figini, P., & Görg, H. (2011). Does foreign direct investment affect wage inequality? An empirical investigation. *The World Economy, 34*(9), 1455-1475. doi:10.1111/j.1467-9701.2011.01397.x

17. Girma S., & Görg, H. (2007). Evaluating the foreign ownership wage premium using a difference-indifferences matching approach. *Journal of International Economics, 72*(1), 97–112. doi:10.1016/j.jinteco.2006.07.006

18. Girma, S., Greenaway, D., & Wakelin, K. (2001). Who benefits from foreign direct investment in the U.K.? *Scottish Journal of Political Economy, 48*(2), 119-133. doi:10.1111/1467-9485.00189

19. Görg, H., Strobl, E., and Walsh, F. (2007). Why do foreign-owned firms pay more? The role of on-the-job training. *Review of World Economics, 143*(3), 464–482. doi:10.1007/s10290-007-0117-9

20. Hale, G., & Long, C. (2011). Did foreign direct investment put an upward pressure on wages in China? *IMF Economic Review, 59*(3), 404-430. doi:10.1057/imfer.2011.14

21. Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review, 70*(3), 474-75. doi: 10.2307/1805237

22. Heyman, F., Sjöholm, F., & Tingvall, P. G. (2007). Is there really a foreign ownership wage premium? Evidence from matched employer-employee data. *Journal of International Economics, 73*(2), 355-376. doi:10.1016/j.jinteco.2007.04.003

23. Ho, D. E., Imai, K, King G., Stuart E. A. (2007) Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis, 15*(3), 199–236. doi:10.1093/pan/mpl013

24. Hoi, L. Q., & Pomfret, R. (2010). Foreign direct investment and wage spillovers in Vietnam evidence from firm level data. *ASEAN Economic Bulletin, 27*(2), 159–172. doi:10.1355/ae27-2a

25. Howenstine, N. G., & Zeile, W. J. (1994). Characteristics of foreign-owned U.S. manufacturing establishments. *Survey of Current Business, 74*(1), 34–59.

26. Imbens G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: a review. *Review of Economics and Statistics, 86*(1), 4–29. doi:10.1162/003465304323023651

27. Köllő, J., Boza, I., & Balázsi, L. (2021). Wage gains from foreign ownership: evidence from linked employer–employee data. *Journal for Labour Market Research, 55*(3), 1-21. doi:10.1186/s12651-021-00286-0

28. Leuven, E., & Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. http://ideas.repec.org/c/boc/bocode/s432001.html. This version 4.0.12.

29. Lipsey, R. E. (2004). Home and host country effects of FDI. In R. E. Baldwin and L. A. Winters (eds.), *Challenges to Globalization*. Chicago: University of Chicago Press.

30. Lipsey, R. E., & Sjöholm, F. (2004). Foreign direct investment, education and wages in Indonesian manufacturing. *Journal of Development Economics, 73*(1), 415-422. doi:10.1016/j.jdeveco.2002.12.004

31. Malchow-Møller, N., Markusen, J., & Schjerning, B. (2013). Foreign firms, domestic wages. *Scandinavian Journal of Economics, 115*(2), 292–325. doi:10.1111/sjoe.12001

32. OECD (2012). Accession of Estonia to the OECD: a review of international investment policies. Paris :Secretary-General of the OECD.

33. Peluffo, A. (2015). Foreign direct investment, productivity, demand for skilled labour and wage inequality: An analysis of Uruguay. *The World Economy, 38*(6), 962-983. doi:10.1111/twec.12180

34. Pittiglio, R., Reganati, F. & Sica, E. (2015). Do MNEs push up the wages of domestic firms? *The Manchester School, 83*(3), 346-378. doi:10.1111/manc.12076

35. Raynor, W. J. (1983). Caliper pair-matching on a continuous variable in case control studies. *Communications in Statistics: Theory and Methods, 12*(13), 1499–1509. doi:10.1080/03610928308828546

36. Rosenbaum, P., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika, 70*(1), 41-55. doi:10.1093/biomet/70.1.41

37. Rosenbaum P. R., & Rubin D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 39*(1), 33–38. doi:10.1080/00031305.1985.1047938

38. Sjöholm, F., & Lipsey, R. E. (2006). Foreign firms and Indonesian manufacturing wages: an analysis with panel data. *Economic Development and Cultural Change, 55*(1), 201-221. doi:10.1086/505723

39. Taylor, K., & Driffield, N. (2005). Wage inequality and the role of multinationals: Evidence from U.K. panel data. *Labour Economics*, *12*(2), 223-249. doi:10.1016/j.labeco.2003.11.003

40. Tomohara, A., & Yokota, K. (2011). Foreign direct investment and wage inequality: is skill upgrading the culprit? *Applied Economics Letters, 18*(8), 773–81. doi:10.1080/13504851.2010.491448

41. Vahter P. (2011). Does FDI spur productivity, knowledge sourcing and innovation by incumbent firms? Evidence from manufacturing industry in Estonia. *The World Economy, 34(*8), 1308-1326. doi:10.1111/j.1467-9701.2011.01379.x

42. Vahter, P., & Masso, J. (2007). Home versus host country effects of FDI: searching for new evidence of productivity spillovers. *Applied Economics Quarterly, 53*(2), 165-196. doi:10.2139/ssrn.918070

43. Vahter, P., & Masso, J. (2019). The contribution of multinationals to wage inequality: foreign ownership and the gender pay gap. *Review of World Economics, 155*(1), 105-148. doi:10.1007/s10290-018-0336-2

44. Varblane, U. (2001). Flows of foreign direct investments in the Estonian economy. Faculty of Economics and Business Administration, University of Tartu.

45. Varblane, U., Eamets, R., Haldma, T., Kaldaru, H., Masso, J., Mets, T., Paas, T., Reiljan, J., Sepp, J., Türk, K., Ukrainski, K., Vadi, M., & Vissak, T. (2008). The Estonian economy current status of competitiveness and future outlooks. *Estonia in Focus,* (1).

46. Varblane Ur., Varblane, Uk., Pulk, K., Vissak, T., & Lukason, O. (2020) Nutikate välisinvesteeringute uuring: Eestis tegutseva välisosalusega ettevõtete analüüs, et selgitada välja uute välisinvesteeringute maandamise fookus ja kriteeriumid [Smart Foreign Direct Investment Survey: Analysis of Foreign Companies in Estonia for Developing Criteria to Manage and Attract New Foreign Direct Investments]. RITA 4: TAI poliitika seire. Faculty of Economics and Business Administration, University of Tartu.

47. Wooldridge, J. M. (2012). *Introductory econometrics: a modern approach*. Mason, Ohio: South-Western Cengage Learning.

Appendix A

OLS Models for 1995-2003, 2004-2009, 2010-2018

1995-2003 OLS	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.657***	0.411***	0.408***	0.744***	0.662***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	−0.014*	−0.038**	−0.068	−0.018**	0.007
	(0.054)	(0.018)	(0.154)	(0.041)	(0.720)
Size	0.169***	0.139***	0.141***	0.163***	0.279***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	0.132***	0.173***	0.178***	0.127***	0.149***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	81170	11655	1485	53932	14098
Number of firms	26623	3950	551	17228	4894
R^2	0.227	0.297	0.311	0.226	0.201

Note: Data from Estonian Business Registry, 1995-2003.
[a]OLS model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2004-2009 OLS	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.552***	0.340***	0.160**	0.627***	0.569***
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)
Age	−0.013**	−0.079***	−0.051	0.008	0.003
	(0.029)	(0.000)	(0.252)	(0.298)	(0.821)
Size	0.192***	0.165***	0.139***	0.189***	0.285***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	0.108***	0.126***	0.159***	0.109***	0.129***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	110056	13373	1832	70340	24511
Number of firms	35425	4040	568	22176	8641
R^2	0.1671	0.226	0.209	0.176	0.166

Note: Data from Estonian Business Registry, 2004-2009.
[a]OLS model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2010-2018 OLS	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.461***	0.264***	0.106**	0.497***	0.506***
	(0.000)	(0.000)	(0.045)	(0.000)	(0.000)
Age	0.084***	0.060***	0.060***	0.108***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.243***	0.232***	0.186***	0.235***	0.330***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	0.052***	0.073***	0.076***	0.056***	0.059***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	227305	22381	3287	139333	62304
Number of firms	51129	4782	656	30382	15309
R^2	0.192	0.307	0.286	0.198	0.182

Note: Data from Estonian Business Registry, 2010-2018.
[a]OLS model with standard errors corrected for heteroscedasticity. $p-values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author’s calculations using Estonian Business Registry 1995-2018

Appendix B

FE Models for 1995-2003, 2004-2009

1995-2003 Fixed Effects One Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	−0.028	−0.041	0.088	−0.024	0.030
	(0.222)	(0.478)	(0.377)	(0.389)	(0.671)
Age	0.024	0.017	−0.127	0.007	0.049
	(0.389)	(0.804)	(0.488)	(0.844)	(0.520)
Size	−0.083***	−0.075***	−0.105	−0.081***	−0.039
	(0.000)	(0.003)	(0.226)	(0.000)	(0.246)
Capital Intensity	0.030***	0.041***	0.076**	0.030***	0.017
	(0.000)	(0.002)	(0.027)	(0.000)	(0.132)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	43719	6480	878	29154	7207
Number of firms	15246	2270	327	9998	2651
Within-group R^2	0.046	0.092	0.083	0.043	0.026

Note: Data from Estonian Business Registry, 1995-2003.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p - values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

1995-2003 Fixed Effects Two Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	−0.013	−0.051	0.052	−0.036	0.140
	(0.610)	(0.457)	(0.620)	(0.270)	(0.106)
Age	0.028	−0.096	0.078	0.040	0.012
	(0.318)	(0.167)	(0.693)	(0.251)	(0.880)
Size	−0.011	0.001	−0.048	−0.018	0.087***
	(0.323)	(0.980)	(0.548)	(0.202)	(0.010)
Capital Intensity	0.008*	0.008	−0.003	0.010**	0.005
	(0.065)	(0.500)	(0.925)	(0.050)	(0.630)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	40697	6072	827	27059	6739
Number of firms	14208	2140	308	9289	2471
Within-group R^2	0.042	0.089	0.076	0.039	0.034

Note: Data from Estonian Business Registry, 1995-2003.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p - values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

2004-2009 Fixed Effects One Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.022	−0.055	0.157	0.052	−0.070
	(0.456)	(0.132)	(0.116)	(0.202)	(0.358)
Age	−0.192***	−0.121***	−0.083	−0.216***	−0.167***
	(0.000)	(0.005)	(0.434)	(0.000)	(0.000)
Size	−0.042***	−0.048**	−0.012	−0.052***	0.019
	(0.000)	(0.035)	(0.782)	(0.000)	(0.344)
Capital Intensity	0.002	0.003	−0.051***	0.004	0.006
	(0.486)	(0.717)	(0.009)	(0.214)	(0.360)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	69850	9195	1260	45192	14203
Number of firms	22088	2875	408	13879	4926
Within-group R^2	0.040	0.033	0.053	0.046	0.049

Note: Data from Estonian Business Registry, 2004-2009.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p - values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

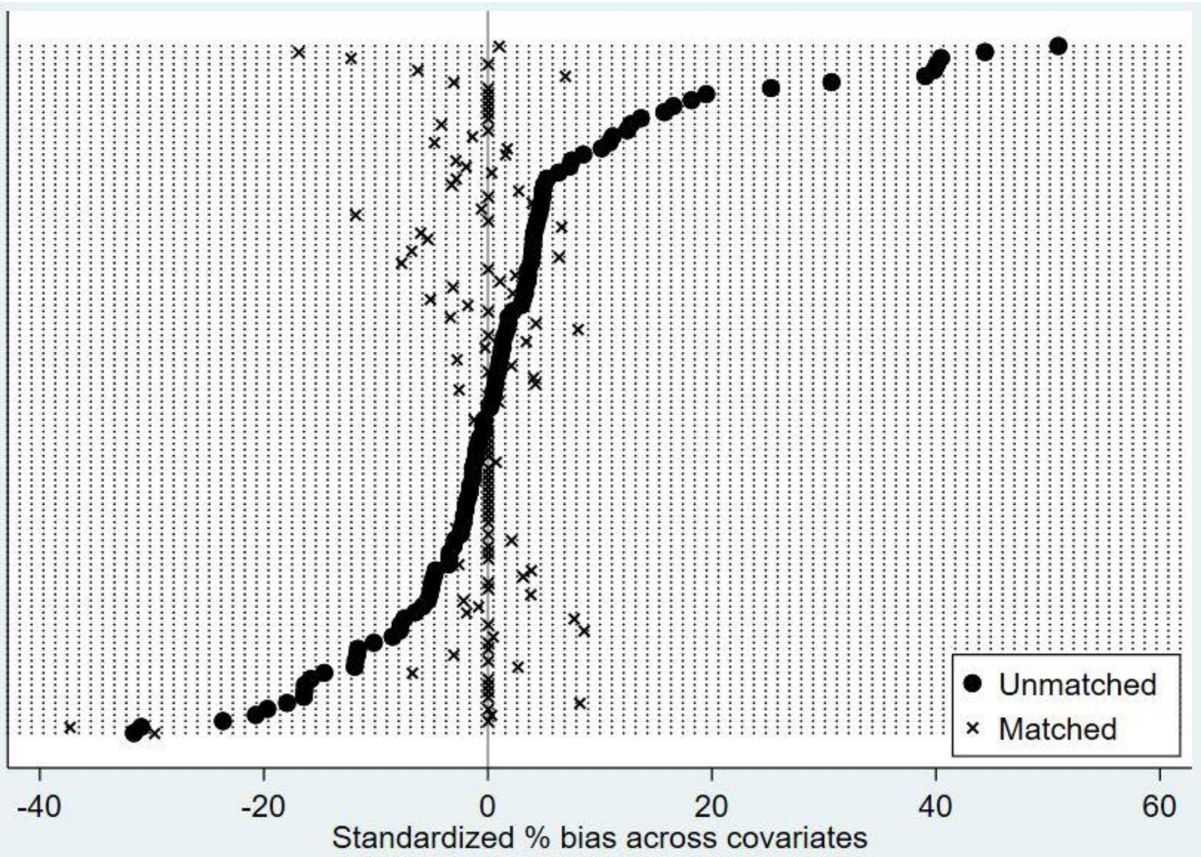
2004-2009 Fixed Effects Two Period Lead	Overall Sample	Manufacturing		Services	
		Low	High	Low	High
Foreign	0.013	−0.054	−0.028	−0.019	0.092
	(0.681)	(0.177)	(0.694)	(0.654)	(0.115)
Age	−0.146***	−0.148***	−0.299**	−0.167***	−0.102**
	(0.000)	(0.001)	(0.019)	(0.000)	(0.031)
Size	0.029***	0.017	0.068	0.027***	0.057***
	(0.000)	(0.536)	(0.176)	(0.004)	(0.007)
Capital Intensity	−0.004	−0.026***	0.004	0.001	−0.005
	(0.166)	(0.007)	(0.835)	(0.758)	(0.481)
Lagged Wage	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of obs.	64638	8498	1179	41810	13151
Number of firms	20823	2730	391	13059	4643
Within-group R^2	0.050	0.023	0.091	0.058	0.072

Note: Data from Estonian Business Registry, 2004-2009.
[a]Fixed effects model with standard errors corrected for heteroscedasticity. $p - values$ reported in parentheses
[b]Manufacturing sector is split based on technology intensity and Services sector is split based on knowledge intensity
*Statistical significance at the 0.1 level
**Statistical significance at the 0.05 level
***Statistical significance at the 0.01 level

Source: author’s calculations using Estonian Business Registry 1995-2018

Appendix C

Example of -pstest- to access the extent of balancing achieved after matching between 1995-2018.



Source: author’s calculations using Estonian Business Registry 1995-2018

Kokkuvõte

Antud magistritöö uurib, kuidas välismaine omandamine mõjutab palkasid Eesti ettevõtetes. Kasutades Äriregistrist saadud Eesti firmade andmeid perioodil 1995 kuni 2018 autor rakendab kalduvusskoori sobitamist ja argiseid fikseeritud mõjusid antud analüüsi sooritamiseks. Lõputöö eesmärk on lisada teadustööle, mis uurib suhet välismaiste otseinvesteeringute ja erinevate sektori klassifikatsioonide vahel, võttes samal ajal arvesse riigi majandusarengut. Tootmise ja teenuste agregaadid on NACE Rev. 2 klassifikatsiooni põhjal. Valimiperiood aastast 1995 aastani 2018 on jaotatud kolmeks kahe sündmuse puhul: Eesti liitumine Euroopa Liiduga 2003. aastal ja suur majandussurutis 2009. aastal. Nende elementide abil autor järeldab, et pärast välismaist omandamist filiaalide palgapreemiad erinevad nii tootmise ja teenuste agregaatide kui ka alamperioodide lõikes. Autor teadustab valimiperioodi lõikes, et esimesest alamperioodist viimaseni on filiaalide palgapreemiad langenud 5%. Tulemused samuti näitavad, et kõige hiljutisema alamperioodi lõikes vahemikus 2010-2018 on filiaalide palgapreemia teadmiste mahukates teenustes 21% kaks aastat pärast välismaist omandamist.

Võtmesõnad: välismaine otseinvesteering, tõenäosuslik sobitamine, lähima naabri sobitamine

JEL Classification: F23, J31

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HOW DOES INWARD FDI AFFECT WAGES IN ESTONIA? (title of thesis)

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