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EUROPEAN FUNDING: DOES IT INDUCE EXPORTS?

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Abstract

Judging by the past five years, history seems to be stress-testing the European Union (EU) like a central bank would its banking sector—with the fallout of the 2008 financial crisis sparking the European debt crisis, which in turn, birthed the Greek financial bailout as well as the looming threat of the Italian debt issue. Such calamities are not limited to monetary and economic matters. All over Europe nationalist politicians such as France's Marine Le Pen and Holland's Geert Wilders are now gaining popularity as the alternative to a seemingly dysfunctional European elite. Today, the odds appear stacked against the Union.

However, since the European Central Bank loosened its monetary policy, there has been an upswing in European competitiveness. Therefore, it is reasonable to look to the exporting sector and its growth prospects to find some glimmer of hope for the EU. In this study, we examine one specific country—Latvia—to find the impact of European Structural and Investment Fund (ESIF) financing on Latvian companies' tendency to export, disaggregated between large and small companies, "experienced" and "less experienced" management, and lastly between ESIF funds. We used a difference-in-differences methodology, combined with propensity score matching to eliminate the impact of any factors other than the "treatment" with EU funding and thus prove a positive relation between receiving EU funding and the exporting decision. We find a statistically significant, positive effect on exports' revenues for the funding recipients over those that had not received ESIF financing, the average treatment effect on the treated of which is 24.7%. What is more, we also find that, as we hypothesized, small companies would experience a greater effect from this influx of capital; more experienced management used the money more efficiently; and the agricultural investment fund had a more pronounced impact on the exporting decision than the regional development one.

It can therefore be concluded that ESIF financing is indeed a boon to the Latvian economy and its competitiveness. These findings should indeed yield the government some insight into more efficient ways to allocate the delegated capital.

Key words: *European funding, exporting, export promotion*

JEL code: C32, C25, O19, F41

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1 Introduction

In recent years, economic growth has become something akin to an "ultimate goal" of modern capitalistic markets in the eyes of both expert economists as well as the general populace. While economists bend over backwards to force their economies to expand, the average worker simply wants to see his paycheck bigger than it was the previous year. There are numerous ways to achieve this growth and most involve trade-offs. This is an absolute truth if one assumes an autarky model of an economy, as in such an economy any choice to consume or produce one good or service would be, at the same time, a choice not to produce some other. However, the modern world is not at all a group of autarkies with no interaction between them. In a world of open economies, the market allows for transfers of goods, services, capital, and other assets from one state to the other, allowing countries to borrow or otherwise take advantage of the wealth that another economy produces. Exporting is one of the channels that allows for such a transfer of wealth as it funnels foreign capital into the recipient economy. Given that Latvia is a net exporter, conversely a net inflow of foreign wealth is thus created.

Furthermore, international trade allows for the exploitation of comparative advantages and specialization, e.g., the United States of America imports cheap consumer goods from China, but at the expense of American manufacturing. Therefore, it comes as no surprise that the activity of exporting has garnered an immense amount of research over the years.

Due to exporting being perceived as such a high value-added activity, many countries go out of their way to support their industries or companies that export. A rather simplistic example of this would be an export subsidy. For example, the United States government's decision to offer a generous tax reduction on Boeing's 777X model was recently found to be a violation of its trade agreement by the World Trade Organization (WTO). The WTO ruled that such tax exemptions are in reality export subsidies simply masquerading as domestic tax policy. (Julie, Andrea, & Ian, 2016). However, export subsidies are no longer an option for governments as all members of WTO have agreed to (excluding agricultural produce and some other exemptions) avoid using export subsidies (World Trade Organization, 2016). Thus, many governments seek to find other means by which to encourage firms to turn to exporting. A viable path to indirectly advocate exporting is investing in high-productivity companies (later this study outlines the strong linkages between productivity and exporting)., however, to shortly note—it is argued that export markets are highly competitive due to the high number of available suppliers. Therefore, it a relatively productive company is required to enter and remain within the international markets. In the case of the European Union (EU), the European Structural and Investment Fund (ESIF) is used as a tool for exactly such investment as will be examined in the *Institutional Details* section of this study).

Contrary the prior example of export subsidizing, the impact of ESIF funding on exporting is not as straightforward. While there is ample academic research on the impact of financial aid on international trade, one would be hard-pressed to find any studies that examine this relation within the EU. Furthermore, Latvia is a prime target to perform many types of tests on ESIF funding due to two reasons: (i) the efficiency of EU funding programs is always a prominent question, especially so due to various known fraud cases (Zālīte, 2013) and (ii) the disproportionately high importance of ESIF funding to the Latvian economy—a fact proven during the whole of 2016 where a stagnant absorption of EU funding resulted in an 17.9% reduction in construction revenues (The Latvian Ministry of Finance, 2017).

Therefore, this is precisely the gap which this study attempts to fill—we seek to determine whether ESIF programs allocate capital to export promotion and answer our research question:

RQ: *Does European Structural and Investment Fund financing promote export activity*?

While there is no clear indication in the ESIF regulatory documents that its financing is intended to promote recipient nation exporting, clearly the funds do so indirectly. Firstly, recipients are able to use the funds to cover sunk costs related to establishing an export activity by, for instance, using this money to pay a participation fee in foreign expositions; Secondly, receiving ESIF funding creates informational channels that allow for easier access to other member markets. This may be done by gaining access to conferences for ESIF recipients; Lastly, one of ESIF goals is to promote competitiveness and productivity. As export propensity is later shown to be linked to these elements, it can be concluded that:

H1: *ESIF recipient companies are more prone to export than those that have not received such financing.*

To answer our research question, we will employ a difference-in-differences analysis methodology with matched control and treatment groups. We believe that, by employing the propensity score matching method to create a control group that is similar to our treatment group, we can single out the effect ESIF funding has on export activity. Our dataset is a survey of 675 companies out of an original dataset of 799 which met our criteria of the variables necessary to conduct our research. Our dataset covers the following variables that are used in our paper: whether the specific firm exports and if it does, what proportion of revenues are earned from exporting, revenues in euros, company age, management experience in years, if a company has received ESIF funding and if it has, what fund did it receive it from, the specific enterprise's ownership structure (foreign vs domestic), and the size of the company in terms of employees.

The remainder of this paper is structured as follows: section two outlines the current literature on exporting, includes the subsection *Institutional Details*, in which we examine the system of ESIF funding distribution and distinguish between various objectives of ESIF funding; section three explains our research method and describes our dataset; section four shows our empirical results, section six discusses them and adds some government policy implications; and section seven concludes.

2 Literature review

To prove a causal relation between ESIF finances and export propensity, we must also justify it with academic literature. To do so, we first ascertain the stronger determinants of exporting and then, from this sample, find such variables that can be either supplemented or increased due to a firm receiving ESIF funding.

Export determinants

Das, Tybout, and Roberts (2007) show that sunk costs have a strong impact on whether a company would become an exporter. They argue that to begin exporting a company is required to put forward a considerable investment of time and money. Therefore, firms that were exporting in the last period, will most likely also export in the next. They test their hypothesis by analyzing three Colombian manufacturing industries—knitted fabrics, basic chemicals, and leather products (in a 2004 revision, knitted fabrics was removed from the dataset, still leaving their conclusions intact). In their model, a firm will choose to become an exporter if their expected profit from exporting outweighs the associated sunk costs which are defined as the initial investment a company will have to make in order to export, such as establishing a relationship with the importer (e.g., legal fees may apply in order to draft a contract) (Das *et al.*, 2007). Their results suggest three important findings. Firstly, that sunk costs are a significant deterrent for companies to begin exporting and that per-unit subsidies are much better than lump sum grants to promote exporting due to higher possible profits. Secondly, that large firms can enter international markets with greater ease than small firms, because their size allows to cover the associated costs with less trade-offs. And lastly, that foreign ownership is associated with a higher probability of exporting, presumably due to reduced costs associated with the creation of informational channels, which are also a significant variable for the exporting decision (Das *et al.*, 2007).

The notion of foreign ownership spillovers is strongly echoed by Aitken, Hanson, and Harrison (1997) as they test for whether Multi-National Enterprises (MNEs) have a positive impact on the indigenous firm's exporting tendencies. They tested this by regressing prices, quantities, production costs, and regional exporting activity on the probability to export. Their model allows them to capture regional spillover effects, i.e., they capture the effect that one exporting firm can have on other nearby companies' tendency to export. They argue that this effect should be positive not only for MNEs, but also indigenous exporters as they would create necessary infrastructures or institutions that would assist in exporting or promoting the activity, such as the construction of, roads, ports and regulatory agencies. Their results concluded that (i) MNEs are, on average, twice as likely to export than domestic firms; (ii) MNE concentration significantly increases export likelihood in the region; and (iii) there is no significant relation between concentration of exporting activities (without the differentiation between MNEs and domestic firms) and exporting of any firm; the fact that there are exporters in a region has no effect on other firms' exporting decision (Aitken *et al.*, 1997). The findings of their study. tie in well with the previously outlined notion of high sunk costs acting as barriers to exporting. They conclude that MNE partners may alleviate various constraints, such as buyer-seller relations, technology requirements, or superior management practices.

The study also concluded higher wages have a positive impact on exporting propensity, because, as they argue, the increase in competitiveness that ensues due to exporting will make the companies pay higher wages. The notion of a positive relation between exporting and high wages is reinforced by Bernard and Jensen (2004) with their research with which they aim to show the full spectrum of reasons due to which a company may choose to go into exporting as well as the opposite—why one may be deterred from beginning an export-based business. They use multiple regressions combining an instrumental variables analysis with lagged variables.

They further took into consideration that that company size, wage rates, productivity, and labor education are significant determinants of exporting. The authors test their model against a vast US firm dataset including 13,550 plants and 94,902 observations (Bernard and Jensen, 2004). What is more, there is another finding that is rather curious in their paper—they find no evidence that US export-supporting programs are working to improve exporting in general. They do mention that this might be due to sample bias, though, the notion remains that the US might be failing to actually support their exporting industries with policies directly targeted at them. We believe that this adds more weight to our findings, as we find that ESIF funding has positive effects on export propensity, therefore, we outline, perhaps, another research gap—the institutional differences between the American and the European funding distribution systems. Knowing, essentially, what these US institutions did "wrong" may prove to be useful information to some governing facilities.

The findings of Das et al., Aitken et al., and Bernard and Jensen, are further strengthened by Masso and Vahter (2015), as they prove that productivity is indeed positively linked with exporting. While the main goal of their study is to prove learning-by-exporting, i.e., that companies tend to become more productive after their entry into the international markets, their results also imply strong selection effects, thus indicating that high productivity may be a prerequisite to begin exporting to cover the associated sunk costs.

Of the set of export determinants, we find that firm size and management experience would have clear a path by which EU funding might affect exports. We outline two hypotheses regarding both variables, i.e., firm size and management experience. Due to how disproportionately strong the export-deterring impact of sunk costs can be to smaller enterprises, assuming ESIF recipient exporters use their funding to cover these costs, we believe that:

H2: *the effect that recipience of EU funding has on exports will be more pronounced for small firms*

While, regarding management experience, we argue that more experienced managers distribute this additional capital much more efficiently than the inexperienced, therefore, we expect:

H3: *higher EU funding impact on exports if the company's management is "experienced*[1]*"*

Institutional details

The European Structural and Investment Fund program was created with two overarching goals: job creation and promoting sustainable economic policies. ESIF consists of five funds: European Regional Development Fund (ERDF), European Social Fund (ESF), Cohesion Fund (CF), European Agricultural Fund for Rural Development (EAFRD), and European Maritime and Fisheries Fund (EMFF). The management of these funds is done jointly by the European Commission (EC) and the national governments through partnership agreements that outline the proposed distribution of funding depending on the specific needs of each country. Budgeting of these funds is made in programming periods, each lasting 7 years (The European Union, 2017). For Latvia, 4.530 billion Euros were distributed in the 2007-2013 programming period, while the current plan is to distribute 4.418 billion Euros in 2014-2020 (Latvian Ministry of Finance, 2016).

The ESIFs fulfilled a vital role in public spending and contributed, on average, 1-2% of annual GDP growth from 2001 to 2016. As mentioned, the goal of the structural funds is improving regional competitiveness, but, at the same time, each of the funds has a specific set of sub-goals that they aim to achieve. In Latvia, the Ministry of Finance manages ERDF, ESF, and CF while the Ministry of Agriculture manages EAFRD and EMFF (Latvian Ministry of Finance, 2016). Due to data availability, it is only necessary to describe in detail the funding distribution practices of ERDF and EAFRD, as we simply do not have enough companies that have received money from other funds. However, this comes as no surprise to us because these are the two funds that invest the most into the private sector.

2.1.1 European Regional Development Fund

The main objective of the ERDF program is to minimize regional welfare discrepancies in the European Union. Financing is targeted toward regions that are poorer (by Gross National Income (GNI) per capita) than the EU average and directed specifically into local infrastructure

[1] a variable whose disentanglement will be provided in the data description

development and fostering entrepreneurial activity in these regions (Latvian Ministry of Finance, 2015). The ERDF directs its funding to what is known as 'thematic concentration' areas:

- Innovation and research;
- The digital agenda;
- Support for small and medium enterprises (SMEs); and
- The low-carbon economy (The European Commission, 2017).

The EC sets out rules regarding minimum funding for policy areas depending on the development level of the specific economy, however, the final decision of funding distribution lies with the managing authority of the fund—the Latvian Ministry of Finance.

2.1.2 European Agricultural Fund for Rural Development

The EAFRD program was created to support the European agricultural industry as well as develop rural regions that may struggle to adapt to the various challenges of the 21st century. The EC has outlined six priorities regarding EAFRD investments:

- fostering knowledge transfer and innovation in agriculture, forestry and rural areas;
- enhancing the viability and competitiveness of all types of agriculture, and promoting innovative farm technologies and sustainable forest management;
- promoting food chain organization, animal welfare and risk management in agriculture;
- restoring, preserving and enhancing ecosystems related to agriculture and forestry;
- promoting resource efficiency and supporting the shift toward a low-carbon and climate-resilient economy in the agriculture, food and forestry sectors;
- promoting social inclusion, poverty reduction and economic development in rural areas (The European Comission, 2017).

As with ERDF, each Member State is given quite a lot of leeway regarding how they decide to distribute the allocated funding, however, the EC requires that at least 4 of the 6 priorities receive funding. EAFRD investments are linked with European Agricultural Guarantee Fund (EAGF) with EAFRD investments more tending toward infrastructure and such, while

EAGF is for payments directly to farmers. Further in the paper, we combine both funds under EAFRD.

Important implications

It is immediately evident that: (a) neither of the two funds' goals contain export stimulation as a funding priority, therefore, the effect our research shows is inadvertent; and (b) the investment areas differ across the two funds, meaning that it is expected that the effect each fund has on export propensity is different. The planning documents of ERDF in Latvia show that 10.5% or (474 million Euros) of its funding was directed toward entrepreneurship and innovation (Latvian Ministry of Finance, 2013). We believe that this is reason enough to believe that ERDF could be promoting export activity indirectly through, e.g., participation in international expositions or conferences—two events in which producers would have an easier time finding importers or buyers of their goods. While, for EAFRD, we find not only rural competitiveness as an investment objective, but also EU agricultural goods' promotion policies meant to advertise European agricultural and maritime produce on the international markets (Latvian Ministry of Agriculture, 2017). It would be a difficult, if not impossible, task, however, to attribute some specific amount of agricultural exports to ESIF funding or these promotion policies, as it would require a separate paper to investigate the success of these programs. In Latvia, rural development and agricultural support financing for the 2007-2013 planning period was 808 million Euros a value that far outweighs ERDF investments[2] (Rural Support Department, 2013). From this we hypothesize that:

H4: *EAFRD funding recipients will, on average, export more than those that have received ERDF support*.

Furthermore, we find that there are varying requirements for different investment objectives, which leads us to conclude that the distribution of our EU funding variable is non-random (European Structural and Investment Fund, 2016). As visible from the binding agreements, the requirements for application to EU funding are not distinctly quantitative—while there are some requirements for minimum turnover, there are no requirements for management

[2] Our intention by showing this comparison of investment size is to show a general trend—that EAFRD tends to invest more in agricultural companies than ERDF does in enterprises. By using said data, we do not mean to draw any conclusions regarding effect size.

experience, company age, and such company characteristics that one could compile into a dataset. The implications of this are outlined in the methodology section.

3 Methodology

If we were to run a simple Ordinary Least Squares (OLS) regression, regressing our binary variable for EU funding on exports, our estimators would be highly biased due to an abundance of omitted variables. Therefore, to escape the various issues surrounding such a simplistic model, we first and foremost employ a difference-in-differences (DID) method as done by Card and Krueger (1995), where they tested the impact a minimum wage increase had on New Jersey's employment in 1992. The DID method relies on finding a control group that fulfills the parallel trend assumption—an assumption that, without "treatment" (in their study, a minimum wage increase; in this one, receiving EU funding), both the treated and untreated groups would develop similarly. Through observation of historic data, Card and Krueger established that New Jersey's economy was highly comparable with that of Pennsylvania. This similarity of economies allowed them to control for all unobserved variables that impact employment changes in either city, such as seasonality and external shocks, . by subtracting the differences in employment statistics before and after the minimum wage was increased in New Jersey. Since then, the DID method has been widely used to determine a causal effect of various treatments on the treated group. The DID method can be described with the following formula:

$$\delta = (\gamma_{11} - \gamma_{21}) - (\gamma_{12} - \gamma_{22}) \tag{1}$$

where, δ denotes the treatment effect, γ_{12} and γ_{11} denote the treatment group before and after treatment, and γ_{22} and γ_{21} denote the control group at both observations (Card & Kreuger, 1995).

However, Card and Krueger's case was quite specific in the sense that they had found the perfect control group to test their hypothesis. We do not have the luxury of the parallel trend assumption between ESIF recipients and all other companies in our dataset, as they are largely different from one another. Therefore, we combine the DID method with propensity score matching to create a control group that is highly similar to our treatment group by a set of covariates. A comparison of EU funding recipients against all other Latvian companies would essentially be similar to comparing professional athletes to hobby runners—we could never know for sure if the funding received truly impacted export propensity of these companies or if they were predisposed to a higher export propensity due to the lack of a base standard of comparison. Hence, to single out the effect of ESIF funding on exports, we compare the companies that received funding to a pool of companies that could have received these funds but did not, while still being similar in all other relevant characteristics to those that did receive funds.

Propensity score matching and the ATT

First published by Paul Rosenbaum and Donald Rubin in 1983, the propensity score matching method tries to deal with the endogeneity problem that occurs when researchers study effects of treatment in a non-experimental setting (Rosenbaum & Rubin, 1983). This methodology has been used multiple times afterwards to estimate the effect of various policies and external events on some characteristics and often it is used in conjunction with propensity score matching (e.g., Girma, Greenaway, & Kneller, (2004), Girma, Gorg, & Strobl, (2007)). Most economic treatment effects are non-random, thus, comparing the performance of a treatment group to the performance of the population leads to strong selection bias. This is also the case given our study, as we previously outline that ESIF funding is not awarded randomly. The propensity score itself is simply the conditional probability of observed individuals to become treated, which yields:

$$p(X) \equiv \Pr(D = 1|X) = E(D|X) \tag{2}$$

where, D is the binary treatment variable (for us, D = 1 if said company has received EU funding and zero if it has not), and X is a set of covariates by which our propensity score is formed (for this study, these are company characteristics by which we form the probability of receiving ESIF funding). We estimate our propensity scores by running a probit regression, regressing our covariates—firm size, foreign ownership, age, labor size, management experience, and whether the firm was an exporter 5 years ago—on our binary ESIF funding variable.

$$\begin{aligned} EUFunds_i = \beta_{const.} + \beta Size_i + \beta Frgn_i + \beta Age_i + \beta Labor_i \\ + \beta Mgmt_i + \beta Exporter_i + \varepsilon_i \end{aligned} \tag{3}$$

where, $EUFunds$ is a binary variable for whether the company has received ESIF funding, $Size$ is the company revenue, $Frgn$ is a binary variable that is one if the company is foreign-owned and zero if it is not, Age shows company age in years, $Labor$ is the number of workers the company employs, $Mgmt$ is the years of work experience that the management has accumulated, $Exporter$ is revenue received from exports five years ago, and β_{const} and ε_i are the intersection and error terms respectively.

As there is no dataset from which we may simply create a control group whose $p(X)$ of the treated would be equal to the p(X) of untreated for every firm, we use the Nearest-Neighbor Matching (NNM) method. This method dictates that each treated observation is matched with an observation from the control group with the nearest propensity score. NNM is also used by Masso and Vahter (2015) and Kangahsharju, (2005). They use very similar microeconomic data and find NNM to be the best way to deal with treated and untreated group differences after obtaining propensity scores., We therefore feel inclined to follow in their path.

In our study, we matched firms with one and two nearest neighbors to show robustness of our results. Another note on our matching method specifies that, due to the size limitations of our dataset, we chose to match with replacement. This means that multiple treated firms may be matched with one control firm. Additionally, as we outline in the Institutional details section, there are no clear determinants of EU funding receipt. Therefore, we simply test for statistical significance among available company characteristics and use those as predictors. We find the greatest significance in variables for company turnover in 2010, foreign ownership, labor size, years of company export experience, management experience, and whether the company was an exporter in 2010.

After matching our samples by NNM, we estimate the Average Treatment effects on Treated (ATT) with a simple OLS regression by following Becker and Ichino (2002) guidelines on implementing Rosenbaum and Rubin (1983) model:

$$\begin{aligned}\tau &= E\{Y_{1i} - Y_{0i} | D_i = 1\} \\ &= E[E\{Y_{1i} - Y_{0\mathrm{i}} | D = 1, p(X_i)\}] \\ &= E[E\{Y_{1i} | D_i = 1, p(X_i)\} - E\{Y_{0i} | D_i = 0, p(X_i)\} | D_i = 1] \qquad (4)\end{aligned}$$

where, τ is the ATT, $p(X_i)$ is the propensity score, and Y_{1i} and Y_{0i} are the two possible outcomes dependent on treatment (D). From Equation (4), we can explain ATT as the difference in the dependent variable between treated and untreated groups, conditional on the propensity score, given that treatment is equal to one, or more intuitively, we match two companies—one that is treated and another that is not—by their propensity scores and take the difference in their dependent variable. As previously mentioned, we will use a DID method, therefore, our dependent variable (exports) will be a difference—this means that we will study the impact of ESIF financing on export growth or conversely, a decrease in export activity. Therefore, as we perform the same analysis as before, that is take the difference in dependent variables, given that we have matched our companies by their propensity score and that one firm receives EU funds, we arrive at a difference in the differences of export revenues achieved through a matched sample.

Dataset description

Our dataset is a survey designed by our supervisor and Professor Tālis Putniņš that consists of 799 Latvian companies. The survey covers both quantitative as well as qualitative questions regarding firm characteristics. Regarding the quantitative description of companies, the survey has three time points: (i) variables such as turnover, export percent of turnover, employee number, management experience are reported five years ago (2010); (ii) the same variables but in present day (2015); (iii) and what is the composition of necessary funding sources in the last three years.

It is immediately visible that the survey was crafted in such a manner to allow for use of DID methodologies to study relations between variables as one of the prerequisites of DID is that treatment is received within the studied timeframe. Of all the available data, we have used the following elements in our model:

- Firm size measured by annual turnover in EUR;
- Number of employees (full-time equivalent), including management;
- Domestic sales (% of turnover), i.e., inverse of proportion exported;
- Year the company was established (used to calculate company age);
- Years of managerial experience of the top management; and
- Whether the controlling owner is local or foreign.

During the initial stage of our research, we found that we required more reliable sources of information regarding a multitude of these variables, as we could see from a brief descriptive statistics analysis that there were numerous overestimates, underestimates, or simply missing values. The variable that caused the most consternation was turnover in EUR, in which most of the values were rounded and sometimes very approximate or indicated as unchanged from period to period. In some instances, they were completely missing. We solve this dilemma by manually obtaining company data from the "ORBIS" database and overwriting the survey. In many cases, the database held multiple companies with the same name. We therefore recommend that for further studies of this kind a company registration code is also obtained as a supplement to ensure statistical integrity and that there is no ambiguity in case the company has a name that can be linked to multiple companies. Such an addition to the survey would have sped up our research significantly.

Many companies indicate whether they have received European funding or not, however, we find responses to this question to be very unreliable. Firstly, when surveyed, the management often indicated that they have received funding in the last three years, while, in truth, the funding had been received six or more years ago. Secondly, the company might have participated in performing a project that is financed by ESIF funding, but when surveyed, they indicate that they have received funding directly. Worse yet, several companies fail to indicate that they have received any funds at all. This possibly may be due to the company representative sincerely not being fully aware of company financing or that the representative harbors some unknown reason for providing misleading or incorrect information. To account for these issues, we run the company names through publicly available lists of ESIF recipients to make sure that we do not overstate or understate the ATT. We use the list of recipients available from Rural Support Department's homepage to cross-check EAFRD financing (Rural Support Department, 2017). In the same manner, we use the Latvian ESIFs' freely available record of recipients to perform the same check for ERDF (Latvian Ministry of Finance, 2017).

After acquiring the necessary information, we consolidate the data into a single file then we "clean" or filter it to the point where we are only left with reliable and accurate variables. For cases in which all key variables were missing, the observations are dropped entirely. For cases of "ORBIS" supplying faulty values, the observation is changed to the self-reported survey value. We purposely remove all government-held companies as they do not operate according to free market constraints, and therefore yield no valuable information regarding ESIF funding and its impact on the exporting decision.

Finally, the dataset discards observations that are below the 1st and above the 99th percentile (and, as a robustness check, 2nd and 98th percentile as well) before the analysis is conducted. After these actions, our dataset now consists of 675 companies for which we most of the necessary data to perform our research. We find that, for a multitude of companies, we are still missing values regarding many control variables, e.g., labor size and management experience. This narrows the scope of our research as we are then limited in the factors we can control for in the model.

Disaggregation of subgroups

To test our hypotheses with a difference-in-differences analysis, we must divide our sample into appropriate subgroups. In terms of our primary research question—whether ESIF funding promotes exporting, and if so to what extent—this would simply be the treatment and control groups. Our dataset contains 93 companies that have received EU funding, thus, if we were to assume random assignment for ESIF funding, our control group would consist of 582 companies. However, as we have concluded that EU funding is non-random, we must form a viable control group.

From the companies in our two sub-groups, we are specifically interested in the performance of companies that were previously exporting but ceased to do so, companies that only began exporting in the last five-year period and companies that exported beforehand and still export now; we denote this group as exporters. Once divided so, our treated sample is 47 ESIF recipients-exporters and 184 untreated exporters.

As outlined in the literature review, we hypothesize that ESIF funding has a more pronounced effect on small enterprises than on big firms. Similarly, we also wish to test the different effects of management experience can have on export growth, conditional on receipt of funding. As our sample is fairly small, we cannot afford to choose arbitrary thresholds for when a company is large or when a manager is "experienced". To overcome this, we have chosen to work with values relative to our dataset: the company is labeled as large if its size is higher than that of the mean treated company; while the converse is true regarding small enterprises. Managers are "experienced" if they have more years of experience than the mean manager of a recipient firm; while the converse is true for inexperienced managers. By employing this kind of logic, we find that, in our sample, a "large" company is one with turnover above 1.1m EUR and "experienced" managers have upwards of 20 years of managerial experience. Table 1 examines summary statistics of our data for the various groups.

In Table 1 we can observe how the subgroups differ in the characteristics most relevant to us. The dataset is not homogenous and the observed variance in all of variables is quite large, there are no clear and useful conclusions that could be drawn without regression analysis.

	Non-recipient exporters				Matched sample					
Parameter of interest	**Mean**	**St.dev**	**Min**	**Max**	**Mean**	**St.dev**	**Min**	**Max**	**Mean**	**S**
Percent of turnover exported (2010)	44.59 %	38.60 %	0%	100%	60.56%	36.35%	0%	100%	49.53%	3
Percent of turnover exported (2015)	43.06 %	37.00%	0%	100%	47.36 %	39.58%	0%	100%	61.13%	3
Number of employees	24.79	41.97	1	360	25.93478	48.82	1	36	71.71	1
Turnover, mln EUR (2010)	2.67	6.91	1057	7.33	4.42 EUR	7.42	6609	26.4	7.35	
Turnover, mln EUR (2015)	3.42	11.2	823	133	4.60 EUR	8.33	1370	29.8	3.81 EUR	
Management experience (years)	15.15819	8.73	2	50	14.83	8.06	2	40	18.42	
Age (years)	15.10	8.06	5	70	17.58	8.73	5	70	19.46	1
Number of observations	177				46					

Table 1. Summary statistics for three groups of samples—all non-recipient exporters, the propensity score-matched non-recipient exporters, and recipient exporters. We summarize mean values and standard deviations.

Limitations

As previously mentioned, our sample size is relatively small, 799 companies before dataset cleaning; this issue becomes significantly more prominent as we refine the dataset and check for missing or false values. Once the dataset narrows down to ~40-45 observations for some specific groups, the issue of missing values becomes an insurmountable obstacle as we cannot, for instance, test for industry-specific effects because the observation count for some industries is too low to gain significant results.

Propensity score matching is a very popular method for distinguishing a comparable sample in a non-random treatment setting. However, it renders our results rather sensitive to the matching principles we choose. The results can vary widely between propensity score matching methods and we show this variation in our robustness check section.

Another concern is that the covariates that we use for propensity score matching may not explain a significant share of probability associated with EU funding allocation. Although our method was to select the best variables from those that were available in our dataset, we encourage the search for other relevant variables if possible. Many of the variables we believe to be relevant are plagued by a dataset-wide omission, i.e., the information was missing for a sizable amount of observations. Nonetheless, we still believe that the questionnaire is reliable despite any possible missing values.

Furthermore, a difficulty arises with the interpretation of our results: when one looks strictly at an increase in the proportion of exports' revenues without an additional view of the absolute changes in turnover, an increase in exports may arise simply by a decrease in domestic sales. However, Table 1 shows that revenues have generally increased for both our non-recipient and recipient exporters. There is still some ambiguity for specific firms, yet, for both samples at large, the argument seems moot.

4 *Analysis of the results*

The first stage of our research determines the conditional probability that a company received EU funding. The variables and their predicting capabilities are shown in Table 2. As this is a probit regression, nothing more than the direction and significance of each of the variables' impact is discernable. We may observe that only the age of the company is insignificant at any level, meaning that we have good predictors of EU funding allocation.

We believe that there is great potential for improvement of this stage of research by finding a better array of covariates. However, as outlined in the Institutional details section, it is a difficult task. These were the most statistically significant explanatory variables available to us from our survey. Additionally, they also have some logic behind them, as discussed previously in the *Propensity score matching and the ATT* subsection of the *Methodology* section.

Probit regression results. Determining the probability of EU finding allocation.

	Unadjusted		**Trimmed at 1 %**		**Winsored at 1%**	
Covariate	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**
Turnover (2010)	0.0000000195	0.080	0.0000000197	0.077	0.0000000195	0.080
Foreign ownership	-0.4422162	0.086	-0.4445407	0.084	-0.4422162	0.086
Age	.0107568	0.114	0.0090787	0.189	.0107568	0.114
Number of employees	.0019365	0.085	0.0020417	0.070	.0019365	0.085
Management experience	.0164145	0.030	0.0155266	0.043	.0164145	0.030
Percent of turnover exported (2010)	0.468405	0.014	0.4574942	0.017	0.468405	0.014
Constant	-1.673751	0.000	-1.633635	0.000	-1.673751	0.000

Table 2. Probit regression results table that is used to estimate the propensity scores for companies. One may observe the coefficients of each variable and their significance.

The difference-in-differences estimate for the treatment group in the sample trimmed at the 1st and 99th percentiles, after applying nearest neighbor matching or, more simply stated, the ATT, is 24.7% at a 99% significance level. This means that when comparing companies which received EU funding to those that did not, we can reliably say that EU funding has had a positive effect on export propensity. In Table 3, this can be seen on the first row of the second column. What is important to note regarding our ATT estimations, is that they are significant at the 1% threshold for all but two configurations of our dataset. This further reinforces our strong conclusions that EU funding does indeed promote exporting and proves our hypothesis (H1) true—European Structural and Investment Fund finances do promote export activity.

	Full sample "ATT"	**NNM with 1NN Or "ATT"**	**NNM with 2NN Or "ATT"**
DID estimate			
(Trimmed @1%)	0.1303107***	0.246956523***	0.193804349***
(Trimmed @2%)	0.0557318 **	0.103488371***	0.08116279**
(Winsored @1%)	0.1153793***	0.208936171***	0.178510638***
(Winsored @2%)	0.1121103***	0.206808512***	0.174255317***
Untrimmed/Without Winsoring	0.1151619***	0.208936171***	0.178510638***

Table 3. ATT estimation for various constructions of the dataset. The first column shows the ATT without matched samples, i.e., the effect of EU funding on export propensity of all firms, the second column shows the base case of ATT with matched samples and NNM with 1NN, and the third column expands with NNM with 2NN

As stated previously, we expand our analysis by disentangling the effect for various sub-groups. Our estimation of the effects of EU funding, differentiated between small and big companies, (see, Table 4) indicates that the ATT for small companies is 31.55% at 99% significance level, which is 7.54% larger than difference-in-differences estimate for large companies. We then test if the difference in means is statistically different from zero. The test indicates that the difference between these estimates is insignificant and we cannot reject the hypothesis that the EU funding impacts exporting tendency for small and large companies equally. This means that we must conclude that there may be no effect differences between small and big companies, thus proving our hypothesis (H2) false—we cannot say with certainty whether EU funding impacts small and big companies differently.

	NNM with 1NN or "ATT"		
Estimate	**Untrimmed**	**Trimmed at 1%**	**Trimmed at 2%**
DID for Small companies	0.2416667**	0.3154857***	0.1371212**
DID for Large Companies	0.2250408***	0.2401339***	0.0874808**
Difference in means	0.0166259	0.0753518	0.0496404

Prob > chi^2	0.8876	0.5828	0.5208

Table 4. The ATT estimation for a dataset disaggregated between small and large companies.

As seen in Table 5, the ATT estimate for companies with more experienced management is 38.93% at the 99% significance level, which is 25.15% larger than the estimate for companies with less experienced management. Here, the statistical test for whether the difference in means is non-zero, indicates that we have enough evidence to reject the null hypothesis at the 5% significance threshold, which states that the companies with more experienced management will not be affected by EU funds to the same extent as those with less experienced management. The data concludes that more experienced management increase their revenue share of exports more than inexperienced management, which suggests our hypothesis (H3) true—more experienced management will use the funding received from ESIFs to increase their exports more than those managers that are less experienced.

	NNM (with 1NN) or "ATT"		
Estimate	**Untrimmed**	**Trimmed at 1%**	**Trimmed at 2%**
DID if experience <20 years	0.121806*	0.137795*	0.0457273
DID if experience >20years	0.3036905 ***	0.3893478***	0.1578468***
Difference in means	0.1818845	0.2515528	0.1121195
Prob > chi^2	0.0659	0.0421	0.0590

Table 5. The difference in ATT when the sample is divided among experienced and inexperienced management.

And lastly, Table 6 disaggregates between companies that receive EAFRD and ERDF funding. The ATT estimates for companies that receive EAFRD funding is 27.66% at the 99% significance level, which is 7.64% larger than the estimate for companies receiving ERDF funding. The statistical test of mean difference concludes that we cannot say with certainty that the effect is different between funds, therefore proving our hypothesis (H4) false—there is no difference between the effects of EAFRD and ERDF funding on export propensity.

	NNM (with 1NN) or "ATT"		
Estimate	Untrimmed	Trimmed at 1%	Trimmed at 2%
ERDF	0.1766768***	0.2002273***	0.0745412**
EAFRD	0.2462222***	0.2765909***	0.1157317***
Difference in means	0.0695454	0.0763636	0.0411905

Prob > chi^2	0.3378	0.3046	0.3760

Table 6. The difference in ATT estimations for funding received from EAFRD vs ERDF

5 *Discussion of Results*

The study was performed to find whether EU Funding has a positive impact on Latvian companies' tendency to export. For this purpose, propensity score matching and difference-in-difference methodology was applied to a dataset obtained by combining survey data, publicly available company data, and publicly available records of ESIF funded projects.

While conducting our research we came across several companies whose primary focus for the EU money was buying equipment to produce higher quality goods (we examine one such case later) or participation in international conferences, which is essentially development of informational channels. This, in addition to the wild fluctuations in the beta coefficient for EU funding, caused by changes in matching principles or the lack thereof, signifies that applying the DID methodology without propensity score matching creates a substantial bias in our estimators, which further strengthens our commitment and confidence in our methodology and results.

The results have answered our research question and proven our first hypothesis (H1) true—there is a positive relation between receipt of EU funding and growth in share of turnover exported over a five-year time-span. All robustness checks indicate a strong, statistically significant effect ranging from 5.57% to 24.69% at varying confidence intervals, that never breach the 95% level. We believe that this is a very positive finding regarding EU funding, as we have previously outlined the beneficial effects of export activity. We visualize our base case of 24.69% effect in Figure 1.

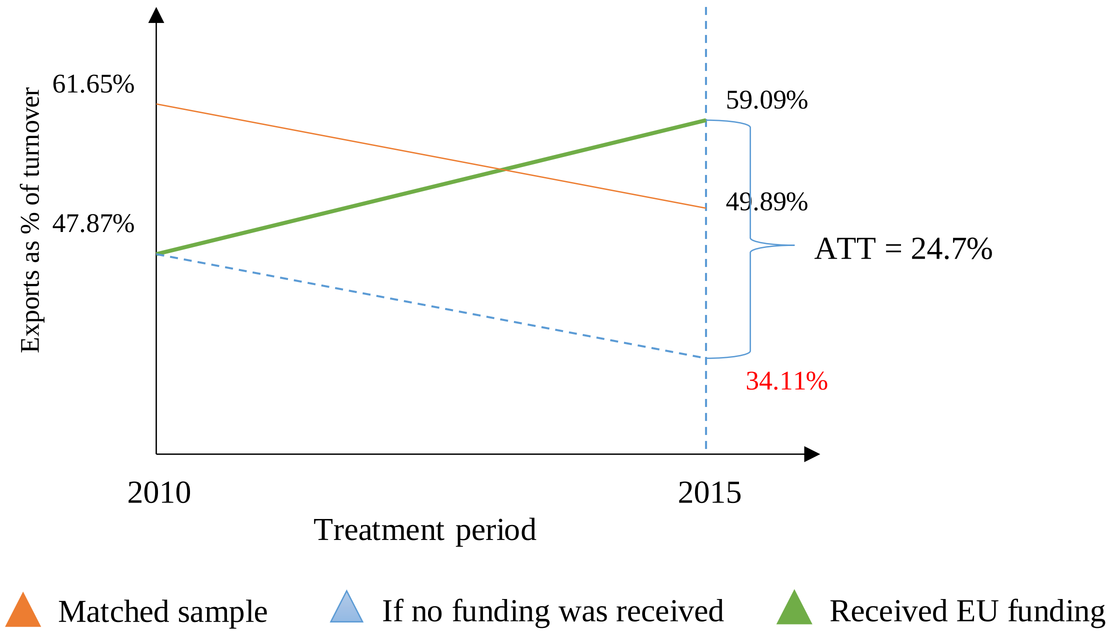

Figure 1. The figure shows the ATT of EU funding. Due to the parallel trend assumption, we assume that the non-recipient and recipient companies would develop similarly over the treatment period, given that neither group receives treatment (hence the dotted line). However, the treated group had their turnover exported increased over the matched sample by 24.7%. As our methodology outlines, we attribute this increase to the receipt of EU funding.

As outlined in the Methodology section, in absence of treatment, the DID method assumes a parallel trend in the development of both groups (see dotted line in Figure 1). In other words, if the companies did not receive the funding, their share of turnover exported would have decreased from 47.87% to 34.11%, but as they did, their share has grown to 59.09%. However, a closer look at the robustness checks reveal that slight changes in the method yield quite a wide range of results. In our opinion, the estimator serves more as an approximation tool than a predictor, a value that could be compared to evidence in other countries or over time. The small sample also could cause our results to be somewhat biased and the actual difference could be much smaller. Even if we suggest not taking this number at face value, we do believe that the results are significant enough to say that the EU funding does impact Latvian company export participation in a positive way. Further, we offer a deeper analysis of the effects of EU funding by disaggregating the effect between various groups.

5.1.1 Small vs big

We expect the effect on smaller companies to be more pronounced due to our determination that sunk costs, the upfront costs of establishing an international business, is a significantly higher issue for smaller enterprises than it is for larger strictly by logic; a large enterprise will be able to cover these costs with ease due to their proportionately higher revenues. The data shows a minor inclination toward this notion. Whereas the estimator is marginally higher for smaller companies than it is for larger enterprises, the statistical significance of it is non-existent. Therefore, we cannot conclude that there is any difference between these effects. From Table 7, we one can see that, for our base case (see, trimmed at 1%), the estimators for both small as well as large companies are significant, demonstrating the strength of the coefficients as standalone predictors. However, once we perform a test for whether these estimators are statistically different from one another (done by testing if their subtraction is equal to zero), we cannot reject the hypothesis that they are not.

	NNM with 1NN or "ATT"		
Estimate	**Untrimmed**	**Trimmed at 1%**	**Trimmed at 2%**
DID for Small companies	0.2416667**	0.3154857***	0.1371212**
DID for Large Companies	0.2250408***	0.2401339***	0.0874808**
Difference in means	0.0166259	0.0753518	0.0496404
Prob > chi^2	0.8876	0.5828	0.5208

Table 7. The ATT estimation for a dataset disaggregated between small and large companies

While this does not prove our hypothesis (H2) true, we believe that the result still somewhat adds to our notion. The effect is more pronounced for smaller companies than it is for larger ones for all variations of the method. We believe that, despite the insignificance of their difference, we can still draw some value from the test.

5.1.2 Managerial experience

We argue that more experienced managers will recognize the benefits of going into export markets and do so with more persistence than those managers that have not spent as much time in the field. The data proves our expectation true—we find that more experienced managers do, in fact, use the additional capital to either enter the international markets more efficiently, as seen in Table 8. We find that the estimator for inexperienced managers is weakly significant and simply low in absolute terms, while the estimator for experienced managers is significant at every level and considerably higher. While, again, we feel the need to emphasize the fact that we believe these values to be more indicative than predicting, as the function of this effect would most definitely not be binary—crossing the 20-year experience mark will not make a manager suddenly three times more likely to go into exporting. The true curve is likely non-linear, however, the form of it we do not predict and could not predict with the size of our dataset, as if we were to divide our sample in more age groups, we, in many cases, fall below 10 observation points, creating immense biases in our estimators.

	NNM (with 1NN) or "ATT"		
Estimate	**Untrimmed**	**Trimmed at 1%**	**Trimmed at 2%**
DID if experience <20 years	0.121806*	0.137795*	0.0457273
DID if experience >20years	0.3036905 ***	0.3893478***	0.1578468***
Difference in means	0.1818845	0.2515528	0.1121195
Prob > chi^2	0.0659	0.0421	0.0590

Table 8. The difference in ATT when the sample is divided among experienced and inexperienced management.

The data reveals that the difference in estimators is statistically significantly non-zero at the 5% confidence level, giving us clear indication that our hypothesis regarding managers (H3) cannot be rejected—more managerial experience translates into more of EU funding being awarded to export activity promotion, development, and anything that increases its revenues.

5.1.3 Fund-specific effects

We argue that the effect for EAFRD would be more pronounced than that of ERDF due to the specifics of their investment objectives as well as the size of them. EAFRD invests more into the private sector than ERDF does, therefore, we expect it to have a greater impact on export propensity. We find that the effect of EAFRD is in fact stronger than that of ERDF, however, the statistical test proves that the estimators are not significantly different from one another (see, Table 9, Prob > chi^2). Still, as with the company size, we feel that it is rather indicative that the effect of EAFRD is, for all variations of our model, stronger than that of ERDF.

	NNM (with 1NN) or "ATT"		
Estimate	Untrimmed	Trimmed at 1%	Trimmed at 2%
ERDF	0.1766768***	0.2002273***	0.0745412**
EAFRD	0.2462222***	0.2765909***	0.1157317***
Difference in means	0.0695454	0.0763636	0.0411905
Prob > chi^2	0.3378	0.3046	0.3760

Table 9. The difference in ATT estimations for funding received from EAFRD vs ERDF.

While we cannot reject the hypothesis that these fund-specific effects are the same, and thus prove our hypothesis (H4) false—we believe that there is some value in the specific estimator sizes for our Government policy implications section.

Overall, results of our study are satisfactory and two of four hypotheses are confirmed:

H1: *EU Funding does promote Latvian company tendency to export more.*

H3: *More experienced managers funnel a higher proportion of EU funding into exporting.*

Anecdotal evidence

To illustrate our data in a more comprehensive way, we choose a specific pair out of our matched samples as anecdotal evidence. "VIT Būve" received funding through ERDF and has increased its export from 0% to 85% of turnover. The company produces wooden panels used to set up modular houses. Sales of such houses skyrocketed during the pre-crisis period and can be found all over western Europe, even as far as the Corsica island (VIT BŪVE, 2017). In the first step of our method, we calculate the propensity score for this company to be 0.1381721. The nearest two neighbors to this score in our dataset are 0.13879994 and 0.13979219 which correspond to companies "HRONOSS AZ" and "AMSERV MOTORS" respectively. In terms of turnover, management experience, and other covariates outlined previously, our model estimates that they have a very similar probability of receiving EU funding to that of the recipient company. The 1st nearest neighbor, "HRONOSS AZ" provides woodcutting services and is based in the same city as "VIT BŪVE". This is an astoundingly close match, as not only do both companies work in our industry, they also operate in one city. For this specific case, our methodology has allowed us to evaluate the performance of "VIT BŪVE" against a company that is astonishingly more comparable to it than the pool of all other Latvian companies. The second nearest neighbor, "AMSERV MOTORS" is already not as impressive a match—an automobile retailer in Riga, which points to our largest limitation—the small sample size. We argue that, with such a small sample, two nearest neighbor matching could be pushing the limits of the dataset and forcing the matching method to accept companies that are much less similar, as a company can match well on revenues, but poorly on, for instance, exporting. Even with this limitation the two nearest neighbor matching method combined with DID shows statistically significant result supporting our hypotheses.

The example of “VIT BŪVE” and “HRONOSS AZ” is an excellent example that shows the power of our methodology, but we do not use this as more than indicative. Rather, these separate cases can guide us towards improvements for further research. For example, we do believe that Das, Tybout, and Roberts (2007) improve the accuracy of their results by comparing companies only within their industry. By following their example, our model would not compare a wooden house manufacturer to a car retailer and the conclusions would be vastly more valuable to a government body that decides on funding allocation. With a larger dataset, we could provide insight for each industry separately.

Illustrative effects

In this section, we roughly estimate the effect of EU funding on export propensity, however, we wish to point out that these calculations are distinctly illustrative and should not be assumed to have any predictive capacity.

The mean amount of EU funding received in our treatment sample is 120,566 EUR and mean turnover of these companies is 7,521,944, growing by 2.8% annually (an approximate growth rate of our treated sample), from which in a 5-year treatment period, the company, on average, will increase exports by 25% due to receipt of EU funding. This means, that a EUR in EU funding over 5-year period could be responsible for directing 17.9 EUR of turnover towards exports in the 5^{th} year. Even if we take the lowest DID estimate of 5.6%, it would mean, that a single EUR in funding is responsible for directing 3.6 EUR of turnover towards exports in the 5^{th} year. As we can see, this estimate varies quite widely, however, there is no doubt that EU funding has positively impacted Latvian company performance by directing a great part of their turnover towards international markets.

We show that management experience has a significant impact on how the recipient companies managed their exports performance. Indeed, one can see that the difference is positive and companies with management with over 20 years of experience have shifted towards exporting more than those with management with less than 20 years of experience. This difference also varies greatly and even reaches more than 20%. By purely speculating we could argue that the more experienced management has more contacts across the borders or understands the importance of diversifying income streams to secure company performance during domestic shocks, but that remains merely speculation. Another argument could be that the success of projects financed by EU funds can be partially explained by management experience and the less experienced management teams simply fail to break into the international markets with their newly developed products or supposed competitive advantage. If this interpretation is reflecting the true causal effect, then one EUR of European funding will help more experienced management to direct 27.9 EUR of turnover towards international markets while the same amount used by less experienced management will help directing only 10 EUR.

Since the sample does not involve companies that are completely bordered themselves from exporting i.e. had zero exports in 2010 and 2015—we can't generalize the results to the whole EU funding amount distributed in Latvia. Rather, we analyze a specific part.

Government policy implications

The previous sections lead us to believe that the Latvian government could improve the efficiency of allocated funding by considering management experience and size as their allocation criteria. The rough estimate shows that the gain from such a move could be upward of 17.9 EUR in exports for each EUR of allocated capital. Additionally, even though there are minimum requirements to apply for financing, the impact could also be improved by specifically targeting companies with turnover below 1 million. While we cannot be certain about the extent of the added benefit, we suggest studying the segment more and determine it.

The importance of this research lies in the possibility of improving the efficiency of allocating EU funding in Latvia. That said, we believe that this research has allowed us to take a glimpse at the necessary prerequisites for successfully evaluating EU programs and improving them. This could add value not only to the system of allocation, but also to the real economy. For instance, the databases holding EU funding recipient information do not possess the company-specific registry numbers (VAT IDs). Furthermore, when there are many companies with the same name, the dataset requires manual intervention, which does not always solve the problem—often, we simply dropped the observations and moved on, further reducing our sample size. By merely adding the registry number to the databases or funding agreements, the government agencies would allow future researchers to obtain a higher level of precision and solve the cases when companies have changed their names. At first glance, this may seem irrelevant, but roughly estimating a 5% of our dataset was affected by this problem and we believe that to be large enough to be noted.

6 Conclusions

We set out to test the effect of EU funding on the Latvian exporting sector—do the programs expand it? Do they limit it? We find that the ESIF financing system is, in fact, a boon to the Latvian economy and it is proven that it increases recipient companies' tendency to export by approximately 25%. We feel that the significance as well as the magnitude of this estimator is immensely valuable to the government institutions responsible for implementation of the program. We further showed that a Euro invested by the ESIF program will yield 17.9 Euros of export turnover over a five-year period for the median company of our dataset.

Furthermore, we disaggregate the effect between small and large enterprises, experienced and inexperienced management, and ERDF and EAFRD funding effects. We find that, while small companies do have a higher estimator, the difference between the two estimators is insignificant, therefore, we cannot say with confidence that smaller companies are more prone to use the funding for exports. We find that experienced management does, in fact, invest more of the received funding into export activity, and the difference between the estimators is significantly non-zero. We argue that this may be due to the managers having better contacts or business prowess, however, the channels by which experienced managers increase their exports will remain unknown until qualitative studies are conducted on their characteristics. We expected EAFRD to have a more pronounced effect on export propensity, an expectation that partially came true—while the fund did have a higher beta coefficient, the difference between the two funds' estimators is insignificantly non-zero, therefore, we cannot say with full confidence that either fund impacts export propensity more.

As we outline in the final sections of our paper, we believe that the results of our research can be used to form more effective funding allocation systems. That is, if exporting and characteristics of the activity are included in the fund's investment objectives. As we have shown, there are none that invest directly into exporting, however, regional development and some of its sub-goals align with the effects of export activity quite well.

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8 Appendices

Appendix A. Summary of subgroups

Table 1: Disaggregation between groups.

	# Received EU Funding	# Did not receive Funding
Parameter of interest		
Total	93	582
Export participant	47	184
Large (>1.1mEUR turnover in 2010)	48	134
Small (<1.1mEUR turnover in 2010)	45	448
Experienced management (More than 20 years)	41	382
Less exp. management (Less than 20 years)	47	188
Foreign owned	5	60
ERDF[3]	58	-
EFF[4] **or EMFF**[5]	1	-
EAFRD[6] **or EAGF**[7]	55	-
CF[8]	1	-

*Some observations are missing; thus, the total is often not the sum of two subsets

Appendix B. Robustness analysis

Table B.1. Robustness analysis of DID estimate.

DID estimate	Full sample “ATT”	NNM with 1NN	NNM with 2NN

[3] European Regional Development Fund
[4] European Fisheries Fund
[5] European Maritime and Fisheries Fund
[6] European Agricultural Fund for Rural Development
[7] European Agricultural Guarantee Fund
[8] Cohesion Fund

		Or “ATT”	Or “ATT”
(Trimmed @1%)	0.1303107***	0.246956523***	0.193804349***
(Trimmed @2%)	0.0557318 **	0.103488371***	0.08116279**
(Winsored @1%)	0.1153793***	0.208936171***	0.178510638***
(Winsored @2%)	0.1121103***	0.206808512***	0.174255317***
Untrimmed/Without Winsoring	0.1151619***	0.208936171***	0.178510638***

(denotes significance at the 1% level, ** at the 5% level and * at the 10% level)***

Effects of European funding on small and large company tendency to export (with Winsored samples)

	Full sample “ATT”			NNM with 1NN or “ATT”			NNM with 2NN or “ATT”		
Estimate	Not Winsored	Winsored at 1%	Winsored at 2%	Not Winsored	Winsored at 1%	Winsored at 2%	Not Winsored	Winsored at 1%	Winsored at 2%
DID for Small companies	0.194322 **	0.194661**	0.1862147**	0.2416667**	0.2416667**	0.235**	0.2381633***	0.2381633***	0.227415***
DID for Large Companies	0.0889867**	0.0889867	0.0889867**	0.2250408***	0.2250408***	0.2250408***	0.1677847**	0.1677847***	0.1677847***
Difference in means	0.1053353	0.1056743	0.097228	0.0166259	0.0166259	0.0099592	0.0703786	0.0703786	0.0596303
Prob > chi2	0.2928	0.2911	0.3123	0.8876	0.8876	0.9309	0.4150	0.4150	0.4759

Table B.2. ATT estimate between small and large companies

Table B.3. ATT estimate between companies with more experienced management vs less experienced management.

Effects of European funding on company tendency to export, depending on the level of management experience (with Winsored samples)

Estimate	**Full sample “ATT”**			**NNM (with 1NN) or “ATT”**			**NNM with (2NN) or “ATT”**		
	Not Winsored	**Winsored at 1%**	**Winsored at 2%**	**Not Winsored**	**Winsored at 1%**	**Winsored at 2%**	**Not Winsored**	**Winsored at 1%**	**Winsored at 2%**
DID if experience <20 years	**0.0535384**	**0.053701**	**0.048784**	**0.121806***	**0.121806***	**0.1174582***	**0.0954635****	**0.0954635****	**0.0873421****
DID if experience >20years	**0.1897951****	**0.1901229****	**0.1878279*****	**0.3036905 *****	**0.3036905*****	**0.3036905*****	**0.2701829*****	**0.2701829*****	**0.2701829*****
Difference in means	**0.1362567**	**0.1364219**	**0.1390439**	**0.1818845**	**0.1818845**	**0.1862323**	**0.1747194**	**0.1747194**	**0.1828408**
Prob > chi2	**0.0986**	**0.0978**	**0.0753**	**0.0659**	**0.0659**	**0.0556**	**0.0181**	**0.0181**	**0.0111**

Table B.4. ATT estimates between companies that received ERDF vs EAFRD funds.

Effects of European funding on company tendency to export – comparison between funding programs (with Winsored samples)

	Full sample “ATT”			**NNM (with 1NN) or “ATT”**			**NNM (with 2NN) or “ATT”**		
Estimate	**Not Winsored**	**Winsored at 1%**	**Winsored at 2%**	**Not Winsored**	**Winsored at 1%**	**Winsored at 2%**	**Not Winsored**	**Winsored at 1%**	**Winsored at 2%**
ERDF	0.0661067	0.0663	0.0657686	0.1766768***	0.1766768***	0.1766768***	0.1382323***	0.1382323***	0.1360101***
EAFRD	0.1437379**	0.143932**	0.1385648***	0.2462222***	0.2462222***	0.2418744***	0.2077778***	0.2077778***	0.2012077***

Difference in means	0.0776312	0.077632	0.0727962	0.0695454	0.0695454	0.0651976	0.0695455	0.0695455	0.0651976
Prob > chi2	0.3337	0.3337	0.3511	0.3378	0.3378	0.3553	0.1740	0.1740	0.1899