Assessing Ukraine’s Role in European Value Chains: A Gravity Equation-cum-Economic Complexity Analysis Approach

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Abstract

We analyze Ukraine's opportunities to participate in European value chains, using traditional gravity models, combined with tools from Economic Complexity Analysis to study international trade (exports) and Foreign Direct Investment (FDI). This toolbox is shown to be predictive of the growth and entry of new exports to the EU's Single Market, as well as foreign direct investments from the Single Market in Ukraine. We find that Ukraine has suffered from a decline of trade with Russia, which has led not only to a quantitative but also a qualitative deterioration in Ukrainian exports. Connecting to western European value chains is in principle possible, with several opportunities in the automotive, information technology and other sectors. However, such a shift may lead to a spatial restructuring of the Ukrainian economy and a mismatch between the geographical supply of and demand for labor.

1 Introduction

Increasingly, production is organized through global value chains. Firms spread their production processes across multiple countries, leveraging cost advantages and market access all over the world. However, this does not mean that geography and proximity do not matter anymore. On the contrary, manufacturing giants like China, Japan, the U.S. and Germany organize the production chains mainly with their neighbors and other nearby countries, through trade of intermediates and final products. Baldwin and Lopez-Gonzalez (2015) posit that "[t]he global production network is marked by regional blocks, what could be

*The views expressed in this paper do not necessarily reflect the opinion of the World Bank Group or its member countries.

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called Factory Asia, Factory North America, and Factory Europe." This presents a predicament for Ukraine, which finds itself caught between the collapse of the production system that was coordinated within the former USSR, and – as we will document – as yet, little participation in the alternative "factory Europe."

Factory Europe has increasingly shifted east. With the entry of the countries of the former Eastern Bloc into the European Union (EU), western European companies gained access to a large reservoir of skilled, yet relatively low-cost labor. The proximity to countries in Europe with strong manufacturing bases, like Germany, Switzerland and Austria, allowed these new EU member states to attract large amounts of foreign direct investment (FDI). For instance, German car producers set up production facilities in Poland, Hungary, Slovakia and the Czech Republic.[1] Moreover, investments were not limited to car producers themselves. Also important suppliers, like Bosch and Continental,[2] moved parts of their operations eastward. Damijan et al. (2013) show that FDI in EU accession candidates grew steadily to peak in the year of their accession into the EU. In subsequent years, the new member states enjoyed permanently higher FDI inflows. Part of the region's successful growth after EU accession must therefore likely be attributed to the expansion of western supply chains' into eastern Europe.

The post-1990s experience of EU accession states contrasts starkly with the experience of Ukraine. Historically, Ukraine had maintained important trade ties with Russia. However, with the financial crisis of 2008 and the political crisis over Crimea, trade with Russia all but fully collapsed. As a consequence, Ukraine currently has a large, skilled workforce but has lost its main export market that ensured employment opportunities for its workers. A potential solution to this predicament is that Ukraine increases its participation in European value chains.

In this paper, we explore this possibility by analyzing Ukraine's existing trade and FDI relations with Europe, as well as whether, in which industries and how, Ukraine could benefit from its proximity to European manufacturing supply chains to provide new employment opportunities to its working population. To do so, we combine traditional gravity models with tools taken from Economic Complexity Analysis. The former model the intensity of economic interactions in analogy to the gravitational pull between physical objects. The latter uses a range of tools from complex network analysis to process the high-dimensional data on product specific trade and industry specific FDI flows between countries. This approach offers new ways to visualize an economy's output mix, as well as to predict future diversification and growth paths.

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[1] Volkswagen operates plants in the Czech Republic, Poland, and Slovakia (source: `https://en.wikipedia.org/wiki/List_of_Volkswagen_Group_factories`) and Mercedes in Hungary (`https://media.daimler.com/marsMediaSite/en/instance/ko/The-production-network-The-worldwide-plants.xhtml?oid=9272049`).

[2] Continental has plants in the Czech Republic and Slovakia (`https://www.continental-tires.com/transport/company/businessunit/headquarters-plants`), Bosch among others in Croatia, Bulgaria, Poland and Romania, (`https://www.bosch.de/webseiten-weltweit/`).

2 Methodology

2.1 Data

Our analyses are mainly based on two large-scale data sets. The first is the international trade data compiled and cleaned by the Growth Lab at Harvard University (`http://atlas.cid.harvard.edu/downloads`). These data provide an exhaustive description of bilateral trade among 235 countries and territories in thousands of different products categories. We focus on the period 2000-2016 and products classified at the 4-digit level of the Harmonized System (HS 1992). From this data set, we drop all countries with fewer than 2.5 million inhabitants in 2017.

The second data set is taken from records provided by Dun and Bradstreet (D&B). These records collect information on economic establishments around the globe. For each establishment, they provide an estimated number of employees, up to six different 4-digit industry codes (coded in the SIC 87 industrial classification system), the establishment's geographical location and, where applicable, which parent company owns the establishment.

We use these ownership relations to construct a proxy for bilateral FDI flows between countries. That is, we measure FDI in terms of the number of workers who are employed in one country in establishments that are owned by firms headquartered in another country. This approach has previously been used by, for instance, Alfaro and Charlton (2009) and Bahar (2020).

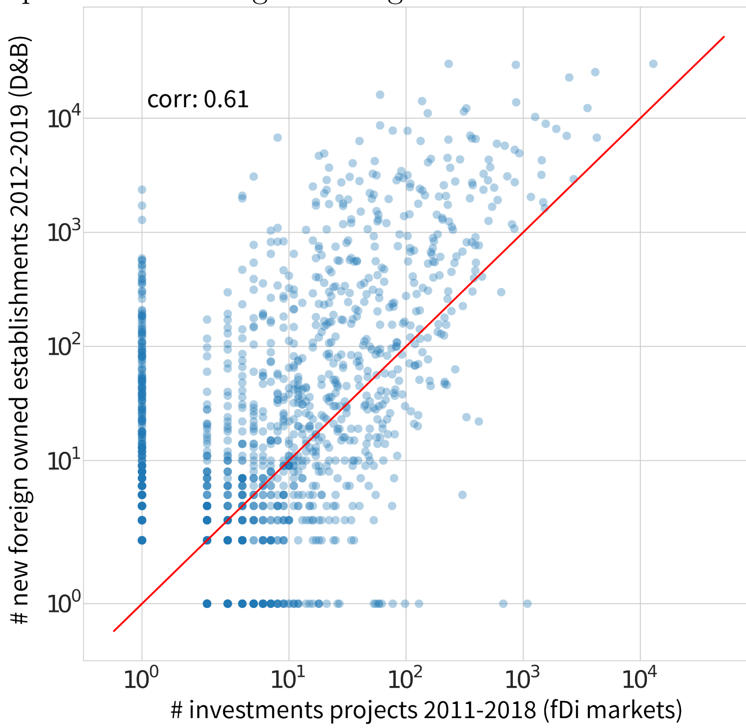
The data set covers about 150 million establishments. Globally, 0.9% of them are owned by Multi-National Enterprises (MNEs) with foreign headquarters. However, these foreign-owned establishments represent 4.9% of global employment in the data.

Figure 1 compares the number of foreign-owned establishments reported in D&B by 1-digit industry and destination country with the number of investment projects in the Financial Times' fDi markets database. The fDi markets database represents another data set that has been widely used to map foreign investments in the global economy. It contains information on greenfield foreign direct investments derived from press releases.

With a correlation of 0.61, the two data sets generally align well, corroborating the representativity of the D&B data. However, the D&B data offer several advantages over the fDi markets database. First, D&B data reflect actually existing foreign-owned establishments, whereas fDi markets data only list the announcements of investments in such establishments. Second, D&B has a greater granularity, both geographically (offering zip-code level instead of city-level information) and in terms of industries (distinguishing among 1,425 different 6-digit NAICS industries against fDi market's 269 proprietary industry classes). Third, D&B has an over six-fold greater coverage than fDi markets: whereas fDi markets reports about 110,000 investment projects in the period 2011-2018 (308 of which in Ukraine), D&B reports about 700,000 foreign-owned establishments founded between 2012 and 2019 (2,080 of which in Ukraine). Fourth and finally, unlike fDi markets data, which only reflect foreign investment projects, D&B also offers information on the domestically owned economy. This latter aspect is important, especially if we want to assess how well certain investments fit a country's existing economy.

We analyze three different waves of the D&B data, corresponding to the years 2011, 2016 and 2019. We restrict our analysis to origin and destination countries with at least 2.5

Figure 1: Comparison of coverage of foreign investments in D&B and fDi markets



million inhabitants in 2017. Furthermore, because data quality differs across countries, we also require that each country of origin has MNEs operating in at least 20 different countries of destination and that each country of destination receives inward investments from at least 20 different countries of origin.

One concern arises from the fact that corporations may choose the official location of their headquarters based on tax laws and other institutional arrangements. As a result, a sizeable share of FDI seemingly originates in places that do not reflect a corporation's center of gravity or corporate control. We therefore omit from our analysis countries – and their establishments abroad – that are likely used as tax havens.

We base the risk that a country acts as a tax haven and distorts FDI flows on the basis of two ratios. First, we calculate for each country of origin the ratio of the number of establishments that firms with headquarters in the country own abroad to the total number of local establishments these firms own: $\sum_{d \neq o} \frac{Q_{od}}{Q_{oo}}$, where Q_{od} represents the number of establishments located in country, d owned by MNEs headquartered in country o. Second, we calculate the ratio of a country's MNEs' establishments abroad to GDP: $\sum_{d \neq o} \frac{Q_{od}}{GDP_o}$. We now drop all countries (both, as origins and as destinations) that are among the top 20% in terms of the former ratio and among the top 5% in terms of the latter ratio. The resulting sample consists of 130×130 bilateral (i.e., country-country) relations.

2.2 Gravity Models

An important tool in the analysis of trade patterns are gravity models. Gravity-based trade models were pioneered by Tinbergen (1962), who proposed that the intensity of interaction between economies can be seen as analogous to the gravitational pull between objects. Accordingly, flows between two countries, such as trade and FDI, depend positively on the sizes of, and negatively on the distance between, two countries. The success with which these models predict economic interaction patterns has ensured them a place in economics as the discipline's workhorse models for the analysis of international trade, FDI and migration.

To estimate the parameters in these gravity models, we rely on the Pseudo-Poisson Maximum Likelihood (PPML) estimator proposed by Silva and Tenreyro (2006). This estimator is known to yield robust estimates of the parameters in gravity models. Moreover, it has the added advantage that it accommodates country pairs for which trade or investments flows are equal to zero. This is a particularly important feature, because we will estimate separate models by detailed product and industry category to assess Ukraine's opportunities for participating in EU value chains, which will differ across products and industries. However, at this level of aggregation, there are many pairs of countries with zero trade or investment flows.

2.3 Economic Complexity Analysis

More recently, trade patterns have been analyzed using economic complexity analysis (e.g. Hidalgo and Hausmann, 2009; Hidalgo et al., 2007; Tacchella et al., 2012). Like gravity models, economic complexity analysis finds its origins in the natural sciences. The main idea behind this approach is that a country's capacity to produce certain products depends on the match between the capabilities these products require and the capabilities that the country can mobilize in its economy. Capabilities are here defined in abstract terms: they cover a wide set of factors of production, from a competent workforce and physical infrastructure to less tangible assets, such as institutions and the cultural traits of a population.

In this framework, capabilities determine the international patterns of comparative advantage. Conceptually, therefore, they should represent endowments of a country that are, at the same time, nonubiquitous (i.e., not all countries own them) and valuable (i.e., they are crucial to productive economic activity). Furthermore, capabilities are typically considered more specific than the factors of production that have traditionally been considered in trade research, such as labor, land, and physical and human capital. For instance, human capital has often been measured as a country's stock of college-educated workers. In contrast, in economic complexity analysis, human capital is supposed to be highly specific: trained actuaries cannot design airplanes, nor are aeronautical engineers skilled in calculating insurance premiums. Aeronautical engineers therefore do not represent just human capital but are part of a country's aeronautical capability, whereas actuaries specialists represent a capability in insurance products. Similarly, a functioning high-speed internet backbone grid and a seaport are both part of a country's capital stock, but represent different capabilities, each facilitating the production and export of different sets of products.

Because the full range of capabilities is *a priori* hard to determine and the capabilities themselves hard to observe, capabilities are *inferred* from trade and production patterns. The main insight supporting this inference is that countries will produce combinations of products that require similar capabilities. As a consequence, the degree to which two products co-occur in the export baskets of the same countries provides an indication of how similar the capability requirements of the two products are (Hidalgo et al., 2007). Similarly, if many economic establishments are active in the same two industries, these industries are likely to be similar in terms of the capabilities they require (Bryce and Winter, 2009; Neffke et al., 2011; Teece et al., 1994).

The product space

To estimate the similarities in capability requirements, we (mostly) follow Hidalgo et al. (2007). First, we determine which products are significantly present in a country's export basket, using the Balassa index of comparative advantage for product p and country c:

$$RCA_{cp} = \frac{X_{cp}/X_c}{X_p/X} \tag{1}$$

where X_{cp} represents the total value of country c's exports of product p across all importers. Furthermore, an omitted subscript indicates a summation over the omitted dimension, e.g.: $X = \sum_{c,p} X_{cp}$.

A product is present in a country if the country exports the product with $RCA > 1$:

$$P_{cp} = \begin{cases} 1 & \text{if } RCA_{cp} > 1; \\ 0 & \text{elsewhere.} \end{cases} \tag{2}$$

Next, we calculate how often two products are present in the same countries:

$$C_{pp'} = \sum_c P_{cp} P_{cp'} \tag{3}$$

These co-occurrences are now normalized by the number of times we would expect products p and p' to co-occur, had co-occurrences taken place at random:[3]

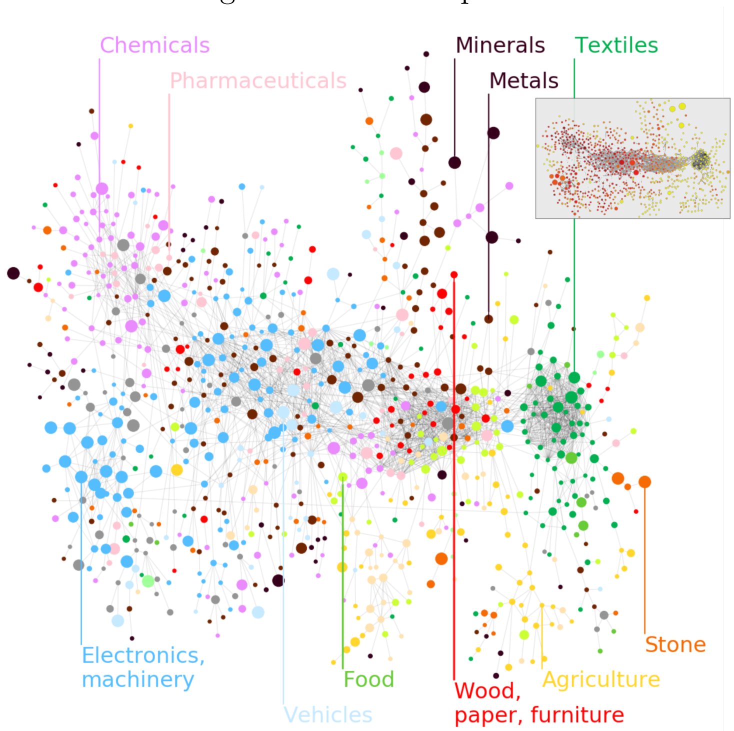
$$\tilde{\pi}_{pp'} = \frac{C_{pp'}}{C_p C_{p'}/C} \tag{4}$$

For product combinations that are overrepresented against the random benchmark $C_p C_{p'}/C$, $1 < \tilde{\pi}_{pp'} < \infty$, whereas for product combinations that are underrepresented against their random benchmark $0 < \tilde{\pi}_{pp'} < 1$. As a consequence, $\tilde{\pi}_{pp'}$ is distributed with a heavy right-skew. To reduce this skew, we use the following transformation that maps $\tilde{\pi}_{pp'}$ symmetrically around 0.5 on the interval $[0, 1)$:

$$\pi_{pp'} = \frac{\tilde{\pi}_{pp'}}{\tilde{\pi}_{pp'} + 1} \tag{5}$$

[3]Note that the product space proximity is calculated in a slightly different manner in Hidalgo et al. (2007). These authors define $\tilde{\pi}_{pp'}$ as the minimum of two conditional probabilities: $\tilde{\pi}_{pp'} = \min\left(\frac{C_{pp'}}{C_p}, \frac{C_{pp'}}{C_{p'}}\right)$. Instead, we define $\tilde{\pi}_{pp'}$ as the ratio of observed to expected co-occurrences as in Neffke et al. (2017), who also offer a more in-depth discussion of the usefulness of this transformation.

Figure 2: Product space



Product space for exported product categories. Colors represent higher level segments of the HS classification and links reflect the fact that products are often co-exported by the same countries. Inset: Complexity (PCI) of products in the product space - low to high from yellow to red.

These similarities can be used to depict economies as networks that connect products or industries, yielding abstract product (Hidalgo et al., 2007) or industry spaces (Neffke et al., 2011). Conceptually these spaces depict economic activities as a set of nodes that are connected if they are similar in terms of the capabilities they require. Local economies can now be mapped into these spaces (see, for instance, Figure 5, which maps the position of Ukraine's export mix on the product space). This helps visualize these local economies in a way that highlights clusters of related products or industries, as well as potential development paths for the economy.

Figure 2 provides a general depiction of the product space. [4] The network shows all traded product categories of the 4-digit level of the Harmonized System (HS 1992 classification). The colors represent broad sectors, such as metal products in brown and chemicals in purple. Sets of related products tend to cluster in specific "zones" in the network. For instance, garments and textile products (green) are found in a tight cluster on the right, whereas electronics products (blue) cluster at the opposite side of the network.

[4] To plot the network, we use the product space that is provided on `http://atlas.cid.harvard.edu/`. This allows the reader to compare our plots against any other country in the online Atlas of Economic Complexity. That is, the depicted product space is based on Hidalgo et al.'s (2007) metric. For the calculations and estimations below, we will however use the proximity as described above.

We can use the product space to assess how close a given product is to a country's total export basket, by calculating the following density of product p in country c (Hidalgo et al., 2007):

$$D_{cp} = \sum_{p'} \frac{\pi_{pp'}}{\pi_p} X_{cp'} \tag{6}$$

That is, a product's density in country c is the weighted sum of the export volumes of other products exported by the country, with the product space proximity of each product to product p as weights.

Product and industry spaces have been successfully applied to predict diversification patterns in a wide variety of applications (for an overview, see Hidalgo et al. (2018)). In particular, countries, regions and firms have all been shown to diversify into new activities that are close to their existing production portfolios in terms of the proximities expressed in these abstract spaces. We will use such spaces to visualize the trade baskets and industry industry mixes of Ukraine and its comparator countries and to predict future growth and diversification paths.

Industry space in D&B data

The D&B data allow us to study these investment flows in terms of the technological proximities between industries. We will refer to this map as the *industry space*. This industry space is constructed analogously to the product space. However, whereas for the product space, we could only observe co-occurrences of export categories in countries, the D&B data allow us to calculate co-occurrences of industries within establishments, by exploiting the fact that D&B lists for each establishment not just a main industry but up to five secondary industries. Given that firms decide to develop these activities in one and the same establishment, frequent combinations of activities should reflect prevalent economies of scope.[5] This logic has previously been used in the strategic management literature (Bryce and Winter, 2009; Teece et al., 1994) and in the literature on regional economic development (Neffke et al., 2011, 2008). The D&B data therefore do not only allows us to widen the scope of the analysis to services, but also to limit the risk of identifying spurious relations due to the fact that countries may produce many, unrelated exports.

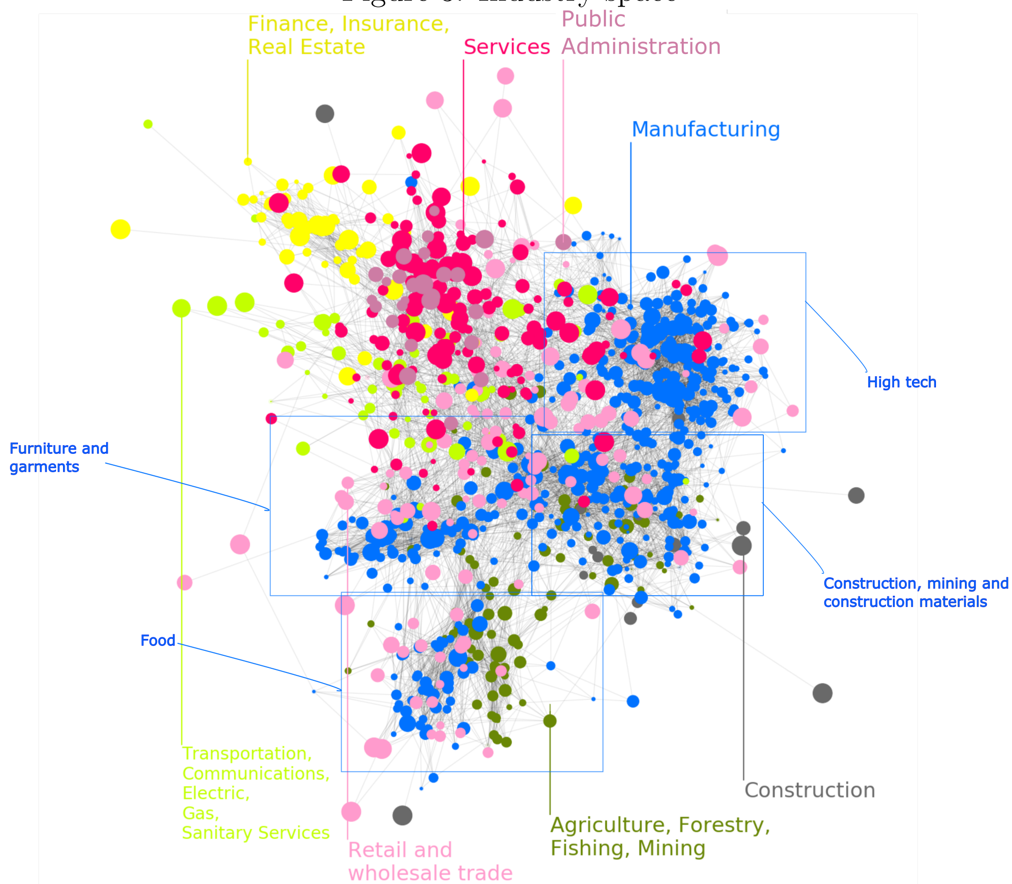
Let P_{ei} be an indicator variable that assumes a value of one if industry i is among one of the six (primary or secondary) industries in establishment e. Co-occurrences are now counted as

$$C_{ii'} = \sum_{e} P_{ei} P_{ei'} \tag{7}$$

As before, we normalize these co-occurrences by the number of times we would expect industry i and i' to co-appear, had co-occurrences taken place at random:

[5] At the establishment level, many of these economies of scope will relate to the production processes in these activities. Therefore, we think of the resulting network as expressing mainly technological relations, such as the use of similar machinery or similarly skilled workers. A closer inspection of the network corroborates such an interpretation (see Neffke et al., 2008).

Figure 3: Industry space



Industry space. Colors represent broad sectors and links reflect the fact that industries often co-occur in the same establishments.

$$\tilde{\pi}_{ii'} = \frac{C_{ii'}}{C_i C_{i'}/C} \tag{8}$$

Furthermore, we again transform $\tilde{\pi}_{ii'}$ such that it is distributed symmetrically around 0.5 on the interval $[0, 1)$:

$$\pi_{ii'} = \frac{\tilde{\pi}_{ii'}}{\tilde{\pi}_{ii'} + 1} \tag{9}$$

The resulting proximities describe how much more often than expected industries co-occur in the same establishments. We will call industries for which $\pi_{ii'} > 0.5$ *related*. The industry space based on these proximities is plotted in Figure 3.

The nodes in the graph depict industries. Colors reflect broad sectors, such as manufacturing in blue, retail and wholesale trade in light pink, business services in darker pink and financial services in yellow. The network shows that industries in one sector are often connected to industries in other sectors. For instance, many manufacturing industries (depicted in blue) are connected to their corresponding wholesale industries in pink. Business (dark pink) and financial services (yellow) are similarly closely intertwined.

Furthermore, we see that sectors often consist of distinct subclusters. For instance, manufacturing industries are distributed across a northeastern, an eastern, a western and a southwestern cluster. The manufacturing industries in the northeast consist of advanced machinery, computing and telecommunications hardware. Here, we also find some business services, such as advertising agencies and computer maintenance (dark pink). The eastern cluster underneath contains manufacturing industries that produce construction materials, as well as some (green) mining and (gray) construction activities. The western cluster consists of furniture and garment-making and includes some service activities in dry-cleaning and laundry services, as well as in the retail and wholesale of clothes and home furnishings. Finally, the southern cluster consists of industries of the food industry such as meatpacking, beverage making and frozen food packaging. Unsurprisingly, this cluster also contains several (green) agricultural activities.

Like the product space, we can use the industry space to determine how close an industry is to a country's entire portfolio of industries. To do so, we calculate the following industry space density, D_{ci}:

$$D_{ci} = \sum_{i'} \pi_{ii'} / \pi_i E_{ci} \tag{10}$$

where E_{ci} represents the number of employees in country c in industry i. That is, D_{ci} represents the relevant size of the economy of country c for industry i.[6] It is calculated as the weighted employment sum across industries, where weights are given by an industry's proximity to industry i in the industry space.

Note, however that, in the trade data, we use calculate the product-space density around a focal product for *exporting countries*, i.e., for the origins of a trade flow. In contrast, in the FDI analysis, we are interested in what kind of foreign investments a country can attract. Therefore, the industry-space density is calculated around a focal industry in the *destinations* of investment flows.

Economic complexity index

A second core quantity in economic complexity analysis is the Economic Complexity Index (ECI) and its counterpart, the Product Complexity Index (PCI). The ECI and PCI were originally developed as iterative algorithms to assess the complexity of economies and the sophistication of product categories. Like the product space, the algorithm uses information on which countries are able to export which products. It operates on the assumption that rich countries make different products than poor countries, an insight that had earlier been successfully leveraged to predict countries' growth in per capita Gross Domestic Product (GDP) (Hausmann et al., 2007).

This method yields an estimate of the complexity of a country's productive system (the ECI), as well as of the complexity of a product's production requirements (the PCI). The

[6] To avoid using information on investment flows themselves, we limit E_{ci} to employment in establishments of local firms, excluding the establishments of foreign MNEs.

PCI and the ECI are related: the PCI of a product is the average of the ECI of the countries that export this product with revealed comparative advantage and vice versa. The ECI is highly predictive not just of a country's GDP per capita, but also of its growth in GDP per capita (Hausmann et al., 2014). Details on these complexity measures are provided in Hidalgo and Hausmann (2009).

The ECI is also depicted in Figure 2 in the inset on the top right of the graph. This inset depicts the product space, but now with its nodes colored by their PCI from yellow (low complexity) to red (high complexity). The most complex products are found in the center left of the product space, like machinery (blue). In contrast, the least complex products are located either in the network's right-most parts, such as wood products (red) and food products (light green), or in the network's periphery, such as agricultural products (yellow, mainly in the bottom of the graph) and minerals (black, in the top of the graph).

We calculate the ECI as in Hidalgo and Hausmann (2009), with one exception. We do not define the complexity of country c as the simple average PCI of all products for which $RCA_{cp} > 1$. Instead, we define it as the weighted average PCI, where weights are given by the value of country c's exports in each product. This allows us to define an ECI for each export market. That is, let $\mathcal{M}$ be the set of countries that together constitute an export market (say, the EU's Single Market). Now, the destination-market specific ECI for country c is defined as:

$$ECI_c^{\mathcal{M}} = \sum_p \frac{\sum\limits_{d \in \mathcal{M}} X_{op}^d}{\sum\limits_{d \in \mathcal{M}} X_o^d} PCI_p \tag{11}$$

where X_{op}^d represents the exports of product p from exporter o to importer d and an omitted subscript indicates the summation over the omitted category: $X_o^d = \sum\limits_p X_{op}^d$.

3 Trade analysis

3.1 The evolution of Ukraine's export mix

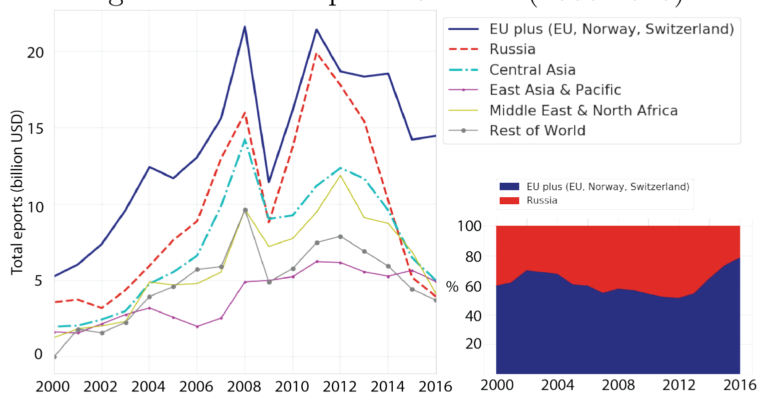
Value of exported goods and services

Between 2000 and 2008, Ukraine saw its exports increase from \$20.7B to \$94.6B. During the following global financial crisis, these exports initially fell back to \$61.9B, but then quickly rebounded. By 2011, export volumes had recovered to pre-crisis levels.

Throughout this period, Ukraine's main trading partner had been Russia, accounting for up to over a quarter of Ukrainian exports. However, in the wake of the Euromaidan protests and armed conflict between the two countries, exports to Russia collapsed. As a consequence, in 2016, Russia accounted for just 9% of Ukrainian exports. Because Ukraine's exports to the rest of the world had dropped by almost 40%, in absolute terms, the fall in exports to Russia was even more pronounced: \$16.2B or 81%.

Not only the level but also the composition of Ukraine's export mix has changed since 2000. In 2000, Ukraine's main exports were metal products, accounting for 33% of total exports, with iron and steel products representing 26% of all exported goods and services.

Figure 4: Total exports Ukraine (2000-2016)



Exports in services contributed another 22%. Agricultural produce accounted for just 10% of exports and minerals – mostly oil and iron ore – for another 8%. By 2016, however, Ukrainian exports had become dominated by agricultural products. The share of these products in overall exports almost quadrupled to 35%, whereas the share of metal products halved to around 17%. The share of services in Ukrainian exports stayed more or less constant. However, in the year 2000, the main service exports were transport related, accounting for 65% of all service exports of Ukraine. In 2016, in contrast, 47% of service exports were in Information and Communication Technology (ICT), up from 26% in 2000. Because bilateral trade data are unavailable for services, in the remainder of this section, we will restrict the analysis to exported products, ignoring exports in services.

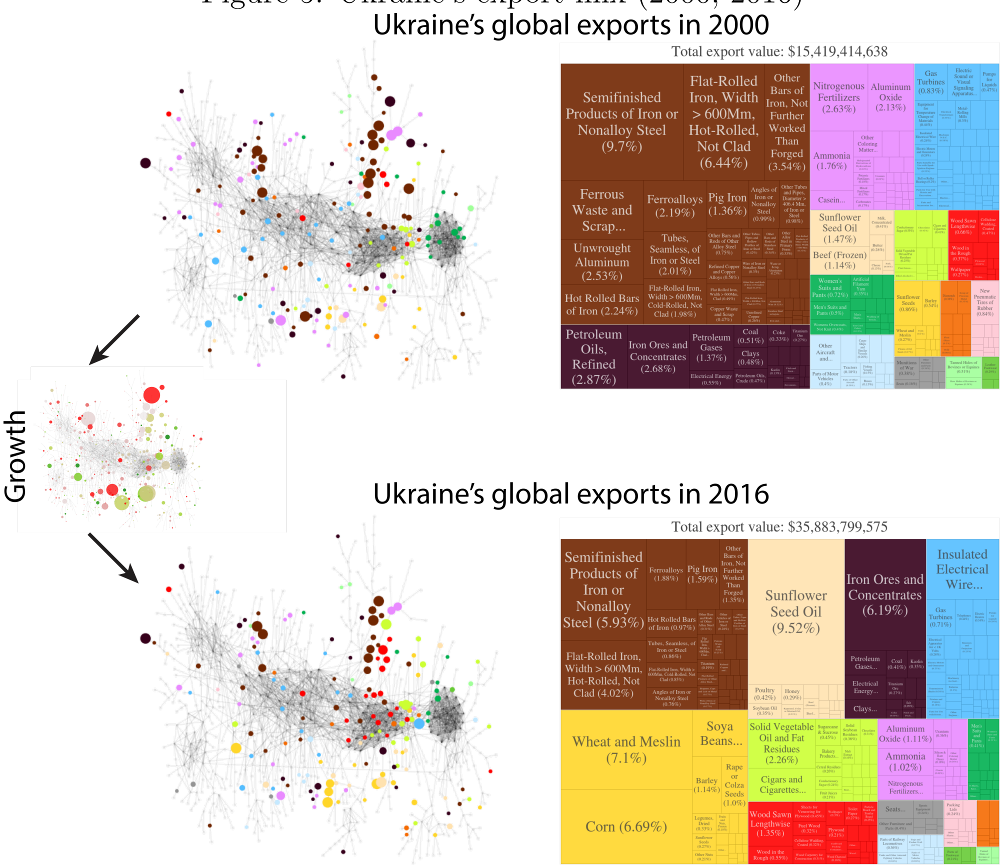
Exports of goods

Figure 4 shows the evolution of Ukraine's goods exports to different destination markets. Exports of goods follow roughly the same dynamics as the combined exports of goods and services. The steady increase in export volumes until the financial crisis is visible across all markets. The impact of the financial crisis is felt mostly in exports to the EU, Russia and Central Asia (with Turkey as the main export destination within this region). In contrast, exports to the Middle East and North Africa (mainly Egypt), as well as to the East Asia and Pacific region, which is increasingly dominated by China, are impacted less.

The inset on the bottom-right illustrates how the importance of the EU and Russia as destinations for Ukrainian exports changed. Until 2012, Russia expanded as a market for Ukrainian exports vis-á-vis the European Union. However, between 2012 and 2016, Russia's role as an importer of Ukrainian exports strongly diminished. Whereas in 2012, the Russian Federation was almost equally important as a trading partner for Ukraine as the EU, by 2016, imports by the EU accounted for about four times those by Russia.

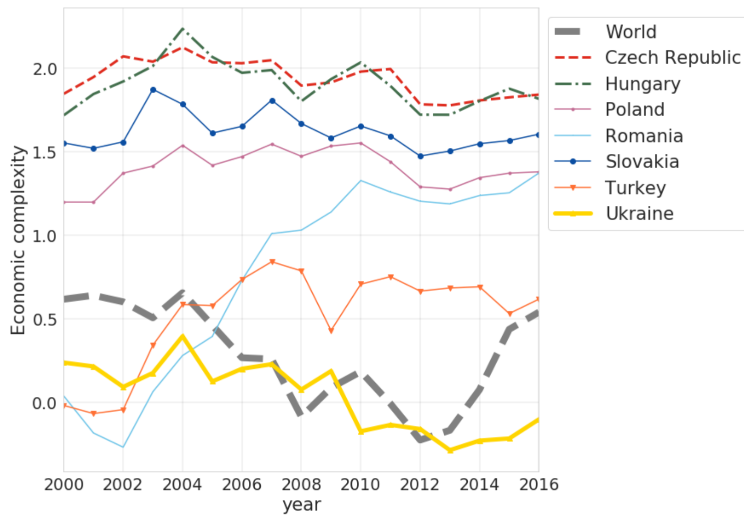
Figure 5 plots the (non-services) export mix of Ukraine in 2000 and 2016. The left panels depict Ukraine's export position in the product space, the right panels display the export mix in tree maps. The graphs clearly show how Ukrainian exports have shifted decidedly towards agriculture, as well as how the country has experienced a strong decline in the export of metal products.

Figure 5: Ukraine's export mix (2000, 2016)



Inset highlights product categories with growing export shares in green and with shrinking investment shares in red. Nodes are sized by the absolute increase (in green) or decrease (in red) of the product's share in Ukraine's overall exports. The intensity of the color reflects the growth rate of product's export value defined as $\frac{\frac{X_{UKR,p,2016}}{X_{UKR,2016}} - \frac{X_{UKR,p,2010}}{X_{UKR,2000}}}{\frac{1}{2}\frac{X_{UKR,p,2016}}{X_{UKR,2016}} + \frac{1}{2}\frac{X_{UKR,p,2010}}{X_{UKR,2000}}}$.

Figure 6: Complexity of exports (2000-2016)



Note: complexity is calculated as a country's export-value weighted average product complexity (PCI)

In the product space, this shift translates into a shift into more peripheral products, away from the product space's center. These dynamics are highlighted in the inset on the left between the top and bottom graphs. This inset depicts the (absolute) change in a product's share in Ukraine's exports, with products whose export share declined depicted in red and products whose export share increased in green. For instance, Ukraine made relative gains in the bottom periphery of the product space, where most agricultural products are located, as well as in some of the upper center branches, where (red colored) wood products are found. Meanwhile, the country shifted out of some of the machinery products (blue) and chemicals (purple) in the left of the product space. As the ECI tends to increase from right to left and from the outer to the inner parts of the product space (see Figure 2), these shifts led to a decline in the average complexity of Ukraine's export basket.

Figure 6 explores this loss of complexity in more detail. The figure displays the average complexity of exports of Ukraine and of a set of comparator countries: the Czech Republic, Hungary, Poland, Romania, Slovakia and Turkey. These countries, like Ukraine, were part of the former USSR and are at a close distance to the EU. Turkey is added as an emerging market in the region, but outside the EU.

As a first observation, we note that, already in 2000, Ukraine lagged behind most of its comparators in terms of export complexity. The exception are Turkey and Romania, which produced even less complex exports than Ukraine. However, these countries were able to quickly move into more complex export categories, with Romania almost fully catching up with its eastern European peers by 2016. In contrast, Ukraine's export complexity steadily declined over this period.

Figure 7 shows Ukraine's export complexity by destination market. The decline in complexity is apparent in all destination markets. However, the figure also highlights the importance of the Russian market for Ukraine's export complexity: the most complex Ukrainian exports are typically destined for the Russian market. In fact, whereas Ukraine generally

Figure 7: Complexity of Ukrainian exports by destination market over time

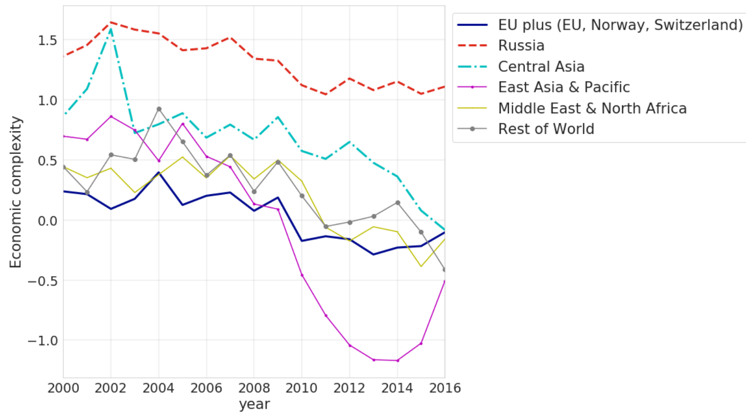
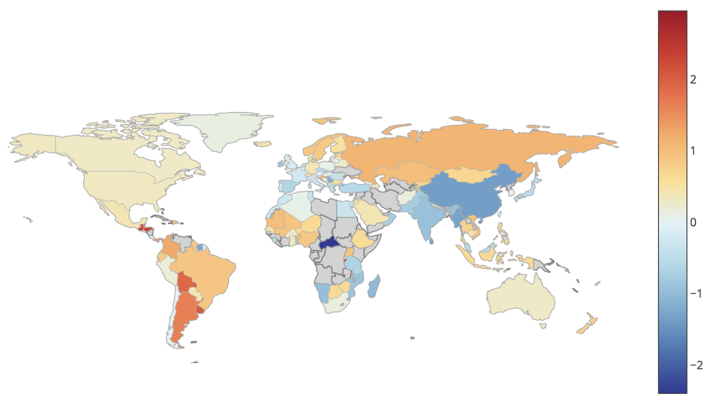


Figure 8: Complexity of Ukrainian exports by destination market in 2016



exports products with a complexity below the global average (see Figure 6), its exports to Russia exceed this global average by a substantial margin.[7]

Figure 8 confirms this impression by showing the complexity of Ukrainian exports across the globe. The most complex products are generally sold to either the Russian Federation or to less developed economies in Latin America and South-East Asia. However, the value of Ukraine's total exports to the latter markets is negligible (see Figure 2).[8]

Figure 9 depicts the export baskets destined for Russia and the EU. Exports to Russia tend to be more diversified than exports to the EU, the latter being dominated by agriculture, textiles and basic chemicals. In contrast, Russia-bound exports include substantial quantities

[7]Note that the ECI is a weighted average of products' PCI, which is expressed in units of standard deviations. Therefore, a difference of one unit in ECI means that on (value-weighted) average, exports shift to products with a one-standard deviation higher complexity.

[8]Interestingly, Ukraine exports small quantities of relatively complex goods to Scandinavia. This shows that some Ukrainian exporters do manage to penetrate European markets with complex products. For instance, since the financial crisis, Sweden has imported increasing quantities of parts for gas turbines from Ukraine. These imports reached a total value of $13.6 M in 2016.

of sophisticated products in machinery and complex chemicals, such as pharmaceuticals.

3.2 Gravity models of trade

To analyze Ukraine's export potential, we estimate augmented gravity models. This follows the work by Jun et al. (2019), with two additions. First, we estimate product-category specific models. That is, for each product, we ask to what extent trade can be predicted from the size of the exporter's and the importer's national economies and the distance between these economies. Second, as a regression model, we use the Pseudo-Poisson Maximum Likelihood (PPML) model as suggested by Silva and Tenreyro (2006):

$$E\left[X_d^o|\mathbf{Z}\right] = exp^{\mathbf{Z}\beta} \tag{12}$$

where $\mathbf{Z}$ contains a constant as well as the following explanatory variables:

- ln (GDP/cap orig.): natural logarithm of the exporter country's GDP per capita;
- ln (GDP/cap dest.): natural logarithm of the importer country's GDP per capita;
- ln (pop. orig.): natural logarithm of the exporter country's population;
- ln (pop. dest): natural logarithm of the importer country's population; and
- ln (dst.): the natural logarithm of the weighted kilometer distance between the importer and exporter countries' main cities as defined by Mayer and Zignago (2011).

These variables are all part of the standard gravity model. They measure the sizes of and distance between exporter and importer economies. Furthermore, we allow EU membership to impact trade, by adding a dummy group that codes whether the exporter, the importer, or both are part of the EU's Single Market:

- $\mathrm{EU_o}$: one if exporter is an EU or EFTA member state, zero otherwise
- $\mathrm{EU_d}$: one if importer is an EU or EFTA member state, zero otherwise
- $\mathrm{EU_{od}}$: one if importer and exporter are EU or EFTA member states, zero otherwise

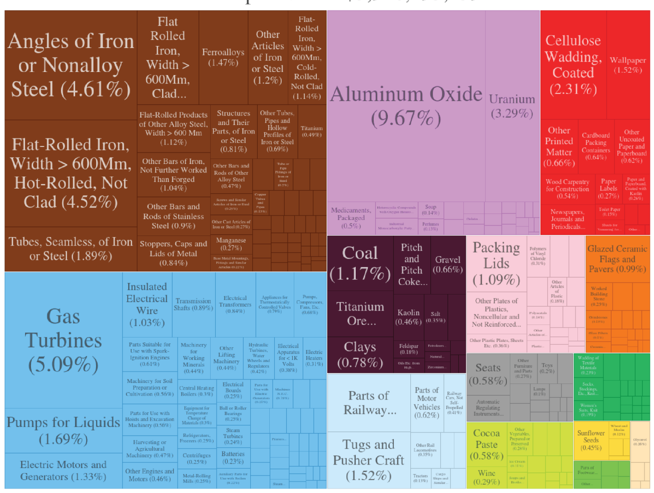
Table 1 shows the results of this estimation, when we aggregate across all products and analyze total trade between countries. As expected, distance has a negative effect on trade and the sizes and wealth of exporter and importer countries positively affect trade. Entering the EU is associated with an increase in exports to the EU (by a factor of $e^{-0.51+0.98} = 1.6$ but a decrease in exports to countries outside the EU (by a factor of $e^{-0.51} = 0.6$.[9] That is, the model predicts trade diversion when countries enter the EU. However, we regard these estimates are purely correlational: they are intended to establish a benchmark for Ukrainian exports, not to determine the root causes of Ukraine's export success.

[9]To see this, note that there are two relevant effects when entering the EU. First, there is the effect of a Ukrainian EU membership on exports to the EU. This can be calculated as the exponentiated sum of the estimated effects of the variables $\mathrm{EU_o}$ and $\mathrm{EU_{od}}$. Second there is the effect of entering the EU on trade with countries outside the EU, which is captured by the exponentiated point estimate for $\mathrm{EU_o}$.

Figure 9: Exports to Russian Federation and to EU

Ukraine's exports to the Russian Federation (2016)

Total export value: $3,946,195,759



Ukraine's exports to the European Union (2016)

Total export value: $14,419,755,854

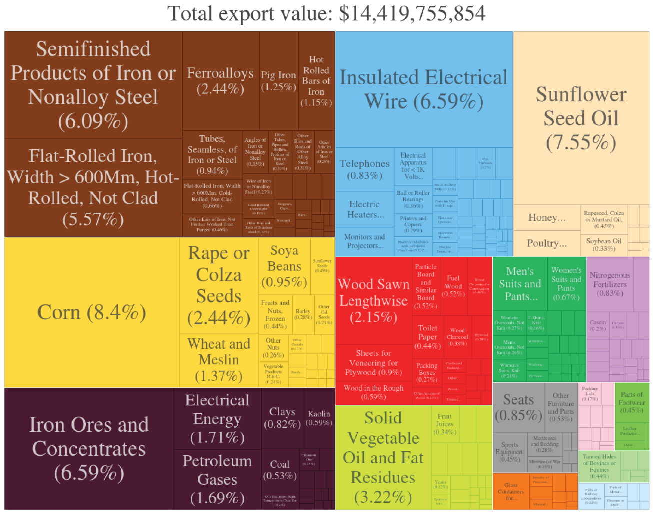


Table 1: Gravity model of total trade

dep. var.: USD value of trade	**point est.**	**s.e.**	**z-value**	**p-value**	**95% C.I.** Lower	Upper
Gravity variables						
ln(distance)	-0.494	0.079	-6.280	0.000	-0.648	-0.34
ln(GDP/cap) - exporter	0.870	0.069	12.65	0.000	0.736	1.005
ln(GDP/cap) - importer	0.789	0.064	12.39	0.000	0.664	0.914
ln(pop) - exporter	0.712	0.038	18.74	0.000	0.638	0.787
ln(pop) - importer	0.810	0.039	20.87	0.000	0.734	0.886
EU / EFTA membership						
exporter? (0/1)	-0.511	0.144	-3.56	0.000	-0.792	-0.229
importer? (0/1)	-0.287	0.13	-2.21	0.027	-0.541	-0.033
both? (0/1)	0.984	0.166	5.93	0.000	0.658	1.309
constant	-17.13	1.54	-11.10	0.000	-20.16	-14.10
pseudo R-squared	0.834					
# observations	34,969					

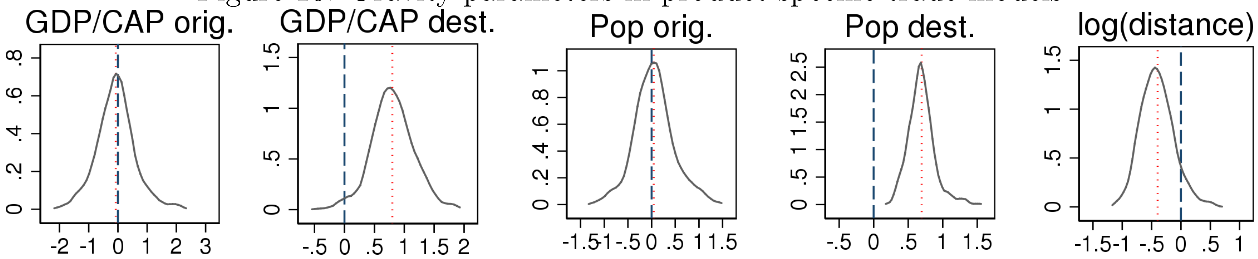
PPML estimation of aggregate trade between country pairs, using robust standard errors.

Next, we reestimate this model for each product category separately. This allows us to ask how important it is that a country exports large quantities of products that are closely related to the focal product. To do so, we add a sixth variable suggested by economic complexity analysis, the product's *density* in the exporter's economy. Density can be interpreted as a measure of the *relevant size* of the exporter economy, namely the proximity-weighted value of existing exports, where "proximity" refers to the proximity to the focal product p in the product space. Moreover, the parameter vector β is replaced by a product-specific parameter vector, β_p. Now, for each variable, we obtain $N_p = 1,005$ point estimates, one for each 4-digit product category.

Figure 10 summarizes the outcomes by plotting a kernel density estimate of the parameters of the gravity-based variables in the model. Likewise, Figure 11 shows the distribution of the parameter estimates of product density. The point estimates for the EU membership dummies are reported in Appendix A.1.

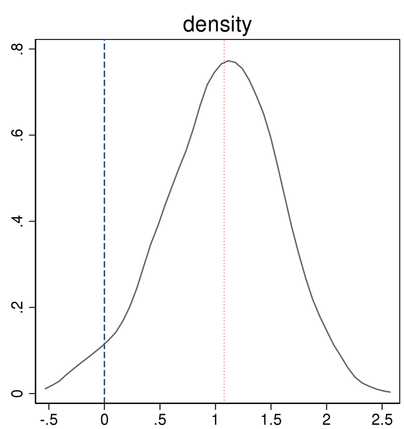
The product-specific parameters that describe gravity-based elements in the regression model are centered on their counterparts in the model for aggregate trade (see Table 1). The exception is the effects of the population size and of the GDP per capita of the exporter (origin) country, which are both centered on zero. However, note that the effect of the median product's product-space density in Figure 11 is positive and large. This density variable assumed the explanatory force of the exporter's size and wealth. Apparently, what matters is not the size of the country in terms of its population or GDP *per se*, but the size in terms of the volume of related exports that the country produces. This suggests that the product space density contains important information about the types of products Ukraine may be able to export to the EU.

Figure 10: Gravity parameters in product-specific trade models



Kernel densities of parameter estimates across 1,005 product categories for the gravity-variables in models of international trade. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

Figure 11: Product-space density parameter-estimate in product-specific trade models



Kernel density of parameter estimates across 1,005 product categories for product space density in the exporter country. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

Predicting export growth

The industry-specific trade models provide a benchmark for how large exports to the EU should be, given a country's size and distance to the EU and its position in the product space. That is, the estimated parameters yield a model-based prediction of the export volume in a given product between two countries. Against this predicted benchmark, we can evaluate the actual export-performance of a country. To do so, we calculate the logarithm of the ratio of actual to predicted export volumes for each origin-destination-product combination (i.e., the model's residuals). The smaller this ratio, the more an exporter underperforms in the given product against the expected benchmark: the export volume is "too small" considering the expectations derived from the regression model.

Do such underperforming products represent latent growth opportunities for the exporting country? We explore this by identifying growth opportunities at three different levels: (1) the exports between all exporters and importers, (2) the exports to the EU's Single Market in general and (3) the Ukrainian exports to the Single Market in particular. To do so, we fit the regression model in 2011 and then predict export growth between 2011 and 2016, following the procedure below:

1. fit PPML models using trade data for 2011;
2. calculate the residuals for each exporter-importer-product combination;
3. calculate the (out-of-sample) log-transformed growth between 2011 and 2016 for exporter-importer-product combinations;
4. regress these out-of-sample growth rates on the residuals calculated in step 2 in three different samples:
   (a) the overall sample, containing all exporter-importer-product combinations;
   (b) the aggregate exports by product to the EU from all exporter countries (i.e., we drop all importers outside the EU and aggregate the predicted and actual export volumes for a given product across all EU destinations); and
   (c) the aggregate exports to the EU by product from Ukraine only (i.e., we drop all origins except for Ukraine, leaving a data set with 1,005 observations, one for each product).

This allows us to assess how well we can identify export opportunities in general and for Ukrainian exports to the EU in particular.

Note that the residuals generated in step 2 tell us whether actual export volumes are "too large" or "too small" when compared to the benchmark derived from the PPML model. If these models are predictive, we would expect that these residuals correlate negatively with future export growth. However, for products that were not traded between an exporter and an importer (a "trade corridor") in 2011, the logarithm of export growth is undefined. Therefore, for such observations (potential "entries") we compare the predicted export volumes in corridors without trade in 2011, but with positive trade in 2016 and corridors where trade volume was zero in both years. Similarly, we compare the PPML's log-transformed residual of products that were present in a trade corridor in 2011 but absent in 2016 ("exits") to the one of products that remained present in both years.

The left panel of Figure 12 shows a scatter diagram of growth in exports in the period 2011 to 2016 against these residuals for all country pairs and products. Each observation in this graph represents a trade corridor (exporter-importer combination) for a 4-digit HS product category. With a correlation of -0.335, the regression residual indeed predicts future export performance.

The PPML model also predicts product entry. The upper-right panel of Figure 12 compares predicted export volumes between new products entering a trade corridor and those that remain absent, using kernel density plots. Entering products exhibit higher predicted export volumes than products that remain absent.

However, product exits seem harder to predict. The lower-right panel of Figure 12 similarly studies exiting product categories. This plot shows the kernel densities of the residual of the PPML models for products that exit a trade corridor against those that remain present. The two distributions are all but in indistinguishable. Therefore, it seems not warranted to use the PPML model to predict product exits.

Figure 13 repeats these analyses for the total exports of an exporting country to the EU and Figure 14 further reduces the sample, keeping only exports from Ukraine to the EU. These graphs show that the PPML model offers a useful benchmark for predicting future entry and growth of exports to EU markets. Although the predictive performance drops somewhat when focusing on EU-bound trade only, this performance rises again when focusing on only Ukrainian export growth to the EU.

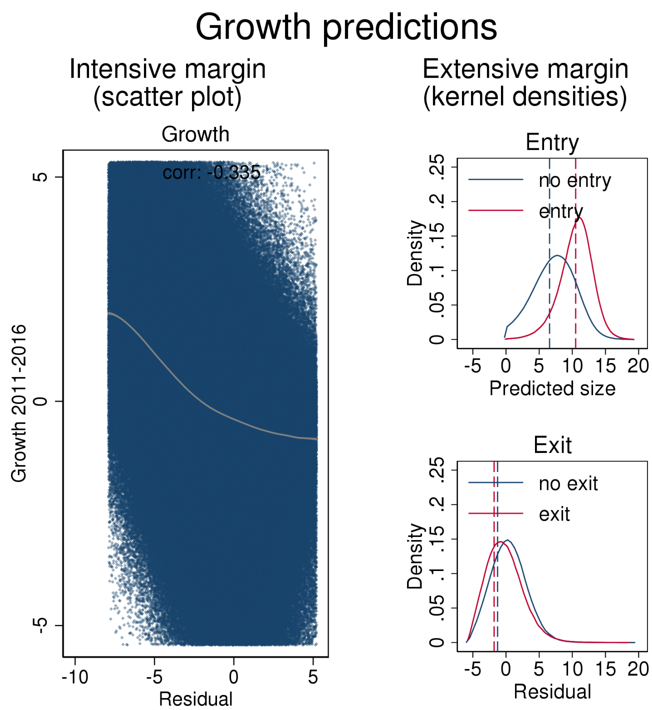
Given the predictive validity of the PPML model, we rerun these models for the year 2016 to determine latent export opportunities for the five-year period from 2016 to 2021. These latent opportunities are summarized in Figure 15.

Ukraine underperforms vis-à-vis its PPML benchmark for EU-bound exports in a range of raw materials produced by the extractive and agricultural sector. Appendix A.2 lists latent opportunities and threats in non-extractive sectors are summarized in Tables 5-10. These tables highlight a number of opportunities in the automotive and textile sectors, such as cars, trucks and car parts, as well as men's and women's suits and footwear. These product categories are well-aligned with western European value chains and represent opportunities for growth and diversification. Threats to Ukraine's current export basket – products of which Ukraine currently exports more than we would have expected given the PPML model's predictions – are mostly concentrated in agricultural and basic metal products.

4 FDI analysis

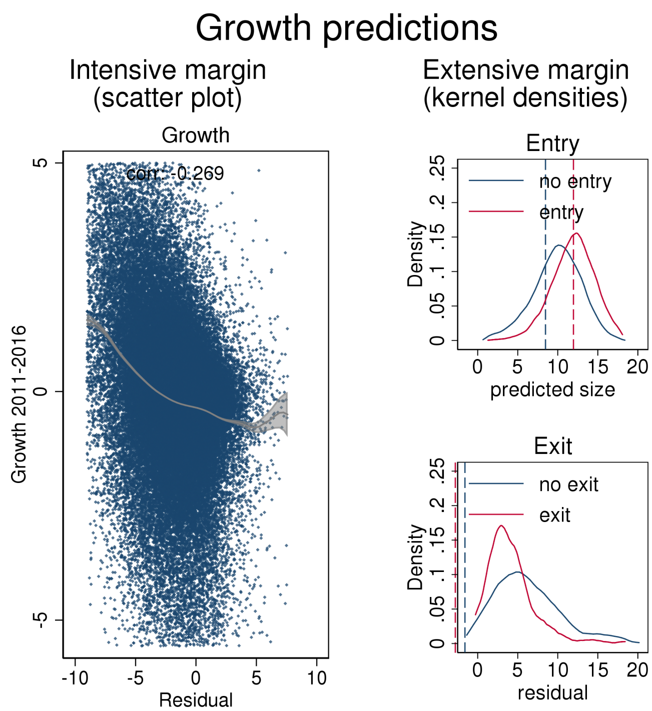
Value-chain trade has increased tremendously in importance over the past decades. Traditional manufacturing economies like Germany, Japan and the US have spread their production chains across multiple countries, exporting intermediates to neighboring, lower-wage countries and reimporting further processed products from them. This process has offered these immediate neighbors the opportunity to enter complex value chains and industrialize at an accelerated pace (Baldwin and Lopez-Gonzalez, 2015). The internationalized value chains that emerged as a result are often organized by multinational enterprises (MNEs),

Figure 12: Validation - predicting export growth 2011-2016



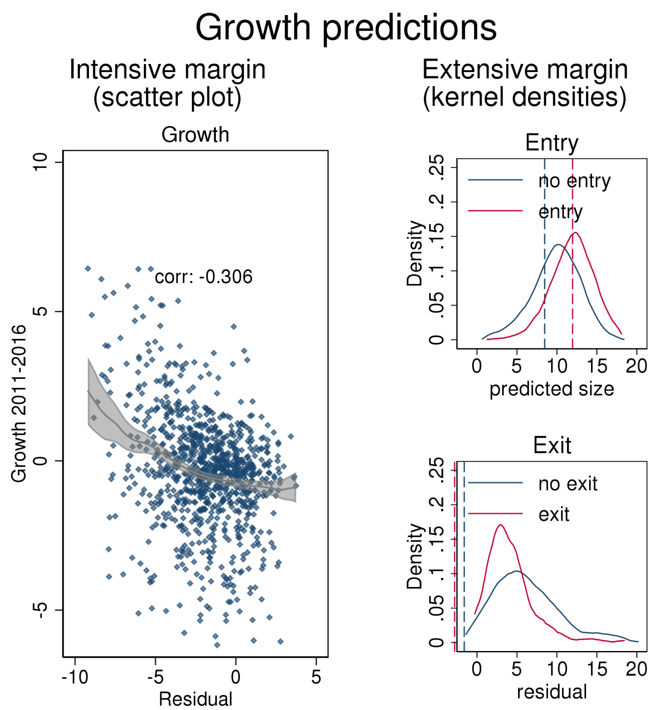
Left panel: *correlation between growth rate in trade and the regression residuals from the PPML models, using only origin-destination-product cells with nonzero exports in both 2011 and 2016. The negative correlation shows that when the observed trade flows exceeded the flows predicted by the PPML models (i.e., when exports were "too large"), growth in exports is low (and possibly negative).* ***Right panel:*** *PPML models' predictive power at the extensive margin. The plots show kernel densities for cells that had no exports in 2011 (upper panel, entry) or in 2016 (lower panel, exit). The upper panel plots the density of the logarithm of the predicted volume of exports, the lower panel the density of the regression residual. The fact that the predicted exports for cells that enter tend to be much larger than for cells that don't shows that entry of export categories can be predicted using the PPML fit. For exiting and non-exiting cells, densities are very similar, implying that the PPML model fails to provide reliable predictions of disappearing trade flows.*

Figure 13: Validation - predicting export growth to EU's single market 2011-2016



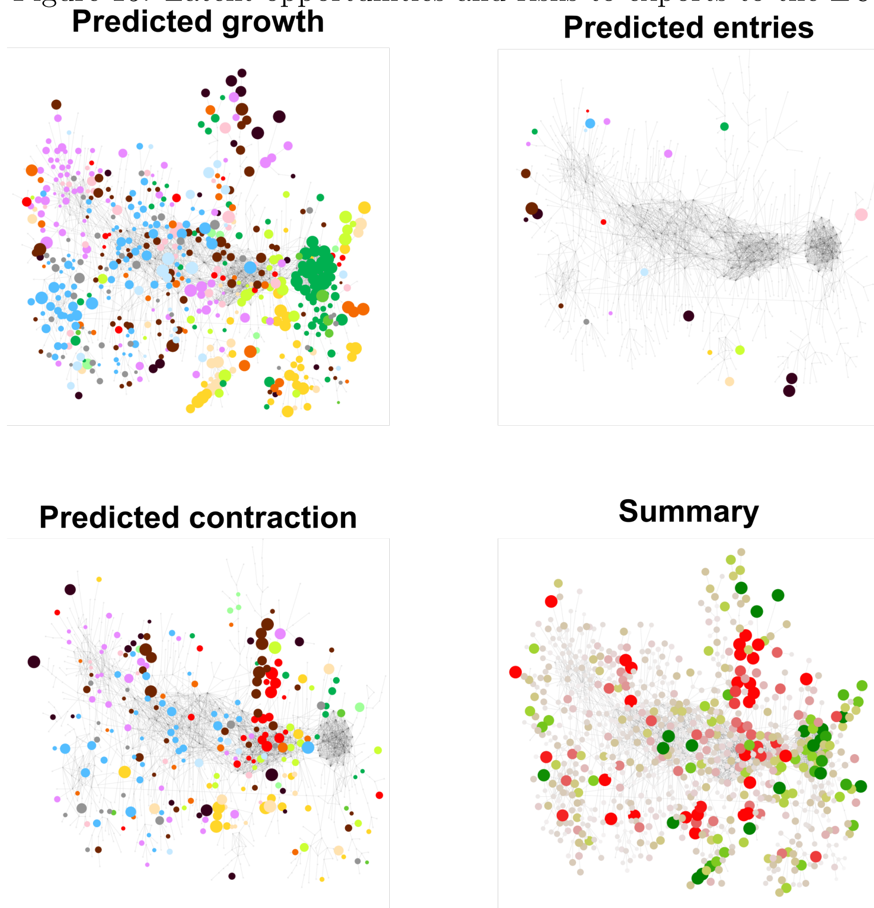
Idem Figure 12, now for exports to the EU at the level of a product-country of origin cell.

Figure 14: Validation - predicting Ukrainian export growth to EU's single market 2011-2016



Idem Figure 13, now for exports from Ukraine only (i.e., one observation per product category).

Figure 15: Latent opportunities and risks to exports to the EU



Upper-left: *Predicted growth with nodes sized by the predicted employment growth (fitted minus current size) in the industry.* ***Upper-right:*** *Predicted entrants with nodes sized by their predicted size.* ***Lower-left:*** *Predicted contraction with nodes sized by the predicted (negative) employment growth (fitted minus actual size).* ***Lower-right:*** *summary of the three panels, green: predicted growth, red: predicted contraction.*

whose production networks span the globe. For instance, Elekes et al. (2019) describe the role of MNEs in Hungary's entry into global value chains by building plants for labor-intensive assembly activities. These MNEs also help local economies diversify, because they provide access to external knowledge sources and international supplier relations (e.g. Elekes et al., 2019; Neffke et al., 2018). In this section, we investigate the activity of MNEs in Ukraine using the Dun & Bradstreet (D&B) data to analyze bilateral investment flows among 130 countries.

D&B data allow us to measure the investment flows between a country of origin and a country of destination in terms of the number of workers employed in establishments in the destination country that are owned by firms headquartered in the origin country. Table 2 provides some basic descriptive statistics for Ukraine and its comparator countries.

Table 2: Descriptive statistics of D&B data

	Ukraine		Comparator countries	
	Domestic	**Foreign**	**Domestic**	**Foreign**
# establishments	1,288,444	2,338	9,695,056	70,033
# employees	8,610,670	128,155	3,4713,513	2,635,115
Average size	6.68	54.81	3.58	37.63

Comparator countries are the Czech Republic, Hungary, Poland, Romania, Slovakia and Turkey.

4.1 Inward FDI in Ukraine

Figure 16 shows how well Ukraine and its comparator countries manage to attract FDI. The upper panel displays the employment in foreign MNEs as a share of total employment as recorded in the D&B data. The lower panel shows the dollar-value of FDI inflows into Ukraine per inhabitant as reported by UNCTAD. Both data sets are largely in agreement. In particular, Ukraine has a relatively poor record when it comes to attracting FDI. According to the D&B database, only one in 50 employees works for a foreign firm in Ukraine. In comparison, in Hungary, this figure is as high as one in five.

Unfortunately, the D&B data were only available for three different years: 2011, 2016 and 2019.[10] Therefore, it is not possible to provide a long-term assessment of changes in FDI. However, over the eight-year period that we do observe, FDI-related employment shares rose in all comparator countries, but Turkey (Figure 17). In contrast, in Ukraine, the share of foreign employment remained mostly flat. Romania offers the starkest contrast: whereas in 2011, the employment footprint of foreign MNEs in Romania was below the one in Ukraine, it quickly surpassed Ukraine's, reaching almost 10% of total employment in 2019.

Figure 18 plots the locations of foreign-owned establishments, where markers are sized by the employment in a location. The subplots break down FDI by country of origin. Whereas European FDI is predominantly located in the west of the country, Russian FDI is more often located in the east. This shows that the shift in participation in value-chains from the former USSR to the EU is accompanied by a westward movement of FDI within the country.

Figure 19 shows the industrial composition of FDI-related employment in Ukraine and Figure 20 shows this composition by country of origin. The largest share of FDI-related employment belongs to companies headquartered in Germany, the Netherlands, England, Switzerland and France. However, the industrial composition of FDI differs drastically across these origins. Germany, the Netherlands and Switzerland all invest heavily in manufacturing activities. Germany's investments are furthermore heavily biased towards parts of the automotive supply chain, whereas Dutch investments tend to focus on the supply chain of the food industry. In contrast, English and French investments seem to be driven by market-seeking motives: both countries target downstream industries, mostly in non-traded services, such as grocery stores, and, in the case of France, banking and insurance. This suggests that Ukraine's current participation in complex global value chains runs mostly through investments by German, and, to a lesser extent, by Swiss and Dutch MNEs.

[10]The data refer to the establishments that existed in the month of March of each year.

Figure 16: Share of employment in foreign MNEs (D&B data) and FDI inflows per inhabitant (UNCTAD).

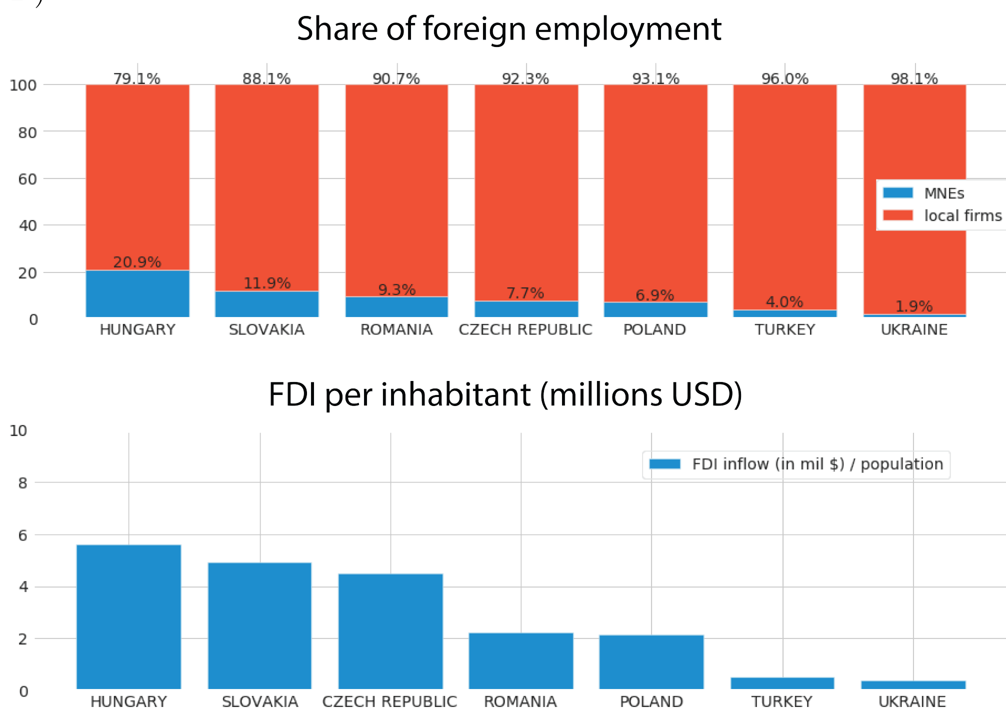


Figure 17: Employment share of foreign MNEs in Ukraine and comparator countries.

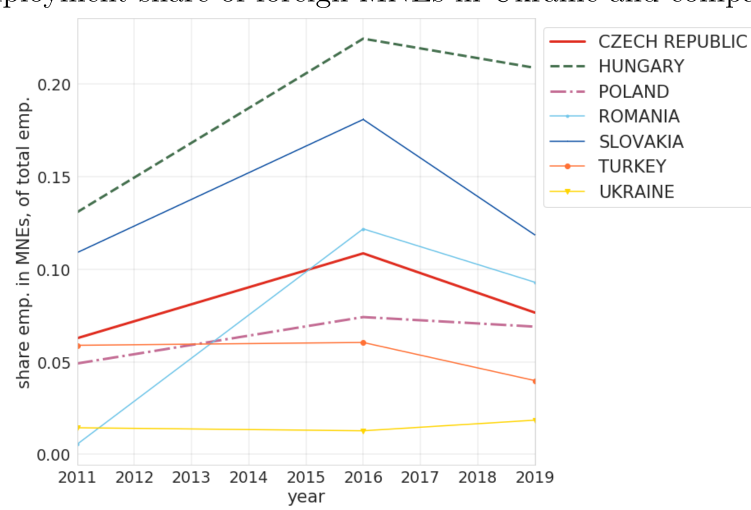


Figure 18: Investment locations by country of origin

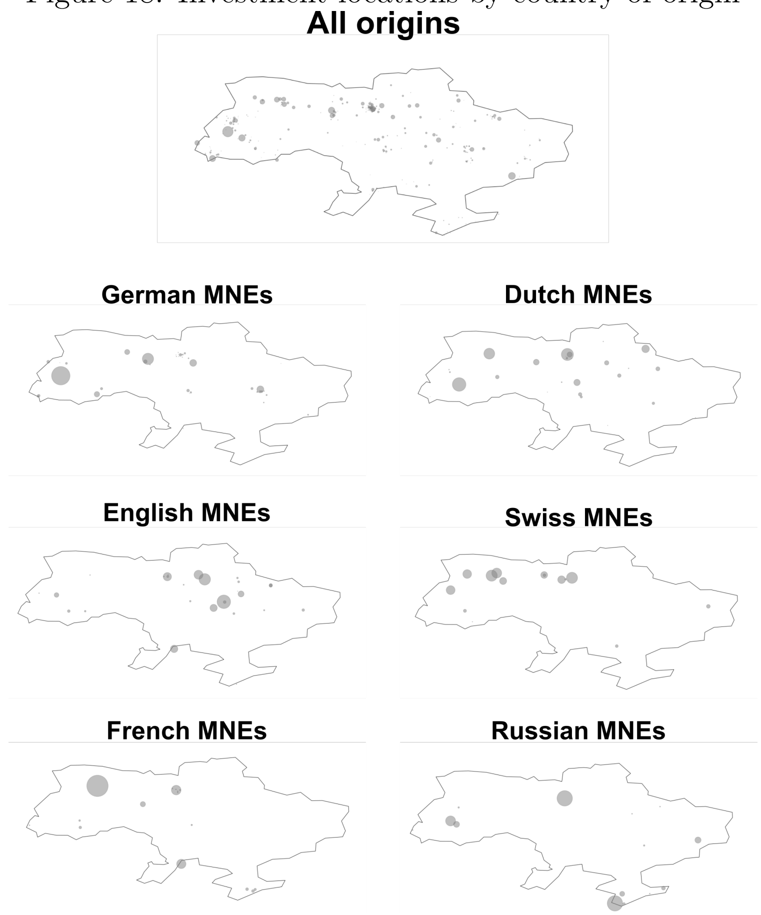


Figure 19: Industrial composition of FDI-related employment in Ukraine

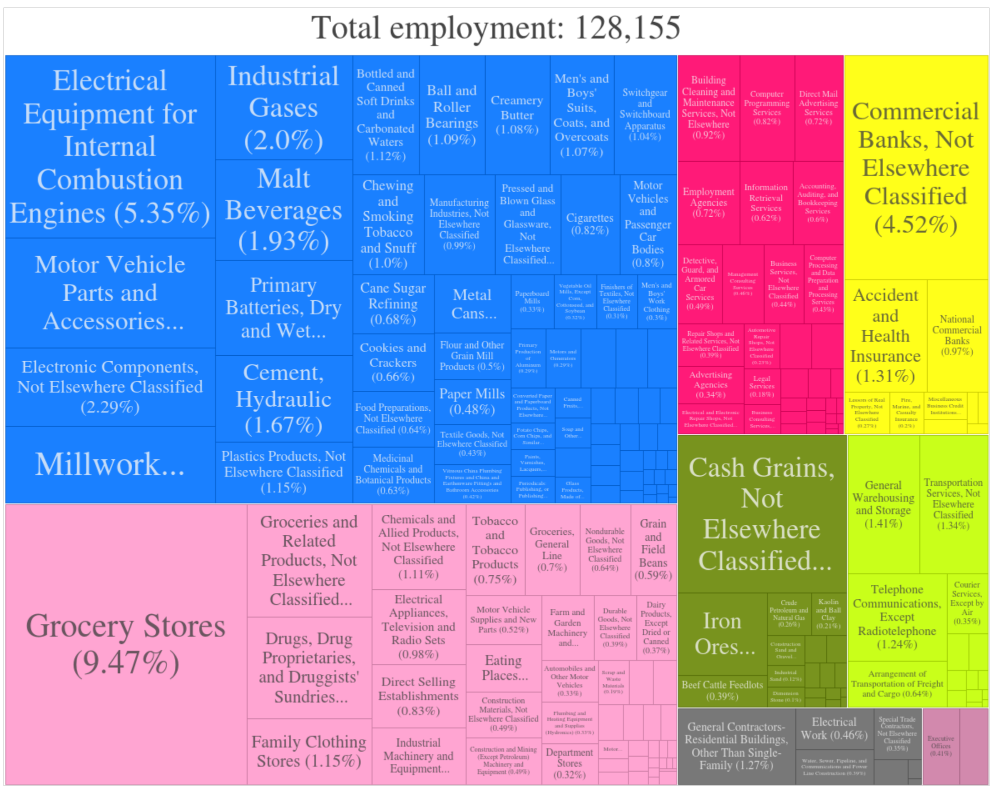


Figure 20: Foreign employment across industries by country of origin (tree maps, Ukraine, 2019)

Figure 21 analyzes the industrial composition of FDI across regions in Ukraine, where we use the Ukrainian *oblast* as our regional unit.[11] Most FDI is concentrated in the greater Kiev area, which accounts for 47% of all FDI-related employment in 2019. The remainder is mainly spread across regions that stretch from Kiev westwards along the northern border with the EU, through Zhytomyr (5%) and Rivne (4%) to the Polish-border region of Lviv (13%). The largest recipient in the eastern part of Ukraine is the iron and steel region of Dnipropetrovsk. In Kiev, foreign MNEs seem mostly to seek access to the Ukrainian market: investments in the city itself focus on wholesale and retail trade, banking and insurance, whereas investments in the wider Kiev-region focus on logistical operations. In the other regions, most FDI targets manufacturing industries that are typically associated with European value chains, such as machinery, textile and automotive production.

4.2 Gravity models of FDI

Just like trade flows, FDI flows can be modelled using gravity equations. We once again use these models to establish a baseline for how large we would expect such flows to be, based on elementary gravity forces, such as the sizes of economies and the distances between them. In analogy to the trade analysis of the previous section, we will estimate industry-specific gravity models. That is, we will estimate the following PPML model for each industry:

$$E\left[E^o_{di}|\mathbf{Z}\right] = exp^{\mathbf{Z}\beta_i} \tag{13}$$

where E^o_{di} represents the FDI-related employment, i.e., the employment in establishments belonging to industry i located in country d, but owned by companies headquartered in country o and $\mathbf{Z}$ contains the same explanatory variables as the trade models of section 3:

- ln (GDP/cap orig.): natural logarithm of the origin country's GDP per capita;
- ln (GDP/cap dest.): natural logarithm of the destination country's GDP per capita;
- ln (pop. orig.): natural logarithm of the origin country's population;
- ln (pop. dest): natural logarithm of the destination country's population; and
- ln (dst.): the natural logarithm of the weighted kilometer distance between the origin and destination countries' main cities as defined by Mayer and Soledad (2011).

Furthermore, we add the EU membership dummy group:

- $\mathrm{EU_o}$: one if origin is an EU or EFTA member, zero otherwise
- $\mathrm{EU_d}$: one if destination is an EU or EFTA member, zero otherwise
- $\mathrm{EU_{od}}$: one if origin and destination are EU or EFTA members, zero otherwise

The effect of a Ukrainian EU membership on FDI inflows to the EU can now be calculated as the (exponentiated) sum of the estimated effects on the variables $\mathrm{EU_d}$ and $\mathrm{EU_{od}}$. Table 3 shows the results when we aggregate investment flows across all industries.

[11] Figure 29 in Appendix B also depicts these investment flows in the industry space.

Figure 21: Share of foreign employment in Ukraine by oblast

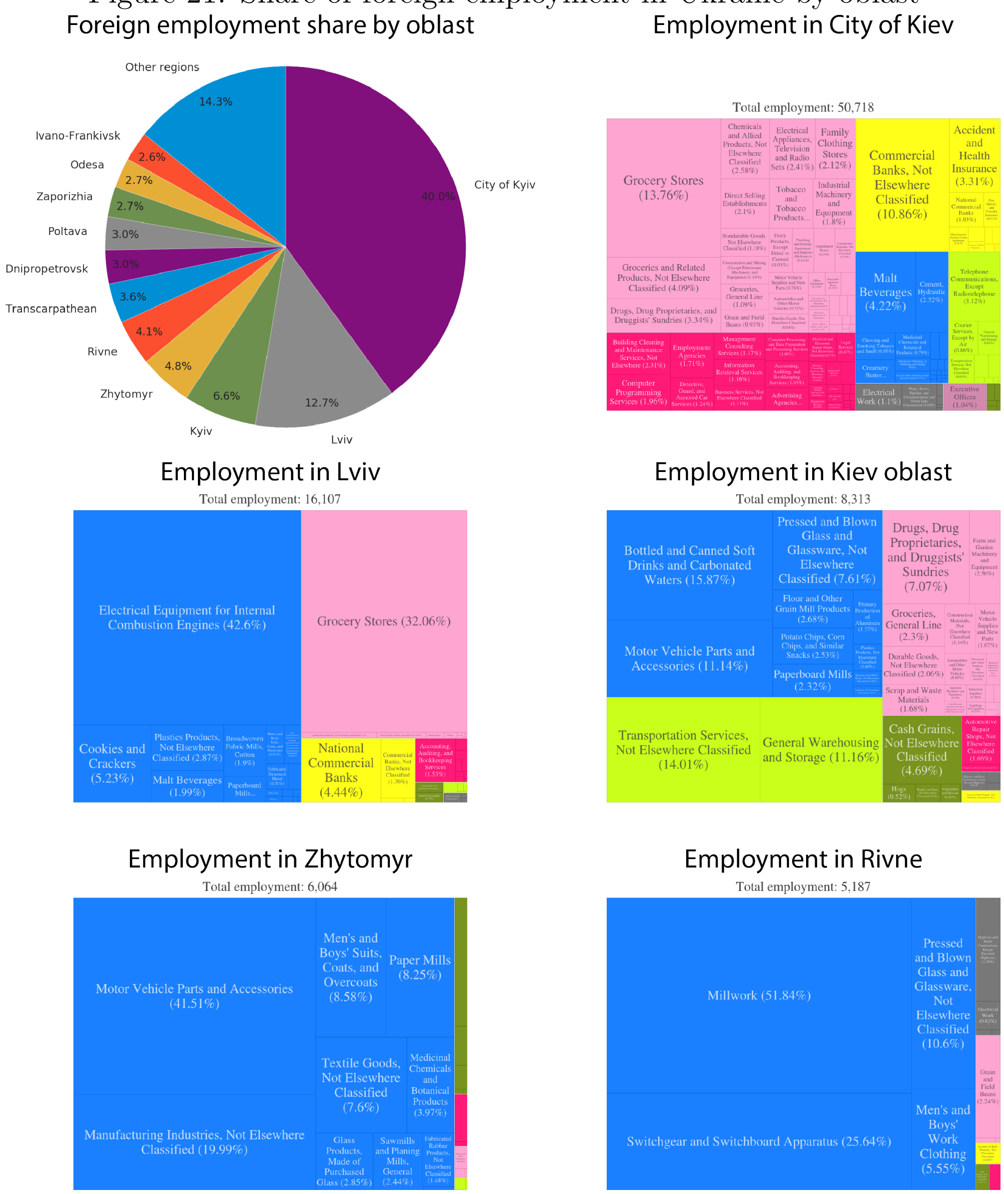
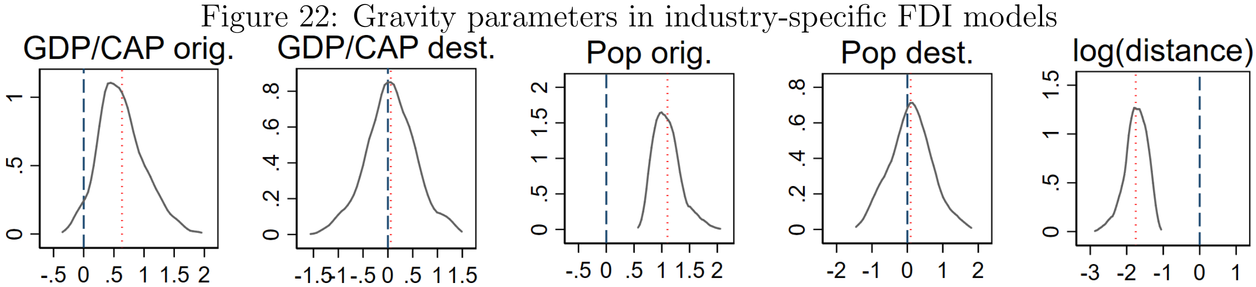


Table 3: Gravity model of total FDI

dep. var.: **USD value of FDI**	**point est.**	**s.e.**	**z-value**	**p-value**	**95% C.I.** **Lower**	**Upper**
Gravity variables						
log(distance)	-1.664	0.135	-12.36	0.000	-1.93	-1.400
log(GDP/cap) - origin	0.590	0.156	3.790	0.000	0.285	0.895
log(GDP/cap) - destination	0.65	0.141	4.600	0.000	0.373	0.927
log(pop) - origin	1.044	0.09	11.6	0.000	0.868	1.220
log(pop) - destination	1.072	0.078	13.7	0.000	0.918	1.226
EU / EFTA membership						
exporter? (0/1)	-1.367	0.469	-2.92	0.004	-2.286	-0.449
importer? (0/1)	-1.947	0.682	-2.86	0.004	-3.283	-0.610
both? (0/1)	2.432	0.810	3.000	0.003	0.844	4.02
constant	-24.5	3.96	-6.17	0.000	-32.2	-16.7
pseudo R-squared	0.835					
# observations	6,111					

PPML estimation of aggregate FDI between country pairs, using robust standard errors.

Figure 22: Gravity parameters in industry-specific FDI models



Kernel densities of parameter estimates across 1,004 industry categories for the gravity-variables in models of FDI. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

The industry-specific regressions allow us to add a variable that quantifies the size of the economy in the recipient country that is relevant to the focal industry. The underlying idea is that investors will target destination countries that have the right capabilities for their intended investments. Accordingly, we will add the density of the focal industry in the destination country as a control variable.

Figure 22 shows the distributions of point-estimates for the gravity-related variables.[12].

In all industries, investment flows diminish with increasing distance. In fact, the median distance decay in FDI is much steeper than in trade. To further illustrate this difference in distance decay between trade and FDI flows, Table 4 uses the point estimate of the distance effect in the gravity models of aggregate trade and FDI flows to predict by which factor these flows decrease when moving from the Czech Republic – the country closest to Ukraine's main foreign investors – to other comparators or to Ukraine itself. Whereas trade

[12]Point estimates associated with the variables in the EU-dummy group also vary across industries. Once again, we caution against a causal interpretation of these parameters: the analysis is set up as purely correlational. A description of these point estimates is provided in Appendix B.2

Table 4: Implied distance decay in trade and FDI from gravity models

	TRADE		
	Germany	**The Netherlands**	**Switzerland**
Czech Republic	1	1	1
Poland	0.834	0.884	0.816
Slovakia	0.804	0.854	0.882
Romania	0.604	0.684	0.698
Turkey	0.476	0.561	0.565
Ukraine	0.538	0.622	0.595
	FDI		
	Germany	**The Netherlands**	**Switzerland**
Czech Republic	1	1	1
Poland	0.543	0.661	0.504
Slovakia	0.480	0.588	0.655
Romania	0.183	0.279	0.298
Turkey	0.082	0.142	0.146
Ukraine	0.124	0.202	0.174

Distance decay factor relative to the Czech Republic of trade to and investments from the top three investment origins of Ukraine implied in the gravity models of Tables 1 and 3.

flows are predicted to drop by less than 50% when comparing Ukraine to the Czech Republic, FDI flows are predicted to drop to 20% or lower. Strikingly, even neighboring Romania is geographically significantly advantaged to attract FDI from western Europe compared to Ukraine. This suggests that Ukraine's distance to European markets represents a much larger obstacle to attracting investments from the EU than to exporting products to the EU.

In most industries, investments increase with the GDP per capita and population size of the country of origin. In fact, the parameter estimates suggest that, in the average industry, as countries double their population, they typically also double their outward FDI. In contrast, the average effect of GDP per capita on outward FDI is well below one, suggesting that there are decreasing returns to scale with respect to the level of a sending country's economic development.

Note, however, that, in logs, we can write the regression model as follows:

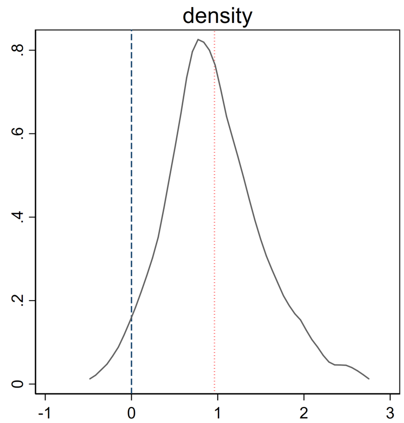
$$\ln E^o_{di} = \beta_1 \ln(\text{GDP/cap orig.}) + \beta_2 \ln(\text{pop. orig.}) + \tilde{\mathbf{Z}}\Gamma \tag{14}$$

where $\tilde{\mathbf{Z}}$ is a matrix that collects all remaining variables in its columns. We can rewrite this expression as:

$$\ln E^o_{di} = \beta_1 \ln(\text{GDP}) + (\beta_2 - \beta_1) \ln(\text{pop. orig.}) + \tilde{\mathbf{Z}}\Gamma \tag{15}$$

This new equation reinterprets the estimated parameter estimates. It attributes investment flows to an origin country's size, but now captured in two different quantities: its population and its GDP. On average, the parameter estimate for the origin country's population (β_2) in the original model is close to one, whereas the parameter estimate for the

Figure 23: Industry-space density parameter in industry-specific FDI models



Kernel density of parameter estimates across 1,004 industry categories for industry space density in the country of destination. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

origin country's GDP per capita (β_1) is somewhat larger than 0.5. Using the rewritten form above, a country's size is expressed in two variables: its GDP and its population. Each size-variable is associated with an effect of around 0.5. This suggests that there are, in fact, constant returns to a country's size in outward investment flows, but that this size should be expressed in two roughly equally weighted components: population and GDP.

In contrast, the GDP per capita and population size of the country of destination has – on average – apparently no effect on investment flows. Just like in the trade models, the explanatory force of this variable was transferred to the industry-space density variable.

Figure 23 shows that the effect of the industry-space density variable is centered on one. Recall that this variable is calculated as the proximity-weighted employment size of a country's industries, where proximity expresses how related industries are to the focal industry. In this sense, the variable captures the "relevant" size of the destination economy, where closely related industries are deemed more relevant to attracting investments than unrelated industries. The fact that the average parameter estimate is close to one means that, with respect to its relevant size, there are constant returns to scale also in the *destination* country's size.[13]

4.3 Predicting growth in FDI

As in the trade models, the residuals of the PPML regressions can be used to assess in which industries Ukraine receives an unexpectedly low amount of FDI from EU countries. The more

[13]If we omit the industry-space density variable from the regression, we indeed find that the estimated effects of the size of the destination economy are of a similar magnitude as estimated effects of the size of the origin country. Moreover, compared to the models with industry-space density as an explanatory variable, the average R^2 of the regressions is about 3 percentage points lower. This corroborates the explanatory force of the density variable vis-à-vis simple size variables.

negative this residual, the larger the gap is between observed and expected investments.

To validate the growth predictions for FDI, we follow the same step-by-step procedure as in trade. That is, we run the PPML models for the patterns of bilateral, industry-specific FDI between all country pairs in the data set. Next, we use the fitted values as predictions for the FDI flow between an origin and a destination country in the focal industry. Below, we assess how well the difference between the actual and fitted values (i.e., the residuals) predict growth in the period 2011-2016 in three different slices of the data:

- using all country pairs;
- using only EU origins, aggregated into one region, the EU's Single Market, but all destinations; and
- using only Ukraine as a destination and the Single Market as a single origin.

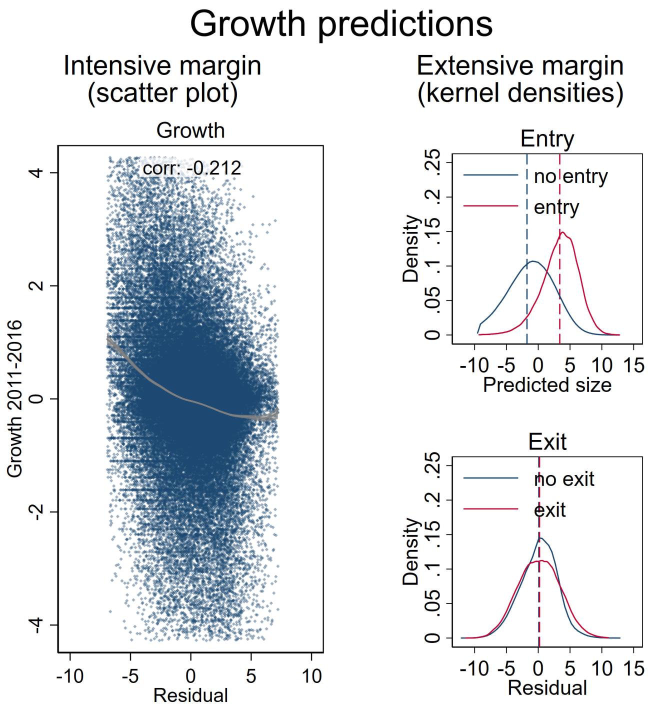
The left panel of Figure 24 shows the relation between the regression residuals and subsequently observed growth rates using all country pairs, but only industries in which investments took place in both 2011 and 2016. The right panel summarizes the predictive power of the models at the extensive margin. The upper part plots the kernel density of the predicted size of an FDI flow for origin-destination-industry cells with zero flows in 2011. The blue line shows the kernel density of all corridors that stayed empty (i.e., without investments in 2011 and in 2016). The red line shows the corridors without FDI in 2011, but with positive FDI flows by 2016. The dotted lines show the means for each group. The bottom part of the right panel shows a similar plot, but now for corridors from which FDI had disappeared by 2016. The graphs now show the kernel densities of the residual of the PPML regression for cells in which we observe exits (red) and those in which we don't (blue). Figures 25 and 26 repeat this analysis for aggregate outflows from the EU's Single Market to all other countries and for flows from the Single Market to Ukraine.

When using the entire sample, the PPML model's predictions of investment growth at the intensive margin are somewhat weaker than in the case of export growth. However, when predicting growth of EU investments in Ukraine, the predictive power of the model residuals becomes very strong, reaching a correlation of -0.65 with observed investment growth. Similarly, like in the case of trade, the intensive margin of growth can be accurately predicted when it comes to new industries entering an investment corridor. In contrast, and again in line with our earlier trade results, the models provide little explanatory force when it comes to predicting which industries will disappear from an investment corridor.

Given these results, we use the residuals from the PPML model when the model is fit on 2019 data to predict the growth of FDI from the EU to Ukraine in the 5-year period between 2019 and 2024. Figure 27 displays these growth opportunities in the industry space. Tables 11-16 in Appendix B.3 summarize the opportunities and threats to investment growth in tabular form.

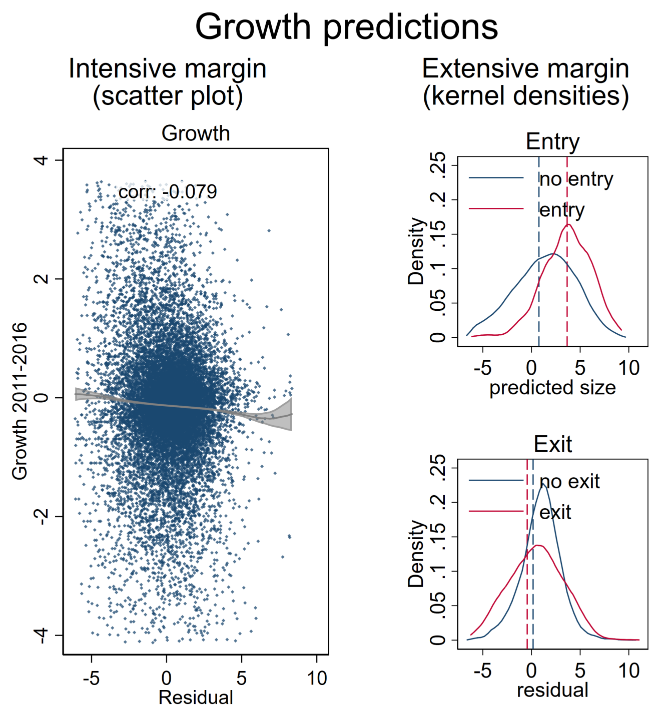
The opportunities to expand FDI in existing industries or attract FDI in new industries from the EU are somewhat spread across different sectors (upper-left and upper-right panels of Figure 27). They include industries that are part of large western European manufacturing value chains, such as car production. Examples are motor vehicle parts, motors and generators, and electronic components. The products of these industries also featured

Figure 24: Validation - predicting FDI growth 2011-2016



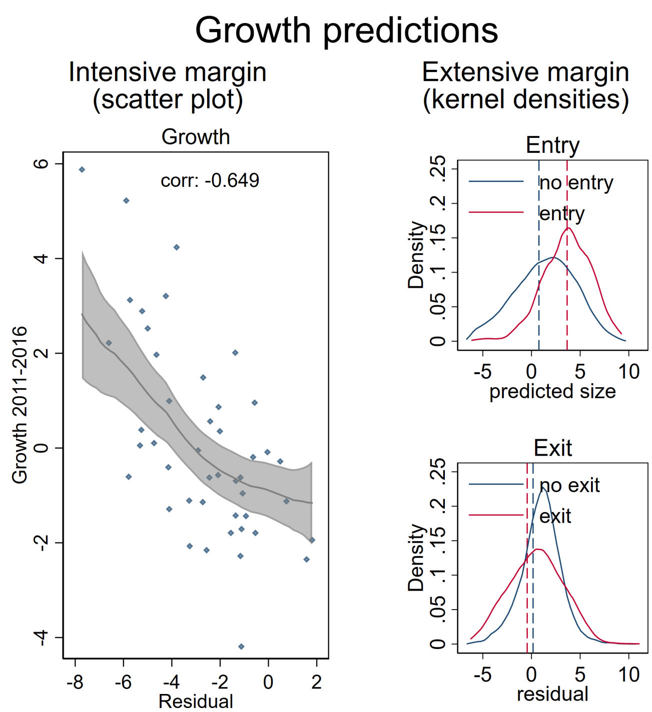
Left panel: *correlation between growth rate in FDI in an origin-destination-industry cell that had at least some FDI in 2011 and in 2016 and the regression residuals from the PPML models. The negative correlation shows that when the PPML models estimated that observed FDI flows exceeded expected FDI flows (i.e., that FDI flows were "too large"), subsequent growth in FDI was low (and possibly negative).* ***Right panel:*** *PPML models' predictive power at the extensive margin. The plots show kernel densities for cells that had no FDI in 2011 (upper panel, entry) or in 2016 (lower panel, exit). The upper panel plots the density of the logarithm of the predicted size of FDI flows, the lower panel of the regression residual. The fact that the predicted flows for entering cells tend to be much larger than for non-entering cells shows that entry of FDI flows can be predicted using the PPML fit. For exiting and non-exiting cells, densities are very similar. Therefore, the PPML model fails to provide reliable predictions of disappearing FDI flows.*

Figure 25: Validation – predicting FDI growth 2011-2016 (EU outflows)



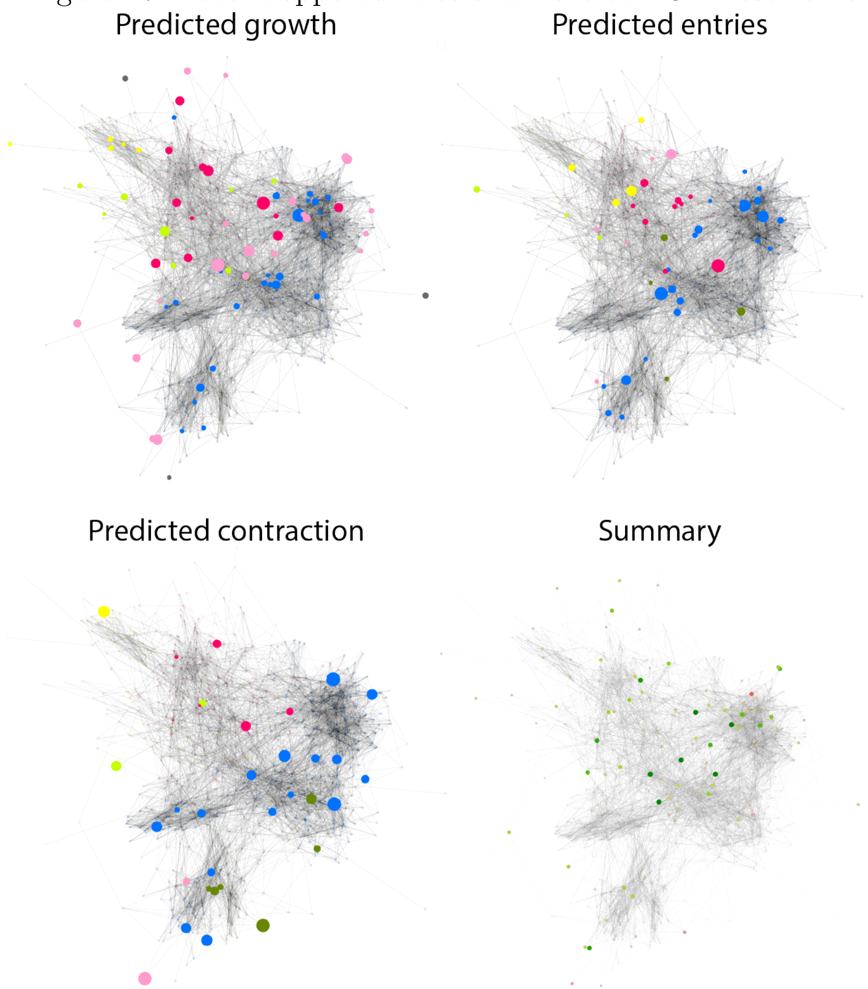
Idem Figure 24, now for exports to EU Single Market only.

Figure 26: Validation – predicting FDI growth 2011-2016 (EU outflows to Ukraine)



Idem Figure 24, now for exports from Ukraine only (i.e., one observation per industry)

Figure 27: Latent opportunities and risks to EU investments



Upper-left: *Predicted growth with nodes sized by the predicted employment growth (fitted minus actual employment) in the industry.* ***Upper right:*** *Predicted entrants with nodes sized by their predicted size.* ***Lower-left:*** *Predicted contraction with nodes sized by the predicted (negative) employment growth (fitted minus actual employment).* ***Lower-right:*** *summary of the three panels, green: predicted growth, red: predicted contraction.*

as opportunities for expanding Ukraine's exports to the EU in the trade analysis. Further opportunities exist in the value chains of chemicals and food products and more service-oriented activities that could supply customers in the EU, such as customized computer programming.

The lower-left panel of Figure 27 shows positive anamolies: industries in which Ukraine manages to attract moe European FDI than our benchmark models predict. Most of these industries are part of the extractive sector or produce agricultural products. Even within the manufacturing sector, the largest positive outliers in terms of FDI are related to industries that are just downstream from these extractive sectors, such as the manufacturing of various food products or basic chemicals. Participation in more complex segments of European value chains is as yet a promise that has not materialized.

5 Conclusions

We investigated the export mix and presence of foreign companies in Ukraine. Over the period 2000 to 2016, the Ukrainian economy witnessed, first, a strong expansion and, then, a precipitous decline in the volume of its exports. Starting in 2012, this decline was exacerbated by the decline of the Russian Federation as a main export destination. Moreover, traditionally, Ukraine had exported its most complex products to the Russian Federation. The losses on the Russian market therefore reinforced an already steady decline in complexity of Ukraine's exports, with agricultural products replacing metal and machinery products as the country's prime exports.

Ukraine's future growth will depend on finding alternative export markets. One possibility is to participate in European supply chains. However, gravity models show that FDI is much more sensitive to the distance between the source and destination of such investment flows than international trade. This puts Ukraine at a disadvantage compared to its comparator countries located closer to Germany, the center of what Baldwin and Lopez-Gonzalez (2015) call "Factory Europe". In line with this, we find that Ukraine manages to attract relatively little FDI from the EU compared to comparator countries in its neighborhood. The main sources of FDI in 2019 are western European countries, with Germany featuring as the top origin. Much of this FDI targets manufacturing industries, although the exact composition varies by source country. Whereas Germany and Switzerland expand their supply chains eastward by targeting automotive- and machinery related industries, French and English investments are mostly market-seeking, targeting non-traded services.

In case Ukraine manages to further integrate into EU supply chains, we would moreover expect a shift in the geography of economic activity within the country. Given the steep distance decay of FDI, most European FDI unsurprisingly locates in the west of Ukraine, along the EU border but away from the former industrial heartland that supplied the complex machinery products connected to trade with Russia. A deepening collaboration with firms based in the EU could therefore lead to a spatial mismatch in the demand of and supply for labor.

References

Alfaro, L. and Charlton, A. (2009). Intra-industry foreign direct investment. *American Economic Review*, 99(5):2096–2119.

Bahar, D. (2020). The hardships of long distance relationships: time zone proximity and the location of mnc's knowledge-intensive activities. *Journal of International Economics*, page 103311.

Baldwin, R. and Lopez-Gonzalez, J. (2015). Supply-chain trade: A portrait of global patterns and several testable hypotheses. *The World Economy*, 38(11):1682–1721.

Bryce, D. J. and Winter, S. G. (2009). A general interindustry relatedness index. *Management Science*, 55(9):1570–1585.

Damijan, J. P., Kostevc, Č., and Rojec, M. (2013). Global supply chains at work in central and eastern european countries: Impact of fdi on export restructuring and productivity growth.

Elekes, Z., Boschma, R., and Lengyel, B. (2019). Foreign-owned firms as agents of structural change in regions. *Regional Studies*, 53(11):1603–1613.

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., and Simoes, A. (2014). *The atlas of economic complexity: Mapping paths to prosperity*. Mit Press.

Hausmann, R., Hwang, J., and Rodrik, D. (2007). What you export matters. *Journal of economic growth*, 12(1):1–25.

Hidalgo, C. A., Balland, P.-A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., Glaeser, E., He, C., Kogler, D. F., Morrison, A., et al. (2018). The principle of relatedness. In *International conference on complex systems*, pages 451–457. Springer.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences*, 106(26):10570–10575.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., and Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837):482–487.

Jun, B., Alshamsi, A., Gao, J., and Hidalgo, C. A. (2019). Bilateral relatedness: knowledge diffusion and the evolution of bilateral trade. *Journal of Evolutionary Economics*, pages 1–31.

Mayer, T. and Soledad, Z. (2011). Notes on cepii distances measures: The geodist database. *Working Papers 2011-25, CEPII Research Center*.

Mayer, T. and Zignago, S. (2011). Notes on cepii's distances measures: The geodist database.

Neffke, F., Hartog, M., Boschma, R., and Henning, M. (2018). Agents of structural change: The role of firms and entrepreneurs in regional diversification. *Economic Geography*, 94(1):23–48.

Neffke, F., Henning, M., and Boschma, R. (2011). How do regions diversify over time? industry relatedness and the development of new growth paths in regions. *Economic geography*, 87(3):237–265.

Neffke, F., Henning, M. S., et al. (2008). Revealed relatedness: Mapping industry space. Technical report, Utrecht University, Department of Human Geography and Spatial Planning ....

Neffke, F. M., Otto, A., and Weyh, A. (2017). Inter-industry labor flows. *Journal of Economic Behavior & Organization*, 142:275–292.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and statistics*, 88(4):641–658.

Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., and Pietronero, L. (2012). A new metrics for countries' fitness and products' complexity. *Scientific reports*, 2:723.

Teece, D. J., Rumelt, R., Dosi, G., and Winter, S. (1994). Understanding corporate coherence: Theory and evidence. *Journal of economic behavior & organization*, 23(1):1–30.

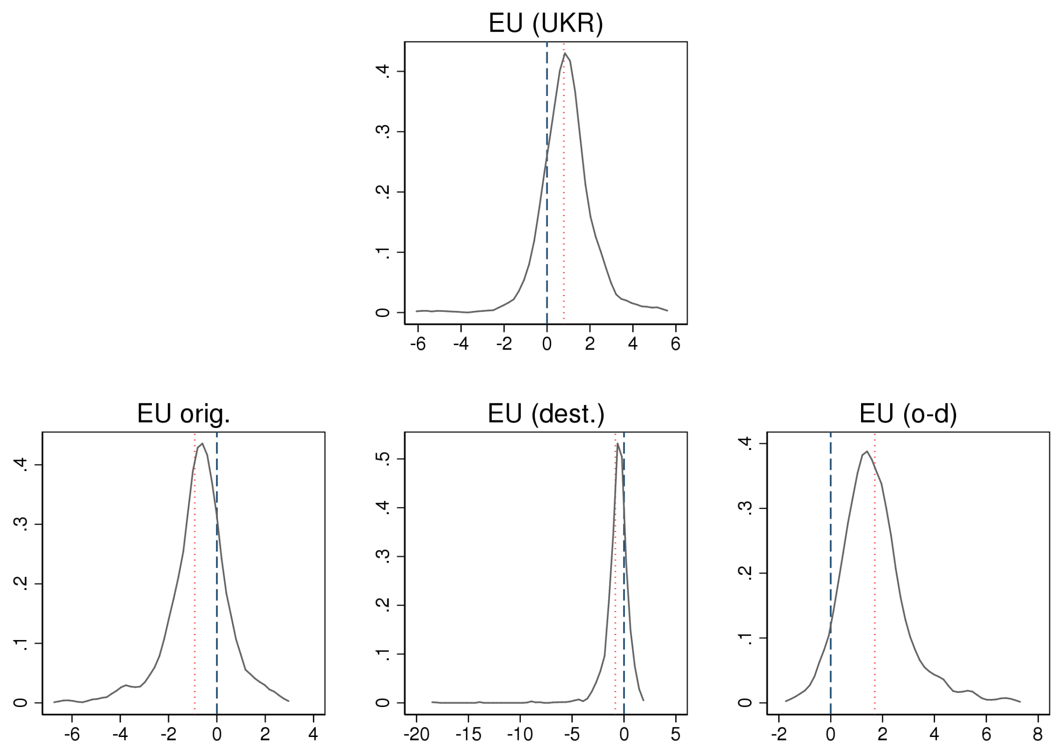
Tinbergen, J. (1962). Shaping the world economy; suggestions for an international economic policy.

A Trade

A.1 Product-specific effects of EU membership

Figure 28 shows the densities of the estimated effect of EU membership on trade. It is important to note that this analysis has no pretense of identifying causal effects. The results should therefore be regarded as indicative only. The upper graph shows the effect of a country entering the EU on exports to EU countries. This is calculated as the sum of the point estimates for the variables $\mathrm{EU_o}$ and $\mathrm{EU_{od}}$. Accordingly, for most products, we should expect a positive effect on the export volume to EU countries when a country enters the EU. However, due to trade-diversion, we also find that exports to third countries often decrease in this case. This effect is shown in the center graph in the bottom row of Figure 28. Such trade diversion effects are also found in the majority of products.

Figure 28: EU membership effect in product-specific trade models



Kernel density of parameter estimates across 1,005 product categories for EU-membership dummies. The upper graph depicts the effects of entering the EU on exports to the EU. The bottom-left graph shows the effect on exports to the rest of the world. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

Table 5: Existing export categories where Ukraine underperforms compared to benchmark

rank	product	Name	RCA	predicted RCA
1	2709	Petroleum oils, crude	0.00	184.35
2	2710	Petroleum oils, refined	0.10	3.25
3	6109	T-shirts	0.31	5.08
4	7108	Gold	0.01	1.54
5	6110	Sweaters, pullovers, sweatshirts, etc	0.13	3.36
6	6203	Men's suits, not knit	1.81	4.35
7	7102	Diamonds	0.07	637.62
8	901	Coffee, not roasted	0.00	6.61
9	1801	Cocoa beans, whole	0.45	6258.67
10	6403	Footwear, with leather body	0.48	2.62
11	7403	Refined copper and copper alloys	0.34	5.31
12	8703	Cars	0.00	0.07
13	6204	Women's suits, not knit	1.11	2.07
14	8708	Parts and accessories of the motor vehicles	0.01	0.09
15	8704	Motor vehicles for transporting goods	0.00	0.49
16	804	Dates, figs, pineapples, avocados, guavas and mangoes	0.02	14.77
17	803	Bananas and plantains	0.00	22.25
18	7601	Unwrought aluminum	0.28	2.5
19	8471	Automatic data processing machines	0.01	0.20
20	6205	Men's shirts, not knit	0.33	3.40

Top 20 export categories in which Ukraine has some exports, but less than the PPML benchmark predictions. Rank: rank of product category (based on absolute difference between PPML model fit and observed export volumes). Product: product's HS code. RCA: current revealed comparative advantage (RCA) in product vis-à-vis group of comparator countries. Predicted RCA: RCA in product vis-à-vis group of comparator countries if exports were at the level predicted by the PPML model.

A.2 Growth predictions for exports

In this section we report on the export categories in which Ukraine over- or underperforms against our statistical benchmark. Note that our export data include reexports. Therefore, not all products that Ukraine exports need to be actually *produced* in Ukraine.

Table 6: New export categories where Ukraine underperforms compared to benchmark

rank	product	Name	RCA	predicted RCA
1	7501	Nickel mattes and other products of nickel metallurgy	0.00	41024.8
2	4001	Natural rubber	0.00	24.7
3	2608	Zinc ores	0.00	3.4
4	5102	Animal hair	0.00	2375.7
5	2607	Lead ores	0.00	9.6
6	2715	Bituminous mix, mastic from asphalt, bitumen-tar-pitch	0.00	23.1
7	2604	Other metal content	0.00	8965.8
8	8401	Nuclear reactors and related equipment	0.00	23.2
9	7203	Ferrous products obtained by direct reduction of iron ore	0.00	27.4
10	2301	Flour or meal for animal feed	0.00	2.4
11	1504	Fats and oils of fish or marine mammals	0.00	8.4
12	905	Vanilla beans	0.00	46.7
13	5510	Yarn of artificial staple fibers	0.00	1.5
14	2841	Salts of oxometallic or peroxometallic acids	0.00	5.1
15	8605	Railway passenger coaches	0.00	1.1
16	7401	Copper mattes; cement copper	0.00	73.1
17	2617	Other ores and concentrates	0.00	5.1
18	5206	Cotton yarn of < 85%	0.00	1.8
19	2609	Tin ores	0.00	443.7
20	2511	Natural barium sulphate	0.00	6.9

Idem Table 5, now for export categories in which Ukraine has no exports to the EU's Single Market.

Table 7: Export categories where Ukraine overperforms compared to benchmark

rank	product	Name	RCA	predicted RCA
1	1005	Maize (corn) seed	36.1	0.4
2	1512	Sunflower-seed or safflower oil, crude	73.2	7.5
3	2601	Iron ores and concentrates	6027.0	73.4
4	7207	Semifinished products of iron or nonalloy steel	61.6	6.7
5	7208	Hot rolled iron or non-alloy steel, coil, w>600mm, t>10mm, myp 355 mpa	13.3	0.8
6	8544	Insulated wire; optical fiber cables	3.3	1.0
7	2306	Cotton seed oilcake	54.7	6.2
8	1205	Rape or colza seeds	12.4	0.2
9	4407	Wood sawn or chipped of a thickness exceeding 6 mm	13.4	1.1
10	7202	Ferroalloys	29.7	8.4
11	2716	Electrical energy	3.7	0.5
12	1001	Wheat and meslin	4.5	0.4
13	7213	Hot rolled bar/rod grooved iron or non-alloy steel in irregular coils	10.1	0.8
14	1201	Soya beans	54.0	0.5
15	7304	Tubes, pipes and hollow profiles, seamless, of iron or steel	6.4	0.4
16	4408	Sheets for veneering for plywood	24.7	1.8
17	2508	Clays	42.9	2.1
18	3102	Mineral or chemical fertilizers, nitrogenous	6.4	2.0
19	7209	Cold rolled iron or non-alloy steel, coil, width>600mm, t>3mm, 355 mp	7.7	1.0
20	2507	Kaolin	54.1	1.1

Idem Table 5, now for export categories in which Ukraine has more exports to the EU's Single Market than expected. These represent positive anomalies with respects to the PPML model's benchmark.

Table 8: Existing export categories where Ukraine underperforms compared to benchmark (non-extractive sector only)

rank	product	Name	RCA	predicted RCA
1	6109	T-shirts	0.3	5.1
2	6110	Sweaters, pullovers, sweatshirts, etc	0.1	3.4
3	6203	Men's suits, not knit	1.8	4.4
4	6403	Footwear, with leather body	0.5	2.6
5	7403	Refined copper and copper alloys	0.3	5.3
6	8703	Cars	0.0	0.1
7	6204	Women's suits, not knit	1.1	2.1
8	8708	Parts and accessories of the motor vehicles	0.0	0.1
9	8704	Motor vehicles for transporting goods	0.0	0.5
10	7601	Unwrought aluminum	0.3	2.5
11	8471	Automatic data processing machines	0.0	0.2
12	6205	Men's shirts, not knit	0.3	3.4

Idem Table 5, showing only products outside the extractive sector.

Table 9: New export categories where Ukraine underperforms compared to benchmark (non-extractive sector only)

rank	**product**	**Name**	**RCA**	**predicted RCA**
1	7501	Nickel mattes and other products of nickel metallurgy	0.0	41024.8
2	4001	Natural rubber	0.0	24.7
3	5102	Animal hair	0.0	2375.7
4	8401	Nuclear reactors and related equipment	0.0	23.2
5	7203	Ferrous products obtained by direct reduction of iron ore	0.0	27.4
6	2301	Flour or meal for animal feed	0.0	2.4
7	1504	Fats and oils of fish or marine mammals	0.0	8.4
8	5510	Yarn of artificial staple fibers	0.0	1.5
9	2841	Salts of oxometallic or peroxometallic acids	0.0	5.1
10	8605	Railway passenger coaches	0.0	1.1
11	7401	Copper mattes; cement copper	0.0	73.1
12	5206	Cotton yarn of < 85%	0.0	1.8

Idem Table 6, showing only products outside the extractive sector.

Table 10: Export categories where Ukraine overperforms compared to benchmark (non-extractive sector only)

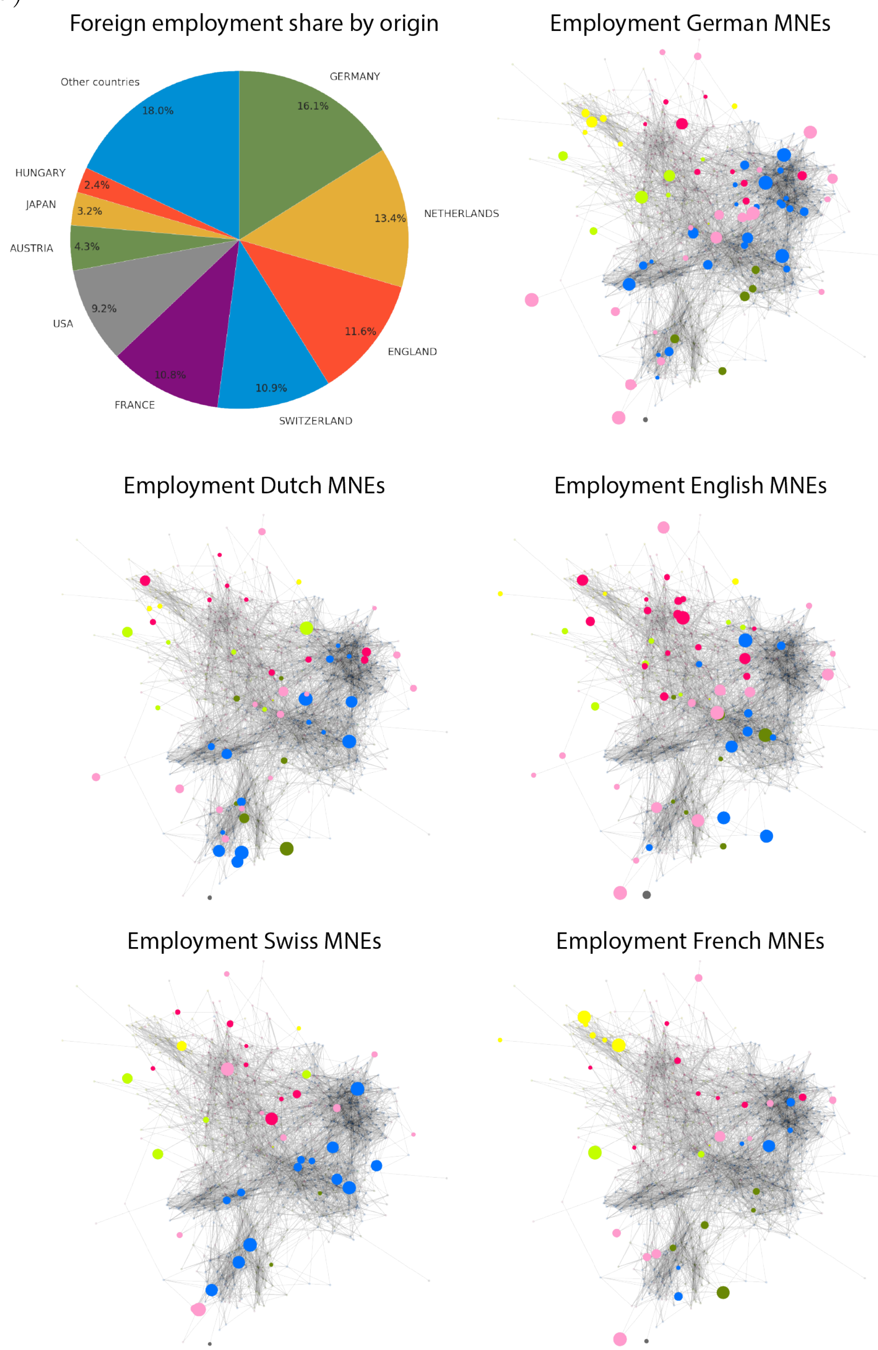
rank	**product**	**Name**	**RCA**	**predicted RCA**
1	1512	Sunflower-seed or safflower oil, crude	73.2	7.5
2	7207	Semifinished products of iron or nonalloy steel	61.6	6.7
3	7208	Hot rolled iron or non-alloy steel, coil,w >600mm, t >10mm, myp 355 mpa	13.3	0.8
4	8544	Insulated wire; optical fiber cables	3.3	1.0
5	2306	Cotton seed oilcake	54.7	6.2
6	4407	Wood sawn or chipped of a thickness exceeding 6 mm	13.4	1.1
7	7202	Ferroalloys	29.7	8.4
8	7213	Hot rolled bar/rod grooved iron or non-alloy steel in irregular coils	10.1	0.8
9	7304	Tubes, pipes and hollow profiles, seamless, of iron or steel	6.4	0.4
10	4408	Sheets for veneering for plywood	24.7	1.8
11	3102	Mineral or chemical fertilizers, nitrogenous	6.4	2.0
12	7209	Cold rolled iron or non-alloy steel, coil, width>600mm, t>mm, 355 mp	7.7	1.0

Idem Table 7, showing only products outside the extractive sector.

B FDI

B.1 FDI by country of origin in the industry space

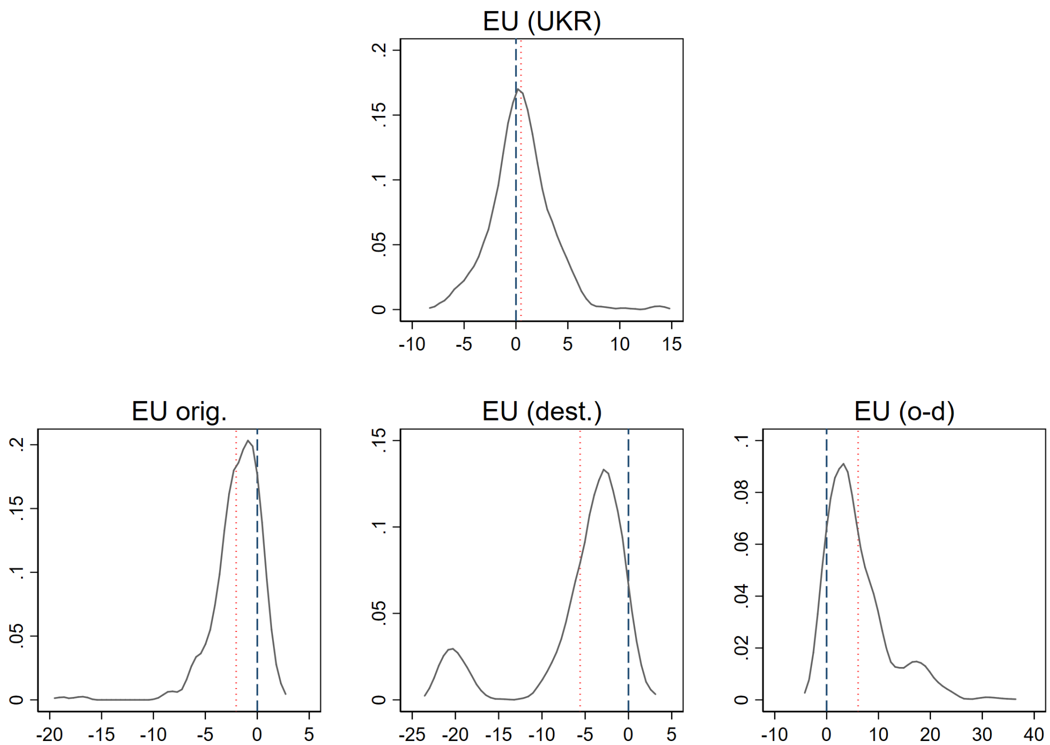
Figure 29: Foreign employment across industries by country of origin (industry spaces, Ukraine, 2019)



B.2 Industry-specific effects of EU membership

Figure 30 evaluates to what extent EU member states exhibit investment patterns that differ from non-member states. As in trade, there is an investment diversion effect of EU membership: controlling for gravity variables, EU members receive fewer investments from non-EU members than countries outside the EU do (bottom-center graph). However, the estimates suggest that, this time, the positive effect from an increase of investments from EU members typically cannot compensate this loss (upper graph).[14] Note, however, that there is quite some variation in this effect across industries.

Figure 30: EU membership effect in industry-specific FDI models



Kernel density of parameter estimates across 1004 industry categories for EU-membership dummies. The upper graph depicts the effects of entering the EU on FDI inflows from the EU. The center bottom graph shows the effect on inflows from the rest of the world. The dashed blue line is centered on 0, the dotted red line on the average parameter estimate.

[14] When a country enters the EU, the dummy group changes as follows (1) the country's EU destination dummy (EU (dest.)) changes from 0 to 1; (2) for FDI inflows from existing EU members, the EU (o-d) dummy changes from 0 to 1, but the EU (orig.) dummy does not change (it remains 1). Therefore, the effect of becoming an EU member on inflows from the EU is calculated as the sum of the effects of the EU (dest.) dummy and the EU (orig.) dummy.

Table 11: Existing industries where Ukraine underperforms in FDI compared to benchmark

rank	industry	Name	RCA	predicted RCA
1	3714	Motor vehicle parts and accessories	11.3	119.3
2	7389	Business services, nec	0.6	26.4
3	8711	Engineering services	0.3	30.1
4	5172	Petroleum products, nec	2.1	191.7
5	8742	Management consulting services	1.7	44.0
6	5122	Drugs, proprietaries, and sundries	7.9	68.1
7	7381	Detective and armored car services	1.3	18.0
8	5149	Groceries and related products, nec	22.8	87.5
9	4731	Freight transportation arrangement	9.5	123.8
10	7371	Custom computer programming services	0.3	20.3
11	5999	Miscellaneous retail stores, nec	0.0	10.3
12	1542	Nonresidential construction, nec	5.0	929.3
13	7011	Hotels and motels	0.0	18.8
14	5084	Industrial machinery and equipment	11.5	97.0
15	7379	Computer related services, nec	0.1	18.5
16	7311	Advertising agencies	1.2	15.7
17	2851	Paints and allied products	2.1	218.9
18	5085	Industrial supplies	0.4	66.5
19	8741	Management services	0.0	13.9
20	7349	Building maintenance services, nec	3.7	16.8

Top 20 industries in which Ukraine attracts some FDI from the EU, but less than the PPML benchmark predictions. Rank: rank of industry (based on absolute difference between PPML model fit and observed FDI-related employment). Industry: industry's NAICS 2017 code. RCA: observed revealed comparative advantage (RCA) in industry vis-à-vis comparator countries. Predicted RCA: RCA in industry vis-à-vis comparator countries if FDI inflows were at the level predicted by the PPML model.

B.3 Growth predictions for FDI

Table 11 lists the top 20 industries in which Ukraine already has some investments from EU countries, but not as much as the PPML model predicted. Table 12 uses the same ranking, but only shows manufacturing industries. The industries in these tables attract "too little" European FDI, given the expectations from our regression models. Because it is likely that FDI inflows will increase in such industries, they should be regarded as latent opportunities to attract FDI from the EU. Similarly, Tables 13 and 14 contain the top 20 industries where Ukraine has had no FDI investments from the EU so far, but where the model predicts that these inward investments should have been substantial. These industries represent opportunities for Ukraine to diversify the investments it receives from the EU.

Tables 15 and 16 highlight the opposite: industries that receive more investments from the EU than the PPML model predicted. These are anomalies, in the sense that Ukraine punches above its weight in attracting European FDI.

Table 12: Existing industries where Ukraine underperforms in FDI compared to benchmark

rank	**industry**	**Name**	**RCA**	**predicted RCA**
1	3714	Motor vehicle parts and accessories	11.3	119.3
22	2099	Food preparations, nec	9.1	53.6
25	3089	Plastics products, nec	2.5	11.7
32	3711	Motor vehicles and car bodies	6.7	24.3
34	3699	Electrical equipment and supplies, nec	1.0	24.8
38	2841	Soap and other detergents	14.7	216.3
41	3241	Cement, hydraulic	457.9	860.1
43	2899	Chemical preparations, nec	5.1	66.8
45	2086	Bottled and canned soft drinks	34.1	81.5
52	3585	Refrigeration and heating equipment	2.0	34.4
59	2082	Malt beverages	154.6	241.0
62	2819	Industrial inorganic chemicals, nec	9.0	142.9
69	2033	Canned fruits and specialties	2.6	18.9
71	2833	Medicinals and botanicals	98.7	547.2
74	3149	Footwear, except rubber, nec	0.5	7.7
78	3069	Fabricated rubber products, nec	2.0	24.4
79	3613	Switchgear and switchboard apparatus	19.1	33.8
83	2052	Cookies and crackers	22.3	46.4
94	2111	Cigarettes	89.6	193.8
99	2299	Textile goods, nec	3.6	7.5

Idem Table 11, now only considering manufacturing industries.

Table 13: New industries where Ukraine underperforms compared to benchmark

rank	**industry**	**Name**	**RCA**	**predicted RCA**
1	1629	Heavy construction, nec	0.0	57.2
2	8999	Services, nec	0.0	87.5
3	2834	Pharmaceutical preparations	0.0	226.1
4	3643	Current-carrying wiring devices	0.0	165.8
5	3679	Electronic components, nec	0.0	73.7
6	5531	Auto and home supply stores	0.0	38.8
7	6719	Holding companies, nec	0.0	79.5
8	2023	Dry, condensed, evaporated products	0.0	91.2
9	3011	Tires and inner tubes	0.0	56.4
10	1021	Copper ores	0.0	1361.7
11	8732	Commercial nonphysical research	0.0	31.7
12	2844	Toilet preparations	0.0	62.9
13	3621	Motors and generators	0.0	22.2
14	2879	Agricultural chemicals, nec	0.0	163.1
15	3674	Semiconductors and related devices	0.0	2442.9
16	6141	Personal credit institutions	0.0	2239.5
17	2869	Industrial organic chemicals, nec	0.0	176.2
18	6211	Security brokers and dealers	0.0	28.2
19	1382	Oil and gas exploration services	0.0	421.5
20	7382	Security systems services	0.0	34.1

Idem Table 11, now for industries in which Ukraine currently receives no FDI inflows from the EU's Single Market.

Table 14: New manufacturing industries where Ukraine underperforms compared to benchmark

rank	industry	Name	RCA	predicted RCA
3	2834	Pharmaceutical preparations	0.0	226.1
4	3643	Current-carrying wiring devices	0.0	165.8
5	3679	Electronic components, nec	0.0	73.7
8	2023	Dry, condensed, evaporated products	0.0	91.2
9	3011	Tires and inner tubes	0.0	56.4
12	2844	Toilet preparations	0.0	62.9
13	3621	Motors and generators	0.0	22.2
14	2879	Agricultural chemicals, nec	0.0	163.1
15	3674	Semiconductors and related devices	0.0	2442.9
17	2869	Industrial organic chemicals, nec	0.0	176.2
21	3357	Nonferrous wiredrawing and insulating	0.0	831.8
24	2024	Ice cream and frozen deserts	0.0	79.4
27	3841	Surgical and medical instruments	0.0	16.7
28	3634	Electric housewares and fans	0.0	31.2
31	2064	Candy and other confectionery products	0.0	51.9
32	3612	Transformers, except electric	0.0	3518.8
34	3499	Fabricated metal products, nec	0.0	7.2
35	2091	Canned and cured fish and seafoods	0.0	40.2
38	3317	Steel pipe and tubes	0.0	102.6
40	3534	Elevators and moving stairways	0.0	39.9

Idem Table 13, now only considering manufacturing industries.

Table 15: Industries where Ukraine overperforms compared to the FDI benchmark

rank	industry	Name	RCA	predicted RCA
1	3694	Engine electrical equipment	119.8	32.7
2	119	Cash grains, nec	32.9	7.7
3	5411	Grocery stores	9.7	7.6
4	2431	Millwork	26.6	1.7
5	2813	Industrial gases	335.9	128.6
6	6321	Accident and health insurance	6686.0	460.5
7	2021	Creamery butter	.	.
8	2311	Men's and boy's suits and coats	362.5	99.0
9	3562	Ball and roller bearings	17702.0	5865.3
10	4225	General warehousing and storage	17.1	7.7
11	1011	Iron ores	12576.0	4188.2
12	2062	Cane sugar refining	400000.0	0.0
13	7331	Direct mail advertising services	.	.
14	3999	Manufacturing industries, nec	11.7	5.6
15	3411	Metal cans	109.5	27.8
16	3261	Vitreous plumbing fixtures	75.3	17.4
17	211	Beef cattle feedlots	156.7	0.0
18	7375	Information retrieval services	14.7	3.9
19	3229	Pressed and blown glass, nec	32.8	22.7
20	2269	Finishing plants, nec	135.1	15.2

Idem Table 11, now for industries in which Ukraine attracts more FDI from the EU's Single Market than expected. These represent positive anomalies with respects to the PPML model's benchmark. Note: "." Reflects that the comparator countries had no FDI inflows from the EU's Single Market in these industries. The RCA's are therefore infinite or undefined.

Table 16: Manufacturing industries where Ukraine overperforms compared to benchmark

rank	industry	Name	RCA	predicted RCA
1	3694	Engine electrical equipment	119.8	32.7
4	2431	Millwork	26.6	1.7
5	2813	Industrial gases	335.9	128.6
7	2021	Creamery butter	.	.
8	2311	Men's and boy's suits and coats	362.5	99.0
9	3562	Ball and roller bearings	17702.0	5865.3
12	2062	Cane sugar refining	420000.0	0.0
14	3999	Manufacturing industries, nec	11.7	5.6
15	3411	Metal cans	109.5	27.8
16	3261	Vitreous plumbing fixtures	75.3	17.4
19	3229	Pressed and blown glass, nec	32.8	22.7
20	2269	Finishing plants, nec	135.1	15.2
21	2515	Mattresses and bedsprings	24.6	4.6
22	2076	Vegetable oil mills, nec	7489.0	1863.3
28	2631	Paperboard mills	196.5	127.7
31	2326	Men's and boy's work clothing	8.3	7.0

Idem Table 15, now only considering manufacturing industries.