Migration and post-conflict reconstruction: The effect of returning refugees on export performance in the former Yugoslavia*

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Abstract

During the early 1990s Germany offered temporary protection to 700,000 Yugoslavian refugees fleeing war. By 2000, many had been repatriated. We exploit this natural experiment to investigate the role of returning migrants in post-conflict reconstruction. Using confidential German administrative data we find that industries with 10% more returning refugees exhibit larger exports between the pre- and post-war periods by 1 to 1.6%. We use exogenous allocation rules for asylum seekers within Germany as an instrument to deal with endogeneity concerns. We show evidence pointing to productivity shifts as the main mechanism behind our results. Consistently, we find our results are driven by refugees in occupations more apt to transfer knowledge, technologies and best-practices.

1 Introduction

As of today, there are over 26 million refugees hosted in a foreign country. This figure is likely to keep increasing as sources of displacement such as ongoing conflict and climate change pose important challenges to stability around the globe. For the most part, refugees in host countries face hurdles to integrate due to negative perceptions of their effect on local labor markets, crime levels, or social cohesion. Despite the negative public sentiment, refugees – and migrants alike – represent important economic opportunities for both their host communities and home countries, as evidenced by a small but growing literature.[1] Yet, to the best of our knowledge, there is no rigorous study documenting the crucial role refugees can play in shaping *large-scale* economic outcomes (such as a country's industrial or export structure) in their home countries upon return. This paper fills this gap by documenting the long-run effect of returning migrants on industry-level exports driven by productivity shifts, using the case of Yugoslavian refugees during the 1990s.

We exploit a natural experiment and document a systematic relationship between refugees spending time and gaining work experience in a foreign country and the subsequent export performance at home of the same sectors in which they had worked while abroad upon their return. The context is the early 1990s, when about 700 thousand citizens of then Yugoslavia fled to Germany escaping war. Most Yugoslavian migrants in the first half of the 1990s were given a *Duldung* status (German for "toleration"), in effect a temporary protection status, or more specifically, a "suspended deportation" permit. After the Dayton peace agreement was signed in 1995, the protection status of temporary migrants was revoked, forcing them to leave the country. By 2000, the majority of these migrants had been repatriated back to their home country or to other territories of the dissolved Yugoslavia.

Using confidential administrative data from the German Institute for Employment Research (IAB), we identify returning Duldung holders as Yugoslavian workers who entered the German labor force (by industry) between 1991 and 1995 and had left it by the year 2000.[2] We link this information to standard disaggregated international trade data and employ a difference-in-differences methodology to estimate changes in export values from the former Yugoslavia to the rest of the world. We find that the industries that perform better in terms of exports in the years following the repatriation are the very same ones in which most refugees worked while in Germany.

In order to address concerns of endogeneity due to, for example, self-selection of workers into certain industries, we instrument for the actual number of returning workers per industry using a spatial dispersal policy that exogenously allocated asylum seekers across the different administrative regions of Germany upon arrival.

Our main finding is that industries with a one percent increase in return migration (as defined by our treatment) experienced an increase in exports to the rest of the world of 0.1 to 0.16 percent between the pre and post-war periods. Based on all the returning refugees in our sample, this represents up to 6 percent of all the export growth of former Yugoslavian nations between 1990 and 2005.

[1] See Becker and Ferrara (2019) for a comprehensive literature review on the economic consequences of forced displacement.

[2] In this sense, our "treatment" reflects the extent to which Yugoslavian refugees were exposed to German productive knowledge.

Our results are robust to an estimation in the form of an event-study, which shows that there are no existing previous trends between products treated at different levels of intensity, and that the treatment effect becomes larger with time. In addition, we complement our main difference-in-difference results by applying the synthetic control method (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015) to create a counterfactual for every Yugoslavian export industry in our sample. We find that real Yugoslavian industries outperform their synthetic counterparts, on average, with this pattern being particularly strong for industries associated to more intense treatment.

When exploring mechanisms driving our main findings we find robust evidence that points to industry-specific productivity shifts brought upon by returning refugees as the main driving force of export performance, while ruling out a number of alternative explanations.[3] In particular, our findings are robust to substituting actual exports with a constructed measure of export productivity based on Costinot et al. (2012); and, for the specific case of Bosnia (for which data is available), we find our results to explain higher levels of exports per worker, as well as employment and number of firms at the industry level.

Consistently with this mechanism, we then document that our results are particularly driven by certain types of workers and occupations which would be more apt to transfer knowledge, technologies and best practices across borders, and thus able to induce productivity improvements. For instance, our results are driven by workers with high educational attainment, in occupations intensive in analytical tasks (as opposed to manual ones), occupations that can be classified as professional and/or skill-intensive, and occupations that have managerial characteristics. We also find that our results are stronger when looking at workers who, while abroad, experienced faster wage growth, and were employed by the top paying firms within each industry.

Our findings contribute to the economic literature at large by documenting substantial industry-specific productivity increases, resulting in changes in the export industrial composition of a country as a whole, as a result of returning migrants who were exposed to foreign knowledge, technologies and best practices. To the best of our knowledge this is the first paper documenting such large-scale and country-level industrial productivity shifts induced by return migration in the context of a natural experiment.[4]

As such, our paper contributes to a number of strands of the literature. First, a burgeoning literature that looks at migrants as drivers of productivity shifts (e.g. Scoville, 1952a,b; Markusen and Trofimenko, 2009; Poole, 2013; Choudhury, 2016; Hornung, 2014; Hausmann and Neffke, 2019; Malchow-Møller et al., 2017; Bryan and Morten, 2019), as well as to the growing literature emphasizing the role of managerial skills as a crucial determinant of productivity (e.g., Bloom and Van Reenen, 2007; Bloom et al., 2013; Giorcelli, 2019), and of exports (Bloom et al., 2018).[5] In addition,

[3] We show our results are not driven by previous trends, scale effects, convergence in structural transformation processes, capital inflows, and lower bilateral transaction trade costs, among others.

[4] Previous studies have focused on the role that return migrants play (mostly through capital accumulation while abroad) in explaining small-scale entrepreneurship (e.g., McCormick and Wahba, 2001; Dustmann and Kirchkamp, 2002; Mesnard, 2004; Piracha and Vadean, 2010; Wahba and Zenou, 2012; Batista et al., 2017). Rapoport and Docquier (2006) provide a review of this literature. Yet, our paper differs from these other studies as we document *large-scale* effects on industry-level outcomes driven by productivity, as opposed to small-scale effects driven by capital accumulation.

[5] Our findings are consistent with anecdotal evidence of Yugoslavian refugees that we've collected and summarized in Online Appendix Section A.

we also contribute to the literature on migrants as drivers of international knowledge diffusion back to their home countries (e.g., Kerr, 2008; Agrawal et al., 2006, 2011; Breschi et al., 2017; Bahar and Rapoport, 2018; Miguélez, 2018; Miguelez and Noumedem Temgoua, 2019). Third, our results speak to the important link between migration and economic development, given the substantial role of migrants affecting structural transformation which in turn is a important driver of economic growth (e.g., Imbs and Wacziarg, 2003; Hausmann et al., 2006; Hidalgo et al., 2007; Koren and Tenreyro, 2007; Cadot et al., 2011). Finally, we also contribute to a growing number of studies that focus on consequences of forced displacement for the refugees' home countries (e.g., Waldinger, 2010, 2012; Acemoglu et al., 2011; Grosfeld et al., 2013; Akbulut-Yuksel and Yuksel, 2015; Bharadwaj et al., 2015; Pascali, 2016; Huber et al., 2018; Testa, 2018; Mayda et al., 2020).[6]

The rest of the paper is divided as follows. Section 2 provides a description of the historical context of the Yugoslavian refugee crisis. Section 3 details the data sources and the empirical strategy. Section 4 presents the main results and performs a series of robustness tests. Section 5 explores possible mechanisms driving our results, while Section 6 exploits heterogeneity effects based on the characteristics and occupations of the refugees. Section 7 concludes.[7]

2 Historical context

2.1 The refugee crisis and integration in Germany

In June 1991 the Socialist Federal Republic of Yugoslavia started to disintegrate following several armed conflicts and ethnic civil wars. Fighting began with the "Ten-Day War" in the summer of 1991 after Slovenia declared its independence. Soon thereafter the conflict spread to Croatia and later on, in 1992, to Bosnia and Herzegovina. It was only in December of 1995, upon the signing of the Dayton Peace Accord involving President Clinton, that the armed conflict officially ended.[8]

During the armed conflict, around 3.7 million people (roughly 16 percent of the Yugoslavian population) were displaced and fled from their homes, making this episode the largest migration flow in Europe since the end of the Second World War (Radovic, 2005). While many affected by the war became internally displaced, about 800 thousand people resettled outside of the boundaries of the former Yugoslavia, hoping to find refuge in foreign countries (Lederer, 1997).[9] Among these countries, Germany was one of the best suited to receive these refugees thanks to the the already significant Yugoslavian community residing there and to Germany's ability and willingness to provide protection to those fleeing the war.[10] The flow of refugees into Germany responded to the dynamics

[6] Our results also relate to the determinants of post-conflict reconstruction literature in general, using the case of former Yugoslavian countries (Black, 2001; Black and Gent, 2006).

[7] The paper is accompanied by an Online Appendix, which is referred to throughout the text.

[8] From 1998 to 1999 the region was affected by the Kosovo War. Our focus, however, is on the conflicts that occurred prior to that.

[9] See Angrist and Kugler (2003) for a summary of migration of Yugoslavian nationals to different European destinations (in the context of a study on the impact they had on local labor markets).

[10] Throughout the paper, we refer to all those people escaping the Yugoslavian civil war as "refugees". This is a much broader use than the legal definition of refugee, which implies having being recognized by a receiving country, on a case-by-case basis, as a refugee (i.e., having an asylum request approved) according to the definitions agreed upon and stated in the Geneva Convention on Refugees of 1951 and the Protocol Relating to the Status of Refugees of 1967 (among other country or region-specific definitions).

of the conflict: in the early stages of the war, involving mostly Croatians, about one hundred thousand of them arrived to Germany; later on, when the war spread to Bosnia, acts of systematic violence triggered massive outflows from those areas and Germany hosted some 350,000 Bosnian refugees. Simultaneously, Germany also received another 250,000 Yugoslavians mainly from Serbia and from Kosovo. Thus, overall during the first half of the 1990s, Germany received roughly 700,000 migrants from Yugoslavia, making it by far the largest recipient foreign country (see Lederer (1997) for a detailed account of these flows).

Most of Yugoslavian refugees that arrived to Germany were given a temporary protection status, known as *Duldung*, which can be translated to English as "toleration".[11] The temporary character of the *Duldung* status constituted a "suspended deportation" status. In other words, *Duldung* holders were allowed to remain in Germany until the permit expired, after which they were obliged to leave the country immediately. While the *Duldung* duration upon issuance was set to six months, the authorities had the option to renew it. De facto, the *Duldung* status was renewed for all holders as long as the war was still going on.

Another less popular option for Yugoslavians fleeing the war and arriving to Germany was to apply for asylum. According to Article 16(a) of the German Basic Law (*Grundgesetz*), an individual is eligible to seek asylum if he or she faces individual persecution and is able to prove so. If granted asylum, the individual enters a path towards permanent residency (Hailbronner, 2003). Asylum recognition rates, however, were very low for citizens from the former Yugoslavia.[12] This is because most of them could not prove to the German authorities they were facing individual persecution at home following the standards set by the German authorities at the time (Dimova, 2006). Importantly enough, however, asylum seekers whose request was denied also to received a *Duldung*, becausey the could not be sent back into war zones.

A large number of Yugoslavian refugees integrated into the German labor force after their arrival. For instance, in 1992 alone, the number of workers from (former) Yugoslavia rose by 15.3% to 375,000 (Deutscher-Bundestag, 1994). Overall, both *Duldung* holders and asylum seekers had relatively good access to the labor market.[13] But there was an important difference between the two statuses concerned with respect to their mobility. *Duldung* holders faced no geographical limitation. Asylum seekers, on the other hand, were subjected to mandatory residency (*Residenzpflicht*) within the region in which their application was initiated while it was processed.[14] The decision on which region would process the application was made by the authorities based on pre-established quotas.

[11] In the early 1990s, as a response to the legal difficulties faced by the hundred of thousands of refugees seeking protection –of which almost none were eligible for asylum– the German government applied this status on a large scale. In principle, from 1993 onwards there existed a legal status for civil war refugees, which granted temporary protection without a case-by-case assessment, but this status was not applied till 1999 because federal and state governments could not agree on distributing the costs. The *Duldung* status was also granted relatively quickly, making it possible for Germany to process large numbers of arrivals. Compared to other European countries this was a considerable humanitarian gesture on the side of the German government (Dimova, 2006; Lederer, 1997).

[12] Between 1992 and 1995 only 1 percent of Bosnian applicants were granted asylum (Lederer, 1997).

[13] Labor market access conditions for asylum seekers and *Duldung* holders changed a few times. Until 1991, immediate access to labor market was possible. Between 1991-1997, they could apply for a general work permit and with an additional waiting period of three months for asylum seekers. Modifications in the law in 1997 further restricted the access to the labor market. This changed again in 2001 when 1-year waiting time was introduced. For more details see Liedtke (2002).

[14] The rules on mobility while the application was being processed were defined by local governments. Some states restricted movement of the asylum seeker to a district, while others allowed free mobility within the state.

This limitation on geographic mobility for asylum seekers is an important part of our identification strategy, which we detail in Section 3.4.1.

Generally speaking, refugees found employment across diverse sectors and relied on different channels to secure their jobs. Some were able to utilize their network of friends and family relatives, some relied on local employment agencies and some found work by themselves (e.g., Walker, 2010; Ruben et al., 2009).

2.2 End of the war and deportation

The signature of the Dayton Peace Accord in December 1995 officially marked the end of the war that started in 1991. After that date, the German authorities had no reason to further renew the *Duldung* status of refugees and indeed enacted the imminent deportation of refugees back to the former Yugoslavia.[15] In fact, only one day after the signing of the Dayton Accord, Germany formally announced a repatriation plan through which *Duldung* refugees were gradually forced to leave the country (Dimova, 2006), often simultaneously rolling out assisted repatriation programs (Bosswick, 2000).[16]

Repatriation was planned in two main phases. The first phase targeted single adults and childless couples as well as people with family back in their home country. The second phase targeted the rest of the refugees. By the summer of 1996 letters requesting deportation were sent out, and by the end of 1996 people started getting deported. Repatriation and deportations continued until 2000, though most of them had happened by 1998. Figures by international organizations and independent academic research suggest that about 75 percent of Yugoslavians civil war refugees returned to their home country or to another former Yugoslavian nation, with an additional 15 percent settling in third countries and only about 10 percent remaining in Germany (UNHCR, 2005; Ruhl and Lederer, 2001; Lederer, 1997).[17]." With respect to Croatian refugees, Lederer (1997, p.310) explains: *"During the Croatian-Serbian War (1991 to 1993) numerous Croatians were also admitted to the Federal Republic of Germany. According to information from the Federal Ministry of the Interior of 9 October 1996, most of the original 100,000 Croatian refugees should have returned to their homeland within the framework of the repatriation process that began in 1994. However, the Federal Ministry of the Interior notes that there is no precise information on this from the federal states."*

Figure 1 plots the evolution of the population size of Yugoslavia (as a whole) over time, during the period of our study. It can be seen how, consistently with the historic accounts, overall population

[15] For the Croatians, however the deportations started following the signature of the cease-fire agreement known as the Vance Plan in January of 1992. By the end of 1994 almost all of the Croatian refugees had returned (Lederer, 1997).

[16] Voluntary returns were mainly realized as a part of the program of German Government through REAG (Program for Reintegration and Emigration for Claimants of Asylum in Germany) and GARP (Government Program of Assistance to Repatriation) which was implemented in cooperation with the International Organization for Migration (IOM) whose target was to support voluntary return. Both programs were completed in 2001 (Nenadic et al., 2005).

[17] These numbers are confirmed when looking at the return rates with respect to the different nationalities and ethnicities involved in the conflict. For example, when it comes to Bosnian refugees, Rühl and Lederer (2001, p.50) describe: "[t]he number of Bosnian war refugees fell from 345,000 to approximately 28,000 by December 2000, more than 260,000 of which went voluntarily to Bosnia-Herzegovina. About 51,000 have migrated on to other countries (to the USA, Canada and Australia). The proportion of forced repatriations is well below 2% (approximately 5,500 cases)

drops significantly after 1991, and following the end of the war (1995) it grows again. In 2005 the population of the former Yugoslavian countries combined was comparable to the population of Yugoslavia before the war, in 1990.

[Figure 1 about here.]

Figure 2 plots the "mirror image": the inflow of around 700,000 refugees from the former Yugoslavia who arrived to Germany in the first half of the 1990s. In 1980 there were already about 600,000 Yugoslavians residing in Germany. This stock remained steady until the late 1980s when the net inflow of Yugoslavian migrants started to grow at a rate of 25,000 per year, including until the year 1990. This rate skyrocketed to 168,000, 250,000 and 165,000 during 1991, 1992 and 1993, respectively. The sharp increase in the net inflow of migrants was fueled by refugees escaping war. We also see a sharp increase in asylum requests from Yugoslavian citizens during the same years.

[Figure 2 about here.]

Consistently with the accounts, the number of Yugoslavians in Germany sharply declines starting in 1996, after the Dayton treaty was signed. By 2000 close to 350 thousand Yugoslavians had left the country. While some of them left to a third country, it has been estimated that the majority of them returned to countries of the (by then) former Yugoslavia (UNHCR, 2005; Ruhl and Lederer, 2001; Lederer, 1997), consistently with Figure 1.

In the German labor force we see patterns consistent with the historical narrative described so far: both the inflow of Yugoslavian workers into the tradable sector labor force between the years 1991 and 1995 and their outflow by year 2000 is highly unusual as compared to foreign workers from other nationalities, as Figure 4 shows. The figure graphs the yearly share of Yugoslavian workers entering and exiting the labor force of Germany's tradable sector. The share is always computed using the total number of all foreign workers entering and exiting the labor force in those same years at the denominator. It becomes clear from looking at the figure that Yugoslavians entered the labor force in much higher proportion during the first half of the 1990s, as compared to the same proportion in years before 1990 and after 2000. We also see that Yugoslavian workers exited the German labor force in higher proportion during the later half of the 1990s, consistently with the historical events.

[Figure 3 about here.]

3 Data and empirical strategy

3.1 Data sources

We link a number of datasets together for our study. First, we use data on exports for the period 1984-2014 which comes from bilateral trade data compiled by Feenstra et al. (2005) with extensions and corrections suggested by Hausmann et al. (2014) (the original source of the trade data is UN Comtrade). In most cases our dependent variable is exports by product from Yugoslavia to the rest

of the world, excluding to Germany. We exclude Germany as a first attempt to reduce the possibility that our results are driven by lower transaction costs caused by migrant networks between the former Yugoslavian countries and Germany (e.g., Rauch and Trindade, 2002; Parsons and Vézina, 2018).

Products are defined using the 4-digit Standard Industry Trade Classification (SITC) revision 2, and include 786 different varieties. This product classification provides a disaggregation level that enables a meaningful discussion about export diversification patterns. Some examples of products in this level of disaggregation are, for example, "Knitted/Crocheted Fabrics Elastic or Rubberized" (SITC 6553), or "Electrical Measuring, Checking, Analyzing Instruments" (SITC 8748). Following Hausmann et al. (2014), we exclude countries below 1 million citizens and total trade below USD $1 billion in 2010. Other variables created using trade data are explained as they are introduced into the analysis.

The data on migrant workers in Germany are based on records from the German social security system and comprise all persons employed subject to social security contributions, with the exception of self-employed and civil servants.[18] The records indicate the industry where the workers are employed. Our sample is restricted to 40% random draws of foreign nationals observed on June 30 of each year from 1975 to 2014 augmented by the employment history of each individual for our sampling period. This amounts to about 2.4 million workers per year on average, which is a large enough amount for the random draws to form a representative sample.[19] Moreover, since we can observe the full employment history, we can determine whether an individual was employed before or after any given year in Germany, which we exploit to construct our treatment. Beyond individual information such as age, nationality, and educational attainment, the data include detailed occupational codes categorized in more than 300 different occupations.[20]

In order to construct an instrument to deal with endogeneity issues, we use inflow quotas mandated by the government that define the regional distribution of asylum seekers (*Königsteiner Schlüssel*). These quotas are determined yearly by the Joint Science Conference (*Gemeinsame Wissenschaftskonferenz, GWK*). The yearly data between 1990 and 2016 have been sent to us by the GWK upon request.

With these datasets we are able to match the exports of Yugoslavia to the rest of the world with the number of Yugoslavian workers in Germany working in the same product category.[21]

[18]These records have been assembled by the Institute of Employment Research (IAB) into the Employment History (BeH) data file (IAB, 2015). The data or variants of it have been widely used to study a variety of labor market aspects (e.g., Card et al., 2013; Dustmann and Glitz, 2015; Dustmann et al., 2017).

[19]For privacy issues, the sample utilized in this paper is an anonymized version of the original database. In order to comply with data privacy rules, sensitive values –industry-period observations with less than 20 workers– have been replaced with different moments of the distribution of the number of migrant workers in the same industry and year. The number of cells affected depends of course on the level of disaggregation of worker characteristics such as education, occupation, skill etc. More details on this procedure can be provided upon request. The results presented herein, however, are robust to using the non-anonymized version instead.

[20]See more details on this dataset in Online Appendix Section B.

[21]Using our employment sample we compute the number of workers in Germany by nationality and year for all SITC 4-digit product categories. We use the nationality of the worker based on the passport recorded at his or her first appearance in the database. To compute the number of workers by product we rely on the concordance tables produced by the United Nations Statistical Office and the work by Dauth et al. (2014) that matches German 3-digit WZ industry codes to 4-digit SITC (rev. 2) products. When match is one-to-many, we create our own concordance following the same procedure as Cuñat and Melitz (2012) described in their footnote 24. In particular, we use the distribution of German exports in 1995 as a proxy for the distribution of employment across different 4-digit SITC products that correspond to a single 3-digit WZ German industry. Further details on the employment sample, variable

3.2 Main outcome and treatment variables

Our main unit of analysis which we use as our dependent variable in our baseline specification is the combined exports by product of Yugoslavia to the rest of the world, excluding to Germany (to avoid results being driven by lower transactions costs, as explained above). To construct this variable we combine per-product exports of Yugoslavia as a nation until 1991, with exports by product of all countries combined that formed Yugoslavia post 1992: Bosnia and Herzegovina, Croatia, FYR of Macedonia, Montenegro, Serbia and Slovenia (excluding trade within these countries).[22] We focus on all former Yugoslavian countries as one following the disintegration because the German data used to construct our treatment do not allow us to distinguish which is the region of origin of the refugees within Yugoslavia (e.g., we only see that they entered the labor force with a Yugoslavian passport).

The main independent variable –the treatment– is the number of Yugoslavian refugees by (tradable) sector who (i) joined the German labor force between 1991 and 1995,[23] (ii) had not been recorded in our data in 1990 or before, and (iii) had not been recorded in our data in 2000 or after.[24] Applying this filter allows us to proxy for returning refugees with a high degree of certainty, consistently with the historical accounts described above.[25]

As explained above, a limitation of our data is that we cannot distinguish with full certainty whether these workers with Yugoslavian passports that left the labor force indeed returned back to the former Yugoslavia. Thus, in our calculation of return migration we are including workers who, for instance, stayed in Germany working in the informal sector or went to a third country. Yet, all these possibilities work against us in our estimation, implying that our estimates are to some extent understating the true effect of return migration. However, plenty of historic evidence suggest that indeed those who were repatriated went back and worked in related industries. For instance, Ruben et al. (2009) note that those who worked during their time in Germany were more likely to be employed upon return to the former Yugoslavia, with many finding jobs in industries in which they had worked before the war. There is anecdotal evidence, too, suggesting that after returning to their home countries refugees subsequently worked (or founded companies) in the very same sector they had worked at in Germany (or other countries such as Sweden or Austria). In Online Appendix Section A we summarize some of the evidence we've collected on this. As these stories show, refugees benefited from their experiences in Germany in many ways, such as applying the acquired knowledge

descriptions and auxiliary data are provided in Online Appendix Section B.

[22] Very few people left Slovenia while almost none left the FYR of Macedonia as both countries obtained their independence with limited or no armed conflict. While Slovenia was the republic with highest GDP per capita and a much more diversified export basket than the rest of the countries to begin with, Macedonia was one of the poorest republics of the former Yugoslavia with little exports. Our results are robust to excluding both Slovenia and Macedonia from the exports data (see Online Appendix Section D.3).

[23] About 10% of the Yugoslavian workers we see entering the labor force between 1991 and 1995 were 18 years or younger at the year of entry. 75% of them, in contrast, were 20 or older and 50% were 25 or older. This rules out the possibility that the entry of Yugoslavian into the labor force is mostly driven by locals with Yugoslavian passports joining the labor force at a young age, rather than by refugees arriving to Germany.

[24] Finding no entry for a person in our data implies that this person was not employed in any job, industry, or occupation subject to social security contributions on June 30 of any given year.

[25] Our data also show that about half of these Yugoslavian workers who arrived between 1991 and 1995 are still active in the German labor force by 2014. Presumably, these "stayers" were not *Duldung* holders (and therefore, were not subject to deportation). Some of them could have been *Duldung* holders but were allowed to stay for humanitarian reasons.

and skills about different production methods.

Figure 4 describes the treatment variable. It plots the number of Yugoslavian workers that entered the German workforce between the years 1991 and 1995 (horizontal axis), and the number of those workers who remain in the labor force beyond year 2000 (vertical axis), by 4-digit SITC code. All observations are below the 45 degree line, simply because the number of migrants who stay in each industry beyond the year 2000 is a subset of all those who arrived between 1991 and 1995. Thus, the treatment is the difference between each one of the observations and the 45 degree line. As can be seen in the graph, there is variation in the treatment across industries. Some of the codes that stand out as having a large amount of workers returnees are 8219 (furniture parts), 6911 (iron and steel structures), 5989 (chemical products), and 2482 (worked wood of coniferous). Based on our sample (which is limited to wage earners in the tradable sector), it is noticeable that "rate of return" as measured through our filter is substantial (about 30 percent), but not as high than what the historical acccounts suggest as documented in official reports from international organizations (e.g., UNHCR, 2005).[26] Though, the fact that some Yugoslavians stayed beyond 2000 for whatever reason is not a threat to our identification strategy, as long as these cases were not more or less frequent in some industries than in others. We expand on this in Section 3.4.2.

[Figure 4 about here.]

With the treatment defined, before we turn to the econometrics, we report whether products associated with a larger treatment experienced better export performance in the former Yugoslavian countries upon their return. Using only raw data, Figure 5 visualizes the total value of exports of products linked to different levels of treatment (i.e., quartiles), year after year. The figure shows that up until 1995 (the year where our "treatment" begins) products in the four different quartiles had somewhat parallel trends. However, after 1995, the third and fourth quartiles in terms of treatment intensity diverge quite significantly from the first two quartiles. This visualization not only provides some descriptive evidence of the results holding with raw data, but also shows that the parallel trends assumption required for the difference-in-differences methodology is a reasonable one. In any event, we address pre-trend issues more thoroughly in the next section.

[Figure 5 about here.]

3.3 Summary Statistics

Table 1 presents the summary statistics. Our sample includes 786 products, and since we use two points in time for the differences-in-differences estimation, the initial empirical analysis will use up to 1572 observations. The table presents summary statistics for the main variables in the regression. The first two lines of the table present data for the average export value from former Yugoslavian countries to the rest of the world in years 1990 and 2005, all in million US dollars (note that we don't adjust these values for inflation, which is accounted for by our year fixed-effect). These two

[26] However, when focusing on those migrants that we can identify in our data as Bosnians, even though they are a smaller share, the drop-out rate of the labor force is more than 50 percent, closer to the global official figures.

points in time are the ones used in the main specification, which correspond to years before and after the war. However, we also present results for a multi-period analysis as well that uses export data for all the years in between.

[Table 1 about here.]

Table 1 also summarizes the treatment. The third row in the Table presents statistics for the number of sampled workers with Yugoslavian passport that joined the German labor force at some point between 1991 and 1995. The average industry had 74 Yugoslavian workers that, arguably, arrived to Germany because of the war and joined the labor force. The next row is a subset of that group, and corresponds to our main treatment variable: the number of workers with Yugoslavian passport which had joined the German labor force sometime between 1991 and 1995 and had dropped from it by the year 2000. The value for this variable, averaged across all products, is 21.6. Our treatment exploits variation across industries, which we see in the table varies from 0 to 778.[27] All in all, our treatment is based on roughly 17,000 Yugoslavian workers across all industries, representative of the actual distribution.[28]

Note that as mentioned above, our sample of Yugoslavians employed in the tradable industry shows that the rate of return was roughly 30 percent, substantially lower than the anecdotical 75 percent figure, which applies to the Yugoslavian refugee population as a whole (UNHCR, 2005; Ruhl and Lederer, 2001; Lederer, 1997). This discrepancy, however, poses no problem for our identification strategy as long as the rate of return is not biased towards certain industries, which we discussed above in Section 3.4.2.

Also note that despite presenting the summary statistics in nominal values, unless otherwise stated, all right hand side variables are rescaled using the inverse hyperbolic sine for estimation purposes.

3.4 Empirical strategy

Our objective is to study changes in product-level Yugoslavian exports to the rest of the world given different levels of treatment. We do this through a difference-in-differences estimation.

Our baseline results are estimated through the following difference-in-differences specification:

$$exports_{p,t} = \beta^{DID} treat_p \times after_t + \eta_p + \alpha_t + \varepsilon_{p,t} \quad (1)$$

where subscripts p and t represent product and year, respectively. The left-hand side variable ($exports_{p,t}$) measures the value of exports from the former Yugoslavia to the rest of the world excluding Germany for product p during year t.

[27] Non-integer number of workers in an industry is a result of the use of weights based on industry code concordances during the data construction stage. For more information see Online Appendix Section B.

[28] 210,000 Yugoslavian workers appear the first time in our data between 1991 and 1995. If the total flow was of 700 thousand people, it is reasonable that somewhere between a one-quarter and one-half of them were of working age. Our sample is, of course, smaller than the total population, thus the 210,000 figure seems reasonable. Of the 210,000 in our sample, 35% (or 75,000 workers) had exited the sample before the year 2000. Of those roughly 75,000, only 22% (around 17,000 workers) had a job in tradable industries during the 1990s.

The variable of interest $treat_p$ is the treatment as explained above, which corresponds to the number of likely returning refugees for product p, according to the definition detailed earlier. Given the fat-tailed distribution of this variable, we rescale it using the inverse hyperbolic sine, which behaves similarly to a log-transformation but it has the benefit of being defined at zero. The interpretation of regression estimators in the form of the inverse hyperbolic sine is similar to the interpretation of a log-transformed variable (see MacKinnon and Magee, 1990).[29]

We estimate this regression using two periods: "before", which corresponds to 1990, just before the war started, and "after", which corresponds to 2005, five years after most Yugoslavian refugees had returned.[30] Thus, $after_t$ is a dummy variable which equals 1 for the observations corresponding to the second period.

As for the other terms: η_p represents product fixed effects while α_t represents year fixed effects. The two fixed effects are perfectly multi collinear with the terms $treat_p$ and $after_t$, and so there is no need to add the interacted terms separately. $\varepsilon_{p,t}$ represents the error term. Our estimations cluster standard errors at the product level, the level at which the treatment varies (Besley and Burgess, 2004; Bertrand et al., 2004).

Given the fact that the left hand side is calculated in US dollars, we are required to use a monotonic transformation to deal with the fat-tailed distribution. All of our results are presented using three different transformations: $log(exports_{p,t})$, $log(exports_{p,t}+1)$ and $asinh(exports_{p,t})$. The first one is undefined for values where $exports_{p,t} = 0$, and therefore, when using $log(exports_{p,t})$ as the dependent variable the sample size is reduced. The two other transformations deal with the occasions where $exports_{p,t} = 0$ by either adding USD \$1 before the transformation or by computing instead the inverse hyperbolic sine ($asinh$), respectively.[31] Given these monotonic log-type transformations, β^{DID} represents the elasticity of exports to returnee workers. That is, industries with a 1 percent larger pool of returnee workers have larger export value by β_{DID} percent larger between the "before" and "after" periods compared to industries with no returnee workers. Bear in mind that since this is a difference-in-difference setting, our results reflect relative differences in levels across industries based on their exposure to the treatment.

Our identification relies on the exogeneity of arrival and exit of refugees into and out of the German labor force with regards to industry-level export trends back in Yugoslavia. There are two main endogeneity concerns. First, the possibility that upon arrival, refugees self-selected into particular tradable sectors after anticipating their future post-war growth potential in Yugoslavia. Second, the possibility that the exit of refugees from the German labor force by year 2000 –even if it was enforced by across-the-board repatriation efforts by the German authorities– happened more or less frequently in particular industries in a way that is correlated with export dynamics in Yugoslavia. We address each of these possible endogeneity concerns below.

[29] The inverse hyperbolic sine ($asinh$) is defined as $log(y_i + \sqrt{(y_i^2 + 1)})$. Except for small values of y, $asinh(y_i) = log(2) + log(y_i)$.

[30] In fact, we use average exports per product between 1988 and 1990 for the "before" period, and the average between 2005 and 2007 for the "after" period, given the high volatility of yearly export data. Our results, however, are robust to using only data for the actual years for which the "before" and "after" periods are defined: 1990 and 2005.

[31] Since exports are aggregated across all destinations, the number of "zeroes" in the data is not as large as when using bilateral trade data. We explore this in detail in Online Appendix Section C.

3.4.1 Self-selection into industries upon arrival

In order to deal with the possibility that migrants self-selected into particular industries in a way that correlates with future Yugoslavian exports, we construct an instrumental variable that estimates the share of asylum seekers working in each industry by exploiting a spatial dispersal policy. While asylum requests were being processed, asylum seekers were sent to different parts of the country following the Königstein State Convention (*Königsteiner Staatsabkommen*) which was signed in 1949 by all German federal states and defined cost-sharing rules between states in jointly financed projects. The dispersal of asylum seekers is regulated at the federal level by the Asylum Procedure Act (*Asylverfahrensgesetz*), where each state is allocated a certain number of asylum seekers according to its "Königstein" quota (*Königsteiner Schlüssel*). The quota is based on the weighted sum of population (1/3) and tax revenues (2/3), and is re-calculated annually. Our identification strategy is based upon the premise that this allocation was exogenous to the Yugoslavian asylum seekers entering the country, and furthermore, to the future dynamics of Yugoslavian exports.

In practice, upon the arrival of an asylum seeker into the German territory, he or she is absorbed by a reception center in the state of arrival *if* there is any remaining capacity to receive more people, according to the quota described above; alternatively, the person is allocated to the reception center in a different state with the most vacancies according to the quota.[32] The residence obligation ends as soon as asylum is granted. The average duration of the application procedure was between six months and two years.[33]

An illustration of the quota system can be seen in Figure 6, which plots the relative size of those quotas for each of the sixteen German states in year 1995. For example, Nordrhein-Westfalen is the state that should have received the largest numbers of asylum seekers in 1995, followed by Baden-Württemberg and Bayern, while states such as Bremen or Saarland received a very small share.

[Figure 6 about here.]

To construct the instrument we combine two pieces of data: (1) the yearly asylum quotas for German states averaged between 1991 to 1995,[34] and (2) the relative size in terms of employment for each product and state in 1990 (using german workers only), before the arrival of the refugees.[35] The resulting variable can be used to estimate the share of Yugoslavian asylum seekers working in each industry nation-wide. The following equation reflects the calculation:

[32] If more than one reception center fits these criteria, the geographically nearest one to the entrance location of the asylum seeker is appointed.

[33] Concerns might remain given that the geographic allocation of refugees is exogenous conditional on the reception center at the port of arrival being at full capacity. However, our results are robust when using an instrument that excludes the most common ports of arrivals in the calculation.

[34] In fact, since we don't have data pre-1995 for states of eastern Germany, we set those at zero for years 1991 to 1994. However, this lack of variation is not critical, turns out. According to the employment data, in 1995 there were over 367 thousand Yugoslavians employed in western German states across all industries, as compared to only 1400 in eastern Germany, or just 0.38%. Thus, that lack of variation should not affect the relevance of our instrument.

[35] We are aware of the critique by Jaeger et al. (2018) regarding using past spatial distributions of migrants to instrument for current distribution, though in our paper it lacks relevance given that our dependent variable does not reflect economic activity in the same location of the migrants' destination but rather in their country of origin.

$$\underbrace{TreatIV_p}_{\substack{\text{Expected share of asylum} \\ \text{seekers workers in } p}} = \sum_s \underbrace{quota_{s,t}}_{\substack{\text{Quota per state } s, \\ \text{avg. 1991-95}}} \times \underbrace{shareindustry_{s,p,1990}}_{\substack{\text{Germans emp. share} \\ \text{of } p \text{ within } s \text{ in 1990}}}$$

The instrumental variable is a feasible one under two conditions. First, if it correlates with the treatment; and second, if the exclusion restriction holds. In terms of the first condition, we see a strong correlation between the treatment and the instrumental variable. Figure 7 shows plots $TreatIV_p$ in the horizontal axis against the treatment variable. Each observation in the figure is a product, symbolized by its 4-digit SITC code. The variables have been rescaled using the inverse hyperbolic sine. It can be seen in the figure that the number of Yugoslavian workers who left the labor force between 1995 and 2000 in each industry strongly correlates with expected share of asylum seekers in each industry as predicted through the spatial dispersal policy. Table 2 also presents the first stage regression following the specification (e.g., the left hand side is the interaction $treat_p \times after_t$). Column 1 presents results for the sample where $log(exports_{p,t})$ is defined (i.e., $exports_{p,t} > 0$) while Column 2 is for all the sample (i.e., where $log(exports_{p,t} + 1)$ and $asinh(exports_{p,t})$ are defined). The table confirms that the instrument is a relevant one, given that the instrumental variable is able to explain a large variation of the endogenous variable.

[Figure 7 about here.]

[Table 2 about here.]

There are two main reasons for which this strong correlation between the instrument and the endogenous variable is not surprising. First, the geographic allocation of asylum seekers is relevant for all refugees who request for asylum, even if the asylum request turns out not to be approved. That is, all refugees who eventually got a *Duldung* status but who originally requested for asylum, had to comply with this exogenous geographic allocation while their asylum status was being reviewed by the authorities. Second, the exogenous allocation of the share of Yugoslavians who actually requested asylum might as well be explanatory of the location choice of those who received *Duldung* even if they did not request for asylum to begin with, due to pull factors induced by migrant networks.

Our main assumption regarding the second condition –the exclusion restriction– is that both the quota of asylum seekers per state and year (defined by the German federal authorities), as well as the relative size of industries in Germany in 1990 are not correlated with with future product-specific export trends of former Yugoslavian countries to the rest of the world other than through the migrants themselves. We have no reason to think that this assumption could be violated.[36]

[36] One possible violation for this exclusion restriction is convergence in terms of structural transformation: Yugoslavia in the 2000s moved towards industries that were large in Germany in 1990. In robustness tests detailed below (and expanded upon in Online Appendix Section F.2) we rule out this possibility by including the relevant controls in the baseline specification.

3.4.2 Self-selection out of industries upon exit

The other remaining concern is that the *exit* of Yugoslavian *Duldung* holders from the German labor force was endogenous. For example, if workers left the labor force more massively in some industries than in others, in a way that correlates with their future export potential in Yugoslavia, then this could invalidate our identification strategy.

This was not the case, as shown in Figure 8. The figure compares the proportion of Yugoslavians who arrived between 1991 and 1995 working in each 4-digit SITC product on the vertical axis, against the proportion of Yugoslavian who had returned by 2000 (based on the definition of the treatment) in each product on the horizontal axis. The dashed line represents the 45 degree line. If exit from the labor force by Yugoslavians was completely random, we would see a perfect alignment of those dots along the 45 degree line: the share of workers arriving into each industry must be the same as the share of workers leaving that industry. Barring some exceptions, the graph does approximate this scenario. In fact, the correlation between both shares is close to 0.9.

[Figure 8 about here.]

Given that few observations seem to be outliers, we also compute the distance between each value in the plot and the 45 degree line and correlate it with the log-growth rate of Yugoslavian exports by industry between 1990 and 2005. We find small, negative and statistically insignificant correlation coefficients across the board (-0.0295 when computing the growth using logs, and -0.0133 when computing growth using the inverse hyperbolic sine).

Finally, as a way to relieve possible concerns due to endogeneity with respect to exit, it is important to note that our results are robust to using the number of Yugoslavian refugees workers per industry in 1995, without the exit component, which directly addresses this concern (see Online Appendix Table D1).

4 Main Results

4.1 Baseline Results

Results for specification (1) are presented in Table 3. The first three columns report results using an OLS estimation, while the last three columns report results using a 2SLS estimation, making use of the instrumental variable described in Section 3.4. The table reports results using $log(exports_{p,t})$, $log(exports_{p,t}+1)$ and $asinh(exports_{p,t})$ as dependent variables. Since the regressor $treat_p$ is rescaled using the inverse hyperbolic sine transformation –which behaves similarly to a log transformation–we interpret β^{DID} as an elasticity.[37]

[37]The continuous character of our treatment implies, arguably, that our estimator can be characterized as a fuzzy differences-in-differences one (see De Chaisemartin and D'Haultfoeuille, 2018). In our setting, the "control" group is stable over time (e.g., there are no control group "switchers"), which implies our estimation only relies on the common trends assumption. In other words, our setting allows us not to require the "stable treatment over time", nor the "homogenous treatment effect between groups" assumptions (assumptions 5 and 6 in De Chaisemartin and D'Haultfoeuille (2018)). While relaxing assumption 5 in our setting is straightforward, doing the same with assumption 6 might not be. Thus, as a robustness test, we compute the Wald DID estimator following De Chaisemartin and D'Haultfoeuille (2018), defining the treated units as those above the 25th percentile in terms of treatment intensity.

[Table 3 about here.]

In the first three columns, we find all estimates to be positive and statistically different from zero for all different monotonic transformations of the dependent variable. The standard errors are clustered at the product level, which is the level of disaggregation of the treatment.

Column 1 of Table 3 presents the estimates when using the natural logarithmic transformation for the dependent variable. The point estimate in the first column is about two thirds the size of those in the other two columns. This is not surprising as the first column excludes zeros and therefore excludes instances in which products are more likely to grow faster if they have a non-zero value in the second period. Yet, this difference says something more: the fact that the point estimates in columns 2 and 3 are positive and significant –which include instances where a product was inexistent in the export basket of Yugoslavia by 1995–, and are larger than the point estimate in column 1, implies that the effect of return migration on comparative advantage is valid at the extensive margin (e.g., opening a new line of exports) as well as at the intensive margin (e.g., growth of already existing export lines), along the lines of Bahar and Rapoport (2018). In either case, the results show that the elasticity of exports to return workers ranges from 0.09 to 0.14, depending on the transformation of the left hand side variable used (and, thus, on whether zeros are included or not).

Columns 4, 5 and 6 present the analogous 2SLS estimates. For those columns we also report the F statistics which measure the strength of the first stage; they are all above 14, thus we can reject the possibility of weak instrumentation. The elasticities estimated through 2SLS are positive, statistically significant and quite similar to the OLS results with point estimates that are only slightly larger. Given the standard errors, however we cannot reject the hypothesis that the OLS and the 2SLS estimates are equal. Given the setting of the natural experiment, and the use of an instrumental variable, we interpret these results as causal. Thus, based on the 2SLS results, we find that Yugoslavian industries that received 10 percent more return migrants from Germany (that worked in those same industries), exhibited higher exports by 1 to 1.6 percent during the period of the study. Back-of-the-envelope calculations based on our sample size imply that returning refugees explain up to 6 percent of all Yugoslavian export growth between 1990 to 2005.[38]

In the presence of self-selection of workers we would expect results to decrease in magnitude once we instrument. What may then explain why the 2SLS estimates are in fact slightly larger than the OLS ones? One possible explanation is that the 2SLS estimation uses variation in the treatment that is disproportionately coming from refugees allocated to areas in Western Germany (and specifically western and southern German states) where the most productive firms (and workers) are located.

We find our results reassuring: the Wald DID point estimates are between 0.15 to 0.28, depending on the monotonic transformation used, and are all statistically significant at the 10% level. The point estimates are slightly larger than the OLS ones reported in Table 3, but they all fall within the statistical margin of error of the estimators. We thank Clement De Chaisemartin for his guidance on this exercise.

[38] According to our estimates, 10% of returning refugees for the average industry can explain larger exports by 1.6%. For the average industry, these numbers are 2 people and roughly USD $200,000 (based on 1990's exports), respectively. Given that all of our sample corresponds to 17 thousand returning refugees, that would represent an increase in exports of nearly USD $2 billion. This is about 6 percent of the difference in total exports between 1990 and 2005 which corresponds to USD $34 billions.

4.2 Event study estimation

Can our results be explained by a previous trend in exports? Given the availability of exports data across several years, we turn to estimate the effect of return migration in a event study setting. To account for the typical volatility of exports on a yearly basis, we perform the estimation using 5-year averages for the dependent variable and estimate β^{DID} for 6 different periods, from 1985-1989 to 2010-2014. To do this, we simply re-estimate specification (1), this time substituting the dummy $after_t$ for several dummies, each one signaling a time period, along the lines of Autor et al. (2003). We define the period 1990-1994 as the base period, and therefore the other point estimates are relative to it.

The estimation (using 2SLS) are summarized in Figure 9, which shows in the upper panel the evolution of the expected value of exports (across our three different measures) by periods for two groups of products: those for which the value of $treat_p$ equals 0, and the second group is those for which $treat_p$ equals one standard deviation of the treatment. The figures in the lower panel show the difference between the two groups, and it can be seen how the effect becomes positive and statistically significant starting in the period where the refugees start returning, 1995 to 1999. Note that, based on the standard errors (as measured by the whiskers representing 95 percent confidence intervals), we cannot reject the hypothesis that the trends for both groups in periods before 1995 are statistically the same.

[Figure 9 about here.]

These findings suggests an important result: the marginal effect of return migration on the emergence of new exports becomes stronger over time. The figure also reveals that the average industry experiences a drop in export performance during the war –as compared to the base period. Treated industries recover and reach back their 1990-1994 level in period 2000-2004 (or even earlier, when using the log transformation), while non-treated ones recover later on. In that sense, part of what our effect is capturing in the first few post-conflict years is that treated industries, on average, shrunk less than non-treated ones.[39]

4.3 Falsification test using the synthetic control method

Our main strategy compares different product lines based on the intensity of the treatment. We complement those results with implementing the synthetic control method (e.g., Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015) in the context of our empirical strategy. In other words, we create a synthetic product for every single Yugoslavian product that mimics export dynamics up until 1995 (the year our treatment starts "kicking in"), based on over one hundred other countries. We use five main predictors to construct each synthetic product, using data for the period 1986-1995: export value of the product itself (only for years 1990, 1993 and 1995), its export share and the export share of its corresponding 1-digit SITC, as well as GDP per capita, and population size.

[39] Online Appendix Section D.4 exploits the timing of returns of refugees in an event study setting, and finds that industries start outperforming earlier when we identify that our treatment "kicks in" earlier.

We then apply the `synth` algorithm that computes a synthetic control for each product based on a weighted combination of countries other than Yugoslavia (see Abadie et al., 2011).[40]

Figure 10 visualizes the main results of this exercise, ploting the difference between the export value of the real and synthetitc products. The top panel shows the evolution of each one of these differences: up until 1995 there is almost no difference between the real and synthetic products, but after 1995 we see all types of dynamics. The bottom panel groups products in two, averaging the difference between their real and synthetic export values: low treatment and high treatment, which corresponds to the first and fourth quartile of the distribution of $treat_p$ as defined above (analogous to Figure 5). The plot shows how, on average, real Yugoslavian products outperform the synthetic ones, particularly among the high-treatment products. Results using regression analysis are consistent and presented in Online Appendix E.

[Figure 10 about here.]

5 What drives our results? Exploring mechanisms

There are a number of possible candidate explanations for our results, which we explore in this section. We also go over a number of alternative explanations which we are able to rule out through our analysis. The results in this section are consistent with those in Section 6, where we exploit the characteristics of the refugees driving our results, and find that they are precisely the ones that are more apt to transfer knowledge, technology, best practices, etc. that tend to result in productivity-shifts at the industry level.

5.1 Industry-level productivity shifts

Our analysis consistently suggests that productivity shifts caused by the inflows of returning workers –having been exposed to better practices and technologies– are one of the main drivers of our results. This is supported by a number of tests which we expand upon below.

Industry-level productivity parameter

First, we note that our results are consistent when using industry-level productivity measures. In practice, we reestimate our specification using as the dependent variable a product-level productivity or comparative advantage parameter for Yugoslavia ($\Phi_{p,t}$), estimated following Costinot et al. (2012) and Leromain and Orefice (2014).[41] Analogous to our baseline results, we use the same two different monotonic transformations for $\Phi_{p,t}$ (we skip the $log(\Phi_{p,t}+1)$ transformation since there are no zeros). Results are presented in Table 4.

[40] The algorithm fails to converge for 93 of the 786 products in the sample, and thus they are not included in this calculation.

[41] According to Costinot et al. (2012), $\Phi_{p,t} = e^{(\phi_{p,t}/6.53)}$, where the figure 6.53 is their estimation of the elasticity of (adjusted) bilateral exports with respect to observed productivity, and $\phi_{p,t}$ is estimated as the country-product specific productivity parameters for Yugoslavia using the following specification and using the complete matrix of bilateral trade (where Yugoslavia is one of the c countries in the dataset):

$$asinh(exp_{c,c',p,t}) = \phi_{c,p,t} + \Omega_{c',p,t} + \Psi_{c,c',p} + \varepsilon_{c,c',p,t}$$

[Table 4 about here.]

Exports per worker and industry size

We were able to collect and digitize a number of sector-level indicators for the Republic of Bosnia and Herzegovina (the country with the largest number of refugees hosted by Germany) before and after the war, which when applied to our framework, present further evidence of productivity shifts partly driving our results. In particular, we gather sectoral data for export values, number of firms, and number of workers for the years 1990 and 2010 (the latter being the first post-war year for which such data is available).[42] The sources of our collection are the Statistical Almanac (*Statisticki Godisnjak*) and the Structural Business Statistics reports (*Strukturne Poslovne Statistike*) published by the Statistical Agency of Bosnia and Herzegovina (*Agencija za Statistiku BiH*).

We match these data with our main source of data to construct two variations of the treatment meant to capture more precisely the number of Bosnian returning refugees (as opposed to Yugoslavians in general).[43] The first one of these corresponds to Yugoslavian refugees who joined the German labor force between 1991 and 1995 and left sometime between 1996 and 1999 (i.e., since returning to Bosnia was not safe before the end of 1995, most of the returning refugees during 1996 to 1999 are likely to be of Bosnian origin); second, we count workers who had been registered as having a Bosnian passport at some point during their stay in Germany, who had arrived sometime between 1991 and 1995 and had left by year 2000.[44]

Bosnian data for both periods are defined using the 2-digit NACE classification, which is equivalent to German WZ 93. This makes it possible for us to link data for both the left-hand side (i.e., sectoral outcomes) and the right-hand side (i.e., treatment) without need to use correspondence guidelines. We limit our sample to those sectors for which we have information on the number of workers and of firms both in 1990 and 2010. This results in a sample of 22 sectors, and thus 44 observations in total. Consistently with previous estimations, we transform all the variables using the inverse hyperbolic sine and based our estimations on Specification (1). Table 5 presents the OLS results using the two treatment variables described above.

[Table 5 about here.]

Column titles correspond to the outcome variables used in each regression. Columns 1 to 2 present the estimates when using Bosnian exports per worker as the dependent variable. The point estimates are highly significant and are around 0.83, implying that a higher number of returnees translates into higher labor productivity, as proxied by exports per worker. Columns 3-4 and 5-6 estimate the effect of the treatment on the number of firms and the number of workers per industry,

In the specification $exp_{c,c',p,t}$ is the export value from country c to country c' of product p in year t, $\phi_{c,p,t}$ is a exporter-product-year fixed effect, $\Omega_{c',p,t}$ is a importer-product-year fixed effect, $\Psi_{c,c',p}$ is a exporter-importer-product fixed effect and $\varepsilon_{c,c',p,t}$ is the error term.

[42] Consistently with our main estimation we use average outcomes per sector between 1988 and 1990 for the "before" period. Note that, differently from the main exercise, the data does not allow us to exclude exports to Germany.

[43] Our results are robust to using the baseline treatment variable.

[44] While some of these workers entered the German labor force as Bosnian nationals, others obtained Bosnian citizenship during their stay in Germany, and reported it. For constructing this alternative treatment, we consider individuals with Bosnian nationality at any point during their stay.

respectively. There we also see positive effects: sectors with more returnees end up being larger in terms of both firms and employees. A simple look at these coefficeints suggest that, on average, the treated sectors end up having firms that are smaller in terms of workers, which is typically the case for new firms. Consistently, there is rich anecdotical evidence on the creation of new firms by returnees, some of which we compile in Online Appendix Section A.

5.2 Alternative explanations

Scale effects

A possible explanation for the results is simply a "scale effect": workers returning simply are able to produce –and thus export– more quantity. We are able to rule out this possibility through several tests. First, our results are robust to using per capita transformations both in the dependent and independent variables, using the population of the country as the denominator (e.g., we use $exp_{p,t}/pop_t$ to construct our dependent variable). Also, when it comes to the case of exports a "scale effect" would be consistent with a Rybczynski (1955) effect: an inflow of workers into the economy would result into the export basket shifting towards labor intensive goods. Yet, we find that our results are not explained by the degree to which products are labor (or, alternatively, capital) intensive. For more details see Online Appendix Section F.1.

Convergence in Structural Transformation

We also rule out that our effects are driven by pure "convergence" in terms of structural transformation: i.e., Yugoslavia productive structure in the late 2000s reflect that of Germany in the early 1990s. We do this by including in our main specification a "convergence control", which is nothing more than the export share of product p in Germany in 1990 multiplied by that "after" term, and we find that our results are unchanged. For more details see Online Appendix Section F.2.[45]

Foreign Direct Investment

A possible concern is that returning refugees create an incentive for FDI to flow into the country towards the same sectors they worked in.[46] We rule this out by controlling for FDI stocks in our specification, both from Germany as well as from all over the globe, finding our main results are unchanged. For more details see Online Appendix Section F.3.

Bilateral transaction trade costs

Our estimations use as the dependent variable exports from former Yugoslavian countries to the rest of the world, excluding Germany. In that sense, we argue that our results are not explained by possible reductions of fixed costs of exporting to Germany caused by migrant networks. In addition, though, we find our results are not driven by either homogenous nor heterogenous goods (Rauch,

[45] Note that the results using the synthetic controls presented in Section 4 addresses this concern, too.

[46] Note that FDI could be a "bad control": the expansion of the labor force with skills relevant to a particular industry –what our treatment measures– can also attract FDI into those same industries.

1999). This and a number of other tests allow us to rule out this alternative explanation with certainty. For more details see Online Appendix Section F.4.

6 Who drives our results? Heterogeneous effects by workers' characteristics

The findings of the previous section point to productivity shifts as the main driver of export performance in the context of our results. This section complements those findings by digging into the data to study the role of the different characteristics and occupations of the returning refugees in our sample in driving our results. If indeed productivity shifts is behind our results, we should find that the treatment effect is particularly driven by certain workers more apt to transfer knowledge, technologies and best practices. To do so, we expand Specification (1) and rewrite it as:

$$exports_{p,t} = \sum_i \beta_i^{DID} treat_{p,i} \times after_t + \eta_p + \alpha_t + \varepsilon_{p,t}$$

Where each term $treat_{p,i}$ corresponds the total number of returning Yugoslavians in each category i in terms of workers' characteristics. All other terms remain the same as in Specification (1). We present results using characteristics grouped in six different categories:

First, skilled vs. unskilled workers based on their education levels. As unskilled we define workers without post-secondary education, and skilled as workers with education beyond high school, including vocational training, college degree or more. Since education does not devalue, we simply use the highest educational information attached to each worker at any point during the period of observation. To improve consistency of our variable, we correct missing values by using past and future values as developed by Fitzenberger et al. (2006).

Second, we distinguish migrants with occupations intensive in manual tasks vs. occupations intensive in analytical and cognitive tasks, using the classification provided by Dengler et al. (2014), which formalizes German occupations into five task categories, similarly to Autor et al. (2003).[47]

Third, we classify occupations as low skilled and high skilled based on Blossfeld (1987) classification of professions. For example, high skilled occupations include managerial ones as well as professionals (i.e., engineers, lawyers, technicians, accountants, lab technicians), and low skilled occupations include drivers, carpenters, textile processing operatives, etc.

Fourth, we distinguish workers by the supervisory intensity of their occupation based on the German Qualifications and Career Survey (BIBB/BAuA) of 1999. In particular we use the workers' responses regarding their supervisory status[48] and assign to each occupation both the share of

[47] Spitz-Oener (2006) first applied the task-based approach on German occupations based on survey data. The classification we use is based on year 2011.

[48] Based on the answer to the question: "Do you have coworkers for whom you are the direct supervisor?".

workers that self-report acting as supervisors and the share of those that report the opposite.[49]

Fifth, we distinguish workers based on whether they worked in the top 25 percent paying firms in terms of average wages, or in the bottom 75 percent paying firms. Typically, top paying firms are the most productive ones, by being able to attract the best workers and by innovating or adopting innovations that help workers be more productive.

Sixth, we distinguish workers based on the average growth in their wage during their stay in Germany, as proxy for productivity improvements. We separate workers within each industry in two groups: workers with wage growth (based on the compound average growth rate, CAGR) below median and those with wage growth above the median, based on all returnees in our treatment.

The summary of our results are presented in Table 6.[50] Each column present results using a different monotonic transformation of the dependent variable, consistently with all previous results in the paper. Columns show the estimated value of β_i^{DID} for each of the constructed treatments belonging to each of the categories described above (we only present results using OLS, as we don't have instruments for more than one endogenous variable at a time).

[Table 6 about here.]

The first row replicates the main results using the total number of returnees per industry, for comparison purposes. Overall, based on the point estimates and statistical significance, our results show that our findings are particularly driven by workers with higher educational attainment, workers in occupations that are intensive in analytical tasks (as opposed to manual ones) and workers in skilled occupations (as opposed to unskilled ones). The results are also strongly driven by workers with occupations intensive in cognitive and analytical tasks, as opposed to manual ones, as well as by workers in skilled occupations. The results for workers in occupations intensive in supervision are consistent, though not statistically significant, probably due to lack of variance. We also find that the results are particularly driven by workers who worked in the top paying firms during their stay in Germany, and find that workers for whom wages grew faster during their stay in Germany correlate with a higher export performance, though with no statistical significance.

Note that the point-estimates are to be interpreted in terms of percentages, and thus, ultimately, the marginal effect of one worker belonging to each of the categories driving the results is much larger in relative terms than what the point estimate suggests. This is because the types of workers driving the results are a smaller share when looking at the within-industry composition of workers in the sample. Figure 11 estimates the marginal effect of a refugee worker in each category relative to one worker based on the average treatment effect, using $asinh(exports_{p,t})$ as the dependent variable (results using $log(exports_{p,t})$ and $log(exports_{p,t}+1)$ are qualitatively similar).[51] The figure

[49] Online Appendix Section G summarizes the values of these characteristics for each one of the occupations in our dataset, along with the number of workers in our sample in each occupation.

[50] See Online Appendix Section H for tables with all the estimations by group, including both univariate and multivariate regression. While there is multicollinearity, the relative size of the point-estimates remain consistent in univariate and multivariate regressions.

[51] We compute this through a back-of-the-envelope calculation. We first compute what share of the the treatment represents one migrant worker, and multiply this share by the point estimate of $\beta_i^{DID}/\beta_{all}^{DID}$.

shows clearly that the marginal effect for workers with higher educational attainment is infinitely larger than for those with low educational attainment (given that the point estimate for the latter category is below zero), and it is about 7 times larger than for the average worker. Similarly, workers in occupations intensive in analytical tasks drive our resutls when compared to those in occupations intensive in manual tasks, and their effect is about 10 times larger than the average. Workers in occupations that are considered skilled are about 35 times more effective than those in occupations considered unskilled, and in turn are 3 to 4 times more effective than the average worker. Workers in occupations for which supervision is more common are 25 times more effective than those in occupations where supervision is less common (though the difference is not statistically significant), and in turn their effect is about 7 times larger than average. Workers who were employed by the top 25 percent paying firms are, similarly to educational attainment category, infinitely more effective than those who worked in the bottom 75 percent, and 3 times more effective than the average worker in explaining our result. Similarly, a worker that experienced wage growth above the median value is much more effective than those with slower wage growth (though, again, not statistically significant), and the marginal effect is about 4 times larger than the average treatment effect for the average refugee. All in all, these results suggest that the size of the effect we document depends on who the workers are in terms of their skills, the characteristics of their occupations, as well as who did they work for and how successful in their jobs they were while abroad.

[Figure 11 about here.]

The idea that a small number of workers can have such an important effect on exports of a whole industry in such little time might seems implausible at first, but some anecdotical evidence documented by others seems to strongly support that idea. For instance, Rhee and Belot (1990) and Easterly (2001), document the story of the success of the garment sector in Bangladesh. Between 1980 and 1986, the share of garments in Bangladesh's total exports rose from 0.5 to 28.3 percent. The unprecedented take-off of the garment export sector is often attributed to 130 Bangladeshi workers –only four of them in management positions– who spent eight months in 1979 working and being trained in Korea as part of an agreement between their company, Desh of Bangladesh, and the Korean firm Daewoo. The knowhow acquired by these workers seems to have been crucial in making Desh a highly successful exporter firm. Yet, perhaps more importantly, such knowhow eventually spilled over as workers moved to other firms or created new ones, contributing to the massive success of garment exports as one of Bangladesh's most significant export sectors.

In this context, we believe our findings pointing to productive knowledge and managerial knowhow as the main mechanisms driving the export dynamics, as well as the magnitudes of the coefficients we report, are aligned with other studies in the literature.

7 Concluding Remarks

The Balkan wars of the early 1990s created massive forced displacement from and within the former Yugoslavia. Most internationally displaced refugees ended up in Germany, where they could work under temporary protection status. A majority of them eventually returned home after the

Dayton peace agreement of December 1995 and the repatriations that followed. We exploit this natural experiment that resulted in exposure to German industrial know-how, technology and based practices, to investigate the role of returning refugees in explaining the export performance of their home countries. Using confidential German social security data, we find that Yugoslavian exports performed significantly better during the post-war period in industries that returnees had worked in while in Germany. Furthermore, we find that productivity is the underlying mechanism driving export performance in our setting. This is backed by the fact that our results are particularly driven by returnees with characteristics and in occupations more apt to generate productivity improvements.

Our results contribute to a burgeoning literature that emphasizes that migrants can serve as drivers of the diffusion of knowledge, technologies and best-practices resulting in productivity shifts. To the best of our knowledge, we are first to find such evidence using a natural experiment – especially in a context of returning forced migration.

In terms of policy implications, our results speak to the importance of allowing refugees full labor integration in their receiving countries. This is not only for the obvious reasons on the benefits to local hosting communities, but also because of how such policy can be a crucial determinant of the reconstruction of their home countries upon their eventual return.

More generaly, the ability of a worker to become more productive has to do with his or her accumulated experience and his or her ability to learn from others while on-the-job. Migration, therefore, is an important vehicle in the process of knowledge transfers across locations. Better understanding this process and identifying channels through which these dynamics occur are important missing pieces in the literature, and an active part of our future research agenda.

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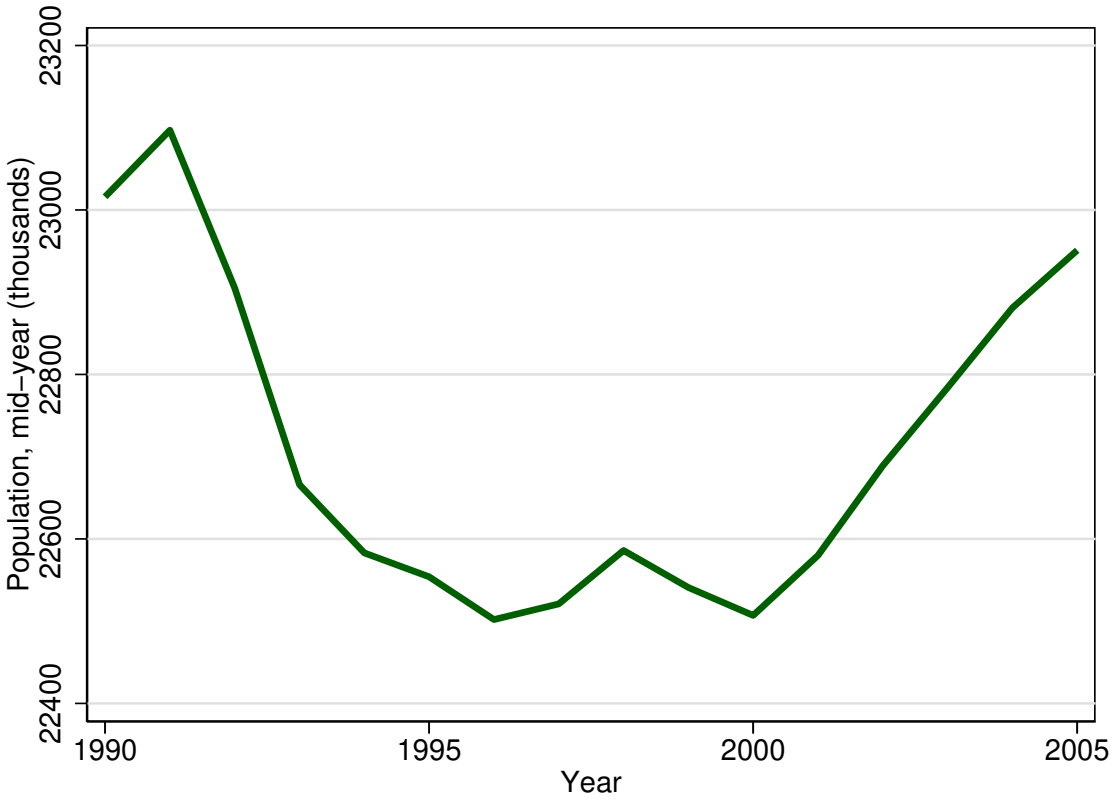
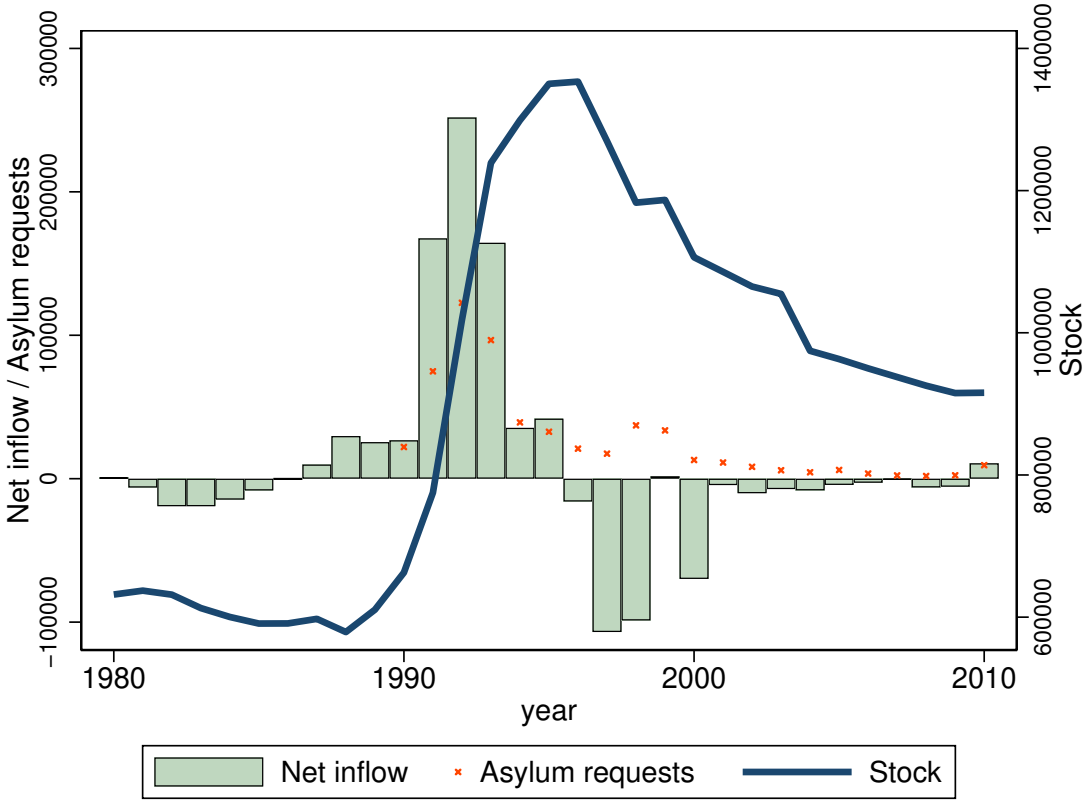
Figure 1: Population in Yugoslavia (thousands)



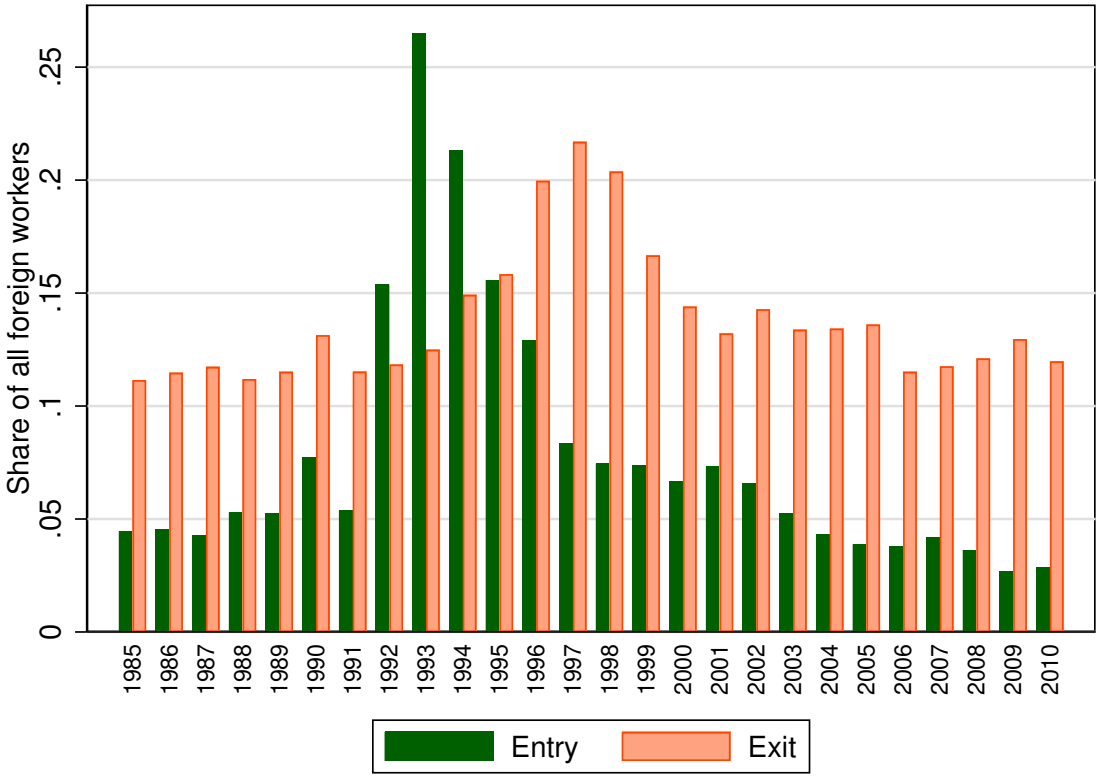
The figure plots the population of Yugoslavia over time, sourced from the Madisson Project Database (2018).

Figure 2: Migration from Yugoslavia into Germany



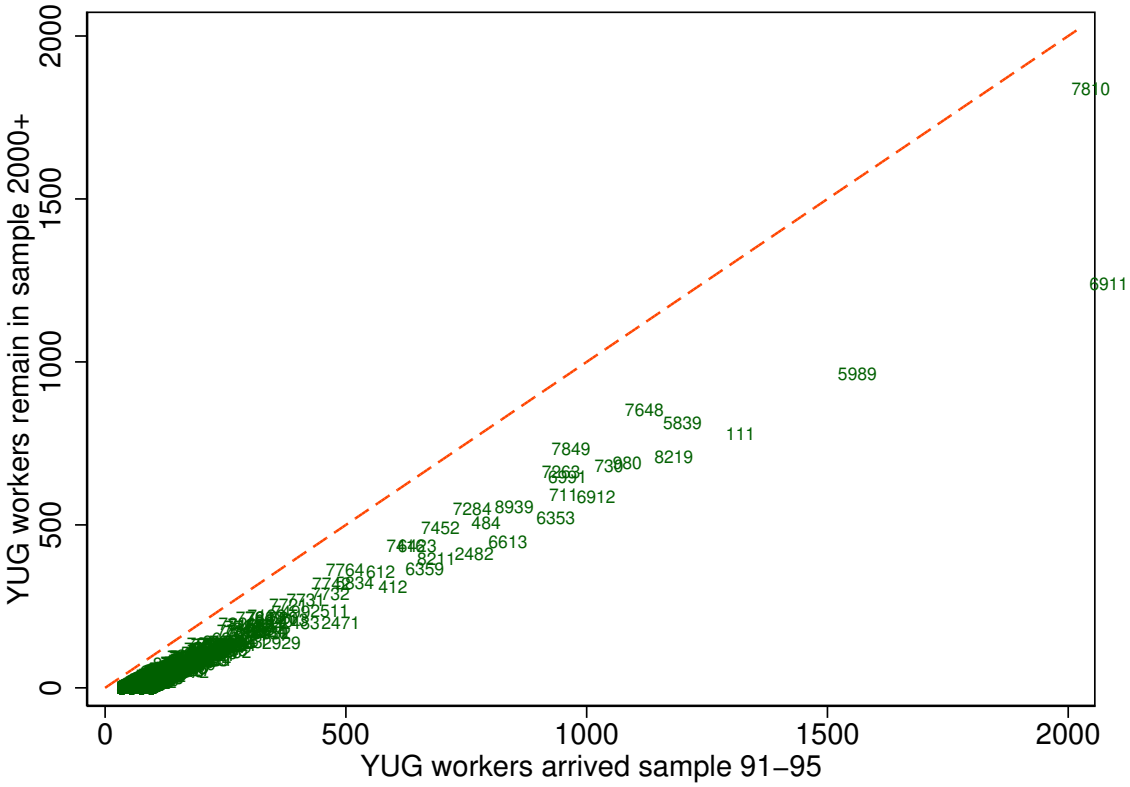
The figure shows the net inflow, stock and asylum requests of migrants from (former) Yugoslavia into Germany, from 1980 until 2010. The number of migrant stocks by nationality is based on the Central Register of Foreigners (*Ausländerzentralregister, AZR*). The data have been downloaded from the GENESIS-online data base of the German Federal Statistical Office (*Statistisches Bundesamt*), Table 12521-0002. Data on migration flows by nationality are from the migrations statistics (*Wanderungsstatistik*) of the German Federal Statistical Office (*Statistisches Bundesamt*) and sent to us upon request.

Figure 3: Yugoslavian workers yearly entry to and exit from German's labor force



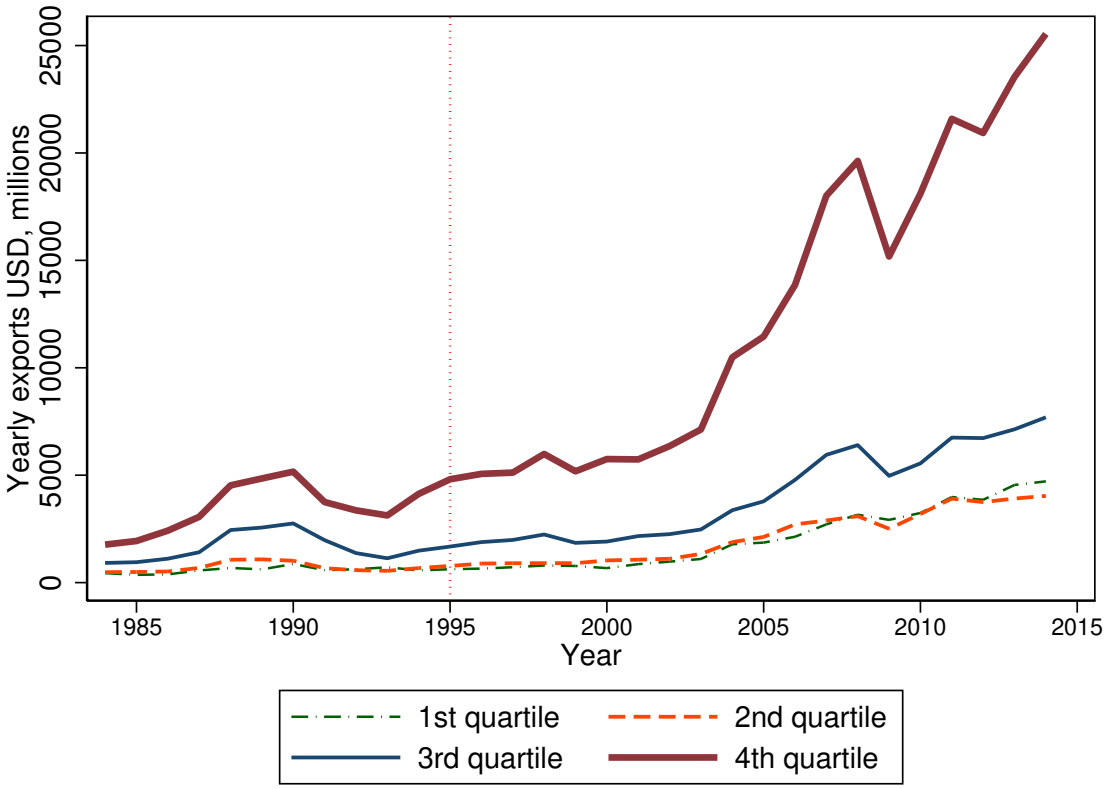
The graph shows the yearly share (out of all foreign workers) of Yugoslavians entering and exiting the labor force of Germany's tradable sector.

Figure 4: Yugoslavians in German workforce, by product



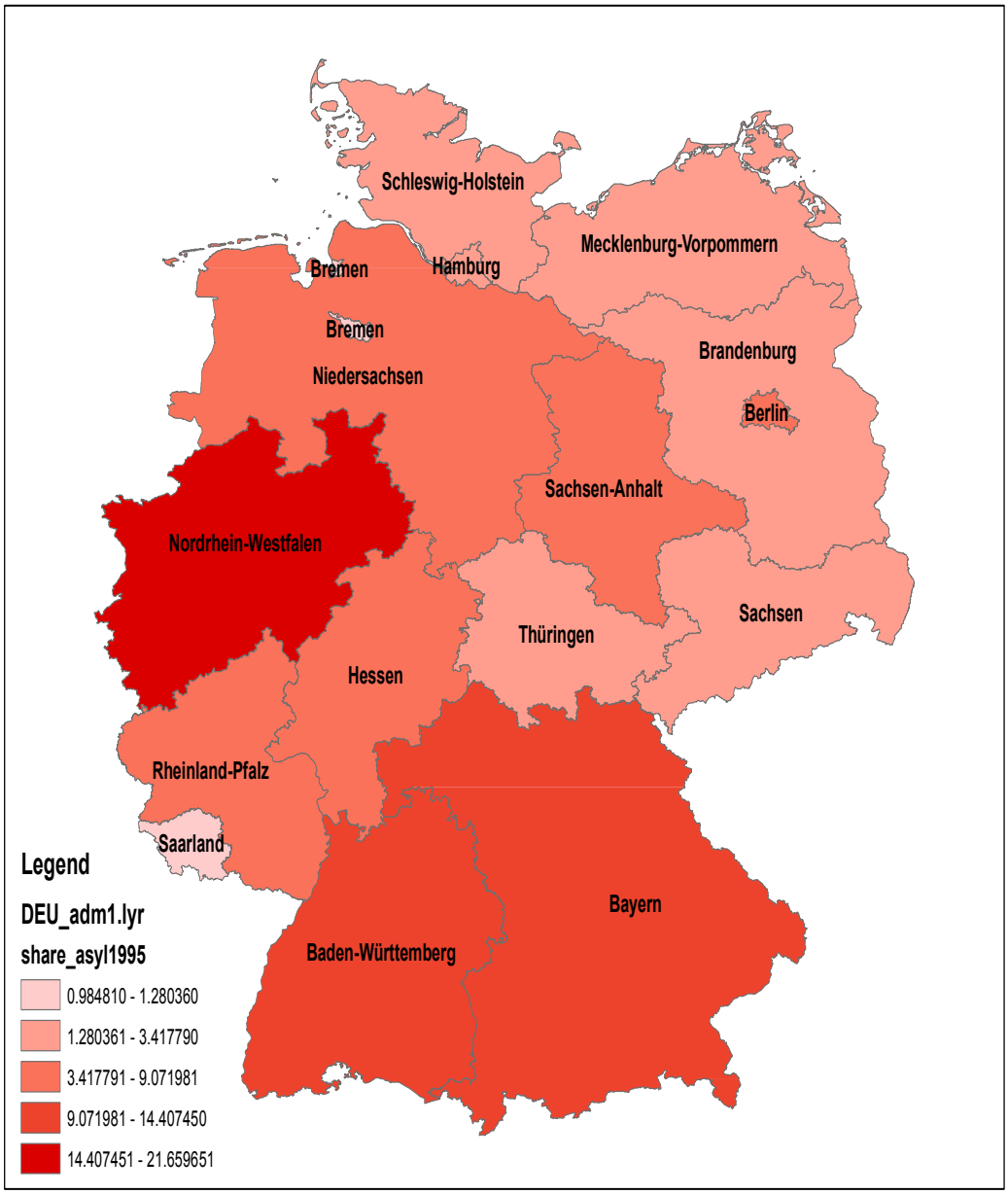
The figure shows the number of Yugoslavian workers in the German workforce that arrived between 1991 and 1995 agains those that remain in year 2000 and beyond, by 4-digit product.

Figure 5: Exports for products with different levels of treatment



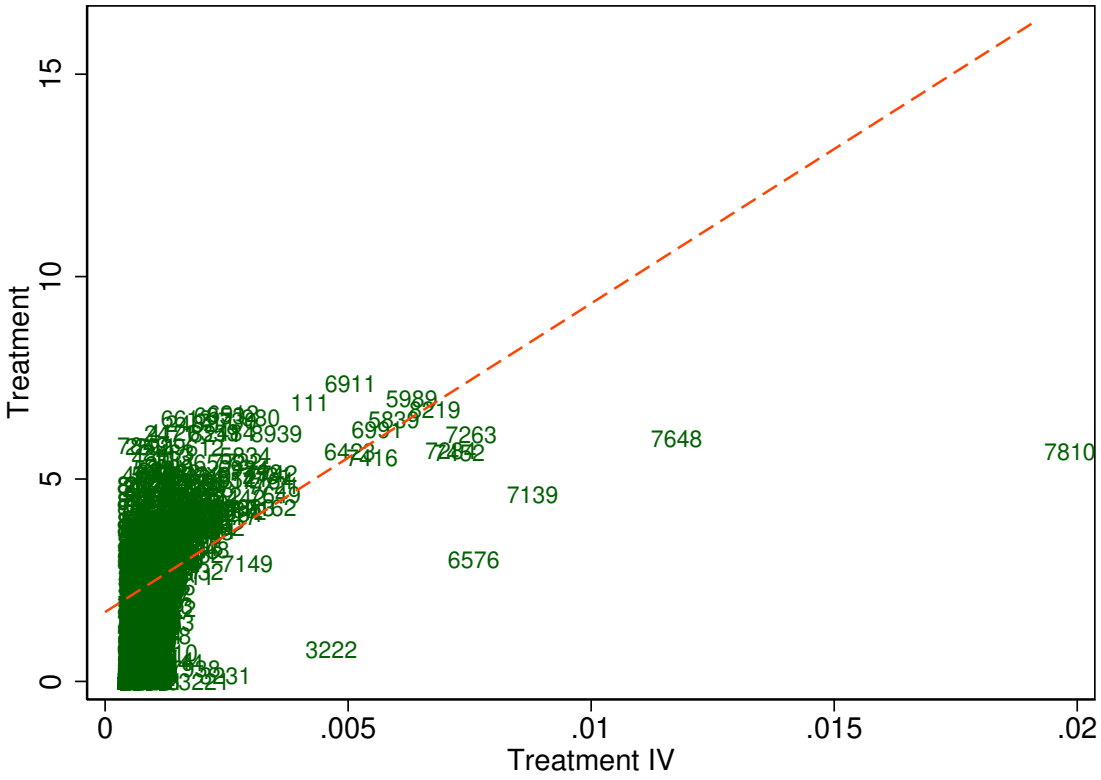
The figure plots the cumulative value of exports of the former Yugoslavia to the rest of the world (vertical axis) across years. Treatment is defined as the number of return migrants from Germany by 2000.

Figure 6: Distribution rule of asylum seekers in Germany 1995



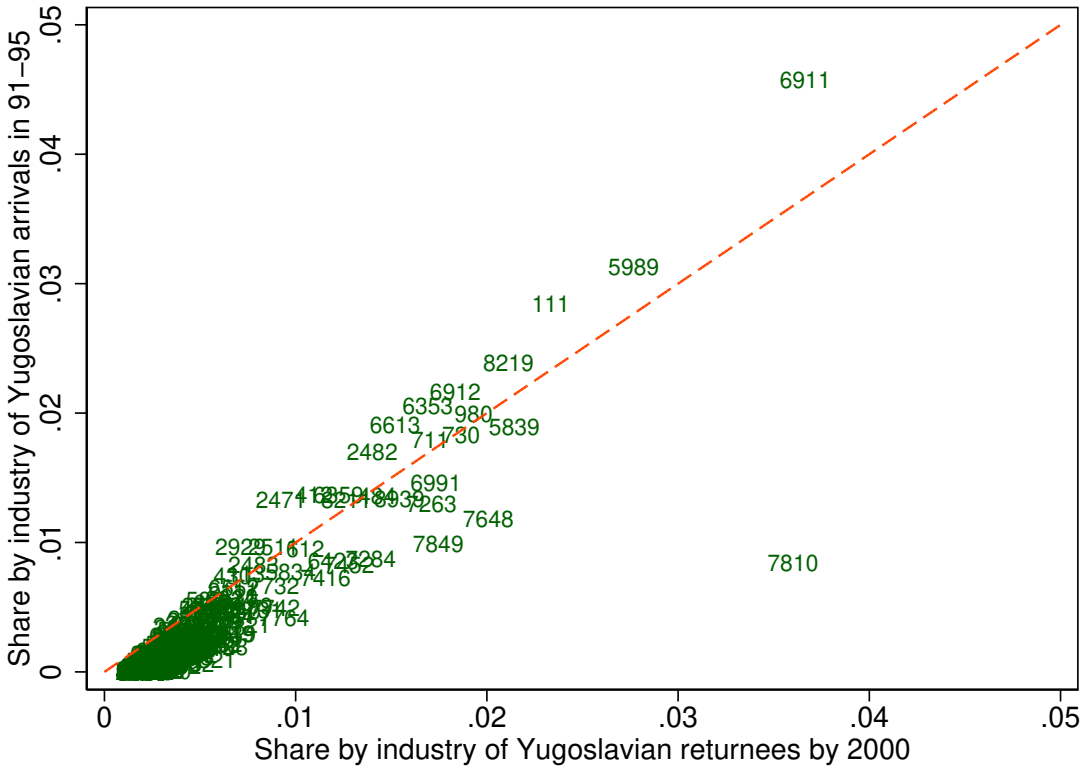
The figure maps the different German states with their shade representing the share of all asylum seekers in Germany they were mandated to receive by law in 1995, based on their population and tax revenues.

Figure 7: Instrumental Variable Relevance



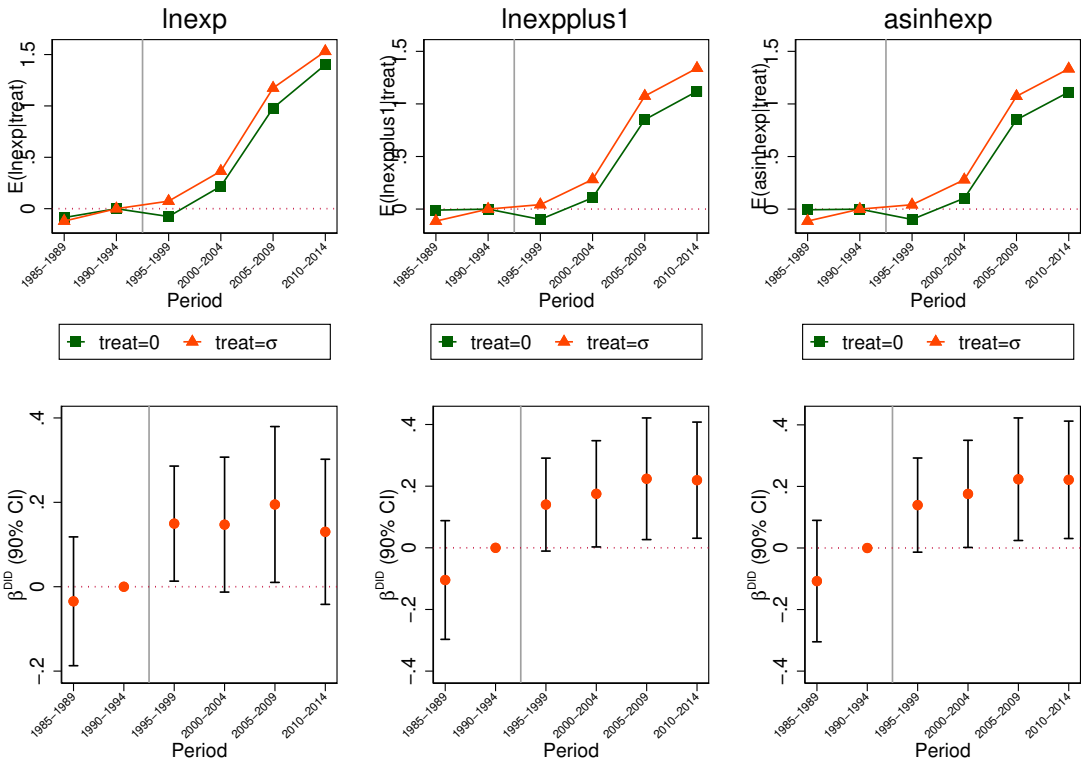
The figure plots in the horizontal axis the share of asylum seekers expected expected to work in each industry based on their geographic allocation in each state and the employment share of each 4-digit SITC code in that state (using data from 1991 to 1995); and in the vertical axis the number of Yugoslavian workers who arrived between 1991 and 1995 and leave the German labor force by 2000, by each 4-digit SITC code. Both variables have been rescaled in terms of their inverse hyperbolic sine. The figure represents a graphical visualization of the first stage of the 2SLS estimation.

Figure 8: Share of arrival vs exit from the German labor force by product



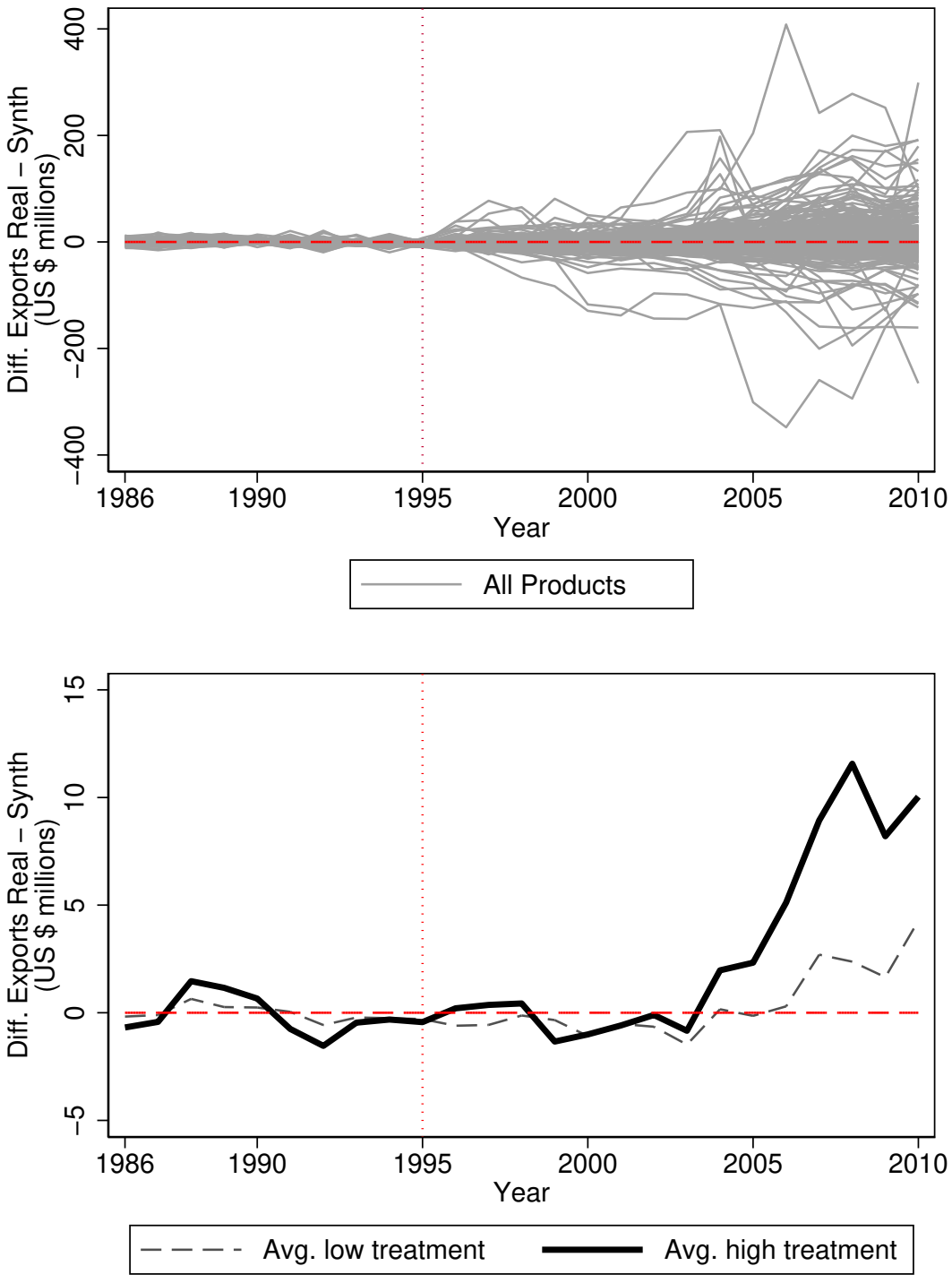
The figure plots the share of Yugoslavian workers in each industry out of the total that joined the labor force between 1991 to 1995 on the vertical axis against the share of Yugoslavian workers in each industry out of the total that dropped out of the labor force by 2000 (according to the way we define the treatment).

Figure 9: Event study (2SLS), 5 year periods



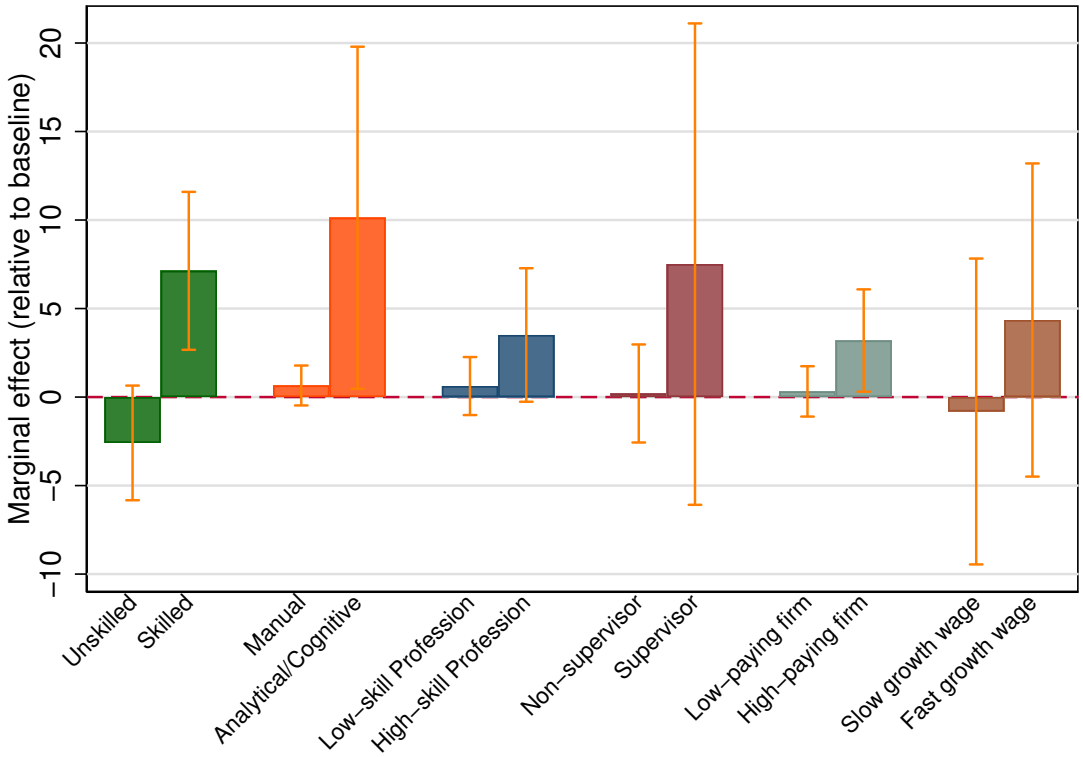
The top figure plots exports over time for two groups: products for which $treat_p$ equals zero and for which $treat_p$ equals one standard deviation of the treatment. The dependent variable is the 5-year average of exports (each column uses a different linear transformation and the period 1990-1994 is used as the base year). The bottom figure plots estimates for β^{DID} for each 5-year period, which corresponds to the difference between the two groups of industries plotted in the top figure. The results are estimated using 2SLS and include the convergence control. 95% confidence intervals for the estimation are represented by the whiskers.

Figure 10: Difference in export value, real vs. synthetic products



The top panel presents the evolution of the difference in export value between real and synthetic for all products in the dataset. The bottom panel groups the differences in high vs. low treatment (4th vs. 1st quartile of the treatment) across years. Results are robust to the inclusion of a small number of outlier products that were removed from this plot for visualization purposes.

Figure 11: Marginal effect by type of migrant



This figure plots the estimated marginal effect of 1 returning refugee on exports based on the levels of migrants of each type in the sample, relative to the average treatment effect. It uses $asinh(exports_{p,t})$ as the dependent variables. Whiskers represent 90 percent confidence intervals.

Table 1: Summary Statistics Yugoslavian Refugees in Germany

Variable	**N**	**Mean**	**sd**	**Min**	**Max**
Exports YUG in 1990, million USD	786	12.472	31.65	0.0	395.0
Exports YUG in 2005, million USD	786	24.458	71.62	0.0	1,090.0
YUG workers in 91-95	786	74.025	190.78	0.0	2,018.7
YUG workers in 91-95 & out by 2000	786	21.641	60.61	0.0	778.5

This table presents the sample summary statistics for the variables used to estimate specification (1).

Table 2: First-stage and reduced form results

Dependent variable: $treat_p \times after_t$		
	(1)	(2)
	treatXafter	treatXafter
treatIV × after2005	739.6538	762.4708
	(195.546)***	(200.797)***
N	1496	1572
Adj R2	0.77	0.77

This table shows result of the first stage based on specification (1). Column 1 presents results for the sample where $log(exports_{p,t})$ is defined, whereas Column 2 presents results for all observations. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table 3: Difference-in-difference estimation

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0875	0.1357	0.1373	0.1053	0.1597	0.1620
	(0.037)**	(0.062)**	(0.064)**	(0.047)**	(0.058)***	(0.059)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				14.31	14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the "before" period and average exports for years 2005 to 2007 in the "after" period. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table 4: DID, Costinot et al. (2012) measures in LHS

Dependent variable: $\Phi_{p,t}$, based on Cosinot et al. (2012)				
	OLS		2SLS	
	lnxp	asinhxp	lnxp	asinhxp
treat2000 × after2005	0.0231	0.0184	0.0355	0.0294
	(0.002)***	(0.002)***	(0.005)***	(0.004)***
N	1572	1572	1572	1572
r2	0.90	0.90	0.90	0.89
KP F Stat			14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for $\Phi_{p,t}$ in each column. $\Phi_{p,t}$ is a measure of comparative advantage estimated following Costinot et al. (2012). The first two columns report results from an OLS estimation, while the last two columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$

Table 5: DID, outcomes in Bosnia

Dependent variable: $asinh(outcome_{s,t})$						
	(1)	(2)	(3)	(4)	(5)	(6)
	asinhexppw	asinhexppw	asinhfirms	asinhfirms	asinhworkers	asinhworkers
treat9699 × after2010	0.8504		0.2689		0.2229	
	(0.349)**		(0.162)		(0.086)**	
treatBIH2000 × after2010		0.8301		0.3596		0.2749
		(0.388)**		(0.172)**		(0.094)***
N	44	44	44	44	44	44
Adj R2	0.86	0.84	0.81	0.82	0.64	0.65

This table shows result of the estimation for specification (1), focusing only on outcomes for the Bosnian economy, using variation of 2-digit sectors. Columns 1-3 uses exports as the dependent variable, columns 4-6 uses number of firms, and columns 7-9 uses number of workers, all transformed using the inverse hyperbolic sine. All columns include sector fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table 6: DID, workers' education and occupations

β_{DID}	$log(exp)$	$log(exp+1)$	$asinh(exp)$
Total	0.088**	0.136**	0.137**
Unskilled	-0.278	-0.190	-0.186
Skilled	0.411***	0.370***	0.367***
Manual	0.022	0.071	0.072
Analytical/Cognitive	0.134*	0.134*	0.135*
Low-skill Profession	0.007	0.059	0.061
High-skill Profession	0.123*	0.122	0.122
Non-supervisor	-0.055	0.020	0.022
Supervisor	0.221	0.183	0.183
Low-paying firm	-0.032	0.027	0.029
High-paying firm	0.152**	0.144*	0.143*
Slow growth wage	-0.052	-0.036	-0.035
Fast growth wage	0.147	0.184	0.185

This table shows result of the OLS estimation for specification (1) using treatments constructed by aggregating workers by groups based on their skills and/or occupations. The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_{p,t}$ in different columns column. All columns include the convergence control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Online Appendix for
Migration and post-conflict reconstruction: The effect of returning refugees on export performance in the former Yugoslavia

Dany Bahar, Andreas Hauptmann, Cem Özgüzel and Hillel Rapoport

October 19, 2020

A Anecdotal evidence: Four individual stories

In 1999, only four years after having returned from Wolfsburg in Germany, Volkswagen's home town, Nijaz Hastor founded the Prevent group, currently one of Bosnia's largest companies. Prevent began manufacturing seat covers in the city of Visoko in Bosnia with a staff of 50, and has since diversified into yacht interiors, protective clothing, brake disks and fashion textiles. By 2016, the Prevent Group employed over 6,500 people and operated from about 15 different sites in Bosnia, exporting its products to a large number of different destinations across Europe and beyond. Hastor started his career working for a local firm supplying car parts in Sarajevo, but it is likely that the knowhow he acquired while working as an immigrant for the auto industry in Germany helped him build a world-class company able to manufacture high-end auto parts with high efficiency.

Almir Gvožđar is another example of a refugee who used his newly acquired skills and contacts to create his own company in a new industry. In 1996, following his return from Germany, Gvožđar invested all of his savings in a second-hand CNC machine tool and founded GAT Ltd in his family garage. Working alone, Gvožđar started producing motorcycle parts and selling them to his former employer in Germany, ABM Fahrzeugtechnik GmbH, a leading manufacturer of high-performance parts for the motorcycle industry, where he had worked as a technician during the war. Over the years, as the number of clients increased, business expanded as well. Currently GAT employs 65 people, operates from a facility of 1100 m^2 and exports motorcycle parts and medical instruments across Western Europe.

Refugees who were hosted in other countries also had similar experiences. For instance, Enes Kahrimanovic left BiH in 1991 and moved to Austria where he started working for the Plaspack Company, one of the largest manufacturers and distributors of nets, transparencies and advertising transparencies in the EU, a sector in which he had no previous experience. As Austria allowed its refugees to become permanent residents, Kahrimanovic continued working at the Plaspack following the peace treaty. While working at the Plaspack, Kahrimanovic realized that some of the intermediary products imported from rest of Europe can be produced in Bosnia. Over the years, Kahrimanovic worked on finding partners in Bosnia that could supply the imported pieces. As deals with local companies were struck, the Plaspack Company supplied more and more of its parts from Bosnia. Finally, Austrian owners of the Plaspack decided to start a production in Bosnia, and gave Kahrimanovic the full responsibility of both establishing and managing the company. In 2007, he

founded Austronet in the city of Kozarac and with a staff of 5 and started manufacturing safety netting for tennis courts and protective netting for the construction industry. Today this company employs 72 people and exports 97% of its production.

Although individual initiative has been an important element for the transfer of knowhow, it was not indispensable as it can be seen in the case of the Kavat Shoe Factory workers. In the beginning of the 1990s shoemaking was a trade that was declining in Sweden and Kavat, a shoe manufacturer specialized in high-quality leather shoes was having difficulties finding skilled craftsmen. When Bosnian refugees from Travnik, a region specialized in the textile industry, arrived to Kumla where the Kavat factory is located, it didn't take long before they were recruited. By working for Kavat, Bosnians acquired skills in shoemaking and learned about modern equipment and technologies. Kavat was so satisfied with its Bosnian employees that when they returned to Travnik after the war it helped them establish a production facility and integrated it to its supply chain. Over the years, as the demand for Kavat shoes increased, the company felt the need to expand its production. The decision for location, as put by the company, came naturally. In 2009 Kavat opened a factory in Travnik and recruited its former employees. Today Kavat is an international company which manufacture about 400.000 pairs of shoes every year, out of which 350.000 are made in their factory located in Bosnia.

B Details on employment data, sample construction and variable description

The data on migrant workers in Germany are based on records from the German social security system for the years 1975-2014 (IAB, 2015) and comprise all persons employed subject to social security contributions, with the exception of self-employed and civil servants. The data contain information on nationality, education, occupation, industry, among others. For data privacy reasons our sample is restricted to 40% random draws of foreign nationals observed on June 30 of each year from 1975 to 2014 augmented by the employment history of each individual for our sampling period. The data was provided by the IT Services and Information Management (ITM) of the IAB. Missing information on educational attainment was corrected by ITM using information on past and future values (see Fitzenberger et al., 2006, imputation procedure IP1).

We keep all spells subject to social security contributions without specific tokens. Specific tokens are given to e.g. apprentices, employees in partial retirement, marginal part-time workers, seamen, or artists liable to social security. We keep one spell for per person-firm combination and focus on spells in tradable industries only. We use the nationality of the worker recorded at his or her first appearance in our database. The BeH contains information on the industry affiliation, but different classifications have been applied over time. Therefore, we use time-consistent industry codes developed for these data by Eberle et al. (2011). In particular we use the German classification WZ 93 which corresponds to the European classification of NACE Rev. 1. When matching German WZ 93 3-digit industry codes to 4-digit SITC product codes we apply correspondence tables provided by the United Nations Statistical Office and Dauth et al. (2014), which provide an unweighted concordance table. If the source 3-digit category applies to more than one 4-digit SITC target category we distribute workers according to the shares of German exports in 1995 based on 4-digit SITC categories for each year separately, along the lines of what implemented by Cuñat and Melitz (2012). Using this weighting scheme we use the implicit assumption that German export shares are a good proxy for employment of Yugoslavians across German at the product level (SITC 4 digits). This is something we cannot directly test for because our data on employment is at the industry level (WZ 93 3-digit). However, when looking at the correlation between German exports and employment share of Yugoslavian workers by industry (WZ 93 3-digit) we find it is reasonably high: for the years 1991 to 1995 is 0.72 and statistically significant. To comply with data privacy rules, the sample utilized herein is an anonymized version, sensitive values (between 1 and 19) of industry-period observations have been replaced with different moments of the distribution of the number of migrant workers. The number of cells affected varies by the level of disaggregation of worker characteristics.

The treatment variable for our main specification is constructed as follows. We keep all records of workers observed in the data for the very first time between 1991 and 1995 and for whom no record exists after 1999. For this we look at the total of records in our original data and can therefore rule out, that workers in our treatment variable have had any other form of employment prior or after the respective cut-off dates. This comprises jobs in other industries (such as services), marginal employment, or any other form of employment which creates a notification to the social security

services. Since a worker may have had two or more jobs in different industries, we assign each worker to his or her main job, before aggregating to the industry level. As main job we define the worker-firm-industry-occupation combination with the longest duration.[52]

In some specifications in our analysis we disaggregate our data further according to several different worker characteristics. Our definition of the main job ensures for each dimension the sum each subcategory by industry (including potential missing values) adds up to the value in our main treatment variable. When distinguishing between skill groups, we define as unskilled, workers without post-secondary education and skilled as workers with education beyond high school (i.e., vocational training, college degree or more). Since education may change over time but cannot depreciate, we use the highest educational attainment. We also group workers according to the task content of their occupation. Occupations in our data are classified according to the German Classification of Occupations 1988 at the 3-digit level which comprises 334 different occupations. We distinguish between manual and analytically intensive tasks. Manual tasks are defined as manual (non-) routine tasks and as analytic tasks we classify analytical or interactive non-routine tasks. The classification is based on BERUFENET, which is, similar to O*NET, an expert's assessment of the tasks usually performed in a specific occupation. It covers originally about 3,900 different occupations and has been mapped to our classification codes by Dengler and Matthes (2014). We use the classification for the year 2011. When classifying occupations by skill we categorize groups according to Blossfeld (1987). Low skilled occupation comprise agricultural, unskilled manual, unskilled services, and unskilled commercial and administration occupations. All other we define as high skilled.[53] We also distinguish workers by the supervisory intensity of their occupation based on the German Qualifications and Career Survey (BIBB/BAuA) of 1999. In particular we use the workers' responses regarding their supervisory status and assign to each occupation both the share of workers that self-report acting as supervisors and the share of those that report the opposite.

Furthermore, our employment data contain information on daily wages and number of days worked in a job per year. We utilize this information and distinguish in one specification Yugoslavian workers by their wage growth and group them by whether their wage growth was above or below the median of workers considered in the treatment variable. To so we use all workers with positive wage information in full-time employment and compute the compound average growth rate for the first and last observed wage. We also group them not only by their own wages but also by the wage levels of their employers. Therefore we group workers by whether they worked (or not) for one of the employers with a median establishment wage in the top quartile of the industry. For this we computed the quartiles of establishment wages by industry, based on IAB Established History Panel (BHP). The BHP comprises the universe of German establishments with at least one employee subject to social security contributions. Our data and the BHP can be linked via a common identifier (for more information on the BHP see Schmucker et al., 2018).

[52] Because we use a relatively short period to construct the treatment variable, the exact definition of the main job has no major influence. About 92% of the workers in our treatment variable do not change the industry and 89% do not change their occupation.

[53] Namely managers, skilled commercial and administration, professions, semi-professions, skilled services, engineers, technicians, and skilled manual occupations.

C Zeroes in the data

There are 38 products that Yugoslavia does not export in either the pre-treatment period (1988-1990) or the post-treatment period (2005-2007). These products are excluded from our model when we examine log exports, but included in two other specifications. Including these products has a large impact on the magnitude of our estimated treatment effect, doubling the size of the coefficient in our instrumental variable specification (see Table 3 in main text).

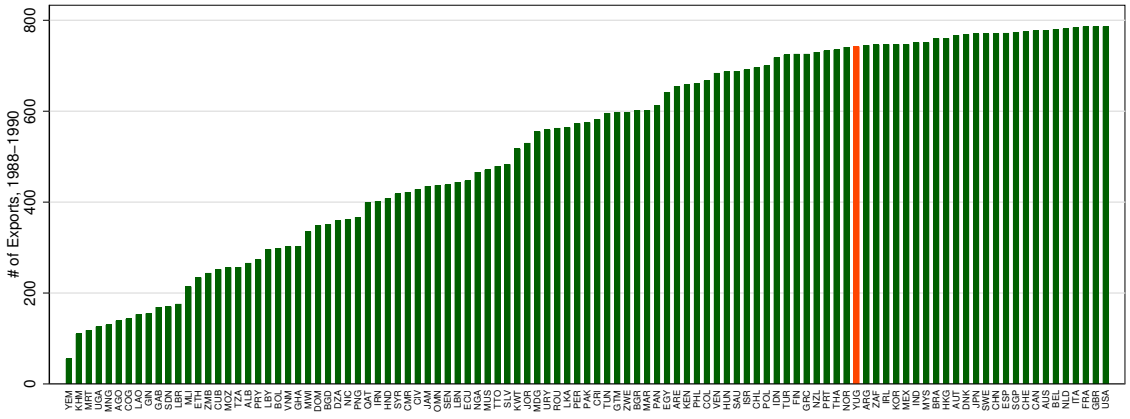
For this reason, we look more closely at the prevalence of zero export products in this appendix. If the zeros mostly occur in the pre-treatment period, we might conclude that returning migrants launched new industries in Yugoslavia, which would explain the increased size of the treatment effect. However, this is not the case. Between the pre- and post-periods, 12 product lines were opened and 16 product lines were closed, and the product lines that were closed are much larger than those that opened. Three of the closed product lines are especially large, with exports over $20 million in the pre-period but nothing in the post period. All three of these products are liquid fuels. Our results are robust to the exclusion of these three fuels, and we find that those products alone do not cause the increase in the size of the estimated treatment effect.

Given that Yugoslavia does export 770 of 786 products in the pre-treatment period, we examine the total number of products exported by other countries in that period to ascertain whether Yugoslavia is unusual in having so many export lines. We find that it is in fact not uncommon for countries to export so many products, and several developing markets a comparable levels of GDP per capita have a greater number of exports. This is shown in Figure C1.

[Figure C1 about here.]

We also consider the possibility that, though Yugoslavia exports many products, most of these export lines are small and insignificant. If this were true, our use of product fixed effects means that our results could be produced by sectors that are largely unimportant to the former Yugoslavian economies today. We therefore ran our main results excluding products with fewer than $25,000 in exports in the pre-treatment period. Our results hold using this sub-sample which excludes only 81 (out of 786) products with exports below $25,000. We therefore conclude that our estimated treatment is not driven by low-value products.

Figure C1: Exploration of zeros in our data



The figure compare the number of products exported to the rest of the world with reported export value above zero in the baseline period. The figure shows that Yugoslavia is no outlier in terms of the number of products exported (or, alternatively, the number of products with export value equal to zero).

D Robustness checks on the main specification

D.1 Using levels as treatment

Table D1 reports the estimation for specification (1) using the baseline stock of Yugoslavian workers per industry in 1995 (rescaled using the inverse hyperbolic sine). The results are robust to this version of the treatment, solving concerns that endogeneity of exit severely biases our results.

[Table D1 about here.]

D.2 Excluding most common ports of entry from the calculation of the instrumental variable

Table D2 presents results where the instrumental variable is computed excluding Bavaria and Baden-Wurttemberg (quotas are re-normalized to account for their exclusion), which were the most common port of entry of Yugoslavian refugees.

[Table D2 about here.]

D.3 Excluding Slovenia and Macedonia from the sample

Table D3 replicates the results of Table 3 excluding Slovenia from the sample. Slovenia was the first Yugoslavian republic to secede and did not suffer from a long war nor a massive exile of its inhabitants to other locations. Our results are robust to its exclusion from the left hand side variable.

[Table D3 about here.]

Table D4 repeats the same exercise and excludes Macedonia. Following Slovenia and Croatia, Macedonia held a referendum and declared its independence in late 1991. Unlike others, Macedonia managed to obtain its independence without going through an armed conflict. This is why, no war refugees from Macedonia went to Germany. Our results are robust to its exclusion from the left hand side variable.

[Table D4 about here.]

D.4 Event study by timing of return

The nature of our dataset allow us to identify for each refugee worker the years of arrival to and exit from the German labor force. We know that most Yugoslavian refugees in Germany started returning to their home countries after 1995, as soon as their Duldung status expired. Thus, we are able to test whether there is a differential effect for industries for which most migrant and refugee workers returned earlier than others. Even if suggestive, this test could be very instructive for one particular aspect of our exercise: that the effect is indeed somewhat driven by returning workers, and less so by all refugees including those who did not return.

To test for this, we replicate the same event study, this time adding new terms to the specification to investigate whether industries with many workers having returned in the earlier part of the period (before 1996, inclusive) experienced a larger marginal effect early on, as compared to the rest of the industries. To do this, we include in the event study, on top of the regular $treat_p \times period_t$ variables for all 6 periods from 1985-1989 to 2010-2014 (again, where 1990-1994 serve as the baseline), a triple interaction $treat_p \times period_t \times earlytreat_p$, where $earlytreat_p$ is defined as 1 if industry p has a share of early returnees above the 90th percentile of the distribution, which corresponds to about 65 percent. In other words, in those industries, at least 65 percent of all migrants returned in 1996 or before, while the rest returned between 1997 and 1999.

In other words, we estimate the following specification:

$$exports_{p,t} = \sum_{t=1}^{6} \beta_t^{DID} treat_p \times period_t + \sum_{t=1}^{6} \beta_t^{DID,early} treat_p \times period_t \times earlytreat_p + \beta_t^C \sum_{t=1}^{6} DEUexpshare1990_p \times period_t + \eta_p + \alpha_t + \varepsilon_{p,t}$$

Where we define the average treatment effect (ATE) for industries with many early returnees (e.g., $earlytreat_p = 1$) for period t as $\beta_t^{DID} treat_p + \beta_t^{DID,early} treat_p$, while for the rest of the industries $\beta_t^{DID} treat_p$.

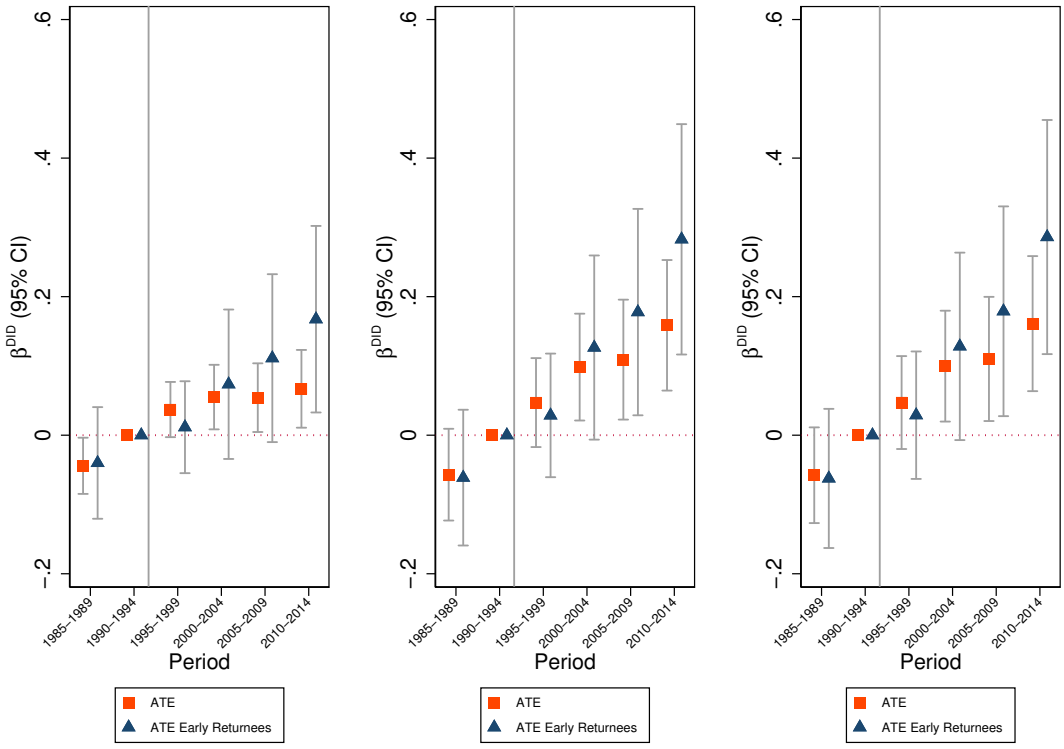
The results are visualized in Figure D1. The squares represent the average treatment effect, (ATE) for all industries in each period, whereas the triangles represents the ATE for the "early" treatment industries in each period.[54] Note that there is one square and one triangle for each one of the six 5-year periods.

[Figure D1 about here.]

The figure consistently shows that there is a "premium" for early treatment industries: the point estimates for the industries identified as having mostly early returnees tend to perform better earlier in time than the rest of the industries. Even though statistically we cannot reject the effects are different from each other, we can reject they are different from zero in the later periods. This suggestive evidence further supports the idea that it is returnees shaping the dynamics of export performance back in their home countries, and not only defined by the total number of refugees including those who return later on or do not return at all. This test is an additional proof that our results are not driven by convergence dynamics.

[54] The ATE for the early treated industries is the sum of the estimated coefficient for the term $treat_p \times period_t$ plus the one estimated for the term $treat_p \times period_t \times earlytreat_i$.

Figure D1: Treatment effect for industries with high share of early returnees



This figure below plots the average treatment effect (ATE) in each 5-year period represented by squares, and the ATE for industries for which the treatment is composed by over about 65 percent (or 90th percentile of the distribution) of worker returnees who returned in 1996 or before. Both ATEs are presented for each 5-year period from 1985-1989 to 2010-2014 (with 1990-1994 serves as baseline). The results are estimated using OLS. 90% confidence intervals for the estimation are represented by the whiskers.

Table D1: DID, different treatments

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat1995level × after2005	0.1141	0.2117	0.2158	0.1066	0.1572	0.1594
	(0.033)***	(0.058)***	(0.060)***	(0.039)***	(0.045)***	(0.046)***
N	1520	1572	1572	1520	1572	1572
r2	0.86	0.80	0.80	0.86	0.80	0.80
F Stat				16.54	16.48	16.48

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column, using the stock of migrant workers in 1995 as the treatment (rescaled using the inverse hyperbolic sine). The estimation uses exports between 1990 and 2005. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$

Table D2: DID, IV without Bavaria and Baden-Wurttemberg

Dependent variable: $exports_{p,t}$			
	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.1129	0.1768	0.1795
	(0.049)**	(0.063)***	(0.064)***
N	1496	1572	1572
r2	0.86	0.81	0.81
F Stat	17.15	17.36	17.36

This table shows result of the estimation for specification (1) using an instrument that excludes the states of Bavaria and Baden-Wurttemberg from the calculation, using different monotonic transformations for $exports_p, t$ in each column. All columns include product and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table D3: DID, excl. Slovenia

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0875	0.1357	0.1373	0.1053	0.1597	0.1620
	(0.037)**	(0.062)**	(0.064)**	(0.047)**	(0.058)***	(0.059)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				14.31	14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column, excluding exports from Slovenia as one of the former Yugoslavian republics post 1992. The estimation uses years 1995 and 2005. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table D4: DID, excl. Macedonia

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0875	0.1357	0.1373	0.1053	0.1597	0.1620
	(0.037)**	(0.062)**	(0.064)**	(0.047)**	(0.058)***	(0.059)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				14.31	14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column, excluding exports from Macedonia as one of the former Yugoslavian republics post 1992. The estimation uses years 1995 and 2005. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

E Synthetic controls: regression analysis

In Section 4 we present graphical results, using simple averages, using the synthetic control methodology. This section presents consistent results using regression methods. In particular, we estimate the following specification:

$$\begin{aligned} exports_{p,t} = \beta^{DID} treat_p \times after_t \\ +\beta^{synth} treat_p \times after_t \times synth_p \\ +\eta_p + \alpha_t + synth_p + \varepsilon_{p,t} \end{aligned} \tag{E1}$$

The results are presented in Table E1. The first three columns presents results using all products, while the last three columns excludes from the sample outlier products in terms of the pre-treatment difference between the real and synthetic ones. There we see that while β^{DID} is positive and significant, β^{synth} is estimated as negative, also statistically different from zero. In that sense, while products performed better the higher the intensity of the treatment, the synthetic ones didn't do as well.

The results of the last three columns assure us that our results are not driven by certain outliers where the effectiveness of the synthetic control methodology in creating credible counterfactuals can be questioned. Outliers where defined by being above the 90th or below the 10th percentile of the minimum squared errors, as defined by pre-1995 differences in export value between real and synthetic.

[Table E1 about here.]

Table E1: DID, Synthetic Controls

Dependent variable: $exports_{p,t}$						
	All			No Outliers		
	(1)	(2)	(3)	(4)	(5)	(6)
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0774	0.1834	0.1889	0.1210	0.1816	0.1846
	(0.031)**	(0.050)***	(0.051)***	(0.034)***	(0.050)***	(0.051)***
treat2000 × after2005 × synth	-0.0142	-0.1186	-0.1255	-0.0203	-0.0579	-0.0601
	(0.017)	(0.025)***	(0.026)***	(0.018)	(0.021)***	(0.022)***
N	2717	2772	2772	2198	2220	2220
Adj R2	0.87	0.78	0.77	0.81	0.74	0.73

This table shows result of the estimation for specification (E1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. The first three columns report results using all the sample, while the last three columns report results excluding outlier products. All columns include a synthetic fixed effect, product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

F Alternative Explanations

F.1 Scale Effects

A possible concern is that our results are purely driven by a simple "scale effect": more workers flowing back into the economy, and into each industry, results in higher output and thus higher export. We rule out this through an extensive number of tests, some of them in the main body of the paper, such as the use of synthetic controls (see Section 4). In addition to this, however, Tables F1 and F2 replicate our main results using per capita transformations on both the left hand side and right hand side variables, respectively.[55] While ideally we would use number of workers per industry (as we do with Bosnia in Section 4), that information is not available to us. Yet, this per capita transformation further suggests our results are not driven purely by a scale effect as it takes into account population dynamics.

[Table F1 about here.]

[Table F2 about here.]

Given that we use exports data, a way to think about "scale effects" would be consistent with a Rybczynski (1955) effect: an inflow of workers into the economy could result into the export basket shifting towards labor intensive goods. We rule out this possiblity by showing that our treatment is not driven by the labor intensity of products.

In particular, we re-estimate specification (1), this time interacting the term $treat_p \times after_t$ with a product-level labor intensity indicator taken from Nunn (2007). The results are in Table F3, which reveal that there is no differential effect for products high in the labor intensity scale.

[Table F3 about here.]

F.2 Convergence

A possible drive of our results is a simple "convergence" story: the industries in which former Yugoslavian countries gain comparative advantage in the mid 2000s are the same ones in which Germany had comparative advantage in 1990. This concern, in fact, could also violate the exclusion restriction of our instrument, given that we exploit the relative size of industries in Germany in 1990 as an input to construct it. However, we rule out this possibility by adding to our baseline specification a control that deals exactly with that possibility. In particular, we include as a control an interaction between the share of exports of each product p in the German export basket in 1990 interacted with the $after_t$ term. The results are presented in Table F4 and are robust to our baseline estimations presented in Section 4.

[Table F4 about here.]

[55] The left hand side in Table F1 is divided by thousands of people, while the right hand side in table F2 is divided by millions of people. We do this different scaling for presentation purposes only.

F.3 Foreign Direct Investment

A possible channel explaining our results is that the distribution of returning refugees by industry are correlated with FDI inflows, which could in turn explain export dynamics. If this is the case, our main specification would suffer from omitted variable bias. We relieve these concerns by showing that our baseline estimations are robust to controlling for FDI in Yugoslavia.

First, Table F5 controls for per-industry FDI stocks (exploiting the before and after) from Germany in Yugoslavia. German FDI data was sent to us by the German Central Bank (*Deutsche Bundesbank*) upon request. We use these data to compute German FDI stocks in former Yugoslavian countries at 2-digit SITC level between the years 1990-2010, to serve as a control.

[Table F5 about here.]

Second, Table F5 controls for Global FDI stocks in Yugoslavia in the same form as explained above. The data comes from The Vienna Institute for International Economic Studies (wiiw).[56]

[Table F6 about here.]

Overall our main results are robust to the inclusion of FDI stocks. Strangely, both tables above show that FDI is negatively correlated with exports, which is puzzling. If anything, we would expect this control to have a positive sign. To explore what is that drives this unexpected relationship we reestimate a variation of specification (1) that only includes the FDI variable on the right hand side. That is, we are analyzing the partial correlation between exports and FDI in our setting. The results are presented in Table F7. Columns 1-3 uses both product and year fixed effects, while columns 4-6 only uses year fixed effects. We can see that when excluding the product fixed effects the partial correlation between exports and FDI is estimated to be a positive one, as expected. This occurs, plausibly, because introducing the product fixed effects leave very little variation to be use in the estimation of the FDI coefficient, particularly because the FDI figures are defined at the 2 digit level, and the fixed effects at the 4-digit level. All in all, we find that when excluding the product fixed effects, products that have more FDI during that period explain larger exports, as it is to be expected.

[Table F7 about here.]

F.4 Bilateral transaction trade costs

An alterantive explanation to our results is that the returning refugees, through the networks they've created in Germany, facilitate exports by lowering transaction costs or non-tariff barriers between parties. At first, we should not worry much about this possibility, given that our dependent variable already excludes exports to Germany.

However, we rule out this possibility driving our results. We do this by estimating the effect of the treatment for both differentiated and homogenous or reference-priced goods, using the classification

[56] Given the lack of data of FDI stocks in Yugoslavia disaggregated by product before its dissolution, we assume the stock was zero in the "before" period of 1990. This assumption would arguably "work against us".

by Rauch (1999). We do so by re-estimating specification (1), this time interacting the term $treat_p \times after_t$ with indicator on whether the product under consideration is a classified as a differentiated good. The results are in Table F8, which reveal that there is no premium of our treatment on differentiated goods.

[Table F8 about here.]

We also test for and rule out an additional related explanation: returning refugees fostering imports of intermediate inputs needed for the production of the exported good. To explore this possibility we use the US historical benchmark input output tables put together by the Bureau of Economic Activity for year 2002 based on the NAICS classification,[57] and match the input-output coefficients to SITC 4-digits using the same procedure as Cuñat and Melitz (2012) (described in their footnote 24 and their subsequent documentation). Note that both the input-output coefficients as well as the concordances is based on US data. While not ideal, we believe this is a good approximation for our purposes. We then incorporate in the estimation as a control, for each product p, the weighted sum of imports from Germany based on the input-output coefficient (e.g., US dollars of each input needed to produce 1 US$ of output), both in the "before" and the "after" period (using the inverse asymptotic sine transformation). This estimation is presented in Table F9, and they are robust to our main results.

[Table F9 about here.]

Finally, if our results were mostly driven by transaction costs we would find a much stronger coefficient when including exports to Germany in our left hand side variable. However, that is not the case. Table F10 presents results with total exports from Yugoslavian countries to the rest of the world, including to Germany, and results are quite similar.

[Table F10 about here.]

[57] The data was downloaded from https://www.bea.gov/industry/historical-benchmark-input-output-tables in May of 2019.

Table F1: DID, exports per capita

Dependent variable: $exports_{p,t}/pop_t$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0874	0.1153	0.1127	0.1051	0.1435	0.1368
	(0.037)**	(0.034)***	(0.036)***	(0.047)**	(0.044)***	(0.046)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.86	0.86	0.86	0.86	0.86
F Stat				14.31	14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for exports per capita (with population rescaled in thousands of people) in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table F2: DID, returning refugees per capita

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000pc × after2005	0.1578	0.2379	0.2405	0.2108	0.3260	0.3306
	(0.073)**	(0.102)**	(0.105)**	(0.094)**	(0.119)***	(0.122)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				15.61	15.76	15.76

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. The treatment is divided by the Yugoslavian population (rescaled in millions of people) for year 2000. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table F3: DID, labor intensive

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
TreatmentXAfter	0.0948	0.1546	0.1558	0.0559	0.0768	0.0766
	(0.039)**	(0.078)**	(0.081)*	(0.062)	(0.075)	(0.077)
treatXafterXlaborint	0.0028	-0.0059	-0.0062	0.0194	0.0185	0.0185
	(0.017)	(0.023)	(0.024)	(0.023)	(0.025)	(0.025)
N	1280	1364	1364	1280	1364	1364
r2	0.86	0.79	0.78	0.86	0.79	0.78
F Stat				6.28	6.34	6.34

This table shows result of the 2SLS estimation for specification (1), interacting the term $treat_p \times after_t$ with one variable indicating the intensity of labor usage in the industry. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table F4: DID, incl. convergence control

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0837	0.1358	0.1376	0.0840	0.1735	0.1775
	(0.038)**	(0.063)**	(0.066)**	(0.059)	(0.072)**	(0.074)**
germanexpshare1990 × after2005	6.3680	-0.1571	-0.4415	6.3419	-4.2325	-4.7445
	(4.325)	(6.815)	(7.001)	(6.719)	(10.753)	(11.072)
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				33.96	34.68	34.68

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. The treatment is divided by the Yugoslavian population (rescaled in millions of people) for year 2000. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table F5: DID, controlling for German FDI

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0917	0.1433	0.1451	0.1271	0.1955	0.1984
	(0.037)**	(0.062)**	(0.065)**	(0.051)**	(0.066)***	(0.067)***
lnfdi	-0.1583	-0.2702	-0.2749	-0.1608	-0.2741	-0.2789
	(0.066)**	(0.126)**	(0.130)**	(0.066)**	(0.127)**	(0.131)**
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.82	0.81	0.86	0.82	0.81
F Stat				14.37	14.45	14.45

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. It includes as a control the German FDI stock in Yugoslavia by industry. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table F6: DID, controlling for Global FDI

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0788	0.1268	0.1284	0.1193	0.1790	0.1814
	(0.037)**	(0.062)**	(0.065)**	(0.046)**	(0.058)***	(0.059)***
lnglobalfdi	-0.1044	-0.1362	-0.1372	-0.0993	-0.1311	-0.1320
	(0.050)**	(0.084)	(0.087)	(0.050)**	(0.083)	(0.086)
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.82	0.81	0.86	0.82	0.81
F Stat				14.41	14.47	14.47

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. It includes as a control the Global FDI stock in Yugoslavia by industry, as opposed to the Germany FDI stock only. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$

Table F7: Exports vs. FDI

Dependent variable: $exports_{p,t}$						
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
lnfdi	-0.1518	-0.2594	-0.2640	0.1421	0.2519	0.2573
	(0.066)**	(0.125)**	(0.130)**	(0.062)**	(0.090)***	(0.092)***
Constant				14.5291	13.8752	14.5372
				(0.146)***	(0.220)***	(0.225)***
N	1496	1572	1572	1524	1572	1572
r2	0.86	0.82	0.81	0.03	0.02	0.02
Product FE	Y	Y	Y	N	N	N

This table shows result of the estimation for specification (1) that only includes FDI stock as the right hand side variable, using different monotonic transformations for $exports_p, t$ in each column. The first 3 columns include product fixed effects and the following 3 columns do not include those product fixed effects. All columns include year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table F8: DID, differentiated goods

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
TreatmentXAfter	0.0712	0.1304	0.1329	0.0178	0.1315	0.1369
	(0.050)	(0.073)*	(0.075)*	(0.068)	(0.112)	(0.116)
treatXafterXdiff	0.0695	0.0678	0.0677	0.0940	0.0375	0.0345
	(0.042)*	(0.042)	(0.042)	(0.055)*	(0.088)	(0.090)
N	1356	1408	1408	1356	1408	1408
r2	0.86	0.80	0.79	0.86	0.80	0.79
F Stat				7.59	7.75	7.75

This table shows result of the 2SLS estimation for specification (1), interacting the term $treat_p \times after_t$ with one variable indicating whether the product is a differentiated one. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table F9: DID, controlling for imports of intermediate goods

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0752	0.1411	0.1436	0.0744	0.1258	0.1276
	(0.036)**	(0.074)*	(0.077)*	(0.051)	(0.068)*	(0.069)*
lnioimpdeu	0.0983	0.0615	0.0623	0.0983	0.0636	0.0644
	(0.149)	(0.304)	(0.317)	(0.149)	(0.308)	(0.321)
N	1428	1572	1572	1428	1572	1572
r2	0.86	0.79	0.79	0.86	0.79	0.79
F Stat				13.91	14.04	14.04

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. It includes as a control the total imports from Germany in each period of intermediate goods used in the production of the product under consideration (weighted by 2002 input-output coefficients based on data from the US Bureau of Economic Activity). The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table F10: DID, including exports to Germany

Dependent variable: $exports_{p,t}$						
	OLS			2SLS		
	lnexp	lnexpplus1	asinhexp	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0875	0.1357	0.1373	0.1053	0.1597	0.1620
	(0.037)**	(0.062)**	(0.064)**	(0.047)**	(0.058)***	(0.059)***
N	1496	1572	1572	1496	1572	1572
r2	0.86	0.81	0.81	0.86	0.81	0.81
F Stat				14.31	14.42	14.42

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses average exports for years 1988 to 1990 in the initial period and average exports for years 2005 to 2007 in the end period. The dependent variable includes exports to Germany. The first three columns report results from an OLS estimation, while the last three columns report results from a 2SLS estimation. All columns include product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

G Occupations by characteristics

Table G1 presents the list of all the occupations in the dataset, with their respective frequency, and associated characteristics.

[Table G1 about here.]

[Table G2 about here.]

Table G1: Occupations List

Occupation	Occurrences	Tasks	Prof. skills	Share supervisor
323 Metal workers (no further specification)	968	2 manual	1 unskilled	.21722362
51 Gardeners, garden workers	858	2 manual	1 unskilled	.18927162
531 Assistants (no further specification)	787		1 unskilled	.11138389
522 Packagers, goods receivers, despatchers	719	2 manual	1 unskilled	.09713266
151 Plastics processors	698	2 manual	1 unskilled	.27068706
181 Wood preparers	602	2 manual	1 unskilled	.09192798
391 Bakery goods makers	555	2 manual	2 skilled	.36883311
744 Stores, transport workers	543	2 manual	1 unskilled	.10129447
501 Carpenters	498	2 manual	2 skilled	.23684861
62 Forest workers, forest cultivators	483	2 manual	1 unskilled	.20126734
402 Meat, sausage goods makers	442	2 manual	1 unskilled	0
271 Building fitters	396	2 manual	2 skilled	.15821244
470 Building labourer, general	386			
933 Household cleaners	376	2 manual	1 unskilled	.07903877
322 Other assemblers	312	2 manual	1 unskilled	.04823485
411 Cooks	266	2 manual	2 skilled	.28007612
682 Salespersons	263	1 analytic	1 unskilled	.1624328
101 Stone preparers	257	2 manual	1 unskilled	.23494546
141 Chemical plant operatives	257	1 analytic	1 unskilled	.28136134
321 Electrical appliance, electrical parts assemblers	250	2 manual	1 unskilled	.14907955
275 Steel structure fitters, metal shipbuilders	250	2 manual	2 skilled	.19518355
112 Shaped brick, concrete block makers	244	2 manual	1 unskilled	.22286043
401 Butchers	239	2 manual	2 skilled	.29524547
442 Concrete workers	232	2 manual	1 unskilled	.41252334
163 Book binding occupations	210	2 manual	2 skilled	.13312343
273 Engine fitters	186	1 analytic	2 skilled	.2418478
521 Goods examiners, sorters, n.e.c.	183	1 analytic	1 unskilled	.17720443
241 Welders, oxy-acetylene cutters	173	2 manual	1 unskilled	.16681339
412 Ready-to-serve meals, fruit, vegetable preservers, preparers	169	2 manual	1 unskilled	0
714 Motor vehicle drivers	168	2 manual	1 unskilled	.07980934
311 Electrical fitters, mechanics	151	1 analytic	2 skilled	.31535207
741 Warehouse managers, warehousemen	146	1 analytic	1 unskilled	.36790809
352 Clothing sewers	141	2 manual	1 unskilled	0
392 Confectioners (pastry)	136	2 manual	2 skilled	.23874688
41 Land workers	135	2 manual	1 unskilled	.03541072
431 Milk, fat processing operatives	119	2 manual	1 unskilled	.18633992
211 Sheet metal pressers, drawers, stampers	111	2 manual	1 unskilled	0
270 Locksmiths, not specified	108	2 manual	2 skilled	.27546819
433 Sugar, sweets, ice-cream makers	107	2 manual	1 unskilled	.55506282
441 Bricklayers	105	2 manual	2 skilled	.39556132
177 Printer's assistants	102	2 manual	1 unskilled	.19699555
432 Flour, food processors	98	2 manual	1 unskilled	.27100673
143 Rubber makers, processors	95	2 manual	1 unskilled	.24792283
482 Insulators, proofers	85	2 manual	1 unskilled	.35678298
221 Turners	84	1 analytic	2 skilled	.23881324
512 Goods painters, lacquerers	83	2 manual	1 unskilled	.25905095
164 Other paper products makers	79	2 manual	1 unskilled	0
261 Sheet metal workers	79	2 manual	2 skilled	.34136059
451 Carpenters	76	2 manual	2 skilled	.32004301

This table presents the first part of the list of all the occupations in the dataset, with their respective frequency and associated characteristics.

Table G2: Occupations List (cont.)

Occupation	Occurrences	Tasks	Prof. skills	Share supervisor
111 Stoneware, earthenware makers	74		1 unskilled	0
212 Wire moulders, processors	72	2 manual	1 unskilled	.3442623
303 Dental technicians	71	2 manual	2 skilled	.19073161
272 Sheet metal, plastics fitters	68		2 skilled	0
472 Other building labourers, building assistants, n.e.c.	66	2 manual	1 unskilled	.12660338
742 Transportation equipment drivers	66	2 manual	1 unskilled	.0789034
781 Office specialists	66	1 analytic	2 skilled	.26168916
162 Packaging makers	60	2 manual	1 unskilled	.04646367
135 Glass processors, glass finishers	60	2 manual	1 unskilled	.14649977
121 Ceramics workers	59	2 manual	1 unskilled	.05361638
274 Plant fitters, maintenance fitters	57	2 manual	2 skilled	.23151613
161 Paper, cellulose makers	54	2 manual	1 unskilled	.49392581
71 Miners	53	2 manual	1 unskilled	.1553002
251 Steel smiths	50	2 manual	2 skilled	.04485785
263 Pipe, tubing fitters	49	2 manual	1 unskilled	.3949083
262 Plumbers	49	2 manual	2 skilled	.26210474
356 Sewers, n.e.c.	48	2 manual	1 unskilled	.04908014
492 Upholsterers, mattress makers	48	2 manual	2 skilled	.12503124
923 Other housekeeping attendants	47	2 manual	1 unskilled	.08383468
376 Leather clothing makers and other leather processing operatives	45	2 manual	1 unskilled	
373 Footwear makers	44	2 manual	1 unskilled	0
937 Machinery, container cleaners and related occupations	44	2 manual	1 unskilled	.05061111
81 Stone crushers	43		1 unskilled	0
313 Electric motor, transformer fitters	39	1 analytic	1 unskilled	.13471446
485 Glaziers	39	2 manual	2 skilled	.1977815
403 Fish processing operatives	36	2 manual	1 unskilled	.5
371 Leather makers, catgut string makers	35	2 manual	1 unskilled	0
225 Metal grinders	35	2 manual	1 unskilled	.28720212
284 Precision mechanics	35	1 analytic	2 skilled	.16234579
285 Other mechanics	34	2 manual	2 skilled	.2512635
462 Road makers	33	2 manual	1 unskilled	.26799082
291 Toolmakers	32	2 manual	2 skilled	.21778998
224 Borers	31	2 manual	1 unskilled	0
931 Laundry workers, pressers	31	2 manual	1 unskilled	.1339676
222 Drillers	30	1 analytic	1 unskilled	.15145272
82 Earth, gravel, sand quarriers	29		1 unskilled	
282 Agricultural machinery repairers	29	2 manual	2 skilled	.30161076
466 Other civil engineering workers	28	2 manual	1 unskilled	.42729718
314 Electrical appliance fitters	28	1 analytic	2 skilled	.26680461
44 Animal keepers and related occupations	25	2 manual	1 unskilled	.35544285
281 Motor vehicle repairers	25	1 analytic	2 skilled	.34470057
234 Galvanisers, metal colourers	24	2 manual	1 unskilled	.14969613
213 Other metal moulders (non-cutting deformation)	24	2 manual	1 unskilled	0
203 Semi-finished product fettlers and other mould casting occupations	24	2 manual	1 unskilled	.1735251
331 Spinners, fibre preparers	24	2 manual	2 skilled	.48452174
935 Street cleaners, refuse disposers	22	2 manual	1 unskilled	.30638207
342 Weavers	21	2 manual	1 unskilled	0
353 Laundry cutters, sewers	21	2 manual	1 unskilled	0
344 Machined goods makers	21	2 manual	1 unskilled	0
423 Other beverage makers, tasters	20	2 manual	2 skilled	.64293598
784 Office auxiliary workers	20	1 analytic	1 unskilled	.09301868

This table presents the second part of the list of all the occupations in the dataset, with their respective frequency and associated characteristics.

H Estimations using treatments by educational attainment and occupations characteristics

Table 6 in the main body of the paper summarized the results exploiting heterogeneity of the treatment in terms of the skills and occupation characteristics of the workers. Tables H1 to H5 below present results for each estimation separately.

[Table H1 about here.]

[Table H2 about here.]

[Table H3 about here.]

[Table H4 about here.]

[Table H5 about here.]

Table H1: Difference-in-differences (OLS), workers' education

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
Unskilled × after2005	0.0816		-0.2783	0.1337		-0.1901	0.1355		-0.1863
	(0.040)**		(0.120)**	(0.064)**		(0.140)	(0.066)**		(0.142)
Skilled × after2005		0.1267	0.4106		0.1747	0.3695		0.1763	0.3673
		(0.042)***	(0.126)***		(0.067)***	(0.138)***		(0.069)**	(0.140)***
N	1496	1496	1496	1572	1572	1572	1572	1572	1572
Adj R2	0.86	0.86	0.86	0.81	0.81	0.82	0.81	0.81	0.81

This table shows result of the estimation for specification (1) using treatments constructed by aggregating workers by groups based on their educational level. The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_p, t$ in different columns. All columns include FDI as control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$

Table H2: Difference-in-differences (OLS), workers' occupation tasks

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
Manual × after2005	0.0794		0.0221	0.1280		0.0706	0.1297		0.0723
	(0.038)**		(0.054)	(0.061)**		(0.074)	(0.063)**		(0.076)
Analytical/Cognitive × after2005		0.1611	0.1339		0.2235	0.1345		0.2256	0.1345
		(0.054)***	(0.076)*		(0.079)***	(0.078)*		(0.081)***	(0.078)*
N	1496	1496	1496	1572	1572	1572	1572	1572	1572
Adj R2	0.86	0.86	0.86	0.81	0.81	0.81	0.81	0.81	0.81

This table shows result of the estimation for specification (1) using treatments constructed by aggregating workers by groups based on the intensity of tasks linked to their occupations (manual vs. analytical). The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_p, t$ in different columns. All columns include FDI as control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table H3: Difference-in-differences (OLS), workers' occupation skill level

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
Low-skill Profession × after2005	0.0825		0.0073	0.1324		0.0590	0.1342		0.0607
	(0.039)**		(0.064)	(0.065)**		(0.094)	(0.067)**		(0.097)
High-skill Profession × after2005		0.1308	0.1232		0.1839	0.1216		0.1857	0.1217
		(0.043)***	(0.070)*		(0.062)***	(0.079)		(0.064)***	(0.080)
N	1496	1496	1496	1572	1572	1572	1572	1572	1572
Adj R2	0.86	0.86	0.86	0.81	0.81	0.81	0.81	0.81	0.81

This table shows result of the estimation for specification (1) using treatments constructed by aggregating workers by groups based on the skill level of their occupation. The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_p, t$ in different columns. All columns include FDI as control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Table H4: Difference-in-differences (OLS), workers' occupation supervision intensity

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
Non-supervisor × after2005	0.0913		-0.0555	0.1396		0.0200	0.1413		0.0218
	(0.039)**		(0.108)	(0.064)**		(0.175)	(0.066)**		(0.181)
Supervisor × after2005		0.1475	0.2215		0.2098	0.1827		0.2120	0.1825
		(0.049)***	(0.136)		(0.074)***	(0.195)		(0.076)***	(0.201)
N	1496	1496	1496	1572	1572	1572	1572	1572	1572
Adj R2	0.86	0.86	0.86	0.81	0.81	0.81	0.81	0.81	0.81

This table shows result of the estimation for specification (1) using treatments constructed by aggregating workers by groups based on the supervision intensity of their occupation. The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_p, t$ in different columns. All columns include FDI as control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Table H5: Difference-in-differences (OLS), workers' wage growth

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
Slow growth wage × after2005	0.0926		-0.0518	0.1453		-0.0357	0.1471		-0.0348
	(0.044)**		(0.210)	(0.068)**		(0.223)	(0.070)**		(0.224)
Fast growth wage × after2005		0.0968	0.1474		0.1495	0.1845		0.1513	0.1853
		(0.043)**	(0.207)		(0.069)**	(0.227)		(0.071)**	(0.229)
N	1496	1496	1496	1572	1572	1572	1572	1572	1572
Adj R2	0.86	0.86	0.86	0.81	0.81	0.81	0.81	0.81	0.81

This table shows result of the estimation for specification (1) using treatments constructed by aggregating workers by groups based on the wage growth during their stay. The table presents OLS estimations. Each group of results uses different monotonic transformations for $exports_p, t$ in different columns. All columns include FDI as control, as well as product fixed effects and year fixed effects. Standard errors clustered at the product level presented in parenthesis.
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

I Expanding to all countries: external validation

After having established the link between migration and comparative advantage, we turn to study the same phenomenon in a multi-country and multi-period setting. In this setting our focus is not on the identification, but rather on externally validating the results, while exploiting a much larger variation allowing us to study differential effects based on the characteristics of the migrants. That is, we expand our difference-in-difference strategy to all countries in the original dataset using as treatment the presence and sizes of their diasporas in Germany working in different 4-digit products.

The sample for this estimation includes 124 countries and 786 products across two periods: 1990 to 2000 and 2000 to 2010. The IAB data allows us to compute the stock of migrants from each country in Germany in both years.

I.1 Empirical strategy and summary statistics

In this section we adapt our difference-in-difference specification to a multi-country multi-period setting. To do that, we follow Besley and Burgess (2004) and estimate the following specification:

$$exports_{c,p,t} = \beta^{DID} migrants_{c,p,t-10} + \beta^{ge} globalexports_{p,t} + \eta_{c,p} + \alpha_{c,t} + \varepsilon_{c,p,t} \quad \text{(I1)}$$

Our dependent variable, $exports_{c,p,t}$, is defined as total export value of product p during year t from country c to the rest of the world, excluding Germany in order to rule out that our results are driven by lower costs to export due to migrant networks. Similarly to the previous section, we present our results for different monotonic transformations of the dependent variable. Our variable of interest, the treatment, in this case is $migrants_{c,p,t-10}$, which is the stock of migrants from country c at time $t-10$ (e.g., we allow for a 10-year lag for the treatment to "kick in") working in product p in the German labor force. We also include a series of fixed effects, crucial for the estimation. Since we have expanded the dimension of our dataset to include countries our unit of analysis becomes now a country-product pair. Thus, we include $\eta_{c,p}$ which is a country-by-product fixed effects, to allow each country-product to have a different intercept and also, in the difference-in-difference setting, allows us to exploit within country-product variation. We also include $\alpha_{c,t}$, a country-by-year fixed effect, which controls for changes at the country level that could explain changes in exports: income, population, institutions, etc. We also include $globalexports_{p,t}$, which in measures the total export value of product p by all countries during year t, to control for total global demand, and as a proxy for the introduction of a technology that explains a global increase in the exports of product p.[58] All of the continuous right hand side variables are monotonically transformed using the inverse hyperbolic sine. Our estimations cluster standard errors at the country-product level (Besley and Burgess, 2004; Bertrand et al., 2004).

Note that this specifications is equivalent to the DID. To see it, suppose the following two specifications: The first one where the treatment is defined as a difference, and the second one where the treatment is defined as a level:

[58] Ideally, we would introduce a product-by-year fixed effect but turns out doing so eliminates most of the remaining variation.

$$y_{p,t} = \beta_1 \Delta migrants_p \times after_t + \delta_t + \eta_p + \varepsilon_{p,t}$$
$$y_{p,t} = \beta_2 migrants_{p,t} + \delta_t + \eta_p + \varepsilon_{p,t}$$

Assume there are only two periods, $t = [0, 1]$. According to the first functional form, we have:

$$E(y_{p,t}|t = 1) = \beta_1 \Delta migrants_p + \delta_1 + \eta_p + \varepsilon_{p,1}$$
$$E(y_{p,t}|t = 0) = \delta_0 + \eta_p + \varepsilon_{p,0}$$

It is clear that $E(y_{p,t}|t = 1) - E(y_{p,t}|t = 0) = \beta_1 \Delta migrants_p + (\delta_1 - \delta_0) + (\varepsilon_{p,1} - \varepsilon_{p,0})$. According to the second functional form, we have:

$$E(y_{p,t}|t = 1) = \beta_2 migrants_{p,1} + \delta_1 + \eta_p + \varepsilon_{p,1}$$
$$E(y_{p,t}|t = 0) = \beta_2 migrants_{p,0} + \delta_0 + \eta_p + \varepsilon_{p,0}$$

Thus, in this case, $E(y_{p,t}|t = 1) - E(y_{p,t}|t = 0) = \beta_2(migrants_{p,1} - migrants_{p,0}) + (\delta_1 - \delta_0) + (\varepsilon_{p,1} - \varepsilon_{p,0})$. Since $\Delta migrants_p = migrants_{p,1} - migrants_{p,0}$ it follows that $\beta_1 = \beta_2$.

Results are presented in Table I1. The elasticity parameter is estimated to be between 0.08 and 0.11, which falls inside the range of the main results of the paper, using the natural experiment setting. In this case, the point estimate when the dependent variable is a simple logarithmic transformation is lower than in the other columns where the monotonic transformation does include the zeros. This suggests, also consistently with the main results, that return migration (this time computed as the difference in the stock) is also explanatory of the extensive margin (e.g., the emergence of new export sectors).

[Table I1 about here.]

Table I1: DID, all countries

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
Migrants (asinh lagged)	0.0822	0.1290	0.1268
	(0.015)***	(0.030)***	(0.032)***
Global exp (asinh)	0.8862	0.4564	0.4763
	(0.016)***	(0.011)***	(0.012)***
Constant	-5.8210	0.7103	0.8078
	(0.367)***	(0.249)***	(0.260)***
N	115170	163488	163488
Adj R2	0.94	0.91	0.90
cpFE	Y	Y	Y

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses years 2000 and 2010 for exports and 1990 and 2000 for migration. All columns include country-by-product fixed effects and country-by-year fixed effects. Standard errors clustered at the country-product level presented in parenthesis.

$^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$