Diasporas, return migration and comparative advantage: a natural experiment of Yugoslavian refugees in Germany*

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Latest Update: August 15, 2017

[PRELIMINARY DRAFT, PLEASE DO NOT DISTRIBUTE]

Keywords: migration, refugees, diaspora, comparative advantage, exports

JEL Classification Numbers: F14, F22, F62, O33, D83

*Authors acknowledge helpful comments by Wolfgang Dauth, Florian Lehmer, Ofer Malamud, Britta Matthes, Ljubica Nedelkoska and Ariell Reshef.

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Abstract

Between 1995 and 2000, hundreds of thousands of Yugoslavian refugees in Germany lost their temporary protection and many returned to their native countries in the former Yugoslavia. In this paper we exploit this episode to provide causal evidence on the role migrants play in expansion of the export baskets of their home countries after their return. We find that the elasticity of exports to return migration is between 0.1 and 0.25 in industries were migrants were employed during their stay in Germany. By expanding the sample to all countries we find our results to be externally valid. We also find that this effect is over ten times stronger for migrant workers in white collar occupations, as opposed to non-white collars. Similarly, the effect is 3 and 4 times larger upon return migration of workers with occupations intensive in analytical and cognitive tasks (as opposed to manual ones) and with high problem-solving content (as opposed to low content), respectively. Our results point to knowledge diffusion as the main channel driving the link between migration and productivity as measured by changes in comparative advantage.

1 Introduction

When Dov Frohman left Intel Corporation in 1974 and returned back to his native Israel, he was tasked to set up Intel's first research and development center outside the United States. This event, arguably, marked the beginning of the subsequent fast growth of the Israeli semi-conductor industry which resulted in the country becoming an important computer hardware manufacturer and exporter. In fact, the economic literature has looked at the role of migrants in serving as vehicles of knowhow between countries that could result in the lower transaction costs for trade (e.g., Parsons and Vézina, 2017), for foreign investment (e.g., Kugler et al., 2017) and transferring productive knowledge that results in the emergence of new export sectors (e.g., Bahar and Rapoport, 2017). In this paper we explore the role of migrants, and in particular diasporas and return migrants, in shaping the composition of the export basket of their home countries.

In particular, we estimate changes in exports to the rest of the world as explained by return migration of workers employed in that same sector in Germany. To do so, we start by focusing on one particular case which its historical context presents a neat natural experiment for this purpose: the case of refugees of Yugoslavian origin in Germany during the early 1990s. Following the Balkan wars, between 300 and 400 thousand Yugoslavian refugees (mostly from Bosnia) were admitted into Germany and given temporary protection status as well and work permits. Yet, after the Dayton peace agreements were signed in 1995, most of the refugees lost their protection status and work permits and thus were forced to leave the country. By 2000, about two thirds of them had left and a large proportion, in fact, returned to the countries of the former Yugoslavia. We exploit the short stay of these refugees in Germany and the subsequent massive inflow of return migrants –with experience in the German workforce– into the former Yugoslavian countries, to study sector-specific productivity shifts as measured by exports.[1] To do so we rely on confidential data from the German Institute for Employment Research (IAB), which we use to compute the number of Yugoslavian migrants working in a particular 4-digit 786 industries before and after the Balkan refugee crisis. We link this information to standard disaggregated international trade data, to employ a difference-in-difference methodology and estimate changes in export values from Yugoslavian countries to the rest of the world caused by return migration of Yugoslavian workers in Germany. We find that, on average, products with a rate of return migration 10 percent higher, experienced an increase in exports to the rest of the world of 0.8 to 1.5 percent between 1995 to 2005. In fact, the estimated elasticity increases the more time goes by after the refugees had returned. Our results cannot be explained by an existing previous trend on exports, nor by lower bilateral transaction costs as our measure of exports from Yugoslavia to the rest of the world excludes exports to Germany.

We then explore the external validity of our results by expanding our methodology to a multi-country and multi-period setting. In this setting we estimate changes in exports for over 100 countries and close to 800 products as explained by changes in stocks of migrant workers in Germany in two periods: 1990 to 2000 and 2000 to 2010. Through this exercise we estimate elasticities that range between 0.09 to 0.11, remarkably similar to the ones

[1]Following Bahar et al. (2014) and Bahar and Rapoport (2017) we assume that, after controlling for global demand, changes in export value for a particular product proxies for productivity improvements.

estimated using the Yugoslavian natural experiment.

We interpret this set of results as driven by the diffusion of productive knowledge: migrant workers exposed to industries in Germany bring back knowledge on methodologies or technologies back home that translates into higher productivity in those same industries. This is consistent with a burgeoning literature that looks at migrants (and descendants) as drivers of knowledge diffusion (e.g., Kerr, 2008; Choudhury, 2016; Hausmann and Neffke, 2016; Bahar and Rapoport, 2017), as the transmission of tacit or non-codifiable knowledge requires human interaction (Arrow, 1969; Polanyi, 1966). To further dig into this, we also exploit variation in the characteristics of the different occupations of the migrant workers with the premise that certain types of workers and their occupations are more suited for diffusing productivity-inducing knowhow across borders. The richness of our data allows us to say something beyond aggregated measures of human capital. In particular, we find that workers in "white collar" occupations are about 11 times more "effective" in explaining changes in exports than non-white collars. Similarly, we find that workers in occupations that intensive in analytical and cognitive tasks or with high problem-solving content are about 3 and 4 times more effective in explaining exports than occupations intensive in manual tasks or with low problem-solving content, respectively. All this put together reinforces the idea that the driving force behind our results is the diffusion of knowledge.

This paper contributes to the literature of international economics and economic development in several ways. First, to the best of our knowledge, is the first study that uses a neat natural experiment as a source of identification to causally estimate changes in exports due to return migration. Thus, our findings suggest that migrants are a determinant in the evolution of the comparative advantage of nations (e.g., Bahar and Rapoport, 2017). Second, we contribute to the literature that studies international knowledge diffusion by exploring differential effects based on occupation types of workers, adding to the evidence that migrants are, in fact, a powerful driver of the international diffusion of knowledge (e.g., Keller, 2004). Third, we contribute to the literature of economic development by linking the role of migrants in the diversification of countries' export baskets, which is evidenced to correlate with economic stability and growth (e.g., Krishna and Levchenko, 2009; Koren and

Tenreyro, 2007; Hausmann et al., 2006; Imbs and Wacziarg, 2003; Hausmann and Klinger, 2007; Cadot et al., 2011).

The rest of the paper is divided as follows: Section 2 provides a historical summary of the Yugoslavian refugee crisis; Section 3 details the data sources; Section 4 explains the empirical strategy and present results for the Yugoslavia case; Section 5 extends the results to all countries and explores differential results based on types of migrant workers' occupations; and Section 6 concludes.

2 Historical context

When the former Yugoslavia started to disintegrate in June of 1991, around 3.7 million people (roughly 16 percent of the population) left their homes to escape the armed conflict. The conflict in the Balkans fueled the largest migration flow in Europe since the end of the second World War. While many affected by the war became internally displaced (moving to areas dominated by their own ethnic group), an important amount of people –about 735 thousand– resettled outside of the boundaries of the former Yugoslavia (Lederer, 1997). While displacement occurred among all regions of the former Yugoslavia, the vast majority were Bosnians (Valenta and Strabac, 2013).

[Table 1 about here.]

Table 1 shows that, outside the former Yugoslavia, Germany was the largest recipient of refugees, admitting about 350 thousand of them in the first half of the 1990s (Radović et al., 2005). This corresponds to almost half of the refugees that took shelter outside of the former Yugoslavia.[2][3]

[2] Of the 350 thousand refugees, about 320,000 are estimated to have come from Bosnia-Herzegovina. Due the size and the speed of the influx, official numbers suffer from measurement error. Moreover, all the refugees held Yugoslavian passports which made the distinction impossible. Appendix Table A1 presents figures for refugees originating from Bosnia-Herzegovina.

[3] There are two major factors behind the large variation in numbers of admitted refugees across countries. First, while most countries opened their borders to refugees in the early 1990s, some of them blocked the inflow of refugees relatively quickly and some others held their borders open for a longer time. Second, countries that had already large Bosnian, Croatian and Serbian migrant communities (such as Germany, Austria and Australia, for example) admitted more refugees, due to the lobby performed by these local migrant communities (Valenta and Strabac, 2013).

A large number of the refugees who arrived to Germany early on were given temporary protection status (TPS), or *Duldung* in German, which means "toleration" in English, implying that refugees with Duldung status were "tolerated" in Germany for a limited period of time. Legally, refugees with Duldung status suspended their deportation temporarily (USCRI, 2000). This status had to be renewed every six months until return to the home country was possible (Liedtke, 2002).

Nevertheless, despite the limitations, refugees who arrived before May 1997 and had a Duldung status could apply for a work permit (*Arbeitserlaubnis*) for a specific job (Liedtke, 2002). This status allowed them to work without any geographical, sectoral nor occupational limit. Yet, according to the law, eligible jobs were those that could not be filled by a German citizen or a lawful permanent resident. Thus, the actual jobs that refugees could get was somewhat limited by the supply of jobs not filled by native and lawful resident jobseekers. While many of the jobs taken by refugees were not skill intensive, there were refugees working in many different sectors of the economy.

Despite accepting the largest share of refugees, Germany firmly maintained the temporary aspect of their protection status. In fact, only a day after the signing of the Dayton Peace Accord on December 14 of 1995, Germany developed a repatriation plan through which refugees were gradually forced to leave the country. To accomplish this, the authorities revoked refugees' work permits and rolled out assisted repatriation programs (Bosswick, 2000). In early 1997 the governments of Germany and Bosnia-Herzegovina signed a treaty to accelerate the repatriation of migrants. Forced repatriation was planned in two phases. The first phase targeted single adults and childless couples as well as people with family back in Bosnia-Herzegovina. The second phase targeted the rest of the refugees. By the summer of 1996 letters requesting announcing deportation were sent and the first actual deportation took place on the end of 1996.

By autumn 1998 more than two thirds (about 250 thousand refugees) had left Germany. By 2005, almost all of the refugees had left. It is estimated that about 250 thousand went back to their home countries, while some other 50 thousand ended up in third countries (e.g., USA, Canada, Australia, etc). Very few of them –about 22 thousand– obtained permanent residency in Germany and avoided deportation (Dimova, 2006).

3 Data and sample

Data on exports comes from bilateral trade data compiled from UN Comtrade by Feenstra et al. (2005) with extensions and corrections suggested by Hausmann et al. (2014). The data covers the period 1984-2014. In most cases our dependent variable is exports by product from each country to the rest of the world excluding Germany (where migrant workers are located). We do this so that our results are not confounded with an increase in trade drive by lower transaction costs caused by migrant networks (e.g., Rauch and Trindade, 2002; Parsons and Vézina, 2017).

Products are defined using the 4-digit Standard Industry Trade Classification (SITC) revision 2.[4] 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 come from the Institute of Employment Research (IAB) of the German Federal Employment Agency.[5] The dataset, known as BeH, follows workers subject to social security contributions in the Germany labor force since 1975. It contains many of the workers' characteristics such as age, gender, education level, income, nationality[6] and occupation. It covers about 80 percent of the German workforce.[7] Our employment sample comes from BeH. It is a 40 percent random draw of foreigners employed (on June of) each year in between 1975 and 2014, amounting to about 2.5 mil-

[4]The words product, good, sector and industry interchangeably refer to the same concept throughout the paper.

[5]Others studies using this dataset are Card et al. 2013; Cornelissen et al. 2017; Dustmann and Glitz 2015; Dustmann et al. 2016

[6]We use the nationality of the worker based on the passport recorded in his or her first appearance in the database.

[7]Civil servants, soldiers and self-employed are not included in the data set.

lion workers per year on average. Using this sample we compute the stock of workers in Germany by nationality, product and year. We rely on the work by Dauth et al. (2014)to match German 3-digit WZ industry codes to 4-digit SITC products.

With these two datasets we are able to match the exports to the rest of the world in a given year for each country-product combination to the number of foreign workers in Germany linked to that country-product. The final sample encompasses 123 countries and 4-digit 786 products. In Section 4 we limit our sample to the former Yugoslavian countries (aggregated as one) to exploit the natural experiment provided by the historic context described above. Section 5 uses all countries in the sample to externally validate the results of the natural experiment as well as to exploit a much larger variation on workers' characteristics.

4 Natural Experiment: Yugoslavian Refugees

We start by exploring the role of return migration using the case of Yugoslavian refugees in Germany as a natural experiment. As pointed out in Section 2, around 400 thousand refugees from the former Yugoslavia –most of them Bosnians– arrived to Germany in between 1990 and 1993, who joined a country that had already a sizable population of Yugoslavian migrants. Figure (1) summarizes these numbers. In 1980 there were already about 600,000 Yugoslavians residing in Germany. This stock remained steady until the late 1980s where the net inflow of Yugoslavian migrants started to grow at a rate of 25,000 per year, until the year 1990. This rate skyrocketed to 168000, 250000 and 165000 during 1991, 1992 and 1993, respectively. The sharp increase in the net inflow of migrants was fueled by refugees escaping the war, which can be seen by the increase of asylum requests which almost reached 400 thousand during 1990 to 1994, combined. By 1995 there were about 1.35 million Yugoslavian migrants residing in Germany.

[Figure 1 about here.]

Yet, the number of Yugoslavian in Germany sharply declines starting in 1995, after the Dayton treaty was signed. By 2000 close to 250 thousand Yugoslavians had left the country.

By 2005, only some 22,000 (7 percent) were still living in Germany. While many of them left to a third country, it has been estimated that about 76 percent of them returned to countries of the (by then) former Yugoslavia. Our natural experiment is based on this sharp inflow and subsequent outflow of Yugoslavian migration into Germany. Our data allows us to identify the 4-digit industries where these migrants worked at during their stay in Germany, which we link to exports from Yugoslavia to the rest of the world in the years to come.

4.1 Empirical strategy and summary statistics

We explore the effect of return migrants from Germany on the export basket of former Yugoslavian countries through a difference-in-difference estimation. Given that the German data does not allow us to distinguish which is the region of origin of the refugees (we only see they entered the labor force with a Yugoslavian passport), our unit of analysis is the combined exports by product of all countries in the former Yugoslavia. That is, the trade data includes export by product of Yugoslavia as a nation until 1991, and we complement this by simply adding up exports by product of all countries that formed Yugoslavia post 1992: Bosnia and Herzegovina, Croatia, Macedonia, Montenegro, Serbia and Slovenia[8]. We end up having a balanced-panel of exports by product for the former Yugoslavia from 1984 until 2014, which is the main input to construct our dependent variable.

On the migration side, the treatment, we look at the number of return migrants post 1995, when the Dayton Accords were signed and when Germany started encouraging Yugoslavian refugees to leave. In particular we compute the number of refugees that left the labor force between 1995 and 2000 by product. We cannot distinguish whether these workers with Yugoslavian passport that left the labor force indeed returned back to the former Yugoslavia. We do know that about 77 percent of the refugees who left after 2000 went back to countries in the former Yugoslavia, but do not have that information at product level. Thus, in our calculation of return migration we are including workers who, for instance,

[8]Very few refugees left Slovenia, while it had a much more diversified export basket than the rest of the countries to begin with. Yet, our results are robust to excluding Slovenia from the exports data.

stayed in Germany working in the informal sector or went to a third country. Yet, all these possibilities work against us in our estimation, and thus our estimates are understating the effect of return migration.

Figure 2 describes the treatment variable. It plots the number of Yugoslavian workers by 4-digit product in German workforce in the tradable sector in 1995 (horizontal axis) and in 2000 (vertical axis). It becomes clear from the figure that there was a strong drop in Yugoslavian workers across the board after 1995, as all values lie below the 45 degree line. We consider this drop to be an exogenous shock. This allow us to construct a continuous treatment which is quite heterogenous across different products. Graphically, the constructed treatment for each product is the difference between the dot and the 45 degree.

[Figure 2 about here.]

Our estimation exploits changes in Yugoslavian exports by product to the rest of the world (excluding Germany) given different levels of return migration. Before we turn to the econometrics, we look at whether products associated with a larger reduction of workers in Germany experienced more exports. Figure 3 plots by product changes in exports from the former Yugoslavia (vertical axis) against changes in number of workers with Yugoslavian passport in Germany (horizontal axis) between 1995 and 2010. Most of the values are concentrated in the upper left quadrant of the scatterplot. This implies that that the exports that grew the fastest are the one for which there was the largest reduction of Yugoslavian workers in Germany in between those two years.

[Figure 3 about here.]

Another way to preview our results is in Figure 4, which follows the cumulative value of exports of products linked to return migrants from Germany (by 2000) with different levels of treatment, year after year. Clearly, it shows that while all sets of products start at similar levels, products in third and fourth quartiles diverge quite significantly from the first two quartiles.

[Figure 4 about here.]

We turn to explore this result using regression analysis and estimate the following:

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

Where p represents a product and t a year. The left hand side variable measures the value of exports from the former Yugoslavia to the rest of the world for product p during year t. $exports_{p,t}$ is the value of exports for product p and year t, of the former Yugoslavia to the rest of the world. We start by estimating this regression using two periods, 1995 and 2005 (below we also estimate it for multiple periods). We assume that 10 years is a reasonable amount of time for the data to catch long-term structural changes in the export basket of a country instead of short-term noise. The variable of interest $treat_p$ is number of workers that left the German labor force in product p after 1995. β^{DID} represents the change in exports caused by changes in returnees ($treat_p$) by the end period ($after_t$), in a typical difference-in-difference setting. η_p represents product fixed effects while α_t represents year fixed effects (which in the main estimation is equivalent to one dummy variable for the year 2005). The two fixed effects are perfectly multi collinear with the terms $treat_p$ and $after_t$ if added separately. $\varepsilon_{p,t}$ represents the error term. Our estimations cluster standard errors at the product level (Besley and Burgess, 2004; Bertrand et al., 2004).

Table 2 presents the summary statistics used for this exercise. Our sample includes 1572 observations, which corresponds to one observation per year per each of the 786 4-digit products. 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 by less than 100 observations. The two other transformations deal with the occasions where $exports_{p,t} = 0$ by either adding USD \$1 before the transformation and by computing instead the inverse hyperbolic sine (asinh), respectively. The inverse hyperbolic sine is defined at zero and behaves similarly to a log-transformation. 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).[9] Our right hand side continuous variables, unless otherwise stated, are transformed using the inverse hyperbolic sine for estimation purposes. Statistics summarizing exports are presented in the first three rows of the table.

[Table 2 about here.]

Table 2 also summarizes the treatment. First, it shows that, on average, there were about 40 workers in Germany working in each 4-digit product by 1995. Some products in Germany never had Yugoslavian workers in 1995 (as the minimum value is zero), and the maximum number of workers we see in a particular product is almost 1000. The last three rows of the table summarize the variables that we use as treatment. Our main treatment variable is the number of workers with Yugoslavian passport active in the German labor force in 1995 that dropped from the sample by year 2000. The value for this variable is 13, averaged across all product. Sometimes we use as a treatment the same number but using 2005 and 2010 instead of 2000. By 2005 this number becomes 15 and by 2010 the number is 18. There is quite a bit of variation across products for these numbers, too, which go from zero to 390 depending on the year used as the end of the period.

4.2 Results

Results for the estimation for specification(1) are presented in Table 3. It uses exports data for years 1995 and 2005, while the treatment is defined as the number of workers of Yugoslavian origin that left the German labor force in between 1995 and 2000, by product.[10] The estimation includes product fixed effects, such that the results use only within-product variation. It also includes year fixed effects, which in this case is equivalent to a dummy variable for year 2005. The three columns uses $log(exports_{p,t})$, $log(exports_{p,t} + 1)$ and

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

[10] Appendix Table (A2) replicates the results using different treatments: return migration between 1995 and 2005 and between 1995 and 2010 (for which the period of estimation is expanded to 2010) and the stock of migrants in 1995. The results are robust to using these different treatments, with the exception of the logarithmic transformation of exports for which the standard errors are increased and the statistical significance of the estimators are reduced, yet they maintain a similar value.

$asinh(exports_{p,t})$ as dependent variables, respectively. For the estimation, we transform the regressor $treat_p$ its inverse hyperbolic sine transformation, so that β^{DID} can be interpreted as an elasticity.

[Table 3 about here.]

All estimates of β^{DID} are positive and statistically different from zero for all different monotonic transformations of the dependent variable. Before interpreting the numbers a few comments are in place. Note that these are exports from former Yugoslavian countries to the rest of the world, excluding Germany. In that sense, the results are not explained by possible reductions of fixed costs of exporting caused by migrant networks (e.g. Parsons and Vézina, 2017). In addition, since the evidence suggests that the treatment variable is exogenous, we interpret the results as causal. Furthermore, we interpret increments in exports as product-specific productivity shifts, since by using global export, they describe the evolution of comparative advantage.

Column 1 of Table 3 presents the estimate when using the natural logarithmic transformation for the dependent variable. The point estimate in the first column is around half 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.[11] Yet, this difference says something more: the fact that results are positive and significant in columns 2 and 3 –which include instances where a product was inexistent in the export basket of Yugoslavia by 1995– 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 the work by Bahar and Rapoport (2017). In either case, the results show that the elasticity of exports to returnee workers ranges from 0.08 to 0.15, depending on the transformation of the left hand side variable used (and thus whether zeros are included or not).[12]

[11] In fact, table (A3) re-estimates columns (2) and (3) of Table (3) excluding observations for with zero exports. In that case, both estimates are exactly the same as in column (1) of Table (3).

[12] In Appendix Table (A4) shows that results are robust to excluding exports from Slovenia from the total exports by former Yugoslavian republics after the separation. This comes from the concern that Slovenia

Can this result be explained by a previous trend in exports? We explore this by estimating the same specification but this time over the period 1985 to 1990, keeping the same treatment, in some sort of placebo test (the treatment that started in 1995 should not affect exports in 1985 to 1990). The results are presented in Table 4, and in this case the estimates for β^{DID} are not statistically different from zero.

[Table 4 about here.]

Multi-period Estimation

Given the availability of exports data across several years, we turn to estimate the multi-period effect of return migration on the comparative advantage of the products in their home countries. To avoid noise in the estimation, we do this taking 5-year averages for the dependent variable and estimate β^{DID} for 6 different periods, from 1986-1990 (which is the base period) to 2011-2014. To do this, we simply re-estimate Specification (1), this time substituting the dummy $after_t$ for several dummies each one signaling a 5-year period, along the lines of Autor et al. (2003). The results are presented in Table 5. In this multi-period setting, α_t are 5-year period fixed effects, and the product fixed effects η_p are maintained allowing for product-specific intercepts. Naturally, the number of observations in this sample is much larger, as it includes 6 observations per each of the 786 products totaling 4716.

[Table 5 about here.]

The estimation presented in Table 5 excludes the period 1986-1990 as it is the base for the estimation. The results show that the elasticity estimated for the period before the treatment (1991-1995, first row) is the smallest. The value of the elasticity starts growing and is statistically different from zero in every period post 1995, when the treatment is activated. For the first column using a log transformation for the dependent variable (which does not include observations where $exports_{p,t} = 0$) the elasticity is estimated to be 0.13 in the first period post-treatment (1996-2000), along the lines of the result in Table 3. This

was less affected by the war (both in terms of refugees and economic capacity) and it has a much more diversified export basket than its peers.

same elasticity is estimated to be 0.16 in the latest period 2011-2014, which is about 23% larger. In the other two columns the elasticity is estimated to be about 0.14, larger than in Column 1 (also consistently with Table 3) which relates to the idea discussed above that return migration can also explain changes among products that were inexistent at the beginning of the period. This elasticity grows up to 0.28 in the latest period, almost a 100% increase. This suggests one more important result: the marginal effect of return migration on the emergence of new exports becomes stronger with time. These results are summarized in Figure 5, which shows the evolution of the estimated elasticity by 5-year period across different measures of the dependent variable.

[Figure 5 about here.]

What is behind these results?

The idea that migrants can play a role in shaping the comparative advantage of countries is part of a growing literature that links migrants and their descendants to the diffusion of knowledge (e.g., Kerr, 2008; Choudhury, 2016; Hausmann and Neffke, 2016; Bahar and Rapoport, 2017), and our results so far are consistent with this idea. Yet, if this were the case, we should be able to see stronger results when looking at migrant workers more suited to acquire and transfer knowledge. This is part of what we explore in the next section, by studying the role of skill accumulation and different types of occupations of migrants in explaining changes in comparative advantage.

5 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.

Our prior for this exercise is that if knowledge diffusion is the mechanisms through which migration explains productivity shifts seen as changes in the comparative advantage of nations, this effect should be stronger among migrants that are skilled and/or work in occupations that are more cognitive and analytical in nature. This is what we explore in this section.

5.1 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:[13]

$$exports_{c,p,t} = \beta^{DID} migrants_{c,p,t-10} + globalexports_{p,t} + \eta_{c,p} + \alpha_{c,t} + \varepsilon_{c,p,t} \tag{2}$$

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

[13] Both specifications are equivalent. 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:

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

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 $\beta_1 = \beta_2$.

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.[14] 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).

As mentioned earlier, 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 migrant stock by different categories, and we exploit that variation in this setting. Table 6 summarizes the statistics for the main variables used in this analysis. The first three rows summarize the export value averaged across countries, products and years 2000 and 2010, using three different monotonic transformations; note that the number of observations using a simple logarithmic transformation is reduced due to zeros in the sample.

[Table 6 about here.]

Table 6 shows that the average number of migrant workers in Germany across all countries and 4-digit products for both 1990 and 2000 (e.g., the baseline years) is 8. The number is surprisingly small, but note that this variable has many zeros (in fact, the median value

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

is zero), and there is a mix of countries from many different sizes. This last fact is reflected in both the large standard deviation and upper bound of the variable which reaches a maximum of over 20 thousand workers. The table summarizes data for each category of workers that we will be using in the analysis, which we explain next.

First we separate migrants as skilled and unskilled, where skilled is defined as having achieved education beyond high school (i.e., vocational training, college degree or more) while unskilled is defined as having a high school diploma or less. These categories were constructed from more disaggregated ones defined in the IAB dataset. Second we group migrant workers by whether their occupation is defined as "white-collar" or not, also defined in the IAB dataset. Third, we distinguish migrants with occupations intensive in analytical and cognitive tasks vs. occupations intensive in manual tasks. To do so we use the classification provided by Dengler et al. (2014), which formalizes German occupations into five task categories, similarly to Autor et al. (2003).[15] Lastly, we distinguish migrants by the problem-solving content of their occupations (above and below median, given it is a continuous variable) using a measure created by Nedelkoska et al. (2015).

5.2 Results

We start by estimating Specification (2) using all workers, without distinction, as the independent variable. The results are presented in Table 7. The elasticity parameter is estimated to be between 0.08 and 0.11, which falls into the lower range of the the results of Section 4. 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 results from Section 4, 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 7 about here.]

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

Results by Skill Levels

So far we have estimated our specifications using the total number of immigrant workers as the main input. If indeed our narrative is correct, and migrants are instrumental in the diffusion of productive knowledge, then we would expect skilled migrants to have a larger impact, as it is safe to assume that they have a greater ability to transfer such knowledge. Table 8presents the results of the estimation using separately of skilled (Columns 1, 3 and 5) vs. unskilled (Columns 2, 4 and 6) migrants.

[Table 8 about here.]

There are two important findings of this table, that are worth noticing. First is that the elasticity parameter is estimated to be between 0.09 and 0.12 for skilled workers whereas it is lower, around 0.06, for unskilled migrants. But second, the point estimates of Columns 3 and 5 are larger than for Column 1, implying as noted in our previous results, that skilled migrants play a role in explaining the extensive margin, too. Yet, the point estimates in all columns that use unskilled migrants for the estimation don't vary depending on the definition of the dependent variable, implying that unskilled migrants are not explanatory of the extensive margin. In fact, Bahar and Rapoport (2017)show that skilled migrants are about 10 times more "effective" in inducing changes at the extensive margin than unskilled migrants, consistently with this finding.

Results by types of occupation

The novelty of our dataset allows us to add another dimension to study, which is the type of migrants' occupations that are more explanatory of the dynamics in comparative advantage in their home countries. We pose that if these results are really being driven by the ability of migrants to transfer knowhow back to their home countries which translates into sector-specific productivity increases, then we should be able to see that this holds for particular types of occupations more than others. In fact, there are two reasons why we choose to include types of occupations in our analysis.

The first reason is that types of occupations might be a better measure of the skill content of a job. Even though educational attainment is considered a very relevant dimension of human capital (e.g. Goldin and Katz, 1996; Acemoglu, 2003), more recent literature argue that it is the type of human capital, rather than the level, what encompasses the most useful information in explaining the causes of the recent trend towards skill upgrading (e.g. Autor et al., 2003; Blinder, 2006). Second, human capital is occupation-specific. In fact, Kambourov and Manovskii (2009) argue that occupational tenure has substantial returns, more so that tenure in an industry or firm, hinting that productive knowledge is occupation-specific.

We start off by estimating Specification (2), this time distinguishing between white collar and non-white collar migrants. White collar jobs –typically linked to management or having technical skills– can be crucial in the diffusion of knowhow. The results of the estimation are presented in Table 9. When using migrants in white-collar occupations as the main regressor the estimated elasticity is between 0.12 and 0.13, and it is somewhat lower for non-white collars ranging between 0.07 and 0.09. While the difference in the point estimates seem trivial, it is important to acknowledge that the sizable differences in the number of white-collar relative to non-white collar workers in the sample. Thus, in measuring the marginal effect we must take into account the distribution of these two different groups. We retake this conversation below.

[Table 9 about here.]

Next, estimate we group migrants by the analytical and cognitive content of their tasks. We distinguish between migrant workers that are doing analytical, cognitive and interactive tasks (either routine or non-routine) and migrants with occupations intensive in manual tasks (both routine and non-routine. The results are presented in Table 10. The elasticity of exports to migrant returnees with occupations intensive in analytical and cognitive tasks is estimated to be between 0.09 to 0.11, while the elasticity for manual tasks is estimated to be between 0.07 and 0.09. Once again our results are consistent with the idea that the channel driving these results is the diffusion of knowledge.

[Table 10 about here.]

Lastly, we perform a test using a continuous measure of problem-solving intensity of the occupation, as a proxy for the ability of migrants to gain and transfer tacit knowledge. We rely on the work by Nedelkoska et al. (2015)who assigns a problem-solving score to each occupation.[16] We divide migrants in two groups, based on whether the problem-solving score of their occupations are above and below the median. Results are presented in Table 11. There, occupations with high problem-solving content are estimated to have a higher elasticity of export value (0.1 to 0.13) than occupations with problem-solving score below the mean (0.07 to 0.09). This adds to the evidence provided above: exposure to problem-solving in a particular sector results in tacit knowledge that boosts productivity in that same sector back home, through human mobility.

[Table 11 about here.]

Marginal Effects

Across the different types of occupations it is important to understand that, ultimately, the marginal effect depends on the distribution of each group, which quite varies. For instance, according to Table (6) there are, on average, 7 white collar migrant workers in each product-year cell, whereas there are in contrast about 121 non-white collars. Thus, a relative increase in those two groups differ very significantly when converted to nominal terms (e.g., number of people). Figure 6 estimates the marginal effect of one migrant worker on exports (using $log(exports_{c,p,t})$ as the dependent variable. There it is clear how when it comes to white collars, for instance, the marginal effect is about 11 times as large as that of non-white collars. Similar differences occur when looking at analytical and cognitive vs. manual tasks as well as for occupations with high problem-solving content compared to occupations with low problem-solving content. The average marginal effect of a migrant in

[16]Nedelkoska et al. (2015) argue that every job is a collection of tasks ("problems") of varying complexity that need to be accomplished. Every task poses a challenge and at the same time provides an opportunity to learn. Thus, jobs create a learning environment, where employees can learn by solving tasks. Just how much they can learn depends on the gap between their current skill level and the level of task complexity. More complex jobs create a better learning environment, as they provide more complex tasks and in larger quantity.In their analysis, first they show that starting salary in complex jobs are higher than simpler ones. More importantly, they show that wages increase faster when the job is complex. They argue that this dynamic effect is due to learning on job.

occupations intensive in analytical vs. non-cognitive tasks is about 3 times larger than for a migrant in occupations intensive in manual tasks. Consistently, the marginal effect of a migrant in an occupation with high (above the median) problem-solving content is about 4 times larger than for low (below the median) problem-solving content. Figure 7 replicates the exercise using $log(exports_{c,p,t}+1)$ as the dependent variable, and finds consistent results.

[Figure 6 about here.]

[Figure 7 about here.]

6 Concluding Remarks

In this paper we exploit a natural experiment to show that return migration is a channel for productive knowledge diffusion between host and sending countries, which can be instrumental in expanding the export basket of their home countries. Our main results show that return of Yugoslavian refugees from Germany has been beneficial both for opening new line of exports and accelerating growth of those which already existed.

To externally validate our results, we expand our analysis using a multi-country and multi-period setting, and show they can be generalized. Moreover, by exploiting individual details of our data set, we further show that effect is much stronger when migrants are skilled and/or work in occupations that are more cognitive and analytical in nature.

Our results contribute to a growing literature that emphasizes that migrants can serve as international drivers of productive knowledge and can thus shape the comparative advantage of their home country. It also contributes to literature about human-capital acquisition by exploiting differences in occupational structure.

Our paper gives a clear idea about how a migrant acquires knowledge in host country and bring it with him to home. Still we are limited in our ability to understand the precise mechanisms that drive the documented relationships. Returnee migrants might play a role in knowledge diffusion by bringing new and better labor and/or management techniques to firms that employ them or by becoming entrepreneurs themselves as suggested by Hausmann and Neffke (2016) and Dustmann and Kirchkamp (2002).

Migrants may also play a role in diffusion through their interactions with their contacts back in the sending country, without even returning. Better understanding what those channels are and how they work is an important missing piece for future research.

References

Acemoglu, Daron. “Patterns of Skill Premia.” *Review of Economic Studies* 70, 2: (2003) 199–230.

Arrow, Kenneth J. “Classificatory Notes on the Production and Transmission of Technological Knowledge.” *The American Economic Review* 59, 2: (1969) 29–35.

Autor, David H, Frank Levy, and Richard J Murnane. “The Skill Content of Recent Technological Change: An Empirical Exploration.” *The Quarterly Journal of Economics* 118, 4: (2003) 1279–1333.

Bahar, Dany, Ricardo Hausmann, and Cesar A. Hidalgo. “Neighbors and the evolution of the comparative advantage of nations: Evidence of international knowledge diffusion?” *Journal of International Economics* 92, 1: (2014) 111–123.

Bahar, Dany, and H. Rapoport. “Migration, Knowledge Diffusion and the Comparative Advantage of Nations.” *The Economic Journal* .

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. “How Much Should We Trust Difference-in-Difference Estimates?” *The Quarterly Journal of ...* 119 (1), February: (2004) 249–275.

Besley, T., and R. Burgess. “Can Labor Regulation Hinder Economic Performance? Evidence from India.” *The Quarterly Journal of Economics* 119, 1: (2004) 91–134.

Blinder, A S. “Offshoring: The Next Industrial Revolution?” *Foreign Affairs* 85(2): (2006) 113–128.

Bosswick, Wolfgang. “Development of Asylum Policy in Germany.” *Journal of Refugee Studies* 13, 1: (2000) 43–60.

Cadot, Olivier, Céline Carrère, and Vanessa Strauss-Kahn. "Export Diversification: What's behind the Hump?" *Review of Economics and Statistics* 93, 2: (2011) 590–605.

Card, David, Jörg Heining, and Patrick Kline. "Workplace Heterogeneity and the Rise of West German Wage Inequality*." *The Quarterly Journal of Economics* 128, 3: (2013) 967–1015.

Choudhury, Prithwiraj. "Return migration and geography of innovation in MNEs: A natural experiment of knowledge production by local workers reporting to return migrants." *Journal of Economic Geography* 16, 3: (2016) 585–610.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. "Peer Effects in the Workplace." *American Economic Review* 107, 2: (2017) 425–456.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum. "The Rise Of The East And The Far East: German Labor Markets And Trade Integration." *Journal of the European Economic Association* 12, 6: (2014) 1643–1675. https://ideas.repec.org/a/bla/jeurec/v12y2014i6p1643-1675.html.

Dengler, Katharina, Britta Matthes, and Wiebke Paulus. "Occupational Tasks in the German Labour Market : an alternative measurement on the basis of an expert database." Fdz methodenreport, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg, 2014.

Dimova, Rozita. "Max Planck Institute for Social Anthropology Working Papers. 87 From Protection To Ordeal: Duldung Status and Bosnian Refugees." *Max Planck Institute for Social Anthropology Working Papers* 49, 87: (2006) 0–12.

Dustmann, Christian, and Albrecht Glitz. "How Do Industries and Firms Respond to Changes in Local Labor Supply?" *Journal of Labor Economics* 33, 3: (2015) 711–750.

Dustmann, Christian, and Oliver Kirchkamp. "The optimal migration duration and activity choice after re-migration." *Journal of Development Economics* 67, 2: (2002) 351–372.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler. “Labor Supply Shocks, Native Wages, and The Adjustment of Local Employment.” *The Quarterly Journal of Economics* 26, 1: (2016) qjw032.

Feenstra, Robert C., Robert E. Lipsey, Haiyan Deng, Alyson C. Ma, and Hengyong Mo. “World Trade Flows: 1962-2000.”, 2005.

Goldin, Claudia, and Lawrence F Katz. “Technology, Skill, and the Wage Structure: Insights from the Past.” *American Economic Review* 86, 2: (1996) 252–257.

Hausmann, Ricardo, César A Hidalgo, Sebastián Bustos, Michele Coscia, Alexander Simoes, and Muhammed A. Yildirim. *The Atlas of Economic Complexity: Mapping Paths to Prosperity.* Cambridge, MA: MIT Press, 2014.

Hausmann, Ricardo, and Bailey Klinger. “The Structure of the Product Space and the Evolution of Comparative Advantage.” *CID Working Paper Series* , 146.

Hausmann, Ricardo, and Frank Neffke. “The workforce of pioneer plants.”, 2016.

Hausmann, Ricardo, Francisco Rodríguez, and Rodrigo Wagner. “Growth Collapses.” *CID Working Paper Series* , RWP06-046.

Imbs, Jean, and Romain Wacziarg. “Stages of Diversification.” *American Economic Review* 93, 1: (2003) 63–86.

Kambourov, Gueorgui, and Iourii Manovskii. “Occupational Specifity of Human Capital.” *International Economic Review* 50, 1: (2009) 63–115.

Keller, Wolfgang. “International Technology Diffusion.” *Journal of Economic Literature* XLII, September: (2004) 752–782.

Kerr, W R. “Ethnic Scientific Communities and International Technology Diffusion.” *Review of Economics and Statistics* 90, 3: (2008) 518–537.

Koren, Miklos, and Silvana Tenreyro. “Volatility and Development.” *The Quarterly Journal of Economics* 122, 1: (2007) 243–287.

Krishna, Pravin, and Andrei Levchenko. "Comparative Advantage, Complexity and Volatility." Technical report, National Bureau of Economic Research, Cambridge, MA, 2009. http://www.nber.org/papers/w14965.pdf.

Kugler, Maurice, Oren Levintal, and Hillel Rapoport. "Migration and Cross-Border Financial Flows Migration and Cross-Border Financial Flows." *World Bank Economic Review* .

Lederer, Harald. *Migration und Integration in Zahlen.* Bonn, 1997, beauftragt edition.

Liedtke, Matthias. "National welfare and asylum in Germany." *Critical Social Policy* 22, 3: (2002) 479–497. http://journals.sagepub.com/doi/10.1177/026101830202200306.

MacKinnon, JG, and Lonnie Magee. "Transforming the Dependent Variable in Regression Models." *International Economic Review* 31, 2: (1990) 315–339.

Nedelkoska, Ljubica, Alexander Patt, and Peer Ederer. "Learning by Problem Solving." Mimeo, 2015.

Parsons, Christopher R., and Pierre-Louis Vézina. "Migrant networks and trade: The Vietnamese boat people as a natural experiment." *The Economic Journal* .

Polanyi, M. *The Tacit Dimension.* Chicago; London: University of Chicago Press, 1966, 2009 edition.

Radović, B, G Opačić, and I Vidaković. "A Brief Retrospective on the Problem of Refugees in the Yugoslav Wars 1991-99." *Living in post-war* .

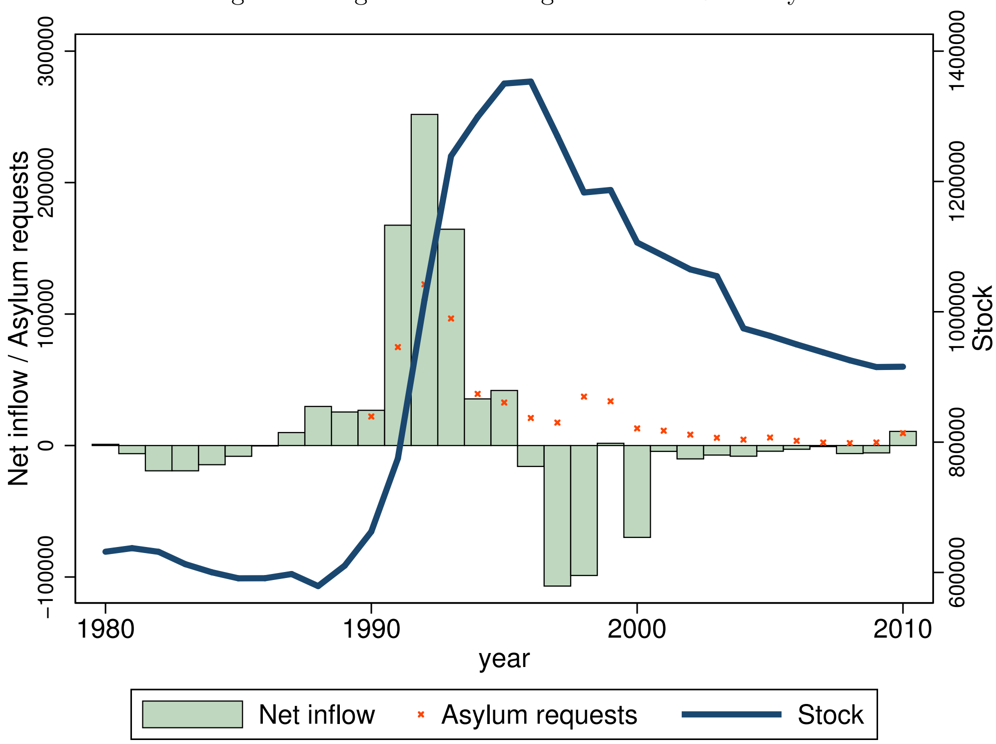
Rauch, JE, and Vitor Trindade. "Ethnic Chinese networks in international trade." *Review of Economics and Statistics* 84, February: (2002) 116–130.

Spitz-Oener, Alexandra. "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure." *Journal of Labor Economics* 24, 2: (2006) 235–270. http://econpapers.repec.org/RePEc:ucp:jlabec:v:24:y:2006:i:2:p:235-270.

USCRI. “Refworld | U.S. Committee for Refugees World Refugee Survey 2000 - Germany.”, 2000.

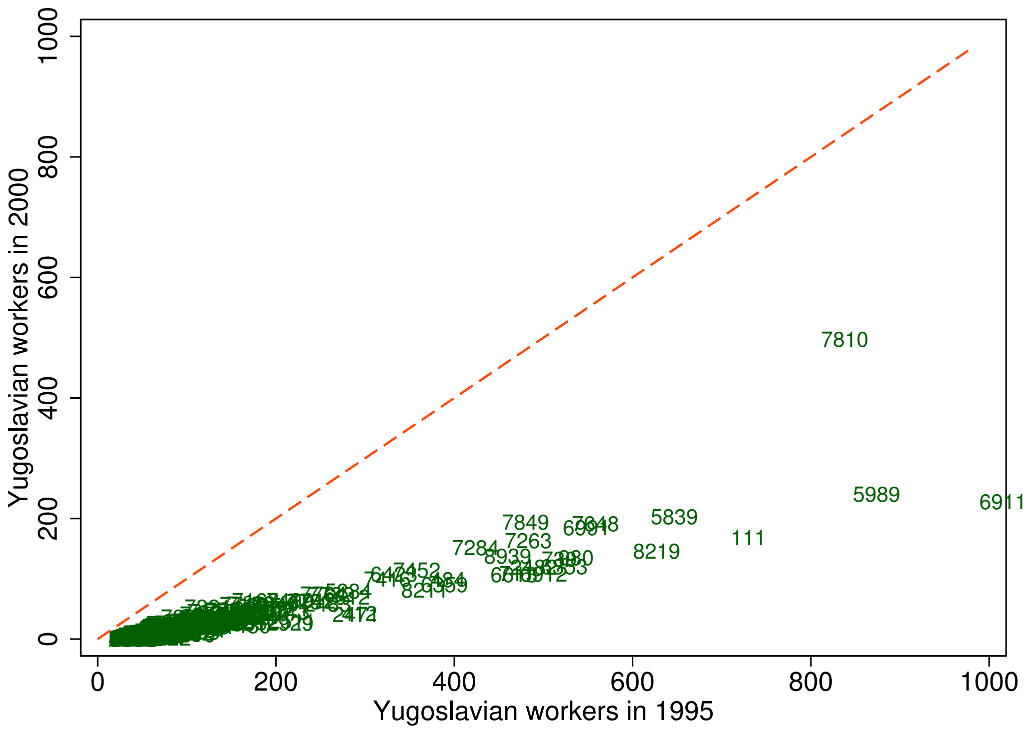
Valenta, M., and Z. Strabac. “The Dynamics of Bosnian Refugee Migrations in the 1990s, Current Migration Trends and Future Prospects.” *Refugee Survey Quarterly* 32, 3: (2013) 1–22.

Figure 1: Migration from Yugoslavia into Germany



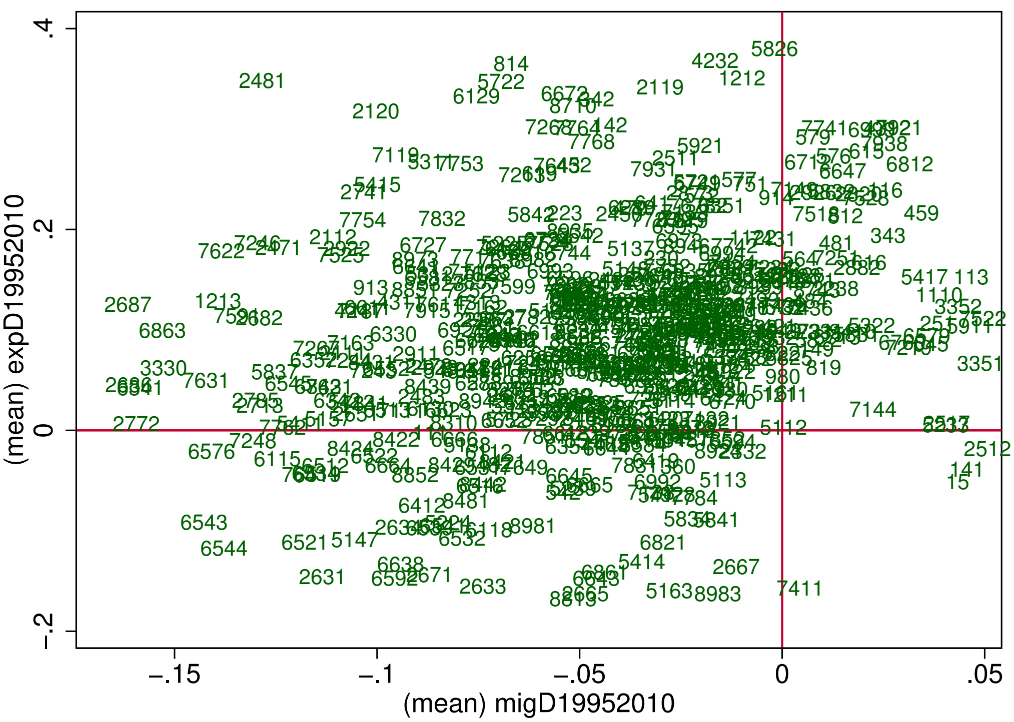
The figure shows the net inflow and stock of Yugoslavian migrants into Germany, from 1980 until 2010. The source of the data is Destatis (2017): Statistics of foreigners. Table 12521-0002, Foreigners: Germany, reference date, sex, country groups/citizenship.

Figure 2: Yugoslavian in German workforce, by product



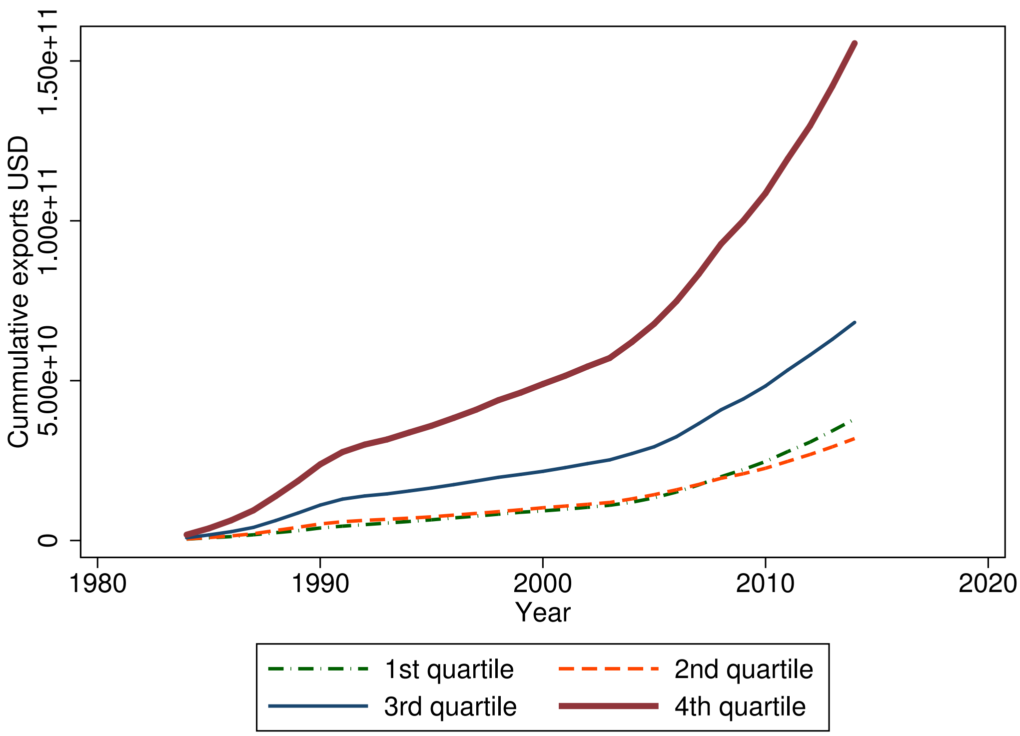
The figure shows the number of Yugoslavian workers in the German workforce by 4-digit product in both 1995 and 2000.

Figure 3: Changes in exports vs. changes in migrant workers in Germany



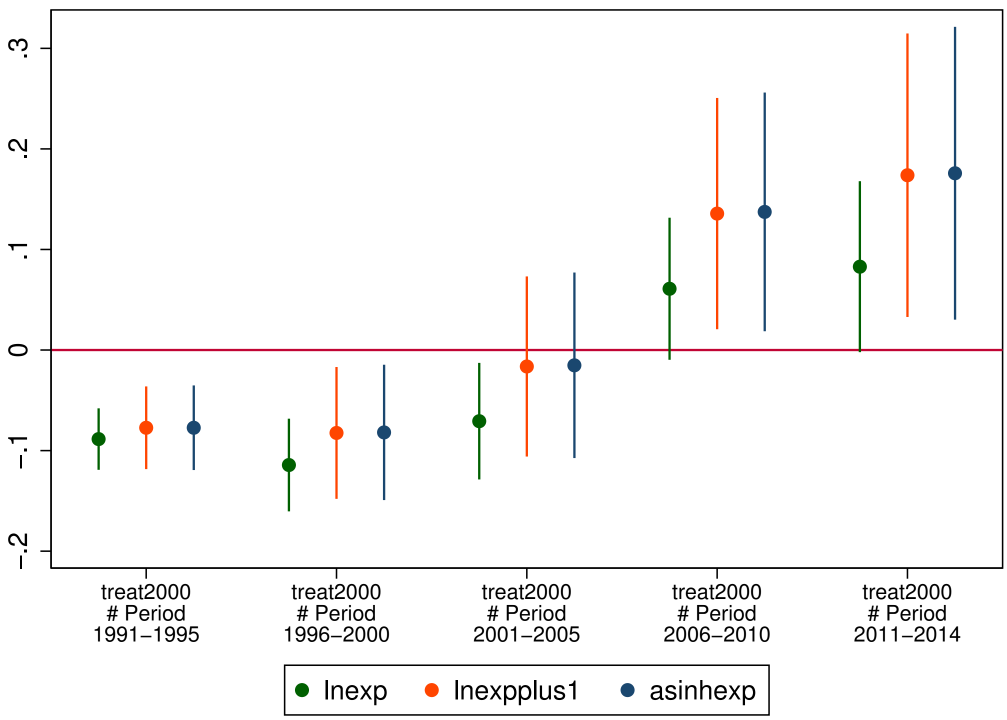
The figure plots changes in the value of exports of the former Yugoslavia to the rest of the world (vertical axis) against changes in number of workers with Yugoslavian passport in Germany, all by 4-digit product and between 1995 and 2000. Outlier values (i.e., below the 5th percentile and above the 95th percentile) are excluded for visualization purposes.

Figure 4: Cumulative exports for products with different levels of treatment



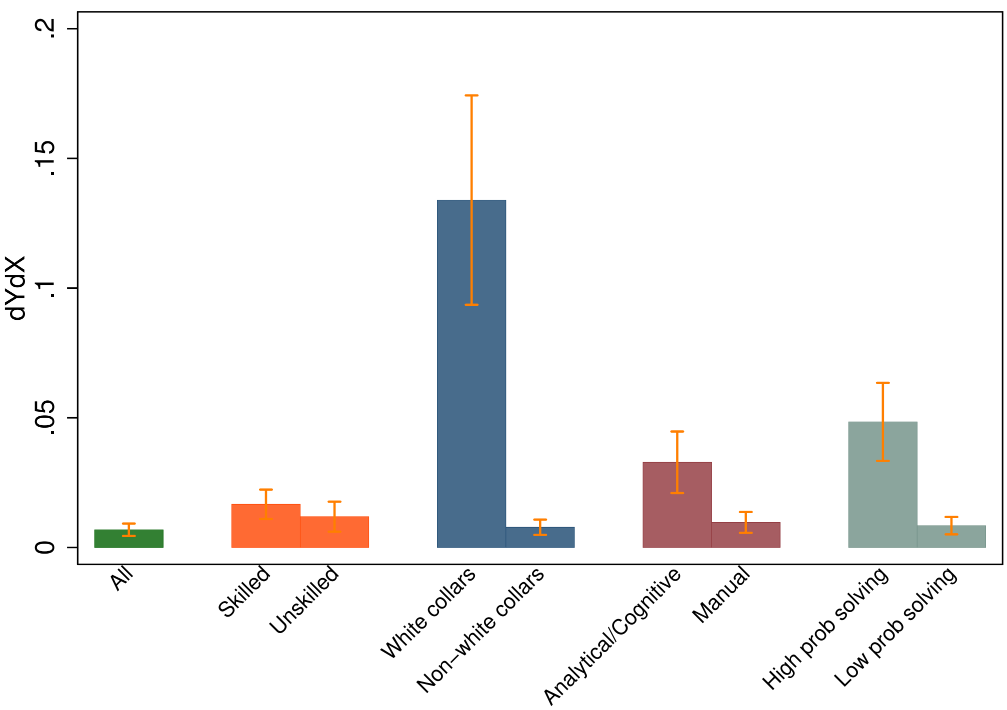
The figure plots the cumulative value of exports of the former Yugoslavia to the rest of the world (vertical axis) across years. Treatment is defined as the number of return migrants from Germany by 2000.

Figure 5: Difference-in-difference, 5 year periods



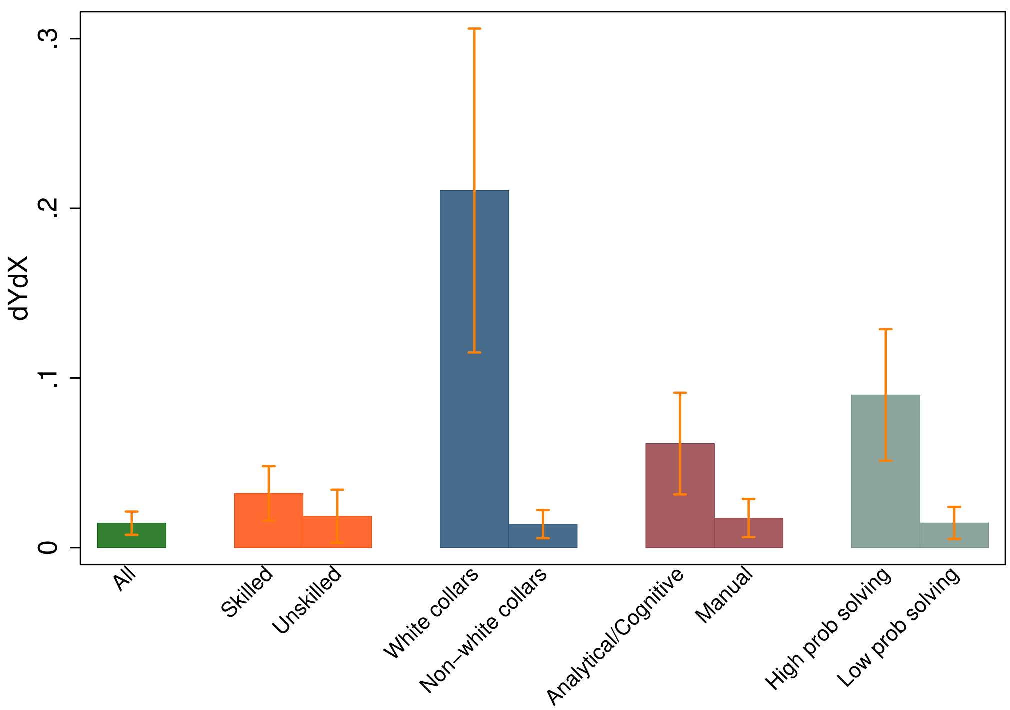
This figure plots coefficients of treatment over time. Dependent variable is 5-year average and 1986-1990 is used as the base year. 99% confidence intervals for the estimation are represented by the whiskers.

Figure 6: Marginal effect by type of migrant, using $log(exports_{c,p,t})$



This figure plots the estimated marginal effect of 1 migrant returnee on exports from the home country based on the levels of migrants of each type in the sample, using $log(exports_{c,p,t})$ as the dependent variable. Whiskers represent 95 percent confidence intervals.

Figure 7: Marginal effect by type of migrant, using $log(exports_{c,p,t} + 1)$



This figure plots the estimated marginal effect of 1 migrant returnee on exports from the home country based on the levels of migrants of each type in the sample, using $log(exports_{c,p,t} + 1)$ as the dependent variable. Whiskers represent 95 percent confidence intervals.

Table 1: Number of Yugoslavian refugees, by recipient country

Recipient	**Refugees (approx.)**	**In %**
Germany	350,000	47.6
Italy	54,600	7.4
Austria	52,000	7.1
Sweden	48,500	6.6
Netherlands	45,000	6.1
Switzerland	32,100	4.4
Turkey	30,000	4.1
Denmark	17,500	2.4
France	15,900	2.2
Australia	14,000	1.9
USA	12,820	1.7
Canada	11,640	1.6
Norway	11,000	1.5
Hungary	8,900	1.2
Great Britain	7,000	1.0
Others	24,010	3.3
Total	**734,970**	**100.0**

Notes: Numbers in this table are based on Lederer (1997, p.314). The numbers refer to estimations of the UNHCR (March 1995). Numbers for Australia and USA also include non-refugee immigrants.

Table 2: Summary Statistics Yugoslavian Refugees in Germany

Variable	**N**	**Mean**	**sd**	**Min**	**Max**
Exports (log)	1,477	14.982	2.55	6.9	21.4
Exports (log +1)	1,572	14.077	4.35	0.0	21.4
Exports (asinh)	1,572	14.728	4.48	0.0	22.1
YUG Workers 1995	1,572	38.732	96.86	0.0	976.4
Workers left by 2000	1,572	12.796	34.75	0.0	392.7
Workers left by 2005	1,572	15.219	40.78	0.0	469.3
Workers left by 2010	1,572	18.202	47.83	0.0	546.0

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

Table 3: Difference-in-difference estimation

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0796	0.1480	0.1500
	(0.039)**	(0.082)*	(0.086)*
N	1418	1572	1572
Adj R2	0.85	0.79	0.78

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 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 4: Difference-in-difference estimation, previous trend

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
treat2000 × after1990	0.0356	-0.1190	-0.1312
	(0.035)	(0.076)	(0.080)
N	1348	1572	1572
Adj R2	0.90	0.83	0.82

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 1985 and 1990. 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: Difference-in-difference, 5 year periods

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
treat2000 × Period 1991-1995	-0.0885	-0.0773	-0.0773
	(0.016)***	(0.021)***	(0.021)***
treat2000 × Period 1996-2000	-0.1143	-0.0824	-0.0819
	(0.023)***	(0.033)**	(0.034)**
treat2000 × Period 2001-2005	-0.0707	-0.0164	-0.0152
	(0.030)**	(0.046)	(0.047)
treat2000 × Period 2006-2010	0.0609	0.1357	0.1374
	(0.036)*	(0.059)**	(0.060)**
treat2000 × Period 2011-2014	0.0829	0.1738	0.1758
	(0.043)*	(0.072)**	(0.074)**
$\text{period}_5 y$	0.3122	0.2465	0.2449
	(0.026)***	(0.046)***	(0.048)***
N	4579	4716	4716
Adj R2	0.84	0.80	0.79

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. It estimates the treatment across different 5-year periods. 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 6: Summary statistics, all sample

Variable	**N**	**Mean**	**sd**	**Min**	**Max**
Exports (log)	136,684	14.029	3.44	6.9	25.8
Exports (log +1)	179,208	10.700	6.68	0.0	25.8
Exports (asinh)	179,208	11.229	6.95	0.0	26.5
All Migrants	179,208	8.047	127.48	0.0	22,803.5
Skilled	179,208	3.769	63.15	0.0	12,501.7
Unskilled	179,208	4.001	67.83	0.0	11,614.6
White collars	179,208	0.636	7.24	0.0	798.1
Non-white collars	179,208	7.093	121.60	0.0	22,497.6
Analytical & Cognitive tasks	179,208	1.913	26.45	0.0	3,816.8
Manual tasks	179,208	5.531	92.33	0.0	15,918.0
High prob solving	179,208	1.480	21.36	0.0	4,193.2
Low prob solving	179,208	6.273	107.56	0.0	19,721.0

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

Table 7: Difference-in-difference estimation, all sample

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
L10.AllMigrants	0.0846	0.1252	0.1232
	(0.015)***	(0.030)***	(0.032)***
lntotalexp	0.8935	0.4403	0.4595
	(0.016)***	(0.011)***	(0.012)***
N	114288	165060	165060
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.

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

Table 8: Difference-in-difference estimation, all sample

Dependent variable: $exports_{p,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
	lnexp	lnexp	lnexpplus1	lnexpplus1	asinhexp	asinhexp
L10.Skilled	0.0965		0.1298		0.1258	
	(0.017)***		(0.033)***		(0.035)***	
L10.Unskilled		0.0734		0.0801		0.0777
		(0.018)***		(0.035)**		(0.036)**
lntotalexp	0.8938	0.8953	0.4403	0.4411	0.4596	0.4603
	(0.016)***	(0.016)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***
N	114288	114288	165060	165060	165060	165060
Adj R2	0.94	0.94	0.91	0.91	0.90	0.90
cpFE	Y	Y	Y	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.

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

Table 9: White vs. non-white collars

Dependent variable: $exports_{p,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
	lnexp	lnexp	lnexpplus1	lnexpplus1	asinhexp	asinhexp
L10.WhiteCollars	0.1313		0.1443		0.1404	
	(0.020)***		(0.033)***		(0.035)***	
L10.NonWhiteCollars		0.0852		0.1058		0.1026
		(0.016)***		(0.032)***		(0.034)***
lntotalexp	0.8954	0.8936	0.4407	0.4407	0.4599	0.4599
	(0.016)***	(0.016)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***
N	114288	114288	165060	165060	165060	165060
Adj R2	0.94	0.94	0.91	0.91	0.90	0.90
cpFE	Y	Y	Y	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.

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

Table 10: Analytical, Cognitive and Interactive vs. Manual tasks

Dependent variable: $exports_{p,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
	lnexp	lnexp	lnexpplus1	lnexpplus1	asinhexp	asinhexp
L10.AnalyticalCognitive	0.0970		0.1267		0.1252	
	(0.018)***		(0.032)***		(0.033)***	
L10.Manual		0.0823		0.1040		0.1006
		(0.017)***		(0.034)***		(0.036)***
lntotalexp	0.8957	0.8942	0.4407	0.4408	0.4599	0.4600
	(0.016)***	(0.016)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***
N	114288	114288	165060	165060	165060	165060
Adj R2	0.94	0.94	0.91	0.91	0.90	0.90
cpFE	Y	Y	Y	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.

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

Table 11: Problem-solving content

Dependent variable: $exports_{p,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)
	lnexp	lnexp	lnexpplus1	lnexpplus1	asinhexp	asinhexp
L10.HiProbSolving	0.1107		0.1437		0.1413	
	(0.018)***		(0.032)***		(0.033)***	
L10.LoProbSolving		0.0812		0.0985		0.0954
		(0.017)***		(0.033)***		(0.034)***
lntotalexp	0.8952	0.8942	0.4407	0.4407	0.4599	0.4599
	(0.016)***	(0.016)***	(0.011)***	(0.011)***	(0.012)***	(0.012)***
N	114288	114288	165060	165060	165060	165060
Adj R2	0.94	0.94	0.91	0.91	0.90	0.90
cpFE	Y	Y	Y	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.

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

Appendix Material

August 15, 2017

[Table A1 about here.]

[Table A2 about here.]

[Table A3 about here.]

[Table A4 about here.]

Table A1: Refugees from Bosnia-Herzegovina, by recipient country

Recipient	**Refugees**	**Returned**	**Remained**	**3rd countries**	**% Remained**
Australia	15,000	800	14,200	-	94.7
Austria	86,500	10,100	70,900	5,500	82.0
Denmark	17,000	1,600	15,400	-	90.6
The Netherlands	22,000	4,000	16,000	2,000	72.7
Croatia	170,000	56,000	62,000	52,000	36.5
Italy	12,100	2,000	8,100	2,000	66.9
Canada	20,000	600	18,400	1,000	92.0
Norway	12,000	2,500	8,200	1,300	68.3
Germany	320,000	246,000	22,000	52,000	6.9
USA	20,000	1,500	17,500	1,000	87.5
Slovenia	43,100	15,000	4,900	23,200	11.4
Serbia and Monten.	297,000	110,000	137,000	50,000	46.1
Sweden	58,700	1,900	56,000	-	95.4
Switzerland	24,500	11,000	10,900	2,600	44.5
Turkey	23,500	4,650	1,050	17,800	4.5
Total	**1,141,400**	**467,650**	**462,550**	**210,400**	**60.0**

Source: Valenta and Strabac (2013).

Table A2: Difference-in-difference estimation, different treatments

Dependent variable: $exports_{p,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnexp	lnexp	lnexp	lnexpplus1	lnexpplus1	lnexpplus1	asinhexp	asinhexp	asinhexp
treat2005 × after2005	0.0790			0.1481			0.1502		
	(0.038)**			(0.081)*			(0.085)*		
treat2010 × after2010		0.0912			0.1985			0.2008	
		(0.043)**			(0.083)**			(0.087)**	
treat1995level × after2010			0.0898			0.1896			0.1919
			(0.040)**			(0.081)**			(0.084)**
N	1418	1414	1414	1572	1572	1572	1572	1572	1572
Adj R2	0.85	0.83	0.83	0.79	0.77	0.77	0.78	0.77	0.77

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column. The estimation uses three different definitions of treatment: (i) return migrants between 1995 and 2005, (ii) return migrants between 1995 and 2010, and (iii) the stock of migrant workers in 1995. Except for the second treatment, the estimation uses exports between 1995 and 2005 (for the second treatment it goes up to 2010). 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 A3: Difference-in-difference estimation, no zeros

Dependent variable: $exports_{p,t}$		
	(1)	(2)
	lnexpplus1	asinhexp
treat2000 × after2005	0.0796	0.0796
	(0.039)**	(0.039)**
N	1418	1418
Adj R2	0.85	0.85

This table shows result of the estimation for specification (1) using different monotonic transformations for $exports_p, t$ in each column, excluding observations for which there were zero exports in either period. 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 A4: Difference-in-difference estimation, excl. Slovenia

Dependent variable: $exports_{p,t}$			
	(1)	(2)	(3)
	lnexp	lnexpplus1	asinhexp
treat2000 × after2005	0.0955	0.1559	0.1544
	(0.048)**	(0.085)*	(0.084)*
N	1388	1530	1530
Adj R2	0.80	0.75	0.75

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.

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