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WP6 Assessing european labour market inequalities from different perspectives

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Summary

Educational mismatch comes with considerable macroeconomic costs. Understanding the determinants of educational mismatch - or skills mismatch more generally - seems important, as it indicates an inefficiency in the labour market that can be detrimental to individual productivity and macroeconomic performance. In the paper of this report we investigate whether big structural changes like globalization (in the form of increased trade with Eastern Europe) and technological progress (in the form of automation) impact the extent of mismatch between jobs and workers in the labour market. To do so, we use data from the European Labour Force Survey for a set of 11 Western European countries over a period of 16 years between 2002 and 2018.

Our empirical analysis exploits the fact that some occupations and countries are much more exposed to globalization and technological progress than others. This is so because of differences in the (initial) mix of industry structure (among other things). We leverage these differences to compute measures of shock exposure to globalization and automation at the country-occupation level.

To measure educational mismatch, we consider overeducation, and find that the extent of educational mismatch has increased significantly between 2002 and 2018. In fact, according to a standard measure of educational mismatch, the average share of mismatched workers (overeducated for the work they do) has doubled from 5% to 10% across all occupations and countries.

Our econometric analysis reveals that, overall, the surge in international trade with Eastern Europe after the turn of the millennium has perhaps little to say about the extent of educational mismatch at the occupational level. However, we find some evidence that exports and imports impact mismatch differently. This would sit well with existing evidence on the short- and medium-run effects of trade on local labour markets, but more research is needed to validate this possibility.

Regarding the impact of technological progress, we find some evidence that automation has contributed to higher levels of mismatch. A major concern in the policy debate is that automation not only reduces the overall number of jobs, but also magnifies skills gaps in the economy. However, the labour market effects in modern economic models are quite complex, and the empirical evidence on the effects of automation on employment levels is also mixed. Our finding that automation aggravates educational mismatch adds another nuance to the already rich picture on the labour market effects of automation.

Trade, Automation, and Educational Mismatch*

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Abstract

The question of how trade and automation impact labor markets is much studied, yet little is known about the effects on the "correct" matching between jobs and workers with different levels of education. We conduct an empirical analysis into the impact of trade and automation on educational mismatch across 11 Western European countries between 2002 and 2018. To do so, we measure educational mismatch at the occupational level using realized matches from the European Labor Force Survey (EU-LFS). To identify the effects of trade and automation, we exploit the emergence of Eastern Europe as a central trade partner for Western Europe along with the unprecedented rise of robots as important sources of variation in the data. We construct exposure measures based on the pre-determined weight of occupations in industries most heavily involved in trade and automation, and address endogeneity concerns using third-country trade and robots as instruments. We find some evidence that exports and imports affected matching differently, while automation caused an increase in the share of workers that are mismatched (overeducated for the work they do).

JEL codes: F16, J24, O33.

Keywords: Educational mismatch; overeducation; skills mismatch; trade; automation; technological change.

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1 Introduction

The question of how trade and automation impact labor markets is much studied, yet little is known about the effects on the "correct" matching between jobs and workers with different levels of education. In this paper, we conduct an empirical analysis into the impact of trade and automation on educational mismatch in Western Europe between 2002 and 2018. Understanding the determinants of educational mismatch—or skills mismatch more generally—seems important, as it indicates an inefficiency in the labor market that can hamper individual productivity[1] and macroeconomic performance (McGowan and Andrews, 2017).[2]

Around the turn of the century, European labor markets were subjected to at least two significant shocks. The first is hyper-globalization. Global trade accelerated dramatically in the late 1990s and into the 2000s. In Europe, the fall of the Iron Curtain and the subsequent transformation of Eastern European countries into market economies facilitated political and economic integration between the East and the West. Between 2002 and 2018, total (real) trade between Eastern and Western Europe increased by 185%.[3] The second was an ongoing technological shock in the form of automation. Over the 20-year period from 1996 to 2016, the total stock of robots installed in Western Europe more than tripled, with annual sales reaching close to 82,000 robots in 2016 alone.[4]

This paper uses repeated cross-sectional data from the European Labor Force Survey (EU-LFS) to investigate the relationship between these two shocks—globalization and automation—and the extent of educational mismatch across 20 different occupations and 11 Western European countries. Overall, we find some evidence that trade affects matching differentially depending on whether we look at exports or imports, while automation has an unambiguously positive effect, raising the share of workers that are mismatched (defined as workers being overeducated for the work they do).

Our finding that imports and exports impact educational mismatch differently squares well with the differential employment effects of import competition and export opportunities found in local labor markets in the U.S. (Autor et al., 2013) and Germany (Dauth et al., 2014), respectively. While we control for business cycle effects in our analysis, it nevertheless also speaks to the literature on

[1] Coraggio et al. (2022) provide recent worker-firm-level evidence from Sweden highlighting the importance of high-quality job-worker matches for firm productivity.

[2] See McGuinness et al. (2018b) for a useful taxonomy of different types of skills mismatch including educational mismatch.

[3] According to UN Comtrade trade data and considering trade between Western Europe (defined here as the old EU-15 countries minus Luxembourg) and Eastern Europe (Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, Russia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan).

[4] These data are from the International Federation of Robotics (IFR) and include the same EU countries as the trade data.

skills mismatch cyclicality (Brunello and Wruuck, 2021). In particular, it suggests that in slack labor markets (where competition among jobs is tough) job seekers are more likely to accept jobs not commensurate with their education, and vice versa in tight labor markets. In Norway, Liu et al. (2016) find a strong counter-cyclical pattern. However, they use a different measure of skills mismatch than we do (viz. wage penalties) and focus on recent college graduates, while we look at the entire labor force. Baley et al. (2022) present evidence suggesting that skills mismatch is pro-cyclical because job destruction during recessions is biased towards "bad" worker-job matches. However, their analysis uses data from the U.S., where lay-offs are less costly than in Europe due to different employment protection legislation.

As for automation, a major concern in the policy debate is that it not only reduces the overall number of jobs, but also magnifies skills gaps in the economy.[5] However, the labor market effects in new task-based models with heterogeneous skills are quite complex (Acemoglu and Restrepo, 2018), and the empirical evidence on the effects of automation on employment levels is also mixed (Acemoglu and Restrepo, 2020; Dauth et al., 2021). Our finding that automation aggravates educational mismatch adds another nuance to the already rich picture on the labor market effects of automation.

2 Data and empirical strategy

Main data source. EU-LFS micro-level data is a comprehensive and repeated European household survey focused on labor participation among individuals aged 15 and above, as well as on individuals outside the labor force.[6] There are at least two key advantages of using EU-LFS data for our analysis. The first is the consistent and harmonized coverage of information across all EU countries over a long period of time.[7] This allows for a rich and convincing analysis of the data across countries and over time. The second advantage is the breadth and level of detail of the data. Most importantly for our purposes, the data include worker-level information on (i) occupation (3-digit International Standard Classification of Occupations—ISCO); (ii) educational attainment (1-digit International Standard Classification of Education—ISCE); and (iii) industry affiliation (1-digit NACE), along with a range of socio-demographic characteristics like age, gender, nationality etc. This rich combination of information available in EU-LFS data allows us to construct mea-

[5] See e.g. European Commission, Directorate-General for Employment, Social Affairs and Inclusion, An Agenda for new skills and jobs – A European contribution towards full employment: communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions, Publications Office, 2011, https://data.europa.eu/doi/10.2767/28479.

[6] EU-LFS data exclude individuals doing military or community service and those living in institutional or collective households.

[7] See https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey for information on country coverage and available time series. The first wave dates back to 1983.

sures of both educational mismatch and shock exposure (to trade and automation) across different country-occupation cells and over different time periods.

To measure educational mismatch, we adopt the realized-matches method based on the highest level of education that an individual has successfully completed (educational attainment). The advantage of using this method for our work is that we can apply it consistently across all EU-LFS survey waves and countries and occupations. In particular, we first compute the benchmark match as the arithmetic mean of educational attainment within each 2-digit occupation, and then classify those individuals whose levels of educational attainment are more than 1.5 standard deviations *above* the mean as mismatched.[8] Importantly, we allow for a flexible benchmark that can vary across countries, but we do not allow the benchmark to change over time.[9] To be precise, we consider 11 Western European countries for which we can put together a comprehensive and consistent data set with information on educational mismatch (along with other necessary data), and we include the years 2002, 2010, and 2018 in our analysis.

Figure 1 plots the share of mismatched workers in 2018 against the same share in 2002. Each marker point represents a unique country-occupation cell. For illustration purposes, and following Autor et al. (2003), we classify occupations by type: (1) cognitive non-routine; (2) cognitive routine; (3) manual non-routine; and (4) manual routine. As the figure shows, educational mismatch varies a lot across cells in both years. The (unweighted) average share of mismatched workers increased from 4.97% in 2002 to 9.89 % in 2018. The standard deviation increased from 0.05 to 0.1 over the same period, indicating divergence over time.[10] The largest increase in the share of mismatched workers can be found in occupations intensive in manual non-routine tasks (+10.4%-points), followed by those intensive in cognitive routine tasks (+9.4%) and manual routine tasks (+6.1%). The share of mismatched workers in occupations intensive in cognitive non-routine tasks has not changed over the time period considered. Overall, there is no clear pattern visible in Figure 1 when it comes to the different occupation types.[11]

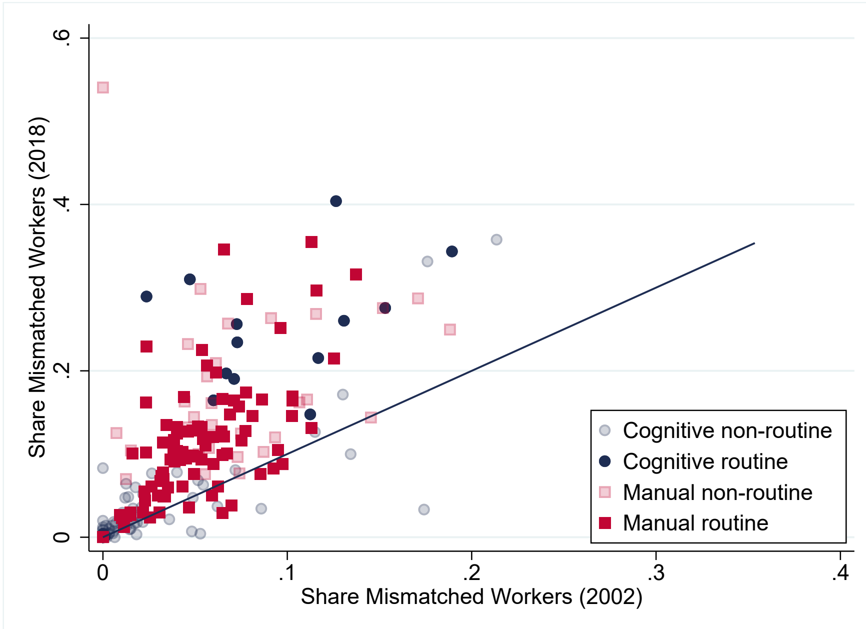
[8]We do not treat mismatch in a symmetric way, because in many jobs individuals can acquire the necessary skills *on the job*.

[9]When computing the benchmark, we only consider the native population in the year 2002. The drawbacks of the realized-matches approach that we follow here are well-known (Leuven and Oosterbeek, 2011; McGuinness et al., 2018b). For example, our mismatch measure is not based on *actual* skill requirements in different jobs. In this regard, the OECD Survey of Adult Skills (PIAAC) has some major advantages over our EU-LFS data, as it includes information on actual skill use at work in different skill domains such as digital, numeracy, literacy, and social skills. However, the PIAAC data for Europe are so far available as a cross-section only, and therefore not suitable for the type of analysis we are interested in.

[10]Focusing on overeducation between 1998 and 2012 and taking a larger set of countries into account, McGuinness et al. (2018a) find evidence for convergence in EU-LFS data.

[11]Guo et al. (2022) link skills information from PIAAC survey data and online job ads, to find that skill *surpluses* are concentrated in occupations intensive in cognitive tasks, and skill *shortages* in occupations intensive in manual tasks.

Figure 1: Educational mismatch across countries and occupations



Note: Each marker point stands for one country-occupation cell. The figure includes 11 Western European countries and 20 occupations; see Tables A.1 and A.2 in the Appendix for a list of occupations and countries included in the analysis, respectively. The share of mismatched workers is computed based on the realized-matches method as described in the text. The line is the 45-degree line. Source: Authors' computations based on EU-LFS data.

Empirical strategy. Our empirical analysis exploits the fact that some occupations are more exposed to the shocks of globalization and automation than others, because they loom large in those industries that become heavily involved in international trade and make intensive use of automation technologies. Our approach is similar to Ebenstein et al. (2014) who link worker-level data with industry-level data from the United States. Complementary to our approach, Autor et al. (2013) and many others adopt a local labor markets approach by exploiting variation across geographical regions (commuting zones) rather than occupations.[12] Specifically, we measure import exposure of occupation o in country c at time t as follows:

$$\Delta\text{Import exposure}_{oct} = \sum_{i} \frac{E_{ocit}}{E_{cit}} \frac{\Delta\text{Imports}_{cit}}{E_{oct}}, \tag{1}$$

where $\Delta\text{Imports}_{cit}/E_{oct}$ is the change in the (real) import value of product i from Eastern Europe into country c in period t scaled by the number of workers in occupation o, and E_{ocit}/E_{cit} is the share of occupation o in total employment in industry i. In words, occupations with larger

[12]Our approach rests on the assumption that individuals do not switch occupations easily. This resembles the assumption of the local labor markets approach that individuals do not move easily from one region to another. See Liu and Trefler (2019) for evidence on occupational switching in the labor market impact of services trade.

employment shares in industries subject to larger increases in imports per worker experience an import shock that is quantitatively more significant. Importantly, we measure the change in imports, $\Delta\text{Imports}_{cit}$, in two different time periods, namely from 2002 to 2010 ($t = 1$) and from 2010 to 2018 ($t = 2$); the employment variables are all measured at the beginning of the two periods, that is, in 2002 and 2010 for $t = 1$ and $t = 2$, respectively. On the export side, we measure the export exposure of occupation o in country c at time t accordingly as $\Delta\text{Export exposure}_{oct} = \sum_i \frac{E_{ocit}}{E_{cit}} \frac{\Delta\text{Exports}_{cit}}{E_{oct}}$, where $\Delta\text{Exports}_{cit}$ is the change in the (real) export value of product i from country c to Eastern Europe in period t.[13]

Figure 2 plots the average shock exposure to exports against the one for imports for different countries (left panel) and occupations (right panel). For the sake of illustration, we use import and export changes over the 16-year period between 2002 and 2018. All countries in our sample are subject to positive trade exposure shocks for both imports and exports, but there is significant cross-country variation in the *intensity* of the shock. Germany and the Netherlands stand out as two countries that display a strong average shock intensity in terms of both imports and exports. Sweden and Finland exhibit quite a strong asymmetry in the shock intensity, in that their import shocks were much more significant than their export shocks. The figure also reveals pronounced heterogeneity in terms of how strongly different occupations are exposed to trade with Eastern Europe. We find the highest degree of trade exposure among occupations with mostly manual routine task content (plant & machine operators; metal, machinery and related trade workers; and elementary trades workers). Here, too, we see an asymmetry, with import shocks being more relevant than export shocks.

As for automation, we proceed similarly as in the case of trade, and measure the automation shock as $\Delta\text{Robot exposure}_{oct} = \sum_i \frac{E_{ocit}}{E_{cit}} \frac{\Delta\text{Robots}_{cit}}{E_{oct}}$, where $\Delta\text{Robots}_{cit}$ is the change in the number

[13] We use BACI bilateral product-level trade data for the changes in imports and exports, respectively; see Gaulier and Zignago (2010). We correct nominal trade data using Eurostat data on producer prices and ECB data on nominal exchange rates. The employment variables in Eq. (1) can be elicited directly from EU-LFS data. To match HS2 products from BACI trade data into NACE1 2-digit industries from EU-LFS data, we use concordance information from the World Bank; see https://wits.worldbank.org/product_concordance.html. As in Dauth et al. (2014), Eastern European countries include Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, Russia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

of robots operating in industry i in country c in period t.[14] Using this variable, Figure 3 shows the average change in robot exposure by country (left panel) and occupation (right panel). We see that some of the same countries that feature high exposure to trade with Eastern Europe are also found among the countries with relatively high exposure to automation (Belgium, Germany, Sweden, and the Netherlands). In a similar vein, we see that the three occupations most exposed to trade are also the ones most exposed to automation. On the other hand, and not surprisingly, teaching- and service-oriented occupations display very low degrees of automation exposure (close to zero).

To identify the effects of trade and automation on educational mismatch, we exploit variation in the data across country-occupation cells and over two time periods (2002-2010 and 2010-2018). Specifically, we estimate variants of the following basic equation:

$$\Delta\text{Share mismatched workers}_{oct} = \gamma\Delta\text{Exposure}_{oct} + \boldsymbol{X}_{oct}^{\top}\boldsymbol{\beta} + \varepsilon_{oct}, \tag{2}$$

where the dependent variable is the 8-year change in the share of mismatched workers in occupation o within country c in period t, $\Delta\text{Exposure}_{oct}$ is the key explanatory variable measuring exposure to trade (imports and exports) or automation (with γ being the corresponding parameter to be estimated), $\boldsymbol{X}^{\top} = (X_1 \cdots X_N)$ is a vector of control variables (with $\boldsymbol{\beta} = (\beta_1 \cdots \beta_N)^{\top}$ being the corresponding vector of parameters to be estimated), and ε_{oct} is the error term.

To control for unobserved factors unrelated to globalization and automation, we include different fixed effects in the estimation. *Time* fixed effects capture global trends that are different across the first and the second period, e.g. due to the global financial crisis. *Country* fixed effects absorb country-specific trends between 2002 and 2018 affecting all occupations within a country in the same way, e.g. due to changes in labor market institutions, an expansion of higher education, or demographic change. *Occupation* fixed effects (at the 1-digit level), on the other hand, capture uniform demand and supply effects within a given occupation, e.g. due to general job-specific trends in technology. Our most stringent specification includes country-and-time fixed effects as well as country-and-occupation fixed effects. In this case, identification comes from differences *within* 1-digit and *between* 2-digit country-occupation cells, controlling for period-and-country-specific trends. Finally, we always include the share of migrants and women at the beginning of

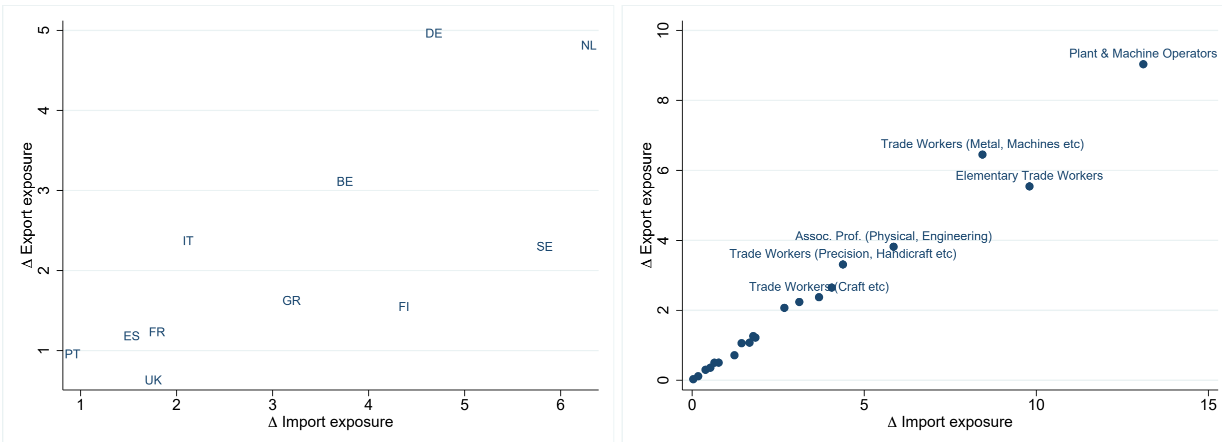
[14] These data come from the International Federation of Robotics (IFR) and are used in Graetz and Michaels (2018), Dauth et al. (2021), and many other studies that followed. The IFR data aim to capture the universe of industrial robots and are based on consolidated data provided by nearly all industrial robot suppliers worldwide. The data are available annually at the country-industry level, with broad industry categories outside of manufacturing, more detailed categories within manufacturing, and a residual category "other non-manufacturing", which comprises a large part of the service sector. We include eight manufacturing industries: (1) food/beverage; (2) textiles; (3) wood and furniture/papers; (4) plastic and chemical products; (5) glass, ceramics, stone and mineral products; (6) metal, electrical/electronics; (7) automotive/other vehicles; and (8) other manufacturing branches. As non-manufacturing industries we include: (1) mining/quarrying; (2) electricity/gas/water supply; (3) construction; and (4) education/research/development.

each period (by country-occupation cell) in all estimations, and we estimate robust standard errors clustered by country-occupation cell.

Figure 2: Change in trade exposure with Eastern Europe (2002-2018)

(a) By country

(b) By occupation



Note: The figure shows changes in export and import exposure with Eastern Europe between 2002 and 2018 as defined in the text and averaged across occupations by country (left panel), and across countries by occupation (right panel). *Source:* Authors' computations based on EU-LFS and BACI trade data.

To identify the causal effects of trade and automation on educational mismatch, we adopt an instrumental variables approach similar to the one used in the literature on the effects of trade on local labor markets (Autor et al., 2013; Dauth et al., 2014). The need for this approach arises from the possibility of omitted variables and reverse causality. For example, it could be that the same factors that minimize educational mismatch in certain industries also facilitate trade integration and the adoption of advanced technologies. By construction of our shock exposure measures, this would induce a negative correlation between trade and automation on the one hand, and educational mismatch on the other hand.

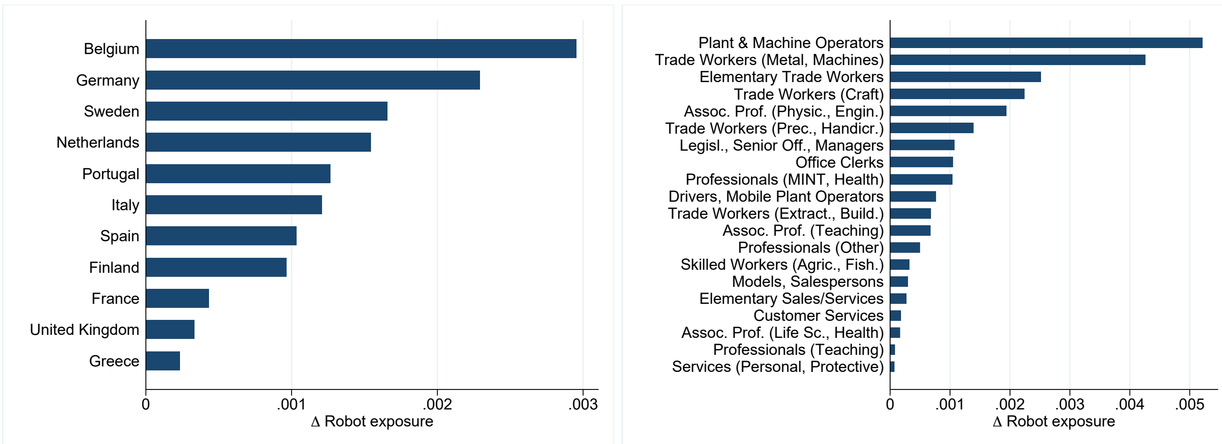
Specifically, we use third-country imports from Eastern Europe to construct our instrument for import exposure, as given in Equation (1), as follows:

$$\Delta\text{Import exposure}_{oct}^{IV} = \sum_{i} \frac{E_{ocit-1}}{E_{cit-1}} \frac{\Delta\text{Imports}_{wit}}{E_{oct-1}}, \tag{3}$$

where the change in imports on the right-hand side, $\Delta\text{Imports}_{wit}$, refers to imports from Eastern Europe into other countries that are not in our sample of analysis, and where the employment

Figure 3: Change in robot exposure (2002-2016)

(a) By country (b) By occupation



Note: The figure shows changes in robot exposure between 2002 and 2016 as defined in the text and averaged across occupations by country (left panel), and across countries by occupation (right panel). *Source:* Authors' computations based on EU-LFS and IFR robots data.

variables are all lagged relative to those used to construct the endogenous variable.[15] The idea behind this instrument is to extract the supply-side component of trade with Eastern Europe, which is unrelated to demand-side factors in the countries in our sample.[16] We proceed accordingly for instrumenting exposure to exports and automation.[17]

3 Results

In Tables 1 and 2 we report two separate sets of regressions regarding the impact of trade and automation, respectively, on educational mismatch. In Table 1 we show estimation results for the effects of import and export exposure. The first five columns show the results based on our IV approach using varying sets of fixed effects, while the last column shows OLS estimates using the most stringent set of fixed effects. Table 2, which shows the results for the effect of automation on educational mismatch, is organized in the same way as Table 1.

As for the impact of trade, we find that throughout all IV regressions the coefficient of the change in *import* exposure is estimated with a positive sign, while the coefficient of the change

[15]For the second period (2010-2018), we lag the employment variables by eight years. For the first period (2002-2010), we lag them by four years due to data constraints.

[16]The countries we include to construct the instrument are: Australia, Canada, Denmark, Ireland, Japan, Norway, South Korea, Singapore, and the United States.

[17]To compute the change in robots for the instrument, we include all countries in the IFR data that are not included in our sample of analysis. The idea behind this instrument is to extract the common component of automation across all countries in the world, which should be independent of the demand for robots in the countries included in our sample.

in *export* exposure is estimated with a negative sign. In column (1), where we include the share of migrants and the share of females as control variables, but no fixed effects whatsoever, the effects of import and export exposure are (marginally) significant.[18] This would square well with the differential employment effects of import competition and export opportunities found in local labor markets in the U.S. (Autor et al., 2013) and Germany (Dauth et al., 2014), respectively. However, neither the import nor the expect effect is statistically different from zero in our preferred specification with the full set of fixed effects in column (5). In fact, once we control for time fixed effects (column (2)) and, additionally, for country fixed effects (column (3)), the impact of trade on educational mismatch is zero (in a statistical sense). The first-stage results suggest that the estimates could suffer from a weak-identification problem, so the estimates should be interpreted with caution.

As for the impact of automation, we find a positive coefficient of the change in robot exposure throughout. This effect is marginally significant in our preferred specification with all fixed effects in column (5). The IV estimate is larger than the OLS estimate indicating that the OLS estimate is downward biased. However, the instrument is not very strong if judged by the F-statistic from the first stage regressions. To get a sense of the quantitative implications, we can consider plant & machine operators, which is the occupation most exposed to automation; see Figure 3(b). Over the 16-year period that we consider, our estimates imply an increase in the share of mismatched workers by 5%-points. This is a sizable effect considering that the initial share of mismatched workers in that occupation was 6% in 2002 on average across countries.

We have carried out additional analyses to verify our results and gain additional insights. First, for the impact of globalization, we have included the net change in trade flows, to capture the joint impact of exports and imports on educational mismatch. The results suggest that net trade (exports minus imports) tends to decrease educational mismatch, in line with the sign pattern found in Table 1. The results are marginally significant (i.e., significant at the ten percent level) in our preferred specification with the full set of fixed effects, but as in Table 1 the instrument is not very strong. Secondly, we have augmented the trade exposure variables with trade with China. We get similar results to the ones without China included, that is, the estimated coefficients of import exposure and export exposure have the same sign pattern as before, but are insignificant in most specifications. Finally, we have also used a variety of different but related measures of educational mismatch. For example, we have used a threshold of two standard deviations above the mean of educational attainment to be classified as mismatched, and we have used the mode of educational attainment instead of the mean as the benchmark, as well as more aggregate educational categories (high, medium, and low). Overall, we do not find that this makes a difference for our results.

[18]The estimated coefficients might seem small, but are quantitatively meaningful, because the values of the change in import and export exposure range between 0 and approx. 13; see Figure 2.

Table 1: International trade and educational mismatch

	Dependent variable: 8-year change in the share of mismatched workers (in %-points)					
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) OLS
ΔImport exposure	0.009**	0.008**	0.006	0.005	0.005	0.001
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.001)
ΔExport exposure	-0.009*	-0.007	-0.006	-0.006	-0.003	0.000
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.002)
Share Migrants	0.085*	0.073	0.057	-0.013	0.007	0.032
	(0.046)	(0.050)	(0.055)	(0.056)	(0.058)	(0.066)
Share Female	0.010	0.012	0.007	0.020	0.024**	0.019*
	(0.014)	(0.015)	(0.015)	(0.014)	(0.011)	(0.011)
Observations	417	417	417	417	417	417
First stage F-test of excl. inst. (ΔImport exp.)	7.29	8.82	10.78	11.54	17.74	
First stage F-test of excl. inst. (ΔExport exp.)	5.33	3.43	5.12	5.31	11.60	
Time FE	No	Yes	Yes	Yes	Nested	Nested
Country FE	No	No	Yes	Yes	Nested	Nested
Occupation FE	No	No	No	Yes	Nested	Nested
Country-Time FE	No	No	No	No	Yes	Yes
Country-Occupation FE	No	No	No	No	Yes	Yes

Notes: The table shows estimates of Equation 2. See the text for details. Robust standard errors (in parentheses) are clustered at the occupation-country level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 2: Robotization and educational mismatch

	Dependent variable: 8-year change in the share of mismatched workers (in %-points)					
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	OLS
ΔRobot exposure	21.559*	20.431*	10.516	13.415	10.873*	3.178
	(11.958)	(11.602)	(9.755)	(9.101)	(5.804)	(2.097)
Share Migrants	0.061	0.057	0.056	-0.017	0.023	0.034
	(0.051)	(0.051)	(0.047)	(0.051)	(0.057)	(0.064)
Share Female	0.033	0.031	0.017	0.030**	0.026***	0.020**
	(0.023)	(0.022)	(0.021)	(0.015)	(0.009)	(0.010)
Observations	417	417	417	417	417	417
First stage F-test of excl. inst.	7.02	7.02	12.50	8.65	14.21	
Time FE	No	Yes	Yes	Yes	Nested	Nested
Country FE	No	No	Yes	Yes	Nested	Nested
Occupation FE	No	No	No	Yes	Nested	Nested
Country-Time FE	No	No	No	No	Yes	Yes
Country-Occupation FE	No	No	No	No	Yes	Yes

Notes: The table shows estimates of Equation 2. See the text for details. Robust standard errors (in parentheses) are clustered at the occupation-country level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

4 Conclusions

Educational mismatch, arguably, comes with considerable macroeconomic costs. In this paper we investigate whether big structural changes like globalization (in the form of increased trade with Eastern Europe) and technological progress (in the form of automation) impact the extent of mismatch between jobs and workers in the labor market. To do so, we use data from the European Labor Force Survey for a set of 11 Western European countries over a period of 16 years between 2002 and 2018.

Our empirical analysis exploits the fact that some occupations and countries are much more exposed to globalization and technological progress than others. This is so because of differences in the (initial) mix of industry structure (among other things). We leverage these differences to compute measures of shock exposure to globalization and automation at the country-occupation level. That we focus on the occupational margin is a significant departure from many previous studies on the labor market effects of globalization and automation, which instead emphasize the regional dimension.

To measure educational mismatch, we consider overeducation, and find that the extent of educational mismatch has increased significantly between 2002 and 2018. In fact, according to a standard measure of educational mismatch, the average share of mismatched workers (overeducated for the work they do) has doubled from 5% to 10% across all occupations and countries.

Our econometric analysis reveals that, overall, the surge in international trade with Eastern Europe after the turn of the millennium has perhaps little to say about the extent of educational mismatch at the occupational level. We do find some evidence that exports and imports impact mismatch differently. This would sit well with existing evidence on the short- and medium-run effects of trade on local labor markets, but more research is needed to validate this possibility. Regarding the impact of technological progress, we find some evidence that automation has contributed to higher levels of mismatch.

References

Acemoglu, D. and P. Restrepo, “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,” *American Economic Review*, 2018, *108* (6), 1488–1542.

__ **and** __ , “Robots and Jobs: Evidence from US Labor Markets,” *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

Autor, D., F. Levy, and R. Murnane, “The Skill Content of Recent Technological Change: An Empirical Exploration,” *Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Autor, D. H., D. Dorn, and G. H. Hanson, “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 2013, *103* (6), 2121–2168.

Baley, I., A. Figueiredo, and R. Ulbricht, “Mismatch Cycles,” *Journal of Political Economy*, 2022, *130* (11), 2943–2984.

Brunello, G. and P. Wruuck, “Skill Shortages and Skill Mismatch: A Review of the Literature,” *Journal of Economic Surveys*, 2021, *35* (4), 1145–1167.

Coraggio, L., M. Pagano, A. Scognamiglio, and J. Tåg, “JAQ of All Trades: Job Mismatch, Firm Productivity and Managerial Quality,” CEPR Discussion Paper No. 17167, 2022.

Dauth, W., S. Findeisen, and J. Suedekum, “The Rise of the East and the Far East: German Labor Markets and Trade Integration,” *Journal of the European Economic Association*, 2014, *12* (6), 1643–1675.

__ **,** __ **,** __ **, and N. Woessner**, “The Adjustment of Labor Markets to Robots,” *Journal of the European Economic Association*, 2021, *19* (6), 3104–3153.

Ebenstein, A., A. Harrison, M. McMillan, and S. Phillips, “Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys,” *Review of Economics and Statistics*, 2014, *96* (4), 581–595.

Gaulier, G. and S. Zignago, “BACI: International Trade Database at the Product-Level. The 1994-2007 Version,” Working Papers 2010-23, CEPII 2010.

Graetz, G. and G. Michaels, “Robots at Work,” *The Review of Economics and Statistics*, 2018, *100* (5), 753–768.

Guo, Y., C. Langer, F. Mercorio, and F. Trentini, “Skills Mismatch, Automation, and Training: Evidence from 17 European Countries Using Survey Data and Online Job Ads,” *EconPol Forum*, 2022, *23* (5), 11–15.

Leuven, E. and H. Oosterbeek, “Chapter 3: Overeducation and Mismatch in the Labor Market,” in E. A. Hanushek, S. Machin, and L. Woessmann, eds., *Handbook of The Economics of Education*, Elsevier, 2011, pp. 283–326.

Liu, K., K. G. Salvanes, and E. Ø. Sørensen, “Good Skills in Bad Times: Cyclical Skill Mismatch and the Long-Term Effects of Graduating in a Recession,” *European Economic Review*, 2016, *84*, 3–17.

Liu, R. and D. Trefler, “A Sorted Tale of Globalization: White Collar Jobs and the Rise of Service Offshoring,” *Journal of International Economics*, 2019, *118*, 105–122.

McGowan, M. A. and D. Andrews, “Labour Market Mismatch and Labour Productivity: Evidence from PIAAC Data,” OECD Economics Department Working Papers, no. 1209, 2017.

McGuinness, S., A. Bergin, and A. Whelan, “Overeducation in Europe: Trends, Convergence, and Drivers,” *Oxford Economic Papers*, 2018, *70* (4), 994–1015.

_, K. Pouliakas, and P. Redmond, “Skills Mismatch: Concepts, Measurement and Policy Approaches,” *Journal of Economic Surveys*, 2018, *32* (4), 985–1015.

A Appendix

Table A.1: List of occupations included in the analysis

ISCO	Description	Type
10	Legislators, senior officals and managers	Cognitive non-routine
21, 22	Physical, mathematical, health, engin. & life science professionals	Cognitive non-routine
23	Teaching professionals	Cognitive non-routine
24	Other professionals	Cognitive non-routine
31	Physical and engineering science associate professionals	Cognitive non-routine
32	Life science and health associate professionals	Cognitive non-routine
33, 34	Teaching and other associate professionals	Cognitive non-routine
41	Office clerks	Cognitive routine
42	Customer services clerks	Cognitive routine
51	Personal and protective services workers	Manual non-routine
52	Models, salespersons and demonstrators	Manual non-routine
60	Skilled agricultural and fishery workers	Manual non-routine
71	Extraction and building trades workers	Manual routine
72	Metal, machinery and related trades workers	Manual routine
73	Precision, handicraft, craft printing and related trades workers	Manual routine
74	Other craft and related trades workers	Manual routine
81, 82	Plant & machine operators	Manual routine
83	Drivers and mobile plant operators	Manual routine
91	Sales and services elementary occupations	Manual routine
92, 93	Elementary trades workers	Manual routine

Table A.2: List of countries included in the analysis

Abbreviation	Country
BE	Belgium
DE	Germany
GR	Greece
ES	Spain
FI	Finland
FR	France
IT	Italy
NL	Netherlands
PT	Portugal
SE	Sweden
UK	United Kingdom

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