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ABSTRACT
This paper analyses the impact of economic complexity on the labour market using annual data on OECD countries for the period 1985-2008 and averaged data over the period 1990-2010 for 70 developed and developing countries with a large number of controls. We show that moving to higher levels of economic sophistication of exported goods leads to less unemployment and more employment, revealing that economic complexity does not induce job loss. Our findings remain robust across alternative econometric specifications. Furthermore, we place the spotlight on the link between products' embodied knowledge (sophistication) and labour market outcomes at the micro-level. We build a product-level index that attaches a product to the average level of unemployment (or employment) in the countries that export it. With this index, we illustrate how the development of sophisticated products is associated with changes in the labour market and show that the economic sophistication of exported goods captures information about the economy's job creation and destruction.

KEYWORDS
Economic Complexity; Product Sophistication; Unemployment; Employment

1. Introduction

Progressing to a more complex economy by developing and producing new sophisticated products is a process of creative destruction that directly affects the labour market by creating and destroying jobs. Although it is relatively straightforward to highlight positive and negative effects in particular cases, it is not that obvious to analyze and measure the overall (net) outcome of the economic complexity advancements throughout the economy. During the last 20 years, new sophisticated products have radically transformed sectors/industries, leading to a destruction of obsolete jobs and, in parallel, to the creation of new ones (Feldmann, 2013). Product sophistication can

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displace labour by reducing or eliminating the demand for particular goods and/or services, in sectors which are specialized in routine activities (Dao, Das, Koczan, & Lian, 2017). In addition, it can reduce employment within 'highly automatable' occupations, through the introduction of machines and robots (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). On the other hand, 'automation' can increase the needs for job requirements of complex tasks and thus high skilled workers, availing employment (D. Autor & Salomons, 2018). Thus, if technological advances in production can lead concomitantly to both creation and destruction of jobs in the labor market, one can reasonably ask: ceteris paribus, what is the net effect (or the sign of the total effect) of the transformation of the productive structure towards more sophisticated industries on employment and unemployment?

A number of recent contributions have introduced the measure of economic complexity in order to explain structural transformations and economic growth as a process of information development and learning how to produce and export more complex products (Abdon & Felipe, 2011; Albeaik, Kaltenberg, Alsaleh, & Hidalgo, 2017b; Bustos, Gomez, Hausmann, & Hidalgo, 2012; Caldarelli et al., 2012; Cristelli, Gabrielli, Tacchella, Caldarelli, & Pietronero, 2013; Cristelli, Tacchella, & Pietronero, 2015; Felipe, 2012; Hausmann et al., 2014; Hausmann, Hwang, & Rodrik, 2007; Hidalgo & Hausmann, 2009; Hidalgo, Klinger, Barabási, & Hausmann, 2007; Rodrik, 2006; Tacchella, Cristelli, Caldarelli, Gabrielli, & Pietronero, 2013). The received literature shows that the development path of a country lies in its capacity to accumulate the 'knowledge' part of the Solow residual. Thus, more developed economies associate with the production of more diversified and complex products and vice versa. Knowledge is required to produce varied and more sophisticated goods; moreover, embedded in countries' productive structures, it also explains the differences in their economic performance (Cristelli et al., 2015; Rodrik, 2006; Saviotti & Frenken, 2008). The relevant question then becomes: how much knowledge is there in an economy?

In recent years, the search for an answer to this question has given rise to an elaborate metric called the Economic Complexity Index (ECI), which quantifies the amount of knowledge/know-how materialized in the country's production of exported goods. To elucidate this, consider producing and exporting an electronic product, like computer hardware. Production of computer hardware requires specific ICT and physical capital inputs, specific knowledge and cognitive skills, such as information technology (IT). Thus the nature of exports offers information about the presence of specific production related faculties in the economy (Albeaik et al., 2017b).

The ECI reflects competencies in production of exported goods produced domestically by quantifying the network representation of the relatedness and proximity between products traded internationally (Inoua, 2016). When a country produces a good located in the core of the product space, many other related goods can also be produced with the same faculties. However, this does not necessarily hold for goods lying in the network's periphery, since those may require a different set of production abilities. The core is formed, for example, by metal products, electronics, machinery and chemicals, while the periphery is populated by product-categories like fishing, animal agriculture, cereal agriculture, garments and textiles.[1] The ECI methodology assigns lower values to countries that export products located at the periphery of the product space, i.e. products that require less specialized know-how, while higher values are assigned to countries with export commodities located in the center of the

[1]See Figure 1 in Hidalgo et al. (2007) for the network representation of the product space for 775 SITC-4 product classes exported in the 1998-2000 period.

product space (Hidalgo & Hausmann, 2009; Hidalgo et al., 2007). Thus, if the bipartite network connecting countries to the products they export is the result of a larger tripartite network connecting countries and products to the capabilities embodied in their production, then becoming a sophisticated (complex) economy is the process of moving from the periphery to the core of the international trade network of products.

Despite the great contribution of structural transformations and industrialization in creating new jobs and learning opportunities for workers (Hartmann, Guevara, Jara-Figueroa, Aristarán, & Hidalgo, 2017), one of the most notable stylised facts that has stigmatized the last decades is deindustrialisation, i.e. the decline in manufacturing employment in the industrialised world. Rodrik (2006) documents a significant deindustrialisation trend in recent years that goes beyond the advanced, post-industrial economies. Buera and Kaboski (2009); Matsuyama (2009); Nickell, Redding, and Swaffield (2008); Rowthorn and Ramaswamy (1999) argue that deindustrialisation is explained by 'the relative productivity hypothesis': faster growth in manufacturing productivity leads to relative price changes and shifts in the economy's productive structure (Bernard, Smeets, & Warzynski, 2017). Other recent works show that manufacturing employment declines as a result of globalization and the strengthening of manufacturing sectors of developing economies (D. Autor, Dorn, & Hanson, 2013; D. H. Autor, Dorn, Hanson, & Song, 2014; Pierce & Schott, 2016).

Recent studies aiming to configure the contribution of technological advancements on labor market outcomes, have revived the debate and concerns about 'technological unemployment'. The conventional wisdom of what Acemoglu and Autor (2011) refer to as the Skill-Biased Technical Change (SBTC) has been resurrected: the introduction of sophisticated production methods partly replaced the demand for low-skilled workers with demand for medium- and high- skilled ones, introducing a skill bias in the labour demand (Katz & Murphy, 1992). As a result, we observe an increase in the demand for high skilled workers followed by a simultaneous drop in employment losses for low skilled ones (Raquel, Biagi, et al., 2018). In this case, if demand rises faster than supply of skilled labor, then we expect to see increasing wage premia for high skilled workers.

However, the SBTC alone is not able to explain the prominent recent decline of middle-skilled jobs, as compared to low and high wage occupations, giving rise to the so-called 'job polarization' phenomenon (Goos & Manning, 2007). D. H. Autor, Levy, and Murnane (2003) introduce the so-called Routine Biased Technological Change (RBTC) hypothesis (D. H. Autor, Katz, & Krueger, 1998; D. H. Autor, Levy, & Murnane, 2002; Bartel, Ichniowski, & Shaw, 2007; Beaudry, Green, & Sand, 2016; Bound & Johnson, 1989; Bresnahan, Brynjolfsson, & Hitt, 2002; David, 2015; Juhn, Murphy, & Pierce, 1993; Katz & Murphy, 1992), offering an innovative approach, able to capture the non-linear effect of computerization on labour demand. The main principle of their model is the fact that technological progress, reflected through robot use, computerisation, and improvements in Information and Communication Technology (ICT), are the main drivers of middle-skill job depletion, due to worker substitution by machines (Raquel et al., 2018).

Given the simultaneous nature of the aforementioned events and the partial complementarity of the two theoretical approaches, there are three parallel waves of labor market outcomes. The occupations mainly affected by technological advances are those susceptible to automation, dealing with tasks that follow well-defined procedures, resulting in a decline in employment of low-skilled workers (Acemoglu & Autor, 2011; Arntz, Gregory, & Zierahn, 2016; Charles, Hurst, & Notowidigdo, 2013; Dao et al., 2017; Frey & Osborne, 2017; Jaimovich & Siu, 2012; Nedelkoska & Quintini, 2018). At the same time, technological progress leading to falling prices of ICT capital, increases the demand for high-skilled workers in occupations involving cognitive tasks (Acemoglu, 2002; Katz & Murphy, 1992; Krusell, Ohanian, Ríos-Rull, & Violante, 2000; Spitz-Oener, 2006). In addition, there is evidence of a labour supply shift from middle-income manufacturing to low-income service occupations due to lower levels of machine substitution possibilities in the latter (D. H. Autor et al., 2003; David & Dorn, 2013; Goos & Manning, 2007).

Within this elaborately established stand of literature focusing mainly on Routine-Biased Technical Change, we suggest the use of a novel proxy of technological progress that we argue to be a better reflection of progress not solely of automated tasks, computerization and use of robots, but also a mirroring of higher level skills, higher end education and knowledge, and rare qualifications. Thus we aim to capture a structural element of higher dimensionality, that other measures do not encapsulate. The ECI, is also a superior measure compared to traditional human capital variables. In fact, ECI includes, but is not limited to, knowledge and the level of human capital in the economy. Last, but not least, our proposed tool reflects improvements in production capabilities for the exported goods produced in the economy.

The contribution of our study is twofold. First, we advance the received literature on the macroeconomic underpinnings of the ECI (Hartmann et al., 2017; Hausmann & Hidalgo, 2011; Hidalgo & Hausmann, 2009), by documenting the robust association of the level of sophistication of exported products with lower unemployment, along some more detailed findings on gender and youth employment. Our results highlight that once we control for a set of control variables, the ECI leads to beneficial responses in labor markets, ceteris paribus. This result is found to be consistent across various specifications, and in both a panel setting, in which we examine a limited sample of OECD countries for the period 1985-2008 and a cross-sectional setting, in which we use a global sample of 70 developed and developing countries taking averages over the period 1990-2010.

Second, we suggest and develop a product-level index that classifies products according to the level of unemployment (or employment) they are associated with (Hartmann et al., 2017). Using this index, we illustrate how the development of sophisticated products is associated with changes in the labour market. Our results suggest that countries' labour markets are conditioned by their 'product space' and hence by the level of sophistication embodied in the production of exported goods. Therefore, our index might be a promising policy tool that could be used to estimate the changes in labour market outcomes (unemployment and employment rates) we would expect if a country were to modify its product mix by adding or removing a product.

The remainder of the paper is structured as follows. Section 2 discusses the data. Section 3 presents the methods used in the paper. Section 4 describes the econometric analysis for studying the impact of economic complexity on labour market outcomes, discusses the control variables and the instruments of ECI included in the model and presents and discusses the results. Section 5 introduces two indexes of the unemployment and employment rates expected for the producers and exporters of 773 different products in the Standard Industrial Trade Classification at the four-digit level (SITC-4 Rev.2). Using these indexes, we put the spotlight on the links between export's sophistication and the unemployment and employment rates, at the micro-level. We illustrate that the development of more complex products is associated with lower unemployment and higher employment rates. Finally, in Section 6, we draw our conclusions.

2. Data

Data on labour market are taken from the International Labour Organization (ILO) as reported in the World Bank's World Development Indicators database. Even though our main focus is on the overall unemployment and employment rates, in the econometric analysis we also experiment with the associated variables for subgroups of the population, i.e. young people and, men and women. To ensure comparability of our results in all instances, we use the same data source, i.e. the ILO national estimates.

To study the effect of ECI on the various labour market outcomes we use two different datasets. The first one includes OECD countries only, while the second includes a total of 70 countries both developed and developing. The OECD sample provides a more reliable dataset regarding the set of control variables (which is discussed in 4.1 and presented in Table 1) and its availability over a longer period of time. Specifically, given the availability of controls, the OECD sample covers the period 1985-2008 and includes the following countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea Rep., Latvia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Rep., Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States. It should be mentioned, however, that some variables, although having the same number of observations, differ in the country/year observations.

In contrast, for non-OECD countries we have a limited set of control variables. In order to maximize the number of countries included in the sample we consider a simple cross-section, taking averages for the period 1990-2010 to the detriment of having temporal variations but for much fewer countries (mainly for the OECD countries as above). In other words, the benefit of having more countries in the sample and available controls is counterbalanced by the absence of time variation. However, we feel that this additional analysis gives valuable insights and further robustification of our results.[2]

We also use freely available international trade data from the Massachusetts Institute of Technology (MIT)'s Observatory of Economic Complexity (`http://atlas.media.mit.edu`). We chose the SITC-4 rev.2 dataset, which provides the longest time series, combining information from a dataset compiled by Feenstra, Lipsey, Deng, Ma, and Mo (2005) for the years 1962-2000 and the UN Comtrade dataset from 2001 to 2008 (`https://comtrade.un.org`), and details about the products exported by every country.

We measure economic complexity using the improved ECI (ECI+). ECI+ measures the diversity and sophistication of a country's export structure corrected by how difficult it is to export each product. It combines information on the diversity of a country, i.e. the number of products it exports, and the ubiquity of its products, i.e. the number of countries that export these products (Hidalgo & Hausmann, 2009). ECI+ is estimated from data connecting countries to the products they export and is freely available at MIT's Observatory of Economic Complexity. The index is calculated by applying the methodology described in Albeaik et al. (2017b) to the international trade data from the MIT's Observatory of Economic Complexity (a brief description of this methodology is discussed in Section 3). Albeaik et al. (2017b) show that ECI+ outperforms the original ECI in its ability to predict economic growth and in the consistency of its estimators across different econometric specifications. ECI+ captures information about an economy's level of development that is different from

[2]Data definitions and summary statistics for this dataset are given in Table 6

what is captured by, for example, gross domestic product (GDP) growth or GDP per capita. ECI+ incorporates the idea that institutions, knowledge and technology are prerequisites for economic growth but, in contrast to other indexes of growth, ECI+ is measured with simple linear algebra techniques that determine the knowledge intensity of economies endogenously – from the countries' export data (Albeaik et al., 2017b). In a very recent working paper, Albeaik, Kaltenberg, Alsaleh, and Hidalgo (2017a) show that the definition of ECI+ is equivalent to the Fitness Complexity metric proposed by Tacchella, Cristelli, Caldarelli, Gabrielli, and Pietronero (2012).

3. Methods

To calculate the improved measure of economic complexity (ECI+) used in this work, we rely on the methodology described in Albeaik et al. (2017b). In short, let us assume that we have trade information for l number of countries and k products. We can calculate the total exports of a country corrected by how difficult it is to export each product using

$$\mathrm{X_c^1} = \sum_{\mathrm{p}} \frac{\mathrm{X_{cp}}}{\sum_{\mathrm{c}} \frac{\mathrm{X_{cp}}}{\mathrm{X_c^0}}}, \tag{1}$$

where $X_c^0 = \sum_p X_{cp}$ is the total exports of country c and $\frac{1}{\sum_c \frac{X_{cp}}{X_c^0}}$ measures how difficult it is for country c to export product p.

We then use this corrected value of total exports (equation 1) to calculate the second order correction:

$$\mathrm{X_c^2} = \sum_{\mathrm{p}} \frac{\mathrm{X_{cp}}}{\sum_{\mathrm{c}} \frac{\mathrm{X_{cp}}}{\mathrm{X_c^1}}}, \tag{2}$$

where X_c^2 represents again the proportion that a product represents of the average country.

Iterating this to the limit:

$$\mathrm{X_c^N} = \sum_{\mathrm{p}} \frac{\mathrm{X_{cp}}}{\sum_{\mathrm{c}} \frac{\mathrm{X_{cp}}}{\mathrm{X_c^{N-1}}}}, \tag{3}$$

and normalizing X_c at each iteration step by its geometric mean:

$$\mathrm{X_c^N} = \frac{\mathrm{X_c^N}}{(\prod_{\mathrm{c'}} \mathrm{X_{c'}^N})^{\frac{1}{[\mathrm{C}]}}} \tag{4}$$

where $[C]$ is the number of countries in the sample. We estimate ECI+ as the total exports of a country corrected by how difficult it is to export each product, minus the average proportion that the country represents in the total exports of a product (which accounts for the size of a country's export economy):

$$ECI_c^+ = \log(X_c^\infty) - \log(\sum_p \frac{X_{cp}}{X_p}). \tag{5}$$

Likewise, but putting the spotlight on products rather than on countries, the improved product complexity index (PCI+) is defined as the following iterative map:

$$\mathrm{X_p^N} = \sum_{\mathrm{c}} \frac{\mathrm{X_{cp}}}{\sum_{\mathrm{p}} \frac{\mathrm{X_{cp}}}{\mathrm{X_p^{N-1}}}} \tag{6}$$

with the initial condition $\mathrm{X_p^0} = \sum_{\mathrm{c}} \frac{\mathrm{X_{cp}}}{\mathrm{X_c^0}}$ being the average proportion of product p in country c.

Again, normalizing at each step X_p by its geometric mean:

$$\mathrm{X_p^N} = \frac{\mathrm{X_p^N}}{(\prod_{\mathrm{p'}} \mathrm{X_{p'}^N})^{\frac{1}{[\mathrm{P}]}}} \tag{7}$$

where $[P]$ is the number of products in the sample, we define the product complexity index, corrected by how difficult it is to export each product,

$$PCI_p^+ = \log(X_p) - \log(X_p^\infty) \tag{8}$$

where X_p is total world trade of product p.

To summarize, ECI+ and PCI+ denote, respectively, the total exports of a country, corrected by how difficult it is to export each product, and the total trade in a product, corrected by how easy it is to export that product (Albeaik et al., 2017b). For simplicity of notation, we will hereafter call these measures ECI and PCI respectively.

4. Regression analysis

We study the effect of economic complexity, measured by the ECI, on various labour market outcomes, using the datasets described in Section 2.

According to Hausmann et al. (2007) higher economic complexity is associated with higher productivity. The ECI ranks traded goods in terms of their implied productivity. This signals an important source of endogeneity in the relationship considered and an obvious problem of reverse causality. Furthermore, given that ECI is an alternative measure of structural transformations, i.e., the reallocation of factors of production from traditional to modern activities, its simultaneity with labour market outcomes cannot be neglected. In order to mitigate the endogeneity of the independent variables, we follow a fixed effects, two-stage least squares/instrumental variables (FE 2SLS/IV) strategy for both datasets (OECD panel sample and cross-section world sample).

We regress the baseline specification described by the following equation:

$$\mathrm{y}_{i,t} = \alpha_0 + \beta_1 ECI_{i,t} + \beta_k controls_{i,t} + \gamma_i + \delta_t + u_{i,t}. \tag{9}$$

Here, labour market outcomes for country i in period t are expressed as a function of the ECI, a set of control variables, time δ_t and country γ_i fixed effects, and a stochastic term $u_{i,t}$.[3] The main dependent variable in all regressions is the overall unemployment rate. To examine the robustness of our results and to generalize our

[3]The cross-section model does not include country and time fixed effects.

findings, we also replicate our analysis for the unemployment and employment rates, among young people and men and women separately.

We suggest the use of lagged and differenced values of the main independent variable (ECI) for up to four years as instruments. The received literature on IVs (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009) shows that lagged differences of the suspected endogenous variable can serve as appropriate instruments, provided that they pass the tests for relevance, weakness and overidentifying restrictions (Feldmann, 2013). Regarding relevance, we argue that changes in the ECI over the previous four years are likely to have a direct impact on the level of ECI in the current year, since technological changes in productive structure are rather cumulative: higher ECI today is more likely to result in higher ECI next year. Statistically speaking relevance is shown in our results through statistical significance of the IVs. Regarding excludability, we argue that lagged ECI affects labour market outcomes in the current year only through the current level of ECI. Weakness and overidentification are addressed and discussed in the results section.

Although relevance is hard to fail above, excludability could still be of concern. Indeed former levels of ECI could have implications to other aspects of the economy, related to and still be relevant for present economic growth. We propose the inclusion of the lagged ECI variables in the main equation, in an attempt to check indeed whether they pose a threat to identification. However, statistical validity of the suggested IVs avails in the opposite direction.

4.1. ***OECD panel sample***

To correctly specify our regression model we use two broad groups of control variables out of the full set, which is listed in Table 1. The first group includes macroeconomic controls, i.e. *Inflation*, *Imports* and *Output Gap*. The inflation rate controls for the standard Phillips curve relationship (Wyplosz, 2001). The *Output Gap* controls for the business cycle, whereas imports as proportion of GDP (*Imports*) controls for the effect of international trade. The second group of controls aims to capture the effect of labour market institutions.[4] More specifically, we use the average tax wedge, denoted *Tax Wedge* (Daveri & Tabellini, 2000), and variables that may encompass key elements of the wage bargaining system as in Aidt and Tzannatos (2008) (namely *Union Density, Coverage, Centralization* and *Coordination*). Last, *Replacement* serves to pick up the generosity of the unemployment benefits system (Lichter, 2016; Scarpetta, 1996).[5]

Table 2 presents our main results. In all cases except column (11), we report the IV results. Our intuition regarding IV appropriateness due to the cumulative nature of the ECI, is verified by the first-stage results (reported in the Appendix), since in all cases, the coefficients of the lagged and differenced ECI have a positive sign and are statistically significant at the 1% level (in only three cases, for the third lag, they are significant at the 5% level). In addition, in order to take into account Angrist and Krueger (2001)'s caution against blindly using lags as instruments, we run the baseline model including also the four lagged variables of ECI as independent variables. Our results, which are available upon request, favor our argument above, by showing that

[4] For variable definitions, data sources and summary statistics see Table 1.

[5] To examine the robustness of our results we also introduce a series of additional variables that capture the strictness of government regulation in the labour market. Specifically, we employ an index of employment protection legislation (*EPL*), an index that measures the strictness of regulation in the economy (*Regulation*), the proportion of public expenditures on active labour market programmes (as a percentage of government spending) and the variable *Min Wage*, which measures the generosity of the minimum wage scheme.

Table 1. Variable sources, definitions and summary statistics; OECD sample

Variable	**Definition**	**Source**	**Mean**	**Std. Dev.**
ECI	Economic Complexity Index	Observatory of Economic Complexity	1.02	0.464
Unemployment	Total Unemployment Rate	World Bank	7.93	4.16
Youth Unemployment	Unemployment Rate for ages 15-24	World Bank	16.97	8.89
Male Unemployment	Unemployment Rate for Males	World Bank	7.67	3.91
Female Unemployment	Unemployment Rate for Females	World Bank	8.56	4.74
Male Employment	Male Employment as % of Male Labour Force	World Bank	63.94	6.25
Female Employment	Female Employment as % of Female Labour Force	World Bank	54.66	6.19
Employment	Employment as % Labour Force	World Bank	45.95	8.49
Inflation	% change in annual Consumer Price Index	IMF	10.34	31.09
Imports	Imports of goods and services as % of GDP	OECD	32.88	16.96
Output Gap	The difference between actual and potential real (GDP) as a per cent of potential real GDP.	IMF	-0.00	0.023
Union Density	Net Union Membership as a proportion of total number of wage and salary earners in employment	Visser (2015)	35.58	19.27
Centralization	Level at which bargaining takes place, higher values indicate more centralized level of bargaining	Visser (2015)	2.71	1.48
Coordination	Coordination of Wage setting, higher values indicate more centralized wage setting institutions	Visser (2015)	2.95	1.41
Union Coverage	Number of Workers covered by wage bargaining	Visser (2015)	59.43	28.12
Replacement	Net Unemployment Replacement Rate for an Average Single Production Worker (with no children)	OECD	0.54	0.187
Tax Wedge	The ratio between the amount of taxes paid by an average single worker (a single person at 100% of average earnings) without children and the corresponding total labour cost for the employer.	OECD	26.81	11.30
EPL	The procedures and costs involved in dismissing individuals or groups of workers and the procedures involved in hiring workers on fixed-term or temporary work agency contracts.	OECD	2.18	0.83
Min Wage	Minimum Wage Setting institutions categorical variable. Higher values indicate higher level of min wage setting institutions	Visser (2015)	1.24	0.92
Regulation	Summary measure of a wide array of regulatory provisions in the economy	OECD	6.96	1.08
ALMP	Expenditure on labour market policies (LMP) targeted at groups of persons with difficulties in the labour market, as % of GDP	OECD	1.77	1.26
Education	Gross enrolment ratio, tertiary, both sexes (%)	World Bank	58.6	17.02
Articles	(log) Number of journal articles in scientific and technical journals, in the fields of physics, chemistry, biology, mathematics, clinical medicine, biomedical research, engineering and technology, earth and space sciences. Scientific and technical article counts are from journals classified by the Institute for Scientific Information's Science Citation Index (SCI) and Social Sciences Citation Index (SSCI)	World Bank	9.546	1.344

Table 2. Fixed Effects 2SLS, OECD sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11-OLS)
ECI	-10.752*	-12.057**	-12.248**	-10.799**	-10.601**	-9.357**	-9.372**	-10.022**	-9.371**	-15.023**	-6.316**
	(-1.840)	(-2.208)	(-2.348)	(-2.311)	(-2.284)	(-2.051)	(-2.024)	(-2.260)	(-2.140)	(-2.092)	(-2.380)
Inflation	-0.269***	-0.328***	-0.324***	-0.400***	-0.400***	-0.370***	-0.373***	-0.355***	-0.341***	-0.217**	-0.323***
	(-4.872)	(-6.746)	(-6.731)	(-7.234)	(-7.424)	(-7.011)	(-6.966)	(-6.769)	(-6.595)	(-2.499)	(-6.854)
Imports		-0.102***	-0.100***	-0.076**	-0.074*	-0.079**	-0.080**	-0.067*	-0.080**	-0.089**	-0.091***
		(-2.711)	(-2.801)	(-1.979)	(-1.938)	(-2.103)	(-2.169)	(-1.917)	(-2.267)	(-2.235)	(-2.989)
Output Gap			-19.363***	-18.802***	-18.370***	-20.307***	-21.550***	-21.714***	-21.645***	-11.360*	-21.995***
			(-2.870)	(-2.843)	(-2.754)	(-3.087)	(-3.288)	(-3.374)	(-3.422)	(-1.766)	(-3.347)
Union Density				0.156***	0.165***	0.166***	0.145***	0.140***	0.142***	0.026	0.139***
				(3.426)	(3.457)	(3.554)	(3.003)	(3.034)	(3.089)	(0.323)	(2.976)
Centralisation					-0.180	0.225	0.155	0.102	0.149	0.185	0.117
					(-0.787)	(0.839)	(0.599)	(0.397)	(0.586)	(0.650)	(0.446)
Coordination						-0.797***	-0.782***	-0.753***	-0.815***	-0.840**	-0.827***
						(-2.623)	(-2.655)	(-2.616)	(-2.887)	(-2.443)	(-2.783)
Union Coverage							0.029	0.027	0.022	0.006	0.016
							(1.462)	(1.405)	(1.103)	(0.535)	(0.814)
Replacement								4.145**	4.339**	-7.478*	4.451**
								(2.044)	(2.135)	(-1.898)	(2.154)
Tax Wedge									0.130***	0.099*	0.134***
									(2.600)	(1.871)	(2.618)
Observations	403	403	403	403	403	403	403	403	403	252	403
R-sq	0.355	0.369	0.384	0.433	0.435	0.458	0.463	0.473	0.483	0.486	0.817
F-test	7.122	7.419	7.920	8.396	8.268	9.789	9.560	10.19	11.23	7.231	48.50
DWH-test	0.500	1.798	2.461	0.899	0.946	0.565	0.310	0.677	0.528	0.574	
Weak-id	14.53	17.20	17.99	21.88	21.31	20.99	21.77	22.27	21.64	22.87	
LM-Underid	37.27	43.08	43.60	50.31	55.68	55.22	54.61	55.84	53.63	15.79	
Hansen(p-value)	0.404	0.497	0.634	0.654	0.639	0.528	0.446	0.401	0.347		

Notes: Dependent variable: unemployment rate. ECI is instrumented. Clustered t- statistics in parentheses. F-test gives the F test for the significance of the model. DWH is the Durbin- Wu- Hausman test of endogeneity of the regressors. Rejection of the null suggests that the IV regression is required. LM-Underid gives the Kleibergen-Paap Wald test of weak identification, with the null hypothesis indicating that the model is weakly identified. Weak-id gives the F statistic for weak identification. Hansen test (p-value) gives the p-value of the Hansen test of overidentification. Rejection of the null implies that the overidentifying restrictions cannot be rejected. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

the variables considered as instruments do not belong in the main model. Hence the use of lagged and differenced ECI per se should not raise concerns on excludability.

On the bottom of Table 2, and respectively in all included Tables of IV results, we present relevant statistics, lending confidence to our model and method. The F-test is the F-statistic on the significance of the model, exhibiting relevance for the included controls. DWH-test is the Durbin-WU-Hausman test of endogeneity of the regressors, the results to which are prompting to the need for an IV regression. Weak-id gives the F-statistic for weak identification, which in all cases is larger than the minimum rule of thumb of 10 for strong instruments, suggested by Staiger and Stock (1997). The LM-Underid gives the Kleibergen-Paap Wald test of weak identification, with the null hypothesis - here rejected - indicating that the model is weakly identified. Last, the Hansen test, shows the p-value of the Hansen test of overidentification. Our p-values are suggesting failure to reject the null, especially in columns 2, 3 and 4, where the values are closer to 1. However, it is suggestive that Hansen test p-values are viewed with caution, due to lack of theoretical justification of the exact thresholds over 0.1 and below 0.25 in the literature (Roodman, 2009). Brief explanation of the presented statistics is given at the bottom of each table of results.

Column 9 of Table 2, presents our baseline specification, whereas columns (1)-(8) report results from our robustness checks regarding the inclusion of additional variables. Column (10) repeats the specification of column (9) using a different IV and is discussed below. Column (11) provides the OLS estimates of column (9) for reference. Across specifications, the coefficient of interest on ECI is statistically significant, at least at the 10% level. Most importantly, and in line with D. Autor and Salomons (2018) for OECD and Ghodsi, Reiter, Stehrer, and Stöllinger (2020) for emerging and transition economies, the estimated effect is negative, suggesting that economic complexity associates with lower unemployment. Our OLS specification already reveals a substantial effect: a one standard deviation increase in ECI is associated with a one standard deviation decrease in the unemployment rate, or equivalently a decrease in the unemployment rate of about six percentage points (column 11). Such an effect should not be considered alone, as if in a vacuum. ECI is highly persistent and of rather rigid nature. Single unit increases require major structural transformations in the economy and would be neither simple nor swift. Where they to materialize however they would be groundbreaking enough to guarantee a vast impact on unemployment.

With regards to the rest of our controls, our results can be summarized as follows: Higher inflation exerts a negative effect on unemployment. This is consistent with the view that in the presence of downward nominal wage rigidity, inflation allows for better wage adjustment, resulting in lower equilibrium unemployment (Wyplosz, 2001). $Inflation$ is negative and statistically significant at the 1% level across specifications. $Imports$ are negative and statistically significant across specifications, highlighting the beneficial role of incoming products for unemployment. The negative sign of $Imports$ is consistent with the view that higher competition from abroad results into more efficient allocation of resources and lower unemployment (Felbermayr, Prat, & Schmerer, 2011). An additional interpretation of the negative coefficient on imports could be the following: imports here could be essentially controlling for the ease of trade, lack of trade barriers, tariffs, quotas, etc. This result holds only for the OECD sample, which is heavily populated and essentially dominated by the presence of EU member states. This interpretation can be strengthened further by the fact that $Imports$ turn positive and non significant in the world sample, which contains 70 -both developing and developed - economies, where is tough to argue that EU is dominant. In line with economic theory, *OutputGap* is found to be negative and statistically significant across, implying that unemployment is higher in a recession.[6] The estimated coefficient implies that a one standard deviation increase on the output gap, i.e. the difference between actual and potential output, is associated with a 0.5% decline in the unemployment rate.

Concerning union variables, only two coefficients exhibit significance. $UnionDensity$ turns positive and significant to unemployment, while higher bargaining $Coordination$ results into lower unemployment (see also, Di Tella and MacCulloch (2005)). Coordinated bargaining induce unions to internalize the positive effects of wage moderation on unemployment.

Similarly, following previous research, we find that higher unemployment benefits, i.e. higher *Replacement*, are associated with higher unemployment. This effect might be attributed, for example, to lower job search intensity by the unemployed when receiving higher unemployment benefits (Bassanini & Duval, 2006; Wyplosz, 2006). However, this result loses significance and flips sign, exhibiting a non robust behavior. Finally, $TaxWedge$ has a positive and statistically significant effect on unemployment, verifying the disincentives created by the heavier burden of employee taxation.

To further convince the reader about our main finding on the importance of economic complexity of exports on unemployment outcomes, in column (10) we adopt an alternative instrument of ECI, namely the (log) number of journal *articles* published in scientific and technical journals in a given year. This index calculates the total number of papers in the fields of physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. Higher values are associated with higher scientific effort and output, which are directly related to the intensity of process and product innovation in the economy. Hence, we naturally expect *articles* to influence economic sophistication as measured by the ECI. It is reasonable to assume that new knowledge appearing in scientific articles is materialized in more sophisticated products. Regarding the exogeneity of the instrument it is plausible to assume that changes in the number of journal articles do not have a direct impact on labour market institutions and outcomes. The relevant statistics at the bottom of Table 2 (column (10)) and the first-stage results reported in Table A3, column (10), in the Appendix reveal a strong instrument. The statistically significant coefficient of ECI on unemployment is confirmed in the second stage results presented in Table 2, column (10).

In Table 3, column (1), we include the baseline results (column (9) of Table 2) for reference.[7] In the other columns we estimate the same econometric specification, however we vary the dependent variable in the following way: unemployment rate for individuals aged 15-24 (column 2); male unemployment rate (column 3); female unemployment rate (column 4). We also use employment measures on the left hand side, namely: the male (column 5), the female (column 6) and the total employment rate (column 7).[8] In all cases, the results of the baseline model are verified. Economic complexity has a negative effect on all types of unemployment and consistently a

[6] To address possible concerns of collinearity between *OutputGap* and $ALMP$, in addition to *Uniondensity*, *Centralization*, *Coordination*, and *UnionCoverage* (or EPL and Minimum Wage when they are used), we provide a correlation matrix in the Appendix. We also rerun all specifications excluding some regressors or at least not considering them (only) altogether. For the union related variables, due to the larger figures in the correlation matrix, we also estimate the Variance Inflation Factor for the panel data. Test statistics are way below the rule of thumb of 10, which is the level above which mutlicollinearity might be a problem (Hair, Anderson, Babin, & Black, 2010). Our results appear robust and do not hint or raise concerns of multicollinearity.

[7] We have chosen to present this specification as our baseline model due to the larger sample incorporated. We verify our baseline results through the inclusion of other variables that offer important insights to our empirical exercise. Our results remain robust.

[8] All first stage results are shown in the Appendix, Tables A3, A4, A5.

Table 3. Fixed Effects 2SLS, Unemployment and Employment in Specific Groups

	(1) Unemployment	(2) Youth Unemployment	(3) Male Unemployment	(4) Female Unemployment	(5) Employment Male	(6) Employment Female	(7) Employment
ECI	-9.371**	-33.412***	-16.902***	-14.391***	10.720***	3.237	7.028**
	(-2.140)	(-3.558)	(-3.547)	(-3.458)	(3.058)	(0.946)	(2.416)
Inflation	-0.341**	-0.427***	-0.269***	-0.115*	0.163***	-0.006	0.077*
	(-6.595)	(-2.966)	(-3.852)	(-1.675)	(3.187)	(-0.095)	(1.674)
Imports	-0.080**	-0.126**	-0.064*	-0.071**	0.009	-0.047**	-0.021
	(-2.267)	(-1.994)	(-1.754)	(-2.466)	(0.361)	(-2.170)	(-1.090)
Output Gap	-21.645**	-26.181**	-16.241***	-14.936**	18.866***	13.464***	15.891***
	(-3.422)	(-2.172)	(-2.579)	(-2.484)	(4.280)	(2.620)	(3.823)
Union Density	0.142**	-0.032	0.113***	-0.146***	-0.103***	0.094**	-0.001
	(3.089)	(-0.358)	(2.668)	(-2.923)	(-3.309)	(2.003)	(-0.044)
Centralisation	0.149	1.209**	0.432	0.990***	-0.363	-0.714***	-0.536**
	(0.586)	(2.144)	(1.470)	(2.999)	(-1.623)	(-2.660)	(-2.389)
Coordination	-0.815**	-2.267***	-1.209***	-1.661***	1.108***	1.018***	1.074***
	(-2.887)	(-3.803)	(-3.821)	(-4.336)	(4.325)	(3.371)	(4.208)
Union Coverage	0.022	0.022	0.016	0.024	-0.016	-0.017	-0.017
	(1.103)	(1.035)	(1.595)	(1.602)	(-1.562)	(-1.328)	(-1.533)
Replacement	4.339**	-23.547***	-5.252**	-5.930**	-0.485	-3.710	-2.038
	(2.135)	(-4.497)	(-2.137)	(-2.194)	(-0.253)	(-1.543)	(-1.107)
Tax Wedge	0.130***	0.227**	0.112**	0.105**	-0.139***	-0.066**	-0.101****
	(2.600)	(1.979)	(2.140)	(2.047)	(-3.707)	(-2.027)	(-3.479)
Observations	403	338	338	338	338	338	338
R-sq	0.483	0.463	0.592	0.566	0.510	0.714	0.634
F-test	11.23	7.920	15.27	11.31	11.55	20.46	17.37
DWH-test	0.528	0.561	0.922	0.0299	0.00643	0.0000431	0.00000224
Weak-id	21.64	23.99	23.99	23.99	23.99	23.99	23.99
LM-Underid	53.63	56.64	56.64	56.64	56.64	56.64	56.64
Hansen(p-value)	0.347	0.507	0.479	0.644	0.514	0.697	0.599

Notes: Dependent variable: as noted in columns. ECI is instrumented. Clustered t- statistics in parentheses. F-test gives the F test for the signifficance of the model. DWH is the Durbin- Wu- Hausman test of endogeneity of the regressors. Rejection of the null suggests that the IV regression is required. LM-Underid gives the Kleibergen-Paap Wald test of weak idendification, with the null hypothesis indicating that the model is weakly identified. Weak-id gives the F statistic for weak identification. Hansen test (p-value) gives the p-value of the Hansen test of overidentification. Rejection of the null implies that the overidentifying restrictions cannot be rejected. * p<0.10, ** p<0.05, *** p<0.01

positive impact on all measures of employment. Female employment is the only case that ECI loses statistical significance. The rest of our explanatory variables remain in line with our baseline results, with the exception of *Replacement*, which, in columns (2) to (4), is negatively signed and statistically significant in contrast to our theoretical priors.

In Table 4 we present robustness checks to our baseline specification (column 9, Table 2), which we display in column 1 for reference. Columns (2)-(6) show that our main finding on ECI is robust regardless of the choice of controls included in each specification. We hereby discuss only results which differ compared to the baseline model as well as certain additional controls examined. As previously discussed, the OECD sample, is heavily dominated by EU member states, and therefore $Imports$ could reflect the ease of trade among them. EU member states could be driving this result because $Imports$ lose statistical significance when EPL, *Regulation* and $ALMP$ come into the picture (columns 2, 4, and 5 respectively). EPL, *Regulation* and $ALMP$ could reflect EU regulations and institutions, i.e. labor policies, that $Imports$ might have captured alongside the trade effect. In addition, $UnionDensity$ and *Replacement* lose significance in certain specifications. In column 2, we introduce EPL, capturing the overall degree of employment protection in the economy. Next, column (3), we control for the minimum wage level ($MinWage$), while in column (4) we introduce regulation intensity of the product markets in the economy (*Regulation*), with higher values indicating lower regulatory intensity. In column (5), we include spending on active labour market policies as a proportion of GDP ($ALMP$). Finally, in column (6) we include *Education* (gross enrolment ratio, tertiary, both sexes, %) to capture the effect of human capital on labour markets. All coefficients on the aforementioned controls, with the exception of $ALMP$ turn out with the expected sign, while all except for $MinWage$ and *Education* are statistically significant.

In Table 5 we exhibit supplementary regressions, which focus on the dynamics of the relationship under investigation. The underlying hypothesis is whether the effect of our explanatory variables comes with a one-year lag. Column (1) presents the estimates of equation (9), where all variables are introduced with a time lag, while in column (2) ECI is considered without a lag. An additional benefit of the time lag hypothesis is that it circumvents potential endogeneity between controls and the ECI. In columns (3) and (4), we also consider the dependent variable with a time lag. In column (3) we estimate a simple ordinary least squares (OLS) panel fixed effects model, whereas in column (4) we employ the Arellano-Bond estimator. In all cases, our main variable of interest remains statistically significant and its magnitude does not change much, at least in columns (1) to (3). Interestingly, the value of the coefficient of ECI in column (4) increases to -3.710.[9]

4.2. Cross-section, world sample

To generalize our findings from the previous section to a wider set of countries, we focus our analysis on a global sample of 70 developed and developing countries.[10] To

[9]We should note that the coefficient represents the short-run effect. In contrast, if we estimate the associated long run effect, it turns out -62.05, however completely loses statistical power.

[10]Albania, Algeria, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt Arab Rep., El Salvador, Estonia, Finland, Georgia, Ghana, Greece, Guatemala, Hungary, India, Indonesia, Iran Islamic Rep., Ireland, Italy, Japan, Jordan, Kazakhstan, Korea, Rep., Kuwait, Latvia, Lebanon, Lithuania, Macedonia FYR, Mexico, Moldova, Morocco, Netherlands, New Zealand, Nigeria, Norway, Peru, Philippines, Poland,

Table 4. Fixed Effects 2SLS, OECD sample; Robustness to additional controls

	(1)	(2)	(3)	(4)	(5)	(6)
ECI	-9.371**	-16.699***	-9.375**	-18.468***	-12.461***	-10.746**
	(-2.140)	(-2.926)	(-2.135)	(-3.667)	(-2.862)	(-2.248)
Inflation	-0.341***	-0.366***	-0.341***	-0.320***	-0.142**	-0.339***
	(-6.595)	(-6.399)	(-6.586)	(-4.608)	(-2.403)	(-6.140)
Imports	-0.080**	-0.025	-0.080**	-0.056	-0.056	-0.094***
	(-2.267)	(-0.626)	(-2.233)	(-1.365)	(-1.623)	(-2.646)
Output Gap	-21.645***	-15.952**	-21.647***	-18.145**	-14.505**	-23.273***
	(-3.422)	(-2.387)	(-3.422)	(-2.448)	(-2.344)	(-3.505)
Union Density	0.142***	0.164***	0.142***	0.055	-0.033	0.141***
	(3.089)	(2.962)	(3.090)	(0.867)	(-0.661)	(2.992)
Centralisation	0.149	0.524	0.148	0.606**	0.417	0.283
	(0.586)	(1.620)	(0.583)	(2.046)	(1.346)	(1.037)
Coordination	-0.815***	-0.911***	-0.814***	-0.859**	-0.898***	-0.917***
	(-2.887)	(-2.621)	(-2.884)	(-2.392)	(-2.908)	(-3.112)
Union Coverage	0.022	0.030	0.022	0.033*	0.123***	0.023
	(1.103)	(1.492)	(1.103)	(1.702)	(2.986)	(1.110)
Replacement	4.339**	-3.155	4.341**	4.234	-0.202	3.807*
	(2.135)	(-1.492)	(2.136)	(1.020)	(-0.050)	(1.877)
Tax Wedge	0.130***	0.066	0.129***	0.100*	0.086*	0.133***
	(2.600)	(1.238)	(2.591)	(1.774)	(1.689)	(2.622)
EPL		2.525***				
		(2.598)				
Min Wage			0.045			
			(0.174)			
Regulation				-0.806*		
				(-1.819)		
ALMP					1.769***	
					(5.649)	
Education						0.023
						(1.385)
Observations	403	362	403	280	344	375
R-sq	0.483	0.494	0.483	0.485	0.575	0.498
F-test	11.23	9.039	11.55	6.126	9.487	7.976
DWH-test	0.528	0.694	0.526	1.140	0.0103	0.870
Weak-id	21.64	18.03	21.44	17.08	22.67	17.78
LM-Underid	53.63	48.85	53.26	38.71	53.26	47.41
Hansen(p-value)	0.347	0.914	0.346	0.791	0.960	0.514

Notes: Dependent variable: unemployment rate. ECI is instrumented. Clustered *t*- statistics in parentheses. F-test gives the F test for the significance of the model. DWH is the Durbin- Wu- Hausman test of endogeneity of the regressors. Rejection of the null suggests that the IV regression is required. LM-Underid gives the Kleibergen-Paap Wald test of weak identification, with the null hypothesis indicating that the model is weakly identified. Weak-id gives the F statistic for weak identification. Hansen test (p-value) gives the p-value of the Hansen test of overidentification. Rejection of the null implies that the overidentifying restrictions cannot be rejected. * p<0.10, ** p<0.05, *** p<0.01

Table 5. Dynamic model; OECD sample

	(1) All Independent Lagged	(2) Lagged excl.ECI	(3) Lagged Unemployment	(4) Arellano Bond
ECI	-9.024*	-12.833**	-7.749**	-3.710**
	(-1.821)	(-2.390)	(-1.972)	(-2.287)
Inflation	-0.305***	-0.320***	-0.168***	-0.065*
	(-4.812)	(-4.944)	(-3.161)	(-1.836)
Imports	-0.130***	-0.101**	-0.072***	0.005
	(-3.357)	(-2.423)	(-2.643)	(0.851)
Output Gap	-14.268**	-13.272*	-12.742***	-12.011***
	(-2.019)	(-1.877)	(-2.742)	(-3.904)
Union Density	0.116**	0.119***	0.043	-0.002
	(2.533)	(2.596)	(1.568)	(-0.380)
Centralisation	0.272	0.309	0.056	-0.252*
	(1.068)	(1.194)	(0.354)	(-1.717)
Coordination	-0.793***	-0.744***	-0.275	0.077
	(-2.808)	(-2.748)	(-1.530)	(0.636)
Union Coverage	0.026	0.029	0.019*	0.003
	(1.193)	(1.406)	(1.717)	(0.820)
Replacement	3.078	3.130	0.798	2.137**
	(1.494)	(1.460)	(0.495)	(2.448)
Tax Wedge	0.119**	0.133**	0.022	0.007
	(2.080)	(2.369)	(0.682)	(0.544)
Unemployment (-1)			0.756***	0.940***
			(11.814)	(20.992)
Observations	407	410	397	402
R-sq	0.400	0.390	0.806	
F-test	5.951	5.894	35.29	41.86
DWH-test			5.280	
LM-Underid	55.22	59.21	25.09	
Sargan(p-value)				0.00
Hansen(p-value)	0.481	0.283	0.647	
AR(1)(p-value)				0.00190
AR(2)(p-value)				0.401

Notes: Dependent variable: unemployment rate. ECI is instrumented. Clustered t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. F-test gives the significance of the model. DWH is the Durbin-Wu-Hausman test of endogeneity of the regressors. Rejection of the null suggests that the IV regression is required. LM-Underid gives the Kleibergen-Paap Wald test of weak identification, with the null hypothesis indicating that the model is weakly identified. Sargan (p-value) and Hansen(p-value) give the p-values of the Sargan and Hansen tests of overidentifying restrictions respectively. AR(1)(p-value) and AR(2)(p-value) give the p-values for the first and second order autocorrelations respectively.

Table 6. Data sources, definitions and summary statistics; world sample

Variable	Definition	Source	Mean	Std. Dev.
ECI	Economic Complexity Index	Observatory of Economic Complexity	0.003	0.97
Unemployment	Total Unemployment Rate	World Bank	8.96	6.10
Youth Unemployment	Unemployment Rate for ages 15-24	World Bank	18.04	11.71
Male Unemployment	Unemployment Rate for Males	World Bank	8.84	8.20
Female Unemployment	Unemployment Rate for Females	World Bank	10.59	7.77
Inflation	% change in annual Consumer Price Index	IMF	37.03	117.02
Imports	Imports of goods and services as % of GDP	World Bank	42.8	21.58
Output Gap	The difference between actual and potential real (GDP) as a per cent of potential real GDP	IMF	-0.001	0.003
Taxes	Share of Tax Revenue to GDP	World Bank	15.59	6.88
Articles	(log) Number of journal articles in scientific and technical journals, in the fields of physics, chemistry, biology, mathematics, clinical medicine, biomedical research, engineering and technology, earth and space sciences. Scientific and technical article counts are from journals classified by the Institute for Scientific Information's Science Citation Index (SCI) and Social Sciences Citation Index (SSCI)	World Bank	5.94	2.7
Genetic Diversity	The expected heterozygosity (genetic diversity) of a country's contemporary national population, as developed by Ashraf and Galor (2013b) and Ashraf and Galor (2013a). This measure is based on migratory distances from East Africa to the year 1500 locations of the ancestral populations of the country's component ethnic groups in 2000 and on the pairwise migratory distances among these ancestral populations	Ashraf and Galor (2013b)	72.63	2.75
Secular Values Index	12-item measure of distance from sacred sources of authority	World Values Survey	0.38	0.1

maximize the number of countries used in the regression, we employ only a subset of the controls used in the previous section empirical exercise and use averages from 1990 to 2010. Data definitions and summary statistics for the world sample are given in Table 6.

Applying a fixed-effects 2SLS/IV regression in a cross-section setting requires a set of exogenous instruments. We experiment with three instruments of ECI and examine the robustness of our results using different subsets of these instruments. Firstly, we employ again the measure of the (log) number of journal articles published in scientific and technical journals in a given year (denoted *Articles*).

The second instrument considered is an index of genetic diversity. Following the comparative development literature (Ashraf & Galor, 2013b), genetic diversity, predominantly determined during the prehistoric 'out of Africa' migration of humans, explains modern ethnic diversity and economic prosperity. Following the relevant literature, "*higher diversity therefore enhances society's capability to integrate advanced and more efficient production methods, expanding the economy's production possibility frontier and conferring the benefits of improved productivity*" (Ashraf & Galor, 2013b, p. 3). Therefore, the proportion of ethnic diversity explained by prehistoric diversity is expected to be correlated with economic complexity, without having a direct effect on contemporary unemployment and employment rates.

The third instrument used is the *Secular Values Index*, which is a 12-item measure of the distance from 'sacred' sources of authority in each country (Welzel, 2013). It is a continuous scale in the [0,1] range, where 0 (1) denotes the less (more) secular position.

Portugal, Russian Federation, Slovenia, South Africa, Spain, Sweden, Switzerland, Tanzania, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela RB, Zambia, Zimbabwe.

Countries that hold high beliefs in 'sacred' sources of authority are expected to be less modernized and less prone to innovation and adoption of sophisticated methods of production.

The top part of Table 7 shows the output of the first-stage regressions for the exogenous instruments of the ECI.[11] The results indicate that ECI is positively associated with both the amount of research undertaken in an economy (*Articles*) and the *Secular Values* Index. On the other hand, it seems that higher levels of economic complexity are associated with lower genetic diversity. The hypothesis of weak identification is rejected in all instances, since the value of the relevant test (F-statistic of the first-stage estimation: *Weak-id*), is well above 10.

Table 7. Cross-section regressions

	(1) Total unempl.	(2) Total unempl.	(3) Total unempl.	(4) Total unempl.	(5) Youth unempl.	(6) Male unempl.	(7) Female unempl.	(8) OLS
First stage results								
Articles	0.245***	0.262***	0.297***		0.252***	0.233***	0.245***	
	(8.425)	(8.484)	(9.714)		(8.477)	(7.428)	(8.425)	
Gen. Diversity	-0.078***		-0.096***	-0.026	-0.080***	-0.068**	-0.078***	
	(-3.124)		(-3.904)	(-0.786)	(-3.151)	(-2.379)	(-3.124)	
Secular Values	2.361***			4.722***	2.377***	2.251***	2.361***	
	(4.560)			(6.579)	(4.623)	(4.363)	(4.560)	
Second stage results								
ECI	-2.467**	-2.046*	-2.849**	-1.873*	-3.616*	-7.519	-4.059***	-1.718**
	(-2.420)	(-1.818)	(-2.564)	(-1.756)	(-1.873)	(-1.570)	(-2.816)	(-2.135)
Inflation	-0.007***	-0.007***	-0.008***	-0.007***	-0.009*	-0.050	-0.010***	-0.007***
	(-3.529)	(-3.312)	(-3.530)	(-3.361)	(-1.952)	(-1.448)	(-3.322)	(-3.544)
Imports	0.028	0.007	0.029	0.025	0.033	0.198	0.016	0.025
	(0.811)	(0.278)	(0.839)	(0.768)	(0.516)	(1.370)	(0.378)	(0.705)
Output Gap	-351.945*	-400.238**	-342.541*	-366.557*	-870.566**	-1261.259	-243.160	-370.387*
	(-1.863)	(-2.254)	(-1.807)	(-1.916)	(-2.287)	(-0.600)	(-0.877)	(-1.869)
Taxes	0.192**	0.168**	0.202**	0.176**	0.351**	0.131	0.221**	0.172*
	(2.196)	(1.985)	(2.288)	(2.005)	(2.071)	(0.361)	(2.157)	(1.863)
Constant	5.761***	6.750***	5.706***	5.847***	13.016***	28.951***	7.719****	5.870***
	(3.811)	(4.605)	(3.678)	(3.998)	(4.137)	(3.516)	(3.476)	3.773)
Observations	70	74	70	70	69	59	70	70
R-sq	0.115	0.109	0.101	0.125	0.0691	0.119	0.0950	0.126
F-test	4.905	4.536	4.951	4.927	3.347	1.227	2.503	4.806
DWH-test	0.566	0.353	2.540	0.0663	2.905	0.0101	3.389	
Weak-id	43.43	71.99	47.23	22.10	42.32	39.70	43.43	
LM-Underid	26.76	26.25	25.18	15.61	25.42	19.82	26.76	
Hansen(p-values)	0.0155		0.0210	0.00559	0.0339	0.00399	0.0805	

Notes: See Table 4. To save space, the first stage results include only the coefficients of the exogenous instruments of ECI.

The second-stage regression results verify the negative and statistically significant relationship between ECI and unemployment, while the effect is slightly smaller than for the OECD sample. With respect to the rest of the (second stage) results, the main conclusions drawn from the OECD sample remain qualitatively intact.

To examine the robustness of our results in columns (2) and (3), we experiment using different subsets of the instruments employed in the main specification (column

[11] To save space, the first-stage results for the independent variables are not included in the Table.

1). Once again, the association of ECI with unemployment is negative and statistically significant. Finally, in columns (5), (6) and (7) we examine the effect of economic complexity on youth, male and female unemployment rates, respectively. Qualitatively, the results are similar to the ones obtained from the OECD panel dataset.[12]

5. Products complexity and the labour market

The ECI methodology provides a useful toolbox that allows us to compute indexes that quantify economic sophistication, for both countries and products. For example, using the same methodology that computes ECI, but placing the spotlight on products rather than on countries, we can calculate the PCI (see Section 3). This index quantifies the sophistication of each product according to the amount of knowledge/know-how involved in its production, reflected by the countries that export the product (Hausmann et al., 2014). In other words, when a product is located in the center of the product space i.e. in the core of the international trade network of products, it ranks higher in the PCI because its production requires more knowledge/know-how. Recently, Hartmann et al. (2017), using the ECI methodology, introduced a measure that associates products with income inequality and showed how the development of new products is associated with changes in income inequality. However, the labour market effects are key to understanding national income disparities, since income differences are, by definition, based on differences in the labour productivity and/or employment level, among other factors. Here, we introduce a measure that links a product to the average unemployment and employment rates of the countries that export it. In this way, we illustrate how labour markets are affected by the level of export's sophistication and we quantify the influence of countries' level of economic complexity on their labour markets' outcomes.

Following Hartmann et al. (2017), we define the *Product Unemployment Index* (PUI) (resp. *Product Employment Index*, PEI) as the average unemployment rate (resp. employment rate) faced by the countries that export the focal product, normalized by the importance of this product to the total exports of the countries that export it. More precisely, we decompose the relationship between economic complexity and unemployment and employment rates into individual economic sectors, by creating product-level estimators of these rates that are expected for the countries exporting a given product.

5.1. Product unemployment and employment indexes

Assuming that we have trade data for l countries and k products, we can fill the $l \times k$ matrix $\mathbf{M}$ so that its matrix element $M_{cp} = 1$ if country c has Revealed Comparative Advantage (RCA) for product p and zero otherwise.[13] For our case, the international trade data from MIT's Observatory of Economic Complexity contains information for 33 OECD countries and 773 products from 1985 to 2008, classified in accordance with

[12] To test for possible differences between developed and developing countries we introduce a dummy for developing countries and interact it with the ECI. The resulting coefficient turns out insignificant, providing no evidence of a difference between developed and developing countries in that regard.

[13] RCA is the ratio between the share of a given product in a country's exports and the share of this product in the total global exports (Balassa, 1965). According to the World Bank: Measures of RCA have been used to help assess a country's export potential. The RCA indicates whether a country is in the process of extending the products in which it has a trade potential, as opposed to situations in which the number of products that can be competitively exported is static.

Table 8. PUI by industry: averages across time and across 4-digit categories

SITC4	Industry	PUI	SITC4	Industry	PUI
76	Telecommunications and sound-recording and reproducing apparatus and equipment	5.52	79	Other transport equipment	7.76
88	Photographic apparatus, equipment and supplies and optical goods	5.69	93	Special transactions and commodities not classified according to kind	7.76
97	Gold, non-monetary (excluding gold ores and concentrates)	5.91	12	Tobacco and tobacco manufactures	7.77
87	Professional, scientific and controlling instruments and apparatus	6.46	65	Textile yarn, fabrics, made-up articles, n.e.s., and related products	7.78
34	Gas, natural and manufactured	6.57	11	Beverages	7.84
35	Electric current	6.73	91	Postal packages not classified according to kind	7.87
73	Metalworking machinery	6.76	53	Dyeing, tanning and colouring materials	7.87
77	Electrical machinery, apparatus and appliances	6.77	54	Medicinal and pharmaceutical products	7.89
25	Pulp and waste paper	6.83	52	Inorganic chemicals	7.90
96	Coin (other than gold coin), not being legal tender	7.02	58	Plastics in non-primary forms	7.92
72	Machinery specialized for particular industries	7.03	69	Manufactures of metals, n.e.s.	7.92
43	Animal or vegetable fats and oils	7.07	24	Cork and wood	7.95
74	General industrial machinery and equipment	7.09	64	Paper, paperboard and articles of paper pulp, of paper or of paperboard	7.95
75	Office machines and automatic data-processing machines	7.1	26	Textile fibres and their wastes	7.97
41	Animal oils and fats	7.17	83	Travel goods, handbags and similar containers	8.03
71	Power-generating machinery and equipment	7.22	84	Articles of apparel and clothing accessories	8.05
89	Miscellaneous manufactured articles, n.e.s.	7.35	67	Iron and steel	8.07
68	Non-ferrous metals	7.4	85	Footwear	8.09
59	Chemical materials and products	7.45	66	Non-metallic mineral manufactures	8.17
81	Prefabricated buildings; sanitary, plumbing, heating and lighting fixtures and fittings	7.49	61	Leather, leather manufactures, and dressed furskins	8.21
28	Metalliferous ores and metal scrap	7.52	27	Crude fertilizers, other than those of Division 56, and crude minerals	8.35
29	Crude animal and vegetable materials	7.53	56	Fertilizers (other than those of group 272)	8.36
23	Crude rubber (including synthetic and reclaimed)	7.53	57	Plastics in primary forms	8.49
78	Road vehicles	7.55	82	Furniture and parts thereof; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings	8.53
51	Organic chemicals	7.57	63	Cork and wood manufacture	8.59
21	Hides, skins and furskins, raw	7.59	62	Rubber manufactures, n.e.s.	8.61
33	Petroleum, petroleum products and related materials	7.6	55	Essential oils and resinoids and perfume materials; toilet, polishing and cleansing preparations	8.93
42	Fixed vegetable fats and oils, crude, refined or fractionated	7.61	32	Coal, coke and briquettes	9.17
22	Oil-seeds and oleaginous fruits	7.65			

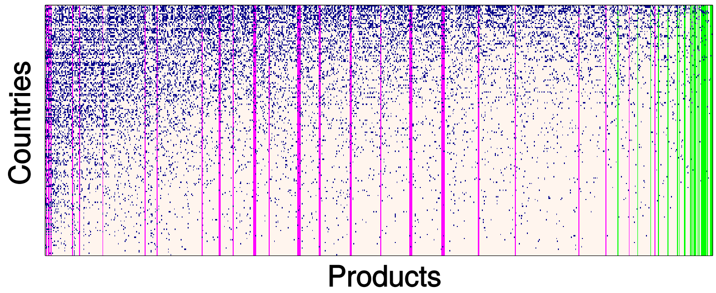

Figure 1. Matrix representation of the links between a country and the products it exports. A visualization of this matrix for the year 2010, where a dark point indicates that country c exports a given product p. The matrix is sorted using the NODF algorithm (Almeida-Neto et al., 2008), which highlights the existence of countries that are very well diversified and countries that export only a small set of products. Highlight in green is the position of the 40 products with the highest PCI values and in red the 40 products with the lowest PCI values. It is clear that the more diversified countries are those that produce the more complex products.

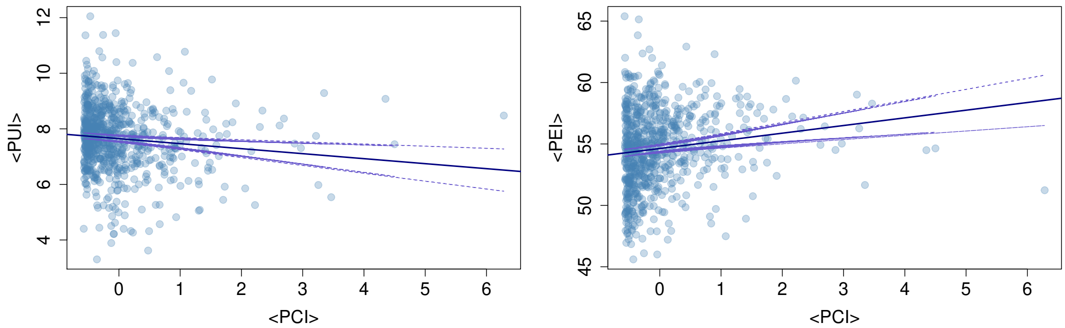

Figure 2. PUI and PEI against PCI. The solid lines represent the fit of a linear model and the dashed lines represent a 95% prediction interval based on the fitted linear model.

the SITC at the 4-digit level. A visualization of matrix $\mathbf{M}$ for this dataset, which is used to calculate the ECI and the PCI is shown in Figure 1.

Every product p generates some value for the country c that exports it. Therefore, for every product p we can calculate the fraction s_{cp}:

$$s_{cp} = \frac{X_{cp}}{\sum_{p'} X_{cp'}}, \tag{10}$$

where X_{cp} is the total export value of product p when exported by country c, while $\sum_{p'} X_{cp'}$ is the value of all exports of country c. If U_c (resp. E_c) is the unemployment (resp. employment) rate of country c, we can calculate the PUI_p and the PEI_p for every product, as:

$$\mathrm{PUI}_p = \frac{1}{N_p} \sum_c M_{cp} s_{cp} U_c, \tag{11}$$

$$\mathrm{PEI}_p = \frac{1}{N_p} \sum_c M_{cp} s_{cp} E_c, \tag{12}$$

Table 9. List of the five products with the highest and lowest PUI and PEI values during the period 1985-2008

SITC4	Product name	Product section	PUI	PEI
Five products with highest PUI				
571	Polymers of ethylene, in primary forms	Chemicals and related products, n.e.s.	11.9	
8994	Umbrellas, sun umbrellas, walking-sticks, etc	Miscellaneous manufactured articles	11.4	
8933	Floor coverings, wall or ceiling coverings	Miscellaneous manufactured articles	11.3	
6624	Non-refractory ceramic bricks, tiles, pipes	Manufactured goods	11.3	
2450	Fuel wood/wood charcoal	Crude materials	11.2	
Five products with lowest PUI				
7612	Monitors and projectors etc	Machinery & transport equipment	4.5	
8982	Musical instruments	Miscellaneous manufactured articles	4.4	
3330	Petroleum oils	Mineral fuels, lubricants	4.4	
7638	Video-recording	Machinery and transport equipment	4.3	
8852	Watches and clocks	Miscellaneous manufactured articles	3.9	
Five products with highest PEI				
3330	Petroleum oils	Mineral fuels, lubricants		65.5
3414	Gas	Mineral fuels, lubricants		65.2
8851	Watches and clocks	Miscellaneous manufactured articles		63.4
2516	Pulp and waste paper	Crude materials		63.0
2222	Oil-seeds and oleaginous fruits	Crude materials		62.7
Five products with lowest PEI				
6597	Floor coverings, etc.	Manufactured goods		47.2
571	Polymers of ethylene, in primary forms	Chemicals and related products		47.0
1211	Tobacco, unmanufactured	Beverages and tobacco		47.0
6624	Non-refractory ceramic bricks, tiles, pipes	Manufactured goods		46.3
4235	Fixed vegetable fats and oils	Animal and vegetable oils		46.2

Notes: PUI: Product Unemployment Index; PEI: Product Employment Index. Average value for 1985-2008.

where $N_p = \sum_c M_{cp}s_{cp}$ is a normalization factor.

Utilizing the information we have for the unemployment and employment rates for the OECD countries we are able to calculate the above indexes. It is important to highlight at this point that the two indices, PUI and PEI, cannot capture differences between sectors on the link between "produced value" and "labour" because the index PUI (resp. PEI) is computed as the average unemployment rate (resp. employment rate) faced by the countries that export the focal product, normalized by the importance of this product to the total exports of the countries that export it. The two indices are product-level estimators that decompose the relationship between unemployment/employment rates and economic complexity into individual economic sectors. In other words, they are tools that illustrate how labour-market outcomes are associated with the countries' RCA in exporting sophisticated products. For every year in the period 1985-2008 we calculate all product-related indexes, i.e. PCI, PUI and PEI, and we obtain their mean value for each product. Table 8 lists the averages of PUI across the sample and across 4-digit SITC4 categories of the 2-digit SITC4 industries. Industries are sorted in order of increasing PUI. Table 8 reveals that the industry group with the lowest average proportion of the total unemployment rate is *'Telecommunications and sound-recording and reproducing apparatus and equipment'*. Similarly, the more sophisticated industry/product categories appear to have the lowest PUI. At the other end of the spectrum, the *'Coal, coke and briquettes'* industry has the highest PUI. As the reader can easily verify, primary sector industries (with low product-sophistication), appear to be associated with higher rates of unemployment. This is also implied by Table 9 which lists the five products with the highest and lowest PUI and PEI values during the period 1985-2008.

In addition, we test the existence of a bivariate relationship between PCI and PUI and PEI. Thus, we calculate Pearson's correlation coefficient for both pairs, i.e. PUI

Table 10. Product sophistication and the labour market

	(1) Unemployment Within Estimation	(2) Unemployment Between Estimation	(3) Employment Within Estimation	(4) Employment Between Estimation
PCI	-0.014	-0.185***	-0.011	0.617***
	(-0.559)	(-3.134)	(-0.247)	(3.759)
Observations	19009	19009	19009	19009
R-sq	0.231	0.106	0.0756	0.0618
F- test	376.5	3.666	94.80	2.044

Notes: PCI: Product Complexity Index. See also Table 4.

against PCI and PEI against PCI. If a relation exists, it should allow us to derive expectations of whether or not the products' complexity can be associated with the unemployment and employment rates. In the case of PUI against PCI, the correlation coefficient is $\rho = -0.10$ with p-value $= 0.0061$, while for the case of PEI against PCI it is $\rho = 0.14$ with p-value $= 0.0002$. In Figure 2, we present the scatter plots of PUI and PEI against PCI for all 773 products in our dataset together with the fitted linear models. The slopes of the linear fits are the corresponding correlation coefficients.

The statistically significant negative (resp. positive) correlation between PUI (resp. PEI) and PCI indicates that the sophisticated products are associated with countries that bear relative low unemployment rates (resp. high employment rates). This adds to our previous discussion about economic complexity at the country level, as it allows us to understand which sets of products are leading to more employment and less unemployment based on their sophistication.

Concluding, in Table 10 we run panel regressions between PCI and PUI and PEI. The results show that the relationship between PCI and PUI and PEI is the outcome of the correlations *between* products rather than *within* products. In other words, lower unemployment (and higher employment) is associated with increases in product complexity between products. It seems that change in economic complexity within products has no effect on the labour market. This suggests that the negative (resp. positive) effect on unemployment (resp. employment) rate is due to changes in the structure of the product space towards the creation of more sophisticated products, rather than increases in the sophistication of existing ones.

6. Conclusions

Our analysis illustrates that the labour market performance of a country is highly predicted by the mix of products that a country produces and exports. Both in a panel and in a cross-country setting we have verified that there is a robust negative (resp. positive) relationship between unemployment (resp. employment) and product sophistication. Moreover, the relationship between these two variables is verified by instrumental variables (IV) estimation techniques. Hence, the evidence presented in this paper suggests that a country's level of economic sophistication, determines its labour market outcomes.

In detail, countries that produce more sophisticated products generally have lower unemployment rates and higher employment rates. As higher sophistication of exported goods results in higher growth rate, there seems to be a capitalization effect at work (Bean & Pissarides, 1993; Pissarides, 1992): the present value for firms creating new jobs is higher when product sophistication increases, and, according to our estimates, this effect is not symmetrical across industries. We built the PUI and the PEI, which associate exported products with the average level of countries' employment and unemployment rates, respectively. With these indexes we show how the development of sophisticated products is associated with changes in the labour market. This result is important from a policy perspective. Using the proposed indexes, it is possible to design sectoral reallocation policies and smart specialization strategies that promote activities/ sectors that are associated with lower unemployment and higher employment. Adding to the above, our analysis provides additional insights for the *ex post* policy evaluation process. As many tax and subsidy policies are associated with sectoral reallocation, our indexes can provide a quantitative measure of the average unemployment cost (or gain) due to the implemented policy.

In sum, this study examined labour market outcomes at the macroeconomic level, but went beyond the standard institutional and economic factors to explain unemployment. We identified economic complexity as an explanatory variable of the observed differences in labour market outcomes across countries. An interesting way to build further on this would be to identify the exact inclusive institutions and technological capabilities that can have a mitigating effect on 'technological unemployment'.

Our study does not come without limitations. One is related to the fact that economic complexity does not capture differences across sectors/industries, making it impossible to capture where the improvements happen and matter. Second, economic complexity focuses only on exported goods, but not all goods produced in the economy, possibly not reflecting accurately the nature of the productive structure. Third, we have not been able to point to an exogenous instrument as an alternative to the lags, offering further robustness and validity to our results. Fourth, we acknowledge that what we learn from the above analysis is that in economies which export more sophisticated products, lower unemployment/higher employment takes place. However, this might be a consequence not only of economic complexity, but of other drivers – like e.g. the quality of human capital available in the country. Considering measures of quality-adjusted educational attainment that have been proposed in the growth literature (Lee & Barro, 2001; Wößmann, 2003) and exploring their effect on economic complexity offers an important avenue for future research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Abdon, A., & Felipe, J. (2011). The product space: What does it say about the opportunities for growth and structural transformation of sub-saharan africa? *Economics Working Paper Archive*, *670*, Levy Economics Institute.

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of economic literature*, *40*(1), 7–72.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *0*(0), 000-000. Retrieved from https://doi.org/10.1086/705716

Aidt, T. S., & Tzannatos, Z. (2008). Trade unions, collective bargaining and macroeconomic performance: a review. *Industrial Relations Journal*, *39*(4), 258–295.

Albeaik, S., Kaltenberg, M., Alsaleh, M., & Hidalgo, C. A. (2017a). 729 new measures of economic complexity (addendum to improving the economic complexity index). *arXiv preprint arXiv:1708.04107*.

Albeaik, S., Kaltenberg, M., Alsaleh, M., & Hidalgo, C. A. (2017b). Measuring the knowledge intensity of economies with an improved measure of economic complexity. *arXiv preprint arXiv:1707.05826*.

Almeida-Neto, M., Guimaraes, P., Guimarães, P. R., Loyola, R. D., & Ulrich, W. (2008). A consistent metric for nestedness analysis in ecological systems: reconciling concept and measurement. *Oikos*, *117*(8), 1227–1239.

Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic perspectives*, *15*(4), 69–85.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29–51.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in oecd countries.

Ashraf, Q., & Galor, O. (2013a). Genetic diversity and the origins of cultural fragmentation. *The American economic review*, *103*(3), 528–533.

Ashraf, Q., & Galor, O. (2013b). The "out of africa" hypothesis, human genetic diversity, and comparative economic development. *The American Economic Review*, *103*(1), 1–46.

Autor, D., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the us. *American Economic Review*, *103*(6), 2121–68.

Autor, D., & Salomons, A. (2018). *Is automation labor-displacing? productivity growth, employment, and the labor share* (Tech. Rep.). National Bureau of Economic Research.

Autor, D. H., Dorn, D., Hanson, G. H., & Song, J. (2014). Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, *129*(4), 1799–1860.

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: have computers changed the labor market? *The Quarterly Journal of Economics*, *113*(4), 1169–1213.

Autor, D. H., Levy, F., & Murnane, R. J. (2002). Upstairs, downstairs: computers and skills on two floors of a large bank. *ILR Review*, *55*(3), 432–447.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, *118*(4), 1279–1333.

Balassa, B. (1965). Trade liberalisation and "revealed" comparative advantage. *The Manchester School*, *33*(2), 99–123.

Bartel, A., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. *The quarterly journal of Economics*, *122*(4), 1721–1758.

Bassanini, A., & Duval, R. (2006). Employment patterns in oecd countries: Reassessing the role of policies and institutions. oecd economics department working papers no. 486. *OECD Publishing (NJ1)*.

Bean, C., & Pissarides, C. (1993). Unemployment, consumption and growth. *European Economic Review*, *37*(4), 837–854.

Beaudry, P., Green, D. A., & Sand, B. M. (2016). The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics*, *34*(S1), S199–S247.

Bernard, A. B., Smeets, V., & Warzynski, F. (2017). Rethinking deindustrialization. *Economic Policy*, *32*(89), 5–38.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115–143.

Bound, J., & Johnson, G. E. (1989). *Changes in the structure of wages during the 1980's: An evaluation of alternative explanations* (Tech. Rep.). National Bureau of Economic Research.

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal*

of Economics, *117*(1), 339–376.
Buera, F. J., & Kaboski, J. P. (2009). Can traditional theories of structural change fit the data? *Journal of the European Economic Association*, *7*(2-3), 469–477.
Bustos, S., Gomez, C., Hausmann, R., & Hidalgo, C. A. (2012). The dynamics of nestedness predicts the evolution of industrial ecosystems. *PloS one*, *7*(11), e49393.
Caldarelli, G., Cristelli, M., Gabrielli, A., Pietronero, L., Scala, A., & Tacchella, A. (2012). A network analysis of countries' export flows: firm grounds for the building blocks of the economy. *PloS one*, *7*(10), e47278.
Charles, K. K., Hurst, E., & Notowidigdo, M. (2013). Manufacturing decline, housing booms, and non-employment.
Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G., & Pietronero, L. (2013). Measuring the intangibles: A metrics for the economic complexity of countries and products. *PloS one*, *8*(8), e70726.
Cristelli, M., Tacchella, A., & Pietronero, L. (2015). The heterogeneous dynamics of economic complexity. *PloS one*, *10*(2), e0117174.
Dao, M. C., Das, M. M., Koczan, Z., & Lian, W. (2017). *Why is labor receiving a smaller share of global income? theory and empirical evidence*. International Monetary Fund.
Daveri, F., & Tabellini, G. (2000, 04). Unemployment, growth and taxation in industrial countries. *Economic Policy*, *15*(30), 47-104.
David, H. (2015). Why are there still so many jobs? the history and future of workplace automation. *The Journal of Economic Perspectives*, *29*(3), 3–30.
David, H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *The American Economic Review*, *103*(5), 1553–1597.
Di Tella, R., & MacCulloch, R. (2005). Partisan social happiness. *The Review of Economic Studies*, *72*(2), 367–393.
Feenstra, R. C., Lipsey, R. E., Deng, H., Ma, A. C., & Mo, H. (2005). *World trade flows: 1962-2000* (Tech. Rep.). National Bureau of Economic Research.
Felbermayr, G., Prat, J., & Schmerer, H.-J. (2011). Trade and unemployment: What do the data say? *European Economic Review*, *55*(6), 741–758.
Feldmann, H. (2013). Technological unemployment in industrial countries. *Journal of Evolutionary Economics*, *23*(5), 1099–1126.
Felipe, J. (2012). *Inclusive growth, full employment, and structural change: Implications and policies for developing asia*. Anthem Press.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280.
Ghodsi, M., Reiter, O., Stehrer, R., & Stöllinger, R. (2020). *Robotization, employment, and industrial growth intertwined across global value chains.* Document d'information élaboré pour le Rapport sur le développement industriel.
Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The review of economics and statistics*, *89*(1), 118–133.
Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768.
Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). *Multivariate data analysis: A global perspective (vol. 7).* Upper Saddle River, NJ: Pearson.
Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. A. (2017). Linking economic complexity, institutions, and income inequality. *World Development*, *93*, 75–93.
Hausmann, R., & Hidalgo, C. A. (2011). The network structure of economic output. *Journal of Economic Growth*, *16*(4), 309–342.
Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yildirim, M. A. (2014). *The atlas of economic complexity: Mapping paths to prosperity.* Mit Press.
Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of economic growth*, *12*(1), 1–25.
Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *pro-*

ceedings of the national academy of sciences, *106*(26), 10570–10575.
Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487.
Inoua, S. (2016). A simple measure of economic complexity. *arXiv preprint arXiv:1601.05012*.
Jaimovich, N., & Siu, H. E. (2012). *The trend is the cycle: Job polarization and jobless recoveries* (Tech. Rep.). National Bureau of Economic Research.
Juhn, C., Murphy, K. M., & Pierce, B. (1993). Wage inequality and the rise in returns to skill. *Journal of political Economy*, *101*(3), 410–442.
Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, *107*(1), 35–78.
Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., & Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, *68*(5), 1029–1053.
Lee, J.-W., & Barro, R. J. (2001). Schooling quality in a cross–section of countries. *Economica*, *68*(272), 465–488.
Lichter, A. (2016). *Benefit duration and job search effort: Evidence from a natural experiment* (IZA Discussion Papers No. 10264). Institute for the Study of Labor (IZA). Retrieved from `https://EconPapers.repec.org/RePEc:iza:izadps:dp10264`
Matsuyama, K. (2009). Structural change in an interdependent world: A global view of manufacturing decline. *Journal of the European Economic Association*, *7*(2-3), 478–486.
Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training.
Nickell, S., Redding, S., & Swaffield, J. (2008). The uneven pace of deindustrialisation in the oecd. *The World Economy*, *31*(9), 1154–1184.
Pierce, J. R., & Schott, P. K. (2016). The surprisingly swift decline of us manufacturing employment. *The American Economic Review*, *106*(7), 1632–1662.
Pissarides, C. A. (1992). Loss of skill during unemployment and the persistence of employment shocks. *The Quarterly Journal of Economics*, *107*(4), 1371–1391.
Raquel, S. L., Biagi, F., et al. (2018). *The routine biased technical change hypothesis: A critical review* (Tech. Rep.). Joint Research Centre (Seville site).
Rodrik, D. (2006). What's so special about china's exports? *China & World Economy*, *14*(5), 1–19.
Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, *71*(1), 135–158.
Rowthorn, R., & Ramaswamy, R. (1999). Growth, trade, and deindustrialization. *IMF Staff papers*, *46*(1), 18–41.
Saviotti, P. P., & Frenken, K. (2008). Export variety and the economic performance of countries. *Journal of Evolutionary Economics*, *18*(2), 201–218.
Scarpetta, S. (1996). Assessing the role of labour market policies and institutional settings on unemployment: A cross-country study. *OECD Economic studies*, *26*(1), 43–98.
Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of labor economics*, *24*(2), 235–270.
Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*(3), 557–586.
Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2012). A new metrics for countries' fitness and products' complexity. *Scientific reports*, *2*, 723.
Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2013). Economic complexity: conceptual grounding of a new metrics for global competitiveness. *Journal of Economic Dynamics and Control*, *37*(8), 1683–1691.
Visser, J. (2015). The institutional characteristics of trade unions, wage setting, state intervention and social pacts. ictwss database, version 5.1. amsterdam institute for advanced labour studies, amsterdam. *Amsterdam: Amsterdam Institute for Advanced Labour Studies*.
Welzel, C. (2013). *Freedom rising*. Cambridge University Press.
Wößmann, L. (2003). Specifying human capital. *Journal of economic surveys*, *17*(3), 239–270.
Wyplosz, C. (2001). Do we know how low should inflation be. *Why price stability*, 15–33.
Wyplosz, C. (2006). European monetary union: the dark sides of a major success. *Economic*

policy, *21*(46), 208–261.

Appendix A.

Table A1. Correlation Matrix, OECD sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Inflation	1.000									
(2) Imports	-0.093	1.000								
(3) Output Gap	0.078	0.076	1.000							
(4) Union Density	0.150	-0.007	-0.030	1.000						
(5) Centralisation	0.235	0.104	0.022	0.430	1.000					
(6) Coordination	0.052	0.196	0.037	0.530	0.695	1.000				
(7) Union Coverage	0.012	0.106	0.007	0.502	0.696	0.610	1.000			
(8) Replacement	-0.233	0.077	0.016	0.083	-0.000	0.219	0.234	1.000		
(9) Tax Wedge	-0.058	0.107	-0.007	0.192	0.199	0.300	0.490	0.177	1.000	
(10) ECI	-0.250	-0.013	0.006	-0.005	-0.256	0.074	-0.057	0.449	0.143	1.000

Table A2. Correlation Matrix, World Sample

Variables	(1)	(2)	(3)	(4)	(5)
(1) Inflation	1.000				
(2) Imports	0.006	1.000			
(3) Output Gap	-0.128	-0.207	1.000		
(4) Taxes	0.054	0.126	-0.020	1.000	
(5) ECI	-0.223	0.099	0.068	0.229	1.000

Table A3. First stage results of ECI in Table 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inflation	-0.007***	-0.005***	-0.005***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.008***	-0.002
	(-3.886)	(-3.527)	(-3.565)	(-4.453)	(-4.486)	(-4.423)	(-5.145)	(-5.492)	(-5.544)	(-0.60)
Imports		0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.002**
		(4.852)	(4.734)	(5.246)	(5.103)	(5.097)	(5.153)	(5.051)	(5.159)	(2.07)
Output Gap			0.232	0.251	0.214	0.213	0.139	0.143	0.142	0.109
			(1.476)	(1.616)	(1.393)	(1.373)	(0.962)	(0.987)	(0.974)	(0.58)
Union Density				0.003***	0.003***	0.003***	0.001*	0.002**	0.002**	-0.002
				(4.632)	(3.289)	(3.283)	(1.871)	(2.016)	(1.976)	(-1.39)
Centralisation					0.013***	0.014**	0.010*	0.010*	0.010*	0.012
					(2.761)	(2.497)	(1.837)	(1.963)	(1.847)	(1.63)
Coordination						-0.001	0.000	0.000	0.001	0.002
						(-0.105)	(0.090)	(0.009)	(0.110)	(0.32)
Union Coverage							0.002***	0.002***	0.002***	0.0004
							(6.163)	(6.350)	(6.508)	(1.36)
Replacement								-0.049	-0.050	-0.071
								(-1.331)	(-1.359)	(-0.86)
Tax Wedge									-0.001	-0.002*
									(-0.762)	(-1.67)
ECI(-1)	0.414***	0.407***	0.399***	0.415***	0.424***	0.424***	0.387***	0.392***	0.389***	
	(3.981)	(3.909)	(4.051)	(4.477)	(4.186)	(4.174)	(4.365)	(4.489)	(4.541)	
ECI(-2)	0.437***	0.476***	0.478***	0.502***	0.473***	0.474***	0.512***	0.511***	0.511***	
	(3.844)	(4.170)	(4.163)	(4.504)	(4.173)	(4.165)	(4.818)	(4.694)	(4.672)	
ECI(-3)	0.234**	0.261**	0.270**	0.278***	0.295***	0.296***	0.300***	0.307***	0.301***	
	(2.122)	(2.424)	(2.474)	(2.701)	(2.894)	(2.879)	(3.227)	(3.225)	(3.111)	
ECI(-4)	0.334***	0.355***	0.360***	0.355***	0.333***	0.333***	0.265***	0.270***	0.271***	
	(3.313)	(3.599)	(3.674)	(3.942)	(3.601)	(3.597)	(2.990)	(2.997)	(2.962)	
Articles										0.219***
										(4.78)

Notes: t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A4. First stage results of ECI in Table 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inflation	-0.008***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-5.544)	(-6.512)	(-6.512)	(-6.512)	(-6.512)	(-6.512)	(-6.512)
Imports	0.004***	0.001	0.001	0.001	0.001	0.001	0.001
	(5.159)	(1.445)	(1.445)	(1.445)	(1.445)	(1.445)	(1.445)
Output Gap	0.142	0.243*	0.243*	0.243*	0.243*	0.243*	0.243*
	(0.974)	(1.725)	(1.725)	(1.725)	(1.725)	(1.725)	(1.725)
Union Density	0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(1.976)	(-2.442)	(-2.442)	(-2.442)	(-2.442)	(-2.442)	(-2.442)
Centralisation	0.010*	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
	(1.847)	(2.379)	(2.379)	(2.379)	(2.379)	(2.379)	(2.379)
Coordination	0.001	0.004	0.004	0.004	0.004	0.004	0.004
	(0.110)	(1.067)	(1.067)	(1.067)	(1.067)	(1.067)	(1.067)
Union Coverage	0.002***	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**
	(6.508)	(2.458)	(2.458)	(2.458)	(2.458)	(2.458)	(2.458)
Replacement	-0.050	-0.113**	-0.113**	-0.113**	-0.113**	-0.113**	-0.113**
	(-1.359)	(-2.102)	(-2.102)	(-2.102)	(-2.102)	(-2.102)	(-2.102)
Tax Wedge	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.762)	(-0.814)	(-0.814)	(-0.814)	(-0.814)	(-0.814)	(-0.814)
ECI(-1)	0.389***	0.595***	0.595***	0.595***	0.595***	0.595***	0.595***
	(4.541)	(5.774)	(5.774)	(5.774)	(5.774)	(5.774)	(5.774)
ECI(-2)	0.511***	0.449***	0.449***	0.449***	0.449***	0.449***	0.449***
	(4.672)	(4.482)	(4.482)	(4.482)	(4.482)	(4.482)	(4.482)
ECI(-3)	0.301***	0.320***	0.320***	0.320***	0.320***	0.320***	0.320***
	(3.111)	(2.867)	(2.867)	(2.867)	(2.867)	(2.867)	(2.867)
ECI(-4)	0.271***	0.354***	0.354***	0.354***	0.354***	0.354***	0.354***
	(2.962)	(3.370)	(3.370)	(3.370)	(3.370)	(3.370)	(3.370)

Notes: t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A5. First stage results of ECI in Table 4

	(1)	(2)	(3)	(4)	(5)	(6)
Inflation	-0.008***	-0.007***	-0.008***	-0.006***	-0.007***	-0.007***
	(-5.544)	(-5.882)	(-5.532)	(-2.816)	(-4.954)	(-4.488)
Imports	0.004***	0.004***	0.004***	0.003***	0.003***	0.004***
	(5.159)	(4.717)	(5.177)	(2.670)	(4.482)	(4.883)
Output Gap	0.142	0.262**	0.141	0.177	0.377***	0.093
	(0.974)	(2.221)	(0.969)	(1.101)	(2.970)	(0.623)
Union Density	0.002**	0.000	0.002*	-0.000	-0.001	0.002**
	(1.976)	(0.515)	(1.965)	(-0.095)	(-0.677)	(2.257)
Centralisation	0.010*	0.010**	0.010*	0.013**	0.014***	0.011*
	(1.847)	(1.977)	(1.810)	(2.378)	(2.618)	(1.855)
Coordination	0.001	0.006	0.001	0.001	0.008*	0.000
	(0.110)	(1.649)	(0.147)	(0.269)	(1.884)	(0.057)
Union Coverage	0.002***	0.001***	0.002***	0.001***	0.001**	0.002***
	(6.508)	(5.915)	(6.506)	(4.473)	(2.463)	(5.210)
Replacement	-0.050	-0.156***	-0.050	-0.126	-0.235***	-0.053
	(-1.359)	(-5.748)	(-1.345)	(-1.405)	(-3.621)	(-1.436)
Tax Wedge	-0.001	-0.001	-0.001	-0.002	-0.002	-0.001
	(-0.762)	(-0.703)	(-0.783)	(-1.496)	(-1.473)	(-0.534)
ECI(-1)	0.389***	0.367***	0.388***	0.405***	0.401***	0.396***
	(4.541)	(4.154)	(4.530)	(4.485)	(4.434)	(4.377)
ECI(-2)	0.511***	0.369***	0.510***	0.574***	0.415***	0.514***
	(4.672)	(4.311)	(4.656)	(3.451)	(4.509)	(4.539)
ECI(-3)	0.301***	0.254***	0.300***	0.258	0.314***	0.300***
	(3.111)	(3.572)	(3.100)	(1.622)	(4.797)	(2.977)
ECI(-4)	0.271***	0.261***	0.271***	0.343***	0.321***	0.245**
	(2.962)	(3.127)	(2.951)	(2.612)	(4.092)	(2.416)
EPL		-0.001				
		(-0.083)				
Min Wage			0.009*			
			(1.952)			
Regulation				0.012		
				(1.088)		
ALMP					0.020***	
					(3.719)	
Education						0.001
						(1.615)

Notes: t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01