WORKING PAPER

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1 Introduction

There is growing recognition of the importance of fairness in the distribution of income and wealth, and

Figure 1: Gini coefficient of income inequality: United States and selected EU countries

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Source: Version 9.2 of the Standardized World Income Inequality Database of Solt (2020). Note: the Gini coefficient is measured on a 0-100 scale. Gross income inequality: the dispersion of income before taxes and redistribution. Net income inequality: the dispersion of income after taxes and redistribution.

Several factors could explain growing income inequality within developed countries (see, for example, Fröster and Tóth, 2015, for an excellent survey). Technological change and globalisation often feature prominently among possible causes. Technological change, by fostering capital-augmenting technical change, capital accumulation and a decline in the relative price of investment goods, could result in increased incomes of capital owners and lower employment due to automation. Technological change might also increase the wages of high-skilled workers relative to low-skilled workers if high-skilled workers are needed to operate new technologies. Globalisation can involve labour-abundant countries in the global economy, foster offshoring of production from developed to emerging and developing countries, facilitate cheap imports to developed countries and intensify competition. All these factors diminish job opportunities in developed countrieq e it l' d ℵ e v ş nge found that the bulk of increased wage inequality arises from variation between firms and sectors, which suggests that firm heterogeneity is crucial in analysing the developments in wage dispersion.

This policy paper summarises the key conclusions from Working Group 5 of MICROPROD, which focused on the distributional consequences of globalisation and technological progress.

2 Globalisation and trade

Globalisation is frequently seen as a key driver of inequality in developed countries. Altomonte and Coali (2020), and follow-up works by the same authors, studied this question by using labour market and inequality outcomes based on a unique firm-level dataset from France, Italy and Spain in the period from 2000 to 2017. Some of their results challenge earlier findings from the literature.

Globalisation can be measured in many ways. A major element of the globalisation process was China's integration into the global economy in the past decades. China experienced rapid economic growth averaging 10 percent per year from 1980-2011, subsequently slowing to the still high level of 7 percent per year on average from 2012-2019. Measured at purchasing power standards, China's output exceeded German output in 1994, Japanese output in 2000, and US output in 2016 to become the largest economy in the world . China's accession to the World Trade Organisation in 2001 helped boost the integration of the country into global trade flows and value chains. The substantial productivity growth over the past decades resulted in lower production costs, while a push for research and technological development has gradually increased the value-added component of Chinese exports. Bernard et al (2006) found that greater exposure to imports from low-wage countries decreased plant survival and growth in the US manufacturing sector, while the surviving firms reduced their number of employees. These findings were subsequently confirmed for Europe (Auer et al, 2013).

Thus, it was a sensible choice by Altomonte and Coali (2020) to measure exposure to globalisation as the increase in imports from China, which they call – in line with the literature – "China shock". Specifically, they used a cross-sectional indicator over a period preceding the global financial and

Data source: April 2022 IMF World Economic Outlook database; series: 'Gross domestic product, current prices', unit: 'Purchasing power parity; international dollars'.

economic crisis, 2000-2007. For each NUTS-2 (Nomenclature of Territorial Units for Statistics) region, the change in real imports from China to a particular industry of a country is normalised by the total number of workers in the same industry of the country. The region-specific indicator is derived as the weighted average of the industry-specific normalised Chinese import changes, with weights corresponding to the relative share of workers in that specific industry within the region. Both the weights and the normalisation factor are taken in the 2000-2007 period to avoid possible endogeneity effects, as the analysis aims to study the impacts of the China shock in the post-global financial crisis period of 2011-2017.

The key labour market and inequality indicators studied are average labour compensation (total labour compensation divided by the number of employees – that hereafter we call 'average wages' for simplicity) and the household relative deprivation rate, which measures the discontent people feel when they compare their socio-economic status to that of other families. Both indicators are averaged at the NUTS-2 level. In addition to the deprivation rate, the authors included also the average Gini coefficient at the NUTS-2 level. The inequality variables are available from 2011-2014 while labour market outcomes cover the whole period 2011-2017

The unique MICROPROD dataset was used for the analysis, which includes firm-level data for the manufacturing industries of France, Italy and Spain between 2000 and 2017. The first challenge was setting up of the dataset, which was based on several vintages of the ORBIS/Amadeus database. A representative sample of the manufacturing industry was created with data from more than 500,000 unique firms. This dataset was merged with other data sources at a more macro level, including robotics data from the International Federation of Robotics (IFR) database, trade data from the BACI database and regional-level economic indicators from Eurostat and OECD databases. An extensive dataset validation process justified the dataset - ṃ ᵐ מ Th Am ᵠ o ! ώ

An important feature of the research was that it not only studied the direct impact of the China shock on inequality indicators and labour market outcomes, but also the indirect effects via average wages and total factor productivity (TFP), by estimating auxiliary regressions. Thereby, the research was able to offer a more comprehensive picture of the China shock impact.

Several interesting results emerged from the research:

- **The China shock had a positive effect on total factor productivity in the medium term. This result is in line with earlier research (eg Auer et al, 2013).**
- **Average wages increased after the China shock, which is consistent with the shock's positive impact on total factor productivity.**
- **However, when controlling for total factor productivity, at the margin, the China shock has had a depressing effect on wages. This finding highlights the importance of studying the channels**

exposed regions only higher levels of productivity help to smooth out the effect of the shock. The effect on inequality suggests that the trade shock effect is mediated by the existing conditions in the labour market .

college degree. The wage reduction was driven entirely by the lower half of the income distribution, ultimately leading to a larger wage gap and rising wage inequality.

However, Autor (2015) argued that automation not only substitutes for labour, but also complements labour and thus increases output. He stressed that the former effect tends to be overstated in public debates to the disadvantage of the latter.

For Europe, Gregory et al (2021) concluded that technologies can create more jobs than they destroy. They found that routine-replacing technologies destroyed 9 million jobs in Europe from 1999-2010 but created about 14-19 million jobs over the same period, resulting from lower product prices, which improve regions' terms of trade, raising their tradable output and employment. In addition, local incomes grew and there were positive demand spillovers to the non-tradable sector. Furthermore, Gregory et al (2021) showed that employment would have grown substantially more had firm mark-ups not increased, in line with the argument and evidence put forward by Autor et al (2020).

Altomonte and Coali (2020) defined the robotic shock similarly to the China shock described in the previous section: the change in the stock of robots in a particular industry of a country is normalised by the total number of workers in the same industry of the country, which is then weighted across industries. Data on country-industry level robot adoption comes from the International Federation of Robotics. The sample period for calculating the robotic shock, 2000-2007, is also identical to the sample period used for calculating the China shock.

The main conclusions of the research were:

- The robotic shock supports higher total factor productivity in the medium-term.
- Average wages increase after the robotic shock, which is consistent with the shock's positive impact on total factor productivity.
- When controlling for total factor productivity, the robotic shock appears to have a positive effect on average wages, which is different from the same impact for the China shock.
- The robotic shock also increases wage skewness when controlling for total factor productivity.
- A higher level of robot adoption increases relative deprivation and Gini coefficient growth, indicating a worsening of regional inequality.

Therefore, following the robotic shock, the authors found higher wages along with higher skewness, but also higher growth in relative deprivation rates. This evidence may suggest two fundamental features of the two shocks.

The skill premium and/or returns from schooling refer to the gain that a worker gets by investing in higher education. It is calculated as the ratio of wages of the high-skilled workers to the wages of low-skilled workers. Autor (2014) noted the dramatic rise in the skill premium in the United States and argues that this contributes substantially to the rise in income inequality. Autor (2014) attributed the sharp increase in the skill premium in the US to the decline in non-college employment in production, administrative and clerical work; the sharp rise in low-skilled labour supply and competition from the developing world; the decline in the bargaining power of labour unions; and reductions in top marginal tax rates.

Linder and Muraközy (2020) examined how different types of technological change affect wage inequality. They investigated the relationship between firm-level skill demand and different innovation activities. Skill demand is proxied by the share and wage premium of college-educated workers. Innovation activities involve the introduction of production processes, products and management methods, which are new for the firm but not necessarily for the market.

The dataset is a unique firm-level innovation survey linked to employee-employer data from Hungary and Norway. The dataset includes five repeated waves of a large-scale innovation survey, each of which covers around 5000 firms. The survey has a panel dimension as well. This allows worker-level wages to be studied and compositional changes resulting from increased skill demand due to innovation to be controlled for.

Hungary and Norway are two different countries in terms of innovation activities and labour markets (Linder and Muraközy, 2020). On average, Hungarian firms are more technology adopters, while Norwegian firms are more technology developers. Labour markets are less regulated in Hungary than in Norway. Thus, findings for these two countries with different characteristics have the potential to offer interesting insights into the effects of the different types of technological developments on the skill-premium, and ultimately on income inequality.

Linder and Muraközy (2020) first derived a theoretical model in which firms have two inputs in the production function: high skilled labour and low skilled labour. The model suggests that if wages are set in a non-competitive environment, then a negative relationship emerges between relative skill demand and relative wages at the firm level as long as there is no skill-biased technological change. They, therefore, examined both the quantity of labour and the wage response. By following the

Data on the adoption of industrial robots at the country-industry level (from the International Federation of Robotics) was combined with regional employment data (either from Eurostat or from national sources). Historical labour market data is from the European Labour Force Survey and

High-quality workers sort into works council establishments (assortative matching). However, this sorting only modestly mutes the positive link between work councils and labour productivity, wages and profits. Thus worker sorting does not invalidate the general result of positive council effects as documented in the literature.

High-wage workers have a strong positive productivity contribution, but this is not influenced by work councils. Thus, worker quality and worker participation in work councils are not complements in performance management.

There is a positive link between council existence and establishment profitability even after controlling for worker quality. This implies that councils can contribute to a fair sharing of productivity gains between labour and capital, thereby contributing to a stable labour share in income at the plant level.

Overall, the findings suggest that work councils have positive effects on productivity, wage and profit at the firm level. This also implies a difference between those firms that have work councils and those that do not. Since firms without work councils do not benefit from the positive effects of such councils, wage inequality could develop between the two types of firm. Another reason for wage inequality is reduced by the China shock, but increases after a robot shock. The marginal impacts of both shocks change when the impact via average wages is filtered out, yet from a policy perspective, the overall impact is crucial. Thus, new findings demonstrate that technological change could have been a major driver of increased income inequalities in developed countries, but trade globalisation has not. Nevertheless, the different marginal impacts suggest that the China shock induced wage falls (ie wages did not increase as much as productivity increase would have implied), while the impact of the robot adoption shock is consistent with an increase in the skill premium.

Other novel research highlighted the important role of low-novelty content innovation, which accounts for at least two-thirds of all innovation activities. Estimates for Hungary and Norway, two countries at different stages of technological development and with different labour markets, reveal surprisingly similar quantitative impacts of innovation on the relative wages of high-skilled workers over low-skilled workers. Both low- and high-novelty innovations are associated with an increase in the college premium with similar magnitudes, but because of its greater prevalence, low-novelty innovation plays a greater role than high-novelty innovation in explaining the skill premium. Thus, skill-biased technological change is not necessarily linked to generating new knowledge or high-novelty products at the firm level.

Increased income inequality, or the causes of income inequality, like increased robot adoption, could have political consequences. New research found a causal relationship from greater exposure to robot adoption to increases in support for nationalist and radical-right parties. A possible reason for this finding is that greater robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy. Since a new wave of automation is on its way, the findings suggest that electorates might further shift to radical parties in the absence of appropriate policies to address the adverse social consequences of automation.

Finally, labour market institutions might mitigate the adverse impacts of technological change on labour incomes and income inequality. For the specific case of German work councils (which are different from trade unions), new research found very positive results: such work councils increase productivity, wages and profits, results that remain significant even when controlling for the efforts of high-quality personnel to seek jobs in high-productivity and high-wage firms, where the prevalence of work councils is higher. Work councils can also contribute to a fair sharing of productivity gains between labour and capital. All these factors benefit workers, yet such benefits do not arise in firms where there are no work councils, so ultimately, work councils could increase inequality between workers at different firms. While further research should explore whether the German model of work councils could be adopted in the labour market structure of other countries, the encouraging findings on the German model suggest that certain labour market institutions could result in a win-win situation

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