Revisiting the drivers of US labor market polarization*

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Abstract

We exploit differences across local labor markets in the exposure to Global Value Chains (GVCs), Chinese import competition and automation to study the drivers of labor market polarization in the US. Using value added trade data, we are able to correctly assign trade-related shocks to local labor markets, based on the source of value added. Across the 722 commuting zones that approximate US local labor markets, we find that employment polarization, measured across wage groups, is mainly driven by their exposure to automation. GVCs lead to an increase in the employment share of relatively high-wage occupations (which we call 'skill upgrading'), while import competition from China leads to an increase in the employment share of relatively low-wage occupations (which we call 'skill downgrading'). Trade as a combination of the two thus contributes to employment polarization but at a lower level than automation.

JEL Classification Codes: F14; F16; E24; J31; O33.

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1 Introduction

Employment polarization – the relative decline in the employment share of middle-skill/middle-pay jobs and the relative increase in the employment share of low-skill/low-pay and high-skill/high-pay jobs – is one of the most striking feature of the US labor market in recent decades (see Autor et al., 2006; Acemoglu and Autor, 2011; and Autor and Dorn, 2013).

The literature has identified various possible drivers of job market polarization, and in particular three competing explanations. First, routine-biased technological change (RBTC) (Autor et al., 2003): routine tasks, typically performed by middle-skilled workers, are easier to automate. Second, offshoring (Blinder and Krueger, 2013): tasks that do not require a presence of the worker are more prone to be offshored and subsequently imported. This tends to affect mostly middle-skilled workers. Third, the rise of China (Autor et al., 2015): import competition from China has particularly hit middle-skilled manufacturing workers.

In this paper, using a standard local labor market approach, we estimate the effect of all three factors identified in the literature on US labor market polarization. We contribute to the literature by considering the simultaneous effect of three factors, and by constructing measures of exposure to Global Value Chains (GVCs) and to Chinese import competition that correctly assign trade-related shocks to local labor markets, based on the source of value added.

Since we measure employment polarization based on the distribution of wages across occupations, our approach allows us to draw implications on the drivers of wage inequality in the US.

Using data on 722 commuting zones (which approximate local labor markets), we find that employment polarization is mainly driven by their exposure to automation. GVCs lead to an increase in the employment share of relatively high-wage occupations (which we call 'skill upgrading'), while import competition from China leads to a decrease in the employment share of relatively low-wage occupations (which we call 'skill downgrading'). While the combined effect of exposure to GVCs and to China is to polarize employment, exposure to automation is the most important driver of polarization.

We contribute to several streams of literature. First, there are several papers showing that the labor markets of other non-US developed countries have also become polarized – see Goos and Manning (2007) for the UK; Dustmann et al. (2009) for Germany; Goos et al. (2009) or Michaels et al. (2014) for most European economies; Harrigan et al. (2016) for France; Keller and Utar (2016) for Denmark.[1]

Second, we contribute to the 'China shock' literature (see, in particular, Autor et al., 2013; 2015).

Third, we contribute to the literature on how trade and technology contribute to within-country inequality (see Helpman, 2018 for a recent overview).

Our paper is mostly related to Breemersch et al. (2017), who consider the effects of offshoring, technology and Chinese import competition on labor market polarization in nineteen European countries. Their analysis, however, is at the level of industries, rather than local labor markets. Moreover, they do not measure wage polarization, which prevents them to analyze how the different forces have affected (wage) inequality.

The rest of this paper is organized as follows: the next section presents the econometric strategy adopted. Sections 3 and 4 describe the data and present descriptive evidence of the link between employment polarization and exposure to GVCs, Chinese import competition and automation across US local labor markets. The results of the empirical analysis are in Section 5, while Section 6 concludes.

2 Econometric strategy

To shed light on the drivers of job market polarization, we use a local labor market approach, exploiting differences across local labor markets in the exposure to GVC integration, Chinese

[1] There is evidence of job polarization also in some *developing* countries, although job polarization is not widespread across all developing countries. See Maloney and Molina (2016), World Bank (2016) and Reijnders and de Vries (2017).

import competition, and automation. Following the literature (see, for instance, Autor et al., 2013; 2015), US local labor markets are represented by 722 commuting zones (CZ's). CZ-level exposure to trade and technology shocks is determined by initial patterns of industry specialization within each CZ. The key identification assumption to exploit such CZ-level variation in exposure to trade and technology shocks is that labor is mobile within CZ's, and immobile across them. If this were not the case, as argued by Autor et al. (2015), CZ-specific labor-market shocks would diffuse across space. It is thus conforting that the literature finds support for this assumption (Topel, 1986; Jean and Katz, 1992; Glaeser and Gyourko, 2005; Autor and Dorn, 2013; Autor et al. 2013).

We formulate the following baseline reduced-form equation:

$$\varDelta Y_i^S = \alpha + \beta_1 GVC_i + \beta_2 China_i + \beta_3 Automation_i + \mathbf{x}_i' \boldsymbol{\gamma} + \varepsilon_{it}, \tag{2.1}$$

where $\varDelta Y_i^S$ is the change of wage group $S = \{Low,\ Middle,\ High\ \}$ in total employment in CZ i in a period (for our estimations, the period 2000-2014). The variables of interest are the local exposure to GVCs (GVC_i), the local exposure to Chinese import competition ($China_i$), and the local exposure to automation ($Automation_i$). We additionally include control variables at the CZ level, as well as Census division dummies (or, in a robustness exercise, State dummies) in the vector $\mathbf{x}$.[2]

Employment polarization would be associated with an increase in the share of low-wage and high-wage groups in total employment, and a contemporaneous decrease in the share of middle-wage groups. Estimating one equation per each of the three wage groups is therefore appropriate to test for employment polarization. In a robustness exercise, we employ a synthetic index of employment polarization as dependent variable. Following in spirit Reijnders and de

[2] Census divisions are the following nine groupings of US states and the District of Columbia: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. Census division dummies – which are added in some specifications in Autor et al. (2013) and in all specification in Autor et al. (2015) – absorb region-specific trends in the manufacturing employment. The inclusion of State dummies is a more conservative way of controlling for such trends.

Vries (2017), this is defined as:

$$EP_i \equiv \min\left\{\gamma_i^L, \gamma_i^H\right\} - \gamma_i^M \tag{2.2}$$

where γ_i^S is the percentage points change in the employment share of wage group S in commuting zone i between 2000 and 2014. As explained by Reijnders and de Vries (2017) (who compute this index at country-level for forty countries) the EP index is positive if and only if the labor market in the corresponding commuting zone polarized, and is higher the greater is the fall in the employment share of the middle-wage group relative to the other two.

2.1 Baseline exposure measures

In this section, we describe in detail the baseline exposure measures.

FVAX-based GVC exposure The baseline GVC exposure measure, GVC_i, is local exposure to foreign value added in US exports. It is defined as:

$$GVC_i \equiv \frac{1}{L_i}\sum_j \frac{L_{ij}}{L_j} \Delta FVAX_j^{US}, \tag{2.3}$$

where, as in equation (2.1), Δ is the change between 2000 and 2014. In equation (2.3), $FVAX_j^{US}$ is Foreign Value Added (FVA) in US exports from the source industry j. This measure is calculated as the sum of FVA in final exports and FVA in intermediate exports. To be more specific, we use the US as the exporting country (thus the superscript US), and sum over all source countries (except the US), all exporting industries and all destination countries.[3] We are left with industry data at the level of the source industries j's (i.e. industries from which value added originates).[4]

Following the methodology of Autor et al. (2013), we assign $FVAX_j$ to CZ's by summing

[3] See Section 3 for a description of the data used and their coverage.

[4] All value added measures needed to build GVC and China exposure are time-varying, since we need compute their change over time (Δ).

across all source industries j, weighting the sum by the CZ i's baseline-year share of national industry employment in j (L_{ij}/L_j).[5] We further normalize by total employment in CZ i (L_i). The measure in (2.3) thus proxies for GVC exposure because it allocates the national change in industry-level $FVAX$ to CZ's according to their baseline industry employment structure. More exposed CZ's are the ones with initial employment structure relatively more skewed towards j industries with relatively larger increases in $FVAX$.

One important difference relative to previous related work (most notably, Autor et al., 2013) is that we are able to decompose trade flows based on source country and industry of value added. In doing so, we calculate the exposure measures with j representing industries where value added originates. This has the advantage to correctly assign trade-related shocks to CZ's, since the true set of industries affected by such shocks can be identified. In fact, $FVAX$ is *not* the FVA in US exports from the source countries' industries that is re-exported by US industries. If, say, foreign industries A and B respectively supply upstream 4\$- and 1\$-worth value added to foreign industry A downstream, and the resulting 5\$ end up constituting the foreign value added embodied in US exports of industry A, we assign FVA values of 4\$ and 1\$ respectively to US industries A and B, rather that 5\$ to US industry A. This is important to be able to correctly assign GVC exposure to local labor markets. As explained by Jakubik and Stolzenburg (2018), goods exported from a downstream industry such as consumer electronics contain inputs from upstream industries such as plastics and fabricated metal products. When FVA is embodied in US electronics exports, the affected local labor markets in the US are the ones with relatively higher share of employment in upstream production activities (plastics and fabricated metal products), not those with relatively higher share of of employment in downstream production activities (consumer electronics).

Chinese DVA-based China exposure The baseline China exposure measure, $China_i$, is local (i.e. CZ-level) exposure to import competition from China, measured by Chinese domestic

[5] We use 2000 as baseline year.

value added in China's exports to the US. It is defined as:

$$China_i = \frac{1}{L_i} \sum_j \frac{L_{ij}}{L_j} \Delta DVA_j^{CN}, \tag{2.4}$$

where DVA_j^{CN} is domestic value added in China's exports to the US from the source industry j. This measure is calculated as the sum of Domestic Value Added (DVA) embodied in final exports and DVA in intermediate exports that are used by the direct importer to produce local final products. To be more specific, we use China as the source and exporting country (thus the superscript CN), the US as the destination and importing country, and we sum over all exporting industries.[6] We are left with industry data at the level of the Chinese source j's.

As for the GVC exposure measure, we assign DVA_j to CZ's by summing across all source industries j, weighting the sum by the CZ i's baseline-year (i.e. 2000) share of national industry employment in j (L_{ij}/L_j). We further normalize by total employment in CZ i (L_i). The measure in (2.4) thus allocates the national change in industry-level Chinese DVA to CZ's according to their baseline industry employment structure. Note, also, that since j represents industries where value added originates, we are able to correctly assign exposure to Chinese import competition across local labor markets.

Automation exposure To measure local exposure to automation, $Automation_i$, we follow Autor et al. (2015). They compute, for each occupation o, a summary measure of routine task-intensity in 1980 (RTI_o). They then classify as routine-intensive occupations those falling in the top-third of the employment-weighted distribution of the RTI measure in 1980 (i.e., they create an occupation-based routine task-intensity dummy variable). Finally, they compute, for each commuting zone i, the fraction of employment at the start of a decade that falls in routine task-intensive occupations, RSH_i. This is the measure of local exposure to automation also used

[6] The data used and their coverage are the same as for the GVC exposure measure – thus reducing the scope for measurement error – and are described in Section 3.

in this study.[7]

2.2 Instruments for exposure measures

A concern when estimating the empirical model in (2.1) is the endogeneity of the three main variables of interest. In particular, there might be unobserved supply and demand shocks that simultaneously affect the described trade and technology shocks and regional employment. To deal with this endogeneity problem, we use an instrumental variable (IV) approach for the exposure variables.

GVC exposure To instrument for GVC exposure we follow Kummritz (2016), who applies Frankel and Romer (1999)'s approach to value added trade data. To get exogenous variation in value added trade flows, the idea is to use a directional value added trade resistance index that combines third country bilateral trade costs with the distance between the involved industries within the value chain.[8] The exogenous predictor for trade in value added can then be used to construct an exogenous measure of CZ-level GVC exposure.

In a first step, we predict bilateral industry-level value added trade flows based on their exogenous determinants only:

$$vae_{jlrkt} = \exp\left\{\alpha + \beta \ln(RI_{jlrkt}) + \gamma_{jk} + \phi_{kt} + \delta_{rt} + \varepsilon_{jlrkt}\right\}, \tag{2.5}$$

where j, r index industries; k, l index countries; t indexes years. In equation (2.5), vae_{jlrkt} is the value added of source industry j from country l in the exports of using industry r from country k, and RI is the value added trade resistance index, which is a ratio. The numerator of this ratio is a trade cost aggregate, given by:

[7] In particular, we use the measure computed by Autor et al. (2015) for the year 2000.

[8] In their seminal paper, Frankel and Romer (1999) used geographical determinants of trade costs to get exogenous variation in (gross) trade flows.

$$\tau_{lkt} \equiv \sum_{c \neq k,l} \tau_{lct} \frac{e_{lct}}{\sum_c e_{lct}}, \tag{2.6}$$

This is a weighted average of country l's bilateral trade costs with all other c countries except k, where the weights are export shares of l to c.[9]

The denominator of the RI ratio – industrial distance – is the product of the upstreamness of source industry j and the downstreamness of using industry r.[10]

In a second step, we aggregate the fitted values of equation (2.5) across all k countries and r industries, to get the following instrument for $FVAX$:

$$FVAX_{ljt}^{IV} \equiv \sum_k \sum_r \widehat{vae}_{jlrkt}. \tag{2.7}$$

Keeping only the US as exporting country l, we the construct the instrument for the GVC exposure measure as:

$$GVC_i^{IV} \equiv \frac{1}{L_i} \sum_j \frac{L_{ij}}{L_j} \Delta FVAX_{ljt}^{IV}, \tag{2.8}$$

where, as in equation (2.3), Δ is the change between 2000 and 2014.[11]

To boost intuition, consider the following example with four (plus one) countries – China (C), India (I), Japan (J) and Thailand (T) (plus the Rest of the World, RoW) – and three industries involved in a Motor veichles' value chain – Basic metals (B), Fabricated metals (F) and Motor vehicles (M). (The example is from Kummritz, 2016). The three industries are ordered according to their position in the value chain: B is downstream with respect to F and M, and F is downstream with respect to M. Figure 1 shows a case in which the final product (Motor vehicles) is manufactured in and exported to RoW by Japan, using Basic metals from

[9] As explained in Section 3, bilateral trade costs are sourced from the ESCAP-World Bank Trade Cost Database. For generic countries a and b, the bilateral trade cost indicator in this database is the geometric average of ab and ba tariffs: $\tau_{ab} \equiv \sqrt{(1 + tariff_{ab})(1 + tariff_{ba})}$, where tariffs are simple average effective import tariff imposed by the exporting country on the importing country.

[10] The industry upstreamness and downstreamness indexes are derived from Antràs et al., (2012); Antràs and Chor (2013); Fally (2012). See equation (6) and Appendix A.3 in Kummritz (2016) for further details.

[11] Employment variables in equation (2.8) are for the year 1990. This is similar in spirit to Autor et al (2013), to take into account reverse causality concerns if employment is affected by anticipated trade shocks.

India, as well as Fabricated metals from China and Thailand. Fabricated metals that Japan sources from China and Thailand are produced using Basic metals that China and Thailand source from India.

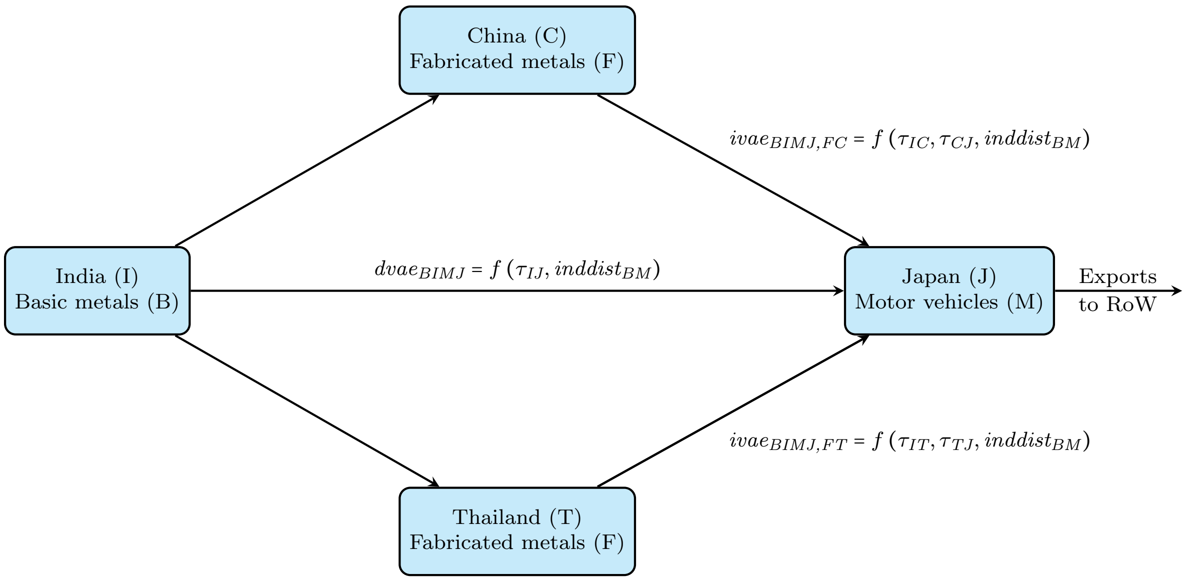
The objective is to find a good instrument for value added of exports, the dependent variable in (2.5). Value added exports are mechanically equal to the sum of all foreign value added – in our example, the value added of Japanese exports of M is equal to the sum of the value added of India's exports of B to Japan; the value added of C's exports of F to Japan (which embodies value added of India's exports of B to China); and the value added of Thailand's exports of F to Japan (which embodies value added from India's exports of B to Thailand). Focus on India's value added in Japanese exports of M. By the very logic of value chains, as shown grahically in Figure 1 and analytically by Noguera (2012), India's value added in Japanese exports of M can be predicted by bilateral trade costs between India and China and by bilateral trade costs between India and Thailand.[12] Such 'indirect' bilateral trade costs, being exogenous to the productivity or value added of the Japanese M industry, are good predictors of the exogenous component of India's value added in Japanese exports of M.

The remaining problem for the instrumentation is that trade costs are at bilateral country-level (see footnote 9), while the instrument for *vae* in equation (2.5) should vary by countries *and* industries. The simple solution is again to use the GVC structure of production, with some industries being clearly more upstream than others. In the example, B is more upstream than F when it comes to providing inputs into the production of M. The larger the 'industrial distance' between B and M (in Figure 1, $inddist_{BM}$), the more likely it is that more intermediate stages will be performed to transform B's input into M's output, and the more likely it is that third countries will be involved in this longer value chain, therefore the more likely it is that third-country (i.e. indirect) bilateral trade costs will affect the foreign value added embodied in

[12] Of course, bilateral trade costs involving Japan are also predictors of Japanese exports of M, but they are potentially endogenous, so they should not be included in the construction of the instrument. Note that bilateral trade costs between generic countries a and b are indicated in Fgure 1 as τ_{ab}, τ_{ba} because tariffs (τ)'s are the components of the bilateral trade cost indicator in the ESCAP-World Bank Trade Cost Database – see footnote 9.

final exports. Therefore, an indicator of industrial distance such as the (inverse of) the product of the upstreamness of B and the downstreamness of M can be legitimately interacted with bilateral trade costs to build the value added trade resistance index. This index, in turn is a good instrument for value added exports in equation (2.5).

Figure 1: Instrument for value added exports: graphical example



Notes: Derived from Table 1 in Kummritz (2016). $dvae_{BIMJ}$ is the direct value added of I's exports of B to J. It is a function of direct bilateral IJ trade costs, τ_{IJ} and the 'industrial distance' between B and the final export industry M, $inddist_{BM}$. $ivae_{BIMJ,FC}$ is the indirect value added of I's exports of B to J, embodied in C's exports of F to J. It is a function of indirect bilateral IC and CJ trade costs, τ_{IC} and τ_{CJ}, and the 'industrial distance' between B and the final export industry M, $inddist_{BM}$. Similarly, $ivae_{BIMJ,FT}$ is the indirect value added of I's exports of B to J, embodied in T's exports of F to J. It is a function of indirect bilateral IT and TJ trade costs, τ_{IT} and τ_{TJ}, and the 'industrial distance' between B and the final export industry M, $inddist_{BM}$.

China exposure To instrument for the exposure to Chinese import competition, we follow the idea of Autor et al. (2013). We use Chinese domestic value added in exports of goods which are exported to and consumed in other developed countries (namely, Australia, Denmark, Finland, Germany, Japan, Spain, and Switzerland) as an instrument for Chinese domestic value added in exports of goods which are exported to and consumed in the US. The instrument for DVA is calculated as the sum of DVA embodied in final exports and DVA in intermediate exports used by the direct importer to produce local final products. Again, China is the source and exporting country, but the destination/importing countries are now the other seven developed countries rather than the US. When summing over all exporting industries, we get industry data at the level of the Chinese source j's. We therefore construct the instrument for the China exposure as:

$$China_i^{IV} \equiv \frac{1}{L_i} \sum_j \frac{L_{ij}}{L_j} \Delta DVA_{ljt}^{IV}, \tag{2.9}$$

where DVA_{ljt}^{IV} is the instrument for DVA described in the above-paragraph and Δ is the change between 2000 and 2014.[13]

Our instrumentation approach for the China exposure variable follows in spirit the one of Autor et al. (2013), with some important differences. Autor et al. (2013) use growth in gross imports from China into eight non-US developed countries as an instrument for the growth in gross imports from China into the US. They justify their instrument based on the assumption that growth of Chinese imports in high-income countries other than the US is correlated with growth in Chinese imports in the US (because they both reflect positive supply shocks in China), but uncorrelated with shocks in US product demand. A problem with their approach is that both gross Chinese exports to the US and gross Chinese exports to non-US developed countries embody US value added. Since US employment is a major contributor to US value added, and US employment is correlated with shocks in US product demand, Autor et al. (2013)'s assumption that growth of Chinese imports in high-income countries other than the US is uncorrelated with shocks in US product demand is likely violated (Jakubik and Stolzenburg, 2018).

We only use Chinese domestic value added in exports in the construction of the instrument. The instrument is therefore relevant insofar the growth of China's domestic value added embodied in Chinese exports to non-US high-income countries is correlated with growth of China's domestic value added embodied in Chinese exports to the US (likely to be true because they both reflect positive supply shocks in China), and it is valid insofar Chinese domestic value added embodied in Chinese exports to non-US high-income countries in uncorrelated with shocks in

[13] Similarly to the instrument for the GVC exposure measure, employment variables in equation (2.8) are for the year 1990.

US product demand (likely to be true because purely Chinese domestic value added does not, by definition, contain value added from other countries – most notably the US – which might be correlated with US product demand along value chains).

Automation exposure The exposure to automation is instrumented as in Autor et al. (2015). They build an intrument for the fraction of employment that falls in routine task-intensive occupations using historical information for 1950 on the local industry mix and the nationwide occupational structure of industries. As argued by Autor et al. (2015), the relevance and the validity of the instrument stem from the fact that it is determined three decades prior to the onset of rapid computerization in the 1980s, so it should be correlated with the long-run component of the routine occupation share but uncorrelated with contemporaneous innovations to this share.

2.3 Alternative exposure measures

We present two robustness exercises where we build alternative exposure measures. In the first, we construct China exposure in a way similar to what is done in Autor et al. (2013), adapting the GVC exposure variable accordingly. In the second, we use an alternative GVC exposure variable, based on foreign value added in US production.

China exposure measure similar to Autor et al. (2013)'s To build their exposure to Chinese import competition, Autor et al. (2013) rely on gross trade flows. This has several disadvantages, most notably the fact that it calls into question the validity of their instrument (see discussion above in this section). We replicate their exercise without introducing mechanical correlation between US employment and Chinese import competition, and assigning import competition to industries where value added originates. To this end, we use the sum of all domestic value added trade flows contained in the value added decomposition proposed by Koopman et al. (2014) (see Section 3): DVA in intermediate exports used by the direct importer to produce local final products; DVA embodied in final exports; DVA in intermediate exports used to produce intermediates that are re-exported to third countries for production of local final products; DVA first exported but which eventually returns and is consumed at home; FVA embodied in intermediate exports; FVA embodied in final exports; pure double counting from domestic source; and pure double counting from foreign sources. We use China as exporting country and the US as destination country, aggregate over all source countries and exporting industries, and allocate the resulting (source) industry-level data to CZ's using employment shares, as described above.[14] Note that we deviate from Autor et al. (2013) by: 1) not including the US as a source country. This breaks the mechanical mechanical correlation between US employment and Chinese import competition; and 2) matching source industries instead of exporting industries to US industries in building China exposure variables.

The construction of the corresponding instrumental variable (which is the variable used in the robustness exercise) is analogous to the the construction of the baseline instrument for the China exposure variable described in Section 2.2. That is, we replace US as the destination country by seven other developed countries (Australia, Denmark, Finland, Germany, Japan, Spain, Switzerland) in the aggregation of DVA flows.

We also adjust the GVC exposure variable to avoid any overlap with the China exposure variable just described. In particular, we subtract from the $FVAX$ measure of Section 2.1 China's exports to the US which are re-exported by the US. The subtracted trade flow is equal to:

$$DVA_{INT,REX} + RDV + \frac{DVA_{INT,REX} + RDV}{DVA_{INT,REX} + RDV + DVA_{INT}} FVA_{INT}, \tag{2.10}$$

where $DVA_{INT,REX}$ is DVA in intermediate exports used to produce intermediates that are re-exported to third countries for production of local final products; RDV is DVA first exported

[14] Recall that our DVA_j^{CN} variable used to compute the baseline China exposure variable is just the sum of DVA embodied in final exports and DVA in intermediate exports that are used by the direct importer to produce local final products. The problems with double counting are discussed in Jakubik and Stolzenburg (2018).

but which eventually returns and is consumed at home; DVA_{INT} is DVA in intermediate exports used by the direct importer to produce local final products; and FVA_{INT} is FVA embodied in intermediate exports.[15]

As usual, we sum over all source countries, destination countries, and exporting industries, and allocate the resulting source industry-level data to CZ's using employment shares.

The construction of the corresponding instrumental variable (which is the variable used in the robustness exercise) is analogous to the the construction of the baseline instrument for the GVC exposure variable described in Section 2.2. That is, we replace US as the destination country by seven other developed countries (Australia, Denmark, Finland, Germany, Japan, Spain, Switzerland) in the aggregation of (the modified) FVA flows.[16]

GVC exposure measure using FVA in production Instead of analyzing the effect of FVA in US exports, we alternatively look at FVA in US production ($FVAY$). The variable is constructed as follows. First, we build a dataset where the US is the exporting country, all countries except the US are the source countries, all countries except the US are the destination countries, and we consider all source and exporting industries. We sum over the following value added trade flows: DVA in intermediate exports used by the direct importer to produce local final products; DVA embodied in final exports; DVA in intermediate exports used to produce intermediates that are re-exported to third countries for production of local final products; DVA first exported but which eventually returns and is consumed at home; FVA embodied in intermediate exports; FVA embodied in final exports; pure double counting from domestic source; and pure double counting from foreign sources. Second, we multiply the resulting VA trade flows with (US) industry production-to-export ratios (sourced from WIOD data), to get

[15] Note that we approximate FVA in Chinese exports which is re-exported by the US by the respective share in DVA.

[16] As a technical note, to build the instrument for $FVAX$ we need to distribute the subtraction term in equation (2.10) – at the level of source country and source industry – over US exporting industries according to the distribution of FVA in US exports (intermediates plus final) over US exporting industries. This is because we need disaggregated data by exporting country, exporting industry, source country, and source industry, while the subtraction term in (2.10) does not include information on US exporting industries (just on Chinese exporting industries).

FVA in US production. Third, we subtract Chinese DVA in intermediate exports that are used by the direct importer (the US) to produce local final products. This is to avoid overlaps with the China exposure variable (which incorporates this Chinese DVA in intermediate exports).

The variable $FVAY$ is then constructed in the same way as the baseline GVC exposure measure $FVAX$. We sum over all source countries, destination countries, and exporting industries. The resulting (source) industry data is allocated to CZ's by using employment shares. The corresponding IV variable is also constructed in the same way as the IV for the baseline GVC exposure measure.[17]

3 Data

The employment data come from the American Community Survey (ACS). By means of various crosswalks, we map the Public Use Microdata Areas (PUMAs) available in the ACS data to CZ's.[18] Industry-level employment is constructed by reclassifying the ACS data (which comprises 246 industries) to the more aggregated industry structure of the trade flow data (56 industries in ISIC Rev. 4).[19]

The three wage groups are built based on wage data from the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS). We order US Standard Occupational Classification (SOC) occupations (23 major groups) by their average national wage in 2000.[20]

[17] In this case, too, to construct IV variable corresponding to $FVAY$ we have to distribute the subtraction term – at the level of source country (China) and source industry – over US exporting industries according to the distribution of FVA in US production over US exporting industries. This approach is necessary because the subtraction term does not include information on US exporting industries (just on Chinese exporting industries), and the required data is disaggregated by exporting country, exporting industry, source country, and source industry.

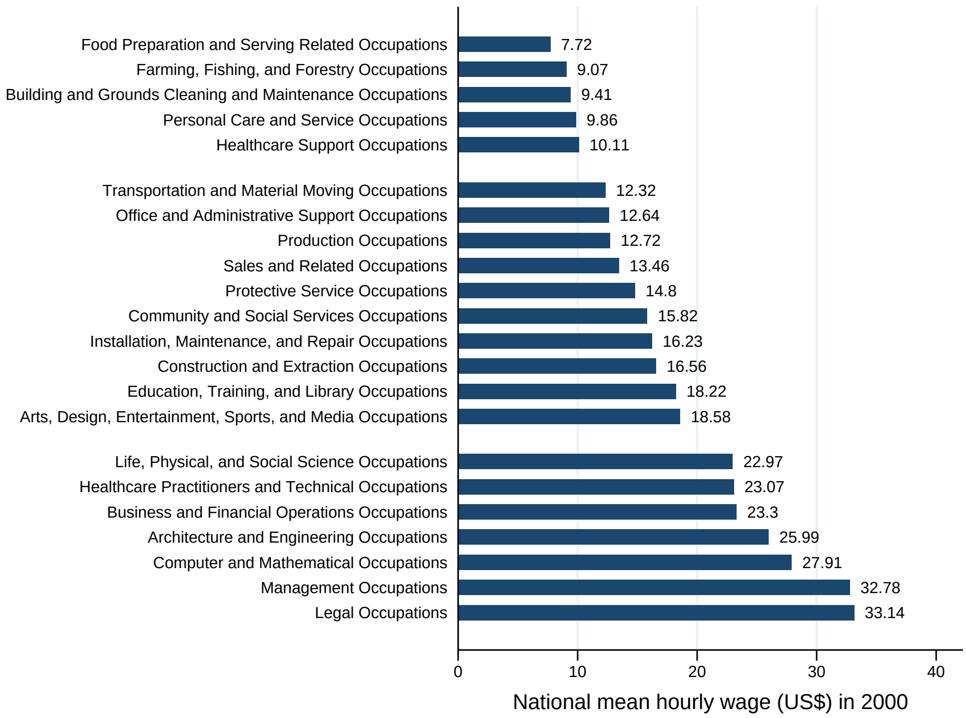
[18] Crosswalks from 1990 PUMAs (used in ACS data for 1990) to 1990 CZ's, and from 2000 PUMAs (used in ACS data for the years 2000 and 2005-2011) to 1990 CZ's are made public by David Dorn – see `www.ddorn.net`. To match 2012 PUMAs (first used in the ACS data in 2012) to 1990 CZ's, we first use the correspondence between 2012 PUMAs and 2000 PUMAs ('puma2k_puma2010.csv') made available by the Missouri Census Data Center (see `http://sas.mcdc.missouri.edu/geography/PUMAs.html`) and then apply the crosswalk from 2000 PUMAs to 1990 CZ's.

[19] To do so, we use the following crosswalks: i) industries in ACS–ISIC Rev. 3 (correspondence prepared by Adam Jakubik); ii) ISIC Rev. 3 – ISIC Rev. 3.1; and iii) ISIC Rev. 3.1 – ISIC Rev. 4. For crosswalks ii) and iii), correspondences are from the UN Statistics Division (see `https://unstats.un.org/unsd/classifications`).

[20] See Goos et al., (2009) for a similar approach. Note that military-specific occupations are not used in the analysis because of missing wage data.

As illustrated in Figure 2, the sorting of occupations in the three categories (Low-, Middle- and High-wage) is straightforward.

Figure 2: Construction of wage groups: Low, Middle, and High



Notes: Authors' calculations based on Bureau of Labor Statistics (BLS) data. Low-wage occupations in the upper panel, Middle-wage occupations in the central panel, High-wage occupations in the lower panel. See Table 1 for the corresponding Standard Occupational Classification (SOC) codes.

We match the SOC occupations to those in the ACS by using a crosswalk from the US Census Bureau.[21]

Trade flow data (56 industries in ISIC Rev. 4) needed to construct measures of exposure to GVCs and to Chinese import competition are decomposed by value added using the accounting framework proposed by Koopman et al. (2014) and provided by the Research Centre for GVCs at the University of International Business and Economics (UIBE) in Beijing.[22]

To build the instrument for the GVC exposure, we rely on bilateral trade costs from the ESCAP-World Bank Trade Cost Database, which are estimated based on the inverse form of

[21] 2010 SOC – 2010 Census, see `www.bls.gov/cps/cpsoccind.htm`.

[22] Appendix Table A-1 provides a list of industries in the trade data, with their ISIC Rev. 4 codes and description. The raw data are from the World Input-Output Database (WIOD), replease 2016.

the gravity model developed by Novy (2013). As argued in Section 2, for generic countries a and b, the bilateral trade cost indicator in this database is the geometric average of ab and ba tariffs: $\tau_{ab} \equiv \sqrt{(1 + \mathit{tariff}_{ab})(1 + \mathit{tariff}_{ba})}$, where tariffs are simple average effective import tariff imposed by the exporting country on the importing country. We match this data with export shares and industrial distance (the product of the upstreamness of source industries and the downstreamness of using industries), all calculated from the World Input-Output Database (WIOD).

Data on the CZ-level share of routine employment used to compute exposure to automation, as well as data used to construct control variables at the CZ level, follow Autor et al. (2015), and are made public on David Dorn's website. They are defined in the baseline year (2000), and include the share of employment in manufacturing, the share of population that is college-educated, the share of population that is foreign-born, and the female employment rate.

4 Descriptive statistics

We show in Table 1 that our data support the conclusion, common in the literature (see Autor et al., 2006; Acemoglu and Autor, 2011; and Autor and Dorn, 2013), that employment polarization has occurred in the US. The upper panel of the table reports, for each of the five occupations classified as low-wage, the ten occupations classified as middle-wage and the seven occupations classified as high-wage, the share in total hours worked in 2000 and in 2014, averaged across commuting zones. The share in total hours worked was higher in 2014 than in 2000 in all low-wage occupations and in four high-wage occupations out of seven, while it was lower in 2014 than in 2000 in six out of ten middle-wage occupations. Occupations that saw the biggest losses are Office and Administrative Support; Production occupations; and Installation, Maintenance and Repair. All these fall into the middle-wage category. The biggest gains were in Food Preparation; Healthcare Practitioners and Technical occupations; Personal Care and Service occupations; and Management. These occupations fall either into the low-wage or the high-

Table 1: Changes in the employment composition, 2000-2014

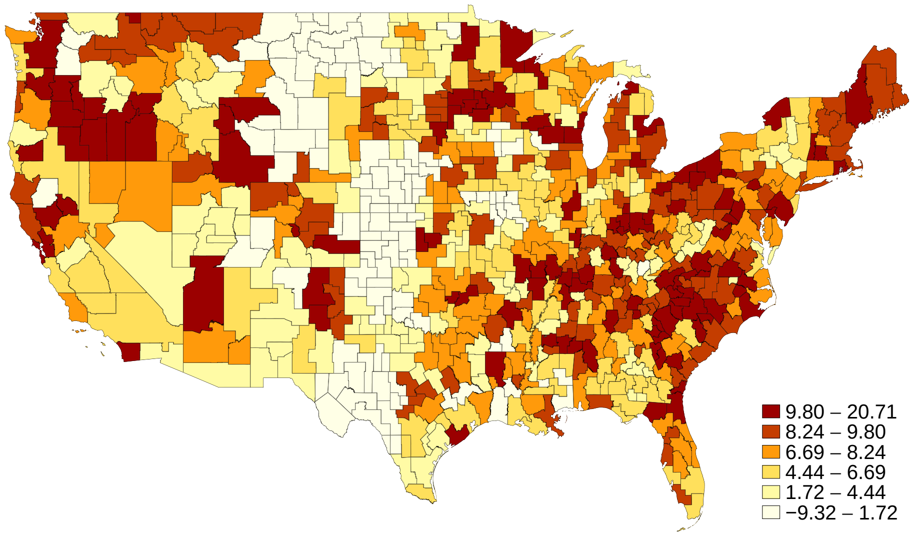
Occupation	SOC code	Share in 2000	Share in 2014	Wage group
Food Preparation and Serving Related	35	3.85	4.87	Low
Farming, Fishing, and Forestry	45	0.77	0.85	Low
Building and Grounds Cleaning and Maintenance	37	2.84	3.55	Low
Personal Care and Service	39	2.25	3.11	Low
Healthcare Support	31	1.81	2.24	Low
Transportation and Material Moving	53	6.54	6.65	Middle
Office and Administrative Support	43	14.36	12.17	Middle
Production	51	8.93	6.60	Middle
Sales and Related	41	10.78	10.06	Middle
Protective Service	33	2.11	2.38	Middle
Community and Social Services	21	1.50	1.67	Middle
Installation, Maintenance, and Repair	49	4.46	3.53	Middle
Construction and Extraction	47	5.89	5.49	Middle
Education, Training, and Library	25	5.38	5.81	Middle
Arts, Design, Entertainment, Sports, and Media	27	1.84	1.80	Middle
Life, Physical, and Social Science	19	0.96	0.87	High
Healthcare Practitioners and Technical	29	4.70	5.94	High
Business and Financial Operations	13	4.50	4.96	High
Architecture and Engineering	17	2.24	1.95	High
Computer and Mathematical	15	2.58	2.93	High
Management	11	10.51	11.37	High
Legal	23	1.20	1.18	High
Averages by wage group				
Low		11.51	14.62	
Middle		61.79	56.18	
High		26.70	29.21	

Notes: Authors' calculations based on data from the American Community Survey (ACS), the Bureau of Labor Statistics (BLS) and David Dorn's webpage (`www.ddorn.net`). SOC stands for Standard Occupational Classification. Shares in 2000 and 2014 expressed as percentages of total usual hours worked per week. In the upper panel, shares are weighted averages across commuting zones (with CZ-population in 2000 as weights). In the lower panel, shares are weighted averages across occupations belonging to the same wage group and across commuting zones (with CZ-population in 2000 as weights). See Figure 2 for the classification of occupations into wage groups.

wage category. It is then not surprising that, on average, as reported in the lower panel of Table 1, employment shares increased for low- and high-wage occupations and decreased by the same amount for middle-wage occupations between 2000 and 2014 – indicating that the US labor market got polarized during this period.

Employment polarized in 643 out of the 722 US commuting zones for which the synthetic Employment Polarization index (equation (2.2)) was calculated. As shown in Figure 3, polarization was highest in the East and lowest in the central part of the country. Importantly for the econometric estimations, polarization varies significantly across commuting zones even within Census divisions or States.

Figure 3: Employment Polarization (EP) index, 2000-2014



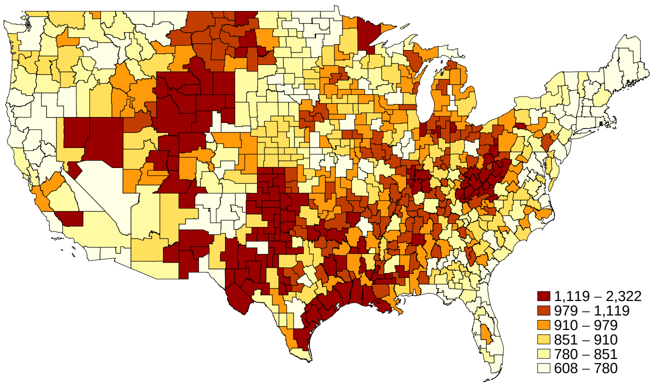
Notes: Authors' calculations based on data from the American Community Survey (ACS) and the Bureau of Labor Statistics (BLS). EP defined in equation (2.2), GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and exposure to automation defined in equation (2) of Autor et al. (2015). Each area is a commuting zone.

In Figure 4 we display the geographical distribution across US commuting zones of the three explanatory variables of interest: exposure to GVCs, exposure to Chinese import competition and exposure to automation.

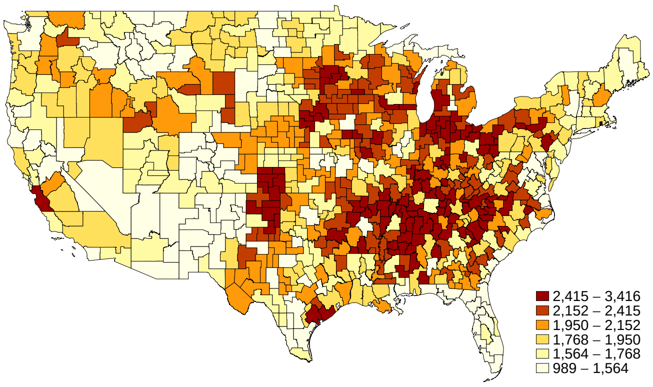
A comparison of the three panels of Figure 4 shows that the geographical patterns vary considerably. While GVCs grew in importance especially in the South and the Mid-West, the rise in import competition from China was concentrated in the Eastern part. Exposure to automation was high in the South-West and in the East, especially in the Great Lakes region and the upper East coast. Note that there is no clear overlap between exposure measures.

Figure 5 shows correlations between the three exposure measures and the Employment Polarization index of equation (2.2). The only clear correlation is the positive one depicted in panel (iii) with exposure to automation. There appears to be no relationship between the exposure to import competition from China and polarization (panel (ii)), while there is a negative relationship between the exposure to GVCs and polarization (panel (i)), mostly driven by few CZ's that experienced very large changes in GVC exposure between 2000 and 2014. We explore these relationships more formally using regression analysis in the next section.

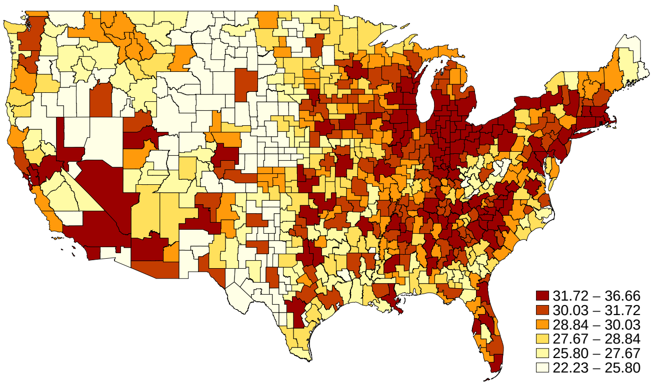
Figure 4: Baseline exposure variables



(i) GVC exposure



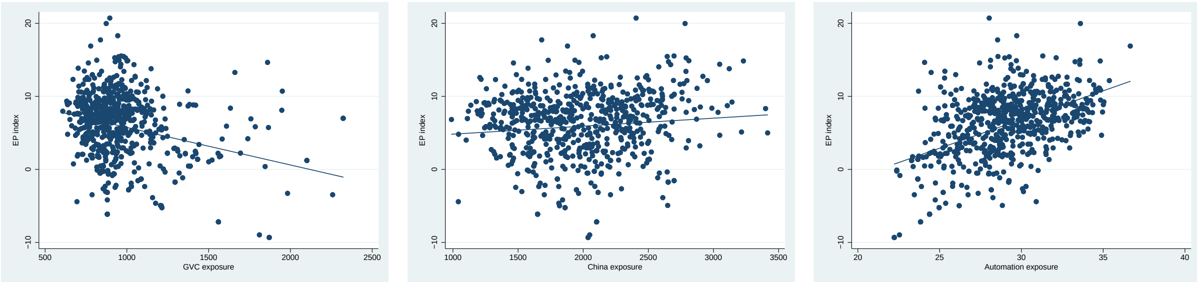
(ii) China exposure



(iii) Automation exposure

Notes: Authors' calculations based on data from the American Community Survey (ACS), the Bureau of Labor Statistics (BLS), the UIBE Research Centre for GVCs and David Dorn's webpage (`www.ddorn.net`). GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). Each area is a commuting zone.

Figure 5: Changes in EP index – correlations at commuting zone-level



(i) GVC exposure (ii) China exposure (iii) Automation exposure

Notes: Authors' calculations based on data from the American Community Survey (ACS), the Bureau of Labor Statistics (BLS), the UIBE Research Centre for GVCs and David Dorn's webpage (`www.ddorn.net`). EP index defined in equation (2.2), GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). Each data point is a commuting zone.

5 Results

We start with ordinary least squares (OLS) regressions in Table 2. GVC exposure is associated with a decrease in the employment shares of the low-wage group, and an increase in the employment share of the high-wage group. This result is consistent with a skill upgrading effect of GVCs. China exposure is associated with an increase in the employment share of the low-wage group, consistently with skill downgrading. Exposure to automation, in turn, is associated with increased in the employment shares of the low-wage and of the high-wage groups, and a decrease in the employment share of the middle-wage group. Automation is, therefore, the driver of wage polarization.

The instrumental variable estimation results which use the exposure variables discussed in Section 2.2 largely confirm the patterns from the OLS regressions. In Table 3, four regression per wage group are displayed: not only the regressions with all the three exposure variables (in columns (4), (8) and (12)), but also regressions with each exposure variable alone (in columns (1)-(3), (5)-(7) and (9)-(11)). If our instrumentation works, the individual effects identified should be free of biases introduced by the absence of the two other variables and thus should not be affected when we include all three variables into the regression. This is for the most part what we see – the only meaningful exception being the effect of exposure to Chinese import competition on low-wage employment. Table 3 strongly confirms the results that GVCs are associated with skill upgrading and automation leads to employment polarization. Exposure to Chinese import competition, when significant (column (4)), is associated with skill downgrading.

Standardized beta coefficients presented in Table 3 allow to get a sense of the relative contribution of the three exposure variables to changes in employment shares across US commuting zones. In column (4), one can see that the positive effect of automation exposure and of China exposure on the low-wage group share are almost identical in size. The same is true for the positive effects of GVC exposure and of automation exposure on the high-wage group share (column (12)). Remarkably, the largest impact across exposure measures and wage groups is the negative effect of exposure to automation on the middle-wage group share (column (8)), which reinforces the conclusion that automation leads to employment polarization by pushing down employment in middle-wage occupations.

First-stage results, presented in Appendix Table A-2, are in line with expectations (the instruments are all positively and significantly correlated with the variables that they instrument) and statistically reassuring, with first stage F-test statistics of 57.74, 30.4 and 22.19 respectively for exposure to GVCs, to China and to automation.[23]

Table 4 presents the IV results with alternative construction of the GVC and of the China exposure variables. In columns (1)-(3), the China exposure is built in a way similar to Autor et al. (2013)'s, and the GVC exposure variable is adjusted accordingly (see discussion in the first part of Section 2.3). (The instrumental variable for automation exposure remains the same as in Table 3). As in baseline results, GVC exposure decreases the employment share of low-wage occupations and increases the employment share of high-wage occupations. The impact of exposure to China becomes not statistically significant on any wage group. This might indicate that any 'China-shock' effects are sensitive, among others, to how the China shock is measured. Finally, exposure to automation significantly reduces medium-wage occupations' employment

[23] These F-test statistics refer to the estimations in columns (4), (8) and (12) of Table 3.

shares, and increase employment shares of low- and high-wage occupations (although the results in columns (1) and (3) are only significant at the 15%). Qualitatively, therefore, regressions of columns (1)-(3) of Table 4 confirm the skill-upgrading effect of GVCs and the employment polarizing effect of automation.

Columns (4)-(6) of Table 4 display IV results using foreign value added in US production, rather than in US exports, as relevant variable to construct GVC exposure (see discussion in the second part of Section 2.3). (The instrumental variables for China exposure and for automation exposure remain the same as in Table 3). The results when using FVA in production are qualitatively the same as, and quantitatively very similar to, the baseline IV results of Table 3.

Next, we estimated regressions using the EP index of (2.2) as dependent variable. The results are displayed in Table 5. Across the four specifications – OLS with the baseline exposure measures of Section 2.1 in column (1), IV with the baseline exposure measures of Section 2.2 in column (2), IV with the alternative exposure measures of Section 2.3 in columns (3) and (4) – it can be seen that exposure to automation is the driver of employment polarization. This is consistent with the descriptive evidence presented in Figure 4, as well as with the regression results using shares of wage groups in total employment as dependent variable presented so far.

All the results presented so far include Census division dummies. We also performed regressions using a richer set of geographical dummies, namely State dummies. The results, presented in Appendix table A-3, largely confirm the results with Census division dummies.

Finally, we also computed employment variables as shares of total hours worked rather than shares of total employment. The results – available in Appendix table A-4 – are in line with the results that use shares of employment.

Table 2: OLS baseline estimations

	Low-wage group (1)	Middle-wage group (2)	High-wage group (3)
GVC exposure	-0.0029** (0.001)	0.0014 (0.001)	0.0015$^+$ (0.001)
China exposure	0.0012** (0.000)	-0.0010 (0.001)	-0.0002 (0.000)
Automation exposure	0.1465** (0.043)	-0.2903** (0.050)	0.1438** (0.035)
Standardized beta coefficients			
GVC exposure	-0.359	0.141	0.167
China exposure	0.346	-0.225	-0.060
Automation exposure	0.260	-0.412	0.232
N	722	722	722
R^2	0.327	0.261	0.271

Notes: $^+$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. Dependent variable: share in total employment of the respective wage group. GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

Table 3: IV baseline estimations

	Low-wage group				Middle-wage group				High-wage group			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GVC exposure	-0.0016*			-0.0031**	-0.0011			-0.0018	0.0027**			0.0049**
	(0.001)			(0.001)	(0.001)			(0.002)	(0.001)			(0.002)
China exposure		-0.0004		0.0015*		0.0003		0.0002		0.0002		-0.0017
		(0.000)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Automation exposure			0.1537	0.1717$^+$			-0.4480**	-0.4723**			0.2942$^+$	0.3006$^+$
			(0.097)	(0.096)			(0.115)	(0.134)			(0.152)	(0.165)
Standardized beta coefficients												
GVC exposure	-0.193			-0.385	-0.110			-0.177	0.301			0.552
China exposure		-0.125		0.429		0.059		0.043		0.047		-0.440
Automation exposure			0.273	0.305			-0.635	-0.670			0.475	0.486
N	722	722	722	722	722	722	722	722	722	722	722	722
R^2	0.275	0.239	0.287	0.325	0.140	0.161	0.231	0.206	0.221	0.240	0.221	0.205

Notes: $^+$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. Dependent variable: share in total employment of the respective wage group. GVC exposure defined in equation (2.8), China exposure defined in equation (2.9), and automation exposure defined in equation (3) of Autor et al. (2015). Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000. First-stage results are in Table A-2.

Table 4: IV estimations with alternative GVC and China exposure variables

	Autor et al. (2013) China exposure			FVA in production		
	Low-wage group	Middle-wage group	High-wage group	Low-wage group	Middle-wage group	High-wage group
	(1)	(2)	(3)	(4)	(5)	(6)
GVC exposure	-0.0035^{+}	-0.0038	0.0073**	-0.0003**	-0.0002	0.0005**
	(0.002)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
China exposure	0.0009	0.0010	-0.0019	0.0014*	0.0001	-0.0015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Automation exposure	0.1657	-0.4345**	0.2687	0.1717^{+}	-0.4723**	0.3005^{+}
	(0.101)	(0.139)	(0.169)	(0.097)	(0.134)	(0.165)
Standardized beta coefficients						
GVC exposure	-0.371	-0.329	0.713	-0.355	-0.164	0.509
China exposure	0.316	0.281	-0.609	0.402	0.031	-0.402
Automation exposure	0.294	-0.616	0.434	0.305	-0.670	0.486
N	722	722	722	722	722	722
R^2	0.325	0.179	0.160	0.323	0.206	0.201
F-test of excluded instruments	25.84	17.05	15.77	60.53	28.71	22.07

Notes: $^{+}p<0.10$, $^{*}p<0.05$,$^{**}p<0.01$. State-level clustered standard errors in parentheses. Dependent variable: shares of total employment. Columns (1)-(3): GVC exposure and China exposure measures presented in Section 2.3 ('China exposure measure similar to Autor et al. (2013)'s'). Columns (4)-(6): GVC exposure presented in Section 2.3 ('GVC exposure measure using FVA in production'); China exposure defined in equation (2.9). Automation exposure defined in equation (3) of Autor et al. (2015) for all columns. Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000. F-test of excluded instruments is the Sanderson-Windmeijer F statistics (Sanderson and Windmeijer, 2016).

Table 5: Estimations with the EP index

	Baseline OLS	Baseline IV	IV with Autor et al. (2013) China exposure	IV with FVA in production
	(1)	(2)	(3)	(4)
GVC exposure	-0.0019	0.0026	0.0053	0.0002
	(0.001)	(0.003)	(0.005)	(0.000)
China exposure	0.0015	0.0000	-0.0011	0.0001
	(0.001)	(0.002)	(0.002)	(0.002)
Automation exposure	0.5017**	0.9301**	0.8785**	0.9301**
	(0.076)	(0.251)	(0.257)	(0.251)
Standardized beta coefficients				
GVC exposure	-0.120	0.162	0.289	0.149
China exposure	0.220	0.005	-0.201	0.018
Automation exposure	0.450	0.833	0.787	0.833
N	722	722	722	722
R^2	0.304	0.219	0.208	0.219

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. Dependent variable: Employment Polarization (EP) index, defined in equation (2.2). Column (1): GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). Column (2): GVC exposure defined in equation (2.8), China exposure defined in equation (2.9), and automation exposure defined in equation (3) of Autor et al. (2015). Column (3): GVC exposure and China exposure presented in Section 2.3 ('China exposure measure similar to Autor et al. (2013)'s'); automation exposure defined in equation (3) of Autor et al. (2015). Column (4): GVC exposure presented in Section 2.3 ('GVC exposure measure using FVA in production'); China exposure defined in equation (2.9); automation exposure defined in equation (3) of Autor et al. (2015). Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000. F-test of excluded instruments presented in the last row of Table A-2 for the regressions of column (2), and in the last row of Table 4 for the regressions of columns (3-4).

6 Conclusions

We have shown that in US local labor markets employment polarization is mostly driven by automation. Since our measure of employment polarization is based on wages, one implication of our research is that technology is the driving force behind wage inequality.

Public attitudes towards job automation show that people are well aware of the link between job automation and increasing inequality. In the United States, for instance, 76% of respondents to the latest PEW Global Attitudes Survey agreed that the inequality between the rich and poor would increase with further job automation (Pew Research Center, 2018).[24]

In future versions of the paper, we plan to include a fourth main trend of the last two decades – servicification of the economy – as yet another possible driver of employment polarizations in the US.

[24] The corresponding percentages in the other developed countries and emerging markets covered by the survey – Argentina, Brazil, Canada, Greece, Hungary, Italy, Japan, Poland, and South Africa – range from a minimum of 63% in Italy to a maximum of 87% in Greece.

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Appendices

A Appendix tables

Table A-1: Industry codes and description

ISIC Rev. 4	Description
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D35	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37-E39	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59_J60	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
J61	Telecommunications
J62_J63	Computer programming, consultancy and related activities; information service activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L68	Real estate activities
M69_M70	Legal and accounting activities; activities of head offices; management consultancy activities
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74_M75	Other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
O84	Public administration and defence; compulsory social security
P85	Education
Q	Human health and social work activities
R_S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

Source: World Input-Output Database (WIOD), replease 2016.

Table A-2: First stage IV results

Dependent:	GVC exposure	China exposure	Automation exposure
	(1)	(2)	(3)
GVC exposure IV	3.7234**	-1.5007^{+}	0.0104
	(0.515)	(0.789)	(0.015)
China exposure IV	0.2788**	0.9170**	-0.0013
	(0.045)	(0.054)	(0.0015)
Automation exposure IV	2.1677^{+}	4.7845**	0.1621**
	(1.143)	(1.308)	(0.039)
N	722	722	722
F-test of excluded instruments	57.74	30.40	22.19

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. First-stage regressions of columns (1), (2) and (3) respectively correspond to the IV estimations in columns (4), (8) and (12) of Table 3. Census division dummies and the following controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000. F-test of excluded instruments is the Sanderson-Windmeijer F statistics (Sanderson and Windmeijer, 2016).

Table A-3: IV estimations with state dummies

	Low-wage group	Middle-wage group	High-wage group
	(1)	(2)	(3)
GVC exposure	-0.0033**	-0.0006	0.0039*
	(0.001)	(0.002)	(0.002))
China exposure	0.0016^{+}	-0.0005	-0.0010
	(0.001)	(0.002)	(0.002))
Automation exposure	0.2765**	-0.5972**	0.3207
	(0.105)	(0.181)	(0.219)
Standardized beta coefficients			
GVC exposure	-0.398	-0.062	0.434
China exposure	0.454	-0.127	-0.269
Automation exposure	0.491	-0.847	0.518
N	722	722	722
R^2	0.453	0.338	0.327

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. Dependent variable: share in total employment of the respective wage group. GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). State dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.

Table A-4: IV estimations with shares in total hours worked

	Low-wage group (1)	Middle-wage group (2)	High-wage group (3)
GVC exposure	-0.1097*	-0.0650	0.1747**
	(0.046)	(0.061)	(0.060)
China exposure	0.0526^{+}	0.0166	-0.0692
	(0.028)	(0.051)	(0.049)
Automation exposure	0.0835	-0.4316**	0.3482^{+}
	(0.105)	(0.131)	(0.179)
Standardized beta coefficients			
GVC exposure	-0.401	-0.170	0.483
China exposure	0.423	0.096	-0.422
Automation exposure	0.159	-0.590	0.503
N	722	722	722
R^2	0.323	0.214	0.236

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. State-level clustered standard errors in parentheses. Dependent variable: share in total hours worked of the respective wage group. GVC exposure defined in equation (2.3), China exposure defined in equation (2.4), and automation exposure defined in equation (2) of Autor et al. (2015). Census division dummies and the following CZ-level controls included in all regressions: manufacturing share of employment in 2000, share of population with college education in 2000, share of foreign-born population in 2000, and female employment rate in 2000.