Polarization of American Workers: The Big Squeeze from Occupational Exposure to Value-added Imports *

Leilei Shen[†] Peri Silva [‡] Han Wang [§]

January 18, 2018

Abstract

We link U.S. industry-level value-added trade data with U.S. worker-level data from the Current Population Surveys from 1995 to 2009. We find that U.S. occupational exposure to value-added imports has a negative effect on the wages earned by intermediate-routine workers, which leads to wage polarization among American workers. In particular, the polarization of wages is primarily driven by occupational exposure to value-added imports of final goods from middle-income countries, while exposure to final goods imported from high-income countries has a negative, albeit more fairly distributed, effect across U.S. workers' wages. On the other hand, occupational exposure to value-added imports of intermediate goods from middle-income countries is associated with a positive wage effect for least-routine workers, signaling to the presence of strong complementarities between the group of least-routine workers and imports of intermediate goods from this group of countries.

Keywords: polarization of wages, value-added trade, import exposure

JEL codes: F14, F16, J3

*We are grateful to the participants of the 2017 Canadian Economic Association Annual Conference and of the Fall 2017 Midwest Economic Theory and International Trade Conference for helpful comments and discussions. We also appreciate the generosity of Avraham Ebenstein and David Autor in making available the datasets used in their paper.

[†]Leilei Shen is an Assistant Professor in the Economics Department at Kansas State University, email: lshen@ksu.edu.

[‡]Peri Silva is an Associate Professor in the Economics Department at Kansas State University and a fellow at the Centro Studi Luca d'Agliano, email: pdasilva@ksu.edu.

[§]Han Wang is a PhD student in the Economics Department at Kansas State University, email: h222wang@ksu.edu.

1 Introduction

It is well known that international trade in goods and services has become increasingly important for the world economy in the past few decades, and this fact is also certainly true for the United States' economy. Statistics on international trade flows reveal that the ratio between U.S. gross trade flows and its GDP has increased from 10 percent in 1960 to 22 percent in 1995[1], and this ratio has continued to expand until reaching 30 percent in 2008.[2] This striking increase in the exposure of the U.S. economy to global trade flows has been uneven in terms of the relative importance between exports and imports. For instance, U.S. gross imports increased by 153 percent between the years 1995 and 2008, while U.S. gross exports increased by only 116 percent between the same years. Needless to say, this gap between the growth in U.S. imports and in U.S. exports has led to an increasing U.S. trade deficit with the rest of the world and has been a source of concerns in many policy circles, particularly on how the increasing U.S. exposure to trade flows has affected U.S. labor market outcomes.[3][4]

There has been a growing literature studying the relationship between the precipitous drop in the U.S. manufacturing employment and the growing U.S. trade deficits (e.g. Autor, Dorn, Hanson (2013), Shen and Silva (2018), Pierce and Schott (2016), Acemoglu et al. (2016)). However, the degree to which U.S. exposure to international trade flows affects U.S. wages is still under debate and it has received less attention from the economics pro-

[1]The latter year coinciding with the creation of the World Trade Organization.

[2]Information obtained from the World bank's World development indicators. In this case, gross trade flows represent the summation of gross imports of goods and services (% of GDP) and gross exports of goods and services (% of GDP).

[3]Authors' own calculation based on data obtained from Koopman, Wei and Wang (2014).

[4]One of the first measures enacted by President Donald Trump's administration has been to issuing an executive order focusing on the review of the causes behind U.S. trade deficits. See article published by the news agency Reuters for details at http://www.reuters.com/article/us-usa-trump-trade-idUSKBN17208O

fession. Most of the literature studying the effect of U.S. exposure to international trade flows on wages has measured exposure using gross trade flows. Acemoglu et. al (2016) find that the greater the industry-level import penetration from China, the higher the average industry-level wages for production workers, while the effect on nonproduction workers is statistically insignificant. Moreover, they find that the combined effect on the average worker is positive albeit statistically insignificant.[5] Shen and Silva (2018) find that an increase in U.S. local market exposure to Chinese exports has a negative but insignificant effect on the wages earned by workers with college education, and a positive albeit insignificant effect on the wages of workers without college education, regardless of whether gross or value-added exports are used.

On the other hand, Ebenstein et al. (2014) find that U.S. industry-level exposure to imports has no significant effect on U.S. wages, while U.S. occupational exposure to imports has a negative and significant effect on the wages of U.S. workers in most-routine occupations.[6] Instead, Hummels et al. (2014) use firm-level data for the Danish economy and show that offshoring increases the wages of Danish high-skilled workers while it decreases the wages of Danish low-skilled workers. Notice that none of the papers mentioned above is able to explain the U-shaped polarization of U.S. wages across skill levels documented in Autor and Dorn (2013), where wages in the middle of the skill distribution present the worst performance overtime. This paper aims at contributing to this debate by examining how value-added trade can explain the polarization of U.S. wages across occupations with

[5] Note that production workers are often considered to be low-skilled workers and non-production workers are often considered to be high-skilled workers such as plant managers.

[6] Measuring international trade in value-added terms, Shen and Silva (2018) find that an increase in U.S. local market exposure to Chinese exports in sectors with low degree of downstreamness has a positive and significant effect on wages, while exposure to goods exported by sectors with high degree of downstream does not have a significant effect on wages.

different degrees of routineness.

Notice that considering the role played by value-added trade rather than gross trade is important for several reasons. First, recent papers by Koopman, Wang and Wei (2014) and by Johnson and Nogueira (2012) show that the value-added trade flows can be very different from gross trade flows at the country and at the industry levels. Second, the degree of routineness in the tasks involved in the production of goods traded between the U.S. and other countries may be very different depending on the income level of U.S. trade partners (middle-income versus high-income countries). These two points are very important since the share of U.S. gross imports from middle-income countries has grown by 126 percent between years 1995 and 2008, while it has increased by 115 percent in value added terms.[7] Needless to say, the importance of U.S. trade with middle-income countries relative to high-income countries has increased over the years, and, therefore, it is important to consider the possible heterogeneous effects of U.S. trade with these two groups of countries.

Third, the effects of trade flows on wages should depend on the role played by imported goods in the production process. It is plausible that imports of goods for final consumption may generate different effects than imports of intermediate goods on wages. For instance, access to foreign inputs could increase domestic firms' productivity (Halpern, Koren, and Szeidl 2015, Topalova and Khandelwal 2011, Kasahara and Rodrigue 2008, Görg, Hanley and Strobl 2008, Amiti and Konings 2007), which may lead firms to expand and, possibly, even driving up wages for workers involved with some occupations. This point seems important since Koopman, Wang and Wei's (2014) dataset suggests that the share of U.S. value-added imports of final goods from middle-income countries has increased from 22 percent to 46 percent during the years from 1995 to 2008, while this dataset suggests a more modest

[7]Calculations made by the authors based on Koopman, Wang and Wei's (2014) dataset.

(but still significant) increase from 15 percent to 36 percent for the share of U.S. value-added imports of intermediate goods from the same countries. In a nutshell, it is important to consider the role played by U.S. value-added trade on U.S. wages, while controlling for possible heterogeneous effects related to the sourcing country (middle-income vs. high-income) and to the role played by traded goods (final vs. intermediate).

Our empirical analysis builds on the strategy used by Ebenstein et al. (2014) to study the effects of U.S. occupational exposure to value-added trade on U.S. workers' wages. Our worker-level dataset is based on the Current Population Surveys from 1995 to 2009 and our dataset with value-added trade flows was made available by Koopman, Wang and Wei (2014). We distinguish between routine and non-routine tasks following Autor and Dorn (2013) and Ebenstein et al. (2014), which allows us to consider the heterogeneous effects of exposure to trade flows from middle- and high-income countries across occupations with different degrees of routineness.[8] Our results suggest that U.S. occupational exposure to value-added imports has a significant and negative effect on wages earned by U.S. workers in occupations with intermediate levels of routineness, leading to wage polarization among American workers. This statistical finding seems economically important since we conclude that a one-standard deviation increase in the U.S. exposure to value added imports tends to decrease the wages earned by U.S. workers in intermediate-routine occupations by about 7 percent. Moreover, the role played by traded goods in the productions process, as well as the level of income of U.S. trade partners, seem rather important to explaining these results. In this case, we find that the polarization of wages is primarily driven by U.S. occupational exposure to value-added imports of final goods from middle-income countries, while we find a

[8]Similar to the findings in Ebenstein et al. (2014), we do not find significant effects on U.S. wages from U.S. industry-level exposure to either gross or value-added trade flows. We discuss results related to U.S. industry-level exposure below and place these empirical results in the appendix of this paper.

smaller and statistically insignificant polarization effect due to U.S. exposure to value-added imports from high-income countries.

Our analysis also highlights other important heterogeneous effects on U.S. wages depending on the type of good and on the sourcing country. For instance, we find that greater U.S. occupational exposure to value-added imports from middle-income countries has a positive and statistically significant effect on the wages earned by least-routine workers, which counters the negative effect found on wages for intermediate-routine workers. Taken together, these findings yield that the effect of U.S. occupational exposure to value-added imports from middle-income countries for the average worker is statistically insignificant. On the other hand, the average effect of U.S. occupational exposure to value-added exports (from middle- and high-income countries) on wages is positive and statistically significant, and it is greater than the effect of U.S. exposure to imports on the average U.S. worker. Therefore, the average effect of U.S. occupational exposure to trade on goods and services on wages is positive for the average worker, lending support to the traditional trade theories that suggest that international trade leads to net gains for the average worker. However, the distribution of the net gains from trade is an entirely different matter. Our results show that the net effect on U.S. wages for the average intermediate-routine worker is not statistically significant. This result lends support to the recent critics of economic globalization claiming that part of the U.S. middle class may be suffering as a result of trade.[9]

The rest of the paper is organized as follows. Section 2 describes our empirical strategy while Section 3 describes the data used to obtain our statistical results. Section 4 presents

[9] In a recent article, then presidential candidate Donald Trump argues that "The great American middle class is disappearing. One of the factors driving this economic devastation is America's disastrous trade policies." See article by President Donald Trump on the newspaper USA Today at https://www.usatoday.com/story/opinion/2016/03/14/donald-trump-tpp-trade-american-manufacturing-jobs-workers-column/81728584/

our baseline econometric estimates and discuss some robustness tests. Section 5 explores potential mechanisms that may explain our baseline results, while Section 6 offers some concluding remarks.

2 Empirical Strategy

Our econometric strategy builds on the strategy used in Ebenstein et. al. (2014) and we extend it to investigate the effects of exposure to value-added imports at the occupation level on individual wages.[10] To achieve this objective, we construct a measure of occupational exposure to value-added imports following the same strategy used in Ebenstein et. al. (2014). In this case, import exposure is measured using the import penetration ratio IMP_{jt-1} which we define as value-added imports in industry j at year $t-1$ divided by the summation of imports and the value of shipments in that industry. We assume that each occupation is exposed to value-added imports according to its distribution of workers across industries using the year 1995 as a benchmark. For each occupation k and industry j, we define the weight $\theta_{kj95} = L_{kj95}/L_{k95}$, where L_{kj95} is the total number of workers in occupation k and industry j in 1995 and L_{k95} is the total number of workers across all industries in occupation k in that same year. We then calculate occupation k-specific import penetration in year $t-1$ as follows:

$$IMP_{kt-1} = \sum_{j=1}^{J} \theta_{kj95} IMP_{jt-1}. \tag{1}$$

We also include three other measures of exposure to globalization in a vector $\mathbf{G}$, namely: export shares and offshoring activities to middle- and high-income countries. Notice that

[10]Ebenstein et al. (2014) also consider the effects of U.S. exposure to gross imports at the industry level. For comparison purposes, we also discuss below the effects of U.S. exposure at the industry level, while placing in the appendix the details of the analysis and of the econometric results.

export shares are occupation-specific and are measured following the same assumptions used in expression (1). In this case, we define the export share for an industry j as the ratio between exports and the value of shipment for that industry, while we rely on the same weights θ_{kj95} to calculate the occupation-specific exposure to value-added exports. Offshoring is measured by the U.S.-based multinationals' log of employment in industry j in middle- and high-income countries. As explained in Ebenstein et. al. (2014), we use lagged measures of trade exposures to allow time for wages to adjust, and to avoid simultaneous shocks that are likely to affect wages and the different measures of trade exposure in a given year.

This leads us to estimate the following specification:

$$W_{ijkt} = \beta_1 IMP_{kt-1} + \mathbf{G}_{kt-1}\Gamma + \mathbf{Z}_{ijt}\Omega + \alpha_{jt} + Comp_{kt} + \alpha_k + \varepsilon_{ijkt}, \quad (2)$$

where k indexes the worker's occupation and W_{ijkt} represents the log wage of worker i involved with occupation k, who works in industry j, at time t. Expression (2) includes occupation fixed effects (α_k) in order to control for time-invariant characteristics of an occupation. We include industry fixed effects that vary by year (α_{jt}) in expression (2), as well as the computer use rates that vary by occupation and year ($Comp_{kt}$), to control for changes in the demand for labor originating from technological progress at the industry level and at the occupation level. As discussed in Autor and Dorn (2013), technological progress in the form of automation has been very important in changing the distribution of earnings across workers according to their skill levels. $\mathbf{Z}_{ijt}$ is a vector of individual characteristics including age, sex, race, experience, education and location. Standard errors are clustered at the occupation level and at the decade level (1990s and 2000s). Following Ebenstein et. al (2014), all regressions use earning weights provided by the CPS-MORG multiplied by the weekly hours worked.[11]

One of our main objectives is to investigate if polarization of wages is driven by exposure to value-added trade. For this reason, we distinguish occupations according to their degree of routineness. We define the different occupation tasks as either routine or non-routine following Autor and Dorn (2013) and Ebenstein et al. (2014). This definition assists us in identifying the impact of value-added import exposure across occupations while controlling for their level of routineness. We construct a measure of routineness for each occupation k by aggregating three measures of the routineness of tasks into a single index:

$$Routine_k = \frac{TaskRoutine_k}{TaskRoutine_k + TaskManual_k + TaskAbstract_k}, \tag{3}$$

where each of the three components used in expression (3) ranges from 1 to 10 where an increasing number for this expression indicates a higher degree of routineness. More specifically, $TaskRoutine$ measures the routineness of tasks by occupation. $TaskManual$ measures the intensity of finger dexterity while the measure $TaskAbstract$ refers to cognitive tasks that are higher order in their complexity.[12] The index $Routine_k$ ranges from 0 to 1 for each occupation. As in Ebenstein et. al (2014), we classify occupations into three categories based on the ratio defined by expression (3). In this case, the group of occupations with tasks defined as least routine corresponds to the occupations with the value of the ratio described by expression (3) less than one-third, occupations with intermediate levels of routineness have value for this ratio between one-third and two-thirds, and the occupations with the highest levels of routineness have values above two-thirds. Table B1 in the appendix provides ex-

[11]Notice that the inclusion of industry fixed effects that vary by year in expression (2) controls for traditional time-varying shocks at the industry level such as the total factor productivity (TFP), the price of investment, capital-labor ratios, among others.

[12]See Autor and Dorn (2013) and Ebenstein et al. (2014) for a detailed description of these variables.

amples of occupations that fall under most routine, intermediate routine and least routine categories, respectively. As expected, the least routine occupations are mostly managerial jobs, intermediate routine occupations include many jobs in the manufacturing sector, and the most routine occupations contain many service sector jobs.

In the next section, we explain the data used in this study and illustrate the relationship between the change in value-added imports at the occupation level and the polarization of wages according to the degree of each occupation's routineness.

3 Data

The previous section made it evident that our main objective is to investigate the causality between the U.S. exposure to economic globalization and U.S. workers' wages with a particular emphasis on the effects of U.S. exposure to value added imports. To achieve this objective, we need data to estimate expression (2) whose dependent variable corresponds to the natural logarithm of wages earned by different workers across industries, occupations and years. Our sample of workers is based on the Current Population Surveys (CPS-MORG) between 1995 and 2009 which were also used in Autor and Dorn (2013). Our worker-level dataset allocates workers across industries using the U.S. Census Bureau's industry aggregation level (IND 1990), and allocates workers across occupations using a modified version of the U.S. Census Bureau's classification of occupations made available by David Dorn.[13]

Our data on trade flows correspond to bilateral value-added imports made available by

[13]The CPS-MORG use the U.S. Census Bureau's IND 1990 industry aggregation level for years 1995-2002, while they rely on the U.S. Census Bureau's IND 2002 and IND 2008 for years 2003-2008 and 2009, respectively. We apply a cross-walk made available by the U.S. Census Bureau to allocate workers across all years using the IND 1990 aggregation level.

Koopman, Wei and Wang (2014). Their dataset is organized at the two-digit of the WIOD (World Input-Output Database) and it covers bilateral trade data among 40 countries from year 1995 to year 2009. As indicated above, the industry aggregation level used in the CPS-MORG relies on the industry aggregation defined by the U.S. Census Bureau, and, therefore, we follow a two-step process to concord the trade information from the two-digit of the WIOD to the aggregation used in the CPS-MORG. We first construct a cross-walk between the two-digit WIOD sectors and the four-digit SIC industries using the U.S. employment shares in each SIC industry. Notice that employment shares rely on labor information from the NBER Manufacturing Survey.[14] Then, we use a concordance made available by the U.S. Census Bureau to re-organize our trade information from the four-digit of the SIC to the industry aggregation level used in the CPS-MORG. Notice that gross trade and offshoring data for the years between 1995 and 2002 are taken from Ebenstein et al. (2014), and their data are already compatible with the aggregation used in the CPS-MORG, while this information for the years 2003-2005 and 2006-2008 were made available by Bernard, Schott and Jensen (2006) and by Schott (2008), respectively.

We use the income-based World Bank's criteria to split countries into middle- and high-income groups.[15][16] The information on occupation's computer use rates for the years between 1995 and 2002 are taken from Ebenstein et al. (2014), and we use the information for this

[14] WIOD sectors are closely related to the revision 3 of the two-digit of the ISIC. Our crosswalk between the two-digit WIOD sectors and the four-digit SIC industries is based on the crosswalk between the two-digit of the ISIC (rev. 3) and the four-digit of the SIC.

[15] The high-income group consists of the following countries: Australia, Austria, Belgium, Canada, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Japan, Luxemberg, Malta, Netherlands, Portugal, South Korea, Sweden, and Taiwan. The middle-income group consists of the following countries: Brazil, China, Indonesia, India, Mexico, and Turkey. The transitional economies group consists of the following countries: Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Slovakia, Slovenia, and Russia.

[16] What we call middle-income countries are classified as low-income countries in Harrison and McMillan (2011). The value-added dataset from Koopman, Wei and Wang (2014) contains only 40 countries, and there are no low-income countries based on the World Bank's country classification in our data.

variable for year 2002 to replace the missing information for the years between 2003 and 2008. The information on workers' characteristics used as control variables in expression (2), and which is represented by vector Z_{ijt}, are taken from the CPS-MORG, while the weights θ_{kj95} used to calculate occupational exposure (see expression (1)) also rely on the sample of workers made available by the CPS-MORG. Lastly, the index of routineness for each occupation, which is represented by expression (3), is constructed using the indicators of routine and non-routine tasks provided by Autor, Levy and Murnane (2003).

A key summary of the U.S. measures of economic globalization related to imports and exports used to estimate expression (2) can be found in Table 1.[17] At the upper-section of this table, we can find the average (standard deviation) occupational measure of U.S. exposure using gross trade flows, while, at the lower-section, we find the counterpart measures of exposure using value-added trade flows. This table also provides descriptive statistics of U.S. exposure while controlling for the degree of routineness of the workers' occupation. The upper-section of Table 1 suggests that the average (standard deviation) U.S. occupational exposure to gross imports is 4.93 (7.64) percent, while the lower-section indicates that its counterpart in value added terms is 3.43 (5.31) percent. This implies that the average occupational measure using gross imports is significantly greater than its counterpart using value-added trade flows. The same situation applies to a comparison between the U.S. exposure to value-added exports and its exposure to gross exports. These numbers represent another example in which measures of exposure using gross trade flows differ from their counterparts measured in value added terms. A comparison across groups of workers based on the degree of routineness of their occupations highlights interesting features

[17]Table A1 provides further details of these measures while controlling for the role of traded goods in the production process (final vs. intermediate) and also controlling for the sourcing middle-income country.

as well. For instance, the U.S. exposure to imports at the occupation level tends to be higher for workers involved with most-routine occupations followed by workers involved with intermediate-routine occupations.

Table 1 also highlights the relative importance between U.S. occupational exposure to value-added imports from middle- and high-income countries as well as between occupational exposure to imports according to the role played by traded goods in the production process. The information shown in Table 1 suggests that most of the U.S. occupational exposure is related to imports from high-income countries rather than imports from middle-income countries, although most of the recent growth in U.S. exposure is related to imports from middle-income countries as discussed in the introduction of this paper. This table also highlights that most of U.S. imports from middle-income countries take the form of final goods, while U.S. imports from high-income countries tend to be balanced between goods for final consumption and intermediate goods. Table 1 indicates that the average (standard deviation) U.S. occupational exposure to imports of final goods from middle-income countries is 0.72 (2.10) percent. Since these numbers are either lower or slightly above 1 percent, our econometric analysis relies on the evaluation of changes in standard deviations, rather than 1 percentage point changes, in order to gauge the economic importance of the results.[18][19]

The evolution of imports and exports from 1995 to 2009 can be exemplified by considering a few industry-level examples. In this case, the textiles industry and the electrical and optical

[18]Table A4 provides information on U.S. occupational exposure to offshoring activities. As expected, the U.S. exposure to offshoring activities in high income countries tend to be greater than the exposure to offshoring activities in middle-income countries, and we can also conclude that the most-routine workers are the most exposed to offshoring activities at the occupation level, followed by the intermediate-routine workers.

[19]According to Table 1, the summation of the U.S. exposure to value-added imports from middle-income countries of final goods and of intermediate goods do not equal the total U.S. exposure to value added imports from these countries. This happens since value-added imports can reach the U.S. economy indirectly through a third country. These trade flows can reach the U.S. shores as an intermediate or final good and, therefore, they can't be clearly distinguished according to their role in the production process.

equipment industry are emblematic examples of the differences between using data on gross imports versus value-added imports. Figure 1 presents the trend of the difference between U.S. gross imports and U.S. value-added imports of textiles from 1995 to 2009. It is clear from Figure 1 that U.S. gross imports of textiles tend to be much greater than U.S. value added imports of these products and the difference between these measures of imports grows considerably during this time frame from $13.8 billion to slightly above $27 billion. Likewise, Figure 2 shows a similar trend related to the electrical and optical equipment sector. In this case, the difference between gross and value-added imports grows from about $7 billion to $17.8 billion in the same period. Notice that imports have increased substantially on both sectors using either measure of trade flows. These facts highlight the important effects that trade flows may have on wages, and, at the same time, make it evident that distinguishing between the contribution of trade according to the official statistics and using value-added data may be very important.

We can also use our dataset to explore the correlation between the degree of U.S. exposure and the degree of routineness of occupations and the correlation between the changes in U.S. workers' wages and the degree of routineness of occupations. To motivate our econometric exercises, we plot the growth in the average logarithm of real hourly wages by occupation across the degree of routineness of the different occupations in Figure 3. Consistent with the findings in Autor and Dorn (2013), we find a U-shaped relationship between the growth in wages and the degree of routineness of different occupations, with larger gains in the upper tail (least-routine workers) and in the lower tail of the distribution (most-routine workers), and with smaller gains in the middle of the distribution (intermediate-routine workers).

One of the key issues we explore in the econometric exercises is whether the effect of U.S.

economic exposure to imports from middle-income countries differ from the effects of U.S. exposure from high-income countries. In Figure 4, we plot the change in U.S. exposure to value-added imports from middle-income countries according to the degree of routineness of occupations. In this case, we find an inverted U-shaped curve for the growth in value-added imports which suggests that workers in occupations with intermediate levels of routineness were the most exposed to the increase in imports from middle-income countries, while workers in least-routine and most-routine occupations were significantly less exposed to the growth in value-added imports from this group of countries. The non-monotonicity of changes in exposure to value-added imports from middle-income countries has not been documented before. It is our goal to show in our econometric exercises that exposure to value-added imports from middle-income countries is contributing to the polarization of wages across U.S. workers.

4 Baseline Estimates

4.1 Polarization of Wages and Exposure to Value-added Trade Flows

Considering the role played by value-added trade flows rather than gross trade flows is important due to significant differences in industry composition between value-added and gross trade flows (Koopman, Wang and Wei 2014, Johnson and Nogueira 2012). Descriptive statistics in Table 1 suggest that U.S. average exposure to value-added imports is smaller than U.S. exposure to gross imports at the occupation level. We begin our econometric analysis by first discussing the OLS estimation of equation (2) using gross and value-added trade flows to calculate U.S. import penetration ratios and U.S. export shares at the occupation level.

The results are presented in Table 2. In particular, the results in columns (1)-(4) use gross trade flows in measuring U.S. exposure, while we use value-added trade flows in the case of columns (5)-(8). The results in columns (1) and (5) indicate that changes in U.S. exposure to imports have a negative and statistically insignificant effect on the U.S. average worker's wage regardless of whether we use gross trade flows or value-added trade flows to measure exposure. However, the results shown in Table 2 also indicate that relying on gross trade flows instead of value-added trade flows to measure exposure seems to be important in determining the effect of changes in U.S. exposure to imports across workers in occupations with different degrees of routineness. This can be seen by comparing the results in columns (3) and (7). In the former case, an increase in U.S. exposure based on gross imports does not have a statistically significant effect on the wages earned by intermediate–routine workers, while, in the latter case, an increase in U.S. exposure based on value-added imports has a negative and strongly statistically significant effect on the wages earned by intermediate-routine workers. In addition, the results shown in columns (2) and (5) suggest that an increase in U.S. exposure to imports leads to a decline in the average wage earned by most-routine workers, while the results in columns (4) and (8) show that the opposite takes place with respect to the wages earned by least-routine workers.

The combination of these results suggest two main conclusions. First, they suggest that an increase in exposure to value-added imports leads to the polarization of the wages earned by U.S. workers, while the same does not apply to measures of U.S. exposure based on gross trade flows. This is true since the coefficient of U.S. exposure to value-added imports in column (7) is negative and it is lower than its counterpart based on gross imports shown in column (6),[20] which indicates that an increase in U.S. exposure leads to a greater decrease on the wages earned by intermediate-routine workers than the decrease faced by most-routine workers. Instead, column (8) suggests that an increase in U.S. exposure to value-added imports leads to an increase in the average wage received by least-routine workers. The combination of greater losses due to exposure to value-added imports for intermediate-routine workers than most-routine workers, while least-routine workers benefit from an increase in exposure, characterizes the polarization of U.S. wages. The same does not apply to the measure of U.S. exposure based on gross imports since the coefficient for this variable in column (3) is not statistically significant while its counterpart in column (2) is negative and statistically significant. We take this result as preliminary evidence that occupational exposure to value-added imports depresses the wages of workers with intermediate-routine occupations, and leads to the polarization of wages that has been documented in Autor and Dorn (2013). Notice that our discussion in the Data section involving the shape of Figure 3 is in line with these econometric results.

Second, the results shown in Table 2 are economically important and are in line with the literature. The results shown in column (2) suggest that a one standard deviation increase in the U.S. occupational exposure to gross imports decreases the most-routine worker' wages by about 3.42 percent. Likewise, our key results shown in columns (6) and (7) suggest that a one standard deviation increase in the U.S. occupational exposure to value-added imports decreases most- and intermediate-routine workers' wages by about 4.55 percent and

[20]The p-value of the difference between these two coefficients is 0.0734 which indicates that they are statistically different from each other.

7 percent, respectively.[21][22] Moreover, a direct comparison between the coefficients of the U.S. exposure to imports from columns (2)-(3) and (6)-(7) suggests that measures of U.S. exposure to value-added imports tend to have a greater negative effect on the wages earned by most- and intermediate-routine workers than measures based on gross imports.[23]

To assess the plausibility of these effects, it is useful to compare the magnitude of our findings with the estimates available in other studies. The recent study by Ebenstein et al. (2014) estimates that a one percentage point increase in the U.S. occupational exposure to gross imports for workers in the most-routine occupations is associated with a 0.44 percent decrease in these workers' wages during the 1997-2002 period. By comparison, our baseline estimates (e.g. column 2 of Table 2) suggest that a one percentage point increase in the occupational exposure to gross imports for U.S. workers in most-routine occupations leads to a 0.34 percent decrease in these workers' wages during the 1995-2009 period. This comparison shows that the economic effect of occupational exposure to gross imports in our context is similar to the effect found in Ebenstein et al. (2014).[24]

Another important point is that our approach outlined in equation (2) controls for industry fixed effects that vary by year to absorb time-varying industry characteristics that may affect wages and exposures to globalization simultaneously. On the other hand, Ebenstein et al. (2014) control for time-varying industry characteristics for workers within the manufacturing sectors, while for workers outside the manufacturing sectors those industry

[21]This effect can be measured by calculating the product between a one standard deviation change in exposure to value-added imports for intermediate-routine workers found on Table 1 (0.0363) and the coefficient of this variable shown in column 6 of Table 2 (-1.927), which equals to a 6.99 percent decrease in wages for U.S. intermediate-routine workers.

[22]Tables 1, A1, and A2 report the standard deviations used for interpretation of point estimates in all the tables in this paper.

[23]The p-value of the difference between the coefficients shown in columns (3) and (7) is 0.0006.

[24]Our data suggests that a one percentage point increase in the occupational exposure to gross imports for U.S. workers in most-routine occupations leads to a 0.48 percent decrease in these workers' wages between the years of 1995 and 2002. These results are available upon request.

characteristics are assumed to be constant. As a result, columns (4) and (8) of Table 2 suggest that the effect of a change in the U.S. occupational exposure to imports on the wages earned by workers in least-routine occupations is positive and strongly significant at the 1 percent level. These results are economically important since they indicate that a one standard deviation increase in exposure tends to increase least-routine workers' wages by 5.1 percent and 6.04 percent, respectively. Given the positive effect on wages earned by U.S. workers in least-routine occupations, as well as the negative effect on wages earned by workers in most-routine occupations, the net effect of occupational exposure to imports on wages for the average worker in the sample is insignificant as shown in columns (1) and (5). Instead, Ebenstein et al (2014) also find a positive effect of occupational exposure to gross imports on least-routine workers but their estimated effect is not statistically significant. Importantly, our finding that the average effect of changes in U.S. occupational exposure to imports has no statistically significant effect on the average worker is consistent with findings in Acemoglu et. al (2016) and Shen and Silva (2018) that examined the effect of U.S. trade exposure to China on wages.

Several additional interesting findings emerge from Table 2 when we consider the effects of changes in U.S. exposure to other dimensions of the globalization process. The results shown in Table 2 indicate that an increase in U.S. occupational exposure to exports has the expected positive effect on the U.S. average worker's wage, regardless of whether we measure it using gross or value-added exports, according to columns (1) and (5). However, the results shown in columns (4) and (8) indicate that workers in least-routine occupations are negatively affected by an increase in their exposure to exports, but these results are not statistically significant.[25] The effects of changes in net trade exposure can also be investigated using

[25]Lake and Millimet (2016) also find that wages earned by most-skilled worker are negatively affected by

the results shown in Table 2. In particular, the estimates described in columns (1) and (5) suggest that a one standard deviation increase in the net occupational exposure to gross and value-added trade flows (exports and imports) is associated with a 2.72 percent and a 4.57 percent increase on the wage earned by the average U. S. worker, respectively, and this effect is statistically significant at the 1 percent level.[26]

On the other hand, the distribution of these gains across workers is heterogeneous since a one standard deviation increase in value-added trade flows is associated with a statistically insignificant increase in the average wage earned by intermediate-routine workers.[27] Thus, the results described in Table 2 provide empirical support to the concerns expressed by policy makers that exposure to globalization may produce unequal results across workers, possibly even decreasing the earnings of some workers in the middle of the social spectrum. The results in columns (1) and (5) also suggest that U.S. occupational exposure to offshoring activities in middle-income countries has the expected negative effect on wages, while occupational exposure to offshoring activities in high-income countries has the expected positive effect on wages. These results related to offshoring activities are also found in Ebenstein et al. (2014).

Ebenstein et al. (2014) focus their analysis on a comparison between the effects of industry-level exposure versus occupational exposure to gross imports. Table A4 in the appendix follows their approach and considers the effects of industry-level exposure to gross and value-added imports for the years between 1995 and 2002.[28] As explained in the appendix,

---

an increase in exports.

[26]Focusing on the results shown in column (5), the summation of the product between the coefficient of the U.S. occupational exposure to imports and its standard deviation, with the coefficient of the U.S. occupational exposure to value-added exports in that column and its standard deviation equals to 0.0457. Moreover, the t-statistics of this sum is 0.0014.

[27]The summation of the product between the coefficient of the U.S. occupational exposure to value-added imports in column (7) and its standard deviation with the coefficient of the U.S. occupational exposure to value-added exports in that column and its standard deviation equals to 0.00044. Moreover, the p-value associated with the test of whether this summation equals to zero is 0.9580.

[28]We use the same industry-level characteristics used in their study. This implies that we do not have the

we follow their approach in this case by controlling for the same industry characteristics used in their study. The results in Table A4 clearly indicate that changes in the U.S. industry-level exposure to imports do not have a significant statistical effect on U.S. wages, regardless of measuring exposure using gross or value-added imports. Overall, in spite of sample differences, we are able to generate results similar to Ebenstein et al. (2014) when examining the different effects of changes in U.S. industry-level and occupational exposures to gross trade flows. Our primary interest below is to investigate the sources of the polarization of wages identified in Table 2, and our analysis then centers on the U.S. exposure to value-added trade flows, on the source of imported goods (middle- vs. high-income countries), and on the role played by traded goods in the production process. In the remainder of the paper, we continue to differentiate workers by the degree of routineness of their occupations albeit focusing our discussion on changes in U.S. exposure to trade flows measured in value-added terms.

4.2 Heterogeneous effects: Middle- and High-income Countries

Krugman (2008) suggests that exposure to imports from countries with different levels of income may have heterogeneous effects on labor market outcomes. In this case, he argues that the increase in U.S. exposure to imports from (much poorer) unskilled labor-abundant countries over the last 25 years may have brought greater consequences to wage inequality than past studies seem to suggest. This argument is certainly well grounded in theoretical models based on comparative advantage (e.g. Hecksher-Ohlin model), but, as indicated by Autor and Dorn (2013), it comes short of explaining the important phenomenon of the polarization of wages in the U.S. economy. However, it is undeniable that the substantial

information for these control variables for the 2003-2009 period.

recent increase in U.S. imports from middle-income countries discussed in the introduction may have caused different effects on U.S. workers' wages relative to the less pronounced increase in U.S. imports from high-income countries. In this section, we explore the possible heterogeneous effects of U.S. value-added imports from middle- and high-income countries and link these effects to the results shown in Table 2 related to the polarization of U.S. workers' wages.

Table 3 reports the estimated effects of U.S. occupational exposure to value-added trade with middle- and high-income countries on wages. The results shown in columns (1)-(4) focus on U.S. exposure to value-added trade with middle-income countries, while the results in columns (5)-(8) focus on U.S. exposure to value-added trade with high-income countries. Columns (1)-(4) show that an increase in occupational exposure to value-added imports from middle-income countries has a negative and significant effect on the wages earned by workers in occupations with high and intermediate levels of routineness, while it has a positive effect on wages of workers involved with occupations displaying low degrees of routineness.

We can use the estimated coefficients shown in column (3) to assess the economic magnitude of our results. In this case, we find that a one standard deviation increase in occupational exposure to value-added imports decreases the wages of workers in intermediate-routine occupations by 5.64 percent.[29] On the other hand, column (4) suggests that a one standard deviation increase in occupational exposure to value-added imports is associated with a 3.62 percent increase in the wages earned by workers involved with occupations displaying low levels of routineness. Overall, the results from columns (2)-(4) suggest that an increase in occupational exposure to value-added imports from middle-income countries leads

[29] This effect can be obtained by mutliplying the coefficient of exposure to value-added imports in column (3), which equals -3.787, by the standard deviation of the exposure to value added imports faced by U.S. workers in intermediate-routine occupations shown in Table 1 (0.0149).

to the U-shaped polarization of wages across increasing levels of routineness, and, moreover, the results also imply that greater U.S. exposure to middle-income countries significantly lowers the wages of workers in occupations with intermediate levels of routineness.[30]

The results shown in columns (5)-(8) of Table 3 focus on the effects of U.S. occupational exposure to value-added trade with high-income countries on wages. These results suggest that changes in U.S. occupational exposure to value-added imports from high-income countries have no significant effect on wages, regardless of the occupations' degree of routineness. Therefore, we do not find any evidence relating U.S. exposure to value added imports from high-income countries and the polarization of wages that is present in our data.[31] It is also worth pointing out that the results in columns (1) to (4) of Table 3 suggest that the average effect of an increase in U.S. occupational exposure to value-added exports to middle-income countries has a positive and statistically significant effect on wages. Moreover, the results shown in column (1) indicate that the effect of changes in net exposure to value-added trade flows with middle-income countries tends to increase the wage earned by the average U.S. worker.[32] This finding is in line with Table 2 and is consistent with traditional trade theory that indicates the presence of gains from trade, or that the average net effect of occupational exposure to trade flows is positive. However, the estimates given in Tables 2 and 3 suggest that the gains from international trade are not distributed equally and not everyone

[30]Notice that the coefficients of U.S. exposure to value-added imports from middle-income countries in columns (2) and (3) are statistically different, yielding a p-value related to the difference between these coefficients equal to 0.0778. The difference in the size between these coefficients, as well as the statistical test of their difference, suggest that an increase in U.S. exposure to value-added imports from middle-income countries has a more pronounced effect in decreasing the wages of intermediate-routine workers rather than most-routine workers.

[31]Notice that the test to verify whether the coefficients of U.S exposure to value added imports in column (6) and (7) are statistically different yields a p-value of 0.3337. As expected, this clearly suggests that they are not different from each other and not different from zero. A similar conclusion applies to the statistical comparison between the coefficients related to U.S. exposure to value-added exports in columns (6) and (7).

[32]The p-value of the summation of the coefficients for the U.S. exposure to value-added imports and exports is 0.0038. Thus, the effect of changes in U.S. net exposure to value-added trade flows with middle-income countries is positive and statistically significant for an average U.S. worker.

is benefiting from trade.

Notice that we have performed some robustness tests involving the key results in Tables 2 and 3. The original specification described in expression (2) controls for measures of U.S. exposure to globalization lagged by one year. We follow this strategy in order to control for estimation biases related to simultaneity between these measures of globalization and the dependent variable. As a robustness check, we have estimated specification (2) for the specific cases discussed in Tables 2 and 3 using two-year lags for the measures of globalization, and have concluded that our main results are robust to this change, i.e., an increase in U.S. occupational exposure to value-added imports contributes towards the polarization of wages in the U.S. economy and this finding is mainly driven by U.S. exposure to value-added imports from middle-income countries. In addition, we have tested the results described in Tables 2 and 3 by changing the clustering of our standard errors to occupation and year (rather than by occupation and decade) and have also concluded that our main results are robust to this specification as well.

In the next section, we explore a potential mechanism to explain the polarization of wages based on the role played by traded goods in the production process.

5 Mechanisms

5.1 The Role of Production: Final vs. Intermediate Goods

The effects of trade flows on wages should depend on the role played by imported goods in the production process. It is plausible that imports of goods for final consumption may generate different effects relative to imports of intermediate goods on wages. Access to foreign inputs could increase firm's productivity (Halpern, Koren, and Szeidl 2015, Topalova and Khandelwal 2011, Kasahara and Rodrigue 2008, Görg, Hanley and Strobl 2008, Amiti and Konings 2007) by either decreasing firm's costs or by enlarging the output choices available to firms. As a result, an increase in productivity allows firms to expand, which can possibly drive wages up. To allow for heterogeneous effects of changes in U.S. occupational exposure to value-added imports according to the role played by traded goods (final vs. intermediate), as well as controlling for the sourcing country (middle- vs. high-income), we construct measures of U.S. occupational exposure to value-added trade flows in final goods and in intermediate goods following expression (1).

In columns (1)-(4) of Table 4, we present the estimated results from equation (2) using U.S. occupational exposure to value-added trade in final goods from middle-income countries, while columns (5)-(8) show results using U.S. occupational exposure to value added trade in final goods from high-income countries. The results shown in columns (2) and (3) indicate that an increase in U.S. occupational exposure to value-added imports of final goods from middle-income countries has a negative and statistically significant effect on wages for workers involved with occupations displaying high or moderate levels of routineness. In addition, note that these two coefficients are statistically different which implies that the effect on wages for U.S. workers in intermediate-routine occupations is significantly different from the effect on wages for workers in most-routine occupations.[33] The economic importance of these results seems relevant since they indicate that a one standard deviation increase in the occupational exposure to value-added imports of final goods from middle-income countries is associated with a 8.31 percent decrease in wages for U.S. workers involved with intermediate-routine occupations, while the decrease in wages for U.S. workers involved with most-routine occupations is 3.03 percent. These results clearly suggest that the workers in intermediate-

[33]The test of the statistical difference between these two coefficients yields a p-value equal to 0.0000.

routine occupations are the ones most negatively affected by U.S. exposure to final goods imported from middle-income countries.

Instead, for the workers in least-routine occupations, the results shown in column (4) indicate that an increase in U.S. exposure to value-added imports of final goods from middle-income countries has a positive effect on wages but this result is moderately statistically significant. Again, columns (2)-(4) in Table 4 suggest that changes in occupational exposure to value-added imports of final goods from middle-income countries leads to the U-shaped polarization of workers' wages according to the degree of routineness of their occupations. Instead, columns (5)-(8) of Table 4 report the estimated results from equation (2) using the U.S. occupational exposure to value-added trade in final goods from high-income countries. The results suggest that occupational exposure to value-added imports of final goods from high-income countries also has a negative and statistically significant effect on wages earned by the average U.S. worker, as well as for workers involved with occupations with different degrees of routineness (including least-routine occupations). In addition, we find that the coefficients of occupational exposure to value-added imports of final goods from high-income countries shown in columns (6)-(8) are not statistically different. This result suggests that changes in U.S. exposure to value-added imports of final goods from high-income countries do not have a significant effect on the polarization of U.S. wages.[34]

It is important to rationalize our findings in terms of the current international trade literature. One possible way to explain the results shown in Tables 3 and 4 is to relate them to a model of trade in tasks (e.g., Grossman and Rossi-Hansberg (2008)) where some of the traded tasks are either complements or substitutes to tasks performed domestically.

[34]The statistical test of the difference between the coefficients in columns (6) and (7) and between the coefficients in columns (7) and (8) yield p-values equal to 0.4405 and 0.3631, respectively.

For instance, the relationship between the degree of substitutability among tasks and labor market outcomes is exploited by Autor and Dorn (2013) to evaluate the effects of technological progress. In our case, the tasks involved in adding value to the goods exported from middle-income countries to the U.S. may be very different from the tasks involved in adding value to goods exported by high-income countries. If these tasks are substitutes to the tasks performed by U.S. workers, then the effect of increases in U.S. exposure on U.S. workers' wages may be negative. On the other hand, if the tasks involved in adding value to U.S. imported goods are complements to the tasks performed by U.S. workers, then the effect of increases in U.S. exposure to imported products on U.S. workers' wages may be positive.

In the case of Table 4, the results suggest that the tasks performed by the workers involved with the production of final goods in middle-income countries may represent substitutes to the tasks performed by most- and intermediate-routine workers in the U.S., and this is particularly more profound for workers in occupations with intermediate level of routineness. On the other hand, the results shown in column (4) suggest that the tasks performed by final good producers in middle-income countries are complements to the tasks performed by U.S. least-routine workers. In the case of U.S. imports of final goods from high-income countries, the estimates shown in column (5) indicate that the tasks performed by workers to produce final goods in high-income countries are also substitutes to the tasks performed by the average worker in the United States, and this conclusion applies equally to the different occupations controlling for their degree of routineness. Consequently, our results do not show statistical evidence that changes in the U.S. exposure to value-added imports of final goods from high-income countries contributes to the polarization of U.S. wages.

Table 5 reports the results using occupational exposure to value-added trade in intermediate goods controlling for the income level of the sourcing country (middle vs. high). The results shown in columns (2)-(4) suggest that U.S. occupational exposure to value-added imports of intermediate goods from middle-income countries has a modest negative statistically significant effect on wages for workers in most-routine occupations, while its effect is insignificant for intermediate-routine workers. On the contrary, the results suggest a positive and significant effect for least-routine workers. The estimates in column (4) suggest that a one standard deviation increase in occupational exposure to value-added imports of intermediate goods from middle-income countries is associated with a 4.45 percent increase in the wages earned by workers in least-routine occupations. This result suggests that the tasks performed by the workers involved with the production of intermediate goods in middle-income countries is complementary to the tasks performed by U.S. workers in least-routine occupations.

In contrast, columns (5)-(8) of Table 5 suggest that an increase in U.S. occupational exposure to value-added imports of intermediate goods from high-income countries has no significant effect on wages earned by U.S. workers in most- and intermediate-routine occupations, as well as for workers in least-routine occupations. Overall, the estimates from Table 5 suggest that U.S. exposure to imports from middle-income countries involve tasks that are complementary to the tasks performed by U.S. workers in least-routine occupations while U.S. exposure from high-income countries involve tasks that are neither clearly substitutes nor complements to the tasks performed by U.S. workers involved with occupations displaying varying degrees of routineness.

The results from Tables 4 and 5 suggest that the polarization of American workers' wages is driven by the U.S. occupational exposure to imports of final goods from middle-income countries while occupational exposure to imports of intermediate goods does not give rise to polarization of U.S. wages. Also notice that while the average net effect of U.S. occupational exposure to trade (exports and imports) is positive for the average worker, we also conclude that workers with different degrees of routineness in their occupations may gain or lose from an increase in U.S. exposure to trade in value added terms. In particular, a one standard deviation increase in occupational exposure to value-added trade (imports and exports) in final goods from middle-income countries is associated with a 2.44 percent decrease in wages for workers with intermediate-routine occupations, which reinforces the polarization of U.S. workers' wages.[35]

5.2 Is one country driving the results?

In this section, we investigate whether the polarization of wages among U.S. workers is driven by a particular middle income country. Our strategy continues to control for heterogeneous effects of occupational exposure to value-added trade flows and we focus on a select list of countries that are often cited in the media as culprits for the decline in U.S. wages.

Table 6 reports the results for the estimation of expression (2) using gross and value-added trade flows to measure U.S. occupational exposure to trade flows with China. The estimates described in columns (1)-(4) suggest that occupational exposure to gross imports from China has a positive and significant effect on least-routine workers, while it has a negative and significant effect on most-routine workers. As a result, the effect of occupational exposure to gross imports from China on the average U.S. worker is statistically insignificant as suggested by the results in column (1). The results shown in columns (5)-(8) refer to the estimation

[35]The test of the sum of the effects related to U.S. exposure to value-added imports and U.S. exposure to value-added exports yields a p-value of 0.0917.

of expression (2) to the case of U.S. occupational exposure to value-added trade flows with China. The coefficients shown in columns (5)-(8) suggest that occupational exposure to value-added imports from China has a negative effect on wages earned by workers in most- and in intermediate-routine occupations and has a positive on the wages earned by least-routine workers. This is consistent with the effect of occupational exposure to value-added imports from middle-income countries discussed in the previous section. The results shown in column (7) suggest that a one standard deviation increase in occupational exposure to value-added imports from China is associated with a 5.79 percent decrease in wages earned by workers in intermediate-routine occupations.

Next, we present the results in Table 7 for the effect of U.S. occupational exposure to value-added trade flows with China in final goods and in intermediate goods. The results in columns (1)-(4) suggest findings that are similar to the results described above in Table 4 for middle-income countries, i.e., U.S. occupational exposure to value-added imports from China in final goods has a negative effect on the wages earned by U.S. workers in most- and intermediate-routine occupations, while it has a positive effect on workers in least-routine occupations. Notice that the negative effect on the wages of intermediate-routine workers is larger than the effect on the wages of most-routine workers, and the difference between these two coefficients is statistically significant.[36] The results suggest important economic effects since they indicate that a one standard deviation increase in occupational exposure to value-added imports of final goods from China lowers the wages of intermediate-routine workers by 5.52 percent, while a one standard deviation increase in occupational exposure to value-added exports in final goods increases wages of workers in intermediate-routine occupations by 2.79 percent. These results suggest that a one standard deviation change in

[36] The statistical test of the difference between these coefficients yields a p-value of 0.0006.

the net occupational exposure to trade flows decreases wages of U.S. intermediate-routine workers by 2.73 percent. This result highlights that China is an important component in understanding the effect from net occupational exposure to value-added trade in final goods from middle-income countries.

The positive effect on U.S. workers in least-routine occupations caused by U.S. value-added imports of final goods from China is precisely estimated and significant at the 1 percent level. The average effect of U.S. occupational exposure to value-added imports of final goods from China on wages earned by the U.S. average worker is not statistically significant. Columns (5)-(8) show our estimates of the effects of U.S. occupational exposure to value-added imports from China in intermediate goods on U.S. workers' wages. The results shown in these columns suggest that U.S. exposure to value-added imports from China has no effect on wages for the U.S. average worker, as well as for the workers involved with occupations of most- and intermediate-routine levels. However, the results in column (8) suggest that the wage of workers involved with occupations displaying low degrees of routineness benefit from an increase in U.S. exposure, a result similar to the ones described above for middle-income countries. In summary, the results shown in columns (4) and (8) suggest that U.S. occupational exposure to value-added imports from China has positive effects on the wages earned by least-routine workers.

Based on the results shown in Tables 6 and 7, exposure to value-added trade from China is certainly contributing towards the polarization of wages in the U.S. It is important then to examine whether or not China is the only middle income country responsible for driving the polarization of wages in the U.S. Table 8 reports the estimated results for expression (2) while focusing on middle-income countries other than China. The results shown on columns

(1)-(4) of Table 8 reveal that changes in U.S. occupational exposure to value-added imports of final goods from other middle-income countries is also contributing to the polarization of U.S. workers' wages. In fact, the estimates shown in Table 8 seem to be precise in the statistical sense since the negative effect on intermediate-routine workers' wages is statistically significant at the 1 percent level. The results shown in columns (5)-(8) suggest that occupational exposure to value-added imports of intermediate goods from other middle-income countries also has a positive effect on least-routine workers, a result that resembles the one found in Table 5 where we consider exposure to trade with all middle-income countries.

In Table 9, we report the results of the estimation of expression (2) for the effects of U.S. occupational exposure to value-added trade flows with Mexico, India, and Indonesia separately. The estimates shown in columns (1)-(4) focus on U.S. exposure to value-added trade in final goods, while columns (5)-(8) focus on U.S. exposure to value-added trade in intermediate goods. The results shown in columns (1)-(4) confirm that an increase in U.S. exposure to value-added imports of final goods has a negative effect on wages of workers in occupations with intermediate levels of routineness, and this result is statistically significant for all the three countries considered in Table 9. These results are economically relevant since a one standard deviation increase in U.S. value-added imports of final goods from India and Indonesia (for example) is associated with a 4.79 and 7.16 percent decrease in the wages earned by U.S. workers in intermediate-routine occupations, respectively. Instead, the results shown in columns (5)-(8) suggest that U.S. occupational exposure to value-added imports of intermediate goods from these countries primarily have a positive effect on wages earned by U.S. workers in least-routine occupations, a finding that strongly resemble the results discussed in Table 5.

In sum, the results from Tables 6 to 9 suggest that the negative effect of U.S. occupational exposure to value-added imports of final goods on intermediate-routine workers' wages is not driven by only one middle-income country. In fact, these results suggest that the negative wage effect of U.S. occupational exposure to value-added imports of final goods among intermediate-routine workers is very persistent across middle-income countries.

6 Conclusion

Different trade models suggest that U.S. least-skilled workers could be negatively affected by international trade competition. In our context, least-skilled workers are mostly related to workers in most-routine occupations. Instead, this paper finds that the U.S. workers involved with occupations requiring intermediate levels of routineness are the most negatively affected by international trade competition. This finding may provide important subsidies to explaining a potential link between economic globalization and the empirically verified polarization of wages in the U.S. economy. One way in which this finding can be rationalized is that the different tasks involved in producing final goods in middle-income countries may serve as substitutes to the tasks performed by U.S. workers in occupations with intermediate levels of routineness. On the other hand, we find a positive association between U.S. occupational exposure to value-added imports of intermediate goods from middle-income countries and wages of U.S. workers in least-routine occupations. This may suggest a strong degree of complementary between the tasks performed by workers producing exported intermediate goods from middle-income countries and U.S. workers involved with occupations displaying low degrees of routineness.

Because the effect of occupational exposure to value-added imports from middle countries of final and intermediate goods is very different for U.S. intermediate- and least-routine workers, the average effect of U.S. occupational exposure to imports on wages is insignificant, lending support to the findings in Acemoglu et. al (2016) and Shen and Silva (2018) arguing that trade flows do not have a significant effect on wages. Moreover, we find that these results are not only due to U.S. exposure to China, but can be readily extended to increasing U.S. exposure to value-added trade flows from other important developing countries such as India and Indonesia. The empirical findings established in this paper are useful for public policy and can be used to extend existing trade models to further understand the distributional effects of exposure to international trade.

References

[1] Acemoglu, D. and D. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." in Orley Ashenfelter and David Card, eds., Handbook of Labor Economics, Volume 4, Amsterdam: Elsevier-North Holland, 104–1171.

[2] Acemoglu, D., D. Autor, D. Dorn, G.H. Hanson, and B. Price. 2016. "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34(1): 141–198.

[3] Amiti, M. and J. Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review*, 97(5): 1611–1638.

[4] Autor, D. 2010. "The Polarization of Job Opportunities in the US Labor Market: Implications for Employment and Earnings.," Center for American Progress and The Hamilton Project

[5] Autor, D. and D. Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103(5):1553–1597.

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

[7] Autor, D., L. F. Katz and M. S. Kearney. 2008. "Trends in U.S. Wage Inequality: Re-Assessing the Revisionists," *Review of Economics and Statistics*, 90(2): 300–323.

[8] Autor, D., R. J. Murnane and F. Levy. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quaterly Journal of Economics*, 118(4): 1279–1334.

[9] Bernard, A. B., J. B. Jensen and P. K. Schott. 2006. "Survival of the Best Fit: Exposure to Low Wage Countries and The (Uneven) Growth of US Manufacturing Plants," *Journal of International Economics*, 68(1): 219–237.

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

[11] Ebenstein, A., A. Harrison,and M. McMillan. 2015. "Why are American workers Getting Poorer? China, Trade and Offshoring," National Bureau of Economic Research No. w21027.

[12] Grossman, G.M. and E. Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*,98(5): 1978–1997.

[13] Görg, H., A. Hanley and E. Strobl. 2008. "Productivity Effects of International Outsourcing: Evidence from Plant-level Data," *Canadian Journal of Economics*, 41(2): 670–688.

[14] Halpern, L., M. Koren, and A. Szeidl. 2015. "Imported Inputs and Productivity," *American Economic Review*, vol. 105 (12), pp. 3660–3703.

[15] Harrison, A. and M. McMillan. 2011. "Offshoring Jobs? Multinationals and U.S. Manufacturing Employment," *Review of Economic and Statistics*, 93(3), 857–875.

[16] Hummels, D., R. Jørgensen, J. Munch, and X. Chong. 2014. "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, 104(6): 1597–1629.

[17] Husted, S. and S. Nishioka. 2013. "China's Fare Share? The Growth of Chinese Exports in World Trade," *Review of World Economics*, 149(3): 565–585.

[18] Kasahara, H. and J. Rodrigue. 2008. "Does the Use of Imported Intermediates Increase Productivity? Plant-level Evidence," *Journal of Development Economics*, 87(1): 106–118.

[19] Lake, J. and D. Millimet. 2016. "Good Jobs, Bad Jobs: What's Trade Got to Do with It?," Working paper.

[20] Johnson, R. C. and G. Noguera, 2012. "Accounting for Intermediates: Production Sharing and Trade in Value Added," *Journal of International Economics*, 82(2): 224–236.

[21] Koopman, R., Z. Wang, and S.J. Wei. 2014. "Tracing Value-Added and Double Counting in Gross Exports," *American Economic Review*, 104(2): 459–494.

[22] Krugman, Paul. 2008. "Trade and Wages, Reconsidered." *Brookings Papers on Economic Activity*, 1, pp. 103-154.

[23] Pierce, J. R. and P. K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review*, 106(7): 1632–1662.

[24] Schott, P. K. 2008. "The Relative Sophistication of the Chinese Exports," *Economic Policy*, 53:5–49.

[25] Shen, L. and P. Silva. 2018. "Value-added Exports and U.S. Local Labor Markets: Does China Really Matter?," *European Economic Review*, 101 (2018), pp. 479-504.

[26] Topalova, P. and A. Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India," *Review of Economics and Statistics*, 93(3): 995–1009.

[27] Wang, Z., S.J. Wei, and K. Zhu. 2014. "Quantifying International Production Sharing at the Bilateral and Sector Levels," NBER Working Paper No. 19677.

[28] World Trade Organization. 2015. "International Trade Statistics 2015."

Figure 1

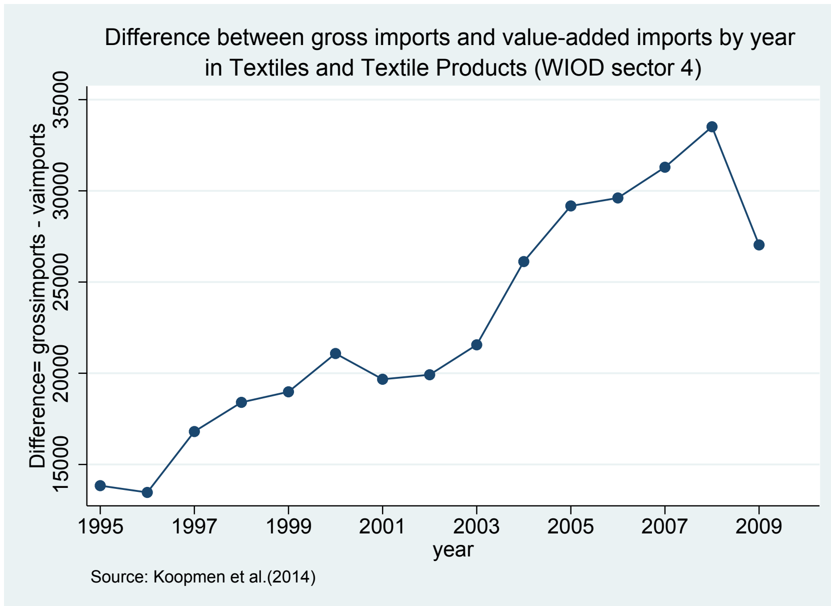


Figure 2

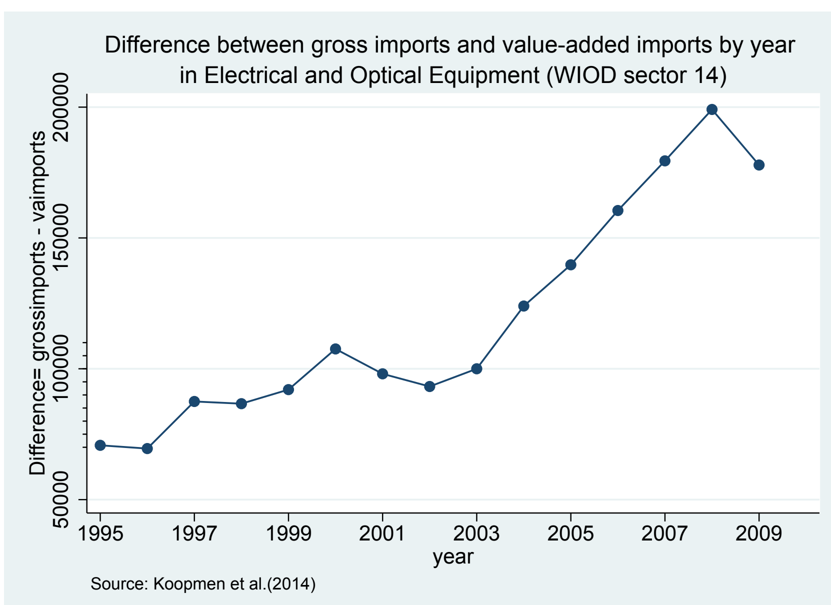
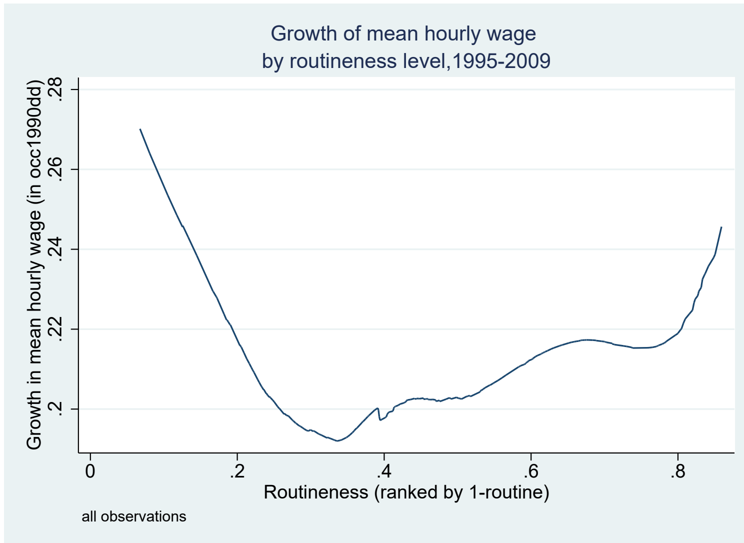
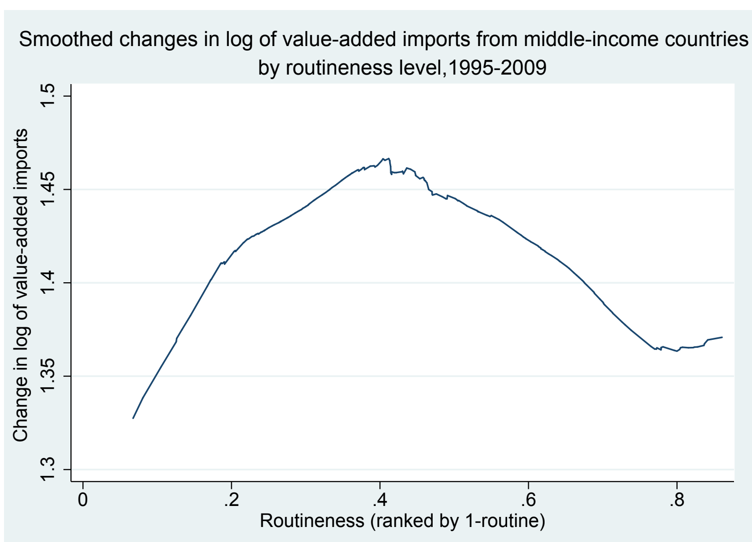


Figure 3



Notes: The smoothed changes in occupations' average log wage growth are plotted against occupations' routineness index. An increase along the x-axis indicates that an occupation is less routine.

Figure 4



Notes: The smoothed changes in log occupational exposure to value-added imports from middle-income countries are plotted against occupations' routineness index. An increase along the x-axis indicates that an occupation is less routine.

Table 1: Descriptive Statistics,1996-2009

Occupation-time measures	All occupations	Most routine	Intermediate routine	Least routine
	Occupation exposures to gross trade			
IMP all countries	0.0493	0.0802	0.0388	0.0141
	(0.0764)	(0.1020)	(0.0554)	(0.0209)
Export share all countries	0.0403	0.0611	0.0343	0.0133
	(0.0526)	(0.0620)	(0.0465)	(0.0216)
IMP China	0.0095	0.0176	0.0060	0.0023
	(0.0324)	(0.0496)	(0.0165)	(0.0046)
Export Share China	0.0012	0.0017	0.0010	0.0004
	(0.0021)	(0.0027)	(0.0017)	(0.0008)
N of observations	3,534	1,260	1,672	602
	Occupation exposures to value-added trade			
IMP all countries	0.0343	0.0579	0.0255	0.0091
	(0.0531)	(0.0715)	(0.0363)	(0.0130)
Export share all countries	0.0173	0.0280	0.0136	0.0054
	(0.0215)	(0.0256)	(0.0177)	(0.0080)
IMP middle-income	0.0115	0.0211	0.0074	0.0025
	(0.0280)	(0.0417)	(0.0149)	(0.0039)
final goods	0.0072	0.0138	0.0044	0.0015
	(0.0210)	(0.0319)	(0.0105)	(0.0023)
intermediates	0.0033	0.0056	0.0025	0.0008
	(0.0061)	(0.0085)	(0.0041)	(0.0013)
IMP high-income	0.0222	0.0358	0.0176	0.0064
	(0.0287)	(0.0349)	(0.0234)	(0.0093)
final goods	0.0100	0.0161	0.0080	0.0027
	(0.0147)	(0.0184)	(0.0120)	(0.0042)
intermediates	0.0093	0.0149	0.0074	0.0028
	(0.0119)	(0.0146)	(0.0096)	(0.0042)
N of observations	3,534	1,260	1,672	602

Table 2: OLS Estimates of Wages Determinants Using Occupational Exposures to Gross Trade and Value-Added Trade,1996-2009

Dependent Variable: Log Wage

	Gross Trade Measured by Occupation-Specific Exposures All Sectors				Value-Added Trade Measured by Occupation-Specific Exposures All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged import penetration	-0.146	-0.335***	-0.416	2.442***	-0.195	-0.636***	-1.927***	4.649**
	(0.095)	(0.119)	(0.510)	(0.897)	(0.229)	(0.237)	(0.694)	(2.264)
Lagged export share	0.729***	0.294	0.594***	-0.454	2.174***	1.836**	3.977***	-4.048
	(0.178)	(0.202)	(0.219)	(0.705)	(0.718)	(0.786)	(1.288)	(2.711)
Lagged log of middle-income	-0.139**	-0.096***	0.001	-0.539**	-0.083*	-0.083**	0.022	-0.338
affiliate employment	(0.057)	(0.036)	(0.101)	(0.227)	(0.050)	(0.036)	(0.062)	(0.205)
Lagged log of high-income	0.126**	0.078**	0.002	0.511**	0.070	0.060*	-0.020	0.334*
affiliate employment	(0.052)	(0.032)	(0.087)	(0.205)	(0.045)	(0.033)	(0.057)	(0.180)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.449	0.335	0.459	0.445

Note:

1 Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

2 Offshore employment data,import penetration (1995-2002) and export share in gross terms (1995-2002), computer use rates are taken from Ebenstein et al.(2014). We extend the gross import penetration and export share to 2008 using the data from Schott(2008). Value-added trade data are taken from Koopman,Wang and Wei (2014), 40 countries are included. Value-added export share and import penetration are followed the constructions of Ebenstein et al.(2014).

3 CPS worker data from 1996 to 2002 are from Autor, Katz and Kearney (2008), data from 2003 to 2009 are from Acemoglu and Autor (2011).

4 The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

5 Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, and state fixed effects. Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation respectively. Computer use rates from 2003 to 2009 are frozen at the level of 2002 following the construction in Ebenstein et al.(2015).

6 Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 3: OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade from Middle- vs. High-Income Countries,1996-2009

Dependent Variable: Log Wage

	Value-Added Imports from Middle-Income Countries Measured by Occupation-Specific Exposures, All Sectors				Value-Added Imports from High-Income Countries Measured by Occupation-Specific Exposures, All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged value-added	-0.474	-0.957***	-3.787**	9.292**	-0.171	-0.491	-1.564	0.202
import penetration	(0.342)	(0.318)	(1.583)	(4.182)	(0.588)	(0.538)	(0.998)	(2.338)
Lagged value-added	6.885***	4.062**	8.006**	-6.698	2.819***	1.672	3.852*	0.282
export share	(2.552)	(1.881)	(3.233)	(9.646)	(1.002)	(1.052)	(2.041)	(3.095)
Lagged log of middle-income	-0.108*	-0.094**	0.070	-0.465**	-0.071	-0.094**	-0.000	-0.115
affiliate employment	(0.057)	(0.036)	(0.076)	(0.217)	(0.046)	(0.036)	(0.062)	(0.133)
Lagged log of high-income	0.096*	0.071**	-0.063	0.466**	0.059	0.072**	0.001	0.152
affiliate employment	(0.051)	(0.032)	(0.069)	(0.202)	(0.042)	(0.033)	(0.057)	(0.119)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.449	0.335	0.459	0.445	0.448	0.335	0.459	0.445

Note:

[1] See table 2 for the source. Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] Countries are classified by income level using the classification from World Bank. Transition economies are excluded from the sample.

[3] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[4] Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 4: OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final Goods from Middle- vs. High-Income Countries,1996-2009

Dependent Variable: Log Wage

Variable	Value-Added Imports in Final Goods from Middle-Income Countries Occupation-Specific Exposures, All Sectors				Value-Added Imports in Final Goods from High-Income Countries Occupation-Specific Exposures, All Sectors			
	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged value-added	-0.374	-0.950***	-7.918***	11.085*	-2.315**	-1.817**	-3.222**	-6.807*
import penetration	(0.525)	(0.350)	(1.719)	(5.685)	(0.911)	(0.825)	(1.626)	(3.516)
Lagged value-added	11.039*	3.724	29.356***	6.379	7.689***	3.710**	8.410**	7.630
export share	(6.611)	(3.041)	(5.989)	(24.379)	(2.285)	(1.808)	(3.514)	(8.254)
Lagged log of middle-income	-0.107*	-0.100***	0.053	-0.453**	-0.077	-0.094**	-0.018	-0.070
affiliate employment	(0.059)	(0.036)	(0.078)	(0.224)	(0.046)	(0.036)	(0.066)	(0.142)
Lagged log of high-income	0.098*	0.080**	-0.051	0.444**	0.066	0.073**	0.014	0.121
affiliate employment	(0.053)	(0.032)	(0.071)	(0.203)	(0.042)	(0.032)	(0.060)	(0.126)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.448	0.335	0.459	0.445

Note:

[1] See table 2 for the source. Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] Value-added trade final inputs are taken from Koopman, Wang and Wei (2014).

[3] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[4] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, state, 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 5: OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Intermediate Inputs from Middle- vs. High-Income Countries,1996-2009

Dependent Variable: Log Wage

	Value-Added Imports in Intermediate Goods from Middle-Income Countries Occupation-Specific Exposures, All Sectors				Value-Added Imports in Intermediate Goods from High-Income Countries Occupation-Specific Exposures, All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged value-added	0.437	-2.354*	1.957	34.222***	2.102	0.836	-1.739	9.628
import penetration	(1.581)	(1.248)	(5.481)	(9.848)	(2.111)	(1.367)	(2.589)	(6.624)
Lagged value-added	9.589***	6.699**	-4.013	-24.979**	3.588	1.614	3.973	-12.720
export share	(3.659)	(3.098)	(7.812)	(12.455)	(2.908)	(2.305)	(5.088)	(7.644)
Lagged log of middle-income	-0.100*	-0.091**	0.050	-0.502**	-0.035	-0.080**	0.030	-0.130
affiliate employment	(0.055)	(0.037)	(0.072)	(0.217)	(0.040)	(0.038)	(0.059)	(0.120)
Lagged log of high-income	0.089*	0.069**	-0.040	0.509**	0.024	0.057	-0.023	0.158
affiliate employment	(0.051)	(0.034)	(0.067)	(0.203)	(0.037)	(0.037)	(0.055)	(0.111)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.449	0.335	0.459	0.445	0.449	0.335	0.459	0.445

Note:

[1] See table 2 for the source. Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] Value-added trade intermediate inputs are taken from Koopman, Wang and Wei (2014).

[3] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[4] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, state, 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 6: OLS Estimates of Wages Determinants Using Occupational Exposure to Gross and Value-Added Trade from China,1996-2009

Dependent Variable: Log Wage

	Gross Imports Occupation-Specific Exposures, All Sectors				Value-Added Imports Occupation-Specific Exposures, All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged import	-0.217	-0.624***	-0.808	7.232**	0.090	-0.723**	-6.436***	14.103**
penetration	(0.202)	(0.188)	(1.370)	(3.284)	(0.397)	(0.297)	(1.629)	(6.889)
Lagged export	9.422***	6.091*	8.272**	-24.268	10.411**	4.681	22.422***	-22.875
share	(3.351)	(3.274)	(4.061)	(20.356)	(5.107)	(3.829)	(5.163)	(24.409)
Lagged log of middle-income	-0.134**	-0.126***	-0.019	-0.370*	-0.119**	-0.108***	0.041	-0.405**
affiliate employment	(0.059)	(0.040)	(0.085)	(0.217)	(0.061)	(0.038)	(0.079)	(0.191)
Lagged log of high-income	0.127**	0.104***	0.022	0.385*	0.113**	0.087**	-0.032	0.416**
affiliate employment	(0.054)	(0.036)	(0.079)	(0.203)	(0.056)	(0.034)	(0.072)	(0.180)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.448	0.335	0.459	0.445

Note:

[1] See table 2 for source. Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] Gross trade data from China from 1995-2001 are taken from Bernard et al.(2006) and data from 2002 to 2008 are from Schott(2008). Value-added trade from China are taken from Koopman, Wang and Wei (2014). The construction of occupational import penetration ratios from China are following the occupational exposures in Ebenstein et al.(2014).

[3] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[4] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, state, 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 7: OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final vs. Intermediate Goods from China,1996-2009

Dependent Variable: Log Wage

	Value-Added Imports in Final Goods Occupation-Specific Exposures,All Sectors				Value-Added Imports in Intermediate Goods Occupation-Specific Exposures,All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged value-added	0.094	-1.098***	-8.494***	21.513***	1.780	-2.572	-11.959	56.728*
import penetration	(0.560)	(0.407)	(2.145)	(8.035)	(2.988)	(2.053)	(8.736)	(32.232)
Lagged value-added	33.503	16.713	69.913***	-71.604	12.448	7.562	17.316	-61.644
export share	(20.639)	(12.882)	(19.638)	(70.238)	(8.973)	(6.761)	(15.091)	(56.236)
Lagged log of middle-income	-0.117*	-0.112***	0.028	-0.368*	-0.113*	-0.107***	0.065	-0.416*
affiliate employment	(0.064)	(0.039)	(0.083)	(0.191)	(0.058)	(0.038)	(0.076)	(0.209)
Lagged log of high-income	0.110*	0.090***	-0.022	0.382**	0.108**	0.087**	-0.054	0.429**
affiliate employment	(0.058)	(0.034)	(0.076)	(0.178)	(0.054)	(0.034)	(0.069)	(0.198)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.448	0.335	0.459	0.445

Note:

[1] Robust standard errors are reported in parentheses.The standard errors are by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] See table 5 and 6 for the source. The construction of value-added import penetration ratios in final goods and in intermediate inputs are following the occupational exposures in Ebenstein et al.(2014).

[3] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[4] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, state, 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 8: OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final vs. Intermediate Goods from Middle-Income Countries (Excluding China),1996-2009

Dependent Variable: Log Wage

	Value-Added Imports in Final Goods from Middle-Income Countries (Exclude China) Occupation-Specific Exposures, All Sectors				Value-Added Imports in Intermediate Goods from Middle-Income Countries (Exclude China) Occupation-Specific Exposures, All Sectors			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged value-added-	-1.963	-3.586***	-17.492***	-1.937	4.901	-2.553	11.420	85.483***
import penetration	(2.103)	(1.169)	(3.668)	(11.248)	(3.418)	(2.551)	(8.630)	(22.813)
Lagged value-added-	15.831	7.909*	48.196***	73.724**	11.844**	8.850**	-9.918	-29.814*
export share	(10.512)	(4.312)	(9.622)	(30.739)	(4.773)	(3.988)	(9.536)	(17.204)
Lagged log of middle-income	-0.095*	-0.093***	-0.024	-0.337*	-0.081*	-0.086**	0.022	-0.492**
affiliate employment	(0.053)	(0.034)	(0.072)	(0.201)	(0.049)	(0.036)	(0.063)	(0.195)
Lagged log of high-income	0.087*	0.072**	0.015	0.315*	0.071	0.064*	-0.014	0.476***
affiliate employment	(0.048)	(0.031)	(0.066)	(0.176)	(0.045)	(0.033)	(0.059)	(0.175)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.449	0.335	0.459	0.445

Note:

[1] See table 5 and 6 for the source. See table 8 for the occupational exposures in final goods and in intermediate inputs. Robust standard errors are reported in parentheses.The standard errors are clustered by occupation and decade in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-third of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-third, and least-routine being less than one-third.

[3] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, state, 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation.

[4] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table 9: OLS Estimates of Wages Determinants Using Occupational Exposures toValue-Added Imports in Final vs. Intermediate Goods from Some Middle-Income Countries,1996-2009

Dependent Variable: Log Wage

Variable	Value-Added Imports in Final Goods Occupation-Specific Exposures, All Sectors				Value-Added Imports in Intermediate Goods Occupation-Specific Exposures, All Sectors			
	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
				Mexico				
Lagged value-added-import penetration	-2.550	-8.751***	-10.040***	-86.573***	12.453	-3.273	23.834**	127.390***
	(5.318)	(2.954)	(3.740)	(18.709)	(7.565)	(6.160)	(11.869)	(46.061)
Lagged value-added-export share	15.783	9.977	34.995***	195.149***	13.183**	8.608*	-15.948	-32.870
	(13.882)	(6.042)	(13.191)	(46.866)	(6.371)	(4.802)	(11.153)	(24.026)
				India				
Lagged value-added import penetration	3.004	-4.983**	-59.795***	42.242	54.261	-14.602	-62.876	490.979***
	(2.695)	(2.173)	(13.203)	(43.196)	(39.513)	(32.314)	(64.203)	(184.646)
Lagged value-added export share	9.539	12.097	82.833***	140.457**	-3.822	30.188	30.445	-5.623
	(16.294)	(12.367)	(28.308)	(64.488)	(31.567)	(27.020)	(55.307)	(84.128)
				Indonesia				
Lagged value-added import penetration	1.974	-12.018***	-89.521***	192.986*	6.520	-10.048	-84.652	360.721*
	(3.725)	(4.282)	(25.230)	(102.180)	(7.879)	(9.822)	(59.611)	(199.693)
Lagged value-added export share	89.148	130.106*	279.071**	-908.335***	190.680**	150.268**	21.712	-284.170**
	(98.110)	(73.436)	(122.344)	(273.028)	(76.416)	(59.512)	(90.432)	(138.788)
Observations	1,849,039	462,985	827,826	558,170	1,849,039	462,985	827,826	558,170
R^2	0.448	0.335	0.459	0.445	0.449	0.335	0.459	0.445

Note:
[1] See table 5 and 6 for the source.
[2] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Appendix. Industry-level Specification

In this paper, our main focus is the effects of U.S. occupational exposure to trade flows on U.S. workers' wages. On the other hand, Ebenstein et al. (2014) focus on the comparison between the effects of U.S. industry-level and occupational exposures to gross trade flows on U.S. wages. Below we investigate our results using industry-level exposure by estimating the following equation:

$$W_{ijt} = \beta_1 IMP_{jt-1} + \mathbf{G}_{jt-1}\Gamma + \mathbf{X}_{jt-1}\Lambda + \mathbf{Z}_{ijt}\Omega + \alpha_j + \alpha_t + \varepsilon_{ijt}, \tag{4}$$

which is similar to expression (2) except for a few important modifications. First, our measure of exposure to imports corresponds to the industry-level import penetration ratio lagged by one year (IMP_{jt-1}), while exposure to exports is measured using the industry-level export rate also lagged by one year. Second, we include industry fixed effects (α_j) in expression (2) to control for time-invariant industry-level shocks that may affect wages and exposure to globalization similarly. We follow this strategy since including industry fixed effects that vary by year, following our strategy used in expression (2), would also control for our measure of exposure, preventing us from investigating this issue. Notice that this strategy also follows Ebenstein et al.'s (2014) approach to investigate this issue. Third, since we are unable to control for time-varying industry fixed effects, we control for time-varying shocks at the industry level by including the following controls in lags which are represented in expression (4) by vector $\mathbf{X}$: (i) TFP to capture changes in productivity that could affect the demand for labor, (ii) price of investment to capture the impact of labor-saving technology, (iii) capital labor ratio to capture the impact of industry factor intensity, and (iv) an industry level measure of computer use rate to control for an industry's ability to substitute computers for labor.

The industry-level results are shown in Table A4 and these results are based on a sample of workers between years 1996 and 2002. In columns (1)-(4), we measure U.S. industry-level exposure using gross trade flows, while, in columns (5)-(8), we measure exposure using value-added trade flows. Our results confirm the main findings described in Ebenstein et al. (2014), which suggest that that the effect of an increase in exposure to imports has no significant effect on U.S. workers' wages regardless of their occupations' degree of routineness. Likewise, these results apply equally to either using measures of exposure based on gross or value added trade flows.

Additional Summary Statistics

Table A1. Descriptive Statistics for Trade Exposures, Means and Standard Deviations,1996-2009

Occupation-time measures	All occupations	Most routine	Intermediate routine	Least routine
	Occupation exposure to value-added trade			
IMP middle-income excluding China				
final goods	0.0033	0.0061	0.0021	0.0007
	(0.0084)	(0.0126)	(0.0043)	(0.0010)
intermediates	0.0018	0.0030	0.0014	0.0005
	(0.0029)	(0.0039)	(0.0022)	(0.0007)
IMP China	0.0060	0.0114	0.0037	0.0013
	(0.0176)	(0.0266)	(0.0090)	(0.0023)
final goods	0.0040	0.0077	0.0023	0.0008
	(0.0133)	(0.0204)	(0.0065)	(0.0014)
intermediates	0.0015	0.0027	0.0011	0.0004
	(0.0034)	(0.0050)	(0.0021)	(0.0007)
IMP Mexico				
final goods	0.0017	0.0029	0.0012	0.0004
	(0.0033)	(0.0047)	(0.0021)	(0.0007)
intermediates	0.0010	0.0015	0.0008	0.0003
	(0.0014)	(0.0017)	(0.0012)	(0.0004)
IMP India				
final goods	0.0005	0.0012	0.0003	0.0001
	(0.0018)	(0.0027)	(0.0008)	(0.0002)
intermediates	0.0002	0.0004	0.0002	0.00005
	(0.0004)	(0.0005)	(0.0003)	(0.00007)
IMP Indonesia				
final goods	0.0004	0.0009	0.0002	0.00007
	(0.0016)	(0.0025)	(0.0008)	(0.00011)
intermediates	0.0002	0.0003	0.0001	0.00004
	(0.0005)	(0.0008)	(0.0002)	(0.00006)
N of observations	3,534	1,260	1,672	602

Table A1 cont. Descriptive Statistics for Trade Exposures, Means and Standard Deviations,1996-2009

Occupation-time measures	All occupations	Most routine	Intermediate routine	Least routine
	Occupation exposure to value-added exports			
Export share high-income	0.0122	0.0194	0.0097	0.0038
	(0.0150)	(0.0177)	(0.0125)	(0.0057)
final goods	0.0062	0.0101	0.0049	0.0019
	(0.0080)	(0.0094)	(0.0068)	(0.0028)
intermediates	0.0047	0.0075	0.0037	0.0016
	(0.0060)	(0.0074)	(0.0047)	(0.0024)
Export share middle-income	0.0047	0.0078	0.0036	0.0014
	(0.0062)	(0.0076)	(0.0049)	(0.0021)
final goods	0.0019	0.0033	0.0014	0.0005
	(0.0028)	(0.0036)	(0.0020)	(0.0008)
intermediates	0.0026	0.0042	0.0021	0.0008
	(0.0034)	(0.0042)	(0.0028)	(0.0012)
Export share middle-income excluding China				
final goods	0.0016	0.0027	0.0011	0.0004
	(0.0023)	(0.0031)	(0.0016)	(0.0006)
intermediates	0.0019	0.0032	0.0015	0.0006
	(0.0025)	(0.0031)	(0.0021)	(0.0008)
Export Share China	0.0011	0.0017	0.0009	0.0004
	(0.0017)	(0.0021)	(0.0014)	(0.0007)
final goods	0.0003	0.0005	0.0003	0.0001
	(0.0005)	(0.0006)	(0.0004)	(0.0002)
intermediates	0.0007	0.0011	0.0005	0.0002
	(0.0010)	(0.0013)	(0.0009)	(0.0004)
Export Share Mexico				
final goods	0.0011	0.0020	0.0008	0.0003
	(0.0019)	(0.0027)	(0.0012)	(0.0004)
intermediates	0.0014	0.0024	0.0011	0.0004
	(0.0019)	(0.0024)	(0.0015)	(0.0006)
Export Share India				
final goods	0.0002	0.0003	0.0001	0.00005
	(0.0004)	(0.0005)	(0.0003)	(0.00009)
intermediates	0.0002	0.0003	0.0001	0.00005
	(0.0003)	(0.0004)	(0.0002)	(0.00009)
Export Share Indonesia				
final goods	0.00004	0.00007	0.00003	0.00001
	(0.00007)	(0.00009)	(0.00006)	(0.00002)
intermediates	0.00007	0.0001	0.00006	0.00002
	(0.00010)	(0.0001)	(0.00008)	(0.00004)
N of observations	3,534	1,260	1,672	602

Table A2. Summary Statistics for Current Population Survey Merged Outgoing Rotation Group Workers, Means and Standard Deviations

	Demographic Information			
	1996-2009	2003-2009	1996-2002	
	All	All	All	Manufacturing
Age	38.68	39.32	38.01	39.74
	(12.26)	(12.50)	(11.97)	(11.01)
Female	0.47	0.48	0.47	0.32
	(0.50)	(0.50)	(0.50)	(0.47)
Years of Education	13.18	13.26	13.10	12.96
	(2.24)	(2.26)	(2.21)	(2.15)
Hourly Wage	18.49	19.07	17.88	19.67
	(14.01)	(14.17)	(13.82)	(13.37)
N of observations	1,849,039	941,771	907,268	109,104

Table A3. Descriptive Statistics for Offshore Employment, Means and Standard Deviations

	Occupation-Specific Measures			
	All Occupations	Most Routine	Intermediate Routine	Least Routine
Panel 1: Offshore Employment.1996-2009				
Middle-Income	12,529	17,054	12,076	4,318
Affiliate Employment	(20,930)	(23,498)	(21,231)	(7,355)
High-Income	17,695	24,911	16,594	5,648
Affiliate Employment	(27,396)	(31,368)	(26,922)	(8,820)
N of observations	3,534	1,260	1,672	602
Panel 2: Offshore Employment.2003-2009				
Middle-Income	14,419	19,644	13,957	4,785
Affiliate Employment	(23,806)	(26,634)	(24,233)	(7,935)
High-Income	18,391	26,187	17,080	5,748
Affiliate Employment	(28,578)	(32,951)	(27,868)	(8,757)
N of observations	1,770	630	839	300

Table A3 cont. Descriptive Statistics for Offshore Employment, Industry Controls, and Computer Use Rates, Means and Standard Deviations, 1996-2002

	Industry-Specific Measure	Occupation-Specific Measures			
	All Occupations	All Occupations	Most Routine	Intermediate Routine	Least Routine
Panel 1: Offshore Employment.1996-2002					
Middle-Income	40,069	10,634	14,464	10,182	3,867
Affiliate Employment	(60,312)	(17,378)	(19,555)	(17,512)	(6,717)
High-Income	61,930	16,996	23,635	16,105	5,567
Affiliate Employment	(80,429)	(26,147)	(29,672)	(25,942)	(8,904)
N of observations	276	1,764	630	833	301
Panel 2: Industry Controls and Computer Use Rates,1996-2002					
Real Price of Investment (×100)	114.94	.	.	.	.
	(15.32)	.	.	.	.
Total Factor Productivity	1.16	.	.	.	.
	(0.81)	.	.	.	.
Capital to Labor Ratio (000s per worker)	129.57	.	.	.	.
	(121.51)	.	.	.	.
Computer Use Rates	0.79	0.49	0.41	0.49	0.64
	(0.15)	(0.34)	(0.31)	(0.35)	(0.32)
N of observations	276	1,764	630	833	301

Table A4. OLS Estimates of Wages Determinants Using Industry Exposures to Gross Trade and Value-Added Trade,1996-2002
Dependent Variable: Log Wage

	Gross Trade Measured by Industry-Specific Exposures Within Manufacturing				Value-Added Trade Measured by Industry-Specific Exposures Within Manufacturing			
Variable	All Occupations (1)	Most Routine (2)	Intermediate Routine (3)	Least Routine (4)	All Occupations (5)	Most Routine (6)	Intermediate Routine (7)	Least Routine (8)
Lagged import penetration	0.070	0.077	0.160	-0.093	-0.029	-0.031	-0.665	0.713
	(0.098)	(0.112)	(0.167)	(0.248)	(0.314)	(0.421)	(0.478)	(0.754)
Lagged export share	0.013	-0.040	0.034	0.111	0.372	0.126	1.061*	-0.404
	(0.044)	(0.076)	(0.064)	(0.070)	(0.448)	(0.476)	(0.569)	(1.103)
Lagged log of middle-income	-0.009	-0.016*	-0.021**	0.035*	-0.007	-0.014	-0.018*	0.035*
affiliate employment	(0.009)	(0.009)	(0.010)	(0.019)	(0.008)	(0.009)	(0.009)	(0.019)
Lagged log of high-income	0.010	0.010	0.026	-0.027	0.007	0.007	0.019	-0.026
affiliate employment	(0.012)	(0.012)	(0.016)	(0.028)	(0.011)	(0.012)	(0.014)	(0.025)
Observations	109,104	48,632	40,464	20,008	109,104	48,632	40,464	20,008
R^2	0.390	0.273	0.357	0.324	0.390	0.272	0.357	0.324

Note:

[1] Robust standard errors are reported in parentheses.The standard errors are clustered by industry and decade in industry-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours.

[2] Offshore employment data,import penetration and export share in gross terms, and computer use rates are taken from Ebenstein et al.(2014). Value-added trade data are taken from Koopman,Wang and Wei (2014),40 countries are included. Value-added export share and import penetration are followed the constructions of Ebenstein et al.(2014).

[3] CPS worker data from 1996 to 2002 are from Autor, Katz and Kearney (2008) with their lagged values of the independent variables taken from 1995 to 2001.

[4] Wage specification control for a worker's demographic information such as gender, race, age, experience, education and include industry, year, and state fixed effects. Computer use rates are by industry respectively.

[5] Superscript "***","**","*" represent statistical significance at the 1,5 and 10 percent levels.

Table B1. Examples of occupations in each routineness category.

most-routine	intermediate-routine	least-routine
proofreaders	machine operators, nec	managers in marketing
file clerks	finishers of metal	social scientists
typists	machinery repairers	purchasing managers
grinders	construction	sales supervisor
bakers	mechanics, nec	managers, nec
cashiers	equipment operators	financial managers
photo processers	machine feeders	real estate managers
meat cutters	sawing operators	vocational counselors
office mach op.	furnace operator	managers in human res

Note:
[1] Constructed using data from Autor, Levy, and Murnane (2003).