# Essays in value-added trade and U.S. labor market outcomes

by

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B.S., Kansas State University, 2012
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AN ABSTRACT OF A DISSERTATION

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# Abstract

This dissertation contains three essays on how value-added trade affect the U.S. labor market outcomes. In the most recent presidential competition, we observed how voter angst against economic globalization had a considerable impact on the election results. This dissertation seeks to shed light on how the changes in exposure to value-added trade affect individual wages, the probability of being unemployed as well as the likelihood of being married with consideration of each worker's occupation, the level of skill, and gender.

In the first essay, 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 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

In the second essay, we investigate the contribution of the degree of occupation routineness and the level of a worker's skill in determining the effects of U.S. exposure to value-added trade on U.S. labor market outcomes. We apply three main approaches to examine how the interplay between routineness and skills is essential in explaining the effects of U.S. exposure to value-added trade flows. First, we find that the increase in occupational exposure to value-added imports

of final goods from middle-income countries is the primary driver of polarization of wages in the U.S. labor market within each skill group, where the effect on workers in the occupations with moderate levels of routineness is most adversely affected. Comparing the wage effects for workers within each routineness group, we find that skilled workers tend to face smaller pressure on their wages from import competition than the unskilled. Second, we examine the impact of exposure to value-added trade on the probability of being unemployed at the worker level. We show that an increase in exposure to value-added imports will raise the employment-related uncertainty for unskilled workers relative to skilled workers. Third, we estimate the transition costs across workers who have trade-induced occupation switches between two consecutive periods. Results suggest that occupation switch is very costly for all unskilled workers as well as for the skilled workers who are involved with the least-routine occupations.

Notice that the effect of trade might not be gender-neutral. In the third paper, we complement the existing literature by providing evidence that increasing import exposure has differential effects on individual outcomes depending on the workers' gender and on the degree of routineness of their occupations. We explore the effects of gender-specific exposure to value-added trade on individual outcomes such as wages, the probability of being unemployed, and the likelihood of being married. Despite that the male-specific exposures to value-added trade are highly comparable to those female-specific measures, we find it is powerful enough to distinguish their differential effects across gender. We find that the effect of trade is symmetric across genders when it comes to wage effects but asymmetric in terms of the probability of being unemployed and in the likelihood of being married. Our findings on wages suggest that an increase in exposure to value-added imports has the most negative effect on intermediate-routine workers for both gender groups, which results in wage polarization for both groups. As for the probability of being unemployed, we find that the greater the male-specific exposure to value-added imports, the greater the chances of being unemployed for male workers in the intermediate-routine occupations, while the effects for other men are insignificant. In the case of female workers, rising import exposure is associated with an increase in the uncertainty related to unemployment for those in least-routine occupations. Finally, for the likelihood of getting married, the effect for female workers is insignificant regardless of the degree of routineness. In the case of men, the likelihood of getting married decreases for males in intermediate-routine occupations when exposure to imported final goods increases, while, on the other hand, males in least-routine occupations are more likely to get married with an increase in exposure to intermediate inputs.

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# Dedication

To my parents, Zhanqun Wang and Qingfen Qin.

# Chapter 1 - Polarization of American Workers: The Big Squeeze from Occupational Exposure to Value-added Imports

## 1.1 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]

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[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 et al. (2014).

[4] One of the first measures enacted by President Donald Trump's administration has been 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 https://www.reuters.com/article/us-usa-trump-trade-idUSKBN17208O

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 et al. (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 profession. 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 a college education, and a positive albeit insignificant effect on the wage of non-college workers, 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,

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[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.

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 over time. 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 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 et al. (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 effect of the value-added 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

[7] Calculations made by the authors based on the dataset obtained from Koopman et al. (2014).

consumption may generate different effects than imports of intermediate goods on wages. For instance, access to foreign inputs could increase domestic firms' productivity (e.g., Halpern et al., 2015, Topalova and Khandelwal, 2011, Kasahara and Rodrigue, 2008, Görg et al., 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 the data provided by Koopman et al. (2014) 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 2009, while this dataset suggests a more modest (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 et al. (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

[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.

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 in 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 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 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.

## 1.2 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

[9] President 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 published by the USA Today at https://www.usatoday.com/story/opinion/2016/03/14/donald-trump-tpp-trade-american-manufacturing-jobs-workers-column/81728584/

[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.

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 $\theta_{kj95} = \frac{L_{kj95}}{L_{k95}}$, where $\theta_{kj95}$ is the total number of workers in occupation k and industry j in 1995 and $L_{kj95}$ 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:

$$IMP_{kt} = \sum_{j=1}^{J} \theta_{kj95} IMP_{jt-1} \qquad (1.1)$$

We also include three other measures of exposure to globalization in a vector G, namely: export shares and offshoring activities to middle- and high-income countries. Notice that export shares are occupation-specific and are measured following the same assumptions used in expression (1.1). In this case, we define the export share for an industry j as the ratio between exports and the value of shipments for that industry, while we rely on the same weights $\theta_{kj95}$ 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 the 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:

$$W_{ijkt} = \beta_1 IMP_{kt-1} + G_{kt-1}\Gamma + \mathrm{Z}_{\mathrm{ijkt}}\Omega + \alpha_{\mathrm{jt}} + Comp_{kt} + \alpha_k + \varepsilon_{ijkt} \qquad (1.2)$$

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 (1.2) includes occupation fixed effect ($\alpha_k$) in order to control for time-invariant characteristics of an occupation. We include industry fixed effects that vary by year ($\alpha_{jt}$) in expression (1.2), 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. $Z_{ijkt}$ 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 five-year period. 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 the 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:

$$Routine_k = \frac{TaskRoutine_k}{TaskRoutine_k + TaskManual_k + TaskAbstract_k} \tag{1.3}$$

Where each of the three components used in expression (1.3) ranges from 1 to 10, where an increasing number for this expression indicates a higher degree of routineness. More specifically, $TaskRoutine_k$ measures the routineness of tasks by occupation.

[11] Notice that the inclusion of industry fixed effects that vary by year in expression (1.2) 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.

$TaskManual_k$ 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 (1.3). 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 (1.3) 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 A.6 in the appendix provides examples 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.

## 1.3 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 (1.2) 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

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

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 Koopman et al. (2014). Their dataset is organized at the two-digit of the WIOD (the World Input-Output Database) which covers bilateral trade data among 40 countries from 1995 to 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

[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.

[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.

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 et al. (2006) and by Schott (2008), respectively.

We use the income-based World Bank's criteria to split countries into the 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 variable for the 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 (1.2), and which is represented by a vector $Z_{ijkt}$ are taken from the CPS-MORG, while the weights $\theta_{kj95}$ used to calculate occupational exposure (see expression (1.1)) 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 (1.3), is constructed using the indicators of routine and non-routine tasks provided by Autor et al. (2003).

[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, Luxemburg, 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 et al. (2014) contains only 40 countries, and there are no low-income countries based on the World Bank's country classification in our data.

A key summary of the U.S. measures of economic globalization related to imports and exports used to estimate expression (1.2) can be found in Table 1.1.[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 1.1 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 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 1.1 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 1.1 suggests that most of the U.S. occupational exposure is related to

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[17] Table A.1 and A.2 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.

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 1.1 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 equipment industry are emblematic examples of the differences between using data on gross imports versus value-added imports. Figure 1.1 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

[18] Table A.4 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 1.1, 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.

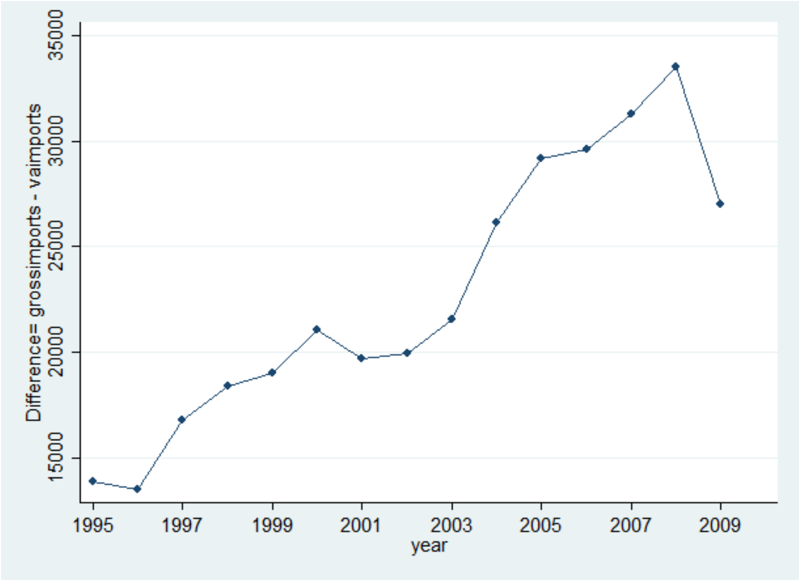
1.1 that U.S. gross imports of textiles tend to be much greater than U.S. value-added imports of these products and the difference between these measures of imports grows considerably during this time frame from $13.8 billion to slightly above $27 billion. Likewise, Figure 1.2 shows a similar trend related 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.[20]

[20] We also compare the share of trade from high- vs middle-income countries in gross and value-added terms for both sectors in Figures A.1 and A.2. When we compare the shares measured in value-added terms to those in gross terms for each country group, we observe the same pattern from both sectors: the shares of U.S. imports from high-income countries in value-added measures are larger than those gross terms from these countries. On the other hand, the shares from middle-income countries in value-added terms are smaller than their gross contribution.

**Table 1.1 Descriptive Statistics, 1996-2009**

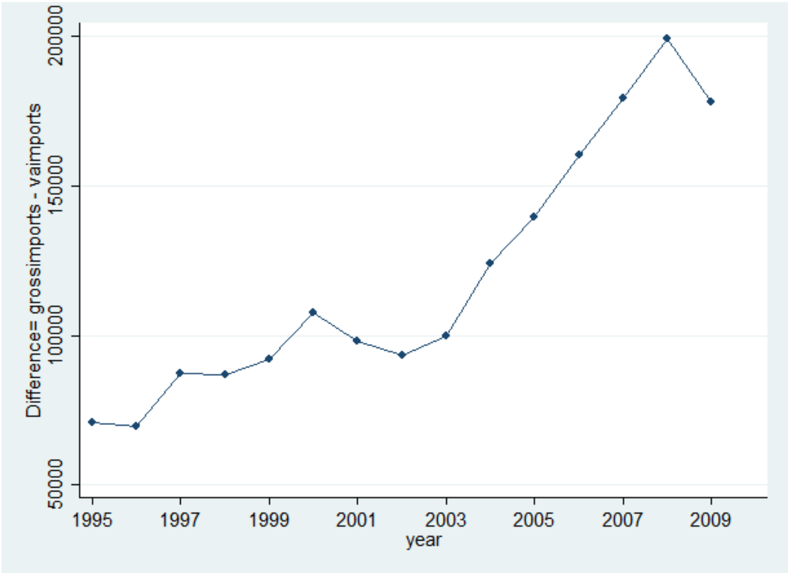
| Occupation-time measures | All occupations | Most routine | Intermediate routine | Least routine |
|---|---|---|---|---|
| | | Occupation exposures to gross trade | | |
| *IMP* all countries | 0.0493 | 0.0802 | 0.0388 | 0.0141 |
| | (0.0764) | (0.1020) | (0.0554) | (0.0209) |
| Export share all countries | 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 | 3534 | 1260 | 1672 | 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 | 3534 | 1260 | 1672 | 602 |

**Figure 1.1 Difference between Gross Imports and Value-Added Imports by Year in Textiles and Textile Products**




Source: Koopman et al. (2014) for trade flows years 1995-2009. The sector-level value-added and gross trade data in Koopman et al. (2014) are classified according to the International Standard Industrial Classification Revision 3 (ISIC Rev. 3). The dark blue line refers to the difference between the dollar value of gross imports and that of value-added imports for the "textile and textile product" sector.

**Figure 1.2 Difference between Gross Imports and Value-Added Imports by Year in Electrical and Optical Equipment**

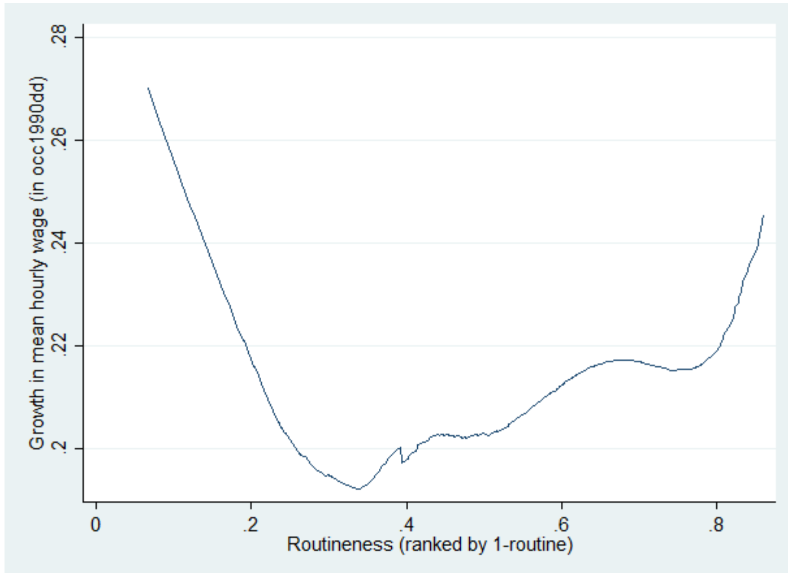



Source: Koopman et al. (2014) for trade flows years 1995-2009. See note to Figure 1.1. The dark blue line refers to the difference between the dollar value of gross imports and that of value-added imports for the "textile and textile product" sector.

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 1.3. 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).

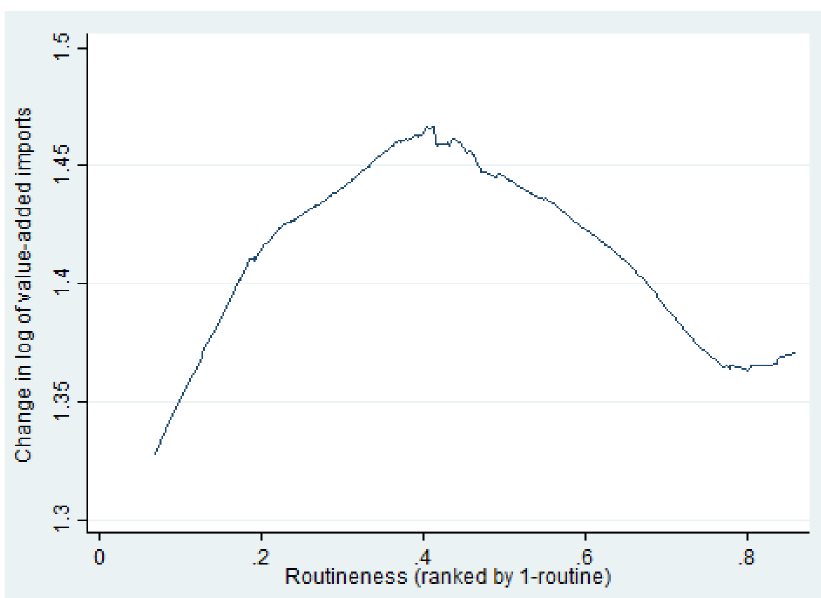
One of the key issues we explore in the econometric exercises is whether the effect of U.S. economic exposure to imports from middle-income countries differs from the effects of U.S. exposure from high-income countries. In Figure 1.4, we plot the change in U.S. exposure to value-added imports from middle-income 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.

**Figure 1.3 Smoothed Changes in Growth of Mean Hourly Wage by Routineness Level**




Source: MORG CPS for hourly wages year 1995-2009. Mean hourly wage for each occupation is the weighted average hourly wages with individual CPS earnings weights. The smoothed changes in the growth of occupations' mean hourly wage from 1995 to 2009 are plotted against occupations' routineness index. An increase along the x-axis indicates that occupation is less routine.

**Figure 1.4 Smoothed changes in log of value-added imports from middle-income countries by routineness level,1995-2009**




Note: 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 occupation is less routine.

## 1.4 Baseline Results

### 1.4.1 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 et al., 2014, Johnson and Nogueira, 2012). Descriptive statistics in Table 1.1 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 (1.2) 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 1.2. 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 are shown in Table 1.2 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 are 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 suggests 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),[21] 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 have 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.

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

**Table 1.2 OLS Estimates of Wages Determinants Using Occupational Exposures to Gross Trade and Value-Added Trade,1996-2009**

| | Gross Trade Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade Measured by Occupation-Specific Exposure All Sectors | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | -0.146 | -0.335*** | -0.416 | 2.442*** | -0.195 | -0.636*** | -1.927*** | 4.649** |
| Lagged import penetration | (0.095) | (0.119) | (0.510) | (0.897) | (0.229) | (0.237) | (0.694) | (2.264) |
| | 0.729*** | 0.294 | 0.594*** | -0.454 | 2.174*** | 1.836** | 3.977*** | -4.048 |
| Lagged export share | (0.178) | (0.202) | (0.219) | (0.705) | (0.718) | (0.786) | (1.288) | (2.711) |
| Lagged log of middle-income affiliate employment | -0.139** | -0.096*** | 0.001 | -0.539** | -0.083* | -0.083** | 0.022 | -0.338 |
| | (0.057) | (0.036) | (0.101) | (0.227) | (0.050) | (0.036) | (0.062) | (0.205) |
| Lagged log of high-income affiliate employment | 0.126** | 0.078** | 0.002 | 0.511** | 0.070 | 0.060* | -0.020 | 0.334* |
| | (0.052) | (0.032) | (0.087) | (0.205) | (0.045) | (0.033) | (0.057) | (0.180) |
| N of 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: Dependent variable is log hourly wage. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Offshoring employment (1995-2008), import penetration, and export share in gross terms (1995-2002) 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 et al. (2014), 40 countries are included. Value-added export share and import penetration have followed the constructions of Ebenstein et al. (2014). The CPS worker data from 1996 to 2002 are from Autor et al. (2008), data from 2003 to 2009 are from Acemoglu and Autor (2011). The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-thirds of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-thirds, and least-routine being less than one-third. 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, which are taken from Ebenstein et al. (2014). Computer use rates from 2003 to 2009 are frozen at the level of 2002 following the construction in Ebenstein et al. (2015). Superscript "**," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

Second, the results shown in Table 1.2 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 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 7 percent, respectively.[22][23] 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.[24]

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 1.2) suggest that a one percentage point increase in the occupational exposure to gross

[22] 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 1.1 (0.0363) and the coefficient of this variable shown in column (6) of Table 1.2 (-1.927), which equals to a 6.99 percent decrease in wages for U.S. intermediate-routine workers.

[23] Tables 1, A.1, and A.2 report the standard deviations used for interpretation of point estimates in all the tables in this chapter.

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

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).[25]

Another important point is that our approach outlined in equation (1.2) 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 characteristics are assumed to be constant. As a result, columns (4) and (8) of Table 1.2 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

[25] 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.

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 1.2 when we consider the effects of changes in U.S. exposure to other dimensions of the globalization process. The results shown in Table 1.2 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 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.[26] The effects of changes in net trade exposure can also be investigated using the results shown in Table 1.2. 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.[27]

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

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[26] Lake and Millimet (2016) also find that wages earned by most-skilled worker are negatively affected by an increase in exports.

[27] 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.

insignificant increase in the average wage earned by intermediate-routine workers.[28] Thus, the results described in Table 1.2 provide empirical support to the concerns expressed by policymakers 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 A.7 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.[29] As explained in Appendix A, we follow their approach in this case by controlling for the same industry characteristics used in their study. The results in Table A.7 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

[28] 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.

[29] We use the same industry-level characteristics used in their study. This implies that we do not have the information for these control variables for the 2003-2009 period.

occupational exposures to gross trade flows. Our primary interest below is to investigate the sources of the polarization of wages identified in Table 1.2, 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.

### 1.4.2 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., Heckscher-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 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 1.2 related to the polarization of U.S. workers' wages.

Table 1.3 reports the estimated effects of U.S. occupational exposure to value-added trade with middle- and high-income countries on wages. The results 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 the wages earned by 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.[30] 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.

[30] This effect can be obtained by multiplying 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 1.1 (0.0149).

**Table 1.3 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade from Middle- vs. High-Income Countries,1996-2009**

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

Note: Dependent variable is log hourly wage. See Table 1.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Countries are classified by income level using the classification from the World Bank. Transition economies are excluded from the sample. Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "**," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

Overall, the results from columns (2)-(4) of Table 1.3 suggest that an increase in occupational exposure to value-added imports from middle-income countries leads 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.[31]

The results shown in columns (5)-(8) of Table 1.3 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.[32] It is also worth pointing out that the results in columns (1) to (4) of Table 1.3 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

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[31] 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.

[32] 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).

tends to increase the wage earned by the average U.S. worker.[33] This finding is in line with Table 1.2 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 in Tables 1.2 and 1.3 suggest that the gains from international trade are not distributed equally, and not everyone is benefiting from trade.

Notice that we have performed some robustness tests involving the key results in Tables 1.2 and 1.3. The original specification described in expression (1.2) 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 (1.2) for the specific cases discussed in Tables 1.2 and 1.3 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 driven by U.S. exposure to value-added imports from middle-income countries. In addition, we have tested the results described in Tables 1.2 and 1.3 by changing the clustering of our standard errors to occupation and year (rather than by occupation and five-year period) and have also concluded that our main results are robust to this specification as well. We also estimate other alternative specifications with alternative cutoffs for those three groups of routineness. The results are shown in Table A. our conclusion about the polarization of wages do

[33] 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.

not alter by it. In addition, instead of classifying occupations into three groups, we also estimate the OLS effects for five groups of occupations according to their degree of routineness.

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.

## 1.5 Mechanisms

### 1.5.1 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 (e.g., Halpern et al., 2015, Topalova and Khandelwal, 2011, Kasahara and Rodrigue, 2008, Görg et al., 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 (1.1).

In columns (1)-(4) of Table 1.4, 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.[34] 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 an 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-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 have a positive effect on wages, but this result is moderately statistically significant. Again, columns (2)-(4) in Table 1.4 suggest that changes in occupational exposure to value-added imports of final goods from middle-income countries lead to the U-shaped polarization of workers' wages according to the degree of routineness of their occupations. Instead, columns (5)-(8) of Table 1.4 report the estimated results from equation (2) using the U.S. occupational exposure to value-added trade in final goods from high-income countries.

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

**Table 1.4 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final Goods from Middle- vs. High-Income Countries,1996-2009**

| Variable | Value-Added Trade in Final Goods from Middle-Income Countries Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade in Final Goods from High-Income Countries Measured by Occupation-Specific Exposure 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 import penetration | -0.374 | -0.950*** | -7.918*** | 11.085* | -2.315** | -1.817** | -3.222** | -6.807* |
| | (0.525) | (0.350) | (1.719) | (5.685) | (0.911) | (0.825) | (1.626) | (3.516) |
| Lagged export share | 11.039* | 3.724 | 29.356*** | 6.379 | 7.689*** | 3.710** | 8.410** | 7.630 |
| | (6.611) | (3.041) | (5.989) | (24.379) | (2.285) | (1.808) | (3.514) | (8.254) |
| Lagged log of middle-income affiliate employment | -0.107* | -0.100*** | 0.053 | -0.453** | -0.077 | -0.094** | -0.018 | -0.070 |
| | (0.059) | (0.036) | (0.078) | (0.224) | (0.046) | (0.036) | (0.066) | (0.142) |
| Lagged log of high-income affiliate employment | 0.098* | 0.080** | -0.051 | 0.444** | 0.066 | 0.073** | 0.014 | 0.121 |
| | (0.053) | (0.032) | (0.071) | (0.203) | (0.042) | (0.032) | (0.060) | (0.126) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Countries are classified by income level using the classification from the World Bank. Transition economies are excluded from the sample. Data of value-added trade in final goods are taken from Koopman et al. (2014). Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "**," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

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.[35]

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 1.3 and 1.4 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. 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.

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[35] 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.

In the case of Table 1.4, 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 an 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 contribute to the polarization of U.S. wages.

Table 1.5 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 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 on 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 are complementaries to the tasks performed by U.S. workers in least-routine occupations.

In contrast, columns (5)-(8) of Table 1.5 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 1.5 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 1.4 and 1.5 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 the 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.[36]

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[36] 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.

**Table 1.5 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Intermediate Goods from Middle- vs. High-Income Countries,1996-2009**

| | Value-Added Trade in Intermediate Goods from Middle-Income Countries Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade in Intermediate Goods from High-Income Countries Measured by Occupation-Specific Exposure 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 | 0.437 | -2.354* | 1.957 | 34.222*** | 2.102 | 0.836 | -1.739 | 9.628 |
| | (1.581) | (1.248) | (5.481) | (9.848) | (2.111) | (1.367) | (2.589) | (6.624) |
| Lagged export share | 9.589*** | 6.699** | -4.013 | -24.979** | 3.588 | 1.614 | 3.973 | -12.720 |
| | (3.659) | (3.098) | (7.812) | (12.455) | (2.908) | (2.305) | (5.088) | (7.644) |
| Lagged log of middle-income affiliate employment | -0.100* | -0.091** | 0.050 | -0.502** | -0.035 | -0.080** | 0.030 | -0.130 |
| | (0.055) | (0.037) | (0.072) | (0.217) | (0.040) | (0.038) | (0.059) | (0.120) |
| Lagged log of high-income affiliate employment | 0.089* | 0.069** | -0.040 | 0.509** | 0.024 | 0.057 | -0.023 | 0.158 |
| | (0.051) | (0.034) | (0.067) | (0.203) | (0.037) | (0.037) | (0.055) | (0.111) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Countries are classified by income level using the classification from the World Bank. Transition economies are excluded from the sample. Data of value-added trade in intermediate inputs are taken from Koopman et al. (2014). Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

### 1.5.2 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 1.6 reports the results for the estimation of expression (1.2) 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 in columns (5)-(8) refer to the estimation of expression (1.2) to the case of U.S. occupational exposure to value-added trade flows with China. The coefficients 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.

**Table 1.6 OLS Estimates of Wages Determinants Using Occupational Exposure to Gross and Value-Added Trade from China,1996-2009**

| | Gross Trade Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade Measured by Occupation-Specific Exposure 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 | -0.217 | -0.624*** | -0.808 | 7.232** | 0.090 | -0.723** | -6.436*** | 14.103** |
| | (0.202) | (0.188) | (1.370) | (3.284) | (0.397) | (0.297) | (1.629) | (6.889) |
| Lagged export share | 9.422*** | 6.091* | 8.272** | -24.268 | 10.411** | 4.681 | 22.422*** | -22.875 |
| | (3.351) | (3.274) | (4.061) | (20.356) | (5.107) | (3.829) | (5.163) | (24.409) |
| Lagged log of middle-income affiliate employment | -0.134** | -0.126*** | -0.019 | -0.370* | -0.119** | -0.108*** | 0.041 | -0.405** |
| | (0.059) | (0.040) | (0.085) | (0.217) | (0.061) | (0.038) | (0.079) | (0.191) |
| Lagged log of high-income affiliate employment | 0.127** | 0.104*** | 0.022 | 0.385* | 0.113** | 0.087** | -0.032 | 0.416** |
| | (0.054) | (0.036) | (0.079) | (0.203) | (0.056) | (0.034) | (0.072) | (0.180) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. 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 flows from China are taken from Koopman et al. (2014).Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "**," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

Next, we present the results in Table 1.7 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 1.4 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 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 of 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

**Table 1.7 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final vs. Intermediate Goods from China,1996-2009**

| | Value-Added Imports in Final Goods Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade in Intermediate Goods Measured by Occupation-Specific Exposure 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 | 0.094 | -1.098*** | -8.494*** | 21.513*** | 1.780 | -2.572 | -11.959 | 56.728* |
| | (0.560) | (0.407) | (2.145) | (8.035) | (2.988) | (2.053) | (8.736) | (32.232) |
| Lagged export share | 33.503 | 16.713 | 69.913*** | -71.604 | 12.448 | 7.562 | 17.316 | -61.644 |
| | (20.639) | (12.882) | (19.638) | (70.238) | (8.973) | (6.761) | (15.091) | (56.236) |
| Lagged log of middle-income affiliate employment | -0.117* | -0.112*** | 0.028 | -0.368* | -0.113* | -0.107*** | 0.065 | -0.416* |
| | (0.064) | (0.039) | (0.083) | (0.191) | (0.058) | (0.038) | (0.076) | (0.209) |
| Lagged log of high-income affiliate employment | 0.110* | 0.090*** | -0.022 | 0.382** | 0.108** | 0.087** | -0.054 | 0.429** |
| | (0.058) | (0.034) | (0.076) | (0.178) | (0.054) | (0.034) | (0.069) | (0.198) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2, 1.5, and 1.6 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. 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). Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

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 1.6 and 1.7, 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 1.8 reports the estimated results for expression (1.2) while focusing on middle-income countries other than China. The results shown on columns (1)-(4) of Table 1.8 reveal that changes in U.S. occupational exposure to value-added imports of final goods from other middle-income countries are also contributing to the polarization of U.S. workers' wages. In fact, the estimates shown in Table 1.8 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 1.5 where we consider exposure to trade with all middle-income countries.

**Table 1.8 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**

| | Value-Added Imports in Final Goods from Middle-Income Countries (Exclude China) Measured by Occupation-Specific Exposure, All Sectors | | | | Value-Added Trade in Intermediate Goods from Middle-Income Countries (Exclude China) Measured by Occupation-Specific Exposure, All Sectors | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -1.963 | -3.586*** | -17.492*** | -1.937 | 4.901 | -2.553 | 11.420 | 85.483*** |
| | (2.103) | (1.169) | (3.668) | (11.248) | (3.418) | (2.551) | (8.630) | (22.813) |
| Lagged export share | 15.831 | 7.909* | 48.196*** | 73.724** | 11.844** | 8.850** | -9.918 | -29.814* |
| | (10.512) | (4.312) | (9.622) | (30.739) | (4.773) | (3.988) | (9.536) | (17.204) |
| Lagged log of middle-income affiliate employment | -0.095* | -0.093*** | -0.024 | -0.337* | -0.081* | -0.086** | 0.022 | -0.492** |
| | (0.053) | (0.034) | (0.072) | (0.201) | (0.049) | (0.036) | (0.063) | (0.195) |
| Lagged log of high-income affiliate employment | 0.087* | 0.072** | 0.015 | 0.315* | 0.071 | 0.064* | -0.014 | 0.476*** |
| | (0.048) | (0.031) | (0.066) | (0.176) | (0.045) | (0.033) | (0.059) | (0.175) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2, 1.5, and 1.6 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. 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). Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. All regressions include controls for offshoring employment and worker characteristics from Table 1.2. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

In Table 1.9, we report the results of the estimation of expression (1.2) for the effects of U.S. 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 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 1.9. 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 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 resembles the results discussed in Table 1.5.

In sum, the results from Tables 1.6 to 1.9 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.

**Table 1.9 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Imports in Final vs. Intermediate Goods from Selected Middle-Income Countries,1996-2009**

| | Value-Added Imports in Final Goods from Middle-Income Countries (Exclude China) Measured by Occupation-Specific Exposure, All Sectors | | | | Value-Added Trade in Intermediate Goods from Middle-Income Countries (Exclude China) Measured by Occupation-Specific Exposure, All Sectors | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Mexico | | | | | | | | |
| | -2.550 | -8.751*** | -10.040*** | -86.573*** | 12.453 | -3.273 | 23.834** | 127.390*** |
| Lagged import penetration | (5.318) | (2.954) | (3.740) | (18.709) | (7.565) | (6.160) | (11.869) | (46.061) |
| | 15.783 | 9.977 | 34.995*** | 195.149*** | 13.183** | 8.608* | -15.948 | -32.870 |
| Lagged export share | (13.882) | (6.042) | (13.191) | (46.866) | (6.371) | (4.802) | (11.153) | (24.026) |
| India | | | | | | | | |
| | 3.004 | -4.983** | -59.795*** | 42.242 | 54.261 | -14.602 | -62.876 | 490.979*** |
| Lagged import penetration | (2.695) | (2.173) | (13.203) | (43.196) | (39.513) | (32.314) | (64.203) | (184.646) |
| | 9.539 | 12.097 | 82.833*** | 140.457** | -3.822 | 30.188 | 30.445 | -5.623 |
| Lagged export share | (16.294) | (12.367) | (28.308) | (64.488) | (31.567) | (27.020) | (55.307) | (84.128) |
| Indonesia | | | | | | | | |
| | 1.974 | -12.018*** | -89.521*** | 192.986* | 6.520 | -10.048 | -84.652 | 360.721* |
| Lagged import penetration | (3.725) | (4.282) | (25.230) | (102.180) | (7.879) | (9.822) | (59.611) | (199.693) |
| | 89.148 | 130.106* | 279.071** | -908.335*** | 190.680** | 150.268** | 21.712 | -284.170** |
| Lagged export share | (98.110) | (73.436) | (122.344) | (273.028) | (76.416) | (59.512) | (90.432) | (138.788) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2, 1.5, and 1.6 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

## 1.6 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.

# Chapter 2 - Skills Matter: The Effects of Value-added Imports on U.S. Labor Market Outcomes

## 2.1 Introduction

In 2016, we observed how voters' dissatisfaction in the U.S. "rust belt" states had a consequential impact on the U.S. presidential election outcome.[37] Part of the voters reacted in line with their economic anxieties, which can be traced back to sluggish wage growth and an increase in economic uncertainties due to globalization over the last two decades.[38] During the presidential campaign, Candidate Donald Trump blamed international trade as one of the causes for the economic malaise faced by the U.S. middle-class; thus, U.S. wage polarization has become a central political concern in the U.S. political arena.[39]

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[37] President Donald Trump's victory is partially explained by the support of workers from Pennsylvania, Michigan, Ohio, and Wisconsin, which correspond to the home base of many industries heavily affected by technological change, environmental policy, and by exposure to competing imports.

[38] Compared with former Secretary of State Hillary Clinton, Donald Trump received higher support from counties where routine jobs are more prevalent. See the article published by the news agency FiveThirtyEight: https://fivethirtyeight.com/features/trump-was-stronger-where-the-economy-is-weaker/

[39] Presidential candidate Donald Trump's speech in Monessen, Pennsylvania, claimed that "globalization has made the financial elite, who donate to politicians, very, very wealthy. …But it has left millions of our workers with nothing but poverty and heartache." See the speech transcript published by the *Time*: http://time.com/4386335/donald-trump-trade-speech-transcript/. In addition, he pointed out that "our manufacturing base has crumbled, communities have been hollowed out, wages have declined, and households are making less today than they were in the year 2000" and promised that "we are going to put our miners and our steelworkers back to work" in a talk at the New York Economic Club in Manhattan. See the speech transcript from *Time*: http://time.com/4495507/donald-trump-economy-speech-transcript/

The angst against economic globalization was not limited to the Republican Party's primary process. In fact, within the Democratic Party's presidential election primaries, Senator Bernie Sanders, who had opposed free trade for years, was more welcomed than his opponent within the party, the former Secretary of State Hillary Clinton in the "rust belt" states. This perception was confirmed by the results of the 2016 Democratic presidential primary contests. In addition to Candidate Donald Trump's concerns about the potential contributions of globalization forces to the polarization of U.S. wages, Senator Sanders was particularly worried about the economic uncertainties related to employment, access to health services, and educational opportunities. Moreover, Senator Sanders sought to propose a federal job guarantee plan that, in his opinion, would ensure employment opportunities for U.S. workers. [40][41]

Though government policy might help increase job security and relieve the severity of wage polarization, it is regularly the case that the likelihood of being unemployed and wage levels correlate with workers' skills in advanced and backward market economies. In the case of trade exposure in the U.S. manufacturing sector, published business reports imply that employers in the U.S. will face difficulties in hiring qualified, high-skilled workers in "blue-collar" occupations,

[40] Senator Sanders proposed "Medicare for All," the "Rebuild America Act," and free college during the 2016 election campaign. See the details in the issues published by his official campaign website: https://berniesanders.com/issues/

[41] Democratic senators, such as Cory Booker and Kirsten Gillibrand, have backed Senator Sanders by proposing similar plans. See the article published by the Bloomberg: https://www.bloomberg.com/news/articles/2018-05-18/the-most-radical-economic-plan-in-years-and-now-it-s-mainstream

such as welders, machinists, and electronics assemblers in the next decade.[42] [43] These occupations are no longer expected to perform low-skilled routine tasks with traditional tools such as hammers and pliers in the era of the smart factory but are expected to be involved with more advanced and complicated tasks in their positions such as interface with robots and electronics-controlled systems. Due to a shortage of skilled workers, those with qualification might benefit from it and have more opportunities in employment than unskilled workers. In short, motivated by the public discontent on trade and the concerns of the skill gap in the U.S. employment, in this paper, we study how international trade interacts with U.S. labor market outcomes in three exercises.

In the first exercise, we contribute to the literature regarding how changes in U.S. exposure to trade has affected wages by controlling for the degree of routineness of the workers' occupation as well as the workers' skill level. This exercise is closely related to Ebenstein et al. (2014), Shen and Silva (2018), Shen, Silva, and Wang (2018), Hummels et al. (2014), and Baumgarten et al. (2013).

Shen and Silva (2018) study the effects of an increase in import competition from China at the regional level on U.S. wages and unemployment using the value-added trade data. They propose to use value-added trade data instead of gross trade data to examine the impacts of imports from China on U.S. local labor market outcomes. This because there is a substantial share of foreign contents within the Chinese gross exports. Therefore, the measures of trade exposure constructed using the gross trade between the U.S. and China might lead to a biased conclusion

[42] See the report published by Deloitte: https://www2.deloitte.com/us/en/pages/manufacturing/articles/boiling-point-the-skills-gap-in-us-manufacturing.html

[43] See the article published by the MIT technology review: https://www.technologyreview.com/s/530701/the-hunt-for-qualified-workers/

about how the Chinese import has shaped economic outcomes in the U.S. They also highlight the importance of making a distinction between final goods and intermediate goods in the study of the effect of value-added trade flows on American wages and employment.

Ebenstein et al. (2014) examine the effects of exposure to offshoring and gross trade on U.S. wages using a sample constructed from the Current Population Survey (the CPS). They use the measure of offshoring employment as a proxy of exposure to offshoring. They argue that changes in the U.S. occupational exposures to offshoring and gross trade have significant effects on wages. Their results suggest that the effects of exposure to offshoring and trade on the U.S. wages are heterogeneous depending on the degree of routineness involved in workers' occupation. For instance, they find that an increase in occupational exposure to imports has a negative and significant effect on the wages earned by U.S. workers involved with the highest degree of routine tasks in their occupations, but this significant effect does not apply to the intermediate- and least-routine workers.[44] Notice that they distinguish between the offshoring employment in high-income affiliates and those located in low-income countries. However, they do not differentiate the gross trade flows by these nations' income levels.

In the spirit of Shen and Silva (2018) and Ebenstein et al. (2014), Shen, Silva, and Wang (2018) use value-added trade data to construct measures of exposure to trade at the occupation level and then study its effect on U.S. wages between 1995 and 2009. They sort the value-added trade flows into categories according to the role of traded goods in the production process (final goods vs. intermediate inputs) as well as the income level of exporting countries (middle- vs. high-

[44] See Table 2 and table 4 in Ebenstein et al. (2014).

income).[45] Their estimates indicate that an increase in U.S. occupational exposure to value-added imports in final goods from middle-income countries is critical in explaining the U.S. wage polarization. In particular, an increase in exposure to final goods originating in middle-income countries affects the intermediate-routine workers more than their counterparts in the most-routine occupations. For those involved in the least-routine occupations, they experience a significant wage gain. An increase in exposure to intermediate inputs from middle-income nations has only a significant and positive effect on the wages of the least-routine workers. This indicates that tasks embed in these goods are complementing the tasks performed by the U.S. least-routine workers. By contrast, their results suggest that changes in U.S. exposure to value-added trade from high-income countries are not associated with the polarization of U.S. wages no matter what types of traded goods they use.

Another important paper, Hummels et al. (2014) investigate the effects of firm-specific exposure to offshoring and exports on the wages of Danish workers while controlling for their level of skill. They find that an increase in exposure to offshoring has a negative and significant effect on the wages earned by the unskilled workers, while the effect on the wages of skilled workers is significantly positive. Gross exports, on the other hand, increases the Danish wages irrespective of workers' level of skill. Baumgarten et al. (2013) extend the work of Hummels et al. (2014) by looking at the link between industry-level offshoring and wages within the skill groups. In the case of German workers, Baumgarten et al. (2013) argue that the differences in task characteristics of occupations can explain the differential effects of offshoring on the wages earned

[45] Value-added trade data were originally from Koopman, Wei and Wang (2014) which are available for only forty countries. These forty countries are either middle- or high-income countries following the income criteria published by the World Bank.

by the workers for each skill group. In the case of low-skilled workers, they find that an increase in exposure to offshoring lower the wages of the low-skilled workers on average, and this negative impact mitigates when workers are involved with more non-routine tasks in their occupations. In the case of skilled workers, the effect of offshoring is insignificant regardless of task contents. In this study, we differ from Baumgarten et al. (2013) which focus on the effect of industrial exposure to offshoring on individual wages, by assessing the effects of occupational exposure to value-added trade on the wages of workers within skill groups (skilled and unskilled). [46]

In the study of wages, we find that, in both skill groups, an increase in occupational exposure to value-added imports from middle-income countries leads to the U-shaped trend of wages when the degree of occupational routineness increases. Furthermore, we compare the prevalence of this negative shock, and the results imply that unskilled workers seem to face more pressure than skilled ones on the wages.

In recent years, the topic about how the uncertainty in public policy has affected the economic activities has been debated in the literature (e.g., Pierce and Schott, 2016; Handley and Limão, 2017). In the case of welfare in manufacturing sectors, Pierce and Schott (2016) argue that a reduction in the uncertainty of trade policy between China and the U.S. curtails employment in

[46] Our work is different from Baumgarten et al. (2013) in many dimensions. First, they that classify the tasks involved in occupations into two categories—non-routine and interactive following the approach in Becker et al. (2013). We follow the classification of degree of routineness in Ebenstein et al. (2014). Second, they combine worker-level data with industry offshoring whereas we combine the U.S. individual-level data with occupational exposure to trade and offshoring. Third, our offshoring exposure is not the same as theirs. We study the effects of offshoring employment in middle-and high-income affiliates on wages as in Ebenstein et al. (2014) while they study how the increasing imports in intermediate goods from foreign affiliates and firms (i.e., the increase in offshore outsourcing) has affected wages as in Geishecker and Görg (2008).

U.S. manufacturing industries. They find that when industries are more exposed to the sectors that have bigger changes related to the removal of policy uncertainty, employment loss would be more substantial. In the case of national welfare, Handley and Limão (2017) analyze the impacts of policy uncertainty on U.S. prices and consumers' income. They find that consumers' real income goes up and prices go down when the uncertainty on trade is reduced. In short, the papers discussed in this paragraph are more concerned with the how uncertainty on trade policy has affected economic outcomes and welfare in the U.S., whereas, in this paper, we are interested in how the economic uncertainty at the worker level changes with an increase in exposure to trade.

Thus, our second empirical exercise examines the impact of exposure to value-added trade on the individual probability of being unemployed while controlling for the level of skill. This analysis is essential because workers' education level is a key determinant of their earnings and employment according to the theory of skill-biased technological change (Acemoglu, 2002). Our estimates suggest that unskilled workers are more vulnerable to an increase in value-added import penetration. Greater exposure to value-added trade is more likely to increase the probability of being unemployed for unskilled workers, while the effect on skilled individuals is insignificant.

Since many studies show that an increase in import competition has an adverse effect on U.S. employment in exposed industries and regions. (e.g., Acemoglu et al. 2016, Autor, Dorn and Hanson, 2013), researchers also want to estimate the cost of trade-induced reallocation. On the one hand, Artuç and McLaren (2015) estimate the cost of switching using a structural model. They distinguish American workers by occupations, sectors controlling for the level of skills and find that switching is very costly whether considering sectors or occupations. Moreover, they find that the magnitude of the cost for worker's welfare depends on the level of skill of that worker. On the other hand, Ebenstein et al. (2014) estimate the cost of switching with a reduced-form estimation.

Their results are consistent with the findings in Artuç and McLaren (2015), which suggest that overall, U.S. workers experience a significant wage cut when they switch occupations. However, Ebenstein et al. (2014) do not further investigate the cost of switching controlling for the level of routineness or skills.[47] We extend the work of Ebenstein et al. (2014) by adding an interaction between the index of routineness and the level of skill to see whether differentiating workers by routineness and skill is essential in explaining the changes in wages of different types of workers when they switch. Our estimated coefficients suggest that the impact of trade-induced switching is negative and significant on the wages of unskilled workers regardless of the degree of routineness displayed in their occupations. As for skilled workers, the effect for those in most- and intermediate-routine occupations are insignificant while for the least-routine workers, the impact is negative and significant.

The paper is organized as in the following: Section 2 details our empirical strategy, Section 3 describes the data, Section 4 presents our empirical estimates, Section 5 reports results of several robustness checks, and Section 6 offers concluding remarks.

## 2.2 Empirical Strategy

In this study, we want to investigate the effects of occupational exposure to value-added trade on the wages, probability of being unemployed, as well as costs of switching occupations, controlling for the degree of routineness of workers' occupations and their level of skill. Our empirical strategy is mainly building on the research by Shen, Silva, and Wang (2018), Ebenstein et al. (2014) and Hummels et al. (2014).

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[47] See Table 2 and Table 4 in Ebenstein et al. (2014) for more details.

We begin with the construction of the degree of routineness across occupations. Following Ebenstein et al. (2014) and Shen, Silva, and Wang (2018), our measure of the index of routineness for each occupation k is defined as a share of routine tasks in the summation of routine, manual and abstract tasks:

$$Routine_k = \frac{TaskRoutine_k}{TaskRoutine_k + TaskManual_k + TaskAbstract_k} \quad (2.1)$$

Where $TaskRoutine_k$ measures the intensity of routineness tasks involved in the occupation k, $TaskManual_k$ measures the intensity of physical dexterity related to finger, eye, and foot, and the measure, $TaskAbstract_k$, measures the intensity of creative and analytical tasks in that occupation. Each task measure ranges from 1 to 10, where higher order means higher intensity. The value of the index $Routine_k$ is in the range between 0 and 1. As in Ebenstein et al. (2014) and Shen, Silva and Wang (2019), we classify occupations into three groups: most, intermediate-, and least-routine occupations, by the value of routineness in expression (2.1). Specifically, occupations are defined as least routine occupations when their values for the ratio are below one-third, intermediate-routine occupations are those which have values between one-third and two-thirds, and those with values above two-thirds are classified as most-routine occupations.

Our measure of occupational exposure to value-added trade is an average industrial value-added import competition, weighted by the employment distribution across industries for each occupation k. The value-added import penetration of occupation k in year t-1 is shown in the following:

$$IMP_{kt-1} = \sum_{j=1}^{J} \frac{L_{kj95}}{L_{k95}} IMP_{jt-1} \quad (2.2)$$

Here, $IMP_{jt-1} = \mathrm{M_{jt-1}}/(\mathrm{M_{jt-1}} + vship_{jt-1})$ is the U.S. value-added import penetration for industry j in year t-1. It is calculated as a ratio of the U.S. value-added imports in industry j in year t-1, $\mathrm{M_{jt-1}}$ to the summation of imports and industry shipment in that industry ($\mathrm{M_{jt-1}} + vship_{jt-1}$). The fraction, $\frac{L_{kj95}}{L_{k95}}$ is the employment share of industry j in occupation k's in the base year 1995, which we use as the weight for k-specific import penetration ratio. [48]

Though the occupational import penetration, $IMP_{kt-1}$, could capture the overall value-added trade shocks experienced by occupation k, this occupational measure does not distinguish the heterogeneous effects for skilled and unskilled workers in that occupation. To study the potential uneven wage gains across workers in different levels of skill in occupation k, we interact the k-specific value-added import penetration, $VAIMP_{kt-1}$, with a skill dummy, $S_i$.

Our wage specification takes the form:

$$\mathrm{lnW_{ijkt}} = \beta_1 IMP_{kt-1} + \beta_2 IMP_{k-1} * S_i + \beta_3 S_i + G_{kt-1}\Phi$$
$$+ Z_{ijkt}\Omega + Comp_{kt} + \alpha_k + \gamma_{jt} + \epsilon_{ijkt} \quad (2.3)$$

Where $lnW_{ijkt}$ represents the log hourly wage of worker *i* in the occupation *k*, who employed in industry *j* at time *t*. The skill dummy $S_i$ equals one if worker *i* is a skilled worker. The skill dummy is constructed using a cutoff in educational attainment where individuals holding at least a bachelor's degree are deemed skilled workers in this study. Following Shen, Silva and Wang (2018), the measures of exposure to value-added export shares and offshoring employment in the middle- and high-income countries are included in the k-specific vector at time t-1, $G_{kt-1}$. We use lagged measures of occupational exposure to value-added trade and offshoring employment to deter simultaneous shocks to wages, offshoring, and value-added trade. Besides, as discussed in Ebenstein et al. (2014), labor market adjustments to trade and offshoring likely take more time. $Z_{ijkt}$ is a vector which contains individual characteristics such as age, gender,

[48] We inherit this occupational measure of value-added imports from Shen, Silva and Wang (2018).

race, and location. The occupation-specific computer use rate ($Comp_{kt}$) controls for the influence of technological progress on the labor demand across occupations. The occupation fixed effect ($\alpha_k$) controls for time-invariant shocks specific to that occupation. We also include time-varying industry fixed effect ($\gamma_{jt}$) to control for industrial productivity, capital-labor ratio as well as other unobserved time-variant industry-level characteristics. Following Shen, Silva and Wang (2018), regressions of expression (3) are weighted by the product of earning weights provided by the CPS-MORG and worker's weekly hours worked. Standard errors are clustered by occupation and five-year period.

The coefficients of interest in expression (2.3) are $\beta_1$ and $\beta_2$. $\widehat{\beta_1}$ is the coefficient on lagged import penetration at the occupation level, it represents the effect of an increase in U.S. occupational exposure to value-added imports on the wages earned by unskilled workers in occupation k. $\widehat{\beta_2}$ is the coefficient for the interaction term between import penetration and skill dummy, which measures the relative difference for skilled and unskilled workers in response to such exposure. The sum of coefficients ($\widehat{\beta_1} + \widehat{\beta_2}$), is thus the effect of exposure to imports on the wages earned by skilled workers. Hummels et al. (2014) argue that an increase in import competition from China has a negative impact on the wages of unskilled workers and a positive effect on those for skilled workers in Denmark. Since the U.S. is a developed economy as well, we expect that the signs for the effects of imports on American wages are similar to those recorded for Danish workers. We expect a negative value for $\widehat{\beta_1}$ and a positive value for ($\widehat{\beta_1} + \widehat{\beta_2}$) in this expression.

To study the effect of trade on the probability of being unemployed for U.S. workers, we use a linear probability model as follows:

$$\mathrm{ump}_{\mathrm{ijkt}} = \vartheta_1 VAIMP_{kt-1} + \vartheta_2 VAIMP_{k-1} * S_i + \vartheta_3 S_i + G_{kt-1}\Phi$$

$$+Z_{ijkt}\Omega + Comp_{kt} + \alpha_k + \gamma_{jt} + \epsilon_{ijkt} \quad (2.4)$$

Where $ump_{ijkt}$ is a dichotomous indicator for the employment status, which equals one if worker $i$ is unemployed. The right-hand side variables in expression (4) are the same as in those of expression (2.3). Likewise, the coefficients of interest in expression (2.4) are $\widehat{\vartheta_1}$ and $\widehat{\vartheta_2}$. In particular, $\widehat{\vartheta_1}$ indicate the effect of an increase in value-added import competition on the probability of being unemployed for unskilled workers. The summation of these two parameters implies the effect for skilled workers with occupation k. Regressions of expression (2.4) are weighted only by the earning weights of the CPS-MORG because the hours worked are not applicable for those who are unemployed.

In the specification for the trade-induced mobility costs, we follow Ebenstein et al. (2014) by matching individuals across two consecutive CPS surveys from 1996 to 2009.[49] We regress the change in log hourly wage between period t and period t+1 for each worker on an occupation switching indicator while controlling for the individual characteristics in the first period.[50] The specification for occupation switching is presented in equation (2.5):

$$lnW_{ijkt+1} - lnW_{ijkt} = \eta_1 Diff_{ikt} + \eta_2 Diff_{ikt} \times S_{it} + Z_{ijkt}\Omega + \sigma_{t+1} + \epsilon_{ijk} \quad (2.5)$$

where $lnW_{ijkt+1} - lnW_{ijkt}$ indicates the change in log hourly wage of worker $i$ with occupation $k$ who work in industry $j$ between time $t$ and time $t$+1. $Diff_{ikt}$ equals one if worker $i$ switches to a new three-digit occupation $k$ between these two consecutive periods. $S_{it}$ indicates the skill level of worker i at time t. The $Z_{ijkt}$ vector includes individual characteristics, such as age,

[49]Therefore, our matched sample is a stacked cross-sectional dataset.

[50]Occupation switching dummy is equal to one if worker i shifts to a different three-digit occupation between period t and period t+1.

gender, and race, in the first time period, t. To control for the time trends and unobserved variables that are specific to the location in the second period, we include the time fixed effect $\sigma_{t+1}$ and the location fixed effect.

We estimate the expression (2.5) using the method of two stage least square (2SLS). We consider the switching variable, $Diff_{ikt}$, which might endogenously determine the changes in wages between periods. Therefore, we follow the discussion in Ebenstein et al. (2014) by instrumenting $Diff_{ikt}$ with a proxy for tradable occupation. In the first stage, we estimate the effect of being involved in a tradable occupation on the probability of switching. We use the offshoring data reported by the U.S. firms in 1991 and consider an occupation as tradable when its offshoring employment in middle-income affiliates is above the median level of this variable in that year. As for the skill dummy, $S_{it}$, we treat it as an exogenous variable following Hummels et al. (2014). The 2SLS estimate of $\eta_1$ captures the causal effect of occupation switching among the subset of unskilled workers would switch occupations on being involved in the tradable occupations and would not switch with non-tradable occupations. Similarly, the sum of $\eta_1$ and $\eta_2$ identifies the causal effects for skilled workers.

In the next section, we illustrate the data used in this work.

## 2.3 Data

To estimate expressions (3)-(5), we need data on U.S. workers' wages, employment status, and necessary individual characteristics. Our sample of workers is obtained from the Extracts of the Current Population Survey-Merge Ongoing Rotation Group (CPS-MORG) between 1996 and 2009, which were published by the National Bureau of Economic Research (NBER). To clean the

CPS-MORG data, we heavily rely on the data cleaner provided by Acemoglu and Autor (2011).[51] Given that we consider skilled workers to be those who hold at least a bachelor's degree, we exclude self-unemployed observations and restrict our worker-level sample to workers age 22-64. Workers are either employed or unemployed in our sample.

Notice that the industry and occupational classification scheme in the CPS-MORG had been revised several times between 1996 and 2009 by the U.S. Census Bureau.[52][53] We need to allocate workers from different classification schemes to a consistent classification system for their industry and occupation. Following Shen, Silva and Wang (2018), we allocate workers across industries and occupations using the 1990 U.S. Census industry classification scheme (IND 1990) and a revised version of the 1990 U.S. Census Occupation Classification scheme made available by David Dorn (OCC 1990DD).

[51] The data cleaner provided by Acemoglu and Autor (2011) is targeting on employed workers because their research interests focus on wages. Since our second exercise in this paper is to study the effect of value-added trade on the probability of being unemployed at the worker level, we need unemployment data. Therefore, we slightly remove the restriction on the labor force status in the cleaner of Acemoglu and Autor (2011) so that it could be used to clean unemployment data in the CPS-MORG.

[52] Workers in the period between 1995 and 2002 are classified by the U.S. Census industry classification system in 1990 (IND 1990), while workers in 2003-2008 are classified by the 2000 Census industry scheme (IND 2000) and workers in 2009 are grouped by the 2008 classification system (IND 2008). See the section about comparability between different versions of industry classification system published by the Integrated Public Use Microdata Series (IPUMS) : https://cps.ipums.org/cps-action/variables/IND#comparability_section.

[53] See the section about comparability between different versions of occupation classification scheme published by the Integrated Public Use Microdata Series (IPUMS):
https://cps.ipums.org/cps-action/variables/OCC#comparability_section.

We match individuals age 22-64 across two consecutive periods using the CPS-MORG from 1996 to 2009. Following Ebenstein et al. (2014), we utilize a two-stage matching algorithm proposed by Madrian and Lefgren (2000). In the first stage, we conduct a naïve match based on the worker's household number, household identifier, and the line number. We drop observations with missing values on the log hourly wage.54 As discussed in Madrian and Lefgren (2000), the CPS is an address-based survey which doesn't follow households when they move. The residents might not be surveyed for two consecutive periods due to temporary absence, migration, or mortality. Thus, the match depending on the household number, household identifier, and line number could not accurately reflect that individuals surveyed in the first period also participate in the second period. For this reason, we conduct validity checks in the second stage of the matching process. Successful matches must satisfy the requirements on sex, race, and the difference in age should be either 0,1, or 2 years. Also, the changes in educational attainment should be reasonable.[55] After factoring in the additional criteria in the stage of validation, the merge rate drops a little bit to 74%. This rate is consistent with the literature. Again, our data on occupational computer use rates and exposures to value-added imports and exports are taken from Shen, Silva, and Wang (2018).[56] The data on offshoring employment from different countries were originally made available by Ebenstein et al. (2014).

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[54] In our sample, we have 648,643 individuals match, or 1,297,286 observations out of 1,669,514 observations. Our naïve match rate is in line with merge rate in Madrian and Lefgren (2000).

[55] See Madrian and Lefgren (2000) for more details.

[56] Shen, Silva and Wang (2018) use the value-added trade flows provided by Koopman, Wei and Wang (2014) to construct measures of U.S. occupational exposure to value-added trade. In their study, all the occupational measures of exposure to value-added trade and offshoring are aggregated at OCC1990DD level. This data source provides us

Table 2.1 provides the summary statistics of occupational measures of exposure to value-added trade. It suggests that occupational exposure to value-added trade is more related to the trade flows between the U.S. and high-income countries than the trade flows between the U.S. and middle-income countries. We see that the mean (standard deviation) of import competition from the middle-income countries is 1.15 (2.80) percent while the number from high-income countries is 2.22 (2.87) percent. Table 1 also highlights the fact that trade flows of different types of goods play different roles in exposure from middle-income countries. In particular, value-added imports of final goods accounts for the majority of the exposure to middle-income countries where the mean (standard deviation) of the import competition from value-added imports of final goods from middle-income countries is 0.72 (2.10) percent, whereas the mean (standard deviation) of the import competition from imports of intermediate goods from this group of countries is 0.33 (0.61) percent. Table 2.1 also indicates that the measures of trade vary in different routineness groups. We notice that as the level of occupations routines decreases, so does the exposure to value-added imports and exports.

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various measures of occupational exposure to value-added imports and exports depending on the income level of sourcing country (middle- vs high-income countries) as well as the types of traded goods (final goods vs intermediates).

## Table 2.1 Descriptive Statistics, 1996-2009

| Occupation-time measures | All Occupations | Most Routine | Intermediate Routine | Least Routine |
|---|---|---|---|---|
| *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) |
| 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) |
| Intermediate goods | 0.0026 | 0.0042 | 0.0021 | 0.0008 |
| | (0.0034) | (0.0042) | (0.0028) | (0.0012) |
| *IMP* high-income | 0.0222 | 0.0358 | 0.0176 | 0.0064 |
| | (0.0288) | (0.0349) | (0.0234) | (0.0093) |
| Export share high-income | 0.0122 | 0.0194 | 0.0097 | 0.0038 |
| | (0.0150) | (0.0177) | (0.0125) | (0.0057) |
| N of Observations | N = 3,533 | N = 1,260 | N = 1,672 | N =601 |

## 2.4 Baseline Results

### 2.4.1 Wages, skills, and exposure to value-added trade flows

#### 2.4.1.1 The role of sourcing countries: middle- vs. high-income countries

Shen, Silva, and Wang (2018) argue that the tasks performed by U.S. workers involved with the highest and medium level of routineness could be done in the middle-income countries. Therefore, as long as the exposure to value-added imports from this kind of countries (such as China, India, Mexico, and Indonesia) increases, the wages earned by most- and intermediate-routine workers are negatively affected. In particular, the impact for intermediate-routine workers is the most negative, which leads to polarization of U.S. wages. On the other hand, they find that the effect of greater exposure to value-added imports from high-income countries on U.S. wages is insignificant. We also notice that skilled workers could benefit from trade openness, while the opposite applies to unskilled workers in developed economies (Hummels et al. (2014). Therefore, it is possible that imports from middle- or high-income countries generate dissimilar effects for skilled workers compared to those who are unskilled.

We report the effects of U.S. occupational exposure to overall value-added imports on wages in Panel A of Table 2.2. The coefficient on import penetration in column (1) indicate that the effect of such exposure on the wages earned by the average unskilled worker is statistically insignificant though the coefficient is negative. For the average skilled workers, the sum of the coefficients for import penetration and its interaction with the skill indicator is negative even if it is not statistically different from zero (p-value for the Wald test in column (1) is 0.5087). Thus, for the average workers, the effect of occupational exposure is insignificant regardless of their skills.

Now we turn to look at the effects for workers involved in different levels of routineness in their occupations. Results in columns (2) and (3) imply that an increase in occupational exposure to value-added imports tends to decrease the wages earned by workers involved with a very or moderately routine occupation for skilled and unskilled workers alike. On the contrary, the estimates in column (4) suggest that workers with least-routine occupations enjoy wage gains when they are more exposed to value-added imports no matter what level of skill they have.

Notice that the economic magnitude of our results depends on the estimated coefficients. As for skilled individuals, a one standard deviation increase in this measure of exposure to imports is associated with a 5.64 percent and a 5.66 percent decrease for most- and intermediate-routine occupations respectively.[57] For those involved in the least-routine occupations, there is a 7.21 increase in wages. Thus, greater exposure to value-added imports is also likely resulting in the polarization of wages for U.S. skilled workers. In the case of unskilled workers, a one standard deviation increase in U.S. occupational exposure to value-added imports is associated with a 4.21 percent and a 7.04 percent decrease in the wages earned by workers with most- and intermediate-routine occupations, respectively.[58] By contrast, the wages earned by those with least-routine

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[57] Focusing on the skilled workers with most-routine occupations in column (2), the estimated coefficient equals to the summation of the coefficients of the occupational exposure to imports (-0.589) and its interaction with skill dummy (-0.201), which is -0.79. Therefore, the effect of a one standard deviation increase in exposure to value-added imports for skilled workers with most-routine occupations can be measured by calculating the product between a one standard deviation change in exposure to value-added imports for most-routine workers found on Table 2.1 (0.0715) and the estimated coefficient we got in column (2) of Table 2.2 (-0.79), which equals to a 5.64 percent decrease in wages for skilled workers involved with most-routine occupations.

[58] In column (2) of Table 2.2, the effect for most-routine workers who are unskilled can be obtained by multiplying the coefficient of occupational exposure to value-added imports, which is equal to -0.589, by the standard deviation of this variable faced by U.S. workers involved with most-routine occupations in Table 2.1 (which is 0.0715). Likewise, the effect for intermediate-routine workers who are unskilled in column (3) in the same table, is computed

occupations increase by 6.22 percent with a one standard deviation increase in such exposure. Combining the results in columns (2)-(4) for unskilled workers, we also observe that an increase in occupational exposure to value-added imports is driving the polarization of wages for American workers. These findings support the work of Shen, Silva, and Wang (2018) who find that changes in U.S. occupational exposure to value-added imports can explain the polarization of U.S. wages. In our study, we classify workers according to their level of skill and provide corroborating evidence that changes in exposure to value-added imports are associated with the polarization of wages across skill. Following Shen, Silva and Wang (2018), we want to identify the sources of the polarization of wages for workers with different levels of skill by assessing the U.S. exposure to value-added trade flows according to the sourcing countries (middle- vs. high-income countries).

The results using value-added trade flows from middle-income countries are shown in Panel B of Table 2.2. The results in column (1) represent the effects for the average workers, which indicate that an increase in exposure to value-added imports from middle-income countries has no significant effect on the wages earned by both skilled and unskilled workers. These effects are similar to their counterparts in Panel A. The effects for workers with different levels of routineness in their occupations are shown in columns (2)-(4). We find that the signs of the estimates in column (2)-(4) for unskilled workers are noticeably consistent with those in the previous panel. The results in columns (2)-(4) imply that unskilled workers with most- and intermediate-routine occupations are consistently under pressure from greater exposure to imports while those involved in least-routine occupations could still have a wage gain as those skilled workers in these occupations when they are exposed. By contrast, in the case of skilled workers, we do not see the negative

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by multiplying the coefficient of exposure to value-added imports in column (3) (which is -1.941) by the standard deviation of the corresponding term faced by intermediate-routine workers in Table 2.1 (which is 0.0363).

effects on workers with most- and intermediate-routine workers using value-added imports.[59] Moreover, the coefficient in column (4) for skilled workers is positive, and the effect is statistically different from zero. These numbers indicate that skilled workers who are engaged in the least-routine occupations have wage gains with greater exposure to imports.

Combining the results for skilled workers across different degrees of routineness, we see that the negative impact of exposure to imported goods is much mitigated for skilled workers when imports come from middle-income countries. On the contrary, among unskilled workers, the estimated coefficients in columns (2)-(4) imply that workers with most- and intermediate-routine occupations are consistently under pressure from greater exposure to imports while those involved in least-routine occupations experience wage gains when they are more exposed to imports. Thus, to what extent has been affected by exposure to imports from middle-income countries seems to depend on the level of skill.

[59] The p-value for the Wald test in columns (2) is equal to 0.1686, which suggests that the effect of changes in exposure to value-added imports on the wages earned by skilled workers involved with most-routine occupations is not statistically different from zero. Likewise, the p-value in column (3) is equal to 0.2360, which also suggest that the effect for intermediate-routine workers who are skilled are not statistically different from zero.

**Table 2.2 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Imports and Their Skill Interactions, 1996-2009**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A: All countries | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | -0.160 | -0.589*** | -1.941*** | 4.785** |
| | (0.232) | (0.220) | (0.693) | (2.243) |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | -0.046 | -0.201 | 0.380* | 0.764 |
| | (0.201) | (0.222) | (0.208) | (0.504) |
| Lagged export share | 2.099*** | 1.578* | 3.445** | -4.648 |
| | (0.786) | (0.797) | (1.370) | (2.945) |
| Skill | 0.255*** | 0.154*** | 0.220*** | 0.290*** |
| | (0.012) | (0.011) | (0.011) | (0.015) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.5087 | 0.0205 | 0.0341 | 0.0229 |
| Panel B: Middle-income countries | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | -0.485 | -0.954*** | -3.994** | 9.755** |
| | (0.349) | (0.306) | (1.583) | (4.519) |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | 0.343 | 0.023 | 1.615** | 3.016** |
| | (0.601) | (0.563) | (0.759) | (1.352) |
| Lagged export share | 6.527** | 3.499* | 6.060 | -10.749 |
| | (2.646) | (1.917) | (3.796) | (11.509) |
| Skill | 0.252*** | 0.148*** | 0.218*** | 0.289*** |
| | (0.012) | (0.010) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.8500 | 0.1686 | 0.2360 | 0.0101 |
| Panel C: High-income countries | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | 0.101 | -0.286 | -1.434 | -0.548 |
| | (0.599) | (0.489) | (1.160) | (2.228) |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | -0.187 | -0.465 | 0.425 | 0.924 |
| | (0.293) | (0.302) | (0.290) | (0.760) |
| Lagged export share | 2.461** | 1.113 | 2.949 | 0.800 |
| | (1.056) | (1.012) | (2.285) | (3.712) |
| Skill | 0.257*** | 0.158*** | 0.221*** | 0.292*** |
| | (0.013) | (0.011) | (0.011) | (0.015) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.8758 | 0.2060 | 0.3555 | 0.8743 |
| N of Observations | 1,491,807 | 366,486 | 665,118 | 460,129 |
| $R^2$ | 0.480 | 0.353 | 0.482 | 0.484 |

Note: The dependent variable is the log hourly wage. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Offshoring employment, computer use rates are taken from Ebenstein et al. (2014). Value-added import penetration and export share are obtained from Shen, Silva, and Wang (2018). The CPS data for workers age 22-64 are originated from the NBER MORG database. The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-thirds of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-thirds, and least-routine being less than one-third. Wage specification control for a worker's demographic information such as skill, gender, race, age and include industry-year, and state fixed effects Skill dummy equals one if worker i holds at least a bachelor's degree. Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. Computer use rates are by occupation, respectively. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

In Panel C of Table 2.2, we report the results using the value-added trade flows from high-income countries. Yet, we do not find any significant change in the wages for all skill levels from rising exposure to imports from other high-income countries.

From the analysis of Table 2.2 above, we see that the U.S wage polarization is more affected by value-added imports from middle-income countries than by the higher income ones. Furthermore, the impact of exposure to imports has a more negative effect on unskilled workers than on skilled workers when they are involved with most- and intermediate-routine occupations. For least-routine workers, the wages for both groups increase. In particular, skilled workers involved with the lowest level of routineness collect the largest wage gain with an increase in the exposure to imports from middle-income countries.

The effects of change in exposure to v-added exports are also shown in Table 2.2. In Panel A, we find that the augment of U.S. value-added exports has a positive and significant effect on the wages earned by the average worker. The positive values of estimates in column (1) of Panel B and C suggest that these effects come from exports to both the middle- and high-income countries. The results in columns (2)-(4) of Panel A for workers with different levels of routineness suggest that exposure to exports has more profound effects for those with most- and intermediate-routine workers. The wages earned by workers involved with least-routine occupations are not significantly affected by changes in exposure to exports. The results in Panel B echo the results in Panel A by showing that the expansion of exports to middle-income countries has a positive and significant effect on the wages earned by most-routine workers while the effect for intermediate-routine workers is also positive but insignificant. Again, the effect on least-routine workers is insignificant. In Panel C, the coefficients in columns (2)-(4) suggest that the effects for workers with different level of routineness are insignificant.

#### 2.4.1.2 The role of traded goods: final vs. intermediate goods

Our results using imports from different countries suggest that changes in the exposure to imports from middle-income countries are more related to the wage polarization in the U.S. than those from high-income countries. In the following, we decided to only look at the effect of trade flows from middle-income countries on wages for workers with different skills and occupations. We separate the trade flows by the type of traded products (final goods vs. intermediate inputs) following Shen, Silva, and Wang (2018). Our results are shown in Table 2.3.

We present the results using the data of final goods from middle-income countries in Panel A of Table 2.3. Again, the results in column (1) suggest that the effect for the average workers is insignificant regardless of their level of skill. As for workers with different occupations, the coefficients in columns (2)-(4) imply that an increase in exposure to imported final goods from middle-income countries is leading to the polarization of wages for both skilled and unskilled workers. However, the magnitudes of the effects for workers are varied by skill.

For skilled workers, the results in column (2) suggest that the effect of an increase in exposure to imported final goods from middle-income countries on the wages earned by the most-routine workers does not statistically deviate from zero while the effect in column (3) for intermediate-routine workers is negative and significant. A one standard deviation increase in exposure to final goods from middle-income countries is associated with a 7.26 percent decrease in the wages for intermediate-routine workers. Meanwhile, least-routine workers have higher wages when they are more exposed to such imports. The wages of these workers increase by 3.36 percent with a one standard deviation increase in the same event.

In the case of unskilled workers, the wages earned for most-routine occupations are depressed by more exposure to final goods from middle-income countries. The magnitude of this negative effect increases for those who perform a moderate level of routineness in their occupations. To be specific, a one standard deviation increase in the exposure to final goods from middle-income countries is associated with a 3.4 percent decrease in wages earned by the most-routine workers. For the intermediate routine workers, we find a 9.32 percent decrease in wages with the same exposure. As for the least-routine workers who are unskilled, unlike their skilled counterparts, changes in the exposure to final goods have no significant effect on their wages, albeit the coefficient is positive.

Comparing the effects for skilled and unskilled workers within each degree of routineness in column (2)-(4) of Panel A, we show that the level of skill does matter in the evaluation for distributional effects on U.S. wages. Skilled workers tend to be less harmed by exposure to value-added imports than their unskilled counterparts when they are involved in the most- or intermediate-routine occupations (e.g., decrease by 7.26 percent vs. by 9.32 percent for intermediate-routine workers). In the least-routine occupations, skilled workers significantly benefit from an increase in that exposure while the effect on the wages earned by unskilled individuals is insignificant. (i.e., increases by 3.35 percent vs. insignificant).

In panel B, we examine the impact of intermediate goods imported from middle-income countries on the U.S. wages. We do not observe the U-shaped trend in this panel. Instead, we find that changes in such exposure has no significant effect on the wages of workers with most- and intermediate-routine occupation but have a positive and significant effect on the wages earned by the workers with least-routine occupations. Similar to the effect when considering trade flows in final goods, this positive effect for least-routine workers is much larger for those who are skilled.

**Table 2.3 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Imports in Final and Intermediate Goods from Middle-Income Countries and Their Skill Interactions, 1996-2009**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A: Value-added imports in final goods from middle-income countries | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | -0.562 | -1.066*** | -8.874*** | 9.130 |
| | (0.524) | (0.334) | (1.881) | (6.489) |
| Lagged import penetration $\times$ Skill ($\widehat{\beta_2}$) | 0.455 | 0.105 | 1.961 | 5.477** |
| | (0.891) | (0.756) | (1.195) | (2.409) |
| Lagged export share | 12.086* | 3.680 | 27.596*** | 12.132 |
| | (6.715) | (2.884) | (6.274) | (28.878) |
| Skill ($\widehat{\beta_3}$) | 0.252*** | 0.148*** | 0.221*** | 0.288*** |
| | (0.012) | (0.009) | (0.011) | (0.015) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.9239 | 0.2748 | 0.0031 | 0.0398 |
| Panel B: Value-added imports in intermediate goods from middle-income countries | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | 0.755 | -1.483 | 1.644 | 34.751*** |
| | (1.525) | (1.159) | (5.078) | (11.811) |
| Lagged import penetration $\times$ Skill ($\widehat{\beta_2}$) | 1.885 | -0.689 | 5.811*** | 7.740** |
| | (2.072) | (2.394) | (2.134) | (3.723) |
| Lagged export share | 7.812** | 4.477 | -8.052 | -31.223** |
| | (3.835) | (3.393) | (7.885) | (15.181) |
| Skill ($\widehat{\beta_3}$) | 0.251*** | 0.150*** | 0.216*** | 0.291*** |
| | (0.012) | (0.011) | (0.010) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.2714 | 0.4466 | 0.1874 | 0.0012 |
| N of Observations | 1,491,807 | 366,486 | 665,118 | 460,129 |
| $R^2$ | 0.480 | 0.353 | 0.482 | 0.485 |

Note: Dependent variable is log hourly wage. Skill is a binary variable which equals to one if worker i holds at least a bachelor degree. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. See Table 2.2 for the source. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

occupations by 5.52 percent and by 4.51 percent respectively. In short, our results confirm one of the findings in Shen, Silva, and Wang (2018) that the value-added imports in intermediate inputs from middle-income countries are displaying a strong complementary effect among U.S. workers who perform the lowest level of routineness in their occupations. Furthermore, this complementary effect is larger for skilled workers than for unskilled individuals.

Thus far, we examine the impacts of value-added imports from different countries and different types of goods on the wages of U.S. workers in Tables 2.2 and 2.3. The results suggest that polarization of U.S. wages for both skilled and unskilled workers are driven by the rising import competition from middle-income countries. Particularly, this phenomenon is attributed to the import competition from final goods. The negative effect of greater exposure to final goods is more prevalent among unskilled workers than among the skilled. On the other hand, greater exposure to intermediate inputs from middle-income countries does not lower the wages. Rather, it suggests a complementary effect for those involved with the least-routine occupations. Again, the positive effect is larger for skilled workers

Notice that trade exposure not only affects the wages but also should have a great influence on employment opportunities (e.g., Autor et al. (2013)). Next, we want to study how an increase in exposure to value-added imports affects the uncertainty related to unemployment at the individual level.

### 2.4.2 Value-added imports and the uncertainty of unemployment

In this section, we focus on the effect of various value-added trade imports on the probability of being unemployed for U.S. workers. The results are shown in Table 2.4, which consists of two panels. In Panel A, we report the results for workers age 22 and older.

In Panel A, we see that the economic opportunities for skilled workers and unskilled workers are not affected by the same type of trade flows. In terms of skilled workers, the results in column (1) suggest that an increase in exposure to value-added imports is not significantly associated with an increase in the probability of being unemployed for the average skilled worker.[60] We report the results using the value-added trade flows from different sourcing countries in Columns (2)-(5). The results in column (2) suggest that an increase in exposure to value-added imports from high-income countries has a positive and significant effect on the probability of being unemployed for skilled workers. By the contrary, the effect of exposure to imports from middle-income countries is insignificant for skilled workers according to the results in column (2)-(4). Overall, the results in Panel A suggests that the competitors of U.S. skilled workers are those from high-income countries. Therefore, higher exposure to import from high-income countries, the employment uncertainty is more likely to increase for skilled workers.

[60] In column (1), the p-value of the Wald test is 0.1136, which suggests that the effect of changes in exposure to value-added imports on the probability of being unemployed for the average skilled workers is not statistically different from zero.

**Table 2.4 LPM Estimates of Unemployment Uncertainty Determinants Using Occupational Exposures to Value-Added Imports and Their Skill Interactions**

| | All Occupations | | | | |
|---|---|---|---|---|---|
| | All Countries All goods | High-Income All goods | Middle-Income All goods | Middle-Income Final Goods | Middle-Income Intermediate Goods |
| Variable | (1) | (2) | (3) | (4) | (5) |
| Panel A: Adult population (22-64 years old) | | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | 0.104* | 0.190 | 0.121 | 0.079 | 0.767** |
| | (0.053) | (0.124) | (0.077) | (0.090) | (0.361) |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | -0.007 | 0.038 | -0.198*** | -0.295*** | -0.677*** |
| | (0.028) | (0.042) | (0.070) | (0.103) | (0.260) |
| Lagged export share | -0.301* | -0.537** | -0.388 | -0.024 | -1.204* |
| | (0.162) | (0.243) | (0.468) | (0.959) | (0.705) |
| Skill ($\widehat{\beta_3}$) | -0.009*** | -0.010*** | -0.198*** | -0.008*** | -0.008*** |
| | (0.001) | (0.001) | (0.070) | (0.001) | (0.001) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.1136 | 0.0663 | 0.4697 | 0.1137 | 0.8364 |
| N of Observations | 2,050,808 | 2,050,808 | 2,050,808 | 2,050,808 | 2,050,808 |
| Panel B: Prime-age population (25-54 years old) | | | | | |
| Lagged import penetration ($\widehat{\beta_1}$) | 0.150*** | 0.243* | 0.192*** | 0.180** | 0.959** |
| | (0.052) | (0.126) | (0.070) | (0.087) | (0.409) |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | 0.002 | 0.056 | -0.204*** | -0.314*** | -0.662** |
| | (0.030) | (0.045) | (0.075) | (0.109) | (0.270) |
| Lagged export share | -0.425*** | -0.680*** | -0.687 | -0.766 | -1.555** |
| | (0.160) | (0.256) | (0.462) | (1.009) | (0.720) |
| Skill ($\widehat{\beta_3}$) | -0.010*** | -0.010*** | -0.009*** | -0.009*** | -0.009*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.0122 | 0.0218 | 0.9087 | 0.3430 | 0.5291 |
| N of Observations | 1,650,642 | 1,650,642 | 1,650,642 | 1,650,642 | 1,650,642 |

Note: Dependent variable is the probability of being unemployed, which equals to one if worker i is unemployed at period t. Skill is a binary variable which equals to one if worker i holds at least a bachelor degree. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. See Table 2.2 for the source. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent levels

For the unskilled workers, on the other hand, the effect of an increase in exposure to imports from high-income countries in column (2) is insignificant. Using the trade flows from middle-income countries, we do not find significant effects in column (3). When we distinguish the trade flows from middle-income countries by types of goods in columns (4) and (5). Surprisingly, the effect of an increase in exposure to final goods on the likelihood of being unemployed for unskilled workers is positive but insignificant. The greater the exposure to imports in intermediate inputs from middle-income countries, the more likely to be unemployed for U.S. unskilled workers.

As discussed in Keller and Utar (2018), the degree of trade adjustment also depends on age. The effect of trade shock is more crucial to younger workers due to their family responsibility. Autor et al. (2018) also focus on the effects of trade on the outcomes for young workers. Motivated by these studies, we would like to limit the sample of workers to those who are in the prime age (i.e., workers aged 25-54) and examine the effect of greater exposure to imports on the economic uncertainty for these workers. Our results are shown in Panel B.

In the case of skilled workers, results in column (1) of Panel B suggest that the greater exposure to imports from all sources, the greater the chance of being unemployed. The results in column (2) are similar to those in Panel A for all adult workers, which indicates that an increase in exposure to imports from high-income countries is associated with an increase in the probability of being unemployed. Results in column (3)-(5) show that the effect for prime-age skilled workers is insignificant when we use trade flows from middle-income countries. Thus, the economic uncertainty for the prime-age U.S. workers who are skilled is affected by rising import competition from the high-income countries, not the middle-income countries.

By contrast, for unskilled American workers who are prime-age, the results in Panel B suggest that the probability of being unemployed increases with greater exposure to the value-added imports from all sources as well as all types of value-added trade flows. Results in column (1) suggest that a one standard deviation increase in exposure to imports from all sourcing countries is associated with a 0.8 percentage point increase in the likelihood of being unemployed for unskilled workers who are in the prime age. The results in columns (2) and (3) are also positive and significant, which indicate that the increase of the probability of being unemployed is attributed to exposure to imports from both high- and middle-income countries. The positive and significant coefficients in columns (4) and (5) suggest that unskilled workers are likely to be unemployed when they face greater exposure to both final goods and intermediate inputs. Specifically, a one standard deviation increase in exposure to final goods from middle-income countries is associated with a 0.38 percentage point increase in the uncertainty related to unemployment while the effect from a one standard deviation increase in the exposure to intermediate inputs is around 0.58 percentage point.

In short, our results in Table 2.4 suggest that the increase in value-added trade is more likely to increase the uncertainty related to unemployment for unskilled workers than for skilled workers. The effect is more profound for younger workers (i.e., the prime-age workers), which is in line with Keller and Utar (2018) and Autor et al. (2018).

### 2.4.3 Value-added imports and occupation mobility

In this section, we attempt to assess the cost of trade-induce occupation shifts between period t and period t+1. We build on the empirical strategies in Ebenstein et al. (2014) and Hummels et al. (2014) by including the heterogeneous effects across workers with different skill levels. The switching in this study is defined using the three-digit occupational classification. As stated in Section 2.2, we construct an instrument to explore the effects of trade-induced occupational switching between periods on the wages. Table 2.5 presents the 2SLS results for workers ages 22 and older where the switching dummy is instrumented by a binary indicator which uses the median of offshoring employment in middle-income affiliates in 1991 as the cutoff.

**Table 2.5 Wage Impacts of Switching Three-Digit Occupation, 1996-2009**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A | | | | |
| Switch between T and T+1 ($\eta_1$) | -0.128*** | -0.120* | -0.09* | -0.339*** |
| | (0.043) | (0.062) | (0.052) | (0.089) |
| F-test (first-stage) | 47.20 | 11.94 | 19.88 | 12.79 |
| Panel B | | | | |
| Switch between T and T+1 ($\eta_1$) | -0.152*** | -0.168** | -0.113** | -0.429*** |
| | (0.041) | (0.067) | (0.051) | (0.136) |
| Switch between T and T+1 * $Skill_T$ ($\eta_2$) | 0.068* | 0.247*** | 0.068 | 0.186 |
| | (0 .041) | (0 .083) | (0 .044) | (0 .154) |
| Test $\eta_1 + \eta_2 = 0$ (P-value) | 0.1075 | 0.2227 | 0.4203 | 0.0098 |
| SW F-test for $\eta_1$(first-stage) | 52.52 | 10.22 | 23.55 | 6.90 |
| SW F-test for $\eta_2$ (first-stage) | 48.56 | 12.49 | 23.54 | 11.36 |
| N of Observations | 513,627 | 126,215 | 225,494 | 161,918 |

Note: The dependent variable is the difference in worker's log hourly wage between period t and t+1. The sample is composed of MORG CPS workers age 22-64 who are observed in two consecutive periods. Skill is a binary variable which equals one if the worker holds at least a bachelor's degree. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year level in the period t. In Panel A, we report standard first-stage F-test. In Panel B, we report the Sanderson-Windmeijer F-test instead. See Table 2.2 for the source. Superscript "**," "*," "*" represent statistical significance at the 1,5 and 10 percent levels.

Firstly, we follow the original strategy in Ebenstein et al. (2014) and estimate the general impact across workers without interaction with skills. These results are reported in Panel A. In column (1), we find that trade-induced occupation switches are associated with a 12.8 percent decrease in wage earned by the average worker. This result is comparable to the effect in Ebenstein et al. (2014), where trade-induced occupational switches are associated with a 12.1 percent decrease for the period 1984-2002.[61] Columns (2)-(4) shows the results for the workers in each routineness group. The coefficients are negative and significant for all three routineness groups. Compared with the most- and intermediate-routine workers, least-routine workers suffer the most substantial wage decline (33.9 percent decline in wages earned by the least-routine workers). The cost of shifts in occupations for most- and intermediate-routine workers are close (12 percent for most-routine workers and 9 percent for intermediate-routine workers). A possible explanation for this might be that the human capital formed on the least-routine occupations are less transferable to the other occupations. Thus, least-routine workers face the most significant wage drop. In the lower panel of Table, we add the interaction term between the trade-induced switch and an indicator for whether the worker is skilled, as in expression (2.5), which allows for variations in the costs of occupation shifts within unskilled groups versus skilled groups.

We find that, in panel B of Table 2.5, U.S. unskilled workers experience greater wage drop than skilled workers when they switch. For instance, the results presented in column (1) indicate that trade-induced occupational switches are associated with a 15.2 percent decrease for unskilled workers while the shifting cost for skilled workers does not statistically differ from zero.[62] Columns (2)-(4) show the results for workers involved with occupations in different degree of routineness. Among unskilled workers, the magnitude of the impact of trade-induced occupational switches is larger on the wages earned by the most-routine workers than on the intermediate-routine workers. The size of the wage decline for intermediate-routine workers is 11.3 percent, while the magnitude for most-routine workers is 16.8 percent. While the magnitudes of the wage

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[61] See Table 7 in Ebenstein et al. (2014).

[62] The p-value for Wald test in column (1) is 0.1075.

loss for most- and intermediate-routine workers are similar to the effect for all workers, the wage decline for those in the least-routine occupations is 42.9 percent which seems to be unprecedented.

As for skilled workers, the results in columns (2) and (3) in Table 2.5 imply that the cost of switching in occupation for the workers in the most- and intermediate-routine occupation are not statistically different from zero. However, the wage of skilled workers involved with occupations displaying the lowest level of routineness will decrease if they have trade-induced shifts. In short, switching is costly among all unskilled and the skilled workers in the least-routine occupations.

So far, we have explored the critical role of skill in explaining the heterogeneous effects of exposure to value-added trade across workers involved with occupations displaying different degrees of routineness on the wages, uncertainty related to unemployment and the cost of trade-induced occupation switch. In the next section, we provide results for robustness on our baseline regressions.

## 2.5. Robustness

In this section, we assess the robustness of our results. We show that the main results are not sensitive to the changes in the sample as well as alternative specifications as follows.

### 2.5.1 Prime-age workers

As in Panel B of Table 2.4, here, we re-estimate the effects of value-added trade exposure on U.S. wages and on the cost of mobility using the sample of prime-age workers. The results are shown in Table 2.6-2.8. In the specification for wages, the U-shaped trend on wages, which is resulting from an increase in exposure to value-added imports still exists in Table 2.6. The magnitudes on the unskilled workers who are in the prime age in Table 2.6 are comparable to the results for the full sample in Table 2.2. For example, the results in Panel B of Table 6 suggests that a one standard deviation increase in occupational exposure to value-added imports from middle-income countries is associated with a 4.24 percent decrease (vs. a 3.98 decrease in Table 2) in the wages of the most-routine workers, a 6 percent decrease (vs. a 5.96 decrease) in the wages of the intermediate-routine workers and a 3.53 percent decrease (vs. a 3.8 decrease) in the wages earned by prime-age workers with least-routine occupations who are unskilled. Again, the estimates in Table 2.7 also confirms the role of production good in explaining the heterogeneous effects of exposure to value-added imports on wages. The results in Table 2.2.7 suggest that the negative effect of being exposed to more imported final goods from middle-income countries is more prevalent on the wages earned by unskilled workers, not skilled workers. We report the results for the occupational mobility in Table 2.8 using the sample of prime-age workers. The estimates in this table echo with those in Table 2.5 where we find that occupation switching is very costly for unskilled workers in general. In the case of skilled workers, only least-routine workers are negatively affected by occupation switching.

**Table 2.6 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Imports and Their Skill Interactions, 1996-2009, Prime-Age Workers Age 25-54**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A: All countries | | | | |
| | -0.205 | -0.581** | -1.882*** | 4.779** |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.249) | (0.235) | (0.716) | (2.299) |
| | -0.065 | -0.214 | 0.339 | 0.621 |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.199) | (0.232) | (0.211) | (0.495) |
| | 2.264*** | 1.675** | 3.457** | -4.122 |
| Lagged export share | (0.801) | (0.815) | (1.405) | (3.015) |
| | 0.262*** | 0.164*** | 0.229*** | 0.295*** |
| Skill | (0.012) | (0.012) | (0.011) | (0.015) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.3983 | 0.0246 | 0.0420 | 0.0298 |
| Panel B: Middle-income countries | | | | |
| | -0.634* | -1.016*** | -4.031** | 9.064* |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.368) | (0.323) | (1.604) | (4.713) |
| | 0.403 | 0.030 | 1.643** | 2.847** |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.591) | (0.578) | (0.765) | (1.354) |
| | 7.095*** | 3.916** | 6.437* | -7.867 |
| Lagged export share | (2.649) | (1.941) | (3.774) | (12.313) |
| | 0.259*** | 0.157*** | 0.226*** | 0.293*** |
| Skill | (0.011) | (0.011) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.7553 | 0.1603 | 0.2374 | 0.0207 |
| Panel C: High-income countries | | | | |
| | 0.187 | -0.105 | -1.348 | -0.212 |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.590) | (0.505) | (1.176) | (2.255) |
| | -0.246 | -0.499 | 0.339 | 0.666 |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.288) | (0.316) | (0.292) | (0.734) |
| | 2.450** | 1.038 | 2.965 | 1.150 |
| Lagged export share | (1.059) | (1.031) | (2.314) | (3.765) |
| | 0.264*** | 0.167*** | 0.231*** | 0.298*** |
| Skill | (0.012) | (0.012) | (0.011) | (0.015) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.9140 | 0.3253 | 0.3649 | 0.8498 |
| N of Observations | 1,215,572 | 292,429 | 541,374 | 381,669 |
| $R^2$ | 0.478 | 0.351 | 0.479 | 0.482 |

Note: All regressions include the full set of control variables from Table 2.2. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period. See Table 2.2 for the source. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

**Table 2.7 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in Final and Intermediate Goods from Middle-Income Countries and Their Skill Interactions, 1996-2009, Prime-Age Workers Age 25-54**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A: Value-added imports in final goods from middle-income countries | | | | |
| | -0.755 | -1.145*** | -8.950*** | 8.958 |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.543) | (0.357) | (1.889) | (6.654) |
| | 0.512 | 0.112 | 2.003* | 5.086** |
| Lagged import penetration $\times$ Skill ($\widehat{\beta_2}$) | (0.869) | (0.769) | (1.195) | (2.403) |
| | 13.232* | 4.595 | 28.011*** | 15.451 |
| Lagged export share | (6.742) | (2.934) | (6.169) | (31.368) |
| | 0.259*** | 0.157*** | 0.229*** | 0.292*** |
| Skill ($\widehat{\beta_3}$) | (0.011) | (0.010) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.8259 | 0.2591 | 0.0030 | 0.0548 |
| Panel B: Value-added imports in intermediate goods from middle-income countries | | | | |
| | 0.457 | -1.667 | 1.723 | 32.334** |
| Lagged import penetration ($\widehat{\beta_1}$) | (1.567) | (1.320) | (5.132) | (12.284) |
| | 2.190 | -0.693 | 5.900*** | 7.426* |
| Lagged import penetration $\times$ Skill ($\widehat{\beta_2}$) | (2.071) | (2.509) | (2.198) | (3.766) |
| | 8.402** | 5.065 | -7.343 | -25.931 |
| Lagged export share | (3.886) | (3.482) | (7.728) | (16.896) |
| | 0.257*** | 0.159*** | 0.224*** | 0.295*** |
| Skill ($\widehat{\beta_3}$) | (0.012) | (0.012) | (0.010) | (0.013) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.2781 | 0.4291 | 0.1779 | 0.0031 |
| N of Observations | 1,215,572 | 292,429 | 541,374 | 381,669 |
| $R^2$ | 0.478 | 0.351 | 0.479 | 0.482 |

Note: All regressions include the full set of control variables from Table 2.3. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period. See Table 2.3 for the source. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent levels

### 2.5.2 Potential sample selection resulting from unobservable factors

We focus on the employed workers when we study the effect of trade exposure on wages as shown in expression (2.1). The characteristics of these workers might differ from those who choose not to work in many aspects. As discussed in the labor market outcome literature, work decision is highly related to the individual's self-interest. We cannot ignore the potential selection bias in our sample. In the spirit of Trefler and Liu (2019), we apply the Heckman selection model using the method of maximum likelihood estimation. Since an individual's work decision could be affected by the family decision that has been excluded from our baseline model as well as from model in Ebenstein et al. (2014). In this exercise, we include a binary variable for marital status (i.e., whether the individual is married or not) in the selection equation.[63] The results for the selection equations are shown in Table 2.8. The correlation between equations, $\rho$, and the p-value for the Wald test of the independent equation are reported at the bottom of this table. The statistics for the Wald test indicate that selection bias fails to be rejected in most cases except for intermediate-routine workers. More importantly, the coefficients do not affect much by the correction.

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[63] As discussed in Trefler and Liu (2019), number of children is an alternative variable to be included in the selection equation. We compare these results to those which only include marital status. We find that our conclusion related to wage polarization are barely affected by adding number of children in the selection equation. In addition, number of children is not available for the period between 1996 and 1998 in the CPS-MORG. Therefore, we decided to only include marital status in the selection equation. Results using both marital status and number of children are available upon request.

**Table 2.8 Corrections for the CPS Sample Selection,.1995-2009, Workers Age 22-64**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| Panel A: All countries | | | | |
| | -0.168 | -0.612*** | -1.769** | 3.892* |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.234) | (0.229) | (0.720) | (2.168) |
| | -0.013 | -0.261 | 0.438** | 0.919* |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.206) | (0.233) | (0.215) | (0.535) |
| | 2.176*** | 1.654 | 3.045** | -4.381 |
| Lagged export share | (2.176) | (0.824) | (1.405) | (2.725) |
| | 0.261*** | 0.166 | 0.226*** | 0.294*** |
| Skill | (0.012) | (0.012) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.5677 | 0.0131 | 0.0808 | 0.0397 |
| $\rho$ (the correlation between equations) | 0.037 | 0.028 | -0.021 | 0.069 |
| Wald test of independent equations (P-value) | 0.008 | 0.020 | 0.408 | 0.001 |
| Panel B: Middle-income countries | | | | |
| | -0.533 | -0.990*** | -3.856** | 7.640* |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.354) | (0.323) | (1.630) | (4.315) |
| | 0.367 | -0.115 | 1.785** | 3.317** |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.616) | (0.580) | (0.794) | (1.444) |
| | 6.857** | 3.729** | 5.423 | -8.535 |
| Lagged export share | (2.685) | (1.979) | (3.797) | (10.653) |
| | 0.259*** | 0.160*** | 0.225*** | 0.294*** |
| Skill | (0.012) | (0.011) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.8288 | 0.1170 | 0.3133 | 0.0192 |
| $\rho$ (the correlation between equations) | 0.038 | 0.030 | -0.020 | 0.072 |
| Wald test of independent equations (P-value) | 0.008 | 0.011 | 0.417 | 0.001 |
| Panel C: High-income countries | | | | |
| | 0.138 | -0.330 | -1.143 | -1.184 |
| Lagged import penetration ($\widehat{\beta_1}$) | (0.612) | (0.503) | (1.164) | (2.123) |
| | -0.126 | -0.551* | 0.504* | 1.196 |
| Lagged import penetration × Skill ($\widehat{\beta_2}$) | (0.298) | (0.319) | (0.298) | (0.809) |
| | 2.481** | 1.215 | 2.305 | -0.177 |
| Lagged export share | (1.057) | (1.052) | (2.286) | (3.159) |
| | 0.263*** | 0.169*** | 0.227*** | 0.296*** |
| Skill | (0.012) | (0.012) | (0.011) | (0.014) |
| Test $\widehat{\beta_1} + \widehat{\beta_2} = 0$ (p-value) | 0.9827 | 0.1494 | 0.5611 | 0.9958 |
| $\rho$ (the correlation between equations) | 0.038 | 0.028 | -0.021 | 0.072 |
| Wald test of independent equations (P-value) | 0.007 | 0.018 | 0.396 | 0.001 |
| N of Observations | 204,810 | 22,294 | 80,675 | 101,841 |
| Uncensored N of Observations | 1,684,314 | 416,146 | 751,421 | 516,747 |

Note: In the selection equation, we include the marriage dummy with the full set of control variables used in Table 2.2. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

### 2.5.4 Alternative occupation classification scheme

So far, we define the occupation switch at the three-digit level. In Table 2.9, we report the results when we define occupation switching at the one-digit level as in Ebenstein et al. (2014).[64] The findings are very similar to those in Table 2.5 where the effect on the change in wages between periods is negative and significant for unskilled workers regardless of the degree of routineness in their occupations at the three-digit level. In the case of skilled workers, according to the p-value of the Wald test, wages earned by those involved with most- and intermediate-routine occupations are not significantly affected when they change occupations at one-digit level, while the effect for least-routine workers is negative and significant.

**Table 2.9 Wage Impacts of Switching One-Digit Occupation, 1996-2009**

| Variable | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) |
|---|---|---|---|---|
| | Panel A | | | |
| Switch between T and T+1 ($\eta_1$) | -0.174*** | -0.135** | -0.142* | -0.240*** |
| | (0.046) | (0.065) | (0.077) | (0.051) |
| F-test (first-stage) | 26.84 | 13.42 | 15.55 | 18.34 |
| | Panel B | | | |
| Switch between T and T+1 ($\eta_1$) | -0.206*** | -0.180*** | -0.173** | -0.248*** |
| | (0.043) | (0.068) | (0.071) | (0.054) |
| Switch between T and T+1 * $Skill_T$ ($\eta_2$) | 0.085 | 0.285*** | 0.086 | 0.020 |
| | (0.058) | (0.093) | (0.079) | (0.089) |
| Test $\eta_1 + \eta_2 = 0$ (P-value) | 0.0531 | 0.2499 | 0.3652 | 0.0089 |
| SW F-test for $\eta_1$(first-stage) | 24.27 | 11.68 | 14.16 | 14.68 |
| SW F-test for $\eta_2$ (first-stage) | 34.00 | 14.49 | 17.39 | 17.42 |
| N of Observations | 513,627 | 126,215 | 225,494 | 161,918 |

Note: The dependent variable is the difference in worker's log hourly wage between period t and t+1. The sample is composed of MORG CPS workers age 22-64 who are observed in two consecutive periods. Skill is a binary variable which equals one if the worker holds at least a bachelor's degree. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year level in the period t. In Panel A, we report standard first-stage F-test. In Panel B, we report the Sanderson-Windmeijer F-test instead. See Table 2.2 for the source. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent levels

[64] Ebenstein et al. (2014) aggregate the occupations according to the broad classifications in the 1990 occupation scheme made available by Bureau of Census. The one-digit occupation category contains: executive, administrative, and managerial occupations, management related occupations, professional specialty occupations, technicians and related support occupations, sales occupations, administrative support occupations, housekeeping and cleaning occupations, protective service occupations, other service occupations, farm operators and managers, other agricultural and related occupations, mechanics and repairers, construction trades, extractive occupations, precision production occupations, machine operators, assemblers, and inspectors, transportation and material moving occupations.

## 2.6. Conclusion

We highlight the critical role of skill in explaining the heterogeneous effect of value-added trade on U.S. workers' labor market outcomes. We find that the impacts of value-added trade on workers with different degrees of routineness are varied by skill. We have three contributions to the literature. First, we uncover the variations related to the skill levels of workers hidden in the polarization of U.S. wages. We find that an increase in occupational exposure to value-added trade is resulting in the wage polarization for workers in both skill groups. We categorize the trade flows according to the sourcing countries and the types of traded goods. We find that changes in value-added imports in final goods from middle-income countries have the most negative effect on workers with intermediate-routine occupations regardless of their level of skill. This source of trade flows is driving up the wage polarization in the U.S. Furthermore, we notice that the magnitude of the negative effect of value-added trade on wages depends on the worker's skill level. For instance, skilled workers involved in the intermediate-routine occupations tend to experience a smaller wage drop than their unskilled counterparts. The results using exposure to value-added imports in intermediate goods from middle-income countries suggest that the tasks performed by foreign workers involved with the production of intermediate components are complements to tasks performed by domestic workers who are employed in the least-routine occupations. For those least-routine workers, skilled workers gain more than unskilled individuals.

Second, we consider the role of skill in the analysis of the relationship between value-added trade and economic likelihood related to unemployment. We summarize the impacts of different types of value-added imports on the probability of being unemployed for U.S. workers. We find that those unskilled workers are relatively vulnerable than skilled workers. As long as the exposures to value-added trade increase, the probability of being unemployed for unskilled workers would increase. On the other hand, the likelihood of being unemployed for skilled workers is only associated with the changes in exposure to imports from high-income countries.

Third, we employ a matched sample from the CPS-MORG to measure the changes in wages between period t and t+1 when workers switch occupations due to trade. We find that occupational switching is costly. And this negative effect on wages is more prevalent among unskilled workers.

In short, we examine the effects of value-added trade in more detailed than those earlier studies. Our findings are helpful for policymakers to distinguish between winners and lowers of current trade policy.

# Chapter 3 - Gender and The Heterogeneous Effects of International Trade

## 3.1 Introduction

In recent decades, we have observed that female workers in the U.S. are getting more active in the labor market than before. For example, female workers have experienced an increase in wages and years of working experience. Furthermore, their labor force participation rate has raised, while their male counterpart has declined (Blau and Kahn, 2017). Some economists argue that these changes in U.S. labor market result in the changes in family formation (Bertrand et al., 2015). At the same time, some researchers find that many of these changes in U.S. labor market can, at least in part, be attributed to adverse trade shocks (Autor et al., 2013; Autor et al., 2014; Acemoglu et al., 2016). In addition, international trade may affect workers' family outcomes.

For instance, Keller and Utar (2018) link firm-level import penetration ratio to Danish worker-level family outcomes. They argue that import competition is a "pro-family" shifter in the labor market, and the adjustment is mainly related to female workers, not males. Their results suggest that an increase in exposure to imports has a greater negative effect on the earnings of female workers. Moreover, their results suggest that female marriage rate increases together with import penetration while the effect for men is moderate and insignificant.

Likewise, Autor et al. (2018) relate trade shocks to U.S. wages, employment as well as family outcomes while controlling for workers' gender. Unlike the work of Keller and Utar (2018), they find that the negative effects of exposure to imports at the local labor market level are more concentrated on young male workers than on females. In their opinion, negative trade shock leads to poorer economic prospects for young males, which are associated with a decline in their marriage incentives. As a result, there is a higher rate of never-married women and unmarried mothers in the labor force.

Another paper, Braga (2018) studies the effect of trade exposure on marriage rates by gender in Brazil. He finds that an increase in trade liberalization leads to a substantial decline in local employment. In line with Autor et al. (2018), he finds that this effect is more detrimental to male workers than to female workers. However, he argues that there is no causal relationship between changes in marriage rates and changes in trade exposure at the regional level, which clearly differs from the findings discussed in Autor et al. (2018).

In this paper, we complement the existing literature by providing evidence that increasing import exposure has differential effects on individual outcomes depending on the workers' gender and on the degree of routineness of their occupations. Unlike the previous studies which quantify trade exposure using gross trade data, we build on the work of Shen and Silva (2018) and attempt to study these issues using measures of value-added trade. At the same time, we control for the degree of occupational routineness and gender following Ebenstein et al. (2014).

In the spirit of Autor et al. (2018), we construct gender-specific exposure to value-added trade to investigate the effects of change in trade-related exposure on wages, on the probability of being unemployed and on the likelihood of being married. Our main conclusions can then be presented in three main groups of results. First, our results suggest that an increase in gender-specific exposure to value-added imports leads to wage polarization for both male and female workers. In both gender groups, we find that workers in the intermediate-routine occupations experience the most massive negative impact from an increase in the exposure to value-added imports causing a U-shaped pattern in the distribution. These results make it evident that international trade tends to produce gender-related homogeneous effects on workers' wages. When we make a distinction based on the role of goods in the production process, we see that the polarization of wages is more attributed to final goods rather than intermediate inputs.

Our second set of results indicate that an increase in male-specific exposure to value-added imports has no significant effect on the probability of being unemployed for U.S. male workers regardless of the degree of routineness in their occupations. However, when considering the exposure to finals goods solely, our results suggest that U.S. male workers have a higher risk of being unemployed when performing intermediate-routine occupations. Instead, greater exposure to imports of intermediates inputs leads to the opposite result for male workers in intermediate-routine occupations.

In the case of U.S. female workers, changes in female-specific exposure to all imports are likely to increase the employment uncertainty for the average female worker. Moreover, this effect is mainly present among those female workers involved with the lowest degree of routineness in their occupations. These results highlight an important source of heterogeneity in the effects of international trade according to workers' gender. In the case of final goods, the pattern is consistent with the results using imports from all goods. For intermediate inputs, the effect of female-specific exposure raises the likelihood of being unemployed for women who work in the least-routine occupations, while the effects on other groups of female workers are insignificant.

In the third exercise, we examine the effects of value-added trade on marriage outcomes.[65] Our results suggest that rising male-specific import exposure reduces the likelihood of being married for male workers in intermediate-routine occupations, while the effect on men who work in the most- and least-routine occupations is insignificant. Our findings are consistent with the

[65] We do not investigate the mechanism related to how international trade affect the family formation in this paper.

work of Autor et al. (2018), which supports that rising gender-specific import penetration reduces the fraction of marriages. This paper is among the first to presenting evidence on how gender-specific trade exposure affects individual outcomes using value-added trade flows.

The remainder is organized as follows. Section 2 introduces our empirical approach. Section 3 describes the data. Section 4 shows how an increase in gender-specific exposure to value-added imports leads to the polarization of U.S. wages, the unemployment likelihood, as well as the probability of being married. Section 5 reports the robustness of our results, and Section 6 provides conclusions.

## 3.2 Empirical Strategy

As discussed in Shen and Silva (2018), the effects of gross trade on labor market outcomes can be different from those using value-added trade flows. Additionally, value-added trade flows can be used to investigate how the contribution of different exporters differently affect labor market outcomes in the importing economy. In this paper, we aim to examine the effects of U.S. gender-specific exposure to value-added trade on individual outcomes such as wages, the probability of being unemployed, and the likelihood of being married. Ebenstein et al. (2014) study the effect of occupational exposure to gross trade on the U.S. wages by weighting the import penetration $IMP_{jt-1}$ by the fraction of workers who are working in industry j in occupation k in their base period and summing across industries for each occupation-year observation.[66]

[66] In Ebenstein et al. (2014), the industry exposure $IMP_{jt-1}$ is defined as a ratio of gross imports in industry j at year t-1 to the summation of imports and values of shipments in that industry. We follow their method to construct measures of industry-level exposure to value-added imports in this paper.

The underlying assumption for this measure is that every worker in a particular occupation is exposed to a unified trade shock. However, many U.S. occupations have unbalanced gender ratios. For instance, production occupations, such as machine operators and crafters, are traditionally dominated by male workers. In contrast, some occupations dominated by nonproduction workers, such as human resource managers and administrative assistants, have relatively more women workers. It is then possible that trade flows cause heterogeneous effects across workers of different genders.

We focus on the effects of exposure to trade at the occupational level following Ebenstein et al. (2014). We then modify their measures according to the approach of Schaller (2016) and create gender-specific measures to capture the distinct effects of trade exposure across male and female workers.[67]

We assume that the exposure to increased import penetration for male and female workers in each occupation k depends on its gender-specific occupational employment across industries.[68] We set the initial period of our sample, 1995, as a benchmark since it is the first year for which we have bilateral value-added trade flows. For each gender in occupation k and industry j, we define the weights for male and female workers, respectively, as $\theta_{kj95}^{m} = \frac{L_{kj95}^{m}}{L_{k95}^{m}}, \theta_{kj95}^{f} = \frac{L_{kj95}^{f}}{L_{k95}^{f}}$. In this case

[67] Yu (2019) employs a very similar method to construct a gender-specific exposure to gross imports at the regional level.

[68] Our gender-specific measures are closely related to, but not identical to the measures proposed by Autor et al. (2018). They look at the impact of relative exposure to trade on the outcomes of males relative to females; however, we construct the absolute measures of trade exposure, which is similar to the Schaller (2016) to study the impacts on the changes in individual outcomes in each gender group.

$L^m_{kj95}$ and $L^f_{kj95}$ represent the total numbers of workers for each gender in occupation k in industry j in 1995. Similarly, $L^m_{k95}$ and $L^f_{k95}$ represent the total numbers of male and female workers in occupation k in that year, respectively. Therefore, our gender-specific occupational exposure to value-added imports are defined as follows:

$$IMP^m_{kt-1} = \sum_j^{J=1} \frac{L^m_{kj95}}{L^m_{k95}} IMP_{jt-1} \text{ and } IMP^f_{kt-1} = \sum_j^{J=1} \frac{L^f_{kj95}}{L^f_{k95}} IMP_{jt-1} \qquad (3.1)$$

Where $IMP^m_{kt-1}$ and $IMP^f_{kt-1}$ are weighted averages of industry-specific measure, $IMP_{jt-1}$.

Following Ebenstein et al. (2014) and Shen, Silva and Wang (2018), we also control for the influence of globalization in the U.S. economy using three additional measures, namely: value-added export shares, offshoring employment in the middle- and high-income countries. We define the value-added export share for an industry j as a ratio of value-added export relative to the value of shipments in that industry. Measures of offshoring are defined as the log of offshoring employment in the middle- and high-income countries for an industry j. These data are reported by the U.S.-based multinationals. All these measures are gender-specific at the occupation level, as in expression (3.1). Here, we use one-year lagged measures of trade exposures for two reasons. On the one hand, it is unlikely that individual outcomes could immediately respond to changes in trade exposure. On the other, we want to avoid the simultaneous shocks that might affect individual outcomes, value-added trade, and offshoring in that same year.

To assess the effect of gender-specific exposure to value-added imports on U.S. wages, our first set of results relies on the following specification for workers in each gender group:

$$\mathrm{W_{ijkt}} = \beta_1 IMP^s_{kt-1} + G^s_{kt-1}\Phi + Z_{ijkt}\Omega + \alpha_{jt} + Comp_{kt} + \alpha_k + \epsilon_{ijkt} \qquad (3.2)$$

Where $W_{ijkt}$ represents the log wage of worker i involved in occupation k, who are employed in industry j at time t. $IMP_{kt-1}^{s}$ is the occupational exposure to value-added imports by gender group s (s is either male (m) or female (f)) at time t-1). Likewise, $G_{kt-1}^{s}$ is a vector which includes the other three measures of occupational exposure to globalization by gender. The vector $Z_{ijkt}$ contains individual characteristics: age, race, education, and location. The time-varying industry fixed effect ($\alpha_{jt}$) and occupational computer use rates ($Comp_{kt}$) in expression (3.2) control for changes in the demand for labor susceptible to the impacts of technological progress on industry j and on occupation k. Occupation fixed effect ($\alpha_{k}$) absorbs general shocks specific to the occupation k. Trade exposure is exclusively related within gender. Notice that our econometric strategy weights observations by the product of earning weights (provided by the CPS-MORG) and the reported weekly hours worked.

Next, in our second exercise, we examine the effect of exposure to value-added imports on the individual likelihood of being unemployed when controlling for gender. The linear probability model takes the form:

$$ump_{ijkt} = \beta_1 IMP_{kt-1}^{s} + G_{kt-1}^{s}\Phi + Z_{ijkt}\Omega + \alpha_{jt} + Comp_{kt} + \alpha_k + \epsilon_{ijkt} \quad (3.3)$$

Where $ump_{ijkt}$ is a binary indicator, which equals to one when worker i is unemployed at time t. The set of independent variables are the same as in expression (3.2), where measures of trade and offshoring employment are again gender-specific. Notice that unemployed workers do not have working hours due to their employment status. Thus, regressions in (3.3) are weighted by the earnings weights provided by the CPS-MORG.

Motivated by the work of Autor et al. (2018) and Keller and Utar (2018), we also want to examine the impacts of international trade on the U.S. marriage market. We incorporate our value-added measures with marital status at the individual level. We estimate the following estimation:

$$married_{ijkt} = \beta_1 IMP^s_{kt-1} + G^s_{kt-1}\Phi + Z_{ijkt}\Omega + \alpha_{jt} + Comp_{kt} + \alpha_k + \epsilon_{ijkt} \quad (3.4)$$

where $married_{ijkt}$ is a dichotomous variable, which equals to one if worker i is married at time t. Regressions in expression (3.4) are also weighted by the CPS earnings weights.

Note that the distribution effects of trade are uneven across occupations, as highlighted by Ebenstein et al. (2014). Their findings suggest that the degree of routineness of occupations plays a role in how globalization affects workers. For this reason, we distinguish workers according to the level of routineness in their occupations. Autor and Dorn (2013) distinguish the tasks into three groups: (i) routine tasks (which could be easily computerized and substituted by unskilled workers), (ii) non-routine manual tasks (which relies on physical coordination), and (iii) abstract tasks (which relate to creativity and decision making). As discussed in Shen, Silva, and Wang (2018), the degree of routineness for each occupation k is an index measured by the proportion of routine tasks among all tasks:

$$Routine_k = \frac{TaskRoutine_k}{TaskRoutine_k + TaskManual_k + TaskAbstract_k} \quad (3.5)$$

Following Ebenstein et al. (2014) and Shen, Silva, and Wang (2018), we assign occupations into three categories according to their values of $Routine_k$. If the value of $Routine_k$ in expression (3.5) is less than one-third, occupations are defined as least-routine occupations. The occupations with a ratio that between one-third and two-thirds are intermediate-routine occupations. Finally, the most-routine occupations have values that are greater than two-thirds.[69]

## 3.3 Data

Our U.S. worker-level dataset is taken from the National Bureau of Economic Research (NBER) Extracts of Current Population Survey-Merged Ongoing Rotation Group (CPS-MORG)

[69] See Table B1 in Shen, Silva and Wang (2018), which presents examples of occupations for each routineness group.

between 1995 and 2009.[70] Industry-level measures of value-added import competition and export shares are obtained from Shen, Silva, and Wang (2018). The multinational offshoring employment data is made available by Ebenstein et al. (2014), separated into two groups: offshoring employment in middle-income and high-income countries, according to the list of countries by gross nominal income per capita from the World Bank. Computer use rates at the occupation level are taken from Ebenstein et al. (2014).[71]

Note that we use different datasets to study the effects of value-added trade exposure on U.S. workers' individual outcomes. In expression (3.1), we examine the impact of value-added trade on U.S. workers' wages. In the investigation on how value-added trade affects the outcomes related to unemployment and marriage, we use a sample including all workers in the U.S. labor force. In Table 3.1, we report the summary statistics of gender-specific import exposure ratios and export shares used in our main results. In the left half of Table 3.1, we show the summary statistics of measures for employed workers age 16-64, while, in the right half of Table 3.1, we present those figures for all workers. As in Ebenstein et al. (2014), Shen, Silva, and Wang (2018), we consider

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[70] We rely on the CPS cleaner program provided by David Autor, which is used in Acemoglu and Autor (2011), to clean our CPS dataset. Notice that the CPS industry and occupation classification codes reclassify several times during this period. We use concordances provided by the Census of Bureau, David Autor, and David Dorn to allocate workers from different classification systems to a consistent classification scheme for their industry and occupation during the period. In this study, workers are assigned to the 1990 U.S. Census industry classification (IND 1990) for their industry and a revised version of the 1990 U.S. Census occupation classification provided by David Dorn (OCC 1990DD) for their occupation.

[71] Since the computer use rates provided by Ebenstein et al. (2014) are not available for the period after 2002, we follow Ebenstein et al. (2015) by substituting for computer use rates by using the values in 2002. The summary statistics of occupational computer use rates are reported in Table B.5.

the potential heterogeneous effects of U.S. value-added trade by splitting them into three groups of routineness (most, intermediate and least).

## Table 3.1 Descriptive Statistics for Gender-Specific Occupational Exposures to Value-Added Trade, 1996-2009

| Gender-specific occupation-time measures | Employed workers | | | | All workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations (1) | Most Routine (2) | Intermediate Routine (3) | Least Routine (4) | All Occupations (5) | Most Routine (6) | Intermediate Routine (7) | Least Routine (8) |
| Panel A: Male | | | | | | | | |
| IMP | 0.0341 | 0.0566 | 0.0258 | 0.0098 | 0.0341 | 0.0566 | 0.0258 | 0.0098 |
| | 0.0507 | 0.0684 | 0.0342 | 0.0144 | 0.0507 | 0.0684 | 0.0342 | 0.0144 |
| Export share | 0.0175 | 0.0276 | 0.0141 | 0.0058 | 0.0175 | 0.0276 | 0.0141 | 0.0058 |
| | 0.0216 | 0.0257 | 0.0179 | 0.0089 | 0.0216 | 0.0257 | 0.0179 | 0.0089 |
| IMP final goods | 0.0171 | 0.0292 | 0.0125 | 0.0046 | 0.0171 | 0.0292 | 0.0125 | 0.0046 |
| | 0.0314 | 0.0451 | 0.0183 | 0.0068 | 0.0314 | 0.0451 | 0.0183 | 0.0068 |
| Export share final goods | 0.0084 | 0.0134 | 0.0067 | 0.0026 | 0.0084 | 0.0134 | 0.0067 | 0.0026 |
| | 0.0108 | 0.0129 | 0.0089 | 0.0041 | 0.0108 | 0.0129 | 0.0089 | 0.0041 |
| IMP intermediates | 0.0131 | 0.0209 | 0.0104 | 0.0041 | 0.0131 | 0.0209 | 0.0104 | 0.0041 |
| | 0.0173 | 0.0217 | 0.0134 | 0.0062 | 0.0173 | 0.0217 | 0.0134 | 0.0062 |
| Export share intermediates | 0.0076 | 0.0118 | 0.0061 | 0.0026 | 0.0076 | 0.0118 | 0.0061 | 0.0026 |
| | 0.0096 | 0.0118 | 0.0077 | 0.0041 | 0.0096 | 0.0118 | 0.0077 | 0.0041 |
| N of Observations | 3,497 | 1,254 | 1,648 | 595 | 3,497 | 1,254 | 1,648 | 595 |
| Panel B: Female | | | | | | | | |
| IMP | 0.0371 | 0.0605 | 0.0303 | 0.0075 | 0.0371 | 0.0603 | 0.0303 | 0.0074 |
| | 0.0598 | 0.0763 | 0.0485 | 0.0124 | 0.0597 | 0.0761 | 0.0484 | 0.0124 |
| Export share | 0.0181 | 0.0286 | 0.0151 | 0.0045 | 0.0181 | 0.0285 | 0.0151 | 0.0045 |
| | 0.0234 | 0.0273 | 0.0205 | 0.0076 | 0.0234 | 0.0273 | 0.0205 | 0.0075 |
| IMP final goods | 0.0195 | 0.0321 | 0.0158 | 0.0036 | 0.0195 | 0.0319 | 0.0158 | 0.0036 |
| | 0.0387 | 0.0518 | 0.0301 | 0.0060 | 0.0386 | 0.0516 | 0.0301 | 0.0060 |
| Export share final goods | 0.0087 | 0.0138 | 0.0073 | 0.0021 | 0.0087 | 0.0137 | 0.0073 | 0.0021 |
| | 0.0118 | 0.0138 | 0.0105 | 0.0034 | 0.0118 | 0.0138 | 0.0105 | 0.0034 |
| IMP intermediates | 0.0134 | 0.0213 | 0.0112 | 0.0030 | 0.0134 | 0.0213 | 0.0112 | 0.0030 |
| | 0.0189 | 0.0226 | 0.0163 | 0.0051 | 0.0189 | 0.0226 | 0.0163 | 0.0051 |
| Export share intermediates | 0.0078 | 0.0123 | 0.0064 | 0.0020 | 0.0078 | 0.0123 | 0.0064 | 0.0020 |
| | 0.0104 | 0.0124 | 0.0089 | 0.0035 | 0.0104 | 0.0124 | 0.0089 | 0.0035 |
| N of Observations | 3,387 | 1,206 | 1,601 | 580 | 3,416 | 1,219 | 1,614 | 583 |

Columns (1) and (5) in Table 3.1 provide summary statistics for workers in all occupations. Columns (2)-(4) and (6)-(8) are the summary statistics for each routineness group. We can see that the summary statistics for the employed individuals in columns (1)-(4) of Table 3.1 are very similar to those for the whole labor force in column (5)-(8) since unemployed workers account for a small fraction of the U.S. labor force.[72]

The means and standard deviations of U.S. occupational male-specific exposure to value-added trade are summarized in Panel A of Table 3.1, while we report female-specific ones in Panel B. We find that the means of gender-specific exposure decreases with the degree of routineness for both genders. At the same time, the means of male-specific exposure to value-added trade are overall a bit smaller than those for female workers when they are involved with moderate to the high level of routineness in their occupations.[73] In the least-routine occupations, we see the opposite trend. We also notice that the number of gender-specific occupational exposures is not the same in these two panels, so we double-check whether the distribution in measures of trade exposure is varied with gender. The values of gender-specific exposure at terciles suggest that workers in both groups share the same set of cutoff points of different levels of routineness. Therefore, in our estimation, we use the same threshold for both genders. The summary statistics

[72] See the annual statistics published by the Bureau of Labor Statistics: https://data.bls.gov/timeseries/LNU04000000?periods=Annual+Data&periods_option=specific_periods&years_option=all_years The average U.S. unemployment rate between 1995 and 2009 is 5.3 percent.

[73] This trend in statistics is in line with those in Yu (2019) who find that the mean of industrial female-specific exposure to gross trade within manufacturing sectors is higher than that for males. In Appendix B, we provide some numerical examples to show such a trend in the measures of U.S. occupational exposure to value-added trade between male and female workers is entirely possible.

of offshoring employment are shown in Table B.2. The summary statistics for the CPS worker characteristics are reported and B.4. Below, we report the baseline results in the following section.

## 3.4 Baseline Results

### 3.4.1 Polarization of Wages and Gender-Specific Exposure to Value-Added Trade Flows

In Table 3.2, we present the baseline results using value-added trade flows for all goods. Results for male workers are presented in columns (1)-(4), while those for female workers are shown in columns (5)-(8). The estimates in column (1) suggest the gender-related heterogeneity in the average effect for U.S. workers. In the case of U.S. male workers, results in column (1) suggest that an increase in U.S. gender-specific occupational exposure to value-added imports lowers the wages earned by an average male worker. As for U.S. female workers, the estimates in column (5) suggest that an increase in female-specific occupational exposure to value-added imports also reduce the wages earned by average worker thought the coefficient is insignificant. The results in Table 3.2 also imply that the effects of gender-specific exposure to value-added imports at the occupation level on wages depend on the degree of routineness. Columns (3) and (7) imply that the greater the gender-specific exposure to value-added imports, the lower the earned wages for male and female workers with moderate levels of occupational routineness. As for most-routine workers, the results in column (2) suggest that an increase in gender-specific exposure to value-added imports lessen the wages earned by the male workers, while the coefficient for the female-specific correspondent in column (5) is insignificant. Lastly, the results in columns (4) and (8) imply that both male and female workers who work in the least-routine occupations experience wage gains from greater exposure to value-added imports. The directions of the effects suggest that, for both U.S. male and female workers, changes in trade exposure leads to the polarization of wages.

Comparing the results for workers across different degrees of routineness in Table 3.2, we find that the polarization effect is similar across gender. In particular, male workers with intermediate-routine occupations face greater pressure on wages from a one standard deviation increase in male-specific exposure to value-added imports as compared to those with most-routine positions (-7.27 vs. -4.79 percent). At the same time, a one standard deviation increase in male-specific exposure to imports leads to an 8.29 percent increase in the wages of least-routine males. In the case of females, the coefficients in columns (6)-(8) suggest that a one standard deviation increase in female-specific exposure to value-added imports has no significant effect on the wages earned by most-routine workers. However, it reduces the wages of intermediate-routine female workers by 7.08 percent while it increases least-routine workers' wages by 5.57 percent. Overall, our results in Table 3.2 are in line with the argument in Shen, Silva, and Wang (2018), that an increase in exposure to value-added imports induces the polarization of U.S. wages. This conclusion still holds, regardless of the worker's gender.

In terms of the effects of other globalization related measures, the coefficients on lagged export share in columns (1) and (5) suggest that an increase in male- and female-specific occupational exposure to value-added exports induces an increase in the wages earned by the average worker for both genders. For an average male worker, a standard deviation increase in male-specific exposure to exports induces a 4.87 percent increase in their wages. Likewise, a one standard deviation increase in female-specific exposure increases the wages earned by an average female worker by 4.38 percent. Furthermore, in columns (2) and (6), the results suggest that an increase in gender-specific exposure to exports raise the wages of male workers with most-routine occupations, while the coefficient for female workers is positive though not significant.

**Table 3.2 OLS Estimates of Wages Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -0.494* | -0.700*** | -2.127*** | 5.760** | -0.123 | -0.285 | -2.069*** | 3.869** |
| | (0.267) | (0.250) | (0.727) | (2.512) | (0.206) | (0.192) | (0.688) | (1.634) |
| Lagged export share | 2.253*** | 1.601** | 4.141*** | -5.790* | 1.874*** | 0.946 | 4.471*** | -2.784 |
| | (0.792) | (0.710) | (1.386) | (2.931) | (0.718) | (0.675) | (1.301) | (3.267) |
| Lagged log of middle-income affiliate employment | -0.060 | -0.063* | 0.013 | -0.164 | -0.040 | -0.004 | -0.035 | -0.535** |
| | (0.037) | (0.032) | (0.059) | (0.224) | (0.047) | (0.023) | (0.092) | (0.246) |
| Lagged log of high-income affiliate employment | 0.049 | 0.044 | -0.007 | 0.179 | 0.036 | -0.004 | 0.017 | 0.507** |
| | (0.035) | (0.031) | (0.054) | (0.196) | (0.044) | (0.021) | (0.084) | (0.234) |
| N of Observations | 846,580 | 160,217 | 424,464 | 261,668 | 718,129 | 232,229 | 275,213 | 210,429 |
| $R^2$ | 0.493 | 0.395 | 0.503 | 0.461 | 0.504 | 0.402 | 0.516 | 0.541 |

Note: Dependent variable is log hourly wage. The CPS worker data is from the NBER CPS MORG database. Offshoring employment from 1995 to 2008 is from Ebenstein et al. (2014) Import penetration, and export share in value-added measures are obtained from Shen, Silva, and Wang (2018). All these globalization measures are weighted by the gender distribution across industries for each occupation. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Occupational specifications also include 2-digit occupation and 3-digit industry-year fixed effects. The classification of routineness is determined by the proportion of tasks that are routine in each occupation. Occupation with more than two-thirds of tasks that are routine is classified as a most-routine occupation, intermediate-routine being between one-third and two-thirds, and least-routine being less than one-third. Wage specification control for a worker's demographic information such as gender, race, age, education, and include industry-year and state fixed effects. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent level

In the case of intermediate-routine workers, results in columns (3) and (7) suggest that an increase in gender-specific exposure to exports raise the wages for both male and female workers in the U.S. In contrast, the results in columns (4) and (8) imply that the wages earned by both male and female workers with least-routine occupations are negatively affected by an increase in gender-specific exposure to exports, although the effect on female workers is insignificant.

We also report the results of gender-specific exposure to offshoring employment in the middle- and high-income countries in Table 3.2. The coefficients in columns (1)-(4) suggest that an increase in male-specific exposure to offshoring employment in the middle-income countries reduce the wages earned by male workers who work in the most-routine occupations, which is consistent with the result of offshoring employment in Ebenstein et al. (2014). Results in columns (5)-(8) imply that an increase in female-specific exposure to offshoring employment in middle-income countries has a more pronounced effect on females involved in the least-routine occupations. Changes in male-specific offshoring employment in high-income countries has an insignificant effect on the wages of male workers regardless of the degree of routineness of their occupations while increasing female-specific offshoring employment in high-income countries is likely to raise the wages earned by the females with least-routine occupations.

As highlighted in the theoretical model proposed by Grossman and Rossi-Hansberg (2008), tasks could be performed by foreign workers in the global supply chain. Thus, it is likely that some traded tasks are either complements or substitutes of the tasks performed by domestic workers. Previous empirical studies show that an increase in the usage of foreign inputs is associated with a higher level of productivity for firms (e.g., Halpern, Koren, and Szeidl 2015; Kasahara and Rodrigue 2008). Consequently, the firms might expand, and wages might go up due to an increase in productivity. Building on the study of Shen, Silva, and Wang (2018), we want to investigate the role of traded goods in explaining the effects of value-added trade on wages across gender. The results using value-added trade flows in final goods are reported in Table 3.3, while those using imported intermediate inputs are shown in Table 3.4.

In Table 3.3, the coefficients on gender-specific exposure to imports of final goods in columns (1) and (5) indicate that an increase in exposure to final goods has a negative and significant effect on the wages earned by male workers whereas the effect on the wages earned by female workers is also negative but insignificant. In columns (2)-(4) and (6)-(8), we report the effects on the wages earned by workers involved with different degrees of occupational routineness for each gender.

In the case of male workers, the negative values of the coefficient on the import exposure in columns (2) and (3) indicate that an increase in male-specific occupational exposure to final goods lowers the male wages earned by both most- and intermediate-routine workers. A one standard deviation increase in male-specific exposure to final goods lower the wages earned by males with most- and intermediate-routine occupations by 5.14 and 9.52 percent, respectively.[74] In column (4), the results indicate that the effect of an increase in exposure to final good on the wages of least-routine workers is insignificant. Thus, combining the results in columns (1)-(4), we confirm that changes in U.S. male-specific occupational exposure to value-added imports in final goods have a significant effect on the polarization of U.S. male wages.

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[74] In Table 3.3, the effect for male workers with most-routine occupations in column (2) can be computed by multiplying the coefficient of male-specific exposure to value-added imports in final goods, which is equal to 1.140, by the standard deviation of this variable faced by U.S. workers involved with most-routine occupations in Table 3.1 (0.0451). Likewise, the effect for intermediate-routine workers is obtained by multiplying the coefficient of exposure to value-added imports in final goods in column (3) (5.203) by the standard deviation of the corresponding term faced by intermediate-routine workers in Table 3.1 (0.0183).

**Table 3.3 OLS Estimates of Wages Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Final Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -1.198** | -1.140*** | -5.203*** | 6.212 | -0.540 | -0.624** | -4.190*** | 7.929** |
| | (0.485) | (0.333) | (1.173) | (4.644) | (0.332) | (0.289) | (1.213) | (3.820) |
| | 4.437** | 2.531** | 11.513*** | -5.529 | 4.765*** | 2.582* | 11.466*** | -10.253 |
| Lagged export share | (1.726) | (1.126) | (2.360) | (6.840) | (1.674) | (1.427) | (2.945) | (10.623) |
| Lagged log of middle-income affiliate employment | -0.058 | -0.069** | 0.006 | -0.099 | -0.050 | -0.007 | -0.014 | -0.486** |
| | (0.037) | (0.033) | (0.061) | (0.267) | (0.047) | (0.023) | (0.089) | (0.218) |
| Lagged log of high-income affiliate employment | 0.049 | 0.051 | -0.006 | 0.130 | 0.045 | -0.003 | -0.008 | 0.477** |
| | (0.035) | (0.031) | (0.057) | (0.229) | (0.045) | (0.021) | (0.083) | (0.212) |
| N of Observations | 846,580 | 160,217 | 424,464 | 261,668 | 718,129 | 232,229 | 275,213 | 210,429 |
| $R^2$ | 0.493 | 0.395 | 0.503 | 0.461 | 0.504 | 0.402 | 0.516 | 0.541 |

Note: Dependent variable is log hourly wage. See Table 3.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Wage specification control for a worker's demographic information such as gender, race, age, education, and include industry-year and state fixed effects. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent level

Regarding female workers, the results in columns (6) and (7) of Table 3.3 indicate that when the female-specific occupational exposure to value-added imports in final goods increases, female workers with most- and intermediate-routine occupations in the U.S. face downward pressures on their wages. To be specific, a one standard deviation increase in female-specific exposure to value-added imports in final goods will lower the wages earned of most- and intermediate-routine female workers by 3.23 and 12.61 percent. The positive and significant coefficient on import exposure in column (8) suggests that the wages earned by female workers involved with a low degree of routineness tasks increase with a greater female-specific occupational exposure to value-added imports in final goods. The results in columns (4)-(8)

indicate that an increase in female-specific occupational exposure to final goods is associated with the polarization of their wages.

Overall, the results in Table 3.3 show that changes in gender-specific exposure to final goods have a significant effect on the polarization of wages for both groups, and the effects are homogeneous to a certain extent.

In Table 3.4, we find that the effects of changes in occupational exposure to value-added imports on wages earned by the average workers are positive though insignificant for both gender groups. But this result varies according to the degree of routineness. The coefficient on the import exposure in column (4) is significant and positive, while those in columns (2) and (3) are negative and insignificant. Thus, the results in columns (1)-(4) suggest that only male workers with least-routine occupations benefit from increasing male-specific exposure to intermediate inputs. In the case of female workers, the results in columns (5)-(8) suggest that there is no statistically significant relationship between exposure to imports in intermediate inputs and wages earned by U.S. female workers even controlling for the level of routineness.

**Table 3.4 OLS Estimates of Wages Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Intermediate Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | 0.540 | -0.401 | -1.346 | 18.536*** | 0.500 | 0.010 | 0.805 | 4.448 |
| | (0.983) | (0.744) | (1.801) | (4.956) | (0.477) | (0.360) | (2.505) | (6.117) |
| Lagged export share | 2.676 | 1.847 | 1.701 | -20.627*** | 2.498** | 0.824 | -1.209 | 0.131 |
| | (1.708) | (1.353) | (3.282) | (5.971) | (1.265) | (1.088) | (4.043) | (7.405) |
| Lagged log of middle-income affiliate employment | -0.055 | -0.070** | 0.033 | -0.093 | -0.024 | -0.007 | -0.046 | -0.439* |
| | (0.036) | (0.034) | (0.054) | (0.162) | (0.044) | (0.024) | (0.092) | (0.254) |
| Lagged log of high-income affiliate employment | 0.045 | 0.051 | -0.022 | 0.114 | 0.022 | -0.000 | 0.035 | 0.424* |
| | (0.034) | (0.033) | (0.051) | (0.149) | (0.042) | (0.023) | (0.084) | (0.238) |
| N of Observations | 846,580 | 160,217 | 424,464 | 261,668 | 718,129 | 232,229 | 275,213 | 210,429 |
| $R^2$ | 0.493 | 0.395 | 0.503 | 0.461 | 0.504 | 0.402 | 0.516 | 0.541 |

Note: Dependent variable is log hourly wage. See Table 3.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent level.

### 3.4.2 Uncertainty related to Unemployment and Gender-Specific Exposure to Value-Added Trade Flows

In this section, we link the changes in exposure to value-added imports with the uncertainty related to unemployment. The results are heterogeneous across gender as presented in Table 3.5.

In the case of male workers, the estimates in columns (1)-(4) indicate that an increase in male-specific exposure to imports has no significant effect on the likelihood of being unemployed for these particular workers. Considering female workers, the results in columns (5) suggest that a one standard deviation increase in female-specific occupational exposure to value-added imports is likely to increase the probability of being unemployed for the average female workers by 1.24

percent.[75] This result is due to the significant effect on the probability of being unemployed for females with least-routine occupations. Changes in female-specific exposure to imports have no significant effect on women with most- and intermediate-routine occupations. This finding is not inconsistent with the previous studies on employment, which find that import competition has a negative effect on employment for both male and female (e.g., Autor et al., 2018). It is possibly due to the usage of value-added trade flows from all sources.

**Table 3.5 LPM Estimates of Unemployment Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | 0.061 | 0.123 | 0.188 | -0.191 | 0.208*** | 0.112 | 0.128 | 0.987* |
| | (0.081) | (0.108) | (0.163) | (0.331) | (0.070) | (0.098) | (0.246) | (0.497) |
| Lagged export share | -0.272 | -0.504* | -0.354 | -1.037 | -0.487** | -0.109 | -0.061 | -2.219* |
| | (0.175) | (0.270) | (0.303) | (0.668) | (0.208) | (0.316) | (0.534) | (1.277) |
| Lagged log of middle-income affiliate employment | 0.020** | 0.010 | -0.001 | 0.047** | 0.011 | 0.018 | -0.019 | -0.022 |
| | (0.009) | (0.009) | (0.014) | (0.023) | (0.011) | (0.013) | (0.028) | (0.054) |
| Lagged log of high-income affiliate employment | -0.017** | -0.005 | 0.001 | -0.030 | -0.009 | -0.015 | 0.020 | 0.027 |
| | (0.008) | (0.008) | (0.013) | (0.022) | (0.011) | (0.012) | (0.026) | (0.046) |
| N of Observations | 962,121 | 182,006 | 485,173 | 294,752 | 808,392 | 262,030 | 311,258 | 234,867 |

Note: Dependent variable is the probability of being unemployed, which equals to one if worker i is unemployed at period t. See Table 3.2 for the source. All regressions include the full set of control variables from Table 3.2. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "*," "*" represent statistical significance at the 1,5 and 10 percent level.

Table 3.5 also shows the results for other measures of globalization. The coefficients on export shares are negative in columns (1)-(8) though not always significant across occupations

[75] The effect for the average female workers in column (4) is obtained by multiplying the coefficient of female-specific exposure to imports in column (1) (0.208) by the standard deviation of this variable faced by all female workers in column (1) (0.0597) of Table 3.1.

with different levels of routineness. The findings corroborate the widely accepted idea that an increase in exports tends to increase employment levels. The estimates for offshoring employment in Table 3.5 suggest that changes in offshoring employment in different countries have a more profound effect on male workers than on female workers. In column (1), we find that an increase in offshoring employment in middle-income countries is more likely to increase the probability of being unemployed for the average male worker. Yet, offshoring to high-income countries appears to lower the odds of being unemployed for that same group.

As discussed above, we do not find significant changes in the probability of being unemployed for male workers in Table 3.5. We decided to make a distinction in the trade flows by types of goods (final goods vs. intermediate inputs) and study the effects of exposure to different types of traded goods.

Table 3.6 shows the estimated effects of U.S. gender-specific exposure to value-added trade in final goods for workers of both sexes. In column (3), the results suggest that an increase in male-specific exposure to value-added imports in final goods significantly drives up the risk of being unemployed for workers in occupations with the medium level of routineness, while the effect of the changes in male-specific exposure is insignificant. As for effect on the likelihood of being unemployed for the U.S. female workers, the findings are similar to the results described in columns (5)-(8) of Table 3.5. We find that an increase in female-specific occupational exposure to value-added trade has a significant effect on average workers in all occupations as well as those in least-routine occupations.

**Table 3.6 LPM Estimates of Unemployment Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Final Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | 0.139 | 0.155 | 0.883*** | -0.148 | 0.351*** | 0.174 | 0.204 | 1.513* |
| | (0.129) | (0.153) | (0.283) | (0.602) | (0.108) | (0.156) | (0.332) | (0.824) |
| Lagged export share | -0.530 | -0.888* | -1.681*** | -2.320* | -1.112** | -0.298 | -0.425 | -3.768 |
| | (0.333) | (0.534) | (0.595) | (1.351) | (0.432) | (0.761) | (0.883) | (2.956) |
| Lagged log of middle-income affiliate employment | 0.020** | 0.015 | -0.004 | 0.054** | 0.013 | 0.017 | -0.015 | -0.014 |
| | (0.009) | (0.010) | (0.014) | (0.025) | (0.012) | (0.013) | (0.027) | (0.057) |
| Lagged log of high-income affiliate employment | -0.017** | -0.010 | 0.004 | -0.038 | -0.010 | -0.014 | 0.017 | 0.020 |
| | (0.008) | (0.009) | (0.014) | (0.023) | (0.011) | (0.012) | (0.026) | (0.049) |
| N of Observations | 962,121 | 182,006 | 485,173 | 294,752 | 808,392 | 262,030 | 311,258 | 234,867 |

Note: Dependent variable is the probability of being unemployed. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent level.

In Table 3.7, we study the effect of gender-specific exposure to value-added imports in intermediate inputs on the probability of being unemployed for workers of each gender. The results in columns (1)-(4) imply that an increase in exposure to intermediate inputs would lower the likelihood of being unemployed for the U.S. male workers involved in intermediate-routine occupations. This is not true for those involved in most- and least-routine occupations since, in these cases, the effect of change in exposure to imports of intermediate inputs is insignificant. Columns (5)-(8) present the results for female workers using female-specific exposure. The estimates in column (8) suggest that an increase in female-specific exposure to imports in intermediate inputs leads to an increase in the probability of being unemployed faced by females in least-routine occupations.

**Table 3.7 LPM Estimates of Unemployment Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Intermediate Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | 0.003 | 0.300 | -0.779* | -0.620 | 0.266 | 0.065 | 0.947 | 3.218* |
| | (0.244) | (0.291) | (0.441) | (0.915) | (0.236) | (0.216) | (0.776) | (1.716) |
| Lagged export share | -0.443 | -0.918* | 0.861 | -1.505 | -0.375 | 0.199 | -0.722 | -5.447** |
| | (0.406) | (0.552) | (0.610) | (1.614) | (0.421) | (0.486) | (1.254) | (2.523) |
| Lagged log of middle-income affiliate employment | 0.019** | 0.008 | 0.002 | 0.023 | 0.016 | 0.023* | -0.026 | -0.003 |
| | (0.008) | (0.008) | (0.014) | (0.022) | (0.010) | (0.014) | (0.023) | (0.043) |
| Lagged log of high-income affiliate employment | -0.016** | -0.005 | -0.001 | -0.009 | -0.015 | -0.021* | 0.025 | 0.005 |
| | (0.008) | (0.008) | (0.013) | (0.022) | (0.010) | (0.013) | (0.021) | (0.038) |
| N of Observations | 962,121 | 182,006 | 485,173 | 294,752 | 808,392 | 262,030 | 311,258 | 234,867 |

Note: Dependent variable is the probability of being unemployed. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent level

### 3.4.3 Tendency to Get Married and Gender-Specific Exposure to Value-Added Trade Flows

Autor et al. (2018) argue that since the effect of trade exposure is more substantial to the earnings and employment of "marriageable" men rather than women. These negative effects on the economic capacity for males lead to a decrease in the attractiveness of family formation. Thus, marriage rates fall. In the spirit of their paper, we focus on the effect of value-added trade on individual marriage decisions. To achieve this objective, we link gender-specific exposure to value-added trade to the probability of being married as described in expression (3.4). We report the results in Tables 3.8-3.10. Our results support Autor et al. (2018) by providing corroborating evidence that changes in wages due to the change in occupational exposure to imports have prevalent negative effects on men's family choice. It is more likely to affect men's decision on marriage, not women's decision.

Table 3.8 reports the results of exposure to value-added import from all goods. Results for male workers are shown in columns (1)-(4). The estimates described in column (1) suggest that changes in male-specific occupational exposure have no significant effect on the probability of getting married for an average male. The results in columns (2)-(4) suggest that an increase in exposure to value-added imports is associated with the polarization of individual marriage outcome. In particular, the effect for most-routine workers is insignificant, while the effect for male workers involved in intermediate-routine occupations is negative and significant, while for the least-routine worker, the effect is positive and significant. By contrast, the estimated results in columns (5)-(8) show that the changes in exposure to value-added imports have no significant effects on female workers.

**Table 3.8 LPM Estimates of Marriage Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -0.040 | -0.102 | -1.098*** | 3.204** | 0.011 | -0.105 | -0.245 | -0.228 |
| | (0.139) | (0.198) | (0.345) | (1.587) | (0.123) | (0.144) | (0.495) | (1.377) |
| Lagged export share | 1.103*** | 1.336** | 2.180*** | -4.381** | 0.218 | 0.520 | 0.376 | 1.171 |
| | (0.424) | (0.532) | (0.609) | (1.845) | (0.376) | (0.434) | (1.086) | (2.823) |
| Lagged log of middle-income affiliate employment | -0.065*** | -0.041* | -0.025 | -0.031 | 0.013 | -0.007 | -0.064 | 0.189* |
| | (0.024) | (0.022) | (0.032) | (0.145) | (0.019) | (0.017) | (0.055) | (0.100) |
| Lagged log of high-income affiliate employment | 0.058*** | 0.026 | 0.027 | 0.047 | -0.013 | 0.004 | 0.053 | -0.201** |
| | (0.022) | (0.021) | (0.030) | (0.129) | (0.018) | (0.017) | (0.050) | (0.087) |
| N of Observations | 987,669 | 187,535 | 499,269 | 300,685 | 846,382 | 275,995 | 325,869 | 244,287 |

Note: Dependent variable is the probability of being married, which equals to one if worker i is married at period t. See Table 3.2 for the source. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent level.

Table 3.9 reports the results using gender-specific occupational exposure to value-added trade in final goods. The results in columns (1)-(4) suggest that exposure to final goods is related to the U-shaped trend discussed in Table 3.8. The coefficient of exposure to imports in column (3) implies that changes in exposure to imported final goods have a negative and significant effect on the marriage outcome for intermediate-routine workers. On the contrary, the effects of this male-specific exposure for most and least-routine workers are insignificant. As for females, again, the results in columns (5)-(8) are insignificant, which confirm the results of Table 3.8.

In Table 3.10, we study the effects for workers using value-added trade in intermediate inputs. The results for male workers are shown in columns (1)-(4), and they suggest that an increase in male-specific exposure to value-added imports in intermediate inputs is associated with an increase in the probability of being married for men involved in least-routine occupations. The effects for males in most and intermediate-routine occupations are insignificant. The estimated effects in columns (5)-(8) suggest that the effect for female workers in the U.S. are insignificant.

Based on the results of Table 3.8-3.10, we see that the different types of traded goods have differential effects on male workers while the effect for female workers is insignificant regardless of whether they are exposed to final goods or intermediate inputs. In the case of final goods, the changes in imported final goods have a profound effect on workers involved in intermediate-routine occupations while the effect on other males is insignificant. In the case of value-added imports in intermediate inputs, the exposure has an incentive effect on the likelihood of being married for least-routine workers.

**Table 3.9 LPM Estimates of Marriage Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Final Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -0.200 | -0.238 | -2.125*** | 4.168 | -0.064 | -0.228 | -0.338 | -1.130 |
| | (0.267) | (0.289) | (0.655) | (2.800) | (0.204) | (0.242) | (0.750) | (2.125) |
| Lagged export share | 1.825* | 2.177** | 4.512*** | -3.654 | 1.008 | 1.350 | 1.115 | 5.838 |
| | (1.019) | (1.029) | (1.287) | (4.343) | (0.872) | (1.138) | (2.012) | (6.604) |
| Lagged log of middle-income affiliate employment | -0.064*** | -0.054** | -0.019 | -0.032 | 0.011 | -0.010 | -0.069 | 0.155 |
| | (0.024) | (0.023) | (0.031) | (0.157) | (0.019) | (0.017) | (0.054) | (0.111) |
| Lagged log of high-income affiliate employment | 0.059*** | 0.040* | 0.020 | 0.042 | -0.012 | 0.007 | 0.056 | -0.178* |
| | (0.022) | (0.021) | (0.028) | (0.137) | (0.018) | (0.016) | (0.050) | (0.093) |
| N of Observations | 987,669 | 187,535 | 499,269 | 300,685 | 846,382 | 275,995 | 325,869 | 244,287 |

Note: Dependent variable is the probability of being married. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent level

**Table 3.10 LPM Estimates of Marriage Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade in Intermediate Goods, 1996-2009**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | 0.195 | 0.084 | -1.369 | 9.042** | -0.679 | -0.534 | -1.395 | 0.155 |
| | (0.554) | (0.525) | (0.958) | (4.044) | (0.424) | (0.489) | (1.561) | (4.950) |
| Lagged export share | 2.460*** | 2.679*** | 2.725* | -13.153*** | 0.723 | 0.862 | 0.745 | 0.301 |
| | (0.860) | (0.930) | (1.386) | (4.698) | (0.727) | (0.848) | (2.332) | (6.216) |
| Lagged log of middle-income affiliate employment | -0.053** | -0.022 | -0.028 | -0.002 | 0.004 | -0.021 | -0.056 | 0.253*** |
| | (0.023) | (0.021) | (0.031) | (0.120) | (0.019) | (0.017) | (0.054) | (0.084) |
| Lagged log of high-income affiliate employment | 0.045** | 0.008 | 0.030 | 0.025 | -0.002 | 0.020 | 0.050 | -0.256*** |
| | (0.021) | (0.020) | (0.028) | (0.109) | (0.017) | (0.017) | (0.050) | (0.074) |
| N of Observations | 987,669 | 187,535 | 499,269 | 300,685 | 846,382 | 275,995 | 325,869 | 244,287 |

Note: Dependent variable is the probability of being married. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "**," "**," "*" represent statistical significance at the 1,5 and 10 percent level

### 3.5. Robustness

In this section, we report the robustness of our baseline results. We find that our conclusions still hold in the alternative specifications.

Following Autor et al. (2018), we limit our sample to workers aged between 18 and 39 and re-estimate our baseline regressions using with this restricted sample. We report the summary statistics related to young workers in Tables B.1 and B.3. The average trade exposures are comparable to those for the full sample. The results of robustness tests for wages appear in Table 3.11. The results suggest that young workers with intermediate-routine occupations still face the most negative shock from imports, especially the final goods, which leads to the polarization of wages for both gender groups regardless of whether value-added imports of all goods or final goods are used. Imported intermediate goods serve as complements of male workers with least-routine occupations, not females. Overall, our conclusions related to wages are not affected by using a subset of the full sample.

Likewise, Table 3.12 reports the results of robustness for the probability of being unemployed. In Panel A, we find that the coefficient on import penetration in column (1) using imports of all goods is positive and significant. It indicates that an increase in male-specific exposure to all goods is associated with an increase in the uncertainty of employment faced by the average young males. While in Table 3.5, the effect for average male workers is positive though not significant using the full sample. Likewise, the estimate on import penetration for intermediate-routine workers in column (3) in that panel turns from insignificant to significant, which suggests that these workers, whose wages are most negatively affected among all workers, are more likely to be unemployed with greater exposure to imports. This change in statistical significance indicates that younger workers are more sensitive to the trade shocks as discussed in Utar and Keller (2018).

In the case of intermediate goods, the effects are insignificant for male workers regardless of their occupations. We can see that the effect of changes in gender-specific shock to imports on the likelihood of being unemployed for males differs from those for female workers, which confirms our main results.

The robustness tests on the uncertainty related to marriage are shown in Table 3.13. We find that the results of exposure in this table are alike those in Table 3.8-3.10. For example, the results in Panel B suggest that, with greater exposure to value-added imports in final goods, young men involved with intermediate-routine occupations are less likely to being married. The coefficient on import penetration becomes insignificant in column (4), which suggest that the effect for young men with least-routine occupations is insignificant. The findings above imply that when economic uncertainty increases, male workers are less likely to get married. On the other hand, we do not see an increase in the likelihood of being married for those who benefit from import exposure, such as young men with least-routine occupations. Again, there is no economic statistical relationship between value-added trade exposure and the probability of being married for young women.

**Table 3.11 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade, 1996-2009, Young Workers Age 18-39**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Panel A: All goods | | | | | | | | |
| | -0.213 | -0.518* | -2.199** | 6.111** | -0.306 | -0.397 | -2.188*** | 5.066*** |
| Lagged import penetration | (0.297) | (0.273) | (0.860) | (2.606) | (0.242) | (0.243) | (0.651) | (1.610) |
| | 1.915** | 1.512** | 4.456*** | -8.537*** | 2.731*** | 1.217 | 5.463*** | -7.109** |
| Lagged export share | (0.799) | (0.727) | (1.572) | (3.076) | (0.812) | (0.869) | (1.378) | (3.220) |
| Panel B: Final goods | | | | | | | | |
| | -0.890* | -1.057*** | -5.526*** | 8.006 | -0.799** | -0.821** | -3.886*** | 10.055*** |
| Lagged import penetration | (0.511) | (0.397) | (1.281) | (4.885) | (0.381) | (0.396) | (1.032) | (3.302) |
| | 4.287** | 2.797** | 12.403*** | -10.552 | 5.967*** | 2.812 | 11.528*** | -18.383* |
| Lagged export share | (1.679) | (1.310) | (2.389) | (7.086) | (1.764) | (1.906) | (2.743) | (9.632) |
| Panel C: Intermediate goods | | | | | | | | |
| | 1.070 | 0.337 | -1.203 | 16.417*** | 0.277 | 0.198 | -2.140 | 6.822 |
| Lagged import penetration | (1.028) | (0.792) | (2.246) | (5.474) | (0.586) | (0.473) | (2.596) | (8.238) |
| | 2.036 | 1.317 | 2.052 | -22.995*** | 4.092*** | 1.029 | 5.387 | -8.413 |
| Lagged export share | (1.779) | (1.379) | (3.927) | (6.760) | (1.465) | (1.354) | (4.244) | (9.045) |
| N of Observations | 422,301 | 87,737 | 217,448 | 116,660 | 340,634 | 104,907 | 136,095 | 98,945 |
| $R^2$ | 0.505 | 0.411 | 0.517 | 0.496 | 0.531 | 0.433 | 0.543 | 0.579 |

Note: Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period. See Table 3.2 for the source. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

**Table 3.12 LPM Estimates of Unemployment Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade, 1996-2009, Young Workers Age 18-39**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Panel A: All goods | | | | | | | | |
| | 0.090 | 0.032 | 0.459** | 0.345 | 0.228* | 0.112 | 0.401 | 0.899 |
| Lagged import penetration | (0.090) | (0.115) | (0.205) | (0.467) | (0.136) | (0.144) | (0.343) | (0.567) |
| | -0.312* | -0.194 | -0.910** | -1.009 | -0.518 | 0.026 | -0.730 | -2.129* |
| Lagged export share | (0.182) | (0.266) | (0.363) | (0.701) | (0.316) | (0.417) | (0.684) | (1.222) |
| Panel B: Final goods | | | | | | | | |
| | 0.229* | 0.034 | 1.410*** | 0.344 | 0.376* | 0.093 | 0.525 | 1.711* |
| Lagged import penetration | (0.138) | (0.176) | (0.366) | (0.788) | (0.197) | (0.226) | (0.512) | (0.967) |
| | -0.726** | -0.395 | -2.719*** | -1.881 | -1.129* | 0.416 | -1.172 | -4.839 |
| Lagged export share | (0.351) | (0.519) | (0.761) | (1.454) | (0.609) | (0.966) | (1.194) | (2.984) |
| Panel C: Intermediate goods | | | | | | | | |
| | -0.038 | 0.113 | -0.421 | 1.530 | 0.718 | 0.507 | 2.091* | 1.738 |
| Lagged import penetration | (0.288) | (0.298) | (0.579) | (1.383) | (0.492) | (0.469) | (1.255) | (2.177) |
| | -0.340 | -0.372 | 0.006 | -2.806 | -1.161 | -0.428 | -2.920 | -3.798 |
| Lagged export share | (0.432) | (0.554) | (0.778) | (1.824) | (0.738) | (0.859) | (1.879) | (2.781) |
| N of Observations | 484,166 | 101,080 | 251,578 | 131,106 | 388,099 | 121,029 | 155,164 | 111,280 |

Note: Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

**Table 3.13 LPM Estimates of Marriage Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Trade, 1996-2009, Young Workers Age 18-39**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Panel A: All goods | | | | | | | | |
| | 0.169 | 0.053 | -1.022** | 3.164 | 0.135 | 0.205 | -0.256 | 0.689 |
| Lagged import penetration | (0.194) | (0.208) | (0.477) | (2.170) | (0.135) | (0.191) | (0.685) | (1.648) |
| | 0.751 | 0.468 | 2.662*** | -5.828** | -0.180 | 0.290 | 0.310 | -1.158 |
| Lagged export share | (0.504) | (0.547) | (0.886) | (2.385) | (0.416) | (0.561) | (1.351) | (2.685) |
| Panel B: Final goods | | | | | | | | |
| | 0.073 | -0.102 | -1.901** | 5.431 | 0.121 | 0.227 | -0.293 | 0.303 |
| Lagged import penetration | (0.331) | (0.300) | (0.903) | (3.520) | (0.223) | (0.302) | (1.030) | (2.484) |
| | 1.600 | 1.134 | 5.116*** | -8.572* | 0.234 | 0.781 | 0.733 | 2.453 |
| Lagged export share | (1.153) | (1.047) | (1.793) | (4.495) | (0.921) | (1.340) | (2.536) | (6.291) |
| Panel C: Intermediate goods | | | | | | | | |
| | 0.487 | 0.483 | -1.165 | 6.775 | -0.126 | 0.312 | -1.990 | 4.079 |
| Lagged import penetration | (0.696) | (0.626) | (1.276) | (5.685) | (0.517) | (0.601) | (2.088) | (6.190) |
| | 1.699 | 0.651 | 3.789* | -12.588* | 0.054 | 0.869 | 2.182 | -6.512 |
| Lagged export share | (1.077) | (1.125) | (1.983) | (6.639) | (0.956) | (1.132) | (3.058) | (7.138) |
| N of Observations | 484,166 | 101,080 | 251,578 | 131,106 | 388,099 | 121,029 | 155,164 | 111,280 |

Note: Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

Given the case that workers with different levels of skill are disproportionately affected by trade exposure (e.g., Hummels et al. (2014)), it is then conceivable that the effects of trade exposure on the decision to form a family may also depend on the worker's skill level in addition to gender. Here, we go beyond our baseline specifications by exploring the role of skill in the effects of gender-specific trade exposure to the likelihood of being married. We allocate workers aged 22 to 39 into two groups according to their level of skill. We follow Hummels et al. (2014) by considering workers who have at least a bachelor's degree as skilled workers in both gender groups, and the rest of the workers are defined as unskilled workers. We replace the indicator related to educational attainment in expression (3.4) by a skill dummy. Besides, we add the interaction between gender-specific exposures and this binary variable. Results using value-added imports in all goods are reported in Table 3.14.

**Table 3.14 LPM Estimates of Marriage Uncertainty Determinants Using Occupational Gender-Specific Exposure to Value-Added Imports and Their Skill Interactions, 1996-2009, Young Workers Age 22-39**

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration ($\beta_1$) | 0.122 | 0.092 | -1.270*** | 3.310 | 0.110 | 0.097 | -0.190 | 0.044 |
| | (0.225) | (0.260) | (0.485) | (2.285) | (0.167) | (0.238) | (0.556) | (1.828) |
| Lagged import penetration × Skill ($\beta_2$) | 0.328** | 0.141 | 0.322** | -0.189 | 0.117 | -0.182 | 0.549** | 0.409 |
| | (0.134) | (0.182) | (0.141) | (0.390) | (0.155) | (0.237) | (0.249) | (0.384) |
| Test $\beta_1 + \beta_2 = 0$ (P-value) | 0.0721 | 0.3926 | 0.0611 | 0.1778 | 0.3256 | 0.8096 | 0.5561 | 0.8084 |
| N of Observations | 987,669 | 187,535 | 499,269 | 300,685 | 846,382 | 275,995 | 325,869 | 244,287 |

Note: Dependent variable is the probability of being married. Skill is a binary variable, which equals to one if worker i holds at least a bachelor's degree. See Table 3.2 for the source. See Appendix B for the details of the specifications. Robust standard errors are reported in parentheses. The standard errors are clustered by occupation and five-year period in occupation-specific exposures. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent level.

Results in columns (1)-(4) of Table 3.14 suggest that, among male workers, those who are involved with intermediate-routine occupations are likely to be affected by greater exposure to imported goods while others are not significantly affected. Moreover, the magnitude of the effect for unskilled workers with intermediate-routine workers is larger than that for skilled workers in those occupations. In the case of female workers, the effect for both skilled and unskilled workers are insignificant regardless of their occupations. Comparing with the results in Table 3.8, our conclusion on marriage are not altered by controlling for workers' skills.

## 3.6 Conclusion

The distributional effect of trade is not gender-neutral since the many exposed occupations and sectors are male-dominated. In this paper, we study the effects of value-added trade for U.S.

male and female workers with the consideration of the level of routineness in their occupations. We examine the effects of gender-specific exposure to value-added trade at the occupation level on wages, the probability of being unemployed, and the likelihood of being married using the CPS data. Our results suggest that some effects of gender-specific trade exposures are homogeneous across gender while some are heterogeneous.

Firstly, we find that the wage effects are homogeneous across gender. Our analysis on U.S. wages confirms the findings in Shen, Silva, and Wang (2018) that intermediate-routine workers face the most negative impact from increasing exposure to value-added imports, which leads to the U.S. wage polarization for each gender group.

Regarding the effects of value-added trade on the unemployment uncertainty, the effects of value-added trade are asymmetric across gender. In the case of male workers, the probability of being unemployed for those with intermediate-routine occupations is affected by changes in exposure to final goods from middle-income countries while the effect on the other male workers is insignificant. Among the females, intermediate-routine workers are not affected by this exposure. Instead, the probability of being unemployed for those involved in the least-routine occupations goes up when they face greater female-specific exposure. At the same time, the likelihood of being unemployed for females in the other occupations are not affected by it.

In the exercise for the probability of being married, we find that trade exposure has a significant impact on male workers, not on female workers. In particular, an increase in import penetration decreases the tendency of being married for men who work in the intermediate-routine occupations while the chances of being married are likely to increase for those involved in the least-routine occupations. This negative effect is due to the changes in male-specific exposure to final goods. Combining our findings above, it seems like men’s family formation is sensitive to the changes in their economic standing. However, we do not see this significant effect on the likelihood of being married for female workers.

Our empirical findings complement the existing literature by providing new evidence for the distributional effect of trade within each gender group. In future work, we would like to understand the effects of value-added trade on the non-market outcomes discussed in the literature.

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# Appendix A - Appendix for Chapter 1

**Figure A.1 Share of Gross Imports and Value-Added Imports from Middle- vs. High-Income Countries by Year in Textiles and Textile Products**

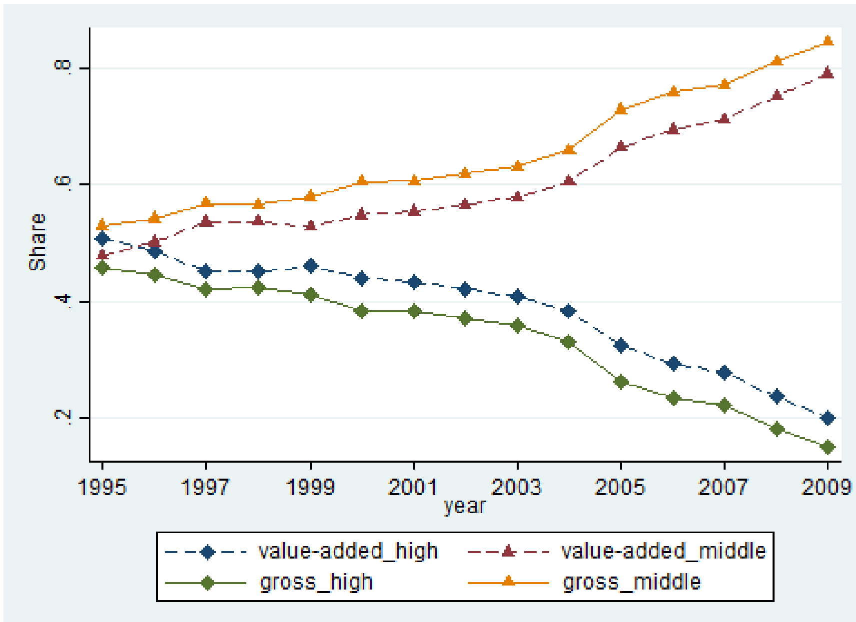
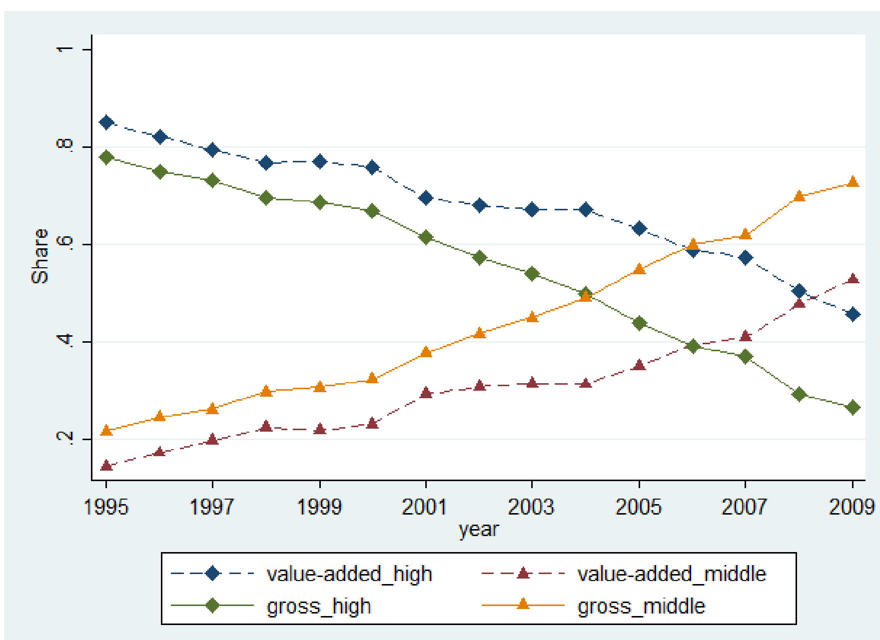



**Figure A.2 Share of Gross Imports and Value-Added Imports from Middle- vs. High-Income Countries by Year in Electrical and Optical Equipment Products**



## Industry-level Specification

In this paper, our 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:

$$W_{ijt} = \beta_1 IMP_{jt-1} + G_{jt-1}\Gamma + X_{jt-1}\Lambda + \mathrm{Z_{ijt}}\Omega + \alpha_j + \alpha_t + \epsilon_{ijt} \qquad \text{(A.1)}$$

Which is similar to expression (1.2) 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 (IM Pjt−1), while exposure to exports is measured using the industry-level export rate also lagged by one year. Second, we include industry fixed effects (αj) in expression (1.2) 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 (1.2), 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 (A.1) by vector 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 A.7, and these results are based on a sample of workers between 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 and Tables

## Table A.1 Descriptive Statistics for Exposure to Value-Added Imports for Selected Middle-Income Countries, Means and Standard Deviations, 1996-2009

| Occupation-time measures | All occupations | Most routine | Intermediate routine | Least routine |
|---|---|---|---|---|
| Occupation exposure to value-added exports | | | | |
| *IMP* middle-income countries 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 | | | | |
| final goods | 0.0060 | 0.0114 | 0.0037 | 0.0013 |
| | (0.0176) | (0.0266) | (0.0090) | (0.0023) |
| intermediates | 0.0040 | 0.0077 | 0.0023 | 0.0008 |
| | (0.0133) | (0.0204) | (0.0065) | (0.0014) |
| *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 A.2 Descriptive Statistics for Exposure to Value-Added Exports 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 A.3 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 A.4 Descriptive Statistics for Offshoring Employment, Means and Standard Deviations**

| | Occupation-Specific Measures | | | |
|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Panel A: 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 B: 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 A.5 Descriptive Statistics for Offshore Employment, Industry Controls, and Computer Use Rates, Means and Standard Deviations, 1996-2002**

| | Industry-Specific Measures | Occupation-Specific Measures | | | |
|---|---|---|---|---|---|
| | All Occupations | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Panel A: Offshore Employment, 1996-2002 | | | | | |
| Middle-Income | 40,069 | 12,529 | 17,054 | 12,076 | 4,318 |
| Affiliate Employment | (60,312) | (20,930) | (23,498) | (21,231) | (7,355) |
| High-Income | 61,930 | 17,695 | 24,911 | 16,594 | 5,648 |
| Affiliate Employment | (80,429) | (27,396) | (31,368) | (26,922) | (8,820) |
| N of observations | 276 | 1,764 | 630 | 833 | 301 |
| Panel B: Industry Controls and Computer Use Rates,1996-2002 | | | | | |
| Real Price of Investment | 114.94 | . | . | . | . |
| (×100) | (15.32) | . | . | . | . |
| Total Factor Productivity | 1.16 | . | . | . | . |
| | (0.81) | . | . | . | . |
| Capital to Labor Ratio (000s | 129.57 | . | . | . | . |
| per worker) | (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 A.6 Examples of occupations in each routineness category, 1996-2009**

| most-routine occupations | intermediate-routine occupations | least-routine occupations |
|---|---|---|
| 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 |

**Table A.7 OLS Estimates of Wages Determinants Using Industrial Exposures to Gross Trade and Value-Added Trade,1996-2002**

| | Gross Trade Measured by Occupation-Specific Exposure All Sectors | | | | Value-Added Trade Measured by Occupation-Specific Exposure All Sectors | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | -0.146 | -0.335*** | -0.416 | 2.442*** | -0.195 | -0.636*** | -1.927*** | 4.649** |
| Lagged import penetration | (0.095) | (0.119) | (0.510) | (0.897) | (0.229) | (0.237) | (0.694) | (2.264) |
| | 0.729*** | 0.294 | 0.594*** | -0.454 | 2.174*** | 1.836** | 3.977*** | -4.048 |
| Lagged export share | (0.178) | (0.202) | (0.219) | (0.705) | (0.718) | (0.786) | (1.288) | (2.711) |
| Lagged log of middle-income affiliate employment | -0.139** | -0.096*** | 0.001 | -0.539** | -0.083* | -0.083** | 0.022 | -0.338 |
| | (0.057) | (0.036) | (0.101) | (0.227) | (0.050) | (0.036) | (0.062) | (0.205) |
| Lagged log of high-income affiliate employment | 0.126** | 0.078** | 0.002 | 0.511** | 0.070 | 0.060* | -0.020 | 0.334* |
| | (0.052) | (0.032) | (0.087) | (0.205) | (0.045) | (0.033) | (0.057) | (0.180) |
| N of 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: Dependent variable is log hourly wage. See Table 1.2 for the source of worker and trade data. Industry controls include the real price of capital, total factor productivity, capital to labor ratio, and industry-specific computer use rates, which are taken from Ebenstein et al. (2014). Computer use rates are by industry, respectively. Robust standard errors are reported in parentheses. The standard errors are clustered by industry and five-year period in industry-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

**Table A.8 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade from Middle-Income Countries,1996-2009, Alternative Percentiles**

| Variable | Value-Added Trade from Middle-Income Countries Measured by Occupation-Specific Exposure, All Sectors | | | | Value-Added Trade in Final Goods from Middle-Income Countries Measured by Occupation-Specific Exposure, All Sectors | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Lagged import penetration | -0.474 | -0.741** | -4.796** | 0.802 | -0.374 | -0.716* | -7.087* | 3.582 |
| | (0.342) | (0.340) | (2.381) | (2.342) | (0.525) | (0.418) | (3.692) | (3.121) |
| Lagged export share | 6.885*** | 5.448** | 10.879** | 5.071 | 11.039* | 7.457 | 34.417*** | 1.807 |
| | (2.552) | (2.314) | (4.236) | (4.411) | (6.611) | (4.596) | (8.948) | (6.518) |
| Lagged log of middle-income affiliate employment | -0.108* | -0.072* | 0.128 | -0.186 | -0.107* | -0.080* | 0.045 | -0.177 |
| | (0.057) | (0.040) | (0.107) | (0.124) | (0.059) | (0.043) | (0.098) | (0.126) |
| Lagged log of high-income affiliate employment | 0.096* | 0.054 | -0.124 | 0.184 | 0.098* | 0.064* | -0.048 | 0.180 |
| | (0.051) | (0.035) | (0.096) | (0.122) | (0.053) | (0.037) | (0.089) | (0.123) |
| N of Observations | 1,849,039 | 615,553 | 409,852 | 823,548 | 1,849,039 | 615,553 | 409,852 | 823,548 |
| $R^2$ | 0.449 | 0.343 | 0.456 | 0.444 | 0.448 | 0.343 | 0.456 | 0.444 |

Note: Dependent variable is log hourly wage. See Table 1.2 for the source. We rank occupations according to their degree of routineness. If the value of routineness is below the 40$^{th}$ percentile, we consider them as least-routine occupations. If the value of routineness is ranked between the 40$^{th}$ and 60$^{th}$ percentile, we consider this occupation as an intermediate-routine occupation. Those whose routineness is larger than the 60$^{th}$ percentile are most-routine occupations. The standard errors are clustered by 2-digit occupation and five-year period in occupation-specific exposures. Weights are earning weights provided by the CPS-MORG multiplied by the weekly hours. Superscript "***," "**," "*" represent statistical significance at the 1,5 and 10 percent levels.

**Table A.9 OLS Estimates of Wages Determinants Using Occupational Exposures to Value-Added Trade in All vs. Final Goods from Middle-Income Countries,1996-2009, Alternative Percentiles**

| Variable | All Occupations (1) | Bottom 20th (2) | $20^{th}$-$40^{th}$ (3) | $40^{th}$-$60^{th}$ (4) | $60^{th}$-$80^{th}$ (5) | Top $20^{th}$ (6) |
|---|---|---|---|---|---|---|
| Panel A: All Goods | | | | | | |
| Lagged import penetration | -0.474 | -0.113 | -0.261 | -4.796** | -7.336*** | 9.292** |
| | (0.342) | (0.850) | (0.268) | (2.381) | (1.385) | (4.182) |
| Lagged export share | 6.885*** | -1.238 | 4.318 | 10.879** | 15.997*** | -6.698 |
| | (2.552) | (2.769) | (2.700) | (4.236) | (3.095) | (9.646) |
| Panel A: Final Goods | | | | | | |
| Lagged import penetration | -0.374 | 0.121 | -0.216 | -7.087* | -8.795*** | 11.085* |
| | (0.525) | (1.030) | (0.281) | (3.692) | (2.029) | (5.685) |
| Lagged export share | 11.039* | -3.530 | 8.696** | 34.417*** | 23.432*** | 6.379 |
| | (6.611) | (4.783) | (4.178) | (8.948) | (5.009) | (24.379) |
| N of Observations | 1,849,039 | 282,410 | 333,085 | 409,852 | 265,263 | 558,170 |
| $R^2$ | 0.449 | 0.318 | 0.366 | 0.456 | 0.460 | 0.445 |

Note: Dependent variable is log hourly wage. See Table 1.2 for the source. All specifications above use the set of control variables from Tables 1.4 and 1.5. We rank occupations according to their degree of routineness and allocate all occupations into five groups according to its routineness distribution. Occupations in the top $20^{th}$ have the lowest degree of routineness in their occupations and are considered as least-routine occupations. Likewise, occupations in the bottom $20^{th}$ percentile have the highest degree of routineness. Thus, these occupations are defined as most-routine occupations.

# Appendix B - Appendix for Chapter 3

## The explanation for Table 3.1

In Table 3.1, we present the summary statistics for the occupational measures of exposure to value-added trade for workers age 16-64. In Table A1, we show the summary statistics for the same set of measures for young workers age between 18 and 39 years old. In these two tables, we see that the measures of female-specific exposure to value-added trade are larger than those that are male-specific. In the following, we provide some numerical examples in a three-industry case to show that these measures are reasonable for occupations with different gender ratios.

Assume an economy consists of three industries: industry A and B are tradable, and industry C is non-tradable. Industry A is a labor-intensive manufacturing industry (e.g., textile) and industry B is a capital-intensive manufacturing industry (e.g., automotive) while the non-tradable industry C is a service industry (e.g., public health). Suppose at time t-1, the import competition ratio for industry A is 0.2, the ratio for industry B is 0.1, and the ratio for industry C is 0.

Example 1: occupation k is male-dominated.

The total number of male workers involved in occupation k across industries is 1,500 while the total number of female workers involved in occupation k across industries is 1,000. In industry A, there are 200 male workers and 100 female workers involved in the occupation k. In industry B, there are 300 male workers and 200 female workers involved in occupation k. In industry C, there are 1,000 male workers and 700 female workers involved in occupation k. Using expression (1), we compute the U.S. occupational exposure to value-added imports specific to male and female workers involved in occupation k. The male-specific import competition ratio for occupation k is 0.03 (where $IMP_{kt-1}^{m} = \sum_{j}^{J=1} \frac{L_{kj}^{m}}{L_{k}^{m}} IMP_{jt-1} = \frac{200}{1{,}500} \times 0.2 + \frac{300}{1{,}500} \times 0.1 + \frac{1{,}000}{1{,}500} \times$

$0 = \frac{50}{1500} = 0.03$) while the female-specific ratio is 0.04 (where $IMP^{f}_{kt-1} = \sum_{j}^{J=1} \frac{L^{f}_{kj}}{L^{f}_{k}} IMP_{jt-1} = \frac{100}{1,000} \times 0.2 + \frac{200}{1,000} \times 0.1 + \frac{700}{1,000} \times 0 = \frac{40}{1000} = 0.04$).

Example 2: occupation k is female-dominated.

The total number of male workers involved in occupation k across industries is 1,000 while the total number of female workers involved in occupation k across industries is 1,500. In industry A, there are 100 male workers and 400 female workers involved in the occupation k. In industry B, there are 200 male workers and 300 female workers involved in occupation k. In industry C, there are 700 male workers and 800 female workers involved in occupation k. The male-specific import competition ratio for occupation k is 0.04 (where $IMP^{m}_{kt-1} = \sum_{j}^{J=1} \frac{L^{m}_{kj}}{L^{m}_{k}} IMP_{jt-1} = \frac{100}{1,000} \times 0.2 + \frac{200}{1,000} \times 0.1 + \frac{700}{1,000} \times 0 = \frac{40}{1000} = 0.04$) while the female-specific ratio is 0.07 (where $IMP^{f}_{kt-1} = \sum_{j}^{J=1} \frac{L^{f}_{kj}}{L^{f}_{k}} IMP_{jt-1} = \frac{400}{1,500} \times 0.2 + \frac{300}{1,000} \times 0.1 + \frac{800}{1,000} \times 0 = \frac{110}{1,500} = 0.07$).

Example 3: occupation k that is equally distributed by gender.

The total number of male workers involved in occupation k across industries is 1,000 while the total number of female workers involved in occupation k across industries is 1,000. In industry A, there are 300 male workers and 100 female workers involved in the occupation k. In industry B, there are 200 male workers and 400 female workers involved in occupation k. In industry C, there are 700 male workers and 700 female workers involved in occupation k. The male-specific import competition ratio for occupation k is 0.033 (where $IMP^{m}_{kt-1} = \sum_{j}^{J=1} \frac{L^{m}_{kj}}{L^{m}_{k}} IMP_{jt-1} = \frac{300}{1,000} \times 0.2 + \frac{100}{1,000} \times 0.1 + \frac{600}{1,000} \times 0 = \frac{40}{1000} = 0.04$) while the female-specific ratio is 0.06 (where $IMP^{f}_{kt-1} = \sum_{j}^{J=1} \frac{L^{f}_{kj}}{L^{f}_{k}} IMP_{jt-1} = \frac{100}{1,000} \times 0.2 + \frac{400}{1,000} \times 0.1 + \frac{500}{1,000} \times 0 = \frac{60}{1,000} = 0.06$).

## Is Skill Playing a Role in the Likelihood of Marriage:

## Alternative Gender-Specific Specification

In the baseline results related to marriage, we focus on comparing the effects of gender-specific exposure to value-added trade on the probability of being married. Below we explore the role of skill by the following specification:

$$married_{ijkt} = \beta_1 IMP^s_{kt-1} + \beta_2 IMP^s_{kt-1} \times \mathrm{Skill_i} + \beta_3 \mathrm{Skill_i} + G^s_{kt-1}\Phi + Z_{ijkt}\Omega + \alpha_{jt}$$
$$+Comp_{kt} + \alpha_k + \epsilon_{ijkt} \quad \text{(B.1)}$$

Which is based on expression (3.4). We make several modifications. First, we replace the variable related to education by a skill dummy. $Skill_i$ is equal to one if worker i is a skilled worker who holds at least a bachelor's degree. Second, we add an interaction between the skill indicator and the lagged gender-specific exposure to value-added trade at the occupation level. Notice that this approach is very similar to Hummels et al. (2014) who study the effects of firm-specific exposure to offshoring and gross exports on Danish wages by skill. In this paper, the coefficient, $\beta_1$ represent the effect of gender-specific exposure to value-added imports on the probability of being married for unskilled workers. The sum of $\beta_1$ and $\beta_2$, on the other hand, is the effect for skilled workers in that group. The results of this specification are shown in Table 3.14.

# Additional Summary Statistics

## Table B.1 Descriptive Statistics for Exposure to Value-Added, Means and Standard Deviations, 1996-2009, Young Workers Age 18-39

| Gender-Specific occupation-time measures | Employed Workers | | | | All Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Male | | | | | | | | |
| *IMP* all goods | 0.0336 | 0.0554 | 0.0257 | 0.0099 | 0.0337 | 0.0555 | 0.0257 | 0.0099 |
| | 0.0490 | 0.0653 | 0.0340 | 0.0144 | 0.0491 | 0.0655 | 0.0340 | 0.0144 |
| Export Share all goods | 0.0174 | 0.0275 | 0.0140 | 0.0058 | 0.0174 | 0.0274 | 0.0140 | 0.0058 |
| | 0.0215 | 0.0257 | 0.0178 | 0.0089 | 0.0215 | 0.0257 | 0.0178 | 0.0089 |
| *IMP* final goods | 0.0168 | 0.0283 | 0.0128 | 0.0046 | 0.0168 | 0.0283 | 0.0124 | 0.0046 |
| | 0.0297 | 0.0422 | 0.0183 | 0.0068 | 0.0298 | 0.0424 | 0.0183 | 0.0068 |
| Export Share final goods | 0.0084 | 0.0133 | 0.0066 | 0.0027 | 0.0084 | 0.0133 | 0.0066 | 0.0027 |
| | 0.0107 | 0.0128 | 0.0089 | 0.0041 | 0.0107 | 0.0128 | 0.0089 | 0.0041 |
| *IMP* intermediates | 0.0130 | 0.0208 | 0.0104 | 0.0041 | 0.0130 | 0.0208 | 0.0104 | 0.0041 |
| | 0.0172 | 0.0216 | 0.0134 | 0.0062 | 0.0172 | 0.0216 | 0.0134 | 0.0062 |
| Export Share intermediates | 0.0076 | 0.0118 | 0.0061 | 0.0026 | 0.0076 | 0.0118 | 0.0061 | 0.0026 |
| | 0.0096 | 0.0118 | 0.0077 | 0.0041 | 0.0096 | 0.0118 | 0.0077 | 0.0041 |
| N of Observations | 3,477 | 1,243 | 1,641 | 593 | 3,480 | 1,246 | 1,641 | 593 |
| Panel B: Female | | | | | | | | |
| *IMP* all goods | 0.0360 | 0.0595 | 0.0290 | 0.0077 | 0.0363 | 0.0598 | 0.0292 | 0.0076 |
| | 0.0588 | 0.0769 | 0.0458 | 0.0125 | 0.0590 | 0.0768 | 0.0461 | 0.0125 |
| Export Share all goods | 0.0176 | 0.0279 | 0.0146 | 0.0047 | 0.0176 | 0.0280 | 0.0147 | 0.0047 |
| | 0.0227 | 0.0266 | 0.0199 | 0.0076 | 0.0228 | 0.0267 | 0.0198 | 0.0076 |
| *IMP* final goods | 0.0190 | 0.0319 | 0.0151 | 0.0037 | 0.0192 | 0.0321 | 0.0152 | 0.0037 |
| | 0.0382 | 0.0527 | 0.0280 | 0.0061 | 0.0383 | 0.0526 | 0.0283 | 0.0061 |
| Export Share final goods | 0.0085 | 0.0135 | 0.0071 | 0.0021 | 0.0085 | 0.0135 | 0.0071 | 0.0021 |
| | 0.0115 | 0.0136 | 0.0101 | 0.0021 | 0.0115 | 0.0136 | 0.0101 | 0.0035 |
| *IMP* intermediates | 0.0129 | 0.0206 | 0.0107 | 0.0031 | 0.0130 | 0.0208 | 0.0108 | 0.0031 |
| | 0.0182 | 0.0221 | 0.0156 | 0.0052 | 0.0184 | 0.0222 | 0.0157 | 0.0051 |
| Export Share intermediates | 0.0075 | 0.0120 | 0.0062 | 0.0021 | 0.0076 | 0.0120 | 0.0062 | 0.0021 |
| | 0.0101 | 0.0121 | 0.0062 | 0.0035 | 0.0101 | 0.0121 | 0.0086 | 0.0035 |
| N of Observations | 3,232 | 1,131 | 1,532 | 563 | 3,283 | 1,157 | 1,556 | 566 |

**Table B.2 Descriptive Statistics for the Current Population Survey Merged Outgoing Rotation Group Workers Age 16-64, Means and Standard Deviations, 1996-2009**

| Occupation-time measures | Employed Workers | | | | All Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Demographic Information for Male Workers, Age 16-64 | | | | | | | | |
| Age | 39.51 | 37.87 | 39.04 | 41.26 | 39.31 | 37.53 | 38.78 | 41.28 |
| | 11.56 | 12.02 | 11.67 | 10.86 | 11.70 | 12.15 | 11.80 | 10.97 |
| Years of Education | 13.20 | 12.32 | 12.98 | 14.10 | 13.14 | 12.29 | 12.90 | 14.05 |
| | 2.29 | 1.78 | 2.21 | 2.39 | 2.29 | 1.79 | 2.21 | 2.39 |
| Married | 0.62 | 0.55 | 0.61 | 0.69 | 0.61 | 0.53 | 0.59 | 0.68 |
| | 0.48 | 0.50 | 0.49 | 0.46 | 0.49 | 0.50 | 0.49 | 0.47 |
| Hourly Wage | 18.53 | 13.74 | 17.68 | 22.85 | . | . | . | . |
| | 13.05 | 7.33 | 11.63 | 16.26 | . | . | . | . |
| N of Observations | 846,580 | 160,217 | 424,464 | 261,668 | 962,121 | 182,006 | 485,173 | 294,752 |
| Panel B: Demographic Information for Female Workers, Age 16-64 | | | | | | | | |
| Age | 29.97 | 28.96 | 29.71 | 31.21 | 29.78 | 28.72 | 29.51 | 31.12 |
| | 5.84 | 6.10 | 5.90 | 5.31 | 5.92 | 6.15 | 5.98 | 5.37 |
| Years of Education | 13.05 | 12.25 | 12.88 | 19.48 | 12.97 | 12.22 | 12.78 | 13.92 |
| | 2.19 | 1.68 | 2.15 | 13.85 | 2.18 | 1.67 | 2.13 | 2.30 |
| Married | 0.50 | 0.43 | 0.49 | 0.57 | 0.48 | 0.41 | 0.47 | 0.56 |
| | 0.50 | 0.50 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 | 0.50 |
| Hourly Wage | 15.90 | 12.21 | 15.47 | 13.98 | . | . | . | . |
| | 10.86 | 6.27 | 9.88 | 2.30 | . | . | . | . |
| N of Observations | 422,301 | 87,737 | 217,448 | 116,660 | 484,166 | 101,080 | 251,578 | 131,106 |

**Table B.3 Descriptive Statistics for the Current Population Survey Merged Outgoing Rotation Group Workers Age 18-39, Means and Standard Deviations, 1996-2009**

| Occupation-time measures | Employed Workers | | | | All Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Demographic Information for Male Workers, Age 16-64 | | | | | | | | |
| Age | 29.97 | 28.96 | 29.71 | 31.21 | 29.78 | 28.72 | 29.51 | 31.12 |
| | 5.84 | 6.10 | 5.90 | 5.31 | 5.92 | 6.15 | 5.98 | 5.37 |
| Years of Education | 13.05 | 12.25 | 12.88 | 19.48 | 12.97 | 12.22 | 12.78 | 13.92 |
| | 2.19 | 1.68 | 2.15 | 13.85 | 2.18 | 1.67 | 2.13 | 2.30 |
| Married | 0.50 | 0.43 | 0.49 | 0.57 | 0.48 | 0.41 | 0.47 | 0.56 |
| | 0.50 | 0.50 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 | 0.50 |
| Hourly Wage | 15.90 | 12.21 | 15.47 | 13.98 | . | . | . | . |
| | 10.86 | 6.27 | 9.88 | 2.30 | . | . | . | . |
| N of Observations | 422,301 | 87,737 | 217,448 | 116,660 | 484,166 | 101,080 | 251,578 | 131,106 |
| Panel B: Demographic Information for Female Workers, Age 16-64 | | | | | | | | |
| Age | 30.09 | 29.85 | 29.88 | 30.63 | 29.94 | 29.65 | 29.75 | 29.75 |
| | 5.85 | 6.08 | 5.83 | 5.59 | 5.93 | 6.15 | 5.90 | 5.90 |
| Years of Education | 13.31 | 12.60 | 13.37 | 13.97 | 13.22 | 12.54 | 13.28 | 13.28 |
| | 2.09 | 1.66 | 2.04 | 2.31 | 2.09 | 1.67 | 2.04 | 2.04 |
| Married | 0.49 | 0.49 | 0.48 | 0.50 | 0.47 | 0.47 | 0.46 | 0.46 |
| | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |
| Hourly Wage | 13.22 | 10.78 | 13.48 | 15.42 | . | . | . | . |
| | 9.26 | 5.67 | 9.01 | 11.73 | . | . | . | . |
| N of Observations | 340,634 | 104,907 | 136,095 | 98,945 | 388,099 | 121,029 | 155,164 | 155,164 |

**Table B.4 Descriptive Statistics for Offshoring Employment, Means and Standard Deviations, 1996-2009**

| Occupation-time measures | Employed Workers | | | | All Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Offshoring Employment for Male Workers, Age 16-64 | | | | | | | | |
| Middle-Income | 13,064<br>21,625 | 17,246<br>23,695 | 28,215<br>22,432 | 5,235<br>8,607 | 13,064<br>21,625 | 17,246<br>23,695 | 12,709<br>22,432 | 5,235<br>8,607 |
| High-Income | 18,511<br>28,517 | 25,450<br>32,499 | 17,445<br>28,215 | 6,840<br>10,480 | 18,511<br>28,517 | 25,450<br>32,499 | 17,445<br>28,215 | 6,840<br>10,480 |
| N of Observations | 3,497 | 1,254 | 1,648 | 595 | 3,497 | 1,254 | 1,648 | 595 |
| Panel B: Offshoring Employment for Male Workers, Age 18-39 | | | | | | | | |
| Middle-Income | 13,072<br>21,570 | 17,358<br>23,758 | 12,651<br>22,263 | 5,253<br>8,617 | 13,062<br>21,563 | 17,319<br>23,743 | 12,651<br>22,263 | 5,253<br>8,617 |
| High-Income | 18,536<br>28,509 | 25,611<br>32,576 | 17,394<br>28,120 | 6,863<br>10,490 | 18,521<br>28,501 | 25,554<br>32,558 | 17,394<br>28,120 | 6,863<br>10,490 |
| N of Observations | 3,477 | 1,243 | 1,641 | 593 | 3,480 | 1,246 | 1,641 | 593 |
| Panel C: Offshoring Employment for Female Workers, Age 16-64 | | | | | | | | |
| Middle-Income | 13,425<br>32,511 | 18,818<br>31,590 | 12,910<br>37,587 | 3,630<br>6,553 | 13,390<br>32,486 | 18,703<br>31,462 | 12,909<br>37,621 | 3,612<br>6,541 |
| High-Income | 18,088<br>40,434 | 24,705<br>34,755 | 17,905<br>49,310 | 4,833<br>7,796 | 18,087<br>40,738 | 24,539<br>34,622 | 18,010<br>49,914 | 4,808<br>7,784 |
| N of Observations | 3,387 | 1,206 | 1,601 | 580 | 3,416 | 1,219 | 1,614 | 583 |
| Panel D: Offshoring Employment for Female Workers, Age 18-39 | | | | | | | | |
| Middle-Income | 12,802<br>29,504 | 18,099<br>30,041 | 12,140<br>33,056 | 3,740<br>6,621 | 12,839<br>29,577 | 18,046<br>29,979 | 12,256<br>33,268 | 3,720<br>6,609 |
| High-Income | 17,389<br>37,673 | 23,979<br>33,485 | 16,979<br>45,138 | 4,979<br>7,867 | 17,464<br>38,050 | 23,847<br>33,317 | 17,228<br>45,955 | 4,953<br>7,854 |
| N of Observations | 3,232 | 1,131 | 1,532 | 563 | 3,283 | 1,157 | 1,556 | 566 |

## Table B.5 Descriptive Statistics for Computer Use Rates, Means and Standard Deviations, 1996-2009

| Occupation-time measures | Employed Workers | | | | All Workers | | | |
|---|---|---|---|---|---|---|---|---|
| | All Occupations | Most Routine | Intermediate Routine | Least Routine | All Occupations | Most Routine | Intermediate Routine | Least Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Computer Use Rates for Male Workers, Age 16-64 | | | | | | | | |
| Computer Use Rates | 0.51<br>0.35 | 0.43<br>0.32 | 0.51<br>0.36 | 0.67<br>0.32 | 0.51<br>0.35 | 0.43<br>0.32 | 0.51<br>0.36 | 0.67<br>0.32 |
| N of Observations | 3,497 | 1,254 | 1,648 | 595 | 3,497 | 1,254 | 1,648 | 595 |
| Panel B: Computer Use Rates for Male Workers, Age18-39 | | | | | | | | |
| Computer Use Rates | 0.51<br>0.35 | 0.43<br>0.32 | 0.51<br>0.36 | 0.67<br>0.32 | 0.51<br>0.35 | 0.43<br>0.32 | 0.51<br>0.36 | 0.67<br>0.32 |
| N of Observations | 3,477 | 1,243 | 1,641 | 593 | 3,480 | 1,246 | 1,641 | 593 |
| Panel C: Computer Use Rates for Female Workers, Age 16-64 | | | | | | | | |
| Computer Use Rates | 0.52<br>0.35 | 0.43<br>0.32 | 0.52<br>0.36 | 0.69<br>0.31 | 0.52<br>0.35 | 0.43<br>0.32 | 0.52<br>0.36 | 0.69<br>0.31 |
| N of Observations | 3,387 | 1,206 | 1,601 | 580 | 3,416 | 1,219 | 1,614 | 583 |
| Panel D: Computer Use Rates for Female Workers, Age 18-39 | | | | | | | | |
| Computer Use Rates | 0.53<br>0.35 | 0.44<br>0.33 | 0.54<br>0.36 | 0.69<br>0.31 | 0.53<br>0.35 | 0.44<br>0.32 | 0.53<br>0.36 | 0.69<br>0.31 |
| N of Observations | 3,232 | 1,131 | 1,532 | 563 | 3,283 | 1,157 | 1,556 | 566 |