ESSAYS ON INTERNATIONAL TRADE AND LABOR MARKET OUTCOMES

By

Tommaso Tempesti

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Approved:

Professor Robert Driskill

Professor Yanqin Fan

Professor Andrea Moro

Professor David Parsley

Professor Joel Rodrigue

To the memory of Matteo Lanzoni.

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CHAPTER I

INTRODUCTION

The effects of globalization on domestic economies have been, and still are, widely debated. In this thesis I contribute to the literature on the effects of international trade on labor market outcomes. In the first chapter I review the more recent work on the subject and notice how the use of datasets that contain data on individual workers is promising for advancing the field. In the second chapter I combine micro level data on U.S. workers from the March Current Population Survey in the 1980s with macro level data on trade for the industries the workers are in. In particular, I focus on trade in intermediate inputs, that I call *offshoring*. Offshoring in U.S. manufacturing grew more than 25% between 1970 and 1990 (Hummels et al. (2001)). I find an effect of offshoring on the wage premium paid to educated workers with respect to less educated ones. This *skill-premium* is an important component of wage inequality. In the third chapter, I study if offshoring has also affected *residual* inequality, i.e. the wage inequality that is not explained by basic observable characteristics of the worker. In order to do this, I study if offshoring has affected the workers' probability of switching their occupations. Previous studies have found that the increase in occupational switching accounts for a large portion of the increase in residual inequality. I find however that offshoring does not affect occupational switching. Taken together, my results imply that, at least for U.S. in the 1980s, offshoring increased wage inequality by increasing the skill-premium but did not affect residual wage inequality.

More specifically, the first chapter surveys recent empirical works that study the effects of trade on labor market outcomes. The focus is on studies that use individual workers' data. These data allow to control for the changing variation of the labor force across industries over time. In this regard, these studies improve over previous ones that do not control for worker level variables. I first review works that are based on regressions. These works find that, at least for the U.S., trade either increases wage inequality or has no effect on it. I discuss the reasons that may explain the variety of these results. These results seem to suggest that, at least for the U.S., the increase in trade did not benefit the poorest among the workers. This is in line to what Goldberg and Pavcnik (2007) find in their review of studies on developing countries. I then review empirical works based on structural models. These models suggest instead that studies based on wage regressions neglect the long-term consequences of trade on the reallocation of resources across sectors and the efficiency gains associated with it. I finally show the usefulness of matched employer-employee datasets and discuss along the way promising avenues for future research.

In recent decades many countries have experienced an increase in both international trade and the skill-premium. The association between these two phenomena has proven elusive in the early empirical literature on the subject. Indeed, the consensus among labor economists seems to be that trade has not been the main cause of such increase in the skill-premium. This view has been challenged by Feenstra and Hanson (1999) who find that offshoring sizably affects the skill-premium. In the second chapter I revisit this debate using individual workers data from the March Current Population Survey combined with industry-level trade data. This strategy improves upon the work of Feenstra and Hanson who do not control for the demographic characteristics of the labor force. I show that industry-level wage regressions overestimate the impact of offshoring on the skill-premium if the demographic characteristics of the labor force are omitted. In addition, I find that offshoring increases the relative employment of skilled workers, thus suggesting that offshoring has played an important role in the increase in the skill-premium by increasing the economy-wide relative demand of skilled workers.

Various studies have stressed the importance of an increase in economic *turbulence* for the understanding of the labor market. Kambourov and Manovskii (2009b) document an increase in the fraction of workers switching occupations since the early 1970s to the mid-1990s. They show how this increase is able to explain a substantial portion of the concurrent increase in residual wage inequality. They attribute the increase in occupational switching to the increased turbulence in the economy. Offshoring seems to be a possible candidate for the increase of turbulence in the labor market. In the third chapter, using data from the March Current Population Survey for the 1983-1990 period, I study if offshoring in manufacturing is correlated with occupational switching. I find that offshoring does *not* increase the probability of switching occupations. The coefficient on offshoring is either non-significantly different from zero or significantly different from zero and *negative*. This result is robust to the use of different measures of offshoring and to controlling for attrition out of the March Current Population Survey from one year to the other. This result suggests that offshoring from U.S. to abroad has not been responsible for the increase in residual inequality.

CHAPTER II

LITERATURE REVIEW

Introduction

Recently, the impact of international trade on labor market outcomes has received a great deal of attention in the press.[1] At the same time, the academic literature has devoted an increasing attention to the impact of international trade on labor market outcomes. In particular, many studies have combined data on individual workers with industry level data to study e.g. the impact of trade on inequality, on the wages of the unskilled workers and on unemployment. The goal of this paper is to survey the recent empirical literature in this area and to point to promising avenues for future research.

Some clarifications are in order here. First, this is not a survey of the theoretical literature on trade and the labor market. I will refer to that literature when relevant but the focus here is on the empirical work, its challenges and results. Second, this is not even a survey of all the empirical literature on the subject. Indeed, I concentrate on studies that make use of individual level data on workers.[2] There is for example a large literature in the 1990s about the effect of trade on wage inequality but that literature mainly uses data on workers that is aggregated at the industry level.[3] Again, I will refer to this literature when relevant but the focus here is on empirical studies that use individual data on workers.

[1] Irwin (2009) and Wolf (2004) detail the various policy debates concerning “globalization”. Amiti et al. (2005) document the importance of service offshoring during the 2004 U.S. presidential election.

[2] A bit of historical perspective may be helpful. One of the most significant development in the recent trade literature is the use, especially since the end of the 90s, of micro level data on firms or plants. A subsequent development has been the use of micro level data on workers, which is the focus of this survey. These two approaches are now being combined in the use of employer-employee matched datasets. In section II.4.3 I review Muendler and Menezes-Filho (2007) who utilize a employer-employee matched dataset.

[3] This literature is reviewed in e.g. Acemoglu (2002, Section 6.3).

Even this narrow focus does not allow me to review all the more recent papers in the literature given their increasing number. Rather my survey is only selective with the intent to delineate some of the main features and challenges of the work in this area.

In the study of the impact of trade on the labor market, the usefulness of individual data on workers can be illustrated in several ways. First, we know that a worker's wage is affected by her observable individual characteristics. Studies that rely only on aggregate wages at the industry level and do not control for the individual characteristics of the workers within each industry omit an important determinant of the level of wages in each industry.[4] If the characteristics of the workers are correlated with the trade regressor of interest, the empirical results will be biased. Including industry fixed effects in the regression (or differencing over time within an industry) alleviates this problem only in part because trade may also involve a changing composition of the labor force within an industry over time. Moreover, even if the characteristics of workers were not correlated with the regressors of interest, their inclusion in the wage regression will likely decrease the standard errors on the estimates on the relevant regressors.

A worker's wage is also affected by her *unobservable* individual characteristics. If workers sort across industries based on these unobservable characteristics, then the estimates of the parameters of interest may be biased. Using *longitudinal* individual worker's level data also allows to control for worker fixed effects. It also also allows the study of other relevant outcomes. For example, one can observe the movement of workers across industries, across occupations and across labor market status (e.g. employed in the formal sector, employed in the informal sector, unemployed).

[4] The same is true of studies that use data on workers that is aggregated at the firm or plant level without controlling for the individual characteristics of the workers within each firm or plant.

Goldberg and Pavcnik (2007) review the literature on the distributional effects of globalization in developing countries. This survey is different from theirs in the following ways. First, the focus of this survey is on studies that utilize individual worker's data. While their paper also reviews some of such studies, this paper updates theirs focusing on more recent developments in this area. Second, many studies that utilize individual worker's data refer to the U.S. experience. Because of this focus I review many papers that study the U.S. labor market and not the developing countries' one. Finally, I use the Mincerian equation to organize the exposition of the material and, to the best of my knowledge, my paper is the first to do that. But some distinctions in the literature are standard (e.g. the distinction between inter-sectoral vs. intra-sectoral reallocation of resources) and Goldberg and Pavcnik (2007) articulate them in an excellent way: I therefore follow their work in some regards and I document when I do so. Another related work is Crinò (2009). He focuses on the labor market effect of offshoring of services, offshoring of manufacturing and foreign direct investment. He reviews only few studies that use individual worker's data and none that uses a structural model. He also does not survey the more recent literature on the labor market effects of trade in final goods while I do not survey the literature on the international movement of capital. In this sense, our two surveys are then complementary.

Section II.2 reviews the stylized facts for the labor market and for trade flows that motivate the works in this area. Section II.3 reviews the methodologies that are usually utilized in the literature, with a special focus on Mincerian wage regressions. Section II.4.1 reviews the results on the effects of trade on the wage premium paid to skilled workers with respect to unskilled workers. Section II.4.2 reviews the results on the effects of trade on other components of wage inequality. The studies reviewed in these sections use wage regressions and find that, at least for U.S., trade either increases wage inequality or has no effect on it. The reasons that may explain the variety of these results are discussed in section II.3. From these results one could be tempted to conclude that the increase in trade did not benefit the poorest among the U.S. workers. This would be in line to what Goldberg and Pavcnik (2007) find in their review of studies on developing countries. However, structural models suggest that studies based on wage regressions neglect the long-term consequences of trade on the reallocation of resources across sectors and the efficiency gains associated with it. These studies are reviewed in section II.4.3. This section also reviews a study that uses matched employer-employee data and shows the advantages of using such data. Table 1 contains an overview of the results. Section II.5 concludes.

Table 1. Literature Review: Summary

Study	Country Period	Methodology	Dataset N	Results
Feenstra and Hanson (1999)	U.S. 1979-1987	Two-stage regression	Industry Panel 450	Offshoring accounts for at least 15% of increase in skill-premium
Lovely and Richardson (2000)	U.S. 1981-1992	OLS with individual fixed effects	Worker Panel (PSID) 6,477	Trade with newly industrialized countries does not increase the industry premium to skilled relatively to unskilled workers
Kosteas (2008)	U.S. 1979-1996	OLS with individual fixed effects	Worker Panel (NLSY) N/A	Wage semi-elasticity w.r.t. imports share from low-wage countries is -.6
Ebenstein et al. (2009)	U.S. 1983-2002	OLS	Worker Cross-section (CPS MORG) 2,505,724	Wage semi-elasticity w.r.t. import share at occupation level is -.27
Liu and Trefler (2008)	U.S. 1996-2005	First Differences	Worker Cross-Section (Matched March CPS) 37,550	Offshoring of services does not significantly affect wages
Attanasio et al. (2004)	Colombia 1984-1998	First Differences	Worker Cross-Section (Household Survey) 225202	Wage semi-elasticity w.r.t. tariffs is 0.05

Source: compilation of the author.

Table 2. Literature Review: Summary, continued

Study	Country Period	Methodology	Dataset N	Results
Artuc et al. (2010)	U.S. 1975-2000	Structural Estimation	Worker Cross-Section (March CPS) N/A	Workers in the import-competing sector sector may benefit from a lower tariff because of higher option value of moving to another sector
Artuc (2009)	U.S. 1983-1994	Structural Estimation	Worker Panel (NLSY) 1190	Middle-aged workers in the import-competing sector are hurt the most by a lower tariff because of industry-specific human capital
Muendler et al. (2007)	Brazil 1990-1998	Logit with individual fixed effects	Matched Employer-Employee, 1% random sample from population	After trade liberalization, job separations are higher, and job accessions are lower, in comparative-advantage sectors and at exporters.

Source: compilation of the author.

Empirical Motivation

Labor Market Outcomes

A large literature has documented the changes in the labor market in recent decades, in both developing and developed countries. Figure 1 graphs the employment of production workers in U.S. manufacturing during the 1972-1996 period. Even though the U.S. population increased during this period, the number of production workers employed in U.S. manufacturing declined by almost 1,400,000.[5] Using data from the Current Population Survey (CPS hereafter), Ebenstein et al. (2009) estimate a decrease in total employment in U.S. manufacturing from 22 millions in 1979 to 17 millions in 2002, with a rapid decrease in the more recent years. A possible explanation for this decline is that the price of foreign manufacturing goods has decreased relatively to the price of domestic manufacturing goods and so the U.S. consumers have substituted away from domestic manufacturing.

Several studies have also documented the changes in the wage structure in U.S. and in other countries. In this regard it is useful to introduce the Mincerian wage equation that has been used extensively in the labor literature. A popular version of this equation is the following:

$$ln(w_s) = \alpha + \beta_1 Race_s + \beta_2 Gender_s + \beta_3 Exp_s + \beta_4 Exp_s^2 + \beta_5 Educ_s + \epsilon_s \qquad \text{(II.1)}$$

where s is a worker, ln is the natural logarithm, w_s her wage, $Race_s$ a set of race dummies, $Gender_s$ a gender dummy, Exp_s a proxy for work experience, $Educ_s$ a measure of education such as years of schooling or a set of dummies for degrees completed, and ϵ_s an error assumed

[5] Data are from the NBER productivity database. I graph the data since 1972 which is the earliest available year for the trade data used in Figure 2. The number of total workers (production and non-production) employed in U.S. manufacturing declined by around 700,000 during this period.

to be random.

If we measure inequality of wages with the variance, then this equation allows to decompose wage inequality in two components: the variance of the predicted wage and the variance of the estimated residual.[6] The first term is also called *between*-inequality because it captures that portion of wage inequality that depends on e.g. men earning on average more than women. The second term is also called *within*-inequality because it captures that portion of wage inequality that does not depend on the demographic characteristics of workers. In other words, there is inequality of wages even among workers who have the same demographic characteristics. This second term is also called *residual* inequality, which is the term I will use in this review.

A remarkable change in the wage structure has been the increase in the wage premium paid to educated workers. This is also called *skill*-premium under the assumption that education is a good proxy of the skill of the worker.[7] In terms of equation (II.1), this means an increase in β_5 over time.[8] Autor et al. (2008, Figure 2, p.303) show that, since 1979 to 2005, the average wage paid to a worker with a college degree grew 20% more than the average wage paid to a worker with only a high-school degree. Given that the relative employment of U.S. skilled workers has also increased, this suggests that the relative demand for skilled workers has increased.[9] Similar patterns for relative employment and relative wages of skilled workers have also been detected in many developing countries,

[6] More specifically, the Mincerian equation allows to decompose the inequality of the *log* of wages. The logarithm is useful for several reasons. First, it reduces the impact of very large incomes on the estimates. Second, the distribution of the log of wages is fairly normal which is useful when using ordinary least squares. Third, the use of logs facilitates the interpretation of the coefficients that become either elasticities (if the regressor is also in logs) or semi-elasticities. In what follows, when I talk about "wage" I actually mean the log of wage.

[7] Some studies proxy unskilled workers with production workers and skilled workers with non-production workers.

[8] Sometimes equation II.1 is run in different years allowing the coefficients to change over time.

[9] This point has been made several times in the literature. See for example Katz and Autor (1999), Acemoglu (2002) and more recently Crinò (2009, p.203).

especially since the 1980s.[10] The increase in the skill-premium has also contributed to the increase in overall wage inequality. In U.S. the wage of workers at the 90th percentile has increased around 25% more than the wage of workers at the 10th percentile (see Autor et al. (2008, Figure 2, p.303)).[11] In Section II.4.1 I discuss the relationship between various forms of international trade and the increase in the relative demand for skill.

The coefficients on the other variables in equation II.1 have also changed over time, at least for U.S, and contributed to the evolution of wage inequality over time.[12] There are only few works that discuss how international trade has affected these coefficients and so this is possibly an area for future research.

Even if the vector of β coefficients does not change, wage inequality may still increase because of an increase in residual inequality. The evidence on residual inequality is mixed. For the U.S. Katz and Autor (1999) at first estimated that the increase in residual inequality could explain up to 2/3 of the increase in overall inequality. Kambourov and Manovskii (2009b, Figure 1, p.736) use the PSID and find that the contribution of the residual inequality to the increase in overall inequality is very large. Lemieux (2006) argues instead that around 3/4 of the increase in residual inequality between 1973 and 2003 disappears when controlling for compositional effects.[13] Bertola and Ichino (1995, Figure 2) document that residual inequality was fairly stable in Great Britain, France and Italy during the 70s and the 80s. Attanasio et al. (2004) document a sizable increase, albeit non-

[10] See the review in Goldberg and Pavcnik (2007, Table 1, p.48).

[11] Obviously, income inequality need not translate in consumption inequality. Early work found evidence that consumption inequality also markedly increased in U.S. in the 1980s (Cutler and Katz (1992)). However, recent work that uses the Consumer Expenditure Survey has reconsidered this result showing that consumption inequality has increased much more moderately than income inequality (Krueger and Perri (2006)).

[12] See Katz and Autor (1999).

[13] In other words, the residual in equation (II.1) is heteroskedastic: the variance of the residual depends on the specific combination of observable characteristics of the worker (e.g. older workers tend to have more dispersed wages). Lemieux (2006) shows that a large part of the increase in the residual inequality can be explained by the increase in the size of the combinations that have a higher variance of the residual (e.g. the workforce getting older).

monotonic, in residual inequality between 1984 and 1998 for Colombia. In section II.4.2 I discuss the relationship between trade and residual inequality.

Trade Flows

The recent decades have also witnessed a remarkable increase in trade across countries. In Figure 2 I graph the import penetration in U.S. manufacturing for the 1972-1996 period. Import penetration was 7% in 1972 but it increased to 22% in 1996.[14]

In its 1998 annual report the WTO documents that, worldwide, "merchandise exports grew by 6 per cent in real terms from 1948 to 1997, compared to an annual average output growth of 3.7 per cent"(p.33). It also reports that "in developed countries, openness measured by the ratio of trade to GDP increased from 16.6 to 24.1 per cent between 1985 and 1997. In developing countries this indicator rose from 22.8 per cent to 38.0 per cent over the same period"(p.33). Finally they also report how the composition of trade has been changing, moving away from agriculture to manufacturing, with the more recent rise in trade in services.[15]

The academic literature has also focused on the specific forms in which trade can take place. Many studies have documented how it is not just trade in final goods that has increased but also trade in intermediate inputs, a phenomenon also referred to as *offshoring*. Crinò (2009, p.198) documents that offshoring in *manufacturing*, measured as the share of

[14]The original data is from Bernard et al. (2006). This data is available at Peter Schott's website. Import penetration by SIC 87 industry is defined as imports/(shipments-exports+imports). Data is available for all years for only 386 industries out of 459 SIC 87 industries. I take the simple average of import penetration across industries, within a year. I also computed the average of import penetration across industries, within a year, using the share of employment in an industry as weight. The data on employment by SIC 87 industry is from the NBER productivity database. The weighted import penetration was 6% in 1972 and 16% in 1996. The pattern of growth over time is similar for both measures of import penetration.

[15]The same document indeed notices that "agricultural exports accounted for almost 47 per cent of total merchandise exports in 1950, and their share had dropped to 12 per cent by 1996. Manufactures, by contrast, accounted for 38 per cent of exports in 1950. This share increased to 77 per cent by 1996" and that "services trade in OECD countries increased at almost twice the rate of merchandise trade between 1980 and 1995"(p.34).

imported intermediate inputs in total non-energy input purchases, has increased in the United States from 5.1% in 1972 to 18.1% in 2002. Hummels et al. (2001, Figure 2) shows how this phenomenon is common to many industrialized countries. Crinò (2009, p.199) also documents the rapid increase of *service* offshoring since the 90s in many industrialized countries.[16]

Empirical Methodology: Regressions

Many studies use a regression approach to estimate the impact of trade on wages. A common strategy consists in adding trade-related variables to the Mincerian equation (II.1):

$$ln(w_{sit}) = \beta X_{st} + \gamma T_{it} + \lambda_i + \mu_t + \eta_{sit} \tag{II.2}$$

where w_{sit} is the wage of worker s at time t in industry i, β and γ are a vector of coefficients, X_{st} is a vector of worker's variables, T_{it} is a vector of trade-related measures for time t in industry i, λ_i are industry dummies, μ_t are time dummies and η_{sit} is the error term. Sometimes the regression comprises also the interaction between T_{it} and some element of X_{st} such as education. This formulation allows for the case in which the dataset is a repeated cross-section of workers and the case in which the dataset is a panel of individual workers.

One challenge of regression (II.2) is that the identification of γ is obtained by the variation of trade across industries.[17] Because of this fact, one would like to have a fairly large number of industries in the sample. On the other hand, the more disaggregated the

[16] The focus of this paper is on trade flows. However, in recent decades the movement of capital and labor across countries has also increased. See Crinò (2009, Figure 1, p.199) for the growth in world FDI outflows and Borjas et al. (1997, Figure 1, p.5) for the increase in immigration to U.S..

[17] More precisely, given the presence of industry and time fixed effects, the identification of γ is obtained by the variation of *changes* in trade, over time, across industries.

industries are, the more likely it is that a shock to a certain industry will have general equilibrium effects on the other industries. Many studies find however only a small reallocation of workers *across* industries after a trade shock and so in the literature many have felt that such concerns can be ignored.[18]

Another concern in regression (II.2) is measurement error in the regressors of interest. For the trade variable, T_{it}, some studies use a "quantity" variable, such as the value of imports, whereas others use a "price" variable such as a tariff.[19] The advantage of using the latter is that usually models have predictions for the relationship between e.g. the price of imports and the price of factors. The disadvantages however are that accurate price data are hard to obtain and that such data may also be misleading. For example, a change in tariff does not capture any change in the world price that the importing economy faces. But if a country is large, then a change in its tariff may have an effect on world prices. Even if the country is small, changes in tariffs may be correlated with changes in world prices, such as an increase in productivity abroad, that may affect the estimate of the coefficients on the price variables. Moreover, there may be barriers to trade other than tariffs so that a change in tariffs need not translate directly into change in domestic prices. So, even if the choice of the volume of trade as regressor is usually dictated by data availability, the quantity approach, though not ideal, is not necessarily unjustified.

Whatever trade variable one uses, (II.2) may still be plagued by endogeneity. Time dummies control for macroeconomic phenomena that affect all sectors and industry dummies control for time-invariant differences across sectors. However, trade may be correlated with some other variable that varies over time at the industry level. This could be productivity, output or technological change. For this reason many studies include other industry-level

[18] See the references in section II.4.1.

[19] Obviously, the value of imports is not a pure quantity variable because it depends on the price of imports as well.

variables in regression (II.2) in the hope to reduce this form of endogeneity. In this regard, however, it is especially concerning that it is hard to have a good proxy for technological change.

Even if T_{it} is exogenous or can be instrumented for, there could also still be endogeneity for the individual-level variables. For example, skill is usually proxied with some measure of education. But if more able workers self-select into schooling, then the coefficient on education will not capture the effect of skill on wages. This may be a problem for studies that want to estimate the impact of T_{it} on wages across different levels of education. Panel data on workers allows to estimate (II.2) adding individual fixed effects that account for time-invariant individual ability. The challenges of studies that use panel data on workers are discussed in Section II.4.1.2 when reviewing the work by Lovely and Richardson (2000) and Kosteas (2008).

A regression such as (II.2) relies on the assumption that the trade shock is unexpected. Some studies use as trade shock a specific episode in time.[20] If one can argue that such shock was unanticipated by the economic actors, then one can compare outcomes before and after the shock to identify the parameters of interest. However, usually the parameters in (II.2) are identified using the variation in trade across industries over some period of time. The assumptions required for exogeneity are that the economic actors not only do not anticipate the first trade shock (assuming the first trade shock hits the economy in the first year of the sample) but also that they do not adjust their decisions after they have been hit by such shock (or have observed others being hit by such shocks). These concerns have motivated the use of structural model that take explicitly into account the

[20] For example, Verhoogen (2008) use as quasi-experiment the sudden, and arguably unanticipated, exchange-rate depreciation of 1994 in Mexico.

forward-looking aspect of economic decisions.[21] I examine some of these models in section II.4.3.

Even if η_{sit} is truly exogenous, for hypothesis testing it is important to have unbiased estimates of the standard errors. In (II.2) the assumption of independence of the errors across observations will probably be violated. First, it is possible that the residuals of workers who are in the same industry at the same time will be correlated. A strategy to deal with this is to first regress wages on individual characteristics, take an average of the residuals within industry-year cells and then regress these average residuals on industry level variables, industry dummies and time dummies.[22] One could be instead be tempted to cluster the standard errors at the industry-time level. However, it is also possible that the residuals of workers who are in the same industry at different points in time will still be correlated. Bertrand et al. (2004) show that this serial correlation may severely underestimate the standard errors and therefore lead to a high probability of Type I error. Using simulations, they determine that clustering standard errors at the industry level, rather than at the industry-year level, will deal satisfactorily with this problem, as long as the number of clusters is large.[23] Therefore many studies that use regression (II.2) cluster the standard errors at the industry level.

[21] This problem is, at least in theory, distinct from the possibility of feedback effects across industries mentioned above. Even if there is no feedback across industries, a worker may react to the shock by changing jobs within its industry or moving out of the labor force. On the other hand, even if a shock to an industry is unexpected, it may be transmitted to other industries as well.

[22] In this way one reduces the dataset to a panel of industries. In this case it is possible to also use first-differences to estimate the relationship between wage and trade.

[23] Bertrand et al. (2004) suggest to have around 50 clusters but it is below 20 clusters that serial correlation impacts standard errors severely.

Trade and the Skill-Premium

The Stolper-Samuelson Model

The Stolper-Samuelson model has been used to explain the increase in wage inequality between skilled and unskilled workers.[24] In the simplest version of this model an economy produces two goods with two factors, skilled and unskilled labor, and exchanges them with the rest of the world. One good, call it A, is intensive in unskilled labor relative to the other good, call it B, which is then intensive in skilled labor. An economy that is abundant in skilled labor, such as the U.S., will export the good that is intensive in skilled labor and import the good that is intensive in unskilled labor. As trade becomes less costly, U.S. will export *more* of good B and import *more* of good A. So, in U.S. resources will have to reallocate from the production of good B to the production of good A. Given that B is intensive in skilled labor, this reallocation will increase the relative demand for skilled workers. Given that in this model the relative supply of labor is fixed, the increase in the relative demand will increase wage inequality between skilled and unskilled (assuming, as usual, that even before the shock skilled workers already were earning more than the unskilled workers). The model implies that the opposite process is happening in the country that U.S. trades with: production is reallocated from good B to good A and the relative demand for unskilled workers *decreases* wage inequality between skilled and unskilled workers. Finally, another implication of the model is that, as the relative wage of skilled workers increase, each sector substitutes away from skilled labor so that the skilled workers' share employment is lower in both sectors.

[24] See e.g. the discussion in Goldberg and Pavcnik (2007, p.58).

This model has however found scant support in the data. Many studies have indeed found that the industry employment shares are pretty constant over time: the reallocation of resources across sectors that is dictated by the Stolper-Samuelson model does not seem to take place.[25] Moreover, wage inequality between skilled and unskilled workers has increased in both developed countries, which are abundant in skilled workers, and in developing countries, which are abundant in unskilled workers. This contradicts the implication of the model that inequality should go down in developing countries. Finally, several studies have documented that the skilled workers' share of employment has increased in *all* sectors, contradicting another implication of the model.[26]

Technology, Quality Upgrading and Offshoring

Because of the empirical problems of the Stolper-Samuelson model, other models have been proposed. These models emphasize how trade may affect the skill-premium *within* sectors. Some studies focus on the link between trade and skilled-biased technological change (SBTC hereafter), which is a usual candidate for the explanation of the increase in skill-premium. These studies show how SBTC can be an endogenous response to competition from abroad. For example, in Thoenig and Verdier (2003)'s model, domestic firms, when faced with competition from abroad, engage in more innovation, which is usually a skill-intensive activity. If for each sector one measures competition from abroad with the volume of sectoral imports, then an implication of this theory is that higher imports will increase the relative demand for skilled workers within that sector. Other models focus on the complementarity between capital and skill: this may affect the skill-premium if trade allows

[25]See the references in Goldberg and Pavcnik (2007, p.59) and Cosar (2010, fn.4). Section II.4.3 discusses studies that allow for intersectoral reallocation of labor.

[26]See Berman et al. (1994) for the U.S. and Attanasio et al. (2004) for Colombia.

to import capital goods at a cheaper price.[27] Alternatively, trade liberalization may be responsible for quality upgrading within one sector, i.e. the shift of the product mix toward higher quality varieties. If these higher quality varieties require a more skilled labor force, this will also increase the relative demand for skill (see Verhoogen (2008)).

Feenstra and Hanson (1996a) emphasize instead the role of trade in intermediate goods within an industry. Suppose that, in order to produce a final good, several inputs are needed and that we can order these inputs as to their skill-intensity. A country that is skill-abundant will tend to produce the skill-intensive inputs and to import the inputs that are intensive in unskilled labor. As developing countries become more productive they will export to U.S. more of the inputs that are intensive in unskilled labor *in U.S.*. For this reason, an increase in productivity in the developing countries will shift resources away, in U.S., from the inputs intensive in unskilled labor to skill-intensive ones. Again, this fact will push up the relative demand of skill *within each industry.*

Lovely and Richardson (2000) is one of the first works to utilize individual level workers' data to study the effect of trade on the skill-premium in the U.S.. They use, for the 1981-1992 period, the Panel Study of Income Dynamics (PSID hereafter), which follows a panel of U.S. workers over time. They focus on the effect of imports and exports, disaggregated by source country and use two estimation approaches. In the first one they regress individual wages on individual workers characteristics (including education), a set of industry dummies and a set of industry dummies interacted with years of schooling of the workers. The first set of industry dummies can be considered as the industry wage premia to labor who does not have any schooling. The second set of industry dummies can

[27] See the review in Acemoglu (2002, p.27) and Goldberg and Pavcnik (2007, Section 5.1.3). Even if these models are related to the the ones that emphasize the importance of SBTC, they remain distinct. SBTC theories focus on the advent of new technologies, especially computer, and their impact on the demand for skilled labor. Capital-skill complementarity theories do not focus only on computers but rather on any kind of equipment. On this distinction, see also Acemoglu (2002, fn.24).

be considered as the premium to skill in the various industries. Average wages for skilled and unskilled workers can vary across industries for many reasons such as compensating differentials, sorting of workers across industries based on unobserved ability and rents.[28] Lovely and Richardson (2000) emphasize the first interpretation but their first approach cannot exclude the other possibilities. They then regress these estimated industry premia (to pure labor and to skill) on various trade measures, other industry level measures and year dummies. They find that trade with the newly industrialized countries tends to increase the industry premium to skilled workers relative to the industry premium to the unskilled workers. They interpret this as evidence that trade with newly industrialized countries increases the relative demand for skilled workers. If one interprets trade with newly industrialized countries as trade in capital goods or trade in varieties that have lower quality with respect to U.S. or trade in intermediate inputs, then this result is compatible with the models outlined above.

An advantage of the PSID is that it allows to control for individual fixed effects: if workers with different unobservable productivities sort into different industries, then the omission of these fixed effects will bias the estimate of the effects of trade on the skill premium. In their second approach Lovely and Richardson (2000) run a regression similar to II.2 but also controlling for individual fixed effects. As other regressors they use individual workers characteristics, a set of industry dummies and their interaction with years of schooling, trade and other industry level measures and their interaction with schooling.

[28] In the case of compensating differentials, identically productive workers may receive different wages because of differences in relevant characteristics across industries (e.g. safety, amenities etc.). In the case of unobserved ability, the industry wage premia are due to the heterogeneity of workers' ability across industries. This heterogeneity is sometimes considered to be ex-ante and so time-invariant and therefore it is modeled with the use of individual fixed effects in the wage equation. Finally, as discussed in section II.4.2, rents may arise both because of a lack of intersectoral workers' mobility or because of imperfect competition in the labor market. The lack of intersectoral mobility may be due to the presence of industry-specific human capital: workers may be identical ex-ante but they are different ex-post, due to the industry they end up in. Imperfect competition, due for example to unionization, is compatible with workers being identical in their productivity.

They again find that trade with newly industrialized countries increases the skill-premium but this result is not robust to the inclusion of year dummies. This is important given that Lovely and Richardson (2000) do not control for skilled-biased technological change (SBTC), which is thought to have changed during this period. This result also suggests that controlling for individual fixed effects may be important when studying the effects of trade on the skill-premium.

Kosteas (2008) uses instead the National Longitudinal Survey of Youth (NLSY hereafter) to estimate the impact of imports from low-wage countries on wages in the 1979-1996 period. The NLSY is a panel dataset that contains observations on individuals in U.S. who were aged 14-21 in 1979. He finds that, for the 1979-1988 period, the import share is correlated with a decrease in the wage of blue collar workers and does not affect the wage of white collar workers.[29] For the 1989-1996 period, he finds no correlation between the import share and wages of either class of workers. He controls also for outsourcing using a measure of imports of parts by industry but he does not include the interaction between outsourcing and the white collar dummy.

The NLSY, as the PSID, is a longitudinal dataset and so it allows to control for individual fixed effects in the estimation of the impact of trade on wages. When these effects are included, the effect of imports on the wage of blue-collar workers increases in absolute value (it is a negative number) and remain significant; moreover, the coefficient on the interaction between the white-collar dummy and imports becomes smaller and less significant (Kosteas (2008, Table 3(a), p. 268)).[30] Therefore, the inclusion of individual fixed effects seem to be important.

[29]Because the source of the trade measure changes in 1989, Kosteas (2008) has to divide the analysis in two periods.

[30]To be more specific, he finds that the semi-elasticity of blue collars' wage with respect to the imports share from low-wage countries is -.6 and significant at the 1% level. The coefficient on the interaction between the white-collar dummy and imports is 0.1 and significant only at the 10% level.

On the other hand, the inclusion of individual fixed effects has its own problems. Indeed, the coefficient on schooling is estimated only using the within-individual variation in years of education. For the period 1979-1988, when including individual fixed effects, the coefficient on years of school remain significant and actually increases (Kosteas (2008, Table 3(a), p. 268)). However, for the period 1989-1996, when including individual fixed effects, the coefficient on years of school decreases and is no more significant (Kosteas (2008, Table 3(b), p. 270)). This is probably due to the fact that in the 1989-1996 period, the individual who were between 14 and 21 years old in 1979 are now between 24 and 31 years old, an age at which most individuals have already obtained an education.[31] When individual fixed effects are included, the small genuine variation in years of schooling may be dominated by the noise of errors in measuring the years of schooling over time.[32]

A limit of the studies based on the PSID and NLSY is their limited sample size. Indeed, these dataset contain data on workers in all sectors but usually the trade measures are available only for the manufacturing sector. Moreover, the trade measures are at the industry level so that the identification of their impact is given by variation of workers across manufacturing sectors. Finally, the NLSY has an additional limit over the PSID. As already mentioned, the NLSY contains data only on individuals in U.S. who were aged 14-21 in 1979. But the reallocation of labor due to trade may involve also workers who are older. For example, suppose that higher imports in an industry bring about a reduction in employment in that industry. If this reduction in employment is mainly achieved via the early retirement of older workers, then the NLSY will not pick up this reduction in

[31] Some individuals may be getting post-graduate education. However, the sample includes only workers who work, at least for two years, in manufacturing. So, the return to post-graduate education would be estimated using data on individuals who e.g.: a) in 1989 work in manufacturing; b) in 1990 enroll in a Master program; c) some years later, after completion of the Master program, come back to work in manufacturing. Given also the small sample size of the NLSY to begin with, it is not surprising that there are only few individuals who satisfy these conditions so that the return to schooling is hard to identify.

[32] Borjas (2000) raises a similar point in his comment to Lovely and Richardson (2000).

employment.

These considerations have motivated the use of a larger sample, the CPS, to study the impact of trade on the U.S. labor market. Ebenstein et al. (2009) study the impact of offshoring to low-wage countries on wage inequality for the 1982-2002 period using the CPS Monthly Outgoing Rotation Group. As a measure of offshoring to low-wage countries they use the number of workers in a low-wage country that are employed in a subsidiary of a U.S. multinational. They can compute this measure for the manufacturing industries. When using industry regressions, they find that offshoring to low-wage countries mildly reduces the relative employment of unskilled workers but does not have any effect on wages.[33] They attribute this result to the fact that the U.S. labor is relatively mobile across industries. They also construct a measure of import competition at the occupation level. Using regressions at the occupation level, they find that offshoring and import competition has some effect on the increase in the skill-premium and markedly reduces the wages of workers in some occupations.[34]

Liu and Trefler (2008) use the March CPS for the 1996-2005 period to study if the increase in trade in services - that they call "service outsourcing" - has had an effect on the labor market. They find virtually no effect of trade in services on the probability of switching occupation, probability of switching industry, the probability of becoming unemployed and wages of skilled and unskilled workers. They therefore conclude that the alarm about outsourcing of services is unjustified. As to the wage regression, it is worth

[33] More precisely, they find that a "10 percentage point increase in offshoring to low-wage countries reduces employment by .2%" (Ebenstein et al. (2009)).

[34] More precisely, when constructing the trade measures by occupation, they find an elasticity of -0.05 of wages with respect to the employment of affiliates in low-income countries (their measure of offshoring) and a semi-elasticity of -.27 of wages with respect to import competition (Ebenstein et al. (2009, Table 6 and 7)). The offshoring coefficient is highly significant for the low-skilled workers but not significant for the more skilled workers: so offshoring seems to increase the skill-premium. Import competition instead does not seem to have an effect on the skill-premium. The average import competition at the occupation level was 2% in 1983 and 4% in 2002. However, for some occupations, this measure had a steep increase during this period: e.g. for shoe machine operators this measure went from 37% in 1983 to 77% in 2002.

noticing that Liu and Trefler (2008) use the minimal panel structure of the March CPS and difference wages across consecutive years for workers who happen to be in the March CPS in two consecutive years.[35] This approach is robust to the fact that wages depend on individual fixed effect. It however comes at the cost of ignoring the cross-sectional variation in wages in identifying the parameters of interest and using only the cross-sectional variation in yearly changes in wages.

To sum up, Lovely and Richardson (2000) find no effect of trade on wages (at least when including year dummies). Kosteas (2008) finds that, for the 80s, trade decreases blue collars wages but not white collar ones whereas in the 90s trade does not have a significant effect on wages of either type of workers. Ebenstein et al. (2009) find no effect of trade at the industry level on wages but find a negative effect on wages of import competition at the occupational level. Liu and Trefler (2008) find no effect of offshoring of services on wages. These results do not present a clear picture and this is not surprising given the endogeneity concerns raised in section II.3. However, this body of evidence seems incompatible with the idea that lower skilled workers benefitted from an increase in international openness. What Goldberg and Pavcnik (2007) found for developing countries seems to be true for the U.S. as well. In section II.4.3 however we will review the results of structural models that suggest that the Mincerian regressions may in practice capture only the short-term effect of trade and neglect its long-term consequences. These models also suggest that these long-term consequences may be beneficial to the workers, even up to the point of compensating them for the temporary wage losses that they may incur in the short-run.

[35] Their dataset is therefore a cross-section of yearly changes in wages. A worker will not be in the March CPS for two consecutive years if she e.g. changes her residence during that year. Liu and Trefler (2008) control for attrition bias with an Heckman's selection model.

Trade and Residual Inequality

The residual of the Mincerian equation (II.1) contributes to overall wage inequality and therefore it is important to understand how it can be related to the increase in globalization documented in section II.2.2. Attanasio et al. (2004) emphasize the fact that trade liberalization may affect the pattern of industry wage premia. They focus on the case of Colombia in the 1984-1998 period and study the effects of the Colombian tariff reductions that occurred in 1990-1991. If the reduction of tariffs decreases industry wage premia and if the sectors with the highest tariff reductions are those where the workers were paid the least before the policy change, then trade liberalization will increase overall wage inequality. Notice that, at least if industry wage premia do not differ by education level, then this wage reduction would not be captured by the coefficients in equation (II.1) and therefore it will be part of the residual.[36] Attanasio et al. (2004, p.355) find this to be exactly the case for Colombia: a 50-point tariff reduction in one industry is estimated to bring about a 2.5% decline in the wage premium of that industry. They report that textiles and apparel reduced their tariffs by around 73 percentage points between 1984 and 1998.

As mentioned above, industry wage premia may arise for many reasons such as compensating differentials, sorting of workers across industries based on unobserved ability and rents. Attanasio et al. (2004) emphasize the latter interpretation but they are not able to distinguish it from the other two. Industry-specific rents may arise in a perfectly competitive model such as the short-run ricardian model where workers are, at least in the short-run, immobile across sectors and so they have to endure a wage decline when facing import competition. But industry-specific rents may also arise in an imperfect competition

[36]In order to study the effects of trade on the skill-premium, most of the studies reviewed in section II.4.1.2 rely on wage regressions where the trade measures vary at the industry level. In doing so, they implicitly assume that the industry wage premia vary across educational categories. They do not however discuss the impact that industry wage premia may have on overall wage inequality even in the case in which these premia do not depend on educational categories.

model: unionized sectors may be able to extract rents above the economy-wide average but trade liberalization may erode this rents.[37]

Analogous considerations can be done to motivate the existence of *occupation* wage premia. Cragg and Epelbaum (1996) find that a large portion of the increase in the skill-premium during the 1987-1993 period in Mexico can be attributed to the increase of the return to specific occupations, such as professionals and administrators. In this case, including occupation dummies in the wage equation (II.1) affects the estimate of the coefficient on skill. They also document that the occupations with the highest wages experienced the largest increase in occupational premia so that occupational premia also increased residual inequality.

As discussed above, Ebenstein et al. (2009) find that import competition affects occupational wage premia, especially those of the least skilled. They also document that the range of such premia diminished in the 1983-2002 period in U.S. making the distribution of these premia less dispersed (Ebenstein et al. (2009, Figure 10)). However, they do not discuss if the occupations that were most affected by import competition were those that paid the lowest wages. If not, import competition may have actually reduced residual inequality and so overall wage inequality.

Dynamic Effects of Trade

The wage regressions examined so far assume the lack of mobility across industries or occupations. But it is possible that workers will react to shocks by moving across industries or occupations. Assuming immobility across sectors seems justified by the empirical studies, mentioned in section II.4.1, that did not detect a reallocation of resources across

[37] See the discussion of industry wage premia models in Attanasio et al. (2004, p.351) and in Goldberg and Pavcnik (2007, Section 5.3).

industries after episodes of trade liberalization. However, the evidence from these studies, though suggestive, is not conclusive. Indeed, many of these studies focus, because of data availability, on the reallocation of resources across *manufacturing* industries. But trade liberalization may also move resources out of manufacturing into services or agriculture. Moreover, the time span of these studies is usually limited: if e.g. capital takes a long time to reallocate across industries, then these studies may not detect any reallocation even if one takes place in the end. Finally, these studies focus on the net flows of resources (e.g. the change over time in the industry employment shares) and not on their gross flows. But the gross flows are found to be large for some countries, such as U.S. (see Davis and Haltiwanger (1992)).

Artuc et al. (2010) build a structural model in which each worker can switch industries, but at a cost. The cost has a component that is common to all workers across time and one component that is specific to the worker and the period the worker is making her choice. This second cost component can be negative, reflecting non-pecuniary motives that workers have in changing industries: for this reason the model then allows for gross job flows across industries. Artuc et al. (2010) estimate the parameters of the model using the CPS and then simulate an episode of trade liberalization.

They find that the mean and the standard deviation of the moving costs are very high. Therefore "US workers change industry a great deal, but those movements do not respond much to movements in intersectoral wage differentials" (Artuc et al. (2010, p.1010)). This then implies that the adjustment of the labor market to a trade shock will be slow. In their simulation they find that, after the removal of a 30% tariff on manufacturing, the new steady state is achieved in 8 years. Given that the average moving cost is high, in order to induce the workers to move out of manufacturing, the wages there have to drop markedly right after the removal of the tariff: the simulation of the model implies a 22% drop in real manufacturing wages.[38] Most surprisingly though, they find that even workers who are in manufacturing at the time of the trade shock may benefit from the trade liberalization. Indeed, after the removal of the tariff the wages in the other sectors are permanently higher due to the increase in efficiency. But a manufacturing worker, even in the absence of the trade shock, may move to one of the other sectors because of her idiosyncratic shock. Because of this *option value*, a manufacturing worker may experience a wage loss because of the trade shock but still enjoy a higher lifetime expected utility.[39]

This result also shows how the results from industry-level regressions such as the one in section II.4.1 may be misleading. These regressions tend to find a negative effect of imports on wages: one may then be tempted to infer that imports hurt workers in the import-competing sector. But this negative effect on the wages of such workers may be temporary and, as Artuc et al. (2010) show, is actually compatible with an increase in the long-time utility of workers.

In Artuc et al. (2010)'s model all the heterogeneity among workers is due to the idiosyncratic shock. However, it is possible that different workers stand to gain differently from trade liberalization. Artuc (2009) develops a model similar to Artuc et al. (2010) but allows workers to accumulate sector-specific human capital. This reduces the mobility of older workers. If a tariff is removed on a certain sector, among the workers in that sector, the younger workers are less hurt because they can move to other sectors, that have become now more productive. Old workers are close to retirement and so they are not hurt much by the decrease in wages. The workers who are hit the most are middle-aged workers: if

[38] In the new steady state, however, the manufacturing wages are just 2.5% lower than the original steady state. So, there is overshooting in the sectoral wage adjustment.

[39] Obviously, there will still be some workers who will be worse-off *ex-post*: they are e.g. those who remain in manufacturing because they are not hit by a large enough idiosyncratic shock that induces them to change sector.

they do not change sector, they have to get lower wages for a long time. But if they change sector, they have to pay a high moving cost because they accumulated sector-specific human capital. In the export-competing sector the situation is different. All workers there benefit from the liberalization but old workers, again, do not benefit much because they are close to retirement. Young workers do not benefit much either because the value of their option of moving to another sector has decreased and this option value is a big part of their utility given that they have not yet accumulated industry-specific human capital. Those who benefit the most are the middle-aged workers. They enjoy the increase in wage due to the efficiency gain while the decrease in their option value does not hurt them much. Indeed, they were not likely to move out of their sector anyway because of the high moving cost due to their sector-specific human capital.

The models in Artuc et al. (2010) and Artuc (2009) have some limitations. First, they do not allow for workers to be unemployed and so they may miss an important effect of trade liberalization. Moreover, in their model trade liberalization dictates, in the long run, a reallocation of resources across sectors. However, recent theories have emphasized how trade liberalization often involves a reallocation of resources within sectors. In Melitz (2003) model, for example, after trade liberalization, the least productive firms in a sector exit the market while the most productive firms, that are also exporters, increase output and so employment. In Melitz (2003)'s model this intrasectoral reallocation of resources increases efficiency. To account for this type of reallocation of labor, one needs data not only on the workers but also on the employers.

Muendler and Menezes-Filho (2007) use matched employer-employee data from Brazil in 1986-1999 to examine the labor market effects of Brazil's tariff reduction at the beginning of the 90s. They find that reduced tariffs increase the odds of a worker moving out of the formal sector into the informal sector, into self-employment and out of the labor force.[40] The reduced tariffs however do not increase the odds that a worker who works in the formal sector transitions into unemployment. They also find that reduced tariffs decrease the odds of a worker moving out of the informal sector into the informal sector and into self-employment. Lower tariffs however have the positive effect of reducing the odds of a worker moving out of the informal sector into unemployment and out of the labor force. Trade theories usually do not distinguish between formal and informal employment. However, informal employment usually pays lower wages.[41] If, as Muendler and Menezes-Filho (2007)'s results suggest, trade liberalization moves workers out of the formal sector into the formal sector, then this might be a policy concern.

Muendler and Menezes-Filho (2007) also show that job separations are higher, and job accessions are lower, in comparative advantage sectors (see tables 9 and 10 in their paper). This result is not surprising in light of the other studies mentioned above that do not find a reallocation of resources across sectors after a trade liberalization episode. However, previous studies have found a reallocation of market shares from the least productive firms to the most productive firms, within a sector, as predicted in Melitz (2003).[42] These results seem to suggest that, even in absence of intersectoral reallocation of resources, trade liberalization may still have beneficial effects because of the importance of within-sector reallocation. However, Muendler and Menezes-Filho (2007) also show that job separations

[40]The model is a multinomial logit. Suppose that the worker is in the formal sector in industry i at time t. Muendler and Menezes-Filho (2007) regress the log of the odds ratio of the workers' alternatives (formal sector, informal sector, self-employed, unemployment, out of the labor force) at $t+1$ on a set of industry covariates, including tariffs, a set of worker covariates and other controls at time t. As to the industry covariates, they control for both product tariffs and intermediate inputs tariffs. A reduction in product tariffs increases the odds of the worker moving out of the formal sector into the informal sector, into self-employment and out of the labor force. A reduction in tariffs on inputs has the opposite effect. But given that product tariffs decrease more than input tariffs, the first effect dominates. When reporting their results I will always refer to this *net* effect of tariff reduction.

[41]Attanasio et al. (2004, table 3) document the informality wage "discount" in Colombia.

[42]See Pavcnik (2002) and the discussion in Goldberg and Pavcnik (2007, p.65).

are higher, and job accessions are lower, at exporting firms (see tables 9 and 10 in their paper). This result suggests that the reallocation of market shares does not imply reallocation of resources and so its benefits should not be overstated. It is worth noticing how one can explore these important distinctions only by using a matched employer-employee dataset.

Goldberg and Pavcnik (2007, p.78) observe that what is missing from trade studies that use firm or plant level datasets "is information on the characteristics of the workers employed by each plant/firm, which is the crucial step needed for establishing a connection to distributional questions." The recent availability of matched employer-employee data seems promising in this regard. In terms of future research, one could for example look at movement of workers across *occupations* and not industries, as it is usually done. Indeed, the results in Ebenstein et al. (2009) and Kambourov and Manovskii (2009b) suggest that there are occupation-specific rents that may be affected by the increase in globalization.

Conclusion

This paper surveys recent empirical works that study the effects of trade on labor market outcomes. The focus is on studies that use individual workers' data. These data allow to control for the changing variation of the labor force across industries over time. In this regard, these studies improve over previous ones that do not control for worker level variables. I first review works that are based on regressions. These works find that, at least for the U.S., trade either increases wage inequality or has no effect on it. I discuss the reasons that may explain the variety of these results. These results seems to suggest that, at least for the U.S., the increase in trade did not benefit the poorest among the workers. This is in line to what Goldberg and Pavcnik (2007) find in their review of studies on developing countries. I then review empirical works based on structural models. These models suggest instead that studies based on wage regressions neglect the long-term consequences of trade on the reallocation of resources across sectors and the efficiency gains associated with it. I finally show the usefulness of matched employer-employee datasets and discuss along the way promising avenues for future research.

Figure 1. Production Workers Employment in U.S. Manuf., 1972-1996

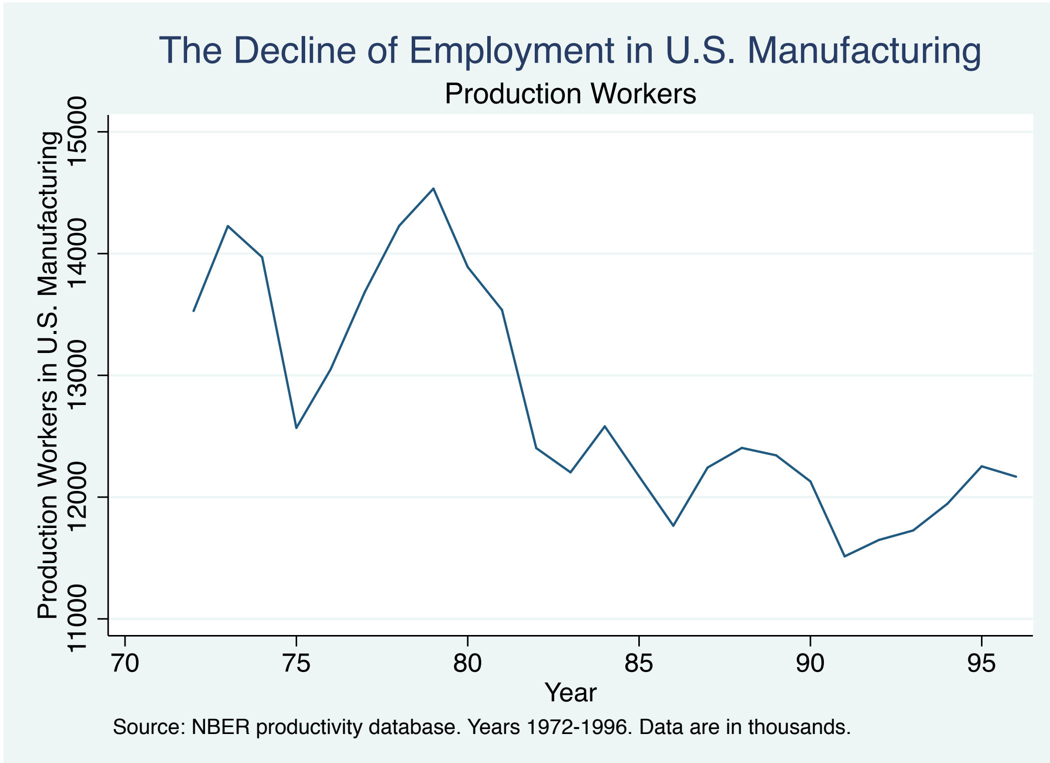
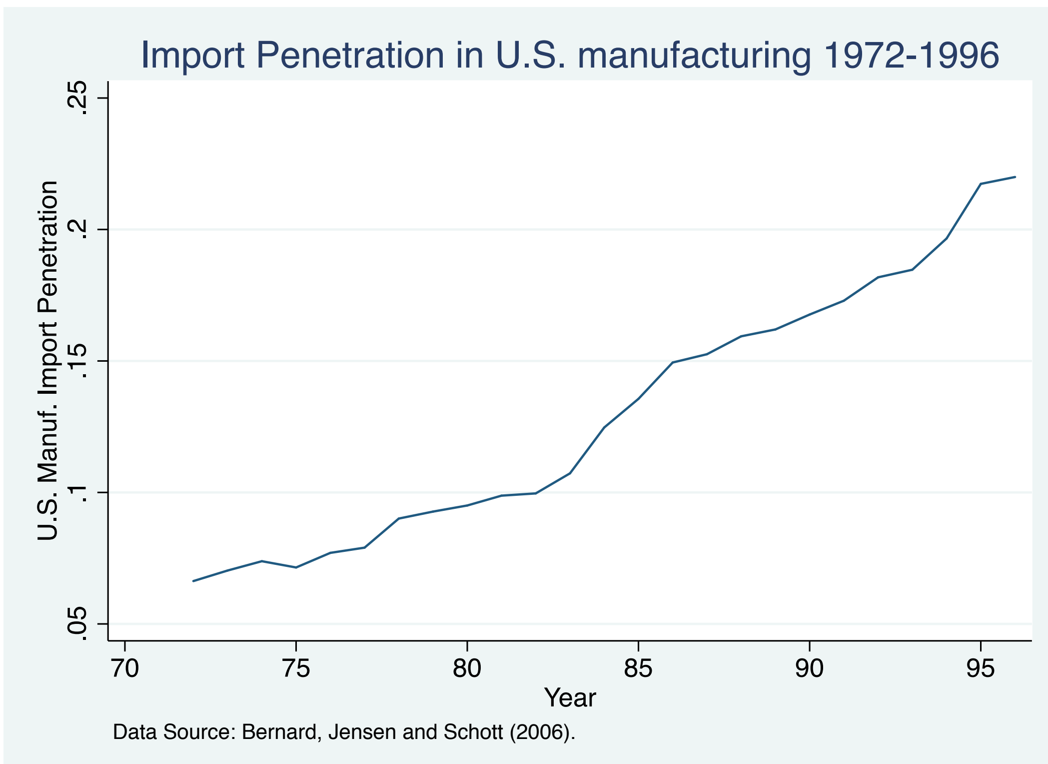


Figure 2. Import Penetration in U.S. Manufacturing, 1972-1996



CHAPTER III

OFFSHORING AND THE SKILL-PREMIUM

Introduction

During the 1980s wage inequality in U.S. went up markedly. One of the reasons behind this surge in inequality was the increase in the relative demand for skill.[1] Even though labor economists have not agreed on the relative importance of the possible explanations for this phenomenon, they tend to rule out that international trade was an important factor. In their undergraduate textbook, Ehrenberg and Smith (2005) write that the "findings among economists who have analyzed the effects of trade on inequality are not unanimous, but the predominant conclusion is that the contributions of international trade to the changes in wage inequality after 1980 were rather small".[2] Indeed, early studies found the importance of trade in *final* goods to be minor.[3] However, in a seminal paper, Feenstra and Hanson (1999) (FH henceforth) find a sizable effect of trade in *intermediate* manufactured inputs on the relative demand for skill in U.S. during the 1980s. Given that this recent result stands in contrast to the previous literature on the subject, the "case" concerning the importance of trade on wage inequality has been reopened. This work aims at bringing new empirical evidence to this debate.

[1] Autor et al. (2008) and Acemoglu (2002) document the increase in the U.S. *skill-premium*, defined as the wage difference between workers with college education and workers without a college education. They also argue that this increase is mainly due to an increase in the relative demand for skill rather than to a decrease in the relative supply of skill.

[2] In his review of the literature on the subject, Acemoglu (2002, p.52) argues that "increased international trade by itself is not the cause of the changes in the U.S. wage structure" even though he then adds that trade may have had a more indirect role on wage inequality by affecting the skill bias of technological change.

[3] See the studies discussed in Acemoglu (2002, p.53-54) An exception, not discussed in Acemoglu (2002), is Revenga (1992) who finds a significant impact of import prices of final goods on employment and wages.

This paper studies the effect of offshoring on the skill-premium, using individual workers' data from the March Current Population Survey (March CPS henceforth).[4] The advantage of this strategy is twofold. First, the March CPS has been widely used by labor economists to document the evolution of the skill-premium over time. Except for Ebenstein et al. (2009), whose contribution I discuss below, the Current Population Survey has not been however used to address the importance of the effect of offshoring of manufacturing on the skill-premium.[5] This may also have contributed to the fact that, even after the contribution of FH, many labor economists seem to be still skeptical about the role of trade on wage inequality in U.S..[6] It is natural to address this gap in the literature by making use of the March CPS dataset.

Secondly, and more substantially, individual workers' data allows me to assess a limitation of FH's contribution. Their work relies on workers' data that are aggregated at the industry level, which does not allow one to control for demographic compositional changes of the labor force within industries that may be spuriously correlated with offshoring. To illustrate the potential importance of this, consider the following argument. We know as a stylized fact that wages are increasing in job experience.[7] Suppose that, for reasons unrelated to offshoring, young graduates do not enter a certain industry where offshoring happens to go up: we observe offshoring going up and the skill-premium going up but this is just a spurious correlation. In the above scenario the estimates in FH of the effect of trade on wage inequality would be biased upward.

[4] I use the term *offshoring* to indicate trade in intermediate inputs.

[5] The first paper that uses the March CPS to address the importance of globalization on the skill-premium in the U.S. is, to my knowledge, Goldberg and Tracy (2003). They study the effect of exchange rate fluctuations, and not of offshoring trade per se, on the U.S. skill-premium. Liu and Trefler (2008) study the effect of offshoring of *services*, not of manufacturing, on various labor market outcomes. Liu and Trefler (2008) also focus on a more recent period than I do.

[6] Autor et al. (2006) however suggest that offshoring may be important to explain the pattern of wage inequality during the 90s and beyond.

[7] See Murphy and Welch (1990).

To overcome this problem, I merge the March CPS dataset, a large representative sample of the U.S. population, with industry-level variables such as offshoring trade and a proxy for skill-biased technological change (SBTC, henceforth), which is usually indicated as one of the main factors driving the increase in the skill-premium. As FH, I focus on the 1979-1990 period and on offshoring trade in manufacturing, abstracting from the services sector.[8] In order to motivate my regression approach, I use the simple model in Feenstra (2004, Ch. 4) to show how offshoring may affect the relative wage of skilled labor.

A related paper is Ebenstein et al. (2009) who also use individual workers' data from the CPS to study the effect of offshoring on the U.S. labor market. As a measure of the offshoring of a sector, they use data on foreign affiliate employment for U.S. multinational firms within that sector. They are also able to distinguish foreign affiliates by low and high-income countries. I use instead FH's measure of offshoring which proxies, for each sector, the share of imported inputs.[9]

Both measures have advantages and disadvantages. On one hand, the measure of Ebenstein et al. (2009) is able to distinguish between the countries from which U.S. is sourcing inputs. This is important because, as the model in Section III.2 suggests, it is offshoring to low-income countries, and not just offshoring *per se*, that is expected to affect wage inequality.[10] On the other hand, my measure captures both channels through

[8] Autor et al. (2008, p.3) document that the pattern of wage inequality in U.S. has changed in the 90s with respect to the 80s. In the 80s the increase in inequality was monotonic: higher incomes rose and lower incomes fell. In the 90s, the gap between the 90th wage percentile and the 50th wage percentile continued to grow but the gap between the 50th wage percentile and the 10th wage percentile stabilized. This evidence suggests that at the end of the 80s there may have been a structural break in the evolution of the U.S. wage inequality. Autor et al. (2008) also document a similar pattern for the skill-premium, not just for overall wage inequality. For this reason, I choose to use a trade model that has the potential of explaining the increase in the skill-premium during the 80s. I leave to future research to explore more complex mechanisms through which international trade may be able to account for the evolution of the U.S. skill-premium in the 80s *and in the 90s*.

[9] See Section III.3 for a discussion of this measure.

[10] Importantly, however, FH do not distinguish between the two kinds of offshoring but still find an impact of offshoring on wage inequality.

which offshoring can take place, i.e. intrafirm and arm's length trade in intermediate inputs. Indeed, a domestic firm can import inputs from a foreign affiliate or it can outsource production of some of its inputs to a foreign, unaffiliated, firm. From the point of view of an offshoring model such as the one in Section III.2, these two channels have the same effect on the skill-premium and so empirically they should be both taken into account.[11]

I study separately the correlation of offshoring with wages and the correlation of offshoring with employment. I document the importance of controlling for demographic characteristics of the labor force in the wage regressions. When these controls are omitted, offshoring explains at least 50% of the increase in the skill-premium. This result is similar to the one in FH. They do not control for demographic characteristics of the labor force and find that, depending on the specification, offshoring explains between 15% and 40% of the increase in the skill-premium. When I include demographic controls, I find that the effect of offshoring on the skill-premium markedly decreases in all specifications. I argue therefore that, in order to determine the effect of offshoring on the skill-premium, one needs to account for the interaction between offshoring and the demographic composition of the labor force.

I also find that offshoring is correlated with a decrease in the employment of less skilled workers and it is uncorrelated with the employment of more skilled workers. According to the estimates, an industry exposed to the average change in offshoring during this period experiences at least an 8% increase in the relative employment of skilled workers. This result suggests that, at least for U.S. in the 80s, offshoring has played an important role in the increase in the skill-premium by increasing the economy-wide relative demand for skilled workers.

[11] See the discussion in Feenstra and Hanson (1996b) and in Antras and Helpman (2004, p.553-554).

The rest of the paper is organized as follows. Section III.2 presents the model of how offshoring affects the skill-premium. Section III.3 describes the dataset and document some of the main features of the data. Section III.4 contains the results and Section III.5 concludes. The Appendix explains more in detail the dataset.

Theory

The literature on wage inequality has documented that in the 80s both the relative supply *and* the relative wage of skilled workers have increased.[12] Therefore the relative demand for skilled workers should also have increased, or accelerated if it was already increasing. In this section I present a variant of the simple model in Feenstra (2004, Ch. 4) that allows me to derive a relationship between offshoring and relative demand for skilled workers. The model assumes that workers cannot move *across* sectors but can move *within* sectors. The model can be seen as an application of the Heckscher-Ohlin model to an industry rather than, as usual, to a country.

The basic idea of the model is that in each industry there are two tasks that need to be performed to produce a unit of the final good and that these tasks differ in skill-intensity. An example can be the car industry that needs tires and managerial services to produce a unit of final output. The production of tires is intensive in unskilled labor relative to the production of managerial services. If there is a decrease in the costs of offshoring from U.S. to countries, such as Mexico, that are relatively abundant in unskilled labor, then U.S. will outsource to Mexico the task that, in U.S, is intensive in unskilled labor, such as the production of tires, and Mexico will outsource to U.S. the task that is intensive in skilled-labor, such as managerial services. This will bid up the relative demand for skilled

[12] See, e.g., the figure at page 15 of Acemoglu (2002).

labor in U.S..

More formally, assume that in U.S. an industry j uses two intermediate inputs, y_{1j} and y_{2j}.[13] Production functions for intermediate inputs are of the Cobb-Douglas form:

$$y_{1j} = L_{1j}^{\alpha} H_{1j}^{1-\alpha}$$

$$y_{2j} = L_{2j}^{\beta} H_{2j}^{1-\beta}$$

where, for input $i = 1, 2$, L_{ij} and H_{ij} are, respectively, unskilled and skilled labor in industry j.[14] Notice that the exponents in the Cobb-Douglas function do not depend on the industry j. We assume that $\alpha > \beta$, i.e. that input 1 is intensive in unskilled labor and input 2 is intensive in skilled labor.[15]

The production of each intermediate input is competitive and the prices of intermediate inputs are exogenously set on the world market. Workers cannot move across sectors but can move within sectors. Assuming incomplete specialization, i.e. that in equilibrium U.S. will produce a positive quantity of both inputs, the zero profit conditions in each industry are:

$$G(\alpha) w_j^{\alpha} q_j^{1-\alpha} = p_j$$

$$G(\beta) w_j^{\beta} q_j^{1-\beta} = 1 \tag{III.1}$$

where p_j is the price of input 1, w_j is the wage of the unskilled workers, q_j is the wage of the skilled workers, $G(x) = \frac{1}{x^x (1-x)^{1-x}}$ for $x = \alpha, \beta$ and both the wages and the price of

[13] I also use the term *sector* as synonymous for the term *industry*.

[14] The main implication of the model is robust to the introduction of a total factor productivity term that is common to the production of both inputs. For this reason this term is omitted here.

[15] Let L be the employment of the unskilled workers and H the employment of the skilled workers. By definition, input 1 is intensive in unskilled labor relative to input 2 if, for any ordered pair (L, H), at (L, H) the marginal rate of substitution of input 1 is higher than the marginal rate of substitution of input 2. Graphically, at (L, H) the isoquant for input 1 intersects from above the isoquant for input 2. An equivalent definition can be formulated in terms of the isocost curves of the two inputs rather than in terms of their isoquants.

input 1 are expressed in terms of input 2.[16]

It is worth spelling out how the various assumptions operate in the formulation of the above equilibrium conditions. First, wages, both for unskilled and skilled labor, vary across industries because of the absence of sectoral mobility and the possible different values of p_j across industries. This is due to the fact that the exogenous market price p_j pinpoints the (w_j, q_j) pair in each industry and that these differences in factor prices cannot be arbitraged away.

Second, I do not index the inputs' cost function to the industry: so, for example, a unit of skilled-intensive input is produced with the same technology in all industries. In other words, α and β have no industry index. Empirically this allows the estimation of the effect of offshoring on wage by using the variation of offshoring across industries.

We assume that, for each sector, the home country, U.S. in our case, imports input 1 and exports input 2. This will be the case if, for each sector, relative to the rest of the world, U.S. is abundant in skilled labor.[17] We refer to p_j as the cost of offshoring in industry j. As p_j goes down, the input that is intensive in unskilled labor becomes cheaper. Therefore U.S. reduces its production of input 1 and increases its imports of input 1. At the same time, the workers released from the production of input 1 move, within the same sector, to the now more profitable production of input 2 increasing thereby the U.S. exports of input 2.[18] In other words, when p_j goes down, in U.S. the production of the skill-intensive input goes up and the production of the input that is intensive in unskilled labor goes down.

[16] Assuming incomplete specialization is equal to assuming that the ratio of factor endowments lies in a certain region of the non-negative orthant. This region is usually referred to as the "diversification" cone. If the ratio of factor endowments lies in it, then, at the factor prices obtained from solving the system of equations (III.1), there exists a non-negative pair (y_{1j}, y_{2j}) that solves the full-employment conditions at home. See Feenstra (2004, chapter 1 and 2). With the Cobb-Douglas assumption there will always exist a unique solution to the zero-profit conditions.

[17] This is just an application of the Heckscher-Ohlin theorem. See e.g. Feenstra (2004, Chapter 1 and 2).

[18] See Feenstra (2004, chapter 1 and 2) for a formal proof of this fact.

In our example, when facing a lower price of tires, the U.S. car industry will decrease the in-country production of tires and increase the purchase of tires from abroad.

This intra-sectoral reallocation of resources from the production of the unskilled labor intensive input to the production of the skill-intensive input increases the relative demand for skilled workers. This can be verified by solving the zero-profit conditions for w_j and q_j and obtaining:

$$ln(w_j) = [\frac{1-\beta}{\alpha-\beta}]ln(p_j) + D \tag{III.2}$$

$$ln(q_j) = [-\frac{\beta}{\alpha-\beta}]ln(p_j) + N \tag{III.3}$$

where D and N are two constants. Therefore we have, in each industry j:

$$\frac{dln(\frac{q_j}{w_j})}{dln(p_j)} = -[\frac{1}{\alpha-\beta}]ln(p_j) \tag{III.4}$$

Given that by assumption $\alpha > \beta$, the skill-premium $\frac{q_j}{w_j}$ increases when p_j decreases. This is the main hypothesis that I will test.

A decrease in p_j can occur for a variety of reasons. For industry j, define p_{jw} as the world price of input 1 in terms of input 2 and assume, as we have done, that the home country is already importing input 1. Assume that, for a unit of input 1 to arrive in U.S. from abroad, $1+t$ units of input 1 must be shipped from abroad, with $t > 0$. t captures in a simplified manner the per unit transportation costs in shipping input 1 from abroad to the home country, ad valorem tariffs imposed by the home country on imports of input 1 and per unit non-tariff barriers to imports. Because of our perfect competition assumption, the domestic relative price of input 1 in terms of input 2, i.e. p_j, is then equal to $(1+t)p_{jw}$. A decrease in t will decrease p_j, leaving unaffected the exogenous world price p_{jw}.

If instead producers of input 1 abroad become more productive, then, because of perfect competition, p_{jw} will decrease and, for any given t, p_j will also decrease. This second scenario may occur because of productivity growth in less developed countries such as Mexico. Feenstra and Hanson (1996a) introduce capital into a model that is more complex than the one presented here but similar in spirit. They find that foreign direct investment from the home country to the foreign country also brings down p_j.[19] In my dataset, my measure of offshoring increases over time. I assume only that a model such as the one presented here captures the main mechanism according to which offshoring increased during this period. I remain agnostic about the source of this increase in offshoring because, as long as it works through a decrease in p_j, it will have the testable implication that the skill-premium should increase.

A large literature in labor economics finds that the skill-premium also depends on skill-biased technological change.[20] SBTC can be accommodated in the model above as follows. Let the production functions for the two inputs be:

$$y_{1j} = (a_L L_{1j})^{\alpha} (a_H H_{1j})^{1-\alpha} \tag{III.5}$$

$$y_{2j} = (a_L L_{2j})^{\beta} (a_H H_{2j})^{1-\beta} \tag{III.6}$$

where a_L and a_H are skilled, respectively unskilled, labor augmenting terms. Then it can be shown that the log of the skill premium depends linearly and positively on the log of

[19] See proposition 6.3 in Feenstra and Hanson (1996a, p.104).

[20] See Katz and Autor (1999) and Acemoglu (2002).

a_H/a_L, that is usually interpreted as a measure of the skill-bias of the technology.

Discussion

This model does not take into account the relationship between different industries in the same country. In practice, this model treats each industry as a single country and focus on the trade of that industry with the corresponding industry abroad, e.g. the trade between the auto industry in U.S. with the auto industry in Mexico. This is done for three related reasons. First, the textbook Heckscher-Ohlin model is usually applied to a single country and predicts that opening the economy to trade will increase the skill-premium if the relative price of the skilled-intensive final goods increases. This change in prices brings then about a reallocation of resources *across* sectors. However, early studies did not detect such change in prices.[21] For this reason, the model used here abstracts from linkages among sectors in the same economy.

Second, SBTC is usually considered a key determinant of the increase in the skill-premium. SBTC is usually assumed to increase the relative demand of skilled workers in *all* sectors and, for this reason, SBTC is considered to reallocate resources mainly *within* each sector rather than *across* sectors.[22] The model above shows how, when focusing on trade in intermediate goods, trade can also reallocate resources within each sector.

Finally, and most importantly from an empirical point of view, treating sectors as independent from one another allows me to test the implications of the model above by using industry-level variation in offshoring.

Suppose instead that both skilled and unskilled workers are allowed to move across

[21] See the discussion in Acemoglu (2002, p. 53).

[22] Berman et al. (1994), an important study in this area, argue, without providing a formal model, that SBTC is likely to reallocate resources within sectors rather than across sectors. Xu (2001) and Haskel and Slaughter (2002), however, show formally how this is not necessarily the case and that the effect of SBTC on the relative demand of skilled labor may depend on the sector in which SBTC occurs.

sectors. Therefore a wage differential across sectors for, say, skilled workers will induce a movement of skilled workers from the sector with a low wage to the sector with a higher wage. In this case, the sectors within the economy will *not* be independent. If so, even if offshoring increases the relative demand for skilled labor at the economy level, a regression that relies on industry-level variation in offshoring will find *no* effect at all of offshoring on the wage differential between skilled and unskilled workers. In order to somehow address this concern I also test the, not modeled, hypothesis that, when offshoring goes up in an industry, the relative employment of skilled workers will go up.[23]

Data Description

My sample is obtained by merging a dataset that contains information at the individual level and other datasets with information about the industry of the worker. I obtain individual level data from the March CPS, for the 1979-1990 period. I restrict the sample to the manufacturing workers because only for those workers I am able to construct a measure of offshoring. These workers amount to about 20% of the U.S. workforce in the 80s.

I compute offshoring as in FH. Besides the fact that I have access to individual workers' data while they do not, there are however three main differences between FH's dataset and mine. First, I use only 19 two-digits industries while they use 450 four-digits industries.[24] Indeed, my model assumes no inter-sectoral mobility of workers: I use very aggregated industries in order to match this assumption. Moreover, the March CPS reports the industry of a worker only at the three and two digit level. The precision of the three-

[23] See Revenga (1992) and Ebenstein et al. (2009) for a similar approach.

[24] I drop the Tobacco industry because in my sample there are only very few workers in this industry each year and so the sample cannot be considered representative of the workforce in this industry.

digits industry has been questioned in previous studies and so I opt to work with two-digits industries.[25] Secondly, FH work with differences between the peaks of the business cycle whereas I work with annual data. Third, as explained below, I use a proxy for SBTC that is different from the one they use.

Following FH, I define offshoring O_{jt} as:

$$O_{jt} = \frac{\sum_i \left(p_{it} q_{ijt}\right) \frac{M_{it}}{Y_{it}+M_{it}-X_{it}}}{\sum_i p_{it} q_{ijt}} \tag{III.7}$$

where, at time t, p_{it} is the price of the final good from sector i, q_{ijt} is the input quantity that the manufacturing industry j buys from the manufacturing industry i, Y_{it}, M_{it} and X_{it} are respectively domestic shipments, imports and exports of industry i and the indexes i and j vary only over manufacturing industries. Notice that in the input-output table we do not observe p_{it} and q_{ijt} independently but only their product $p_{it}q_{ijt}$. Given that $\sum_i p_{it}q_{ijt}$ is the total (manufacturing) cost of production for the final good j, then we can rewrite (III.7) as:

$$O_{jt} = \sum_i \left(s_{ijt}\right) \frac{M_{it}}{Y_{it} + M_{it} - X_{it}} \tag{III.8}$$

where s_{ijt} is the share of (manufacturing) expenditures of sector j on input i at time t and the second term of the product is a measure of import penetration. The measure of offshoring is then an average, with the expenditures shares as weights, of numbers that vary between 0 and 1. Therefore the measure of offshoring varies between 0 and 1 and can be thought as the share of imported intermediate inputs for a given industry. I obtain data on the s_{ijt} terms from the Bureau of Economic Analysis (BEA) input-output tables and the variables to compute import penetration from the NBER manufacturing trade dataset (see

[25]See Kambourov and Manovskii (2004) on the measurement error in the assignment of a worker to an industry in the March CPS.

the Appendix for details).

Following Ebenstein et al. (2009), as a measure of SBTC I use the deflator of industry investment divided by the personal consumption expenditure index. This is then the real price of investment in a certain industry in terms of current consumption.[26] I use this proxy for SBTC under the assumption that, as the real price of investment decreases, SBTC will increase.

The sample is composed by a a cross-section of 141,914 individual manufacturing workers for the 1979-1990 period. As it can be seen from Table 3, the sample is composed mainly by white male workers, 14% of whom have at least a college degree. This sample includes workers, 18-65 years old, who were not self-employed and who earned only wage income during the year.[27] The sample includes both part-time and full-time workers.

Table 3. Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Log Real Hourly Wage	-1.92	0.56	-4.23	3.28
Weeks worked last year	46.53	11.45	1	52
Hours worked per week last year	41.41	6.42	1	99
Ed.n: less than high-school	0.24	0.43	0	1
Ed.n: high-school degree	0.46	0.5	0	1
Ed.n: some college	0.16	0.37	0	1
Ed.n: college or more	0.14	0.35	0	1
Job Experience	19.85	12.67	0	59
White	0.89	0.32	0	1
Female	0.35	0.48	0	1
Lag Offshoring	0.1	0.04	0.03	0.22
Lag Real Price of Investment	-4.1	0.06	-4.2	-3.96
Lag TFP	-0.03	0.04	-0.17	0.06
N		141914		

[26] In a previous version of the paper I also experimented with the measures of SBTC used by FH. Their measure of SBTC is the share of high-technology assets in total capital in a certain industry and year. However, I was not able to replicate the main statistics for their measure. In particular, according to my computations, the mean of the measure I compute is around half of the mean of their measure. More importantly, my computed measure increases over time only slightly and so it does not seem to capture the increase in SBTC that other studies have found to occur in the 1980s. For this reason I abandoned the use of this measure and concentrate on the real price of investment as a proxy for SBTC.

[27] 99% of workers were in the private sector and the rest in government jobs.

As it has been widely documented in the labor economics literature, the skill-premium increased during this period for the population of workers at large.[28] I show that this is the case also when we restrict the sample only to manufacturing workers. In order to do this, for each year of the sample, I regress the log hourly wage on a white race dummy, sex dummy, job experience and job experience squared and education dummies for workers with, respectively, less than a high-school degree, a high-school degree and some years of college but no degree. The omitted category for education is having a college degree. The regression uses as weights the weights provided by the March CPS multiplied by the number of hours each worker worked in the past year. Given that the wage is in log form, the coefficient on an education dummy estimates the percentage difference in a given year between a worker in that education category and a worker with a college degree. I multiply these coefficients by minus one and graph them over time in Figure 3.[29] As it can be seen, the premium of holding a college degree with respect to each other education category increased during the 1980s. In particular, the wage premium of workers with a college degree with respect to workers with only a high school degree increased by 13 percentage points, from 42% to 55%.[30]

As Figure 4 shows, offshoring and SBTC also grew in this period.[31][32] Average

[28]See Katz and Autor (1999).

[29]For each year of the sample, I regress the log hourly wage on a white race dummy, sex dummy, potential job experience and potential job experience squared and education dummies for workers with less than a high-school degree, with a high-school degree and with some years of college but no degree. The omitted category for education is having a college degree. The regression uses as weights the weights provided by the March CPS multiplied by the total number of hours each worker worked in the past year. Given that the wage is in log form, (minus one times) the coefficient on an education dummy estimates, in each year, the percentage difference in hourly wage between a worker with a college degree and a worker in that education category. Source: March CPS 1980-1991.

[30]This result is similar to what Katz and Autor (1999) find for the whole sample of workers, not just manufacturing workers, during the same period.

[31]As mentioned above, I assume that as the relative price of investment goes down, SBTC goes up.

[32]Figure 4. Lag of offshoring and lag of SBTC, U.S. manufacturing, 1979-1990. Offshoring is measured on the left axis while SBTC is measured on the right axis. Offshoring is measured as the share of imported inputs as described in the Appendix. SBTC is measured by the log of the deflator of industry investment divided by the personal consumption expenditure index. Offshoring and SBTC are aggregated, by weighted averages, at the CPS two-digits level, as also described in the Appendix. *Source*: NBER trade and manufacturing

offshoring was 8.4% in 1979 and 12.4% in 1990 and so it increased on average 4 percentage points. The average log of the real price of investment was -4.04 in 1979 and -4.18 in 1990 and so it decreased on average 14 percentage points. The correlation between offshoring and the real price of investment is -0.16 and highly significant. I will not be able to control for the fact that offshoring may induce SBTC. This possibility has been theoretically advanced by Acemoglu (2003) and finds empirical support in Bustos (2010). If offshoring induces SBTC, then the estimates of the effect on offshoring will be biased downward and therefore my estimates should be considered a lower bound on the true effect of offshoring.[33]

As it can be expected, there is cross-sectional variation in the demographic composition of industries. Most importantly for our purposes, the demographic composition of some industries changes over time. Figure 5, 6 and 7 show for each industry the evolution over time, respectively, of the employment share of white workers, of the average potential job experience and of the employment share of female workers. Some industries show considerable variation over time. For example in the textile industry the employment share of white workers is estimated to be 89% in 1979 and 77% in 1990.[34] Since 1979 to 1990 in the petroleum industry the average potential job experience is estimated to have decreased by about 3 years whereas in the rubber industry is estimated to have increased by about 3 years. The female share seems relatively constant over time in all industries.

For each industry I compute the year-to-year changes in offshoring, SBTC, the employment share of white workers and the average experience. Keeping one observation per industry per year I then compute the correlation among these variables. There is no

data.

[33]Obviously, if instead SBTC induces offshoring, then my estimates of the effect on offshoring will be biased upward. I am however not aware of any theory, formal or informal, according to which SBTC may cause offshoring.

[34]These are estimates because we do not have data on all workers in a certain industry, only a random sample of the population, some members of which work in manufacturing industries. We use the sampled workers to estimate the demographic shares for each industry.

correlation between the change in SBTC and the change in the demographic variables. The correlation between the change in offshoring and the change in the employment share of white workers is -0.12 and significant at the 10% level. The correlation between the change in offshoring and the change in the average job experience is 0.15 and significant at the 5% level. During this period the share of employment in the manufacturing sector decreased: suppose that, because of this, fewer young workers entered into manufacturing. Then this fact, together with the increase in offshoring during this period, might rationalize the positive correlation between the change in offshoring and the change in the average job experience.

I then compute the fraction of skilled workers, i.e. workers with a college degree, who are white and the fraction of skilled workers who are female. I do the same for unskilled workers. I also compute the average experience for skilled workers and for unskilled workers. I then compute the yearly changes of all these variables and compute the correlation with the yearly change in offshoring. The change in offshoring has a correlation of 0.15 with the average job experience of skilled workers. This correlation is significant at the 5% level. The correlation between the change in offshoring and average job experience of unskilled workers is 0.12 and significant at the 10% level. So, for both skilled and unskilled workers the average experience increases, which is compatible with the idea that both fewer young skilled and fewer young unskilled workers entered into manufacturing in this period. However, the magnitude of the correlation is larger, and more significant, for skilled workers: this suggests that not controlling for the experience of workers may bias upward the estimate of the impact of offshoring on the skill-premium because experienced workers tend to earn more.

The correlation between the change in offshoring and the change in the fraction of unskilled workers who are white is negative and significant at the 10% level. The change in the fraction of skilled workers who are white is uncorrelated with the change in offshoring. As white workers tend to earn more, this suggests that not controlling for workers' race may again bias upward the estimate of the impact of offshoring on the skill-premium.[35] These simple correlations motivate the use of demographic data to study the effect of offshoring on wages.

Results

Wages: Individual-Level Regressions

My basic regression model for wages has this form:

$$S_{mjt} = \lambda_1 + \phi X_m + \gamma O_{j,t-1} + \psi_1 Tech_{j,t-1} + \psi_2 Ind_{j,t-1} + \zeta_j + \mu_t + \epsilon_{mjt} \tag{III.9}$$

where S_{mjt} is the wage, in log units, of an individual worker m in industry j at time t, λ_1 is a constant, X_m is a vector of demographic characteristics, $O_{j,t-1}$ and $Tech_{j,t-1}$ are, respectively, a measure of offshoring and of SBTC of industry j at time $t-1$, $Ind_{j,t-1}$ are other time-varying industry-level variables, ζ_j is an industry fixed effect, μ_t is a time fixed effect and ϵ_{mjt} is an error assumed to be randomly distributed. I will estimate this regression on four mutually exclusive education categories: the workers who have less than a high-school degree, those with a high-school degree but no further schooling, college drop-outs and workers with at least a college degree.[36] The main hypothesis is that, the higher the skill (i.e. the educational achievement), the higher the coefficient on offshoring. In other

[35] Both for skilled and unskilled workers, there is no significant correlation between the change in offshoring and the change in the fraction of workers who are female.

[36] These variables are defined in the Appendix. See Ebenstein et al. (2009) for a similar approach.

words, offshoring increases the wage of skilled workers relatively to the wage of unskilled workers.

I estimate (III.9) by pooling, for each education category, all workers in all industries in all years in the sample and using industry and year dummies for, respectively, ζ_j and μ_t. As dependent variable I use the log of hourly wage, deflated by the personal consumption expenditure (PCE) index.[37] As demographics I use a female dummy, job experience, the square of job experience and a white race dummy. As a measure of offshoring and of SBTC I use, respectively, the offshoring share and the log of the real price of investment as described in Section III.3. I add total-factor productivity (TFP) as $Ind_{j,t-1}$ in (III.9) to control for the fact that, if there are frictions in moving from one industry to the other, it is possible that an increase in TFP in one industry will bring about an increase in wages in that industry. The industry level variables are lagged one year in order to allow some time for the labor market adjustment to take place.

The industry dummies control for the fact that average wages differ across industries. Moreover, I do not want the identification of the offshoring coefficient to rely on the cross-sectional variation across industries. Indeed, I am interested in knowing whether the *increase over time* in offshoring during the 80s is responsible for the concurrent increase in the skill-premium. For this reason the model in Section III.2 assumes that all industries have the same features. Empirically, however, different industries may have different offshoring levels and, potentially correlated, different average wages because of structural differences across industries that I have not modeled. Therefore, I need to control for time-invariant variation across industries.

The year dummies control for the fact that wages and offshoring may co-move

[37]See the Appendix to see how this hourly wage is computed.

with time. Indeed, if wages track long-run GDP growth, they will tend to increase over time. Also, if, as in gravity equation models, trade increases with GDP, offshoring will also increase with GDP growth.[38] If we do not control for time variation that is common across industries, the coefficient on offshoring may be biased by the correlation of wages and offshoring with time.

The regression uses as weights the weights provided by the March CPS multiplied by the number of hours each worker worked on average in the past year. This reflects the idea that, other things equal, the higher the number of hours a worker collects a certain hourly wage, the higher the information that that observation provides on the distribution of the wage variable.

The error terms in (III.9) are probably correlated. First, even with the industry dummies, workers who are in the same industry in the same year are probably exposed to a common wage shock and so their residuals will be correlated. Second, these industry-level shocks are probably correlated over time and so the residuals of two workers who are in the same industry but in different years may still be correlated. In order to cope with this issue, I follow Angrist and Pischke (2009, p.319) who suggest to cluster the standard errors at the industry level in these cases.

The results are displayed in Table 4. All the demographic variables behave as expected and have significant coefficients. The hourly wage appears to be increasing and concave in job experience. Whites earn more per hour than non-whites. The coefficient on the male dummy is positive.

The coefficients on offshoring do not increase monotonically with skill. However, offshoring is significantly correlated with lower wages for the workers with some years of

[38] According to the gravity equation of trade, trade between two countries is an increasing function of GDP of each country. For a recent theoretical derivation of the gravity equation, see, e.g., Eaton and Kortum (2002).

college and it is not significantly correlated with the wage of workers with a college degree. In this sense, this table offers some mild evidence that an increase in offshoring was correlated with an increase in the skill-premium. A discussion of the magnitudes of these effects is deferred to below.

Contrary to the hypothesis, the coefficients on the proxy for SBTC also do not decrease monotonically with skill.[39] Looking only at the magnitudes of these coefficients, it is true that both workers with some college and workers with a college degree have a more negative coefficient on, and therefore are benefited relatively more by, SBTC than lower skilled workers. However, the gap between workers with some college and workers with a college degree appears to be actually reduced by SBTC.

The results of this set of regressions should however be taken with some caution because of the presence of high collinearity among offshoring, SBTC, the industry and the year dummies. Indeed, there are 18 industry dummies that take away 18 degrees of freedom. As long as collinearity is not perfect, the OLS estimates will still be consistent, conditional on the exogeneity of the regressors. But with high collinearity the coefficient estimates will not be precise and may even have the wrong sign. The offshoring measure especially suffers from this problem.

For this reason I also study a more parsimonious specification. In order to alleviate the collinearity problem I drop the year and industry fixed effects and add instead other variables to control for the potential sources of endogeneity discussed above. To control for the fact that there are wage differentials across industries I add as regressor, for each skill category, the average log wage for that category at the beginning of the sample, i.e. in 1979. To control for the fact that there may be structural differences according to which,

[39] A negative coefficient means that SBTC has a positive effect on wage because, as the real price of investment goes up, SBTC goes up.

cross-sectionally, industries differ in offshoring and SBTC, I add as regressors the value of offshoring and of SBTC in 1979. Finally, we observed above that the wage variation over time may be spuriously correlated with the increase over time of offshoring and of SBTC: in order to control for this, I add the lag of the log of economy-wide real GDP.

The results for this specification are shown in Table 5. The demographic variables are included in all the four regressions but are not reported in the table because their coefficients are unchanged with respect to the previous specification. According to this table, offshoring is correlated with an increase in the skill-premium. Indeed offshoring is significantly correlated with an increase of the wage of workers with a college degree and with a decrease of the wage of workers with only a high-school degree. However, it is still not true that the coefficient on offshoring increases with skill. In particular, offshoring has a negative but weakly significant correlation with the wage of workers with less than a high-school degree. Moreover, this correlation appears to be smaller, in absolute value, than the correlation between offshoring and the wage of high-school degree workers. The pattern of the coefficients on SBTC is similar to the pattern in the previous table with the difference that now all the coefficients for SBTC are significant.

The average (lagged) offshoring increased 4 percentage points in this period. Given that the wage is in logarithms, this increase in offshoring is correlated with a 3.6% (that is, 0.04 times 0.90) increase in the wage of college degree workers and a -4% (that is, -1.00 times 0.04) change in the wage of high-school degree workers. Therefore, according to this table, if one were to take a causal interpretation of the coefficients, offshoring increased the college premium, relative to high-school, by 7.6 percentage points during the 80s. Given that the college premium, relative to high-school, increased by 13 percentage points during this period (see Section III.3), offshoring can explain up to 58% of this increase. For the sake of comparison, FH find that, depending on the specification, offshoring can explain between 15% and 40% of the increase in the wage premium of non-production workers relatively to production workers during the same period. As we will see in the next section, my large estimate is not robust to other specifications.

I also reestimate the previous regressions without including the demographic controls. This allows me to determine how the exclusion of demographic variables affects the estimate of the effect of offshoring on the skill-premium. The results are in Table 6. The coefficient on offshoring for workers with a college degree is still highly significant but it is now more than two times larger than in the regression with demographic controls. The coefficient on workers with a high-school degree is still negative and significant. Using similar calculations to the above, a 4% increase in offshoring can now explain up to 90% of the increase in the college wage premium. This table suggests that, when studying the effect of offshoring on the skill-premium, the omission of the demographic variables inflates the estimate of offshoring. This result will be confirmed even when I use an industry-level regression, as opposed to an individual-level regression.

Wages: Industry-Level Regressions

In all the results reported so far, I have used an individual level regression and clustered the standard errors at the industry level. However, the clustered standard errors may be unreliable when the number of clusters is small.[40] This may be a concern for my case given that I have only 19 clusters, i.e. 19 industries. Bertrand et al. (2004) simulate the behavior of the cluster-adjusted standard errors as the number of clusters vary. They find that with 20 clusters the probability of rejecting the null at the 5% level, when the

[40] See Angrist and Pischke (2009, p.319).

null is true, is 5.8%.[41] Their result suggests that the number of clusters in my dataset is not a big concern. However, Bertrand et al. (2004) do not work with an individual level regression as the one in (III.9). They first aggregate individual data within clusters in each year and then run their simulations on these aggregate data.[42] In order to use the Bertrand et al. (2004)'s result, I must also run a regression that aggregates individual data within industry-year pairs.

For each education category g, I then study this regression:

$$\begin{aligned}\overline{S}_{gjt} =& \lambda_2 + \phi_1 \overline{X}_{gjt} + \beta_1 O_{j,t-1} + \beta_2 Tech_{j,t-1} + \beta_3 TFP_{j,t-1} + \\ & + \phi_2 \overline{S}_{g,j,1979} + \beta_{10} O_{j,1979} + \beta_{20} Tech_{j,1979} + \delta lngdp_{t-1} + \eta_{jt} \end{aligned} \tag{III.10}$$

where $\overline{S}_{gjt}$ is the average log wage of individual workers in industry j at time t in education category g, λ_2 is a constant, $\overline{X}_{gjt}$ is a vector of demographic characteristics (a female dummy, a race dummy and experience), averaged across individual workers in industry j at time t in education category g. $O_{j,t-1}$, $Tech_{j,t-1}$ and $TFP_{j,t-1}$ are, respectively, offshoring, the log of the real price of investment and the log of total factor productivity of industry j at time $t-1$, $\overline{S}_{g,j,1979}$ is the average log wage of individual workers in industry j in 1979 in education category g, and $O_{j,1979}$ and $Tech_{j,1979}$ are, respectively, offshoring and the log of the real price of investment of industry j in 1979, $lngdp_{t-1}$ is the log of GDP at time $t-1$ and η_{jt} is an error assumed to be randomly distributed.

Notice how in the above regression the unit of observation is now an industry-year pair. I do not use industry and year dummies because of the collinearity problem reported above. I follow the same strategy as in Table 5 and so I use the log of GDP and initial

[41] See Bertrand et al. (2004, Table VIII, p.272). In their simulations this probability is very similar whether one uses 20 clusters or 50 clusters, which is the number of clusters they recommend. Bertrand et al. (2004) run their simulations on wage data from the March CPS and so their result is especially useful for my case.

[42] Bertrand et al. (2004) cluster data at the state level rather than at the industry level but their results can be applied to the industry-level clustering as well.

values of the key variables in order to control for the possible endogeneity of offshoring and SBTC.

The weights for each industry-year are computed as follows. First, before aggregating the individual data at the industry-year level, I multiply, for each worker, the March CPS weight by the total number of hours worked during the year.[43] Then, for each education category, I sum the obtained figures at the industry-year level and use those as weights in the industry-year regression.[44] I cluster the standard errors at the industry level.

The results for this specification are shown in Table 7 and Table 8.[45] It is useful to compare these coefficients on offshoring with the ones from the individual level regressions (Table 5): in the industry level regression, the coefficient on offshoring for high-school degree is smaller in absolute value and less significant; the coefficient on offshoring for workers with some college is larger in absolute value and now more significant; the coefficient on offshoring for workers with a college degree is smaller in absolute value and no more significant. The lack of statistical significance on some estimates could be partly attributed to the smaller sample size of the grouped regressions with respect to the individual ones. However, the coefficients on SBTC are very similar in magnitude and significance in both specifications and so sample size does not seem to be a concern.

Overall, the effect of offshoring on the college skill premium is much smaller when one uses data that is grouped at the industry level rather than individual workers' data as in

[43]The total number of hours worked by a worker during the year is obtained by multiplying the number of weeks he worked during the year times the average number of hours he worked per week.

[44]The results are robust to use as weights, for each education category, just the number of workers in that category in a given industry-year pair.

[45]Table 7 and 8. Regressions by education category, one observation per industry-year. The dependent variable is the average log of real hourly wage, computed using individual level data aggregated at the industry-year-education level. Table 8 reports the coefficients on the average, at the industry-year-education level, of, respectively, the female dummy, the white race dummy, and experience. The regressions do not include year and industry dummies. Standard errors are clustered at the industry level. March CPS sampling weights multiplied by number of hours worked last year are used. *Source*: March CPS, NBER trade and manufacturing data.

Section III.4.1. If we use the estimates of the offshoring coefficients, whether significant or not, a 4% increase in offshoring is now associated with a -3.2% change in the wage of high-school degree and with a 1.5% increase in the wage of college degree workers. Therefore, according to this table, offshoring can explain up to 36% of the 13% increase in the college (relative to high-school) wage premium.

I also reestimate the model (III.10) omitting the demographic variables $\overline{X}_{gjt}$. The results are in Table 9.[46] The effect of offshoring on the wage of workers with a high-school degree is now less significant but the effect of offshoring on the wage of workers with a college degree is much larger and now highly significant. If we ignore the effect of offshoring on high-school degree workers (because its coefficient is only weakly significantly different from zero), then a 4% increase in offshoring explains 50% of the increase in the college (relative to high-school) wage premium. If one instead assumes the coefficient on offshoring for high-school degree workers to be equal to its estimate, i.e. -0.71, then a 4% increase in offshoring explains 72% of the increase in the college (relative to high-school) wage premium. Therefore, also for the industry-level regressions, when the demographic variables are omitted, offshoring has a much higher effect on the skill-premium.

Interestingly, the results in Table 9 are qualitatively similar to the results in FH (p. 933, Table V). They use an industry-level regression, do not control for demographics characteristics and find that offshoring affects significantly the wage of non-production workers but barely affects the wage of production workers.[47] My results suggest that the

[46] Table 9 continued. Regressions by education category, one observation per industry-year. The dependent variable is the average log of real hourly wage, computed using individual level data aggregated at the industry-year-education level. The regressions do not include demographic variables, year and industry dummies. Standard errors are clustered at the industry level. March CPS sampling weights multiplied by number of hours worked last year are used. *Source*: March CPS, NBER trade and manufacturing data.

[47] Their dataset does not have data on the education of workers and so, following Berman et al. (1994) they use non-production workers as a proxy of skilled workers and production workers as a proxy of skilled workers.

omission of demographic controls in their regression may have biased their estimates of the effect of offshoring on the skill-premium.

In Table 8, in the regression for workers with a college degree, we see that the average experience and the female share have significant coefficients. Given that omitting these controls affects the coefficient on offshoring, this regression reveals that offshoring is correlated with an increase in the average experience of skilled workers and with a decrease in the female employment share of skilled workers. Omitting these controls inflates the estimates of offshoring because experienced workers earn on average more and female workers earn on average less.[48]

It is possible that an increase in offshoring in one industry may not only affect the relative demand for skill in that industry, as the model in Section III.2 suggests, but also induce a change in other demographics characteristics of the labor force of that industry. If so, then the coefficients on offshoring in Table 9 may be biased, with the sign of the bias depending on how offshoring affects the demographic composition of the labor force. The point of this section is that, in order to determine the effect of offshoring on the skill-premium, we need to account for the interaction between offshoring and other demographic characteristics of the labor force because such interactions are empirically important.

[48]The coefficient on average experience is in line with the simple correlation analysis of Section III.3. However, the pattern for the female share and white share is different, with the regression analysis overturning the results found with simple correlations. The difference is due to the fact that the regression analysis also controls for other confounding factors which simple correlations do not account for.

Employment

In order to study employment, for each education category g, I use the following regression:

$$\begin{aligned}\overline{H}_{gjt} =& \lambda_3 + \chi_1 \overline{X}_{gjt} + \theta_1 O_{j,t-1} + \theta_2 Tech_{j,t-1} + \theta_3 TFP_{j,t-1} + \\ & + \chi_2 \overline{H}_{g,j,1979} + \theta_{10} O_{j,1979} + \theta_{20} Tech_{j,1979} + \xi lngdp_{t-1} + e_{jt} \qquad \text{(III.11)}\end{aligned}$$

where $\overline{H}_{gjt}$ is (the log of) the total number of hours worked in industry j at time t by workers of education g, $\overline{H}_{g,j,1979}$ is the (the log of) the total number of hours worked in industry j in 1979 by workers of education g and $\overline{X}_{gjt}$, $O_{j,t-1}$, $Tech_{j,t-1}$, $TFP_{j,t-1}$, $O_{j,1979}$, $Tech_{j,1979}$ and $lngdp_{t-1}$ are defined as in equation (III.10).[49] In this regression the unit of observation is an industry-year pair. The main hypothesis is that the higher the skill (i.e. the educational achievement), the higher the coefficient on offshoring. In other words, offshoring increases the employment of skilled workers relatively to the employment of unskilled workers.

The results for model (III.11) are contained in Table 10. According to this table, offshoring has a significant and negative effect on workers with less than a high-school degree and on workers with only a high-school degree. The coefficient on offshoring for workers with some college and workers with a college degree are also negative, even if they are not significant. The coefficient on offshoring for workers with a college degree appears to be less negative than the coefficient on offshoring for less skilled workers. In this sense, this table suggests that offshoring has bid up the relative demand for skilled labor. As to SBTC, even if its coefficients appear to be monotonic in skill, only the coefficient for workers with less than a high-school degree is significant at the 5% level. These results are virtually

[49] To compute $\overline{H}_{gjt}$ I first compute the total number of hours worked last year by each individual worker by multiplying his average hours worked per week times his total weeks worked during the year. Then I sum the obtained figures at the industry-year-education level and then take the log.

unaffected when running the same regressions without the demographic controls or using year dummies instead of log of GDP.

As above, consider an increase in offshoring by 4 percentage points, which is the average change in offshoring since 1979 to 1990. Taking a causal interpretation of the regressions, this increase in offshoring will reduce total hours worked by high-school degree workers by about 21%, a very large effect. The coefficient on offshoring for college degree workers is not significant. If one nonetheless takes the magnitude of the coefficient seriously, a 4 percentage change in offshoring decreases total hours worked by college degree workers by 13%. Therefore, offshoring increases the employment of college degree workers, relative to the employment of high-school degree workers, by at least 8%. Given that this relative employment increased by 40 percentage points since 1979 to 1990, offshoring can explain at least 20% of such increase.

In Section III.4.2 we found that the coefficients on offshoring did not increase monotonically with skill. This may cast some doubts on the hypothesis that offshoring increases the skill-premium. As mentioned in Section III.2.1, however, if workers can easily move across sectors, then, for each type of skill, the wage differential across sectors will be arbitraged away. For this reason a wage regression that uses industry-level variation in offshoring will find only a small effect of offshoring on the skill-premium even if such effect is actually important. The large effect of offshoring on relative employment indeed suggests that offshoring has played a significative role in increasing the *economy-wide* skill-premium by increasing the economy-wide relative demand for skilled workers.

Conclusion

In this paper I use individual workers' data to study the effect of offshoring on the relative demand for skilled labor in U.S. during the 80s. In this way I am able to bring new evidence on the still open question of the relationship between international trade and wage inequality. Differently from the previous literature, my dataset also allows me to control for demographic changes of the labor force within industries.

Utilizing a simple model I derive an equation that linearly relates the skill-premium to offshoring. I first show that it is important to control for demographic characteristics of the labor force. When these controls are omitted, offshoring explains at least 50% of the increase in the skill-premium. Instead, when demographic controls are included, the effect of offshoring on the skill-premium markedly decreases in all specifications. This result highlights the importance of accounting for the interaction between offshoring and the demographic composition of the labor force when studying the effects of offshoring on the skill-premium. I also find that, the higher the increase in offshoring in an industry, the higher its increase in the relative employment of skilled labor. This suggests that, at least for U.S. in the 80s, offshoring played an important role in the increase of the economy-wide relative demand for skilled labor.

Data Appendix

Industry Level Data

For the construction of the industry-level variables, I follow FH while I follow Ebenstein et al. (2009) for the proxy of SBTC. I obtain data on the s_{ijt} terms in equation (III.8) from the Bureau of Economic Analysis (BEA) input-output tables. "The Industry Benchmark Division (IBD) prepares benchmark input-output (I-O) accounts for years ending in 2 and 7, which are based on detailed data from the quinquennial economic censuses that are conducted by the Bureau of the Census. [...] The benchmark accounts show how industries interact at the detailed level; specifically, they show how approximately 500 industries provide input to, and use output from, each other to produce gross domestic product".[50]

I use the BEA I-O tables for 1982 and 1987. I keep only manufacturing industries as both buyers and suppliers of inputs. These tables contain data for 368 industries in 1982 and 361 industries in 1987. For each industry these tables tell how much industry i spends on each industry j for its inputs.[51]

I obtain the variables to compute import penetration (the $\frac{M_{it}}{Y_{it}+M_{it}-X_{it}}$ term) in equation (III.8) from the NBER manufacturing trade dataset.[52] These data contain information on 450 manufacturing industries for the 1958-1994 period (I will use only data for the 1979-1990 period). The dataset is described in Feenstra and NBER (1996).

The industry identification code used in the BEA data is the Census one. This code is different from the SIC identification code that is used in the trade data. Moreover, the trade dataset contains information on 450 manufacturing industries while the BEA dataset contains information on a fewer number of manufacturing industries. I use the crosswalks provided by the BEA in 1982 and 1987 to aggregate the trade data at the level of the BEA data[53]. If industry A and B are aggregated in a single industry C, I compute the imports

[50] See the BEA website.

[51] This information is contained in the *use* variable of the *Direct Requirement Coefficients* tables, that are available for download on the BEA website.

[52] This data is available at Robert Feenstra's website and on the NBER website. In theory this measure of import penetration can be larger than 1: algebraically, given that $Y_{it} + M_{it} - X_{it}$ is always larger than zero, this will occur if $X_{it} > Y_{it}$. In my dataset, this happens to industry 3339 in the SIC 1972 code (Miscellaneous primary nonferrous metal refiners and smelting) in years 1979, 1980 and 1981 and to industry 3915 in the SIC 1987 code (Jewelers Findings and Materials and Lapidary Work) for years 1988 and 1989. I trim the import penetration ratio to 1 in this case.

[53] The trade data is coded using the SIC 1972 code. For the 1982 input-output table, the BEA provides a crosswalk with the SIC 1977, that is however very similar to the SIC 1972. For the 1987 input-output table, the BEA provides a crosswalk with the SIC 1987, that is instead quite different from the SIC 1972. I use the conversion tables between SIC 1972 and SIC 1987 to transform the SIC 1972 trade data into the SIC 1987 classification. The conversion tables are available on the NBER website.

(exports, domestic shipments) for C as the sum of imports (exports, domestic shipments) of A and B[54].

I then compute the input shares s_{ijt}, excluding *Petroleum refining* from the industries supplying inputs.[55] I now have the input shares for 1982 and 1987. My imputation of the input shares for other years is as follows. I assume that the input shares in the 1979-1984 period are equal to the input shares in 1982 and that the input shares in the 1985-1990 period are equal to the input shares in 1987. I now have the input shares for the 1979-1990 period. I then merge the BEA data with the aggregated trade data. Now I have all the terms for computing the measure of offshoring for the 1979-1990 period for each manufacturing industry.

The offshoring data is not yet ready for use. Indeed, I use March CPS information on the industry of a worker only at the two digits level. So we need to aggregate the offshoring data at the March CPS level. I first compute, for each year, the level of offshoring for each disaggregated industry and then take a weighted mean of this variable: in this way I obtain the level, in that year, of offshoring for the more aggregated, March CPS-level, industries.[56] I use as weights the share of the wage bill of the disaggregated industries in the more aggregated industries. So, for example, if I aggregate the offshoring of A and B in year t, the weight on the offshoring of A will be the $wagebill_A/(wagebill_A + wagebill_B)$ in year t. I have now the level of offshoring for each March CPS industry. The average offshoring [57] for an industry in my dataset is 10.3% that is very similar to the one of FH (Table II, p. 923).[58]

[54] I do the same for other NBER variables such as capital and wage bill. I take instead a simple mean of the investment price deflator.

[55] In this I follow FH that exclude energy purchases from the computation of the input shares.

[56] I use the variable *indly2* of the March CPS Unicon dataset to identify a two-digits March CPS industry.

[57] This is computed as follows: keep one observation per March CPS industry-year. Compute offshoring for each industry and year. The average of this variable is 10%.

[58] The relevant statistic is the average for broad outsourcing in the 1979-1990 period, which is 9.67% in

For SBTC, I use the log of the industry investment price deflator for each industry minus the log of the personal consumption index for the current year. Data on the investment deflator comes from the NBER manufacturing dataset. This variable can be interpreted as the (log of the) real price of investment. In the appendix of a previous draft of this paper I describe how I computed the proxies for SBTC used by FH. I was not able to replicate the values of their variables and so I ended up not using these variables as a proxy for SBTC.

Worker Level Data

The worker individual level's data are from the March CPS survey. The March CPS randomly samples addresses in U.S.: residents at a certain address are interviewed for four consecutive months; then they are not interviewed for eight months; then again for four months.[59] The March CPS questionnaire has a specific supplement devoted to labor questions: for this reason it has been extensively used in labor studies. I use the March CPS data as processed by the Unicon Research Corporation.

Importantly, the data on income refers to the previous calendar year: so, if a worker is interviewed in the March of year *t*, he will report his total wage and salary income for year *t-1*. Given that I use data from the March CPS 1980 to the March CPS 1991, this gives me data for income for the 1979-1990 period.

I mainly work with workers in the manufacturing sector. In the 1979-1990 period, 20% workers work in manufacturing[60]. I restrict the March CPS sample as follows.[61] I use

FH.

[59] See Madrian (2000) and Liu and Trefler (2008).

[60] This is the fraction of workers in manufacturing out of the individuals in the CPS who are between the age of 18 and 65 (see below) and report a positive income from wage and salary.

[61] These steps are very similar to those followed by Acemoglu (2002, p.64-65) who in turn follows Katz and Autor (1999).

only workers between the age of 18 and 65 (during their earnings years).

I also keep only workers whose class of employment is either *private* or *government* in both years.[62] I also keep only workers who have only wage income as opposed to self-employment income and non-farm income[63]. The rationale for the two above criteria is the following. Suppose that a worker works in a certain year for 40 weeks in a manufacturing job and for 10 weeks as self-employed. We have data on his wage income (i.e. the one from the manufacturing job) and on his self-employment income. However, we do not have his weeks worked last year disaggregated by job. For this reason, when computing his weekly manufacturing wage, we cannot divide his wage income by the recorded weeks worked. The two criteria aim at addressing this problem by keeping only workers who have only a wage income.[64]

I compute the hourly wage as follows. I multiply by 1.5 the topcode of yearly income, then divide it by the average number of weeks worked last year and by average number of hours worked last year. I do not use workers with allocated earnings or who earned less than $67 per week in 1982 dollars (equal to one-half of the 1982 real minimum wage based on a 40 hour week).

I define the various skill categories using years of education.[65] The first category is composed by those workers who did not get a high-school degree, i.e. workers who have completed less than 12 grades. Workers with a high-school degree are defined as those who completed exactly 12 years of school. The category of workers with some College is

[62]This is the variable _clslyr in the Unicon dataset. The main classes of employment of a worker are *private*, *government* and *self-employed*.

[63]In terms of the Unicon variables, this amounts to keep a record only if *incern* equals *incwag*.

[64]Notice that the first criterion is not sufficient. A worker may be categorized as *not* self-employed and yet have some self-employment income. In some cases this additional income is of the same magnitude of the salaried income. The second criterion is, empirically, not sufficient either: there are 89 workers who report a wage income but whose class of employment is neither private nor government.

[65]I use the variable *edu* created in the algorithm described in Madrian (2000). This variable is very similar to the *_educ* variable in the Unicon dataset.

composed by those workers who completed at least 13 years of school but less than 16. The workers in the last category, i.e. college degree and above, have completed at least 16 years of school. Job experience is defined as age minus years of schooling minus seven and negative values are set to zero. I use the March supplemental person weights throughout.

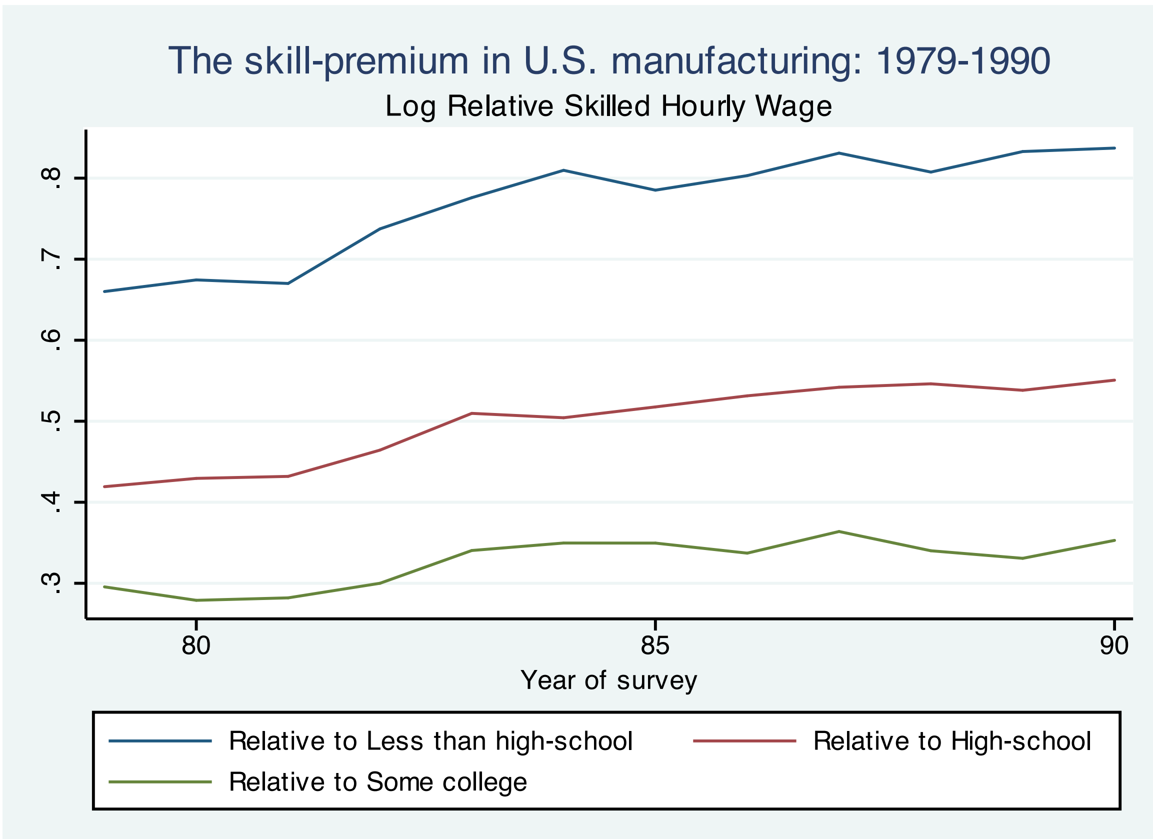


Figure 3. The Skill-Premium In U.S. in the 1980s

Figure 4. Offshoring and Skill-biased Technological Change in U.S. Manufacturing: 1979-1990

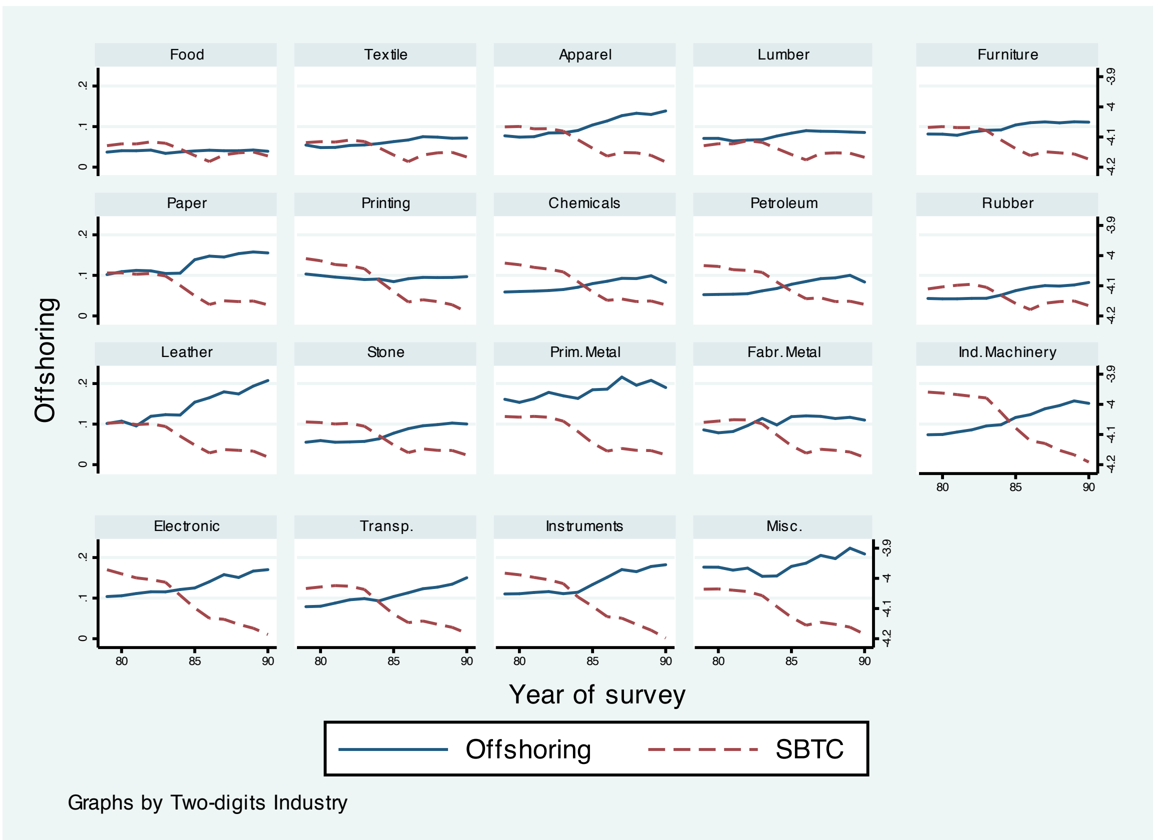


Figure 5. White Workers' Share of Employment in U.S. Manufacturing: 1979-1990

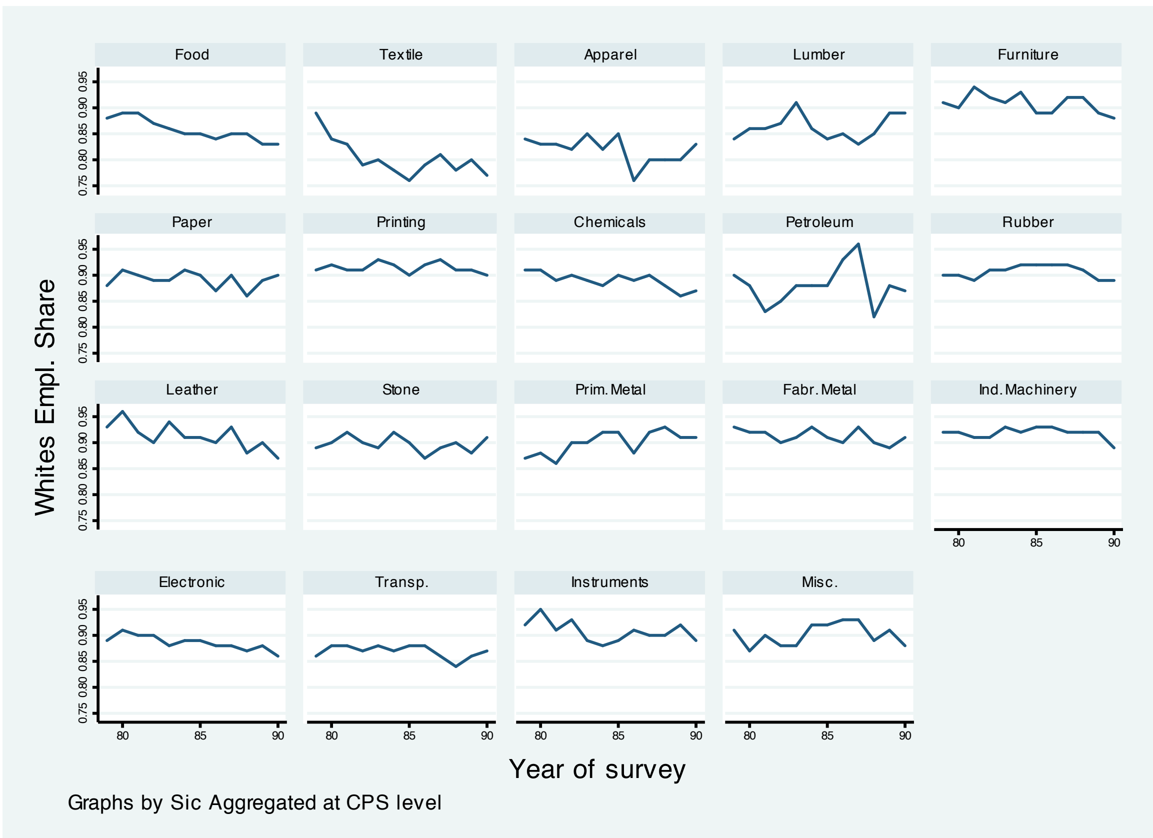


Figure 6. Average Job Experience in U.S. Manufacturing: 1979-1990

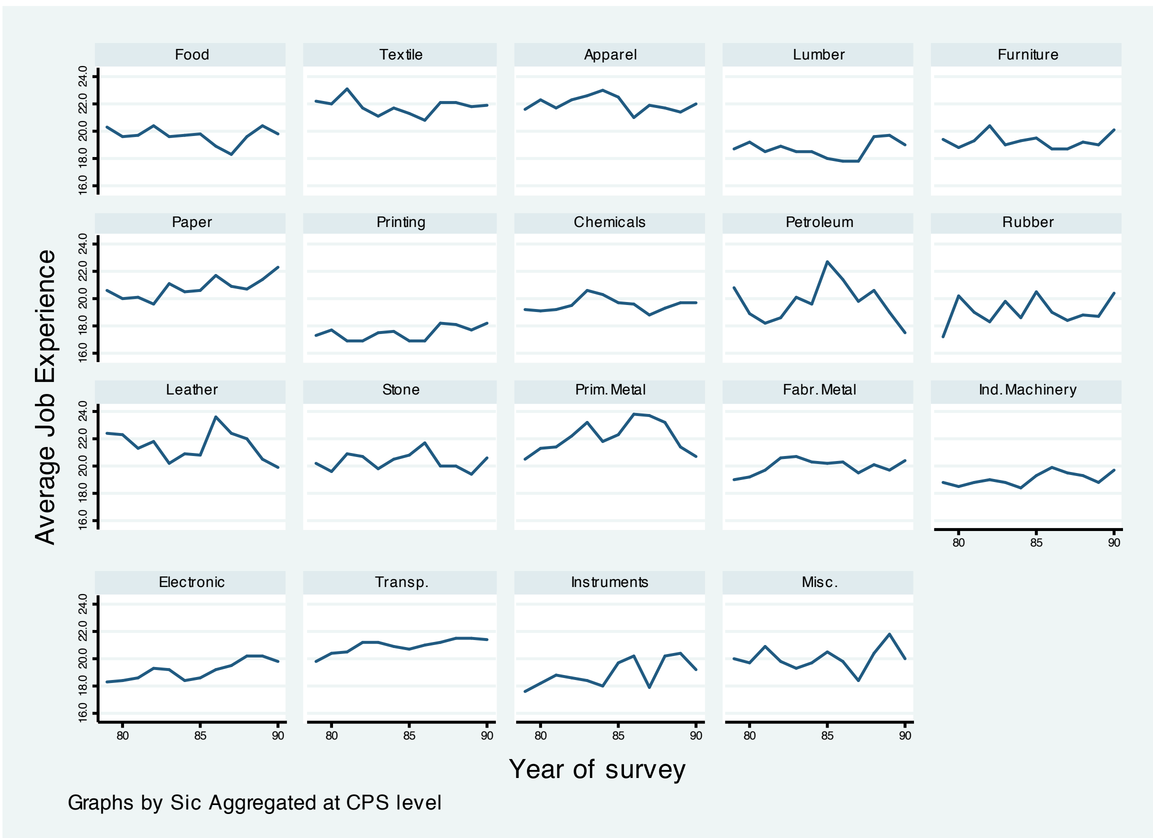


Figure 7. Female Workers' Share of Employment in U.S. Manufacturing: 1979-1990

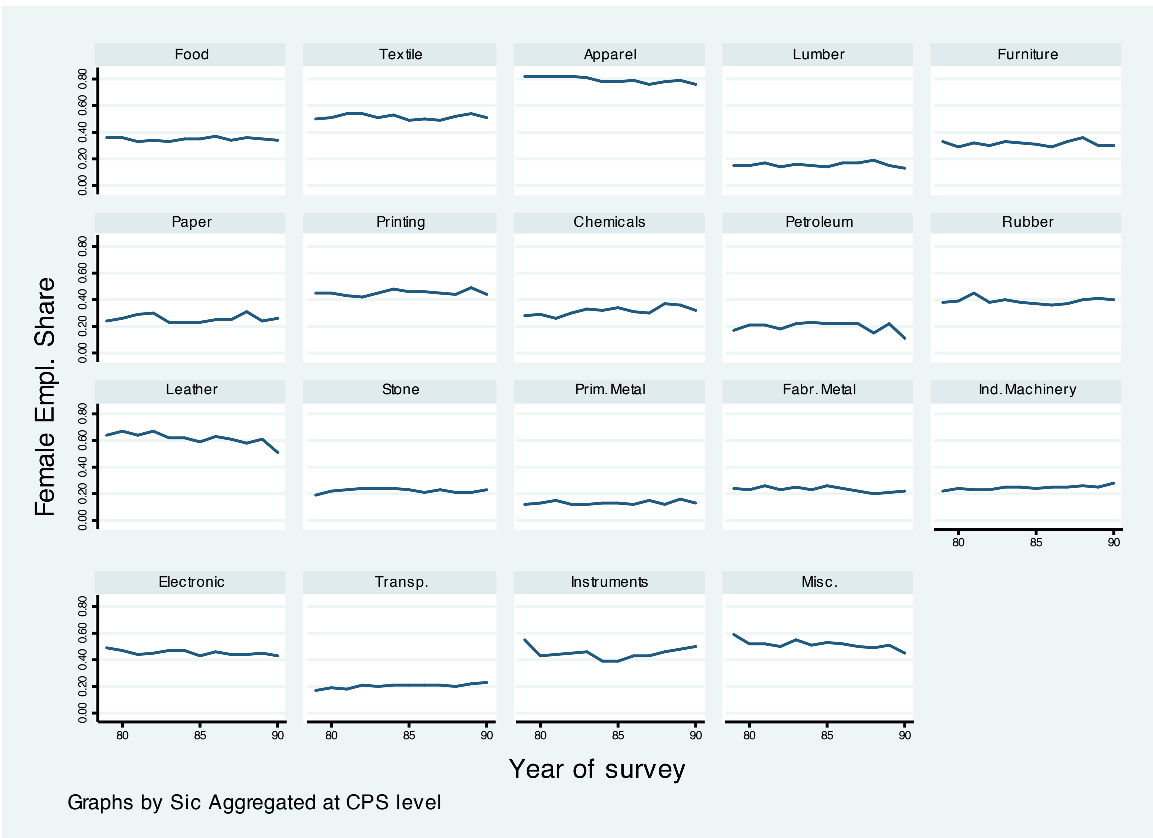


Table 4. Individual wage regressions by education category, with year and industry dummies

	(1) Less than High School b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Experience	0.03***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Experience square	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
White	0.11***	0.14***	0.13***	0.16***
	(0.02)	(0.01)	(0.02)	(0.02)
Female	-0.29***	-0.34***	-0.29***	-0.27***
	(0.01)	(0.01)	(0.01)	(0.02)
Lag offshoring	-0.42	-0.57	-1.06***	-0.09
	(0.36)	(0.35)	(0.22)	(0.38)
Lag log real price of investment	-0.17	-0.39*	-0.79***	-0.57**
	(0.19)	(0.20)	(0.11)	(0.24)
Lag log TFP industry	0.19	0.16	0.19*	-0.08
	(0.14)	(0.10)	(0.11)	(0.14)
Observations	34241	64628	23109	19936
R^2	0.33	0.38	0.33	0.29

* p<0.10, ** p<0.05, *** p<0.01

Regressions by education category. The dependent variable is the log of real hourly wage.

Standard errors clustered at the industry level.

All regressions also include year dummies and industry dummies. March CPS sampling weights times hours last year are used.

Source: March CPS, NBER trade data, NBER productivity database.

Table 5. Individual wage regressions by education, without year and industry dummies, U.S. 1979-1990

	(1) Less than HS b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Lag offshoring	-0.48*	-1.00***	-0.81*	0.90***
	(0.27)	(0.33)	(0.45)	(0.22)
Lag Real price of investment (log)	-0.26**	-0.64***	-0.71***	-0.53***
	(0.13)	(0.13)	(0.14)	(0.16)
Lag Log TFP industry	0.34	0.46***	0.49***	0.06
	(0.21)	(0.14)	(0.14)	(0.16)
Lag offshoring in 1979	0.21	0.96*	0.55	-1.88***
	(0.38)	(0.46)	(0.52)	(0.26)
Lag Log real price investment in 1979	0.73***	1.02***	1.13***	0.96***
	(0.21)	(0.25)	(0.19)	(0.20)
Lag mean log wage in 1979	0.68***	0.60***	0.60***	0.55***
	(0.03)	(0.03)	(0.07)	(0.05)
Lag log real GDP	-0.32***	-0.42***	-0.38***	-0.38***
	(0.10)	(0.08)	(0.07)	(0.10)
Observations	34241	64628	23109	19936
R^2	0.31	0.36	0.34	0.28

* p<0.10, ** p<0.05, *** p<0.01

Regressions by education category. The dependent variable is the log of real hourly wage.

Standard errors clustered at the industry level.

The regressions also include a gender dummy, a white race dummy, experience and experience square.

The regressions do not include year and industry dummies. March CPS sampling weights times hours last year are used.

Source: March CPS, NBER trade and productivity dataset.

Table 6. Individual wage regressions by education, no demographics, no year and industry dummies. U.S. 1979-1990

	(1) Less than HS b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Lag offshoring	-0.12	-0.88**	-0.72	2.04***
	(0.38)	(0.33)	(0.69)	(0.30)
Lag Real price of investment (log)	-0.13	-0.67***	-0.65***	-0.23
	(0.13)	(0.14)	(0.18)	(0.20)
Lag Log TFP industry	0.19	0.43***	0.53***	0.15
	(0.14)	(0.12)	(0.18)	(0.20)
Lag offshoring in 1979	0.06	1.04**	0.54	-2.62***
	(0.39)	(0.42)	(0.71)	(0.31)
Lag Log real price investment in 1979	0.35**	0.83***	1.14***	0.44**
	(0.14)	(0.21)	(0.26)	(0.19)
Lag mean log wage in 1979	0.97***	0.92***	0.88***	0.72***
	(0.03)	(0.04)	(0.12)	(0.08)
Lag log real GDP	-0.30**	-0.32***	-0.18**	-0.39***
	(0.11)	(0.08)	(0.07)	(0.13)
Observations	34241	64628	23109	19936
R^2	0.19	0.15	0.07	0.07

* p<0.10, ** p<0.05, *** p<0.01

Regressions by education category. The dependent variable is the log of real hourly wage.

Standard errors clustered at the industry level.

The regressions do not include demographic variables, year and industry dummies.

March CPS sampling weights times hours last year are used.

Source: March CPS, NBER trade and productivity dataset.

Table 7. Industry-level wage regressions by education, no year and industry dummies. U.S. 1979-1990

	(1) Less than HS b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College b/se
Lag offshoring	-0.12	-0.81**	-1.17**	0.38
	(0.39)	(0.31)	(0.49)	(0.30)
Lag Log Real price of inv.	-0.25**	-0.57***	-0.80***	-0.53***
	(0.11)	(0.15)	(0.17)	(0.16)
Lag Log TFP industry	0.21	0.37***	0.35***	-0.08
	(0.16)	(0.10)	(0.12)	(0.15)
Lag offshoring in 1979	-0.01	0.92**	0.79	-1.42***
	(0.39)	(0.41)	(0.58)	(0.31)
Lag Log Real Price inv. in 1979	0.40*	0.61**	1.29***	1.11***
	(0.21)	(0.25)	(0.25)	(0.15)
Hourly wage for edlesshs in 1979	0.84***			
	(0.05)			
Lag log real GDP	-0.32***	-0.33***	-0.31**	-0.20*
	(0.10)	(0.08)	(0.11)	(0.11)
Hourly wage for edhs in 1979		0.80***		
		(0.07)		
Hourly wage for edsomco in 1979			0.55***	
			(0.10)	
Hourly wage for edcol in 1979				0.56***
				(0.05)
Observations	227	228	228	228
R^2	0.96	0.96	0.86	0.86

* p<0.10, ** p<0.05, *** p<0.01

Table 8. Industry-level wage regressions by education, no year and industry dummies. U.S. 1979-1990, continued

	(1) Less than HS b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Average Experience	0.01*			
	(0.00)			
Average White Share	0.01			
	(0.14)			
Average Female Share	-0.10**			
	(0.04)			
Average Experience		0.01***		
		(0.00)		
Average White Share		0.18		
		(0.15)		
Average Female Share		-0.11		
		(0.09)		
Average Experience			0.02***	
			(0.00)	
Average White Share			0.06	
			(0.15)	
Average Female Share			-0.40***	
			(0.12)	
Average Experience				0.01***
				(0.00)
Average White Share				-0.19
				(0.13)
Average Female Share				-0.38***
				(0.06)
Observations	227	228	228	228
R^2	0.96	0.96	0.86	0.86

* p<0.10, ** p<0.05, *** p<0.01

Table 9. Industry-level wage regressions by education category without demographics. U.S. 1979-1990

	(1) Less than HS b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Lag offshoring	0.15	-0.71*	-0.92	1.62***
	(0.40)	(0.37)	(0.79)	(0.38)
Lag Real price of investment (log)	-0.21	-0.68***	-0.66***	-0.23
	(0.14)	(0.14)	(0.22)	(0.20)
Lag Log TFP industry	0.14	0.35***	0.45**	0.04
	(0.13)	(0.10)	(0.18)	(0.23)
Lag offshoring in 1979	-0.16	0.97*	0.73	-2.31***
	(0.36)	(0.47)	(0.82)	(0.40)
Lag Log real price investment in 1979	0.22	0.69***	1.11***	0.51**
	(0.17)	(0.21)	(0.31)	(0.21)
Hourly wage for edlesshs in 1979	0.97***			
	(0.03)			
Lag log real GDP	-0.33***	-0.32***	-0.12	-0.27*
	(0.10)	(0.08)	(0.09)	(0.13)
Hourly wage for edhs in 1979		0.94***		
		(0.04)		
Hourly wage for edsomco in 1979			0.92***	
			(0.13)	
Hourly wage for edcol in 1979				0.79***
				(0.09)
Observations	227	228	228	228
R^2	0.95	0.95	0.78	0.81

* p<0.10, ** p<0.05, *** p<0.01

Table 10. Industry-level hours of employment regr. by education, no demog., no year and industry dummies.

	(1) Less than High School b/se	(2) HS Degree b/se	(3) Some College b/se	(4) College Degree b/se
Lag Offshoring	-4.28**	-5.25***	-4.39	-3.27
	(1.57)	(0.89)	(2.77)	(2.04)
Lag Real price of investment (log)	1.72**	0.58	0.31	-1.47*
	(0.60)	(0.40)	(0.53)	(0.72)
Lag offshoring, 1979	4.20*	3.07***	4.14	0.78
	(2.01)	(0.85)	(2.42)	(1.83)
Lag log real price of investment, 1979	-1.37	0.35	0.85	5.50***
	(0.79)	(0.58)	(1.66)	(1.71)
Log hours, less than hs, 1979	1.08***			
	(0.06)			
Lag log real GDP	-0.10	0.78***	1.10***	0.78**
	(0.26)	(0.25)	(0.34)	(0.28)
Log hours, hs degree, 1979		0.99***		
		(0.04)		
Log hours, some college, 1979			1.01***	
			(0.08)	
Log hours, college or more, 1979				0.89***
				(0.07)
Observations	227	228	228	228
R^2	0.91	0.95	0.91	0.92

* p<0.10, ** p<0.05, *** p<0.01

One observation per industry-year. The dependent variable is the log of total hours of employment in each industry-year. Demographics controls added. No year and industry dummies are included. Standard errors clustered at the industry level. Weights are as described in the text. Source: March CPS, NBER trade and productivity data.

CHAPTER IV

OFFSHORING AND OCCUPATIONAL SWITCH

Introduction

Various studies have stressed the importance of an increase in economic *turbulence* for the understanding of the labor market. In a seminal study Gottschalk and Moffitt (1994) decompose the change in the variance of the log of wages into the change of the variance of a permanent component and the change of the variance of a transitory component. They find that the variance of the transitory component of log wages increased by 40% from the 1970s to the 1980s in U.S.[1] Ljungqvist and Sargent (1998) observe that in the 1983-1995 period Europe faced a unemployment rate that was higher than the average for the OECD countries. They attribute this fact to the interaction between the distorted incentives of the european welfare states on workers' labor supply and the increase in turbulence in the economy. However, the sources of the increase in turbulence are usually left unexplained.[2] This paper studies one of such possible sources, i.e. one form of "globalization". In particular, I study the impact of trade in intermediate inputs, *offshoring* for short, on the probability of switching occupation.

Kambourov and Manovskii (2009a) document that the fraction of workers switching occupations in the U.S. was as high as 16% a year in the early 1970s and had increased to 21% by the mid-1990s. Kambourov and Manovskii (2009a) also find "substantial returns

[1]They also find that the variance of the permanent component increased by the same amount in that period. See Katz and Autor (1999, p. 1495).
[2]See Katz and Autor (1999, p. 1497).

to tenure in an occupation - an increase in wages of at least 12% after five years of occupational experience, holding other observables constant." Kambourov and Manovskii (2009b, p. 733) then argue that "the observable increase in occupational mobility is one possible manifestation of the increased turbulence". Motivated by this insight I use the probability of switching occupation as dependent variable in my empirical models.

The studies of the impact of offshoring on the labor market have tended to focus on how offshoring affects the skill-premium. This link has been the object of several theoretical and empirical studies. However, there are only few empirical studies that try to determine whether offshoring affects the variance of the transitory component of wages or not. Given that offshoring reallocates the production process across different countries, offshoring possibly involves a certain amount of "creative destruction". Offshoring in manufacturing from U.S. to abroad grew substantially between 1970 and 1990 (Hummels et al. (2001)).[3] For this reason, offshoring seems a good candidate as a source of turbulence in the labor market.

I use data from the March Current Population Survey (March CPS hereafter) for the 1983-1990 period. This dataset is a large random sample of U.S. addresses and it has been extensively used to document the evolution over time of the U.S. wage structure. Some manufacturing workers are surveyed in two consecutive years and this allows me to determine whether the worker has switched occupation or not from one year to the other. I merge this individual level data with trade data that is at the industry level. Following Ebenstein et al. (2009) I construct a measure of *occupational* offshoring, i.e. a measure of how much a certain occupations is exposed to offshoring from abroad. I then regress the probability of switching occupation on occupational offshoring and other controls.

[3]Hummels et al. (2001) find that offshoring in manufacturing from U.S. to abroad grew by more than 25% during this period. My measures of offshoring also increase during this period. They are described in section IV.3.2.

Contrary to the hypothesis, I find that offshoring does not increase the probability of switching occupation. The coefficient on offshoring is either non-significantly different from zero or significantly different from zero and *negative*. This result is robust to the use of different measures of offshoring and to controlling for attrition out of the March CPS from one year to the other. This result suggests that offshoring from U.S. to abroad, at least for the 1983-1990 period, has not been responsible for the increase in wage variability.

Section IV.2 reviews the literature, section IV.3 describes the dataset and the empirical model, section IV.4 presents the results and section IV.5 concludes.

Literature Review

The works that are closest to mine are Liu and Trefler (2008), Ebenstein et al. (2009) and Krishna and Senses (2009). They all study the impact of various measures of openness on labor market outcomes in U.S. making use of individual level data on workers. Liu and Trefler (2008) use the March CPS data for 1996-2005 and find that offshoring of *services* does not affect the probability of switching occupations. My result echoes theirs in that I also find that the offshoring of *manufacturing* does not affect the probability of switching occupations.

Ebenstein et al. (2009) use the CPS Merged Outgoing Rotation Groups and construct a measure of occupational offshoring. They find that, if an occupation is exposed to offshoring to low-income (high-income) countries, then the U.S. workers in that occupation experience a decline (increase) in wages. Ebenstein et al. (2009) do not study however how workers react to the offshoring shock. If in response to it, the workers leave their occupation, then they lose the human capital that is specific to their occupation. Kambourov and Manovskii (2009a) document that the returns to tenure in an occupation are substantial. Therefore, this paper complements Ebenstein et al. (2009) by looking at an additional channel through which occupational offshoring may affect wages. Moreover, my paper complements their work by using a more inclusive measure of offshoring, as discussed in Tempesti (2011). In section IV.4 I discuss more in detail how my empirical results relate to their findings.

Krishna and Senses (2009) studies the impact of international trade on labor market risk in U.S.. While the motivation of their work and mine is very similar, there remain some differences. First, they use as dependent variable a measure of income risk aggregated at the industry level while I use the probability of switching occupation. While their measure is a more direct measure of wage turbulence, my regressions shed light on a particular channel through which trade may affect wage turbulence, i.e. through the loss of occupation-specific human capital. Second, as independent variable they use import penetration at the industry level whereas I use offshoring at the occupational level. Both forms of openness may affect wage turbulence and so my work complement theirs in this regard. Third, I focus on the 1980s while they focus on the 1990s and early 2000s.

In Kambourov and Manovskii (2009b) the increase in occupational switch is linked to the increase in residual inequality, i.e. the wage inequality that is unaccounted by experience, gender and race.[4] They use a model with occupation-specific human capital and parametrize turbulence as the variance of the productive shocks to occupations. They calibrate this model and find that an increase in the variance of the productive shocks to occupations can explain almost all of the increase in residual wage inequality.[5] In their

[4]Katz and Autor (1999, p. 1468 and p. 1477-1478) document that "wage dispersion increased substantially for both men and women from the end of the 1970s to the mid 1990s" and that wage differentials distinguished by sex, education, and age/experience account "for only one third of overall wage variation so that changes in wage dispersion within these groups are likely to be an important part of changes in the overall wage inequality."

[5]The log of wage w_{st} for individual s at time t can be decomposed as follows:

$$ln(w_{st}) = \beta_t X_{st} + \lambda_t \alpha_s + \eta_{st}$$

model, all the occupations are identical and face the same variance of the productive shocks. In my regression the identification comes from the fact that different occupations are exposed to different offshoring shocks and so in this regard my regressions cannot be considered a direct test of their model.

Data and Empirical Model

Worker-Level Data

My sample is obtained by merging a dataset that contains information at the individual worker's level and other datasets that contain information at the level of the industry the worker is in. I obtain individual worker's data from the March CPS that were collected between 1983 and 1991. Each survey contains data for the previous calendar year and so I work with data for the 1982-1990 period. As explained below, due to survey limitations I cannot use data that refer to year 1984.

The March CPS has been extensively used in labor economics to document the increase in residual inequality.[6] Even though the March CPS is not conceived as a panel,

where X_{st} is a vector that contains sex, race, education, age and possibly their interactions, β_t is the possibly time-varying price associated to these characteristics. An increase in the variance of $\beta_t X_{st}$ increases the wage inequality *between* workers' categories (e.g. skilled vs. unskilled workers). The α_s terms capture the permanent individual productivity that is not observable to the statistician (e.g. effort) whereas λ_t is the possibly time-varying price associated to such productivity. An increase in the variance of $\lambda_t \alpha_s + \eta_{st}$ increases the wage inequality *within* workers' categories. This inequality is also called residual inequality. The explanation for the increase in residual inequality are of two types. Some focus on the increase in the variance of the return λ_t to individual fixed effects α_s. According to these theories, workers are already heterogeneous ex-ante. Other theories, such as the one in Kambourov and Manovskii (2009b), ignore the α_s terms and their prices and focus instead on the increase in the variance of the time-varying error term η_{st}. According to these theories, workers are homogeneous ex-ante but heterogeneous ex-post because of the shocks.

[6] See e.g. Katz et al. (2005) and Acemoglu (2002). Lemieux (2006) argues that the MORG CPS and the March CPS differ as to residual inequality and that the latter overstates the true extent of residual inequality with the former dataset being more accurate. However, Figure 2 in Katz et al. (2005, p. 303) graphs residual inequality over time in both the March CPS and the MORG CPS. From the figure we can see that residual inequality does not differ much across the two datasets during the 1980s. In any event, I do not use the March CPS to measure residual inequality. I use it to study how offshoring relates to the probability of switching occupations.

some workers will be in the survey in two consecutive years if, as explained in the appendix, they do not change their residence address from one year to the other.

I keep only workers who are in a manufacturing industry in the first year that they appear in the sample. So, they need not be in manufacturing in the second year that they are in the sample. It is not possible to match workers who appear in the survey for the first time in March 1985 and so I do not use those workers. I use Madrian (2000)'s algorithm to match individuals across CPS surveys. According to this algorithm, 67% of the manufacturing workers have a valid match.

I construct a variable that assumes a value of 1 if the worker changes her/his three-digit occupations in the second year s/he is in the survey and 0 otherwise.[7] I keep only workers who are employed in both years that they are in the survey. So, I ignore the flow in and out of unemployment and in and out of the labor force.

This measure of occupational mobility is noisy.[8] I use a similar filter to the one proposed in Moscarini and Thomsson (2007) to reduce the number of invalid occupational switches.[9] In particular, I consider a switch of occupation valid only if at least one of the three following conditions is satisfied: a) the worker changes her class of employment; b) the workers switches industry; c) last year the worker worked at least one week year but at most 49 weeks and s/he looked for a job.[10]

After this filter is applied, out of the workers who are matched across years and are of 19-65 years old at the time of the survey, 27% switch occupation at the three-digit level. Kambourov and Manovskii (2008) use the PSID data and find that during the 1968-1997 period occupational mobility increased from 16% to 20% at the three-digit level. My

[7] I use the variable *occlyr* in the Unicon dataset.

[8] See Moscarini and Thomsson (2007) and Kambourov and Manovskii (2004).

[9] See Liu and Trefler (2008) for a similar approach.

[10] I use the variable *class1* for class of employment; *indly2* for industry affiliation; *wkslyr* for weeks worked last year and *lkedpy* for looked for a job last year.

measure of mobility is higher and this could be partly due to the fact that the measure of occupational mobility in the CPS is noisier. This noise will be absorbed by the residual of my regression. As long as the error in the measurement of occupational mobility is not correlated with the regressors, the regression will generate unbiased estimates of the coefficients.[11] Table 11 contains the descriptive statistics.

Industry-Level Data

I construct two measures of offshoring at the occupational level. Following Feenstra and Hanson (1999), I define offshoring IndOff_{jt} at the industry level as:

$$\text{IndOff}_{jt} = \frac{\sum_i (p_{it}q_{ijt}) \frac{M_{it}}{Y_{it}+M_{it}-X_{it}}}{\sum_i p_{it}q_{ijt}} \tag{IV.1}$$

where, at time t, p_{it} is the price of the final good from sector i, q_{ijt} is the input quantity that the manufacturing industry j buys from the manufacturing industry i, Y_{it}, M_{it} and X_{it} are respectively domestic shipments, imports and exports of industry i and the indexes i and j vary only over manufacturing industries. Notice that in the input-output tables we do not observe p_{it} and q_{ijt} independently but only their product $p_{it}q_{ijt}$. Given that $\sum_i p_{it}q_{ijt}$ is the total (manufacturing) cost of production for the final good j, then we can rewrite (IV.1) as:

$$\text{IndOff}_{jt} = \sum_i (s_{ijt}) \frac{M_{it}}{Y_{it}+M_{it}-X_{it}} \tag{IV.2}$$

where s_{ijt} is the share of (manufacturing) expenditures of sector j on input i at time t and the second term of the product is a measure of import penetration. The measure of industrial offshoring is then an average, with the expenditures shares as weights, of numbers that vary between 0 and 1. Therefore the measure of industrial offshoring varies between 0

[11] See Liu and Trefler (2008, p.11) for this point.

and 1 and can be thought as the share of imported intermediate inputs for a given industry. I obtain data on the s_{ijt} terms from the Bureau of Economic Analysis (BEA) input-output tables and the variables to compute import penetration from the NBER manufacturing trade dataset. I compute industrial offshoring at the more disaggregated Census industry level and then average offshoring within CPS two-digits industries. I end up with offshoring data for 20 two-digits industries. The Appendix contains additional details.

I then compute a measure of *occupational* offshoring. Define L_{ij82} and L_{i82} as, respectively, the number of workers who are in occupation i and industry j in 1982 and the total number of workers who are in occupation i in 1982. Define then α_{ijt} to be the fraction of workers in occupation i who are in industry j in year t. I set α_{ijt} equal to $\frac{L_{ij82}}{L_{i82}}$. I set the weights in any year equal to the weights in 1982 because these weights may be endogenous with respect to offshoring. In constructing these weights I use all workers in 1982, not just those who have a valid match in the next survey. I have a total of 316 three-digits occupations and 46 two-digits occupations.

Following Ebenstein et al. (2009), I define OccOff_{it}, a measure of occupational offshoring for occupation i in year t, as following:

$$\text{OccOff}_{it} = \sum_{j=1}^{\#Industries} \alpha_{ijt}\text{IndOff}_{jt} \tag{IV.3}$$

So, I obtain a measure of how much each occupation is exposed to offshoring in manufacturing. I do not study the increase of offshoring in services, which seems to be a relatively more recent phenomenon.[12] This measure has an average value of 9% in 1982 and 12% in 1989.

I compute analogously a measure of skill-biased technological change (SBTC hence-

[12]See Amiti et al. (2005) and Amiti and Wei (2009). Liu and Trefler (2008) and Crinò (2010) study the effects of offshoring of services on the U.S. labor market.

forth) at the occupational level. As a measure of SBTC at the industry level I use the deflator of industry investment divided by the personal consumption expenditure index. This is then the real price of investment in a certain industry in terms of current consumption. I use this proxy for SBTC under the assumption that, as the real price of investment decreases, SBTC will increase.[13] As above, I then average this variable at the occupational level using the α_{ijt} weights. The final measure has an average value of -0.07 in 1982 and 0.06 in 1989.

I also compute another measure of occupational offshoring using intermediate manufacturing imports as a measure of industrial offshoring. Define vs_{jt} and mp_{jt} as the nominal value of total shipments, respectively, the nominal value of parts that are imported, by a certain industry j at time t. This alternative measure of industrial offshoring is:

$$\text{IndOffParts}_{jt} = \frac{mp_{jt}}{vs_{jt} + mp_{jt}} \tag{IV.4}$$

The data on the nominal value of shipments is from the NBER productivity dataset (Bartelsman and Gray (1996)). The imported parts data is available on Peter Schott's website.[14] Intermediate imports are defined here to be the sum of product-level U.S. imports that contain variants of the word "part". This variable is constructed using TSUSA import codes for 1972-1988 and HS import codes for 1989-2001. This change in the construction of the variable produces a break in the evolution of this variable over time. For this reason, when I use this variable, I do not use data on workers who appear in the data for the first time in the March CPS 1990. This measure is at the SIC 1987 four-digit level. I first aggregate this variable at the CPS two-digit level using as weights the employment share at the industry level. I obtain data on employment at the SIC 1987 four-digit level from the NBER productivity dataset. As above, I then average this variable at the occupational level using

[13] See Ebenstein et al. (2009).

[14] See Peter Schott's website and Schott (2004). Kosteas (2008) also uses this variable to study the effect of offshoring on wages.

the α_{ijt} weights. The final measure has an average value of 2% in 1982 and 4% in 1988.

Empirical Model

The main regression I study has this form:

$$\text{Switch}_{st(s)} = \alpha + \beta\text{OccOff}_{i(s),t(s)-1} + \gamma\text{OccPinv}_{i(s),t(s)-1} + \\ + \delta X_{s,t(s)-1} + \lambda_{i(s)} + \lambda_{j(s)} + \lambda_{t(s)} + \epsilon_{st(s)} \tag{IV.5}$$

where s varies over workers, $t(s)$ is the second year for which we have data about worker s, $i(s)$ ($j(s)$) is the occupation (industry) in which worker s is in year $t(s)-1$, $\text{Switch}_{st(s)}$ is equal to 1 if the worker switches occupation between year $t(s)-1$ and $t(s)$ and 0 otherwise, $\text{OccOff}_{i(s),t(s)-1}$ is occupational offshoring, $\text{OccPinv}_{i(s),t(s)-1}$ is occupational SBTC, $X_{s,t(s)-1}$ is a vector of individual characteristics of worker s in year $t(s)-1$, $\lambda_{i(s)}$ is a vector of two-digits occupation dummies, $\lambda_{j(s)}$ is a vector of two-digits industry dummies, $\lambda_{t(s)}$ is a vector of year dummies and $\epsilon_{st(s)}$ is an error, that is assumed to be exogenous to the regressors.

An example may help. Suppose a worker's occupation in his longest job held during 1983 is technician: we have this information from the CPS survey that is collected in the March of 1984. We study the probability that this worker's occupation, in his longest job held during 1984, is different from technician. We regress this probability on the offshoring of technician services, as constructed above, in 1983.

I use a linear probability model in order not to impose any distributional assumptions on the probability of switching occupation. The year dummies control for the fact that occupational switch may be systematically higher in some years rather than others, maybe because of macroeconomic effects that affect all workers. The occupation (industry) dummies control for the fact that occupational switch may be systematically higher in some occupations (industries) rather than others.[15] I use two-digit occupation and industry dummies. I cluster the standard errors at the two-digit occupation level to account for the potential correlation of the residuals for workers who are in the same two-digit occupation, even if in different years.[16]

Results

Table (12) contains the results for the regression of occupational switch at the three-digit level on the measure of occupational offshoring constructed using the measure of industrial offshoring in Feenstra and Hanson (1999), a measure of SBTC at the occupational level, demographic variables, year dummies, two-digits industry and occupation fixed effects.

Relative to the omitted category of being non-black and non-white, a white (black) person seems to have a lower (higher) probability of switching occupation. However these coefficients are not precisely estimated. Women switch occupations more frequently. The probability of switching occupation decreases in a convex manner in potential job experience.[17] More educated people also switch occupation less frequently. The higher occupational SBTC (proxied by the inverse of the real price of investment), the lower the occupational switch. However, this coefficient is not precisely estimated because occupational SBTC appears to be highly collinear with the other regressors.[18]

The coefficient on occupational offshoring is negative and significant at the 10% level. This suggests that workers who are in occupations that are exposed to offshoring are less likely to switch their occupations. This can happen because offshoring allows to import

[15]See Wooldridge (2002, p. 272-274) for this estimation strategy.

[16]See Bertrand et al. (2004).

[17]Potential job experience is defined as age minus years of schooling minus six: negative values are set to zero. So, this is not actual job experience or tenure in the currently held job or occupation.

[18]I have rerun the same regression omitting the occupational SBTC measure. The results are unchanged except for the fact that the coefficient on occupational offshoring is slightly less precisely estimated.

inputs that are complementary rather than substitutes to domestic inputs. Occupational offshoring increased from 9% to 12% during the 1982-1989 period. So, this coefficient suggests that the probability of switching occupations decreased approximately by 13%.[19]

It is helpful to compare this result to the results in Ebenstein et al. (2009). For each occupation, they construct a measure of the employment abroad in affiliates of U.S. multinationals that is potentially substitute or complement of the U.S. workers in that occupation. They are also able to distinguish employment abroad in low-income countries vs. employment abroad in high-income countries. They find that the higher the occupation-specific employment in affiliates in low, respectively high, income countries, the lower, respectively the higher, the wage of U.S. workers in that occupation. In other words, workers in U.S. multinationals' affiliates in low-income countries are substitute of U.S. workers whereas workers in U.S. multinationals' affiliates in high-income countries are complement of U.S. workers. My measure of offshoring does not distinguish between offshoring to low and high income countries and so its coefficient can be interpreted as the net effect of the two types of offshoring. Overall, therefore, at least for this period, offshoring does not seem to increase the probability of switching occupation. In this regression, offshoring is actually correlated with a decrease in the probability of switching occupation. This effect however becomes non significantly different from zero in other specifications studied below. In this sense, the substitution and complementarity effects of the two types of offshoring cancel out each other.

The CPS samples residences and not individuals and so it is possible that a worker who is sampled one year is not sampled in the next year because she changes residence. I am able to match only 67% of the workers, across the two consecutive March CPS surveys

[19] I have rerun the above regression using a Probit model instead of a linear probability model. The marginal effect of occupational offshoring, evaluated at the means for all the other regressors, has the same magnitude and significance as the coefficient from the linear probability model.

in which they may appear. It is possible that selective attrition biases the estimates in the above regression.This may happen if e.g. a worker whose occupation is hit by an offshoring shock leaves her current residence because of the shock. In order to control for attrition, I run the linear probability model with the correction from the Heckman's two step estimator using the command *heckman twostep* in Stata. This command adjusts the standard errors on the model estimates if the inverse Mills ratio is significantly different from zero. On the other hand, this command does not allow the use of weights and the clustering of standard errors.[20]

I include in the selection equation all the regressors in equation (IV.5) plus the following: number of members of the family, number of children below the age of 6 years, a house ownership dummy, a dummy to indicate whether the respondent changed residence with respect to last year, a married dummy.[21]

Table 14 contains the results for the selection equation. Except for number of children below 6 years, all excluded regressors are highly predictive of the probability of being in the sample. Instead, occupational offshoring does not affect such probability. Relative to the omitted category of being non-black and non-white, both white and black persons are more likely to be in the sample as are more experienced and more educated individuals.

Table 13 contains the results for the linear probability model when corrected using the Heckman two-step estimator. The inverse Mills ratio is highly significant. However, the coefficient and significance on the individual level variables do not change much with respect to the uncorrected model of table 12. The coefficient on occupational offshoring is

[20]I have also tried to use the Heckman maximum-likelihood estimator, which requires more stringent assumptions than the two-step estimator but that is more efficient if these assumptions hold. However, the Heckman maximum-likelihood estimator did not converge because of a failure of the concavity of the log-likelihood function.

[21]See Liu and Trefler (2008) for a similar approach to model selection in this context.

instead smaller in absolute value and less significant.

Table 15 contains the results for the regression of occupational switch at the three-digit level on the measure of occupational offshoring constructed using the imported parts data described in Schott (2004), a measure of SBTC at the occupational level, demographic variables, year dummies, two-digits industry and occupation fixed effects. The magnitude and significance of the coefficients on the demographic variables is very similar to the ones in table 12. However, now the coefficient on occupational offshoring is not only much less precisely estimated but also much smaller in magnitude. Occupational offshoring of parts increased 2 percentage points during this period: multiplying this number by the corresponding coefficient, occupational offshoring of parts appears to have decreased the probability of switching occupation by .01 percentage points.[22]

In order to control for sample attrition I run the two-step Heckman estimator. Table 16 contains the results for the selection equation. The results are very similar to the ones in Table 14. Table 17 contains the results for the linear probability model when corrected for sample attrition. The coefficient and significance on the individual level variables are not affected by the correction. The coefficient on occupational offshoring remains imprecisely estimated but it is now positive, even if very small in magnitude.

Conclusion

Using data from the March CPS from the 1983-1990 period, I study if offshoring in manufacturing is correlated with occupational switch. I find that offshoring does not increase the probability of switching occupation. The coefficient on offshoring is either non-

[22] I have rerun the above regression using a Probit model instead of a linear probability model. The marginal effect of occupational offshoring, evaluated at the means for all the other regressors, is -.056. Again, multiplying this number by 2 percentage points, occupational offshoring of parts appears to have decreased the probability of switching occupation still by .01 percentage points. This marginal effect is also still highly imprecisely estimated.

significantly different from zero or significantly different from zero and *negative*. This result is robust to the use of different measures of offshoring and to controlling for attrition out of the March CPS from one year to the other. This result suggests that offshoring from U.S. to abroad has not been responsible for the increase in wage variability.

Data Appendix

Worker Level Data

The worker individual level's data are from the March CPS survey.[23] The CPS randomly samples addresses in U.S.: residents at a certain address are interviewed for four consecutive months; then they are not interviewed for eight months; then again for four months.[24] Each month some addresses exit the interview group (after their eighth interview) and other addresses enter the interview group. The March questionnaire has a specific supplement devoted to labor questions: for this reason it has been extensively used in labor studies. I use the CPS data as processed by the Unicon Research Corporation.

The CPS is not conceived as a panel. However, if an individual does not change the address where he is living, he is interviewed more than once over time. In particular, if he is in the sample during two consecutive March surveys, then we may have data to take the differences needed in our estimating equation. There are however many reasons why the across-years match of individuals may be less than 100%. These are migration, death, non-response and recording errors.

As to the latter, as argued in Madrian (2000), in the 1980s the CPS did not use

[23] These are the w_{sjt} and X_{st} terms and the index j, i.e. the industry to which a worker belongs.

[24] The discussion in this section follows closely Madrian (2000) who devised an algorithm to merge different March CPS surveys. I also follow Liu and Trefler (2008) that use Madrian (2000)'s algorithm.

a completely reliable person-identifier for the different months. For this reason the match is prone to error. A way to reduce the error is to validate the match using demographic variables: for example, if the data of two different years are referring to the same individual, sex should not usually change across years.

We would like to maximize the number of good matches (i.e. matching data that really belong to the same individual) while at the same time minimizing the number of bad matches (i.e. *not* matching data that do *not* belong to the same individual). Madrian (2000) experiment with various validation methods based on demographic variables and find that there is a trade-off between the above goals. She recommends using the S_R_A algorithm as able to provide a good balance among the two competing goals. According to this algorithm, the data for two consecutive years are first matched using the household and person identifiers. Then a match is considered invalid if: i) gender differs; ii) race differs; or iii) the difference in age between t and t+1 is less than -1 or greater than 3. I use the S_R_A algorithm as well. According to this algorithm, 67% of the workers have a valid match.[25]

Potential job experience is defined as age minus years of schooling minus six: negative values are set to zero. I use the March supplemental person weights throughout.

Industry Level Data

For the construction of the industry-level variables, I follow Feenstra and Hanson (1999) while I follow Ebenstein et al. (2009) for the proxy of SBTC. I obtain data on the s_{ijt} terms in equation (IV.2) from the Bureau of Economic Analysis (BEA) input-output tables. "The Industry Benchmark Division (IBD) prepares benchmark input-output (I-O) accounts for years ending in 2 and 7, which are based on detailed data from the quinquennial

[25]Out of the workers who potentially have a match i.e. the workers who potentially are in the survey in two consecutive years.

economic censuses that are conducted by the Bureau of the Census. [...] The benchmark accounts show how industries interact at the detailed level; specifically, they show how approximately 500 industries provide input to, and use output from, each other to produce gross domestic product".[26]

I use the BEA I-O tables for 1982 and 1987. I keep only manufacturing industries as both buyers and suppliers of inputs. These tables contain data for 368 industries in 1982 and 361 industries in 1987. For each industry these tables tell how much industry i spends on each industry j for its inputs.[27]

I obtain the variables to compute import penetration (the $\frac{M_{it}}{Y_{it}+M_{it}-X_{it}}$ term) in equation (IV.2) from the NBER manufacturing trade dataset.[28] These data contain information on 450 manufacturing industries for the 1958-1994 period (I will use only data for the 1979-1990 period). The dataset is described in Feenstra and NBER (1996).

The industry identification code used in the BEA data is the Census one. This code is different from the SIC identification code that is used in the trade data. Moreover, the trade dataset contains information on 450 manufacturing industries while the BEA dataset contains information on a fewer number of manufacturing industries. I use the crosswalks provided by the BEA in 1982 and 1987 to aggregate the trade data at the level of the BEA data[29]. If industry A and B are aggregated in a single industry C, I compute the imports

[26] See the BEA website.

[27] This information is contained in the *use* variable of the *Direct Requirement Coefficients* tables, that are available for download on the BEA website.

[28] This data is available at Robert Feenstra's website and on the NBER website. In theory this measure of import penetration can be larger than 1: algebraically, given that $Y_{it} + M_{it} - X_{it}$ is always larger than zero, this will occur if $X_{it} > Y_{it}$. In my dataset, this happens to industry 3339 in the SIC 1972 code (Miscellaneous primary nonferrous metal refiners and smelting) in years 1979, 1980 and 1981 and to industry 3915 in the SIC 1987 code (Jewelers Findings and Materials and Lapidary Work) for years 1988 and 1989. I trim the import penetration ratio to 1 in this case.

[29] The trade data is coded using the SIC 1972 code. For the 1982 input-output table, the BEA provides a crosswalk with the SIC 1977, that is however very similar to the SIC 1972. For the 1987 input-output table, the BEA provides a crosswalk with the SIC 1987, that is instead quite different from the SIC 1972. I use the conversion tables between SIC 1972 and SIC 1987 to transform the SIC 1972 trade data into the SIC 1987 classification. The conversion tables are available at the NBER website

(exports, domestic shipments) for C as the sum of imports (exports, domestic shipments) of A and B.

I then compute the input shares s_{ijt}, excluding *Petroleum refining* from the industries supplying inputs.[30] I now have the input shares for 1982 and 1987. My imputation of the input shares for other years is as follows. I assume that the input shares in the 1979-1984 period are equal to the input shares in 1982 and that the input shares in the 1985-1990 period are equal to the input shares in 1987. I now have the input shares for the 1979-1990 period. I then merge the BEA data with the aggregated trade data. Now I have all the terms for computing the measure of offshoring for the 1979-1990 period for each manufacturing industry.

The offshoring data is not yet ready for use. Indeed, I use March CPS information on the industry of a worker only at the two digits level. So we need to aggregate the offshoring data at the March CPS level. I first compute, for each year, the level of offshoring for each disaggregated industry and then take a weighted mean of this variable: in this way I obtain the level, in that year, of offshoring for the more aggregated, March CPS-level, industries.[31] I use as weights the share of the wage bill of the disaggregated industries in the more aggregated industries. So, for example, if I aggregate the offshoring of A and B in year t, the weight on the offshoring of A will be the $wagebill_A/(wagebill_A + wagebill_B)$ in year t. I have now the level of offshoring for each March CPS industry. The average offshoring [32] for an industry in my dataset is 10.3% that is very similar to the one of Feenstra and Hanson (1999) (Table II, p. 923).[33]

[30]In this I follow Feenstra and Hanson (1999) that exclude energy purchases from the computation of the input shares.

[31]I use the variable *indly2* of the March CPS Unicon dataset to identify a two-digits March CPS industry.

[32]This is computed as follows: keep one observation per March CPS industry-year. Compute offshoring for each industry and year. The average of this variable is 10%.

[33]The relevant statistic is the average for broad outsourcing in the 1979-1990 period, which is 9.67% in Feenstra and Hanson (1999).

For SBTC, I use the log of the industry investment price deflator for each industry minus the log of the personal consumption index for the current year. Data on the investment deflator comes from the NBER manufacturing dataset. This variable can be interpreted as the (log of the) real price of investment. In the appendix of a previous draft of this paper I describe how I computed the proxies for SBTC used by Feenstra and Hanson (1999). I was not able to replicate the values of their variables and so I ended up not using these variables as a proxy for SBTC.

Table 11. Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Female	0.33	0.47	0	1
White	0.89	0.32	0	1
Black	0.08	0.28	0	1
Age	40	11.64	19	65
Job Experience	21.5	12.3	0	58
Years of Education	12.5	2.73	0	19
Switch 3-digit Occupation	0.27	0.44	0	1
Married	0.73	0.44	0	1
Weeks worked last year	47.97	9.83	1	52
Occupational Offsh. 3-digits, Feenstra-Hanson	0.11	0.02	0.03	0.22
Occupational Offsh. parts 3-digits	0.03	0.02	0	0.14
Occupational SBTC 3-digits	-0.02	0.05	-0.14	0.07
N		31857		

Table 12. Switch of Occupation Regression

	(1) Switch 3-digit Occupation b/se
Occupational Offsh. three dig., fixed wgt	-0.440*
	(0.259)
Occupational Price of Invest. three dig., fixed wgt	0.306
	(0.324)
Female	0.019**
	(0.008)
White	-0.013
	(0.016)
Black	0.026
	(0.023)
Experience	-0.011***
	(0.001)
Experience Squared	0.000***
	(0.000)
Years of Education	-0.003*
	(0.002)
Observations	31857
R^2	0.041

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The dependent variable is occupational switch at the three-digit level. Standard errors clustered at the two-digit occupation level. The regression also includes year dummies and two-digit occupation and industry dummies. March CPS sampling weights are used.

Source: March CPS 1983-1990 (year 1985 excluded, see text), NBER productivity data, BEA I-O tables.

Table 13. Switch of Occupation Regression, corrected for attrition

	(1) Switch 3-digit Occupation b/se
Switch 3-digit Occupation	
Occupational Offsh. three dig., fixed wgt	-0.260
	(0.179)
Occupational Price of Invest. three dig., fixed wgt	0.258
	(0.230)
Female	0.021***
	(0.006)
White	-0.008
	(0.015)
Black	0.022
	(0.017)
Experience	-0.008***
	(0.001)
Experience Squared	0.000***
	(0.000)
Years of Education	0.000
	(0.001)
mills	
lambda	0.134***
	(0.014)
Observations	47381

* p<0.10, ** p<0.05, *** p<0.01

The dependent variable is occupational switch at the three-digit level. There are 15524 censored observations.

All regressions also include year dummies and two-digit occupation and industry dummies. The Heckman two-step estimator is used to model attrition.

Source: March CPS 1983-1990 (year 1985 excluded, see text), NBER productivity data, BEA I-O tables.

Table 14. Switch of Occupation Regression, continued. Attrition Model

	(1)
	Switch 3-digit Occupation
	b/se
Number of persons in family	-0.027***
	(0.005)
Num of kids in fam under 6	0.007
	(0.012)
Owns the house?	0.696***
	(0.015)
Mover at t-1?	-0.267***
	(0.017)
Married	0.221***
	(0.016)
Occupational Offsh. three dig., fixed wgt	0.511
	(0.443)
Occupational Price of Invest. three dig., fixed wgt	-0.556
	(0.578)
Female	0.021
	(0.016)
White	0.102***
	(0.035)
Black	0.233***
	(0.041)
Experience	0.028***
	(0.002)
Experience Squared	-0.000***
	(0.000)
Years of Education	0.043***
	(0.003)
Observations	47381

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

First step of the two-step Heckman estimator to control for attrition.

The dependent variable is occupational switch at the three-digit level.

The regression also includes year dummies and two-digit occupation and industry dummies.

The Heckman two-step estimator is used to model attrition. 15524 censored observations.

Source: March CPS 1983-1990 (year 1985 excluded, see text), NBER productivity data, BEA I-O tables.

Table 15. Switch of Occupation Regression on Imported Parts

	(1) Switch 3-digit Occupation b/se
Occupational Offshoring Parts, three dig. fixed weights	-0.035
	(0.229)
Occupational Price of Invest. three dig., fixed wgt	0.289
	(0.322)
Female	0.016*
	(0.008)
White	-0.011
	(0.018)
Black	0.029
	(0.026)
Experience	-0.012***
	(0.001)
Experience Squared	0.000***
	(0.000)
Years of Education	-0.003
	(0.002)
Observations	27293
R^2	0.038

* p<0.10, ** p<0.05, *** p<0.01

The dependent variable is occupational switch at the three-digit level. Standard errors clustered at the two-digit occupation level. The regression also includes year dummies and two-digit occupation and industry dummies. March CPS sampling weights are used.

Source: March CPS 1983-1989 (year 1985 excluded), Schott's imported parts measure as detailed in text.

Table 16. Switch of Occupation Regression, Attrition Model

	(1) Switch 3-digit Occupation b/se
select	
Number of persons in family	-0.025***
	(0.005)
Num of kids in fam under 6	0.006
	(0.013)
Owns the house?	0.689***
	(0.016)
Mover at t-1?	-0.258***
	(0.018)
Married	0.219***
	(0.017)
Occupational Offshoring Parts, three dig. fixed weights	0.058
	(0.432)
Occupational Price of Invest. three dig., fixed wgt	-0.211
	(0.631)
Female	0.019
	(0.017)
White	0.118***
	(0.038)
Black	0.232***
	(0.044)
Experience	0.028***
	(0.002)
Experience Squared	-0.000***
	(0.000)
Years of Education	0.043***
	(0.003)
Observations	40565

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The dependent variable is occupational switch at the three-digit level.

The regression also includes year dummies and two-digit occupation and industry dummies.

The Heckman two-step estimator is used to model attrition. 13272 censored observations.

Source: March CPS 1983-1989 (year 1985 excluded, see text), NBER productivity data, Schott(2004) data.

Table 17. Switch of Occupation Regression on Imported Parts, corrected for attrition

	(1) Switch 3-digit Occupation b/se
Switch 3-digit Occupation	
Occupational Offshoring Parts, three dig. fixed weights	0.082
	(0.171)
Occupational Price of Invest. three dig., fixed wgt	0.225
	(0.249)
Female	0.017***
	(0.007)
White	-0.003
	(0.017)
Black	0.028
	(0.019)
Experience	-0.009***
	(0.001)
Experience Squared	0.000***
	(0.000)
Years of Education	0.001
	(0.001)
mills	
lambda	0.137***
	(0.015)
Observations	40565

* p<0.10, ** p<0.05, *** p<0.01

The dependent variable is occupational switch at the three-digit level.

The regression also includes year dummies and two-digit occupation and industry dummies. The Heckman two-step estimator is used to model attrition.

Source: March CPS 1983-1989 (year 1985 excluded, see text), NBER productivity data, Schott(2004) data.

CHAPTER V

CONCLUSION

The debate over the effects of globalization remains lively. The first chapter of the dissertation makes the point that the use of datasets that contain data on individual workers holds the promise of advancing this debate. These datasets bridge the gap between the labor literature and the trade literature. Indeed, they allow one to control for changes in the demographic composition of the labor force across industries over time. They also allow the study of some important labor market outcomes such as the probability of a worker changing her occupation and thereby potentially losing her occupation specific human capital.

Because of this insight, in the second chapter I combine individual workers data from the March Current Population Survey with industry level trade data and study the effects of offshoring on the skill-premium. I show that industry-level wage regressions overestimate the impact of offshoring on the skill-premium if the demographic characteristics of the labor force are omitted. This result shows the importance of using datasets that contain individual data on workers when studying the effects of an economy's internationalization. In addition, I find that offshoring increases the relative employment of skilled workers, thus suggesting that offshoring has played an important role in the increase in the skill-premium by increasing the economy-wide relative demand of skilled workers.

In the third chapter, using data from the March Current Population Survey for the 1983-1990 period, I study whether offshoring in manufacturing is correlated with occupational switching. I find that offshoring does *not* increase the probability of switching occupations. The coefficient on offshoring is either non-significantly different from zero or significantly different from zero and *negative*. This result suggests that offshoring from U.S.

to abroad has not been responsible for the increase in residual inequality. Taken together, my results imply that, at least for U.S. in the 1980s, offshoring increased wage inequality by increasing the skill-premium but did not affect residual wage inequality.

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