Does Offshoring Lift All Boats? The Role of Induced Technology Adoption and Innovation

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Abstract

This paper develops and evaluates a novel mechanism through which imports of unskilled intermediates (offshoring) increase employment and wage-bills of *both* skilled and unskilled workers by inducing skill-biased technology adoption and innovation in developed countries. Data for a panel of manufacturing industries in the United States over 1974-2005, show that while doubling offshoring in an industry increases the relative employment and wage-bills of skilled workers by 9%, unskilled workers also gain, with their employment and wage-bills rising by 21% and 19% respectively. Data also strongly support the proposed technology channel with a doubling of offshoring increasing equipment-labor ratio by 13% and innovation intensity by 40%. This is the primary channel through which offshoring impacts U.S. workers. The labor market effects of offshoring through the substitution of unskilled workers, as predicted by the standard Heckscher-Ohlin theory, are small.

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"Increasing numbers of Americans...perceive offshoring...as an actual or potential threat to their jobs or to their wages even if they hold onto their jobs."

— Jagdish Bhagwati and Alan S. Blinder, 2007, Offshoring of American Jobs

1 Introduction

Offshoring[1] from the United States to developing countries grew tenfold from 1.8% in 1974 to 19% in 2005.[2] In recent years, offshoring has been an issue of heated political debate, amidst fears that it hurts unskilled workers by creating job losses and a more unequal labor force. Alan Blinder (2007) predicts that 22-29% of U.S. manufacturing and service jobs are offshorable over the next decade or two.[3] Inequality, or the skill premium, has also risen remarkably over the last three decades, with the wage gap between college and high school graduates growing nearly 50% (21 log points), between 1979 and 2005.[4] Economists link the rise in offshoring, measured as imports of intermediate goods from unskilled labor-abundant countries, to the growth in inequality through the Heckscher-Ohlin (H-O) mechanism in which these imports substitute for unskilled workers in developed countries.[5] Skill-biased technological change (SBTC) is established to be another important factor underlying the growth in inequality, with a large literature documenting a remarkable correlation between skill upgrading and the adoption of computer-based technologies within industries.[6] Thus far, offshoring and SBTC have been seen as distinct phenomena driving the growth in the skill premium.

This paper proposes and evaluates a novel technology channel through which offshoring affects the labor market in developed countries by inducing capital deepening and innovation. Through this technology adoption, offshoring generates productivity growth leading wage and employment gains for both skilled and unskilled workers. Thus, I show that, contrary to conventional wisdom, offshoring creates wage and employment gains for *all* workers, although amplifying wage inequality. Moreover, this mechanism shows that SBTC is endogenous to offshoring. Using detailed empirical analysis, I show that the impacts of offshoring on the skill-premium and skill-mix are overwhelmingly mediated through investments in equipment and innovation; the H-O effects through substitution of unskilled labor are small. Notably, the demand for *both* skilled and unskilled workers rises in response to offshoring through these

[1]The distinction between the terms "outsourcing" and "offshoring" is blurred in the literature. In this paper, "offshoring" refers to the relocation of tasks (measured as imports of intermediate goods) to a foreign country regardless of whether the provider is external or affiliated with the firm. While this is termed as "offshoring" by some authors, eg. Rodriguez-Clare (2010), some others, eg. Feenstra and Hanson (1996, 1999) have previously referred to this as "outsourcing."

[2]See Figure 1(a). Offshoring is measured as the value of intermediates imported from developing countries, as a proportion of total value of intermediates used by U.S. manufacturing industries.

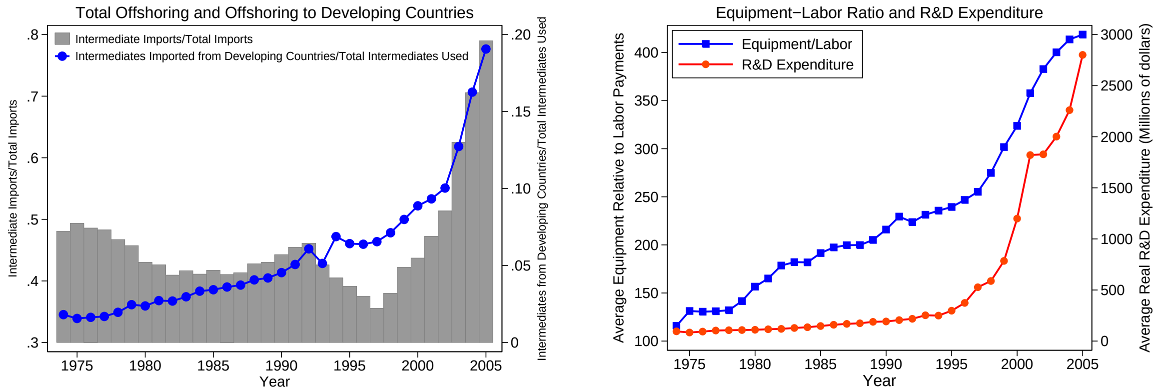
[3]Other empirical studies, however, find mixed evidence of the effect of offshoring on unskilled employment. See Mankiw and Swagel (2006) for a review.

[4]Autor, Katz and Kearney (2008).

[5]See, for example, Feenstra and Hanson (1996, 1999), and Grossman and Rossi-Hansberg (2008).

[6]See Katz and Autor (1999) and Katz (2000) for a detailed review.

Figure 1: Growth in Offshoring with Rise in Equipment & Innovation[a]



(a) (b)

[a]Source: U.S. Imports and Exports data, NBER-CES Manufacturing Productivity database, Input-Output tables, Compustat. Imported intermediates in each industry are calculated by first multiplying the import penetration ratio for each input to the total dollar value of that input used in the industry, and then aggregating over all inputs used. Offshoring to developing countries is calculated as total intermediates imported from developing countries relative to total value of intermediates used in U.S. industries. Payments to equipment capital stock are measured at prices that are not adjusted for changes in quality. The payments to equipment capital are divided by the total payments to workers for each industry. R&D for each industry is measured as the total expenditures on product R&D of all publicly traded U.S. firms belonging to that industry. Offshoring, equipment-labor ratio and R&D expenditure are averaged across all 459 4-digit SIC (1987) industries.

channels.

The technology channel that I propose is motivated by the observation that the growth in offshoring to developing countries is accompanied by capital deepening and increasing innovation, with all three accelerating after the mid-1990s. Figure 1(a) shows that imported intermediates, as a share of total imports, fluctuated with a declining trend from 1974 until the mid-1990s, but then turned sharply upwards to reach nearly 80% by 2005.[7] However, offshoring to developing countries consistently grew between 1974 and 2005. Simultaneously, the average equipment-labor payments ratio rose from about 115 points to 420 points and the average product R&D-sales ratio grew from 1.5% to 2.4% (corresponding to a growth in average real product R&D expenditure from 95 million dollars to 2,800 million dollars, as shown in Figure 1(b)). The timing suggests that these trends may be causally related. My work demonstrates that the growth in offshoring to developing countries induces investments in R&D and equipment, benefiting all U.S. workers, although magnifying the skill premium and skill upgrading.

Firms offshore if it is cheaper to import inputs from a developing country than to produce them domestically. Then, an increase in offshoring entails a decline in the marginal cost of

[7]The upturn in imports of intermediates may have been driven by the Uruguay round of trade negotiations between the advanced and developing countries as well as by the East Asian crisis. The Uruguay round was followed by several subsequent negotiations that liberalized trade regimes even further. The East Asian crisis of 1997-98 also led many countries to depreciate their currencies dramatically.

production. This triggers two reinforcing effects, that constitute the technology channel.[8] First, firms are induced to expand their output, thus demanding more of both skilled and unskilled workers. As they hire more skilled workers, they also invest in skill-complementary equipment capital (technology adoption).[9] For example, if the firm hires an engineer, it also provides her with a computer - a skill-complementary equipment. Second, with lower production cost, and larger markets resulting from trade, firms find it more profitable to invest in product innovation and improvement of technology. This leads to higher R&D expenditures. Both effects increase the productivity of the firms, generating increased demand and productivity for both skilled and unskilled workers. Thus, the technology channel competes with the negative H-O substitution effects for unskilled workers, making it an empirical question as to which channel is stronger.

To empirically examine the presence of these channels and their implications for the labor market, I combine data for a panel of four-digit manufacturing industries in the United States for the period 1974-2005 (NBER-CES Manufacturing Industry database) with U.S. import and export data, using input-output tables to construct a measure of imported intermediates. The key outcome variables are the skill premium, skill-mix, wage-bills of both groups of workers, innovation (measured as R&D expenditures obtained from Compustat), and capital-embodied technology adoption. I measure offshoring, the main explanatory variable, using the industry-specific imports of intermediate inputs from developing countries (middle- and low-income countries in the World Bank income classification).[10] Focussing on imports from unskilled-labor abundant, developing countries, provides a close proxy for imported intermediates that compete with domestic unskilled labor. However, offshoring is an endogenous regressor as it is jointly determined with the outcomes of interest. To identify the exogenous variation in imported intermediates, I construct instruments using country-specific exchange rates (obtained from the Penn World Tables). The intuition is that fluctuations in exchange rates influence import prices. And to the extent that these fluctuations are due to macroeconomic factors,

[8]The H-O effects are also triggered. Imported intermediates substitute for the unskilled labor hitherto employed to produce them domestically. Grossman and Rossi-Hansberg (2008) have provided two other ways by which offshoring of unskilled tasks can increase the skill premium - the relative price effect and the labor supply effect. First, the cost reduction resulting from offshoring can lead to a decline in the relative price of unskilled labor-intensive goods. Second, an increase in offshoring increases the effective supply of unskilled labor in the North. Both effects reduce the relative wages of unskilled labor. Further, Feenstra (2008) show that the cost reduction leads to an expansion of output in the North, causing an absolute increase in the skill-intensive tasks and skilled wages.

[9]I use the term "technology adoption" to imply equipment capital deepening. Equipment capital (as against structures capital) embodies technology that favors skilled workers over unskilled workers. In the SBTC literature, an increase in the use of computers in industries, and growth in skill-complementary capital equipment, more generally, have been taken to indicate technological change. I use the relatively conservative term, "adoption," since greater employment of equipment capital may not necessarily be associated with employment of equipment that embodies superior (or different) skill-biased technology. Another, more technical, reason for this terminology is that in the data, capital is measured at prices that are unadjusted for quality. Gordon (1990) showed that quality-adjusted prices declined at a faster rate than unadjusted prices. This decline in quality-constant prices may be the reason why industries may increase their employment of capital (Krusell et al.(2000)). Without such price data, I do not have a way to distinctly identify greater employment of embodied technology from employment of superior technology.

[10]This measure includes all imported inputs in a given industry, regardless of whether their providers are external or affiliated with the firms in that industry.

they are exogenous to the four-digit industries that I observe in my data. Further, in order to generate industry-year variation in exchange rates, I employ a weighting scheme that uses countries' export shares in various industries, and input-output tables. More detail on the method of constructing these instruments is available in the section describing my empirical strategy.

Variations across industries and time indicate, that skill upgrading and the skill premium respond strongly to offshoring from low-income countries. My preferred set of estimates show that doubling offshoring leads to 8.6% and 9.6% increase in the relative employment and wage-bill of skilled workers, respectively. Although the wage gap between skilled and unskilled workers increases with offshoring, the total employment and wage-bills of *both* groups of workers in an industry increase, indicating that offshoring benefits *all* workers. In particular, unskilled employment and wage-bill increase 21% and 19% when offshoring doubles. These estimates indicate the composite effect of offshoring on the labor market variables, being agnostic about the underlying mechanism. The technology channel suggested in this paper is strongly supported in my regressions - a doubling of intermediates increases the equipment-labor ratio by 13.4% and R&D expenditures by 37.6% (and R&D intensity by nearly 40%). While the existing literature greater technology adoption is simply taken as SBTC, independent of offshoring, the fact that large increases in these technology measures are driven by exogenous increases in intermediate imports strongly suggests that a substantial proportion of this technological upgrading is induced by increased offshoring.

Finally, I analyze the impact of the offshoring-induced technology adoption on the labor market outcomes. My results show that the impact of offshoring on skill premium and skill-mix are almost entirely due to increases in these technology measures - controlling for equipment-labor ratio and R&D expenditures yields a small and insignificant coefficient on imported intermediates. Thus, the strong impacts of offshoring on the labor market as obtained from the composite estimates are overwhelmingly due to the technology channel. Eliminating the technology effects shows that the independent H-O substitution effects of offshoring, emphasized in previous literature, are negligible. Thus, the technology channel dominates the H-O channel.[11]

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 details the empirical strategy. Section 4 describes the data sources and presents some descriptive statistics. The empirical results are presented in section 5. The last section concludes.

2 Contribution to Related Literature

A growing literature examines the implications of offshoring for labor markets in advanced countries. In particular, studies have found that imports of unskilled intermediates increase skill premia in advanced countries (see, for example, Feenstra and Hanson (1996, 1999), Grossman and Rossi-Hansberg (2008)). The extant studies interpret the total impact of offshoring on

[11] Although my empirical analysis is restricted to manufacturing industries for reasons of data availability, the mechanism that I propose is more widely applicable to industries in other sectors of the economy.

the skill premium as reflective of only the H-O effects of offshoring. But, as I show, offshoring may also increase the skill premium by inducing innovation and technology adoption. To my knowledge, this is the first study to consider the impact of offshoring on skill-biased technology adoption.

Methodologically, my work complements that of Feenstra and Hanson (1999), who use a two-step estimation strategy to assess the impact of offshoring on wage-bill shares of skilled workers in U.S. manufacturing industries. In the first stage, they regress changes in effective productivity and value added prices on various structural variables, including offshoring and high-technology capital. In the second stage, they decompose changes in factor prices (in particular, the wage-bill shares of non-production workers) into distinct shares attributable to offshoring and purchases of high-technology capital. This methodology does not address the endogeneity of imports and high-technology capital in the equations for factor prices. In my estimation strategy, instead of employing this two-step procedure, I adopt a fixed-effects, instrumental variables strategy in order to identify the exogenous variations in imported intermediates and purchase of equipment capital. Also, I establish that there is a causal relationship between equipment capital purchase and offshoring. Further, the measure of offshoring used by Feenstra and Hanson (1996, 1999) was imported intermediates from all countries, regardless of their stage of development. However, skill-intensive intermediate inputs from skill-abundant countries may not substitute for the unskilled workers employed in domestic firms. In my empirical analysis, I measure offshoring by including imports only from developing countries.

The evidence on the employment impact of offshoring is mixed. Theoretically, the presumption is that imported unskilled intermediates perfectly substitute for domestic unskilled intermediates. In this environment, while the substitution of unskilled workers by imported intermediates implies a decline in unskilled employment, the cost savings and resulting expansion in domestic output can also increase employment of both skilled and unskilled labor. The latter "productivity effect," first suggested by Grossman and Rossi-Hansberg (2008), has also been emphasized by Ottaviano, Peri and Wright (2011), among others. Empirically, the results are mixed with some studies finding a small negative effect of offshoring on unskilled employment (see, for example, Mann (2005), and Groshen, Hobijn and McConnell (2005)) and others finding a positive effect (see, for example, Landefeld and Mataloni (2004)). My empirical findings suggest that imports of unskilled intermediates have a large positive impact on the total employment of unskilled workers in U.S. manufacturing industries. Further, my results indicate that this positive impact is not only because of the productivity effect but also because imports substitute imperfectly for domestically produced intermediates.

Very few studies have analyzed how offshoring influences innovation. Glass and Saggi (2001) argue that higher profits resulting from offshoring makes innovation affordable for firms, and Rodriguez-Clare (2010) shows that innovation increases as the North reallocates its resources with increased offshoring. Naghavi and Ottaviano (2008), however, argue that offshoring to the South reduces innovation because of less information generated from production tasks. The mechanism that I develop suggests a novel channel by which offshoring can create incentives for firms to invest in innovative activity. I also provide empirical evidence that R&D investment increases in response to a rise in offshoring. This empirical analysis complements the largely theoretical analyses of Glass and Saggi (2001) and Rodriguez-Clare (2010).

This paper also relates to the large literature on skill biased technological change. Many previous studies analyzing the increase in the skill premium in the United States and other OECD countries argue that SBTC is the primary cause and that trade plays a secondary role. Katz and Murphy (1992), and Berman, Bound and Griliches (1994), among others, argue that trade, by creating competition in the product markets, only leads to demand shifts between industries. Since most of the skill-upgrading has occurred within industries, they consider the contribution of trade small.[12] However, Feenstra and Hanson (1996, 1999) showed that imports of intermediate inputs raise the skill premium within industries, and find that 15-40% of the growth in the skill premium is attributable to the growing importance of trade.

My paper contributes to this "trade versus SBTC" debate by showing that skill-biased technology adoption is driven by trade. Imports of intermediates induce industries to innovate and adopt skill-biased technology. This suggests that policies that influence the offshoring decisions of firms will also have implications for their innovation activities and the level of embodied technology that they use domestically.[13]

Finally, the argument that the adoption of skill-biased technology may be endogenous to offshoring adds to the broader literature on endogenous skill-biased technical change. Acemoglu (1998, 2002a, 2002b) shows that the skill-bias of new technologies responds to autonomous changes in the supply of skilled labor. The technology channel that I propose instead generates endogenous SBTC from the demand side. The increase in the production of skilled intermediates and innovation, resulting from offshoring, generates higher demand for skilled labor, leading to the adoption of skill-complementary (capital-embodied) technology. Another strand of this literature explores how trade in *final* goods with developing countries induces technological change in advanced countries (see, for example, the theoretical analysis Thoenig and Verdier (2003) and the empirical work of Bloom, Draca and Van Reenen (2011)). While these studies consider final goods-trade induced technical change, I suggest a mechanism by which intermediate goods trade can induce technical change.

[12]Several other observations have led scholars to conclude that trade is not an important factor underlying the rising skill premia in the developed countries. Lawrence and Slaughter (1993) showed that the relative price of skill-intensive goods did not increase - an observation they argued to be inconsistent with the possibility of trade increasing wage inequality. Berman, Bound and Machin (1998) showed that the unskilled labor-abundant countries also witnessed an upsurge in inequality. If the predictions of the Heckscher-Ohlin-Samuelson (HOS) trade model were to hold empirically, inequality should have fallen in these countries.

[13]A related strand of literature analyzes consequences of trade for SBTC in *developing* countries. Studies show that as developing countries increasingly liberalize their trade regimes, they import capital equipment that embodies skill-biased technology developed in the North. This phenomenon, known as skill-biased trade, is theoretically modeled (eg. Burstein, Cravino and Vogel (2011), Parro (2011)) and documented in several empirical studies (eg. Robbins (1996), Chamarbagwala (2006), among others). Other channels by which trade with advanced countries can lead to skill upgrading and rising skill-premia in developing countries have also been analyzed. See, for example, Verhoogen (2008), and Trefler and Zhu (2005).

3 Empirical Strategy

I first describe the strategy to estimate the total impact of offshoring on skill-upgrading, the skill premium, and the absolute wage payments to skilled and unskilled workers. Next, I focus on the outcomes of the technology channel. Specifically, I describe the strategy to estimate the effect of offshoring on innovation, technology adoption, the number of varieties, and their aggregate prices. Finally, I explain the strategy to parse out the distinct contributions of the H-O and technology channels to the total effects of offshoring on absolute and relative wages.

3.1 Effects of Offshoring: H-O and Technology Channels

My first objective is to analyze how the skill premium,[14] skill-mix, and wage-bills of unskilled workers are impacted by increases in intermediate goods imported from developing countries. For this purpose, I estimate the following fixed effects regressions:

$$\ln\left(\frac{S}{U}\right)_{jt} = a_1 \ln M_{jt}^{\text{low}} + b_t + c_j + \epsilon_{1jt} \tag{3.1}$$

$$\ln\left(\frac{WB_s}{WB_u}\right)_{jt} = a_2 \ln M_{jt}^{\text{low}} + b_t + c_j + \epsilon_{2jt} \tag{3.2}$$

$$\ln WB_{ujt} = a_3 \ln M_{jt}^{\text{low}} + b_t + c_j + \epsilon_{3jt} \tag{3.3}$$

In the above equations, M_{jt}^{low} denotes all intermediate goods imported from developing countries and used as inputs in industry j in year t, relative to all intermediates used in that industry and year. $M_{jt}^{\text{low}} = \frac{1}{X_{jt}} \sum_{k=1}^{n} r_{jkt} * Q_{jt} * (\frac{\text{Imp}_{kt}^{G}}{Q_{kt} + \text{Imp}_{kt} - \text{Exp}_{kt}})$, where r_{jkt} is the direct requirement coefficient in year t for commodity k used as an input in industry j, Q_{jt} is the output (value of shipments) of industry j, Imp_{kt} and Exp_{kt} are the total imports and exports belonging to industry k, respectively, and X_{jt} is the value of non-energy materials used in industry j. As constructed, the measure of imported intermediates corresponds to the "broad measure of foreign outsourcing"[15] developed by Feenstra and Hanson (1999). The employment ratio, $(\frac{S}{U})_{jt}$, and the wage-bill ratio, $(\frac{WB_s}{WB_u})_{jt}$ are the measures for within-industry skill-mix and skill premium, respectively. To consider the absolute outcomes for unskilled workers, I

[14] Note that, conventionally, the skill premium is defined as the wages of skilled workers relative to the wages of unskilled workers. However, in reality, workers may not be perfectly mobile across industries. If they were perfectly mobile, we would have a unique wage-ratio across all industries. That is not substantiated in the data, suggestive of industry-specific skills or other labor market frictions. And yet, workers are not completely immobile across industries either; this would entail each industry to have a different wage-ratio uninfluenced by the wages that similar workers receive in other industries. Thus, in my empirical analysis, I measure the skill premium as the ratio of the wage-*bills* of skilled and unskilled workers, instead of wage-ratios. This alternative measure allows for some, but not perfect, mobility of workers across industries.

[15] The narrow measure of foreign outsourcing is obtained by considering only those inputs that belong to the same two digit industry as the one to which the output industry belongs. This measure captures offshoring of only those production activities that could have been performed within the same two-digit industry domestically.

consider the impact of imported intermediates on WB_{ujt}, as shown in equation 3.3. Other outcome variables that I examine are the total employment of unskilled workers, the wage-bill and employment of skilled workers and gross industrial output. All variables are in natural logarithms. Additionally, the regressors also include time and industry fixed effects denoted by b_t and c_j, respectively.

3.2 The Technology Channel

To quantify the effects of offshoring via the technology channel, I estimate regressions with the same set of regressors as above, but innovation and technology adoption (measured by the real capital stock, or capital relative to labor) as the outcomes. Thus, I estimate the following regressions:

$$\ln\left(\frac{K}{L}\right)_{jt} = a_4 \ln M_{jt}^{\text{low}} + b_t + c_j + \epsilon_{4jt} \tag{3.4}$$

$$\ln \text{RD}_{jt} = a_5 \ln M_{jt}^{\text{low}} + b_t + c_j + \epsilon_{5jt} \tag{3.5}$$

Here, $\left(\frac{K}{L}\right)_{jt}$ is the real value of capital stock relative to the total number of workers employed and reflects embodied technology adoption in the industry. RD_{jt}, is the real R&D expenditure in industry j in year t and is a measure of the innovation activity performed in an industry. Consistent with the technology channel, I expect the coefficients on imports in both the equations to be positive.[16] Alternative outcome measures are real capital stock (for technology adoption), and R&D intensity (for innovation).

To delve further into the technology channel, I analyze the effects of imported intermediates on real final goods prices and the number of varieties. I expect a rise in the number of varieties and the prices of these goods. To assess the effect of offshoring on final goods prices, I estimate regressions similar to those described above. However, the number of varieties produced within each industry is a count variable. Hence, a non-linear estimation is required. I estimate a FE Poisson regression model for this purpose.

Since imports may be correlated with disturbances in these equations, the above fixed effects (FE) regressions will give biased and inconsistent estimates of the impact of imports on the outcome variables. Ex ante, the direction of bias is unclear, with both upward and downward bias possible. For instance, an unobserved technology shock may make some capital equipment cheaper for an industry. This equipment may make it cheaper to perform some tasks domestically rather than offshore them. Such shocks will reduce intermediate imports and increase the relative employment and wages of skilled workers. In this case, our estimates will be biased towards zero. Alternatively, policy changes, such as an increase in the real minimum

[16] I also estimate specifications in which I include the industrial output as an additional control variable. The resulting estimates for the coefficients on imports are close to those obtained from regressions that do not control for output.

wage, may increase the relative wages of unskilled labor, making it more expensive for industries to employ unskilled labor. Such a policy may simultaneously increase the relative employment of skilled labor and offshoring, biasing the estimated coefficient on imports upwards. Other factors, like demographic and policy changes, may also bias the coefficient estimates in either direction. Moreover, the imported intermediate input measure are constructed from raw data as described earlier and hence potentially includes some measurement error leading to attenuation bias.

To address these biases, I use fixed effects with instrumental variables (FE-IV). Following Revenga (1992), I construct source-weighted industry nominal exchange rates. These are constructed as the natural logarithm of the weighted geometric mean of the nominal exchange rates of source countries vis-a-vis the U.S. dollar. The weights used are the shares of each source country in the total U.S. imports in a given industry in 1980. I average these industry exchange rates over all inputs used in an industry (weighted by the average direct requirement coefficient of each input used in the industry over the entire sample period). These exchange rate constructs vary over years and four-digit industries. Exchange rates determine import prices and, thus, are highly correlated with imported intermediates used in the U.S. industries.

The validity of these instruments is also plausible for two reasons. First, to the extent that exchange rates are influenced mainly by macroeconomic factors rather than by industry-level shocks, they are likely to be independent of the unobservable industry-year variations in my dependent variables. This is especially plausible since the specifications include industry and year fixed effects. Second, using static country-specific weights, and weighting the observations by constant industry size, avoid the possibility that instruments may be endogenous due to joint determination of import shares of countries and exchange rates in any given year.[17]

3.3 Decomposing Contributions of the H-O and Technology Channels

To isolate the technology effects of offshoring from those via the H-O channel, I control for the variables that change in the technology channel. In this specification, the coefficient on imports is an estimate of the effect of an increase in offshoring on the outcome variable via only the H-O channel. The difference between these and the former set of estimates provides a measure of the impact of the technology channel.

While I do not have instruments to identify the exogenous variations in all control variables, I use the ratio of the lagged price index for investment as an instrument for capital-labor ratio,[18] which should result in smaller estimates of the coefficients on imports in the following

[17]Tariff rates imposed by the U.S. on imports from foreign countries can also be used as instruments. Instrumental variables using tariff rates are constructed following the same approach as described above for exchange rates.

[18]The data provide me with a price index for investment, but not for capital stocks. Since changes in the current cost of investment may affect future capital stocks, I use the lagged price index of investment to construct the instrument. Further, I only present results that use one year-lagged values of this index as the instrument. I estimated regressions using upto four lags of this index as instruments. After the first lag, the future lags become insignificant. The results obtained are also qualitatively similar. The validity of this instrument is plausible

regressions:

$$\ln\left(\frac{S}{U}\right)_{jt} = a_6 \ln M_{jt}^{\text{low}} + q_1 \ln\left(\frac{K}{L}\right)_{jt} + b_t + c_j + \epsilon_{6jt} \tag{3.6}$$

$$\ln\left(\frac{WB_s}{WB_u}\right)_{jt} = a_7 \ln M_{jt}^{\text{low}} + q_2 \ln\left(\frac{K}{L}\right)_{jt} + b_t + c_j + \epsilon_{7jt} \tag{3.7}$$

$$\ln\, WB_{ujt} = a_8 \ln M_{jt}^{\text{low}} + q_3 \ln\left(\frac{K}{Y}\right)_{jt} + b_t + c_j + \epsilon_{8jt} \tag{3.8}$$

But these regressions underestimate the quantitative impact of the technology channel as the other variables are not held fixed. I expect the estimated coefficients on capital-labor ratio in these equations to be positive, reflective of capital-skill complementarity. It is noteworthy that in the equations for wage-bills and employment of skilled and unskilled workers, the control used for technology adoption is $\left(\frac{K}{Y}\right)_{jt}$. The ideal control, instead, is $\left(\frac{K}{L}\right)_{jt}$. However, using this measure creates a division bias. Again, this may result in underestimation of the impact of the technology channel on these outcomes variables.

I weight each industry-year observation by the square root of the average share of the industry in the total wage-bill of U.S. manufacturing industries over the sample period. These static weights control for any sectoral shifts and changes in industry size that may have occurred over the period, which can otherwise potentially influence the exchange rates used as instruments.[19] The standard errors are robust to arbitrary heteroskedasticity and are clustered at the level of four-digit industries.

I measure offshoring as the shift of some fraction of the production tasks to a foreign country, regardless of whether the offshored activity is performed by a firm that is external or affiliated to the offshoring firm. This is consistent with the definitions adopted by Feenstra and Hanson (1996, 1999), Grossman and Rossi-Hansberg (2008), and Rodriguez-Clare (2010), among others. However, the relocation of production tasks is no longer limited to the intermediate stages of production. Increasingly, the assembly of final goods for domestic consumption also takes place offshore. Thus, the extent of offshoring is not entirely captured by measuring the imports of intermediate goods and so the results in this paper may serve as lower bounds for the true effects of offshoring.

because the cost of purchasing physical capital affects the outcome variables in these regressions only through its effect on the the demand for capital. Hence, conditional on including the capital-labor ratio, it is valid to exclude this instrument from the second stage regression.

[19] As a robustness check, I also use the square root of the industry's average share in the total manufacturing output over the sample period as weights. Results using both weights are qualitatively similar.

4 Data and Descriptive Statistics

4.1 Data

I combine data from several sources. In this section, I provide an overview of these data sources. More detail is available in the data appendix.

U.S. Imports and Exports

Highly disaggregated U.S. imports and exports data are available from the Center for International Data at the University of California, Davis. The data on manufacturing industries are classified according to 4-digit SIC 1987 codes. I first aggregate the imports (exports) data to four-digit imports (exports)-based Standard Industrial Classification (MSIC (XSIC))[20] (1987) using various concordances. Next, I follow the method developed by Feenstra, Romalis and Schott (2002) to bring these imports and exports to the (domestic) SIC 1987 classification. After this conversion, there still are some industries (in the domestic SIC 1987 classification) for which there are no imports or exports (see Feenstra, Romalis and Schott, 2002, for details). Additionally, there are some industries in which imports and/or exports are reported for certain years but do not appear in the data in some other years.[21]

The countries of origin of these imports have been classified by the World Bank into five groups on the basis of their per capita income levels - High Income OECD, High Income non-OECD, Upper Middle Income, Lower Middle Income and Low Income. I combine the high-income OECD and non-OECD countries into the group of high-income countries. Similarly, I combine the other three groups into the group that I refer to as low-wage (income) or developing countries. In my analysis, I make a distinction between the imports coming from high-income countries and those coming from low-income countries. Imports values used in the analysis are the c.i.f. (cost, insurance, freight) values of imports for consumption.[22] The c.i.f values are available only after 1973.

Industrial Characteristics

I obtain annual data on output (shipments), employment, wages, and capital stocks in 459 four-digit manufacturing industries (classified according to the Standard Industrial Classification, 1987) from the NBER-CES Manufacturing Industry Database (Bartelsman and Gray, 1996).[23] Employees are classified as production and non-production workers. I consider non-production

[20] As detailed in Feenstra, Romalis and Schott (2002), MSIC and XSIC differ from domestic-based SIC because the latter often depends on the method of processing used to manufacture the good which is not known for imports or exports. Thus, no imports or exports are reported for a few SIC categories.

[21] These include SIC classifications 2024, 2141, 2259, 2387, 2512, 2732, 2791, 3263, 3273, 3322, 3365, 3451, 3462, 3645, 3731, 3761, 3769, 3953 and 3995.

[22] General imports are a better measure of imports. However, until 1994, only the consumption values of imports are available.

[23] The NBER database includes variables from yearly rounds of the Annual Survey of Manufactures.

workers as high skilled and production workers as low skilled.[24] Nominal wage bills for both categories of workers are provided. I use the value of shipments as the measure of output of industries. The database separately provides real values of stocks of capital equipment and structures. The industrial classification changed in 1997 from the Standard Industrial Classification to the North American Industrial Classification System (NAICS). The NBER database provides a uniform SIC 1987 classification over all the years by concording the two classification systems. But, as described in Feenstra, Romalis and Schott (2002) the change in industrial classification does not yield a clean concordance; i.e., the mapping is not always one-to-one. This affects some industry definitions. Observing the raw data shows that for some industries there are substantial differences in the employment or wage ratios, amongst other variables, between 1996 and 1997 after which the series follow similar trends as before. This is chiefly attributable to altered industry classifications. To control for this change in industrial classification, in all the regressions I include a vector of interactions of 2-digit industry dummies with an indicator for whether the year is before or after 1997 (the year of the classification change).[25] The last year for which these data are available is 2005.

Data on innovation expenditures incurred in these industries are not available in the NBER database. Compustat is a database that provides financial statistics for all the publicly traded firms in the United States. Among other things, these data include information on sales and the non-federally funded R&D expenditures of these firms. Keeping only the firms legally incorporated in the U.S., I aggregate these firm level sales and R&D expenditures to create a series of 4-digit industry level annual sales and innovation expenditures for the sample period. To the extent that innovation activity is also performed in the unincorporated firms in the country, these data provide lower bounds for the total innovation expenditures incurred in the 4 digit industries. Note that this measure of R&D primarily reflects product innovation. According to the documentation for Compustat, the R&D expenditures include all costs incurred to develop new products and services but excludes the costs to improve the quality of existing products. Thus, this measure captures all expenditures made to develop new products that may be both horizontally and vertically differentiated (since the new products may also be better in terms of quality). An alternative measure of innovation that I use for my analysis is R&D intensity (R&D expenditure/Sales).[26]

[24]Berman, Bound and Griliches (1994) show that the classification of workers as production/non-production closely corresponds to the educational levels of high school and college respectively.

[25]As a robustness check, I estimate all regressions with data only until 1996 so that I have a uniform industrial classification throughout the sample period. Results are qualitatively similar to those obtained using the full sample.

[26]Patents can provide another measure of innovation activity. The measure, however, may not be ideal for two reasons. First, not all firms patent the knowledge created from their innovation efforts. Second, often the patenting firm may sell the license for use by other firms. In such cases, the industry that the patenting firm belongs to may not be the industry benefiting from the innovation.

Input-Output Tables

In order to assign imports as inputs into the manufacturing industries, I use the direct requirement coefficients in the benchmark input-output tables available from the Bureau of Economic Analysis.[27] Direct requirement coefficients are defined as the amount of a commodity required as an input to produce one unit of output in a given industry.[28] The benchmark tables are provided every five years between 1972 and 2002. For the interim years, I linearly interpolate (extrapolate for 2003-2005) the direct requirement coefficients.[29] Multiplying these coefficients with the output of each industry gives me the total dollar value of each good used as an input in the production of an industry every year.

Exchange Rates

The exchange rate data needed to construct instruments for the potentially endogenous import variables are obtained from the Penn World Tables. These tables provide data on nominal exchange rates for all countries vis-a-vis the U.S. dollar. As an alternative to exchange rates, I also use tariffs to construct instruments in order to identify the exogenous variation in imported intermediates. Average industry level tariff rates imposed by the U.S. on commodities imported from various countries are calculated from the U.S. imports data files (available from the Center for International Data, University of California, Davis) as $100 * \frac{\text{Total Duties Paid}}{\text{Total Customs Value of Imports}}$ for all imported product categories belonging to each 4 digit SIC (1987) industry.

In my final sample, I have 14563 observations on 459 four-digit SIC 1987 industries spanning 32 years from 1974 to 2005.[30] All nominal values are deflated, wherever needed, using the U.S. CPI obtained from the Bureau of Labor Statistics. The shipments of four digit industries are deflated using the shipments deflator available in the NBER-CES manufacturing industry database.

4.2 Descriptive Statistics

It is highly informative to see the patterns in the data that help us relate the changes in industrial characteristics to the growth in offshoring. I begin by documenting several trends that reveal the growing importance of various developing countries in U.S. imports. Next, I show how various characteristics of U.S. manufacturing industries have evolved over time as the extent of offshoring increases.

[27] I establish concordances between the SIC 1987 codes and the industry codes that are different for each year of the input-output tables.

[28] These coefficients are not directly available for 1972 and 1977 and need to be computed.

[29] Voigtlander (2011) shows that the use values of inputs in various industries are quite stable over time. So it is reasonable to linearly interpolate the direct requirement coefficients for the interim years and extrapolate for the years 2003-2005.

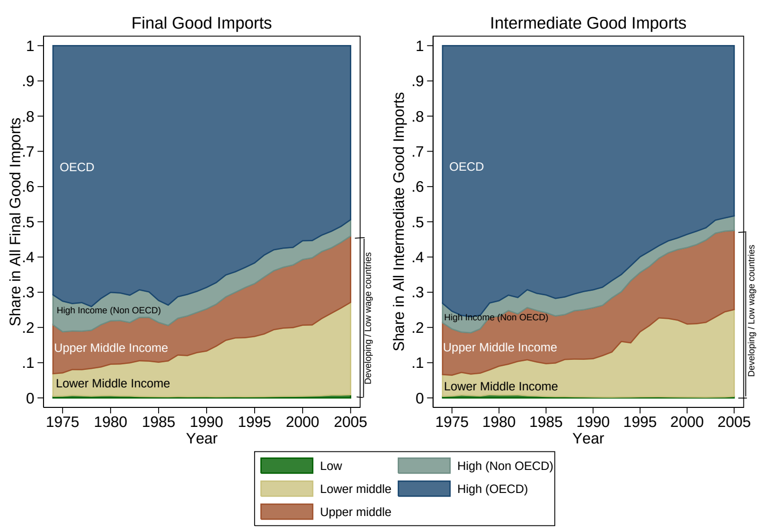
[30] No import data are available for some industries in a few years.

Patterns in U.S. Imports

Figure 1 showed the growth in the share of U.S. imports from developing countries as a whole. This growth is not a result of rising imports from just one or two developing countries. The first graph in Figure 2 plots the shares of different (income) groups of countries in the total final good imports of the United States. The second graph plots the corresponding shares for the intermediate good imports. It is evident that the final and intermediate goods imported from lower-middle income countries (including China) grew the most, followed closely by those from upper-middle income countries. Although the share of OECD countries continues to be the largest, it fell sharply from around 70% (75%) to nearly 50% (45%) of all final (intermediate) good imports. The share imported from high income non-OECD countries has been almost constant after falling slightly until the mid-1980s. The U.S. imported only a negligible share from low-income countries.

Table 1 shows the top 20 exporting countries for the years 1975, 1990 and 2005, and their shares in total U.S. imports. In each year, the developing countries are in boldface. The number of developing countries among the top exporters increases over time. While China did not even appear in the top 20 countries in 1975, in 2005 it accounted for the largest share of imports of the U.S. (18%), displacing Canada and Japan from their top positions in 1975 and 1990, respectively. The shares imported from other developing countries like Mexico, Brazil and Thailand also increased considerably. In contrast, the shares of the advanced countries like Canada, Germany, and the United Kingdom fell overtime.

Figure 2: Shares of Income Groups in Final and Intermediate Good Imports[a]



[a]Source: U.S. Imports and Exports data, NBER-CES Manufacturing Industry database, Input-Output tables, World Bank Income Classification. Imported intermediates in each industry are calculated by first multiplying the import penetration ratio for each input to the total dollar value of that input used in the industry, and then aggregating over all inputs used.

Table 1: Top Twenty Exporters of Manufactured Goods to United States

1975		1990		2005	
Country	**Share***	**Country**	**Share***	**Country**	**Share***
Canada	23.02	Japan	21.36	**China**	17.79
Japan	17.12	Canada	18.24	Canada	14.84
Germany	7.86	Germany	6.50	Japan	9.61
United Kingdom	5.15	**Taiwan**	5.51	**Mexico**	9.54
Italy	3.60	**Mexico**	4.94	Germany	5.73
Taiwan	2.98	South Korea	4.47	South Korea	3.08
France	2.87	United Kingdom	3.94	United Kingdom	3.05
Mexico	2.59	**China**	3.48	**Taiwan**	2.43
Belgium/Luxembourg	2.36	Italy	3.03	**Malaysia**	2.36
Hongkong	2.32	France	2.87	France	2.18
Venezuela	2.26	Singapore	2.25	Italy	2.15
South Korea	2.15	Hongkong	2.24	Ireland	1.95
Netherlands Antilles/Aruba	1.70	**Brazil**	1.75	**Brazil**	1.56
Australia	1.51	**Thailand**	1.16	**Thailand**	1.34
Netherlands	1.44	**Malaysia**	1.15	**India**	1.30
Bahamas	1.28	Sweden	1.15	Israel	1.15
Sweden	1.27	Belgium/Luxembourg	1.08	**Venezuela**	1.00
Spain	1.23	Netherlands	1.06	Singapore	0.99
Brazil	1.14	Switzerland	1.00	**Russia**	0.97
Switzerland	1.10	**Venezuela**	0.96	Sweden	0.95

Notes: *: Share of country in total imports of the U.S.
Bold indicates developing country

Industrial Trends

Figure 3 shows the rising skill-premia and skill upgrading in manufacturing.[31] The figure plots the (weighted) average [32] wages and employment of non-production workers relative to production workers over the 32-year period from 1974 to 2005. The relative wages of skilled (non-production) workers grew from 1.55 in 1974 to more than 1.69 in 2000, but then they declined to 1.59. Even as the relative wages of skilled workers grew, the industries upgraded their skill-mix. The average employment ratio increased from 0.46 to 0.54 over the same period, except during the late 1970s and mid-1990s.[33]

Capital used in manufacturing industries also rose relative to labor. Until the mid-1990s this upward trend was driven mainly by equipment, with structures remaining nearly constant relative to labor. However, as offshoring picked up in the mid-1990s, both components accelerated.

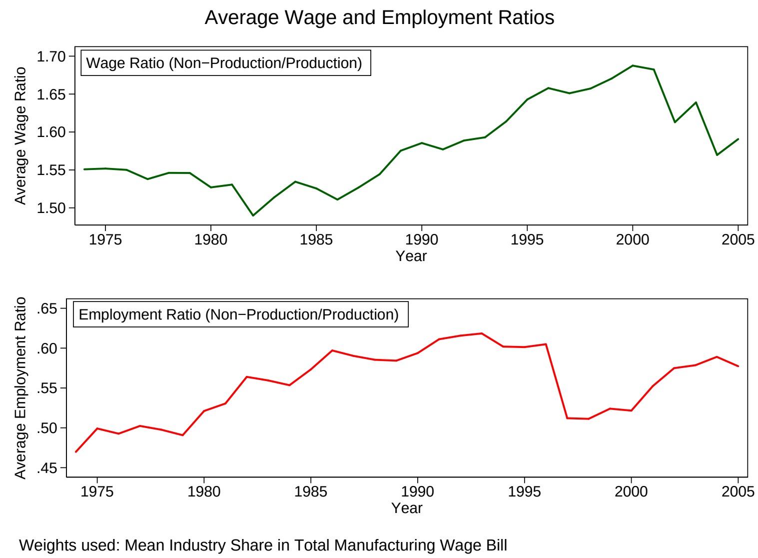
The average real value of industrial shipments has uniformly risen over the sample period,

[31] The rise in the relative wages and employment of non-production workers in U.S. manufacturing industries is very well established.

[32] The average (over the sample period) shares of the industries in the total manufacturing output of the economy are used as weights.

[33] The break in the relative employment series between 1996 and 1997 is because of the change in the industrial classification from SIC 1987 to NAICS 1997 mentioned earlier. The trends in the series before and after the break are similar, however.

Figure 3: Rising Relative Wages and Employment of Skilled Workers[a]



[a]Source: NBER-CES Manufacturing Industry database. The top figure plots the ratio of average annual wages of non-production to production workers. The bottom figure plots the ratio of number of non-production to production workers employed. Both ratios are averaged over all 4 digit SIC (1987) industries.

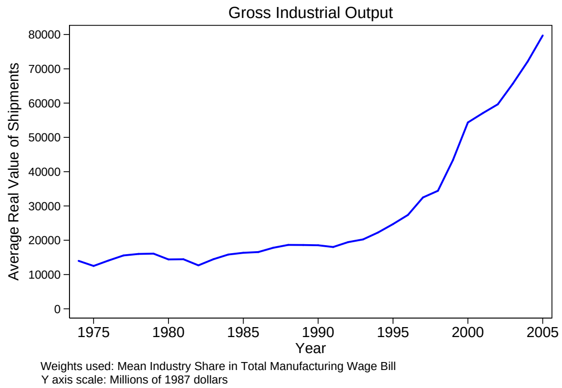
accelerating after the mid-1990s when offshoring starts rising rapidly (Figure 4). The total output of an industry is the aggregate of the output of each product or variety produced within that industry. In the absence of firm level data, I do not have a precise measure for the number of varieties produced in an industry. One proxy for the number of varieties produced is the number of ten-digit exported product categories in each 4-digit industry. The number of exported varieties may be less than the total number of varieties produced domestically. Also, the product classification changes over time.[34] To minimize changes in classification, I construct the number of varieties exported for only the post-1988 period. The maximum number of exported varieties in an industry increased from 302 in 1990 to 398 in 2005. The average trend in the number of varieties is clearly positive (see second graph in Figure 4), albeit it seems to rise in discontinuous jumps. These jumps may be an artifact of changing definitions of product categories.

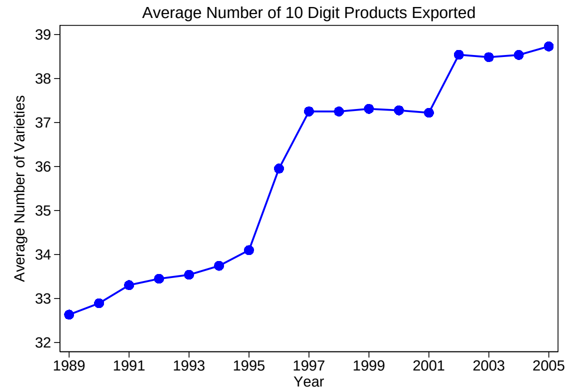
Table 2 presents the average characteristics of two-digit industries for the years 1975 and 2005 along with the average intermediate imports from developing countries within each industry.[35] For both the years, I also rank the industries in decreasing order of imported intermediates. In 2005, the electronics industry (code 36) had the highest proportion of imported inputs. Even in 1975, it was second only to "miscellaneous" manufacturing (which includes jewelry, toys and sporting goods, silverware, musical instruments, office supplies etc.). Note that the

[34]Until 1988, the products were classified at the 7-digit level under the TSUSA classification. After 1988, the classification changed to HS 10-digit level. Even within these classifications, the definitions change over the years.

[35]The intermediate imports are reported as a percentage of the non-energy materials used in an industry.

Figure 4: Rising Output and Average Number of Products[a]





[a]Source: NBER-CES Manufacturing Industry database. Figure 5(a) plots the real value of annual shipments averaged over all 4 digit SIC (1987) industries. Figure 5(b) plots the total number of 10-digit product categories (under the Harmonized System classification) exported by U.S. manufacturing industries.

proportion of imported inputs was only 2.6% for the electronics industry in 1975 but rose to 42% in 2005. Even the lowest ranking industry in 2005 (printing and publishing) had a higher proportion of imported inputs than the highest ranking industry in 1975. It is clear that all industries witnessed a dramatic increase in the extent of offshoring. Simultaneously, several characteristics of these industries changed. The high positive correlations of the employment and wage-bill ratios with offshoring in both years suggest that the industries with a higher proportion of non-production workers in their total employment and wage bill offshored more. The same is true of real R&D expenditures. In regard to the real wage-bills of production workers, while the correlation was negative in 1975, it is positive and large in 2005. In both years, the industries that are more high-tech (i.e. have a higher equipment to labor ratio) offshore less to low income countries. However, but the sharp decline in this negative correlation from -0.24 in 1975 to -0.08 in 2005 suggests that, over time, increasingly more high-tech industries are importing their intermediate inputs.

Table 2: Average Offshoring by Industries and Their Characteristics

		1975							2005						
Industry Code	Description	Rank	Offshoring**	Employment Ratio*	Wage Bill Ratio*	Production Workers Wage Bill***	Equipment/ Labor	R&D***	Rank	Offshoring**	Employment Ratio*	Wage Bill Ratio*	Production Workers Wage Bill***	Equipment/ Labor	R&D***
39	Miscellaneous Manufacturing Industries	1	0.027	0.313	0.612	454.504	10.889	11.178	7	0.216	0.539	0.996	476.796	41.459	82.260
36	Electronic and Other Electric Equipment	2	0.026	0.524	0.923	757.355	18.721	261.780	1	0.421	0.823	1.515	697.647	147.257	12564.700
20	Food and Kindred Products	3	0.026	0.526	0.703	1005.170	35.933	34.561	18	0.100	0.427	0.619	937.449	105.670	63.110
38	Instruments and Related Products	4	0.022	0.789	1.250	1270.843	11.526	323.590	3	0.379	1.453	2.486	794.693	59.252	1161.296
25	Furniture and Fixtures	5	0.022	0.252	0.439	627.374	8.411	6.530	11	0.168	0.313	0.542	610.365	28.288	54.666
31	Leather and Leather Products	6	0.019	0.159	0.340	374.217	5.841	0.560	12	0.156	0.295	0.599	51.102	26.216	6.960
28	Chemicals and Allied Products	7	0.018	0.712	1.036	933.303	65.684	761.459	13	0.153	0.752	1.126	974.888	220.471	3644.444
33	Primary Metal Industries	8	0.017	0.282	0.380	4694.232	64.594	125.505	15	0.125	0.270	0.377	1395.793	221.256	27.356
37	Transportation Equipment	9	0.015	0.519	0.710	4460.612	26.909	2063.363	2	0.394	0.657	0.852	4118.491	97.797	6564.820
23	Apparel and Other Textile Products	10	0.014	0.161	0.349	724.737	5.085	2.703	9	0.195	0.326	0.667	192.797	23.747	0.798
22	Textile Mill Products	11	0.013	0.166	0.330	826.519	22.742	9.735	4	0.325	0.204	0.366	252.130	89.472	9.657
24	Lumber and Wood Products	12	0.010	0.181	0.327	1004.426	22.731	31.399	16	0.120	0.250	0.414	1039.375	39.223	33.580
32	Stone, Clay, and Glass Products	13	0.008	0.294	0.413	685.631	36.895	17.471	6	0.226	0.285	0.442	718.814	125.268	11.065
34	Fabricated Metal Products	14	0.008	0.329	0.501	1063.771	22.328	17.744	14	0.143	0.368	0.602	920.393	72.703	22.744
29	Petroleum and Coal Products	15	0.008	0.442	0.592	1522.310	151.425	758.420	8	0.197	0.619	0.742	1459.754	651.776	377.665
35	Industrial Machinery and Equipment	16	0.007	0.558	0.857	1226.434	18.493	93.849	5	0.290	0.757	1.196	1027.952	84.300	18132.040
26	Paper and Allied Products	17	0.007	0.308	0.453	1261.191	57.051	79.485	19	0.072	0.283	0.451	1108.512	220.512	207.160
27	Printing and Publishing	18	0.005	1.091	1.457	2190.654	13.795	4.214	20	0.059	0.403	0.614	3075.353	51.368	8.599
30	Rubber and Miscellaneous Plastics Products	19	0.005	0.304	0.513	1581.401	29.893	80.364	10	0.193	0.299	0.519	2859.820	76.973	173.268
21	Tobacco Products	20	0.003	0.184	0.275	653.400	28.268	55.919	17	0.120	0.337	0.585	294.028	194.832	260.351
	Correlation with Offshoring			0.053	0.163	-0.175	-0.240	0.058			0.608	0.621	0.547	-0.079	0.531

Notes: All numbers are averages over all 4 digit industries within each 2 digit industry.
*: Ratios are for non-production workers relative to production workers.
**: Sum of imported inputs as a proportion of non-energy materials.
***: Millions of dollars (1987=1)

Trends in Exchange Rates and Tariffs

Finally, a brief note on the trends in the source weighted industry exchange rates and tariff rates. These are the instrumental variables I use to identify the exogenous variation in the imported intermediate goods measure. On average, the U.S. dollar appreciated vis-a-vis the currencies of developing countries over time. Moreover, there was substantial variation in these exchange rates within each year with considerably more spread after 1997. These trends reflect the liberalization of their trade regimes by several developing countries over this time period. On the other hand, the U.S. tariffs on the imports from these countries were low on average and their spread fell throughout the time span. The mean tariff rate fell by about 6 percentage points and the range in any given year was never more than 8 to 9 percentage points. The variation in tariffs is considerably smaller after 1997.

5 Empirical Results

Using the empirical strategy described in section 3, I now present results that provide evidence that the industrial trends described in the previous section are causally related to increased offshoring by U.S. manufacturing industries. First, I briefly describe the results obtained from fixed effects (FE) regressions. Next, I describe the results obtained from fixed effects - instrumental variables (FE-IV) regressions. Lastly, I decompose the H-O and technology effects of offshoring on the real and relative employment and wages of skilled and unskilled workers.

5.1 Fixed Effects Estimates

Table 3 presents the FE estimates of the effects of offshoring on several outcome variables. The results are categorized on the basis of whether I expect the dependent variables to be influenced via the technology channel only or also in the H-O channel. The employment and wage-bills ratios (and levels) of non-production to production workers are affected via both the channels. In the H-O channel, the relative wages and employment of non-production workers are expected to rise as offshoring unskilled inputs causes a shift towards skilled tasks. In the technology channel, these ratios rise due to capital-skill complementarity and increased innovation. Consistent with this intuition, Table 3, columns 1 and 2, show that offshoring is positively associated with employment and wage ratios. The levels of employment and wage-payments to both groups of workers also rise via both channel due to cost-savings and expansion of output (see columns 3 to 6). Gross output is also affected by both channels - because firms' outputs rise with offshoring, and also because the number of firms within industries also increases. The positive coefficient on imports in column 7 is consistent with this intuition. The technology channel relies on offshoring leading to higher R&D investment and technology adoption. Furthermore, I expect prices to be positively correlated with offshoring (because of increased variety). For the technology channel (Table 3, columns 8 to 10), all coefficients except for R&D and equipment-labor ratio is in line with expectations.

Table 3: Fixed Effects Estimates for Various Outcome Variables

	Both Channels							Technology Channel			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9a)**	**(9b)**	**(10)**
	Employment Ratio[1]	Wage Bill Ratio[1]	Non-Production Wage Bill	Non - Production Employment	Production Wage Bill	Production Employment	Gross Output	R&D[2]	Equipment	Equipment / Labor	Price[3]
Imported Intermediates[4]	0.009	0.010	0.013	0.015	0.003	0.005	0.004	-0.138***	0.007	-0.003	-0.003
	(0.007)	(0.008)	(0.013)	(0.013)	(0.013)	(0.013)	(0.025)	(0.043)	(0.015)	(0.012)	(0.018)
Observations	14,569	14,568	14,568	14,569	14,570	14,570	14,570	13,746	14,570	14,570	14,570
R-squared	0.259	0.326	0.122	0.162	0.272	0.302	0.260	0.124	0.587	0.762	0.348
Number of 4 digit industries	459	459	459	459	459	459	459	456	459	459	459

Notes:

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

[1]: Ratios are for non-production workers relative to production workers.

[2]: Real R&D Expenditure for the firms for which data on R&D expenditure are available.

[3]: Price Index for industry deflated by U.S. CPI.

[4]: As a proportion of total non-energy materials used in the industry.

All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996.
Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.
All variables are in natural logs.

Though largely qualitatively supportive of the mechanism, the coefficients estimated from the fixed effects regressions are small in magnitudes and likely to be biased because of endogeneity and measurement error as discussed in section 3. Thus, these coefficients do not have a causal interpretation. The negative coefficients in the equations for capital and equipment relative to labor may just be reflecting the pattern that more high-tech industries offshore less, as shown in Table 5.[36]To address endogeneity and attenuation bias, I turn to FE-IV estimates.[37] This approach provides me with consistent estimates of the causal effects of offshoring on the variables of interest.

5.2 Fixed Effects - Instrumental Variables Estimates

First Stage Results

I use contemporaneous and lagged exchange rate constructs as IVs for imports.[38] Results from the first stage estimates from various specifications are presented in Table 4. From columns 1 to 3, I successively increase the number of lags of exchange rates. While the contemporaneous and one year lagged exchange rate is significant, the two years lagged exchange rate is not. The coefficients on the exchange rates in these three specifications are economically and statistically highly significant. Also, they reveal the familiar J-curve effect (see, for example, Guadalupe and Cunat (2009)). Immediately after an appreciation of the U.S. dollar vis-a-vis another currency (ie, an increase in the exchange rate), imports become cheaper. But the quantity of imports demanded rises only after some time has elapsed. Thus, we see that the total dollar value of imports falls in the first year, but rises thereafter. In all three specifications, the F-statistic is well above ten indicating that the instruments are powerful predictors of imported intermediates.

[36]I also regress employment and wage-bill ratios, respectively, on imported intermediates, controlling for the variables expected to change only as part of the technology channel. As explained in section three, this would be an appropriate strategy to parse out the quantitative effects of imports on employment and wage-bill ratios via the two channels only if the control variables were exogenous. But here, all the regressors are endogenously chosen by the firms belonging to these industries. Thus, the estimates do not reflect causal effects. The coefficients are also small and statistically insignificant as in Table 3.

[37]Measurement error in the dependent variable does not bias the estimates of the coefficients on the regressors. However, the standard errors are larger. Also, the IV strategy corrects for measurement error in the constructed variable denoting imported intermediates under the condition that the error is classical, i.e., errors are independent of truth, have a mean of zero and a constant variance.

[38]In other specifications (not reported), I use lagged tariffs as instruments. Following Guadalupe and Cunat (2009), I do not include contemporaneous tariffs as they may be endogenous with industrial characteristics due to political economy reasons. However, in these specifications, the coefficients do not match my expectations; an increase in tariffs imposed by United States on imports from foreign countries makes imports more expensive. So over time I expect to see a fall in imports. However, the coefficients are positive, suggesting a rise in the value of imports even after two years. The reason for such estimates is not quite clear. I expect the imports to respond similarly to prices, regardless of whether the price change occurs because of a change in exchange rates or a change in tariffs. The small range over which these tariffs vary across years and industries, as described in the previous section, may be driving this result. Further, including both exchange rates and tariffs, I find a similar pattern.

Table 4: FE-IV Estimation - First Stage

Dependent Variable: Imported Intermediates[1]			
Exchange Rate	-0.197***	-0.272***	-0.287***
	(0.038)	(0.044)	(0.057)
One Year Lagged Exchange Rate		0.109***	0.098***
		(0.042)	(0.030)
Two Years Lagged Exchange Rate			0.052
			(0.048)
Observations	14,568	14,103	13,638
Number of Industries	459	459	459
F statistic[2,3]	26.36	19.05	14.07
Shea's Partial R-squared	0.014	0.013	0.012

Notes: $***p < 0.01, **p < 0.05, *p < 0.10$ [1]: As a proportion of total non-energy materials used in the industry. [2]: Kleibergen-Paap Wald rk F statistic with degrees of freedom $= L1 - K1 + 1$; $K1 =$ no. of enodogenous regressors, $L1 =$ no. of excluded instruments
[3]: Degrees of freedom correction for F statistic $= ((N - L)/L1) * ((N - 1)/N) * (N_c lust - 1)/(N_c lust)$. So F-statistic is slightly different when the dependent variable in second stage is R&D. Reason: Sample size and number of clusters are different due to some missing observations.
All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996. Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries. All variables are in natural logs.

Second Stage Results

In Table 5, I present the second stage results for variables that are influenced by offshoring through both channels. Panel A identifies the exogenous variation in imports using only the contemporaneous exchange rates. Panels B and C successively include one and two lags of exchange rates. All variables are in logs. The specification with contemporaneous and one lag of exchange rates fails to reject the joint null hypothesis of instrument validity, and has the strongest first stage. Hence, the results in Panel B are my preferred estimates. I describe these estimates below.

In columns 1 and 2 of Table 5, I present the FE-IV estimates for the employment and wage-bill ratios that measure the skill-mix and skill-premia within industries. Columns 3-6 present results for the wage-bills and employment of non-production and production workers, respectively. Column 7 presents the FE-IV estimate for the gross real outputs of industries. These variables are impacted by imports via both channels. Panel B shows that doubling imported intermediates within a year and industry leads to 8.6% increase in the employment ratio and 9.6% increase in the wage-bill ratio of non-production workers relative to production workers. Thus, offshoring leads to substantial increases in the relative wage-bill and employment of skilled workers. However, estimates in columns 3-6 show that both groups of workers benefit in terms of absolute wage-bill and employment. Doubling offshoring leads to 18.6% increase

Table 5: FE-IV Estimation Second Stage - Both Channels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Excluded Instruments - Contemporaneous Exchange Rate							
	Employment Ratio	Wage Bill Ratio	Non-Production Wage Bill	Non - Production Employment	Production Wage Bill	Production Employment	Gross Output
Imported Intermediates	0.068	0.087*	0.290**	0.317***	0.203*	0.249**	0.126
	(0.048)	(0.050)	(0.120)	(0.118)	(0.111)	(0.110)	(0.138)
Observations	14,569	14,568	14,568	14,569	14,570	14,570	14,570
F statistic	35.31	26.37	19.40	16.87	45.44	43.30	28.82
Panel B: Excluded Instruments - Contemporaneous and One Year Lagged Exchange Rate							
	Employment Ratio	Wage Bill Ratio	Non-Production Wage Bill	Non - Production Employment	Production Wage Bill	Production Employment	Gross Output
Imported Intermediates	0.086**	0.096**	0.282***	0.300***	0.186*	0.215**	0.119
	(0.042)	(0.044)	(0.109)	(0.106)	(0.099)	(0.097)	(0.114)
Observations	14,104	14,103	14,103	14,104	14,105	14,105	14,105
F statistic	34.06	21.84	18.78	16.34	44.80	44.74	28.94
Hansen's J statistic (p-value)[1]	.11 (.75)	1.45 (.23)	3.28(.07)	3.16(.08)	1.90(.17)	3.21(.07)	.08 (.78)
Panel C: Excluded Instruments - Contemporaneous, One Year and Two Years Lagged Exchange Rate							
	Employment Ratio	Wage Bill Ratio	Non-Production Wage Bill	Non - Production Employment	Production Wage Bill	Production Employment	Gross Output
Imported Intermediates	0.100**	0.105**	0.294***	0.301***	0.189**	0.201**	0.166*
	(0.043)	(0.045)	(0.109)	(0.105)	(0.096)	(0.093)	(0.099)
Observations	13,639	13,638	13,638	13,639	13,640	13,640	13,640
F statistic	34.56	21.68	17.54	16.54	42.46	45.70	24.33
Hansen's J statistic (p-value)	6.74 (.04)	6.58 (.04)	6.29(.04)	6.17(.05)	2.54(.28)	3.17(.21)	2.03 (.36)
Number of 4-digit industries	459	459	459	459	459	459	459

Notes:

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

[1]: The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of (L-K) overidentifying restrictions. The p-value shows that in all cases (except in the regression for R&D intensity in the bottom panel) we are unable to reject the null hypothesis that the instruments are valid. In the first panel, the equations are exactly identified. So overidentification test is not possible.

All regressions include year fixed effects, 4-digit industry fixed effects and interactions of 2 digit industry dummies with an indicator for whether the year is post 1996.

Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.

All variables are in natural logs.

in the wage-bill and 21.5% increase in the employment of production workers. Gross output also rises by an economically significant amount, although the estimate is imprecise.[39] These coefficients imply that a one standard deviation change in imported intermediates (=1.22) leads to 0.18 and 0.21 standard deviation changes in the relative employment and wages of non-production workers. However, for the same change in imported intermediates, production workers' employment and wage-bill also rise by 0.25 and 0.2 standard deviations. The estimates in Panels A and C are also similar to those in B. Including two lags of exchange rates (Panel C), I find that the coefficients on imports in the regression for gross output is statistically significant and suggest that the total industrial output rises by 16.6% when offshoring doubles.

The increase in the wage-bill and employment of unskilled workers who might be substituted for by imported unskilled intermediates is consistent with some existing work. Even under perfect substitution, Feenstra (2008) and Grossman and Rossi-Hansberg (2008) have shown the possibility of a positive effect. Feenstra (2008) shows that offshoring can generate an increase in real wages of domestic unskilled workers if it leads to a larger decline in final good prices than in nominal wages. Grossman and Rossi-Hansberg (2008) showed that real wages can rise due to "productivity effect." This effect derives from the cost savings that result from offshoring. Cost savings in the unskilled stages of production are akin to an unskilled labor augmenting technological change that increases the unskilled labor productivity. These cost savings create incentives for industries to expand their output causing them to demand more unskilled workers putting an upward pressure on their wages. If these effects dominate the negative effects of offshoring on unskilled wages and employment, then we expect to see a net positive relationship between the two.

I show that, in addition to these effects, the gains for unskilled workers are also driven by imperfect substitution between imported and domestic intermediates, and more importantly by the technology channel. The productivity effect exists only when there is an expansion in the output of the industry that offshores; if output remained constant, then there is no increase in the demand for unskilled workers. This, however, is not supported in the data. I find that the aggregate time series correlation between offshoring and production workers' wages, weighted by constant industry size, is 0.08. Additionally, offshoring has a large positive effect on the wage-bill of unskilled workers, controlling for output. Since in the H-O channel that considers imported intermediates as perfect substitutes for unskilled workers, wages could increase only through expansion in output, these results suggest that imported intermediates are not perfect substitutes for domestically produced unskilled intermediates. Further, as I will show in the empirical decompositions, the technology channel creates large wage and employment gains for unskilled workers. The technology channel is not only a theoretical possibility, but is also strongly supported in the data. These are the results I present next.

Consider the outcomes of the technology channel (Table 6). The most important outcome

[39] To the extent that offshoring takes the form of sub-contracting the production of final products themselves, the theoretically predicted rise in domestic output of industries may fall in magnitude.

Table 6: FE-IV Estimation Second Stage - Technology Channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Excluded Instruments - Contemporaneous Exchange Rate								
	Equipment	Total Capital	Equipment / Labor	Total Capital / Labor	R&D	R&D Intensity	Number of Exported Varieties	Price
Imported Intermediates	0.362***	0.362***	0.097	0.104	0.344	0.442**	0.054[2]	0.195**
	(0.115)	(0.115)	(0.088)	(0.084)	(0.252)	(0.192)	(0.091)	(0.094)
Observations	14,570	14,570	14,570	14,570	13,746	13,746	6,589	14,570
F statistic	31.72	20.79	133.0	105.1	13.36	37.25	_	30.62
Panel B: Excluded Instruments - Contemporaneous and One Year Lagged Exchange Rate								
	Equipment	Total Capital	Equipment / Labor	Total Capital / Labor	R&D	R&D Intensity	Number of Exported Varieties	Price
Imported Intermediates	0.374***	0.365***	0.134*	0.125*	0.324	0.399**	0.054	0.180**
	(0.106)	(0.101)	(0.078)	(0.073)	(0.227)	(0.174)	(0.091)	(0.076)
Observations	14,105	14,105	14,105	14,105	13,293	13,293	6,589	14,105
F statistic	31.74	21.39	121.0	102.7	12.68	36.50	_	31.19
Hansen's J statistic (p-value)[1]	2.93 (.09)	3.89 (.05)	.09 (.76)	.32 (.57)	1.48(0.23)	7.22 (.01)	_	3.08 (.08)
Panel C: Excluded Instruments - Contemporaneous, One Year and Two Years Lagged Exchange Rate								
	Equipment	Total Capital	Equipment / Labor	Total Capital / Labor	R&D	R&D Intensity	Number of Exported Varieties	Price
Imported Intermediates	0.419***	0.393***	0.182**	0.156**	0.376*	0.398**	0.054	0.153**
	(0.111)	(0.104)	(0.079)	(0.073)	(0.228)	(0.179)	(0.091)	(0.063)
Observations	13,640	13,640	13,640	13,640	12,839	12,839	6,589	13,640
F statistic	28.79	19.59	109.7	99.02	12.19	35.25	_	34.00
Hansen's J statistic (p-value)	7.62 (.02)	7.71 (.02)	3.52 (.17)	2.38 (.30)	2.84(0.24)	12.3 (.00)	_	6.17 (.05)
Number of 4-digit industries	459	459	459	459	394	459	456	456

Notes:

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

[1]: The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of (L-K) overidentifying restrictions. The p-value shows that in all cases (except in the regression for R&D intensity in the bottom panel) we are unable to reject the null hypothesis that the instruments are valid. In the first panel, the equations are exactly identified. So overidentification test is not possible.

[2]: The marginal effect in all three panels = 0.047 with a standard error of 0.064. The bootstrapped standard errors are in parenthesis. The standard errors need to be bootstrapped because the fitted residuals from the first stage regression (of imported intermediates on excluded instruments, and year and industry dummy variables) are included as a regressor in the second stage Poisson regression to correct for the endogeneity of imports.

All regressions include year fixed effects, 4-digit industry fixed effects and interactions of 2 digit industry dummies with an indicator for whether the year is post 1996.

Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.

All variables are in natural logs.

variables of interest are innovation (measured by R&D expenditure and R&D intensity) and technology adoption (measured by real stocks of equipment or total capital, or as ratios of total labor employed). In Panel B (my preferred set of estimates), the effects of offshoring on these outcome variables are economically and statistically significant. Doubling the imports of inputs from low-wage nations leads to about 40% rise in the innovation intensity. In response to the same increase in offshoring, real equipment stock increases by 37.4%, while the equipment-labor ratio increases by 13.4%. Thus, the data strongly support my technology channel. In terms of standard deviations, these estimates imply that a one standard deviation change in imported intermediates leads to a 0.17 standard deviation change in equipment-labor ratio and a 0.3 standard deviation change in R&D intensity.

Moreover, the product variety mechanism is supported in the data. According to the mechanism, offshoring induces firms to produce new varieties leading to an increase in the number of products and final goods prices. The results for these two variables are presented in columns 7 and 8. We can see that offshoring positively impacts the number of exported varieties within an industry, although the estimates are imprecise. Since this coefficient is obtained from a non-linear (Poisson) regression, I look at the marginal effect. At the mean of the dependent variable, the number of products increases by 4.7% when offshoring doubles.[40] Column 8 in Panel B indicates that doubling offshoring from low-wage countries causes 18% growth in an industry's final goods price level. Thus, in net terms, the rise in prices because of the variety effect more than compensates for the decline in the price level due to a fall in costs of production. The estimates in Panels A and C are also similar to those in Panel B. These results indicate strong technology effects of offshoring on developing countries.

The results presented so far are for regressions in which the outcome variables are measured contemporaneously with offshoring. However, capital deepening and innovation are relatively slower process than changes in labor employment and wage bills. In Table 7, I present results for estimations in which current values of technology adoption and innovation are regressed on lagged values (1-3 years) of offshoring. Results are qualitatively similar to those presented in Tables 5 and 6. As expected, innovation is more responsive to lagged than to contemporaneous offshoring. The magnitudes for technology adoption are very close to those obtained from contemporaneous regressions. This indicates that the dynamic effects of offshoring on technology adoption and innovation are larger than the short run effects. Offshoring also impacts the future non-production and production workers' wage bills, although the latter is statistically insignificant.

[40] To ascertain the causal effect of offshoring on the number of varieties, I perform a two-step estimation. In the first step, I regress the imported intermediates on the current and lagged values of exchange rates, along with the year and industry fixed effects. In the second step, I estimate a fixed-effects Poisson regression of the number of exported varieties on imports and other fixed effects, additionally including the fitted residuals from the first step as a regressor. This procedure controls for the endogeneity of imports. I also bootstrap the standard errors so as to account for the two-step estimations.

Table 7: Dynamic Effects of Offshoring

	Equipment / Labor	Total Capital / Labor	R&D Intensity	Production Wage Bill	Non Production Wage Bill
			One Year Lag		
Imported Intermediates[1]	0.129*	0.126*	0.579***	0.153	0.260**
	(0.077)	(0.073)	(0.193)	(0.094)	(0.103)
			Two Years Lag		
Imported Intermediates	0.105	0.106*	0.421**	0.130	0.219**
	(0.066)	(0.061)	(0.165)	(0.079)	(0.086)
			Three Years Lag		
Imported Intermediates	0.113*	0.125**	0.491***	0.078	0.175**
	(0.062)	(0.059)	(0.165)	(0.074)	(0.079)

Notes:
*** p<0.01, ** p<0.05, * p<0.10
Excluded instruments: Current and lagged exchange rates, lagged price deflator for investment
[1]: As a proportion of total non-energy materials used in the industry.
All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996.
Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.
All variables are in natural logs.

Decomposing the Heckscher-Ohlin and Technology Channels

Summarizing the results so far, a rise in offshoring to low income countries leads to substantial increases in innovation, technology adoption, and wages and employment of both skilled and unskilled workers, with skilled workers benefiting more. However, the quantitative estimates for wages and employment confound the distinct impacts of offshoring via the H-O and technology channels. Estimating the distinct effects of the two channels is empirically challenging as I do not have a way to identify the exogenous variations in all the variables that must be held constant on the right hand side. However, the lagged price deflator for investment can serve as an instrument for capital-labor ratio. Thus, I control for capital (or equipment) to labor ratio on the right hand side in addition to the imports measure. In addition to exchange rates, I use the lagged price deflator for investment as an excluded instrument.

The first stage results are presented in Table 8. There are two first stage regressions for two endogenous regressors: offshoring and technology adoption (measured as total capital-labor or equipment-labor ratio). The first three columns include only the contemporaneous exchange rates while columns (2a)-(2c) also include a lag. Results in both specifications are very similar. We can again see the J-curve effect. The negative coefficients on the price deflator in columns 1b and 1c show that industries invest less in capital when investment becomes more expensive. The Kleibergen-Paap Wald rk F statistic is greater than ten in all cases, suggesting a strong first stage.

As Table 9 shows, including the equipment-labor ratio, substantially reduces the 2sls co-

Table 8: First Stage - Decomposing the Heckscher-Ohlin and Technology Channels

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Imported Intermediates[1]	Total Capital / Labor	Equipment / Labor	Imported Intermediates	Total Capital / Labor	Equipment / Labor
Lagged Price Deflator for Investment	0.184	-1.029***	-1.239***	0.191	-1.029***	-1.238***
	(0.332)	(0.101)	(0.102)	(0.332)	(0.101)	(0.102)
Exchange Rate	-0.185***	-0.017	-0.016	-0.275***	-0.014	-0.017
	(0.040)	(0.015)	(0.016)	(0.044)	(0.010)	(0.011)
Lagged Exchange Rate				0.110***	-0.003	0.001
				(0.041)	(0.010)	(0.010)
Observations	14,109	14,109	14,109	14,103	14,103	14,103
Number of 4 digit industries	459	459	459	459	459	459
Kleibergen-Paap rk Wald F statistic	11.04	51.71	74.52	13.43	34.94	50.43
Shea's Partial R-squared	0.012	0.104	0.13	0.013	0.104	0.13

Notes:
*** p<0.01, ** p<0.05, * p<0.10
[1]: As a proportion of total non-energy materials used in the industry.
[2]: Kleibergen-Paap Wald rk F statistic with degrees of freedom = L1-K1+1; K1 = no. of enodogenous regressors, L1 = no. of excluded instruments
All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996.
Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.
All variables are in natural logs.

efficients on offshoring relative to those in Table 4. The coefficients also become statistically insignificant. And yet, equipment-labor ratio is just one of the variables that change in the technology channel. Not controlling for the other variables means that the H-O effects of imports are overestimated. Controlling for innovation using R&D intensity (columns 1(b) and 1(d)), albeit without treating endogeneity, the estimated effects of import fall even more. These results suggest that the effect of offshoring on the relative wages and employment of skilled workers is almost entirely through the induced investment in innovation and capital. Finally, it is noteworthy that the positive coefficients on the equipment-labor ratio in these equations for employment and wage-bill ratios reflect capital-skill complementarity.[41]

The decomposition of channels is more challenging when the outcome variables are the levels of employment and real wage-bills of non-production and production workers. Controlling for technology adoption using the equipment-labor ratio is infeasible as this measure creates division bias. Hence, I use equipment relative to output as an alternative measure. The lagged price deflator for investment, that I have so far used as the instrument for technology adoption, however, is a weak instrument for capital-output ratio; the first stage Kleibergen-Paap Wald rk F statistic is less than 10. Instead, I use the lagged price deflator for investment divided by the price deflator for output as an alternative instrument. The first stage results using this as

[41]The results presented in Table 9 are for the specifications in which the excluded regressors are current and one-year lagged exchange rate constructs, and lagged price deflator for investment; results with only the contemporaneous or an additional lag of exchange rate-based excluded instruments are very similar.

Table 9: Second Stage - Decomposing the Heckscher-Ohlin and Technology Channels

	Employment Ratio				Wage Bill Ratio			
	(1a)	**(1b)**	**(1c)**	**(1d)**	**(2a)**	**(2b)**	**(2c)**	**(2d)**
Imported Intermediates[1]	0.028	0.020	0.034	0.031	0.040	0.039	0.046	0.050
	(0.045)	(0.045)	(0.043)	(0.043)	(0.046)	(0.046)	(0.044)	(0.045)
Total Capital / Labor	0.459***	0.462***			0.450***	0.445***		
	(0.125)	(0.130)			(0.135)	(0.139)		
Equipment / Labor			0.383***	0.387***			0.375***	0.371***
			(0.106)	(0.111)			(0.113)	(0.119)
R&D Intensity		-0.002		-0.004		0.003		0.001
		(0.006)		(0.006)		(0.007)		(0.007)
Observations	14,104	13,292	14,104	13,292	14,103	13,291	14,103	13,291
Number of 4 digit industries	459	456	459	456	459	456	459	456
F statistic	39.29	38.52	41.28	40.18	26.83	37.71	27.89	40.01
Hansen's J statistic (p-value)[2]	0.02 (.90)	.05 (.82)	.01 (.91)	.02 (.90)	.62 (.43)	.54 (.46)	1.08 (.30)	1.15 (.28)

Notes:
*** p<0.01, ** p<0.05, * p<0.10
Excluded instruments: Current and lagged exchange rates, lagged price deflator for investment
[1]: As a proportion of total non-energy materials used in the industry.
[2]: The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of (L-K) overidentifying restrictions. The p-value shows that in all cases we are unable to reject the null hypothesis that the instruments are valid. In the left panel, the equations are exactly identified. So overidentification test is not possible.

All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996.
Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.
All variables are in natural logs.

variable as the excluded instrument show that it is a strong IV with the Kleibergen-Paap Wald rk F statistic well above 10. Results from the second stage are presented in Table 10. As expected, controlling for technology adoption reduces the coefficient on imported intermediates for all outcome variables. Additionally controlling for R&D intensity shows that higher investments in innovation are associated with higher wage-bills and employment for both groups of workers.

The small drop in the coefficients on imports in these specifications may suggest that the positive impact of offshoring on wages and employment of production and non-production workers is primarily through the H-O channel. But it also suggests that imported and domestic intermediates are indeed imperfect substitutes. However, this decomposition strategy has several limitations, so that the results should be interpreted with caution. First, as already mentioned, instead of measuring technology adoption as equipment relative to labor, I measure it as equipment relative to output. Second, R&D intensity is endogenous in these regressions (and other variables like number of varieties and prices would also be endogenous control variables). Third, the validity of the instrument for technology adoption is suspect because the price deflator for output may have an independent effect on the outcome variables in addition to its effect through the capital-output ratio.

A few concerns remain. First, it is possible that the results for imported intermediates are being driven by movements in final good imports. To address this concern, I divide the sample

Table 10: Second Stage - Decomposing the Heckscher-Ohlin and Technology Channels

	Non-Production Workers Wage Bill		Non-Production Workers Employment		Production Workers Wage Bill		Production Workers Employment	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Imported Intermediates[1]	0.270**	0.238**	0.288***	0.259**	0.189*	0.163*	0.209**	0.194**
	(0.106)	(0.104)	(0.103)	(0.102)	(0.098)	(0.097)	(0.096)	(0.095)
Equipment / Output	0.049	0.030	0.052	0.035	-0.011	-0.023	0.024	0.013
	(0.087)	(0.079)	(0.075)	(0.069)	(0.089)	(0.085)	(0.086)	(0.084)
R&D Intensity		0.042***		0.033**		0.030**		0.025*
		(0.015)		(0.015)		(0.014)		(0.014)
Observations	14,103	13,291	14,104	13,292	14,105	13,293	14,105	13,293
Number of 4 digit industries	459	456	459	456	459	456	459	456
F statistic	17.95	16.50	15.70	15.94	44.30	39.45	43.35	41.33
Hansen's J statistic (p-value)[2]	3.19 (.07)	1.90 (.17)	3.03 (.08)	1.90 (.17)	2.05 (.15)	1.19 (.28)	3.21 (.07)	2.34 (.13)

Notes:
*** p<0.01, ** p<0.05, * p<0.10
Excluded instruments: Current and lagged exchange rates, lagged price deflator for investment
[1]: As a proportion of total non-energy materials used in the industry.
[2]: The joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of (L-K) overidentifying restrictions. The p-value shows that in all cases we are unable to reject the null hypothesis that the instruments are valid. In the left panel, the equations are exactly identified. So overidentification test is not possible.
All regressions include year fixed effects, 4-digit industry fixed effects and interactions of two digit industry dummies with an indicator for whether the year is post-1996.
Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.
All variables are in natural logs.

of industries into two halves based on the average import penetration from developing countries in these industries. The top half industries have above-median import penetration from low-wage countries and the industries in the bottom half have below-median import penetration from low-wage countries.[42] If the final good imports are driving the main results, I expect to see that the results are very similar to the main results for the industries in the top half but much less so for the industries in the bottom half. The first stage for the top half sub-sample of industries has a F-statistic greater than ten (13.69) when the contemporaneous and one lag of exchange rates are used as the excluded instruments. For the bottom half sub-sample of industries, the specification with the contemporaneous exchange rate used as the excluded instrument yields the strongest first stage with a F statistic of 14.07. The second stage results for these specifications are presented in Table 11. The top panel presents results for the industries in the top half of the sample. The estimates suggest that offshoring in these industries has negative effects on employment and wage-bill ratios as well as on R&D intensity. The coefficients for technology adoption measures are positive but small in magnitude. On the other hand, the results in the bottom half of the industries that face less import competition from developing countries than the median industry show a similar pattern as for the full sample

[42] An alternative strategy is to include both final imports and offshoring as regressors in equations for the various outcome measures. However, the exchange rate constructs used as instruments for both of these endogenous regressors are very highly correlated with each other yielding a very noisy first stage.

of industries. All the outcome variables (except the real price level) are impacted positively by increased offshoring. For all outcome variables, the coefficients on imports are also statistically significant. This pattern is inconsistent with the expected results if the final good imports were strongly influencing the main results. Thus, I conclude that my results are not being driven by movements in the final good imports.

A second concern is that the measure of offshoring used in this paper includes both related party and arm's length trade. It is likely that a substantial fraction of imported intermediates are from transactions between related parties, eg. multinational firms may shift some part of their production processes to foreign countries. A narrow measure of offshoring that includes intermediate imports belonging to the same two digit industry (suggested by Feenstra and Hanson (1999)) may be a closer proxy for related party trade. Related party trade data for 2002-2007 is also available. Multinational firm production data (available from BEA) may also be used for this purpose. Existing evidence shows that relatively more productive and capital intensive firms engage in greater levels of related party trade. Nonetheless, I expect the labor market implications of such trade to be qualitatively the same as the results obtained from the measure used in this paper.

Finally, the empirical estimates presented above could also be capturing other mechanisms in addition to the H-O and technology channels that the paper focuses on. This may particularly be the case for innovation. I suggest a few alternative mechanisms underlying the positive relationship between offshoring and innovation. With falling costs of transport and communication technologies, firms may find greater opportunities to offshore. This may lead them to invest in innovation to standardize production techniques and make organizational changes. Alternatively, firms may innovate to maintain their market shares. The subcontractor firms in the developing countries that perform the offshored tasks may eventually become competitors as they gain knowledge and expertise about the production of the final goods themselves. To secure themselves against such competition, firms in the advanced countries may defensively innovate to produce superior products with technologies that are not readily imitable. To my knowledge, these alternative mechanisms have not been examined before. Yet another possibility, offered by Glass and Saggi (2001), is that the higher profits caused by offshoring make it feasible for them to invest in innovation. All of these channels imply a positive relationship between offshoring and innovation and may be picked up by the estimated coefficient on offshoring in the equation for R&D expenditures. Nonetheless, regardless of which one is the strongest underlying mechanism, my results point towards a strong and robust positive impact of offshoring on innovation in the U.S. industries.

Table 11: FE-IV Estimates for Sub-Samples of Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Employment Ratio	Wage Bill Ratio	Production Wage Bill	Production Employment	R&D Intensity	Total Capital	Equipment	Total Capital / Labor	Equipment / Labor	Price
Industries with Above Median Import Penetration from Developing Countries[2]										
Imported Intermediates[1]	-0.070**	-0.081**	0.065	0.047	-0.081	0.023	0.049	-0.017	0.009	-0.033
	(0.035)	(0.040)	(0.064)	(0.062)	(0.129)	(0.052)	(0.059)	(0.050)	(0.054)	(0.040)
Observations	6,940	6,939	6,941	6,941	6,379	6,941	6,941	6,941	6,941	6,941
Number of 4 digit industries	225	225	225	225	224	225	225	225	225	225
Industries with Below Median Import Penetration from Developing Countries[3]										
Imported Intermediates[1]	0.133*	0.163*	0.124	0.189	0.705***	0.358**	0.306*	0.122	0.070	-0.034
	(0.075)	(0.087)	(0.142)	(0.138)	(0.261)	(0.162)	(0.166)	(0.111)	(0.112)	(0.060)
Observations	7,145	7,145	7,145	7,145	6,907	7,145	7,145	7,145	7,145	7,145
Number of 4 digit industries	226	226	226	226	224	226	226	226	226	226

Notes:

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

[1]: As a proportion of total non-energy materials used in the industry.

[2]: Excluded instruments: Contemporaneous and one year lagged exchange rate (Kleibergen-Paap Walk rk F statistic = 13.69)

[3]: Excluded instruments: Contemporaneous exchange rate (Kleibergen-Paap Walk rk F statistic = 14.07)

All regressions include year fixed effects, 4-digit industry fixed effects and interactions of 2 digit industry dummies with an indicator for whether the year is post-1996.

Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the level of 4-digit industries.

All variables are in natural logs.

6 Conclusion

This paper develops a new mechanism by which a rise in offshoring to developing countries induces the adoption of skill-complementary technology and innovation, impacting labor markets in advanced countries. Empirical results lend strong support to the presence of this technology channel in the U.S. manufacturing industries. Results show that this channel is the primary mechanism underlying the effect of offshoring on the relative wage-bills and employment of skilled labor. Although it increases inequality, offshoring does not hurt unskilled workers - the absolute wage-bills and employment of unskilled workers increases with offshoring. Thus, induced technology adoption and innovation generate quantitatively important gains for all workers. These results suggest that instead of discouraging offshoring, policies that encourage innovation, and facilitate investment will prove helpful.

Future work will extend the analysis by analyzing firm level data. Firms with different skill intensities, different costs of innovation and different levels of technology use may respond to different degrees to similar increases in offshoring. This research agenda will help examine two questions: What are the characteristics of firms that offshore? And, amongst the firms that offshore, what is the extent of heterogeneity in their responses to offshoring with regard to their total employment, skill mix, output, technology adoption and innovation?

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Appendices

Appendix A Data Appendix

U.S. Imports and Exports Data

The imports data for the United States are obtained from the Center for International Data at University of California, Davis. The c.i.f. (cost, insurance, freight) values of imports are available for the years after 1973. Thus, the first year of my sample is 1974. For years up to 1994, the Center for International Data also provides imports data aggregated to the 4 digit domestic SIC 1972 level. I directly use these aggregated data for the period until 1994. I concord these data at SIC 1972 to the domestic SIC 1987 classification (for uniformity with manufacturing industry data). Also, I group the imports from various countries into two groups - imports from developed, and miports from developing countries using the World Bank Income Classification. For the period 1995-2005, I use the disaggregated imports data. These data are available at the level of 10 digit HS categories. Grouping the source countries as developed and developing, I aggregate the dollar value of imports in each product category from these two sets of countries. The next step is to aggregate these imports to the level of 4 digit industries under the SIC 1987 classification. For this purpose, I first aggregate these imports to the level of 4 digit import based SIC 1987 and then map them into the domestic SIC 1987 classification using the procedure described in Feenstra, Romalis and Schott (2002).

NBER-CES Manufacturing Productivity Database

Data on 459 four digit manufacturing industries in the United States are available from the NBER website. These data are available for the period 1958 to 2005 at a uniform Standard Industrial Classification of 1987, i.e., the data are adjusted for changes in industry definitions and classifications over time. Many of the variables are taken from the Census Bureau's Annual Survey of Manufactures and the quinquennial Census of Manufactures. The variables that I obtain from this databse include nominal values of annual shipments, the number of non-production and production workers employed and their average wages, nominal values of non-energy materials, real values of total capital stocks, and of equipment and structures (calculated according to the perpetual inventory method), and the industry level price indexes for shipments and investment.

Compustat

Compustat is a database that provides data on all publicly traded firms in the United States. From these data, I obtain annual expenditures of public firms on research and development and their annual sales. The R&D data include all non-federally funded expenditures of the firms in any given year for the purpose of producing and improving their products and services. The database includes firms that are not legally incorporated in the U.S. I drop these firms from the sample so as to retain only the domestic firms. Each firm is identified uniquely with a GV key. The four digit SIC 1987 industry that a firm belongs to is also provided. I aggregate the R&D expenditures incurred by all firms belonging to the same SIC 1987 industry to create an industry level R&D measure. Similarly, I aggregate the sales of all firms belonging to any given industry to create an industry level sales measure. R&D divided by sales gives me a measure of R&D intensity in an industry. Some firms may belong to more than one 4 digit SIC industry. In this case, Compustat provides only a 2 digit SIC 1987 code. I assign the R&D expenditures of these firms to the constituent 4 digit industries using the following procedure: I calculate the share of each constituent 4 digit industry in the total value of shipments in the broader 2 digit industry for each year. Using these shares as weights I split the R&D expenditures of the firm over all the 4 digit industries it belongs to. Also, for a few firms, the R&D and sales data are reported in Canadian dollars. I convert them to U.S. dollars using the exchange rates prevailing in those years.

Input-Output Tables

The Bureau of Economic Analysis provides detailed benchmark Input-Output (I-O) Accounts (make tables, use tables, and direct requirements coefficients tables) every five years. I use the direct requirement coefficients tables provided every five years for the period 1972-2002. For 1972 and 1977, the direct requirement coefficients were not provided. I constructed them from the use tables. The I-O industry codes for various years are based on the Standard Industrial Classification of various years until 1992. The I-O codes for 1997 and 2002 are based on NAICS 1997 and 2002, respectively. I concorded the I-O codes for all the years to 4-digit SIC 1987. Direct requirement coefficients are defined as the dollar value of an input required by an industry to produce one dollar of its output. Voigtlander (2010) shows that these coefficients are stable across years. For this reason, and following Feenstra and Hanson (1996), I linearly interpolate the coefficients for the interim years between each pair of years for which the benchmark I-O tables are available. For the period 2003-2005, I linearly extrapolate the coefficients for the year 2002.

Other Data Sources

Penn World Tables: From this database, I obtained the annual averages of the nominal exchange rates of the currencies of foreign countries relative to the U.S. dollar. for the period 1974 to 2005. An increase in the exchange rate implies an appreciation of the U.S. dollar vis-a-vis the foreign currency.
World Bank Income Classification: The World Bank classifies all countries into one of five categories: High Income: OECD, High Income: non-OECD, Upper Middle Income, Lower Middle Income and Low Income. These classifications are uniform over the sample period 1974-2005. I obtain these classifications

from the World Bank website. For the empirical analysis in this paper, I group upper middle income, lower middle income and low income countries together as "developing" or "low income" countries. High income OECD and non-OECD countries are grouped together as "advanced," "developed," or "high income" countries.

Tariffs: I construct a series of average tariffs for intermediates imported in an industry using data on the customs value of imports and the duties paid on them. I aggregate the total customs value and total duties paid for all imported product categories belonging to a given 4 digit industry, separately for imports from developed and developing countries. Taking the ratio of total duties to total customs value, and multiplying by 100, provides a measure of the average tariff rate in the 4 digit industry for each year, separately for imports from developed and developing countries. Between 1974 and 1988, the data provide the four digit SIC 1972 industries that the imported product categories belong to. For the years after 1988, the data provide the import based SIC 1987 industries that the products belong to. I concord the SIC 1972 and import based SIC 1987 classifications to domestic SIC 1987 classification using the same method as described above for the U.S. imports data. This provides me with the average tariff rates imposed on imports belonging to all 4 digit SIC 1987 industries. To get a measure of tariffs imposed on imported intermediates, I follow the same procedure as that used for exchange rates.

CPI: The U.S. consumer price index data are obtained from the Bureau of Labor Statistics. This price index is used to construct a series of real prices for 4 digit industries by dividing the industry level price index by the U.S. CPI.