Immigration, Offshoring and American Jobs

By Gianmarco I.P. Ottaviano and Giovanni Peri and Greg C. Wright*

Following Grossman and Rossi-Hansberg (2008) we use an assignment model of tasks of varying complexity to workers of varying skill in order to develop and test systematic predictions regarding the effects of immigration and offshoring on U.S. native manufacturing workers. We find that immigrants and natives do not compete much with one another due to the fact that they tend to perform tasks at opposite ends of the task complexity spectrum, with offshore workers performing the tasks in the middle. The null effect of offshoring and the positive effect of immigration on native employment suggest that both immigration and offshoring improve industry efficiency, thereby creating new jobs, some of which go to natives.
JEL: F22, F23, J24, J61
Keywords: Employment, production tasks, immigrants, offshoring

The relocation of jobs abroad by multinationals and the increased labor market competition due to immigrant workers are often credited with the demise of many manufacturing jobs once held by American citizens. While it is certainly true that manufacturing production and employment, as a percentage of the total economy, have declined over recent decades in the U.S., measuring the impact of those two aspects of globalization on jobs has been difficult. This is due to the possible presence of two opposing effects. On the one hand, there is a direct "displacement effect": offshoring some production processes or hiring immigrants to perform them directly reduces the demand for native workers. On the other hand, there is an indirect "productivity effect": the cost savings associated with employing immigrant and offshore labor increases the efficiency of the production process, thus raising the demand for native workers–if not in the same tasks that are offshored or given to immigrant workers, then certainly in tasks that are complementary to them.

Several recent papers have emphasized the potential productivity effect of offshoring, arguing that this effect could offset or even reverse the displacement effect and thereby generate an overall non-negative effect on the wage or employment of native workers (Grossman and Rossi-Hansberg, 2008; Costinot and Vogel, 2010; Harrison and McMillan, 2011; Wright

* Gianmarco I.P. Ottaviano, Department of Economics, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK. Email: g.i.ottaviano@lse.ac.uk. Giovanni Peri, Department of Economics, UC Davis, One Shields Avenue, Davis, CA 95616. Email: gperi@ucdavis.edu. Greg C. Wright, Department of Economics, University of Essex, Wivenhoe Park, Colchester CO4 3SQ. Email: gcwright@essex.ac.uk. This paper was written as part of the project "Mobility of People and Mobility of Firms" coordinated by the Centro Studi Luca d'Agliano (LdA) and funded by the Fondazione CRT. For detailed disclosure statements please consult the journal's website. We thank Daron Acemoglu, Giorgio Barba-Navaretti, Rosario Crinò, Gordon Hanson, Rob Feenstra, Gene Grossman, Alan Manning, John McLaren, Peter Neary, Esteban Rossi-Hansberg, Dan Trefler and participants in several seminars and conferences for useful comments and suggestions.

2012). These papers focus on the patterns of substitutability between native and offshore workers. Other papers have suggested that immigrants may generate an analogous productivity effect by increasing the demand for native workers, especially in production tasks that are complementary to those performed by immigrants (Ottaviano and Peri, 2012; Peri, 2009; Peri and Sparber, 2009). These papers look at the patterns of substitutability between native and immigrant workers. Little attention has been paid so far to the simultaneous patterns of substitutability between native, immigrant and offshore workers.

In this paper we argue that the joint investigation of the interactions among these three groups of workers is useful in order to improve our understanding of the impact of globalization on the U.S. labor market and, in particular, to answer two hotly debated questions. First, how do declines in offshoring and immigration costs affect the employment of native workers? Second, what kinds of jobs suffer, or benefit, the most from the competition created by offshore and immigrant workers?

At the core of our argument are two observations: first, that jobs ("tasks") vary in terms of the relative intensity of use of complex tasks and, second, that native, immigrant and offshore groups differ in their efficiency in performing complex tasks. Throughout the paper we consider the complexity of a task to be increasing in the intensity of use of communication and cognitive skills and decreasing in the manual content of the task. Communication skills may be important because the execution of complex tasks often requires a sophisticated dialogue between workers whereas, in contrast, manual tasks are much easier to describe and carry out in the absence of these skills. It is therefore natural to think that the cost of performing tasks in other countries (offshoring) or assigning these tasks to people with limited knowledge of the local language and culture (immigrants) increases with the complexity of the task. Efficiency gains can then be reaped by hiring these workers to perform tasks in which they have a comparative advantage, that is, in which they generate a lower cost per efficiency unit of labor,[1] while also giving native workers the opportunity to specialize in the tasks in which they exhibit their own comparative advantage. If strong enough, the productivity effect associated with this efficient pattern of task specialization may offset the displacement effect of immigration and offshoring on native workers' employment.

We develop this argument in three steps. First, we present some new facts on 58 industries, which together comprise the U.S. manufacturing sector, from 2000 to 2007. We argue that these facts are consistent with a scenario in which: (a) there is stronger substitutability between immigrants and offshore workers than between immigrants and natives; (b) immigrant, native and offshore workers are relatively specialized in tasks of different skill complexity; and, in particular, (c) immigrants are relatively specialized in low complexity tasks, natives in high complexity tasks, and offshore workers in medium complexity tasks.[2]

[1]See Costinot and Vogel (2010) for the equivalence of the trade concept of "comparative advantage" and the matching concept of "log-supermodularity".

[2]The choice to focus on manufacturing and not include services reflects the research questions we have chosen to address. It is also forced on us by data availability as there is limited data on services offshoring. Moreover, the production function approach at the core of our analysis is much better understood in the context of manufacturing than in the context of services. Lastly, the range of skills spanned by tasks is richer in manufacturing than in services,

Unfortunately, the complexity of the tasks performed by offshore workers is not directly observable.

In the second step we build on Grossman and Rossi-Hansberg (2008) to design a partial equilibrium model of task assignment among heterogeneous native, immigrant and offshore workers within an industry that is consistent with the observed facts. We then use the model to draw systematic predictions of the effects of falling barriers to immigration and offshoring on the tasks, the employment share and the employment level of native workers. An important assumption of the model, consistent with a series of facts that we present, is that offshore workers specialize in tasks of intermediate "complexity" between those of immigrants and natives. The model generates two main sets of predictions. First, borrowing the terminology of Costinot and Vogel (2010), a decline in immigration costs leads to "task upgrading" of immigrants as these workers are assigned some medium complexity tasks that were previously performed by offshore workers. Second, lower immigration costs have little impact on the task complexity of native workers, who are located at the high end of the task complexity spectrum. On the other hand, a decline in offshoring costs simultaneously leads to task upgrading of natives and task downgrading of immigrants: offshore workers are assigned the most complex among the low complexity tasks previously performed by immigrants, as well as the least complex among the high complexity tasks previously performed by natives. In this case, the result is increased task polarization between immigrants and natives in the domestic labor market.

The other set of predictions concerns the response of industry employment following the reallocation of tasks described above. Employment shares move as dictated by the "displacement effect": a group of workers from which tasks are taken away sees its employment share fall; a group of workers to which new tasks are assigned sees its employment share increase. If the "productivity effect" is weak, employment levels move in the same direction as employment shares. On the other hand, when the efficiency gains from immigration or offshoring are strong enough, employment levels may increase for all groups of workers and not only for those whose employment shares go up. Intuitively, the changes in employment *shares* are determined by movements along the relative labor demand curves of the different groups of workers, as dictated by changes in their relative efficiency. The changes in employment *levels*, however, are also affected by the outward shifts in labor demand produced by the increase in the overall efficiency of the production process.

In the end, whether the employment of natives rises or falls when immigration and offshoring become easier, and whether the observed change is consistent with our story, is an empirical issue. By using employment data on immigrants and natives from the American Community Survey (ACS) and on offshore workers by U.S. multinational affiliates from the Bureau of Economic Analysis (BEA), we indeed find that easier offshoring reduces the employment shares of both native and immigrant workers while easier immigration reduces the employment share of offshore workers only, with no impact on the employment share of natives. Nonetheless, when we look at employment levels (rather than shares), we find that easier offshoring does not have any significant effect whereas easier immigration has

leaving more room for gains due to their reallocation.

a positive and mildly significant impact on natives. This is consistent with the existence of positive productivity effects due to immigration and offshoring.

By matching occupation data from the ACS with the manual, communication and cognitive skill content of tasks performed in each occupation (from the U.S. Department of Labor's *O*NET* abilities survey), we then assess the response of the "complexity" of those tasks to immigration and offshoring. Here we find that easier offshoring raises the average complexity of native tasks, increasing the gap between native and immigrant task complexity. In contrast, easier immigration has no effect on the average complexity of native tasks. Overall, our findings imply that immigrants do not compete directly with natives. We suggest that the reason for this is that immigrants and natives are concentrated at opposite ends of the task complexity spectrum. Offshore workers, instead, are specialized in tasks of intermediate complexity (though we do not directly observe this) generating some competition with both immigrants and natives, as revealed by the effect on employment shares and on task intensities of those two groups.

The rest of the paper is organized as follows. The next section describes the novel contributions of this paper in the context of the existing literature. Section II presents the data, highlighting some key facts that inform the subsequent analysis. Section III presents a theoretical model consistent with those facts, deriving predictions to be brought under econometric scrutiny. Section IV produces the econometric evidence on the predictions of the theoretical model. Section V concludes.

I. Related Literature

Several recent papers have analyzed the effect of offshoring on the demand for domestic labor and are relevant to the present analysis. On the theoretical front, Grossman and Rossi-Hansberg (2008) provide a simple model of trade in production tasks. This model will serve as the framework for our analysis, though we will focus on employment rather than on wage effects. [3] Recent and relevant empirical work includes Crinò (2010), Hummels, Jorgenson, Munch and Xiang (2010), Harrison and McMillan (2011) and Wright (2012), each of which have tested some of the implications of existing theories with respect to the wage and employment effects of offshoring. Crinò (2010), who focuses on services offshoring, and Hummels, Jorgenson, Munch and Xiang (2010), who focus on Denmark, both find positive wage and employment effects of offshoring for relatively skilled workers, especially for those performing more complex production tasks, but find that less skilled workers may suffer displacement. Wright (2012) finds a positive productivity effect of offshoring for domestic firms but, on net, an aggregate decline in low-skill employment. Harrison and McMillan (2011) find that a crucial distinction is between "horizontal" and "vertical" offshoring (the first aimed at locally serving foreign markets and the second aimed at producing intermediates that the multinational then re-imports to its domestic

[3] It is worth mentioning that this theory owes much to previous work on trade in intermediates, including seminal work by Jones and Kierzkowski (1990) and Feenstra and Hanson (1996, 1999), who present models in which trade in intermediate goods has consequences for labor demand much like those described in Grossman and Rossi-Hansberg (2008).

market), with the first hurting and the second stimulating domestic employment.

The present paper combines the above literature with the literature on the labor market effects of immigrants (e.g. Card, 2001; Card 2009; Borjas, 2003), proposing a common structure to think about offshoring and immigration within manufacturing industries. To do this, we extend the offshoring model by Grossman and Rossi-Hansberg (2008) to allow for immigration, which provides a simple, though still rich, way of thinking about these two phenomena within a unified framework. While the immigration literature has also analyzed the impact of immigrants on task allocation and productivity (e.g., Peri and Sparber, 2009; Peri, 2012; Chassamboulli and Palivos, 2010), we expand on it by considering a multi-sector environment and an open economy.[4] What we find is that the joint analysis of immigration and offshoring indeed generates novel insights that get overlooked when considering each of those two phenomena in isolation.

The only other papers we are aware of that tackle the analysis of immigration and offshoring in a joint framework are Olney (2009) and Barba Navaretti, Bertola and Sembenelli (2008). The first paper assumes that immigrants are identical to natives and that their variation across U.S. states and industries is exogenous. Moreover, native workers are assumed to be immobile across states and industries so that the impacts of immigration or offshoring manifest themselves entirely through wages. We think our model and its derived empirical implementation constitute a step forward from the reduced form approach of that study. The second paper presents a model of immigration and offshoring and tests its implications on firm-level data for Italy. It does not look, however, at the skill endowments of workers and the skill intensity of tasks nor at industry-level employment effects.

The importance of assortative matching between the skill requirements of tasks and the skill endowments of workers has been recently stressed by Costinot and Vogel (2010). By focusing on a Roy-like assignment model, in which a continuum of factors ("workers") are employed to produce a continuum of goods ("tasks"), they show that the comparative advantage of high skill workers in high complexity tasks provides sufficient conditions for rich comparative static predictions on the effects of various shocks to labor demand and supply. They explicitly analyze the consequences of easier offshoring, which they model as an increase in offshore labor productivity. Assuming that offshore workers have a comparative advantage in low complexity tasks, they conclude that easier offshoring induces task upgrading of all workers and rising wage inequality due to the increase in the effective supply of poorer low-skill workers. They do not consider immigration explicitly but they discuss the effects of changes in the composition of labor supply. If one assumes that immigrants are relatively less skilled than natives, the impact of immigration is then similar to the impact of offshoring: task upgrading for all workers and increasing wage inequality. Since our model also features a Roy-like assignment problem, their tools and

[4]Blinder (2007), Jensen and Kletzer (2007), Levy and Murnane (2006), Becker, Ekholm and Muendler (2007) find that tasks that intensively use cognitive-communication and non-routine skills are harder to offshore. Peri and Sparber (2009) find that immigrants have a comparative disadvantage (lower productivity) in performing communication-intensive tasks. None of these contributions, however, tackles the issue of the joint effects of offshoring and immigration on the employment shares, the employment levels and the task assignment of native, immigrant and offshore workers as we do.

techniques can be used to generalize our theoretical results, with two important differences. First, our focus is on the employment effects rather than on the wage effects. Second, our joint consideration of immigration and offshoring uncovers a differential response of native employment to shocks to the cost of immigrating or offshoring workers.[5]

Finally, also related to our paper is work on the determinants of "job polarization", defined as rising employment shares in the highest and the lowest wage occupations (Autor, Katz and Kearney, 2006; Goos and Manning, 2007). Three main explanations of job polarization have been put forth: the technological substitution of non-manual, routine jobs in the middle of the wage distribution (Autor and Katz, 1999; Autor, Levy and Murnane, 2003); the offshoring of these jobs (Blinder, 2007); or the "butlerization" or demand-driven explanation, whereby a rising income share at the top of the distribution leads to increased demand for low-skill services (Manning, 2004). In summarizing the findings of this literature, Goos, Manning and Salomons (2009) conclude that technical substitution of non-manual, routine jobs seems to be a better explanation of job polarization than offshoring and butlerization because of the pervasive effect of technology across sectors and countries. The present paper focuses on manufacturing jobs only, while also bringing immigration into the picture. We provide a somewhat different characterization of polarization in the US labor market, defined as the increasing difference in the types of jobs performed by immigrants relative to those performed by natives.

II. Data and Descriptive Statistics

In this section we present simple statistical evidence on U.S. manufacturing industries that is consistent with a story of task specialization among native, immigrant and offshore workers according to a specific pattern of comparative advantages. In particular, the data show that natives and immigrants have revealed comparative advantages in high and low complexity jobs, respectively. The revealed comparative advantage of offshore workers is not directly observable. However two related facts are observed. First, the cognitive and communication intensities of native jobs are higher (and the manual intensity lower) in manufacturing industries in which offshoring is relatively important. Second, within manufacturing the cognitive, communication and manual intensities of native jobs are not related to the relative importance of immigration. Third, a positive and significant relationship between immigration and the cognitive and communication intensities of native jobs exists in non-manufacturing industries where offshoring is negligible. These facts suggest that, in manufacturing industries, immigrants specialize in low complexity tasks, natives specialize in high complexity tasks and offshore workers specialize in intermediate complexity tasks. Specialization according to comparative advantages implies not only that immigration has a weaker "displacement effect" on natives relative to offshoring, but also

[5]Costinot and Vogel (2010) are not the first to deal with assignment models in an international context. Applications to trade can be found, for instance, in Grossman and Maggi (2000), Grossman (2004), Yeaple (2005), Ohnsorge and Trefler (2007), Blanchard and Willmann (2008), Costinot (2009), Monte (2011), and Sly (2011). Examples of applications to offshoring are Kremer and Maskin (2006), Antras, Garicano, and Rossi-Hansberg (2006), and Nocke and Yeaple (2008). None of these papers, however, deals jointly with offshoring and immigration.

that immigration and offshoring may generate a positive "productivity effect".[6] Again, it is important to note that throughout the paper we consider the complexity of a task to be increasing in the intensity of use of communication and cognitive skills and decreasing in the manual content of the task.

We formalize this story in Section III through a simple theoretical model. Section IV then brings these predictions to the data. It should be noted that, while the theoretical model is designed to be consistent with the descriptive evidence that we present, the econometric scrutiny will involve a more rigorous methodology and will test moments of the data different from those on which the assumptions of the model are based.

A. *Employment*

To measure the employment of native, immigrant and offshore workers in each industry-year using a consistent and comparable industry classification, we merge data on multi-national employment from the Bureau of Economic Analysis (BEA) with data on native and foreign-born workers from the IPUMS samples (Ruggles, et al, 2008) of the Census and the American Community Survey (ACS). The only years in which this merger can be consistently and reliably done are those from 2000 to 2007. We therefore take these eight years as our period of observation.

Information on offshore employment is obtained from the BEA U.S. Direct Investment Abroad dataset, which collects data on the operations of U.S. parent companies and their affiliates. From this dataset we obtain the total number of employees working abroad in foreign affiliates of U.S. parent companies, by industry of the U.S. parent.[7] These are jobs directly generated abroad by multinationals.[8] Data on native and immigrant workers come from the ACS and Census IPUMS samples for the period 2000-2007.[9] We add up all workers not living in group quarters, who worked at least one week during the year, weighting them by the sample weights assigned by the ACS in order to make the sample nationally representative. "Immigrants" are all foreign-born workers who were not

[6] In non-manufacturing sectors offshoring tasks is relatively costly. Thus tasks are assigned primarily to natives or immigrants with a higher likelihood of substitution between them. The productivity effect may still exist, however.

[7] As is standard in this literature, here we do not include in the definition of offshoring jobs that are sub-contracted abroad by purely national firms.

[8] Jobs created by U.S. multinational firms outsourcing production to unaffiliated foreign sub-contractors, so-called *arm's length* offshoring (see, e.g., Antras, 2003) were not included in our analysis. We constructed a proxy for this variable, however. Assuming that a large part of the production output of these offshored jobs is subsequently imported as intermediate inputs by the U.S. parent company, we calculated the ratio of imports of intermediates by the U.S. parent coming from affiliates and employment in those affiliates. We then scaled the imports of the U.S. parent coming from *non-affiliates* (data that are also available from the BEA) by this ratio to impute the employment in sub-contracting companies. This procedure assumes that the labor content per unit of production of sub-contracted intermediate inputs is the same as for production in U.S. affiliates in the same industry. Adding the imputed employment increases offshore employment by 60-80 percent in most industries, confirming the importance of arm's length offshoring. The regression results using this measure of off-shore employment are very similar to those presented in IV and we do not report them here. They can be found in a previous version of this paper (Ottaviano, Peri and Wright 2010).

[9] For year 2000 we use the 5 percent Census sample. For 2001 we use the 1-in-232 national random sample. For 2002, we use the 1-in-261 national random sample. For 2003 we use the 1-in-236 national random sample. For 2004 we use the 1-in-239 national random sample. For 2005, 2006 and 2007 the 1-in-100 national random samples are used.

citizens at birth. “Natives” are all other U.S. workers. The relevant industry classification in the Census-ACS data 2000-2007 is the INDNAICS classification, which is based on the North American Industry Classification System (NAICS). Since the BEA industries are also associated with unique 4-digit NAICS industries, we are able to develop a straightforward concordance between the two datasets.

The 58 industries on which we have data and their BEA codes are reported in Table A1 in the Web Appendix, while Figure A1 (also in the Web Appendix) reports the evolution of the employment shares of immigrant and offshore workers across industries in each year with the connecting lines showing averages over time. From 2000 to 2007 there was only a fairly modest increase in the overall share of immigrant and offshore employment in total manufacturing (the former increased from 12.8 percent to 14 percent and the latter from 22.3 percent to 29.3 percent). The figure shows both that all industries hired some immigrant and offshore workers and, further, that the differences across industries are potentially large enough to allow for the identification of the differential effects of immigration and offshoring over the period.

Figure 1 here

While the employment shares of the different groups of workers vary across industries, there are interesting patterns of co-variation. Panel (a) of Figure 1 depicts the correlations between native and immigrant employment shares over the period of observation. Panel (b) provides the same type of information for native and offshore workers and panel (c) shows employment shares for immigrant and offshore workers. The figure reveals a lack of correlation between the shares of immigrant and native workers. In contrast, it highlights a strong negative correlation between the shares of offshore and native workers, and a significant (but less strong) negative correlation between the share of immigrants and offshore workers. These correlations suggest that competition for jobs may be strongest between natives and offshore workers, intermediate between immigrant and offshore workers and weakest between natives and immigrants.

Figure 2 here

Figure 2 looks at yearly employment- and wage-growth rates across 58 manufacturing industries over eight years. Panel (a) reveals a positive correlation between the growth rates of employment of natives and immigrants whereas panel (b) shows no correlation between the growth of native and offshore workers. This is consistent with weaker native-immigrant employment competition relative to native-offshore worker competition in the presence of positive productivity effects due to both immigration and offshoring. Panels (c) and (d) look at the correlations between changes in native wages and changes in immigrant and offshore employment.[10] The two panels do not suggest any significant correlation between changes in native wages and changes in immigrant and offshore employment across sectors. We interpret this as consistent with the equalization of native wages across manufacturing

[10]The wages of natives are constructed as follows. From the Census-ACS data we consider only U.S.-born individuals who are employed (i.e., who have worked at least one week in the year and at least one hour in the week) and who have non-zero wage income, excluding the self-employed. We take yearly wage income deflated by the consumption price index to constant 2005 dollars and average it at the industry level, weighting each individual by the corresponding sample weight in the Census.

industries due to worker mobility between them, with the effect that the wage variation across sectors is random.[11]

B. Tasks

Data on the tasks performed by immigrants and natives is constructed using the U.S. Department of Labor's *O*NET* abilities survey, which provides information on the characteristics of each occupation. Based on the Standard Occupation Classification (SOC), the dataset assigns numerical values to describe the importance of distinct abilities ("skills") required by different occupations ("tasks"). Each numerical value measures the intensity of a skill in a given task. Following Peri and Sparber (2009), we merge these task-specific values with individual workers in the 2000 Census, re-scaling each value so that it equals the percentile score in that year. This gives a measure of the relative importance of a given skill among U.S. workers ranging between 0 and 1. For instance, a task with a score of 0.02 for some skill indicates that only 2 percent of workers in the U.S. in 2000 were supplying that skill less intensively. We then assign these *O*NET* percentile scores to individuals from 2000 to 2007 using the ACS variable *occ1990*, which provides an occupational crosswalk over time.

We focus on three skill indices: Cognitive Intensity, Communication Intensity and Manual Intensity. These are constructed by averaging the relevant skill variables. Specifically, Cognitive Intensity includes ten variables classified as "cognitive and analytical" in *O*NET*. Communication Intensity includes four variables capturing written and oral expression and understanding. Manual Intensity includes nineteen variables capturing dexterity, strength and coordination.[12] We have also calculated a synthetic Complexity index summarizing the intensity of a task in cognitive-communication skills *relative* to manual skills. This index is defined as: Complexity = ln((Cognitive Intensity+Communication Intensity)/Manual Intensity). It ranges between $-\infty$ and $+\infty$.

Overall, our sample consists of 295 occupations ("tasks") in the manufacturing sector over 8 years, 2000-2007. This type of information is available for immigrants and natives but not for offshore workers. Absent direct information on the specific occupations of offshore workers, a crucial challenge for us is to indirectly assess the average complexity of offshore tasks. The four panels of Figure 3 plot the share of hours worked by immigrants relative to the total number of hours worked by immigrant and native workers as a function of Cognitive Intensity, Communication Intensity, Manual Intensity and Complexity across occupation-years.[13] The figure clearly shows that immigrants are disproportionately

[11] We also provide a more formal analysis of the correlation between offshore/immigrant employment and native wages in the Web Appendix. Table A3 shows the estimated effects of log offshore employment and log immigrant employment on (log) native wages. The effects are estimated using 2SLS with tariffs as an instrument for offshoring and imputed immigration as an instrument for actual immigration (as described in section IV.A below). In all cases we obtain small and insignificant coefficients.

[12] The exact definition and list of the variables used for each indexcan be found in the Web Appendix of this paper.

[13] A very similar picture would be obtained if we only considered workers with low educational attainment (i.e., workers with a high school diploma or less) This was shown in Ottaviano, Peri and Wright (2010). Even within the low educated, immigrants are relatively specialized in tasks with low cognitive and communication content, low complexity and high manual content.

represented in occupations characterized by low Cognitive Intensity, low Communication Intensity, high Manual Intensity and low overall Complexity.[14]

Figure 3 here

While the complexity of offshored tasks is unobservable (because we do not observe offshore occupations), we can nonetheless gauge some indirect evidence from the way offshoring affects the complexity of native and immigrant tasks. Figure 4 reports this type of information in the case of all immigrants and natives. It plots the change in the Complexity of tasks performed by natives and immigrants against the change in the shares of offshore and immigrant employment, across manufacturing industries over the period 2000-2007. The figure conveys a clear message: increases in the share of offshore workers are associated with significant increases in the complexity of tasks performed by natives as well as decreases in the complexity of tasks performed by immigrants. In contrast, increases in the share of immigrants are not associated with any significant change in the complexity of native or immigrant tasks. Hence, a stronger presence of offshore workers is associated with a larger polarization in task complexity between natives and immigrants. Similar patterns arise when we focus on Cognitive Intensity, Communication Intensity and Manual Intensity separately but we do not report them for conciseness.

Figure 4 here

The finding that changes in native complexity are not significantly correlated with changes in the share of immigrants may surprise readers familiar with Peri and Sparber (2009), as these authors find that native task complexity is sensitive to the share of immigrants. This can easily be explained in a manner that is consistent with our theory. In this study we focus on (mostly-tradable) manufacturing industries whereas Peri and Sparber (2009) consider all employment, most of which is in (non-tradable) services. Since offshoring was still negligible outside the manufacturing sector during our period of observation, we interpret this discrepancy as a signal that, when viable, offshore workers play an important role in weakening the competition between immigrants and natives. Table 1 explores this interpretation by regressing native complexity on immigrants' complexity and employment share across industries and over time, distinguishing between manufacturing ("tradable") and non-manufacturing ("non-tradable") industries. All workers are included. The table shows significant positive correlation between native complexity and immigrant employment share within non-tradable industries (Column 2), but no correlation is detected between native complexity and immigrant employment share in tradable industries (Column 1).[15] This supports the idea that in non-tradable industries the competition between natives and immigrants is more direct and immigration pushes native workers to "upgrade" their jobs. In tradable industries this does not happen because offshore workers perform a large part of the intermediate-complex tasks and are therefore in direct competition with immigrants. While the results shown are not direct evidence of this they are consistent with this explanation.

[14] This finding concurs with existing evidence. Peri and Sparber (2009) show that, due to their imperfect knowledge of language and local norms, immigrants have a relative advantage in tasks with high manual intensity and a relative disadvantage in tasks with high communication intensity.

[15] In the regressions in Table 1 we also control for time and industry fixed effects.

Table 1 here

Our overall interpretation of the descriptive evidence presented in this section is that natives compete more directly with offshore workers relative to immigrant workers. This can be explained by a specific pattern of comparative advantages across the three groups of workers, with immigrants specializing in low complexity tasks, natives in high complexity tasks and offshore workers in intermediate complexity tasks.

III. A Labor Market Model of Task Allocation

A simple partial equilibrium model consistent with the descriptive evidence reported in the previous section can be designed following Grossman and Rossi-Hansberg (2008). Consider a small open economy that is active in several perfectly competitive sectors, indexed $s = 1, .., S$. We focus on one of these sectors and leave both the sector index s and the time dependence of variables t implicit for ease of notation. We will make them explicit when we get to the empirics.

The sector employs two primary factors, workers with employment level N_L and a sector-specific factor with endowment H. To match the descriptive evidence on wages in Section II, the sector is small enough to face infinitely elastic labor supply at given wages.[16] All workers are endowed with one unit of labor each but differ in terms of productivity. They are employed in the production of intermediates ("tasks"), which are then assembled in a composite labor input L. This, in turn, is transformed into final output Y according to the following Cobb-Douglas production function

$$Y = AL^{\alpha}H^{1-\alpha} \tag{1}$$

where $A \in (0, \infty)$ and $\alpha \in (0, 1)$ are technological parameters. The price of final output p_Y is set in the international market.

Specifically, the composite labor input L is produced by assembling a fixed measure of differentiated tasks, indexed $i \in [0, 1]$ in increasing order of complexity, through the following CES technology

$$L = \left[\int_0^1 L\left(i\right)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where $L\left(i\right)$ is the input of task i and $\sigma > 0$ is the elasticity of substitution between tasks.[17]

[16] This leads to a crucial difference between our model and those by Grossman and Rossi-Hansberg (2008) and by Costinot and Vogel (2010). Both these models consider the general equilibrium effects of offshoring on wages under economy-wide full employment constraints. In the Web Appendix we propose an extension of our model in which the assumption of perfectly elastic labor supply at given wages does not hold. There we show that, when the native wage is endogenous, immigration and offshoring generate wage effects, however the corresponding employment effects discussed in Section III.B remain qualitatively the same.

[17] In Grossman and Rossi-Hansberg (2008) tasks are not substitutable. This corresponds to the limit case of $\sigma = 0$ where (2) becomes a Leontief production function.

A. Task Assignment

Each task can be managed in three modes: domestic production by native workers (D), domestic production by immigrant workers (M) and production abroad by offshore workers (O). The three groups of workers are perfect substitutes in the production of any task but differ in terms of their productivity as well as in terms of their wages, which we call w, $\widetilde{w}$ and w^*, respectively. To allow for a "productivity effect" to arise from both immigration and offshoring, we assume that employers can discriminate between the three groups of workers so that w, $\widetilde{w}$ and w^* may not be equal. We assume, however, that immigrant and offshore wages are linked, with a fixed gap between them determined by a differential "cost of hardship" that immigrants face with respect to their fellow countrymen who stay at home. In particular, if a foreign worker immigrates, she incurs a frictional cost $\delta \geq 1$ in terms of foregone productivity. In other words, an immigrant endowed with one unit of labor in her country of origin is able to provide only $1/\delta$ units of labor in the country of destination. The migration decision therefore entails a choice between earning w^* in the country of origin or $\widetilde{w}/\delta$ in the country of destination.[18] Positive supply of both immigrant and offshore workers then requires the migration indifference condition $\widetilde{w} = w^*\delta$ to hold.[19]

In light of the descriptive evidence reported in Section II, we now introduce assumptions that ensure that immigrant, offshore and native workers specialize in low, medium and high complexity tasks, respectively. In so doing, we follow Grossman and Rossi-Hansberg (2008) and define tasks so that they all require the same unit labor requirement a_L when performed by native workers. Accordingly, the marginal cost of producing task i employing native workers is $c_D(i) = wa_L$. If task i is instead offshored, its unit input requirement is $\beta t(i)a_L$ with $\beta t(i) \geq 1$. This implies a marginal cost of producing task i employing offshore workers equal to $c_O(i) = w^*\beta t(i)a_L$. Lastly, if task i is assigned to immigrants, its unit input requirement is $\tau(i)a_L$ with $\tau(i) \geq 1$ so that the marginal cost of producing task i employing immigrants is $c_M(i) = \widetilde{w}\tau(i)a_L = w^*\delta\tau(i)a_L$. Hence, in all tasks natives are more productive but, due to wage differences, not necessarily cheaper than immigrant and offshore workers. We interpret a lower value of the frictional parameter β as "easier offshoring" and a lower value of the frictional parameter δ as "easier immigration".

Since native, immigrant and offshore workers are perfectly substitutable, in equilibrium any task will be performed by only one type of worker: the one that entails the lowest marginal cost for that task.[20] Hence, a set of sufficient conditions for immigrant, offshore

[18]For simplicity, in the theoretical model we consider only one country of origin for all immigrants.

[19]There is much empirical evidence that, for similar observable characteristics, immigrants are paid a lower wage than natives. Using data from the 2000 Census, Antecol, Cobb-Clark and Trejo (2001), Butcher and DiNardo (2002) and Chiswick, Lee and Miller (2005) all show that recent immigrants from non-English speaking countries earn on average 17 to 20 percent less than natives with identical observable characteristics. Our data provide estimates in the same ball park. Hendricks (2002) also shows that the immigrant-native wage differential, controlling for observable characteristics, is highly correlated with the wage differential between the U.S. and their country of origin. See, however, Section III.B and the Web Appendix for a detailed discussion of how the predictions of the model would change were firms assumed to be unable to discriminate between native and immigrant workers.

[20]If native, immigrant and offshore workers were imperfectly substitutable, each task could be performed by "teams" consisting of the three types of workers. Then, rather than full specialization of workers' types in different tasks, one would observe partial specialization, with the shares of the three types in each task inversely related

and native workers to specialize in low, medium and high complexity tasks can be stated as:

PROPOSITION 1: *Suppose*

$$\frac{dt(i)}{di} > 0, \quad \frac{w}{w^* t(1)} < \beta < \frac{w}{w^* t(0)} \tag{3}$$

Then there exists a unique "marginal offshore task" $I_{NO} \in (0,1)$ *such that* $c_O(I_{NO}) = c_D(I_{NO})$, $c_O(i) < c_D(i)$ *for all* $i \in [0, I_{NO})$ *and* $c_O(i) > c_D(i)$ *for all* $i \in (I_{NO}, 1]$. *This task is implicitly defined by* $w = w^* \beta t(I_{NO})$. *Suppose in addition that*

$$\delta \frac{d\tau(i)}{di} > \beta \frac{dt(i)}{di}, \quad \frac{\tau(0)}{t(0)} < \frac{\beta}{\delta} < \frac{\tau(I_{NO})}{t(I_{NO})} \tag{4}$$

Then there exists a unique "marginal immigrant task" $I_{MO} \in (0, I_{NO})$ *such that* $c_M(I_{MO}) = c_O(I_{MO})$, $c_M(i) < c_O(i)$ *for all* $i \in [0, I_{MO})$ *and* $c_M(i) > c_O(i)$ *for all* $i \in (I_{MO}, 1]$. *This task is implicitly defined by* $\beta t(I_{MO}) = \delta \tau(I_{MO})$.

See the Appendix for the proof. Intuitively, the first condition in (3) implies that the productivity of offshore workers relative to natives decreases with the complexity of tasks. The second condition in (3) requires offshoring frictions to be neither too large nor too small in order to generate a trade-off in the assignment of tasks between native and offshore workers. The first condition in (4) also implies that the productivity of immigrants falls with the complexity of tasks, and falls faster than in the case of offshore workers. The second condition in (4) requires offshoring frictions to be neither too large nor too small relative to migration frictions such that there is a trade-off in the assignment of tasks between immigrant and offshore workers. Conditions (3) and (4) together thus imply that tasks of complexity $0 \leq i \leq I_{MO}$ are assigned to immigrants, tasks of complexity $I_{MO} < i \leq I_{NO}$ to offshore workers and tasks of complexity $I_{NO} < i \leq 1$ to natives, where marginal tasks have been arbitrarily assigned to break the tie.[21]

Figure 5 here

The allocation of tasks among the three groups of workers is portrayed in Figure 5, where the task index i is measured along the horizontal axis and the production costs along the vertical axis. The flat line corresponds to c_D and the upward sloping curves correspond to $c_M(i)$ and $c_O(i)$, with the former starting from below but steeper than the latter. Since

to the corresponding marginal costs. In reality several tasks are indeed performed by a combination of different types of workers, nonetheless the intuition behind the key results of the model is better served by assuming perfect substitutability.

[21] Readers familiar with Costinot and Vogel (2010) will recognize the log-supermodularity of this assignment problem in which, due to their different skills, native, immigrant and offshore workers have a relative advantage in high, medium and low skill intensity tasks. Indeed, the approach of Costinot and Vogel (2010) could be used to go beyond the stark view expressed in our theory by introducing skill heterogeneity among the three groups of workers. This could be achieved by matching the assumption that higher skill workers have a comparative advantage in more skill intensive tasks (see Costinot and Vogel, 2010, Section III.A) with the assumption that natives are more skilled relative to offshore and immigrant workers (see Costinot and Vogel, 2010, Section VII.B).

each task employs only the type of workers yielding the lowest marginal cost, tasks from 0 to I_{MO} are assigned to immigrants, tasks from I_{MO} to I_{NO} are offshored, and tasks from I_{NO} to 1 are assigned to natives.

B. Comparative Statics

We are interested in how tasks, employment shares and employment levels, vary across the three types of workers when offshoring and migration costs change. The solution of our task assignment problem summarized in Proposition 1 implies that marginal tasks exhibit the following properties

$$\begin{aligned}\frac{\partial I_{NO}}{\partial \beta} &< 0, \frac{\partial I_{MO}}{\partial \beta} > 0\\ \frac{\partial I_{NO}}{\partial \delta} &= 0, \frac{\partial I_{MO}}{\partial \delta} < 0\end{aligned}$$

These highlight the adjustments in employment occurring in terms of the number of tasks allocated to the three groups of workers. They can be readily understood using Figure 5. For example, a reduction in offshoring costs (lower β) shifts $c_O(i)$ downward, thus increasing the number of offshored tasks through a reduction in both the number of tasks assigned to immigrants ($\partial I_{MO}/\partial \beta > 0$) and the number of tasks assigned to natives ($\partial I_{NO}/\partial \beta < 0$). Analogously, a reduction in the migration costs (lower δ) shifts $c_M(i)$ downward, thus increasing the number of tasks assigned to immigrants through a decrease in the number of offshored tasks (higher I_{MO}).

While the theoretical model identifies the marginal tasks as cutoffs between tasks performed by different groups of workers, the distinction is not so stark in reality as workers are also heterogeneous within groups and some overlap among individuals belonging to different groups is possible along the complexity spectrum.[22] For the empirical analysis it is, therefore, also useful to characterize the "average task", I_M, I_O or I_D, performed by each group, defined as the employment-weighted average across the corresponding i's.[23] Average tasks exhibit the following properties

$$\begin{aligned}\frac{\partial I_D}{\partial \beta} &< 0, \frac{\partial I_M}{\partial \beta} > 0\\ \frac{\partial I_D}{\partial \delta} &= 0, \frac{\partial I_M}{\partial \delta} < 0\end{aligned} \tag{5}$$

These are driven by compositional changes due to adjustments both in the number of tasks allocated to the three groups and in the employment shares of the different tasks allocated to the three groups. Note that changes in migration costs also have a negative impact on the average offshored task ($\partial I_O/\partial \delta < 0$). The impact of offshoring costs on the average

[22] See the previous footnote on how the model could be extended to the case of within-group heterogeneity.
[23] See the Appendix for a formal definition of average tasks.

offshore task ($\partial I_O/\partial\beta$) is, instead, ambiguous. This is due to opposing adjustments in the allocation of tasks given that, when β falls, some of the additional offshore tasks have low i (i.e., I_{MO} falls) while others have high i (i.e., I_{NO} rises).

The impacts of declining β and δ on employment shares, s_M, s_O and s_D, are all unambiguous.[24] By making offshore workers more productive and thus reducing the price index of offshore tasks P_O relative to the price index of all tasks P_L, a lower offshoring cost, β, reallocates tasks from immigrants and natives to offshore workers. By reducing the price index of immigrant tasks P_M relative to the price index of all tasks P_L, a lower migration cost, δ, moves tasks away from offshore and native workers toward immigrants:

$$\begin{aligned} \frac{\partial s_M}{\partial\beta} &> 0, \frac{\partial s_O}{\partial\beta} < 0, \frac{\partial s_D}{\partial\beta} > 0 \\ \frac{\partial s_M}{\partial\delta} &< 0, \frac{\partial s_O}{\partial\delta} > 0, \frac{\partial s_D}{\partial\delta} > 0 \end{aligned} \tag{6}$$

These results capture the signs of the "displacement effects" for the three groups of workers.

Turning to the impact of declining β and δ on the employment levels N_M, N_O and N_D, there is an additional effect beyond the substitution among groups of workers in terms of employment shares.[25] This is due to the fact that lower β and δ ultimately cause a fall in the price index of the labor composite P_L because, as a whole, workers become more productive. This is the "productivity effect" of offshoring and immigration. Specifically, a fall in the price index P_L of the labor composite has a positive impact on sectoral employment (due to the productivity effect), which is then distributed across groups depending on how the relative price indices of the three groups of workers P_M/P_L, P_O/P_L and P_D/P_L vary (due to the displacement effects).

The impact of declining β and δ on employment levels can be signed only when the productivity effect and the displacement effects go in the same direction. In particular, since $\partial P_L/\partial\beta > 0$ and $\partial P_L/\partial\delta > 0$, we have

$$\frac{\partial N_O}{\partial\beta} < 0, \frac{\partial N_M}{\partial\delta} < 0 \tag{7}$$

while the signs of $\partial N_M/\partial\beta$, $\partial N_D/\partial\beta$, $\partial N_O/\partial\delta$ and $\partial N_D/\partial\delta$ are generally ambiguous. In other words, whether the productivity effect is strong enough to offset the displacement effect for all groups of workers is an empirical question that we will address in the next section. Lower β and δ certainly raise total sector employment $N_L = N_M + N_O + N_D$, as long as there is a non-zero productivity effect.

Results (5), (6) and (7) are the reduced form implications of the model that we will bring to the data in the next sections.[26]

[24] See the Appendix for the expressions of employment shares and price indices.

[25] See the Appendix for the expressions of employment levels.

[26] Employers' ability to discriminate between natives and immigrants is crucial for the productivity effects of immigration to materialize. If employers were unable to discriminate, immigrants would always be paid native wages w earning rents $w - w^*\delta$. Thus, any reduction in δ would simply increase immigrants' rents with no impact on

IV. Empirical Specifications and Econometric Results

In this section we bring the predictions of our model to the data. We target the three sets of predictions highlighted in the previous section regarding the effects of easier immigration and easier offshoring on the employment shares, the employment levels and the average task assignments of natives and of the other groups of workers, as highlighted in (5), (6), and (7), respectively. The empirical specifications are derived from the theory but can be justified in a very general way. First, the impact of immigration or offshoring on the share of native employment allows us to infer the degree of direct competition (substitutability) between types of workers. Second, estimating the impact of immigration or offshoring on total employment allows us to quantify the productivity effects of those activities. Finally, the impact of immigration or offshoring on native task assignment tests whether the distribution of tasks across worker types according to task complexity is consistent with our hypothesis and with the estimated pattern of cross-substitution.

The predictions of the model have been derived for a single industry leaving industry and time indices implicit for notational convenience. Hence, in order to implement (B5), (B2), and (B4) empirically we begin by identifying the parameters that vary across industries (to be indexed by s) and over time (to be indexed by t) and those that do not (and carry no index). First, the offshoring and immigration cost parameters vary across industries and over time, and thus we label them β_{st} and δ_{st}. We motivate this in Section IV.A in which we present our empirical measures. Second, we consider the specific factor endowment H_s to be industry-specific but not time-varying. The same holds for the baseline sector-specific total factor productivity A_s. We allow, however, for random productivity shocks through a possibly serially correlated error term ε_{st}. Both H_s and A_s will be captured by an industry fixed effect. Finally, as wages have been assumed to be equalized across industries, we allow them to vary only over time, writing w_t and w_t^*, which calls for a time effect.

In sum, we will exploit differences in immigration and offshoring costs within industries over time in order to identify the impact on native and immigrant employment as well as on native and immigrant task specialization.

A. *Costs of Immigration and Offshoring*

Driving the shifts in β_{st} and δ_{st} are changes in the accessibility of offshore and immigrant workers. Since we do not observe industry-specific offshoring and immigration costs, we begin by using direct measures of the employment share of immigrant and offshore workers across industries and over time as explanatory variables. If the variation in costs, once we control for industry and time effects, were the main source of variation in immigration and offshoring within an industry, then the OLS regression would identify the effect on native outcomes of changes in the cost of immigration and offshoring. As we are aware that this is an heroic assumption, we instrument the share of immigrants and offshore workers with

firms' costs. Note, however, that our assumption of perfect discrimination is not crucial to generate the productivity effect due to immigration since even partial discrimination generates rents for the firm. See the Web Appendix for additional details.

variables proxying their cross-industry costs and availability.

The assumption that offshoring costs vary across industries departs from Grossman and Rossi-Hansberg (2008), who suggest that this cost is more or less the same across industries. This is probably true if one wants to stress, as they do, the technological dimension of offshoring costs, which implies very little variation across similar tasks in different industries. Our focus is, instead, on the trade cost dimension of offshoring, which hampers the re-import of the output generated by offshored tasks and is affected by industry-specific characteristics. In this respect, in order to capture exogenous variation in offshoring costs and generate an instrument for offshore employment in an industry-year, we collect two types of U.S. tariff data, each by year and product: Most Favored Nation (MFN) tariffs and Information Technology Agreement (ITA) tariffs.[27] These are then aggregated up to the BEA industry level for each year, weighting the tariffs by the value of imports in each detailed industry, where we obtain U.S. imports from Feenstra, Romalis and Schott (2002).[28] We call this variable $(Tariffs)_{st}$.

The instrument we use to proxy cost-driven immigration by industry and year extends the method first proposed by Altonji and Card (1991) and Card (2001) to identify cost-driven local shifts in immigrants. We exploit the fact that foreigners from different countries have increased or decreased their relative presence in the U.S. according to changes in the cost of migrating and to domestic conditions that are specific to their countries of origin. Differences in the initial presence of immigrants from different countries in an industry make that industry more or less subject to those shifts in origin-specific cost- and push-factors. Using these two facts we impute the population of each of 10 main groups of immigrants across industries over time.[29] Specifically, we use the share of immigrant workers, by origin-group, in each industry in year 2000 and we augment it by the aggregate growth rate of the specific immigrant group's population in the U.S. relative to the total U.S. population. Then summing over origin-groups within an industry we obtain the imputed share of foreign-born in total employment. We call this measure $(Imputed\_s_M)_{st}$ and note that it varies across industries and over time.[30]

Our identification approach is valid as long as industries, like localities, are important conduits for immigrant networks. This is likely to be more true for industries that are geographically concentrated. In Section IV.E we focus exclusively on industries that are

[27] These data come primarily from UNCTAD's TRAINS dataset, but were extended somewhat by Yingying Xu as part of her dissertation at UC Davis. The ITA data was added by the authors. ITA data is available via http://www.wto.org

[28] The MFN tariffs are mandated for all WTO signatories, while the ITA tariffs had been adopted by 43 countries at the end of our period (2007), covering 97 percent of world trade in technology products. The ITA covers a range of manufactured technology products (see the Web Appendix for a full list of products and adopters) and, for our purposes, is an important source of time-series variation, as MFN tariffs do not change much within industries over our period.

[29] The ten countries/regions of origin are: Mexico, Rest of Latin America, Canada-Australia-New Zealand, Western Europe, Eastern Europe, China, India, Rest of Asia, Africa, and Other.

[30] This index is similar to the constructed shift-share instrument often used in studies of immigration in local labor markets (e.g., Card, 2001; Card and DiNardo, 2000; Peri and Sparber, 2009), except that it exploits differences in the presence of immigrant groups (from different countries) across industries, rather than across localities. There are some recent papers that document the existence of industry- and occupation-specific immigrant networks (e.g. Patel and Vella 2007), arising in part due to the geographic concentration of industries.

highly concentrated geographically. Because of localized ethnic networks (Bartel, 1989), we would expect that the initial distribution of immigrants in such industries would be an even stronger predictor of future immigration flows.

B. *Effects on Employment Shares*

We begin by estimating the impact of variation in immigration and offshoring costs on the *shares* of native, immigrant and offshore workers, thereby exploring the relative substitutability of these worker types through the extent to which they displace one another. In Section IV.C we will then analyze the impact on the employment *levels* of these groups, which includes the productivity impact of the changing costs of immigration and offshoring. Finally, in Section IV.D, we will explore the impact on the *task specialization* of natives and immigrants. Using the same notation as we used in the theoretical model but making industry and time indices explicit as discussed above, we implement (B4) empirically by estimating the following three regressions:

$$s_{Dst} = \phi_s^D + \phi_t^D + b_{DO}(s_{Ost}) + b_{DM}(s_{Mst}) + \varepsilon_{st}^D \tag{8}$$

$$s_{Mst} = \phi_s^M + \phi_t^M + b_{MO}(s_{Ost}) + \varepsilon_{st}^M \tag{9}$$

$$s_{Ost} = \phi_s^O + \phi_t^O + b_{OM}(s_{Mst}) + \varepsilon_{st}^O \tag{10}$$

where s_{Dst}, s_{Ost} and s_{Mst} are the employment shares of domestic (native), offshore and immigrant workers in industry s at time t, the ϕ_s's are industry fixed effects, the ϕ_t's are time effects, and the ε_{st}'s are (potentially) serially correlated errors. Estimation is based on 2SLS using the instruments $(Tariffs)_{st}$ for s_{Ost} and $(Imputed\_s_M)_{st}$ for s_{Mst} as described in Section IV.A.

Equation (8) estimates the impact of variation in the offshoring and immigration share, driven by push and cost factors as captured by $(Tariffs)_{st}$ and $(Imputed\_s_M)_{st}$, on native workers' share of employment. By including industry effects we only exploit variation within industries over time. We also control for common-year effects and, as a result, any time-invariant difference in offshoring costs across industries and any common trend in offshoring costs over time will not contribute to the identification of the effect. Equation (9) estimates the effect of variation in offshoring costs on the immigrant share of employment and, conversely, equation (10) estimates the effect on the share of offshore workers due to a decrease in immigration costs.

Specifications (8) to (10) combine two desirable features. First, the coefficients can be easily interpreted as the percentage variation in native (immigrant/offshore) employment in response to a 1 percent change in immigrant/offshore employment. In addition, since we use $(Tariffs)_{st}$ and $(Imputed\_s_M)_{st}$ as instruments we only rely on variation driven by changes in the costs of immigration and offshoring. These will be our main specifications. Alternatively, we could regress employment shares directly on the constructed measures of offshoring costs $(Tariffs)_{st}$ and ease of immigration $(Imputed\_s_M)_{st}$. This is more consistent with the model, as we can interpret $(Tariffs)_{st}$ as a measure of β_{st} (cost of offshoring) and $(Imputed\_s_M)_{st}$ as an inverse measure of δ_{st} (cost of migration). However the quantitative interpretation of the coefficient will be less straightforward (because the constructed variables have a somewhat arbitrary scale). The significance and sign of the estimates, however, should be consistent. We will use this more direct regression as an alternative specification.

Table 2 here

From Section III.B the predictions of the model are as follows: $b_{DO} < 0, b_{DM} \approx 0, b_{MO} < 0$ and $b_{OM} < 0$. Table 2 reports the estimated effects. First, columns (1)-(2) show the 2SLS effects of increasing shares of immigrant and offshore workers on the share of native workers. Because the shares must sum to 1, the immigrant and offshore worker shares are collinear, and so we must estimate their effects separately (as the sole regressors in separate regressions). We therefore estimate each effect, with instrumental variables. In column (1) we use the tariff measure as an instrument for the offshore share of employment while in column (2) we use the imputed immigration shares to instrument actual immigration.[31] The impact of the cost of offshoring (tariffs) and ease of immigration (imputed immigrants) on the explanatory variables, displayed in the first stage of the regressions, is quite significant and has the expected sign. Furthermore, the measures of ease of offshoring and migration are strong instruments, with a Wald F-statistic that is above the Stock and Yogo critical value (15 percent maximal IV size) equals to 8.96 (see last row of Table 2). Columns (3) and (4) show the coefficients from the corresponding "direct regressions". The native share of employment is regressed directly on the sector-specific tariff (column 3) and on the imputed immigration (specification 4). Columns (5) and (6) report the effects of variation in offshoring costs on the share of immigrants, first using the 2SLS specification and then the direct regression with tariffs as a measure of offshoring costs. Columns (7) and (8) show the effect of variation in immigration costs on the share of offshore workers either directly (specification 8) or using imputed migration as an instrument for the share of immigrants (specification 7). The standard errors reported in each regression are heteroskedasticity robust and, in the case of the OLS regressions, they are clustered at the industry level to account for potential serial correlation of errors.

The results are encouraging as the four predictions of the model are mostly matched by the estimates and the 2SLS and the direct OLS regressions provide the same qualitative evidence. Focussing on the 2SLS coefficients, and looking along the first row, we see that increased immigration in an industry has a non-significant effect on the share of native employment in that industry and a negative (but marginally non-significant, with a $p-value$ of 0.18) effect on the share of offshore employment (recall that the model predicted no effect on natives and a negative effect on immigrants, respectively). Stronger results are obtained in the second row, which shows that there is a negative effect of offshore

[31] Using the definition of offshore employment that is inclusive of arm's length offshoring we obtain an effect of off-shoring on native share –in a specification as that in column 1- equal to -0.71, (with a standard error of 0.18). The estimated effect on the immigrant share -in a specification as that in column 5- is -0.29, (with a standard error of 0.18).

employment on the share of both native and immigrant workers in an industry, exactly as predicted in (6). Each of the estimates is significantly different from zero. Similarly, the direct regression coefficients show that an increase in the cost of offshoring (tariffs) has a positive and significant effect on the native and immigrant share of employment, while an increase in the ease of immigration has a negative (but non-significant) effect on the offshore share and a non-significant effect on the native share of employment.

These findings are in line with our model. More generally, they suggest that immigrants and natives compete more with offshore workers than with one another. This is consistent with a large part of the labor literature (e.g., Card, 2001; or Ottaviano and Peri, 2008) that does not find a significant negative impact of immigrants on native employment. Moreover, the decline in offshoring costs is shown to have a significant impact on the employment share of natives and immigrants, but one that is quantitatively larger for the first group. This suggests that over the 8 years considered (2000-2007) the tasks that were offshored were more likely to be at the high end of the task spectrum for offshore workers.

C. Effects on Employment Levels

Another important implication of our model, highlighted in Section III.B, is the existence of a "productivity effect" that results from the cost decline associated with hiring immigrant and offshore workers. Such an effect leads to an increase in the aggregate demand for all worker types. This productivity effect, if significant, combined with the effect on shares described in the previous section, should imply a mitigated, null, or perhaps even positive effect of offshoring on native employment. Additionally, immigration should have a positive effect on native employment.

Table 3 here

Table 3, which replicates the structure of Table 2, presents the estimated coefficients from the following four regressions, the empirical counterparts to (B2):

$$N_{Dst} = \phi_s^D + \phi_t^D + B_{DO}(N_{Ost}) + B_{DM}(N_{Mst}) + \varepsilon_{st}^D \tag{11}$$

$$N_{Mst} = \phi_s^M + \phi_t^M + B_{MO}(N_{Ost}) + \varepsilon_{st}^M \tag{12}$$

$$N_{Ost} = \phi_s^O + \phi_t^O + B_{OM}(N_{Mst}) + \varepsilon_{st}^O \tag{13}$$

where N_{Dst}, N_{Mst} and N_{Ost} are the logarithm of the employment levels of native, immigrant and offshore workers, respectively. Similar to Table 2, columns (1) and (2) show the 2SLS estimates using the cost-driven offshoring and immigration instruments $(Tariffs)_{st}$ and $(Imputed\_s_M)_{st}$. In columns (3) and (4) we show the direct regressions. Similarly, columns (5) and (6) report the effect of offshoring costs on immigrant employment and columns (7) and (8) show the effect of ease of immigration on offshore employment. In Table 4 we then present the estimates for the aggregate employment regression:

$$N_{Lst} = \phi_s^L + \phi_t^L + B_{LO}(s_{Ost}) + B_{LM}(s_{Mst}) + \varepsilon_{st}^L \tag{14}$$

where N_{Lst} is the logarithm of aggregate employment in industry s and year t. Again we report the 2SLS estimates (columns 1 and 2) and then the direct regression results (columns 3 and 4). In all specifications the ϕ_s's are industry fixed effects, the ϕ_t's are time effects, and ε_{st}'s are (possibly) serially correlated errors. The effects estimated in Table 3 combine the productivity effects with the displacement effects. Regression (14), instead, captures the pure productivity effects of offshoring and immigration at the industry level. A positive estimate of B_{LO} and B_{LM} would imply a positive overall productivity effect of a drop in offshoring and immigration costs. Heteroskedasticity-robust standard errors are reported and in the direct regression estimates we also cluster them by industry.

Table 4 here

The results presented in Table 3 are in line with the predictions of the model. Firstly, it is important to note that the first-stage Wald F-Statistics are always above the Stock and Yogo test critical value for weak instruments, equal to 8.96 (15 percent maximum IV size). They are slightly different from those in Table 2 because the explanatory variables are now employment levels (rather than employment shares) but their strength is similar. The employment estimates seem to reveal a positive and significant productivity effect of immigration, and an implied positive productivity effect of offshoring, on native-born workers. A decline of the costs of immigration associated with a 1 percent increase in immigrants produces a significant increase in the employment of natives equal to 0.42 percent (Table 3, column 2) and has no significant effect on the total employment of offshore workers (Table 3, column 7). The productivity effect of offshoring is revealed by the fact that, whereas offshoring unambiguously reduced the share of natives and immigrants in an industry (Table 2, columns 1 and 5), it has no significant effect on the aggregate employment of natives or immigrants (Table 3, columns 1 and 5). Thus, while offshore workers compete with natives and immigrants, their employment seems to generate productivity gains that "increase the size of the pie", leading to an overall neutral impact on native and immigrant employment.

Table 4 shows the results from specification (14) which are informative on the size and significance of the productivity effects. The coefficients represent the impact of decreasing costs of offshoring and immigration on the overall size of the "employment pie" to be distributed across workers. As evidenced by the 2SLS results, both offshoring and immigration have positive productivity effects on an industry. The effect is quantitatively larger in the case of immigration.[32] Columns (1) and (2) in Table 4 show that an increase in the immigrant share equal to 1 percent increases aggregate employment by 3.9 percent, implying a significant expansion, again driven by the productivity effect. This is a substantial effect, particularly if we keep in mind that manufacturing employment actually declined over this

[32]The results on offshoring are broadly consistent with Amiti and Wei (2005), who also find evidence of productivity effects by estimating conditional and unconditional labor demand functions.

period. At the same time an increase in the share of offshore employment by 1 percent is associated with an increase in aggregate employment by 1.7 percent. Columns (3) and (4) of Table 4 show the direct OLS regression of aggregate employment on the imputed share of immigrants and on sector-specific tariffs. The regression confirms that an increase in cost-driven availability of immigrants increases the employment of the sector. A decrease in offshoring costs, on the other hand, has a positive, but not significant, effect on employment. The presence of productivity effects due to immigration and offshoring implies that, even taken together, these two forms of globalization of labor have not harmed native employment in the industries most exposed to them. To the contrary, the cost savings obtained from the tasks performed by immigrants and offshore workers have promoted an expansion of these industries relative to others and have ultimately led to increased demand for native workers relative to a scenario in which all tasks were performed by natives.

D. Effects on Tasks

Finally we test the model's predictions regarding the effects of offshoring and immigration costs on the complexity of the tasks performed by the three groups of workers. To see whether these predictions find support in the data, we focus on the average rather than the marginal task. Since in the data there is significant idiosyncratic heterogeneity across workers, there is, of course, a region of task overlap between workers of different types (native/offshore and immigrants). It is therefore impossible to define a marginal task in the clear and deterministic way suggested by the model. However, the predictions on average tasks hold also in a probabilistic environment where individual heterogeneity produces a less sharp and more continuous transition between the tasks performed by native, offshore and immigrant workers. Therefore, we test the model's predictions in terms of average tasks. Formally, we compute the average task for each group by weighting the individual indices of complexity described in Section II by hours worked.

Given that complexity measures are only available for natives and immigrants, we implement (B5) empirically for these two groups by estimating the following two regressions:

$$I_{Dst} = \phi_s^D + d_{DO}(s_{Ost}) + d_{DI}(s_{Mst}) + \varepsilon_{st}^D \tag{15}$$

$$I_{Mst} = \phi_s^M + d_{MO}(s_{Ost}) + d_{MI}(s_{Mst}) + \varepsilon_{st}^M \tag{16}$$

where the variables I_{Dst} and I_{Mst} in (16) are the average skill intensities of tasks assigned to natives and immigrants, respectively; s_{Ost} and s_{Mst} are the employment shares of offshore and immigrant workers in industry s at time t; and the ϕ_s's represent industry fixed effects. Finally the ε_{st}'s are (possibly) serially correlated errors.

Table 5 here

Table 5 shows the results from the 2SLS specifications (upper part of the Table) where we use, as always, the instruments $(Tariffs)_{st}$ and $(Imputed\_s_M)_{st}$ and from the direct OLS regressions (lower part of the table). We present the effects on the summary indices of Complexity, I_D and I_M (in columns 1 and 5, respectively), as well as the effect on

Cognitive Intensity (column 2), Communication Intensity (column 3), and Non-Manual Intensity (the inverse of the Manual index, in column 4) separately. We focus on the 2SLS results, reported in the first and second row. The direct regression confirms those estimates. In this case the coefficients on offshoring and immigration are estimated in the same regression (since now we do not face the issue of collinearity of shares). The first stage F-Statistics are well above the critical value for the Stock and Yogo test (15 percent maximal IV size) which in the case of two endogenous variables and two instruments is 4.58. The first column of the upper part of Table 5 shows a positive and significant effect of offshoring and no effect of immigration on the Complexity of native tasks. The same holds true for their Communication Intensity, Cognitive Intensity and Non-Manual Intensity. Again this is consistent with the predictions of the theoretical model. [33] Columns (5) and (6) indicate that offshoring has little effect on the complexity of immigrant tasks but, at the same time, has a large positive impact on the gap between immigrant and native tasks ($I_D - I_M$). This suggests that offshore workers affect native workers mainly by pushing them into more complex tasks, effectively hollowing out the task spectrum. This is consistent with the the results found on employment shares (of native and immigrants) in Table 2. These results are also consistent with Hummels, Jorgenson, Munch and Xiang (2010) who find a positive effect of offshoring on the productivity of highly educated workers and with Harrison and McMillan (2011) who find that "vertical" offshoring has positive employment effects, mainly for the highly skilled. In summary we can say that offshoring leads to increased polarization in native and immigrant specialization, mainly by pushing natives towards more complex jobs. This effect is not negligible. Since the standard deviation across sectors in the share of offshore workers during the period is around 14 percent, when multiplied by the coefficient on the complexity index estimated in column (1) we find a difference in task complexity relative to natives of 9 percent. This is about half of the standard deviation of complexity across sectors, and also half of the average difference in complexity of tasks performed by immigrants and natives.

E. Extensions and Checks

Before concluding we briefly discuss the implications of three key assumptions of our theoretical framework. A more detailed discussion of these issues and details on the empirical results can be found in the Web Appendix of the paper.

First, ours is a model of "vertical" offshoring. Namely, offshoring takes place in order to reduce costs and the intermediate tasks performed by offshore workers are combined to produce a good sold at home. Hence our implications on the impact of offshoring on native tasks should work better in industries that are engaged primarily in vertical offshoring. This is confirmed when we split the sample between industries that re-import a large share of their offshore production (vertical-offshoring) versus those that sell a larger share abroad (horizontal-offshoring). When running a specification as in (1) in Table 5, and

[33]The lower part of Table 5 shows the corresponding direct regression coefficients. We see a significant effect of decreasing tariffs on native task complexity and no significant effect of migration. The magnitudes of the coefficients cannot be interpreted as the instruments have somewhat arbitrary scale.

focusing only on sectors doing vertical-offshoring, the impact of offshore employment on native complexity is large and significant (1.10 with standard error of 0.59). In contrast, the same regression run using the sample of sectors doing horizontal offshoring produces non-significant estimates (0.17 with standard error of 0.23).[34]

Second, whereas we assumed perfect mobility of workers, in the presence of imperfect mobility or barriers to transferring skills from one industry to another a portion of the industry-specific effects of immigration and offshoring could be captured by wage rather than employment differentials. In particular, while the U.S. labor force is mobile geographically, as well as across industries, in the short run wages may not be perfectly equalized. We check directly whether industry wages are affected by offshoring and immigration by running a specification like (11), except using the average wage of natives instead of their employment as the dependent variable. The estimates (reported and described in Web Appendix, Table A3) do not show any significant effect of offshoring and immigration on wages.

Finally, as discussed in Section IV.A, imputed immigration, an instrument routinely used in the immigration literature, is usually constructed using variation across localities rather than industries. As a further check that industry-specific network effects are also driven, in part, by the geographic concentration of an industry, we re-run regression (11) focusing on industries that are particularly concentrated in space. Since our 2SLS approach relies on a strong relationship between the flow of immigrants from a particular country into an industry and the share of U.S. immigrants from the same country already working in that industry, the first-stage regression should show increased power when we consider only highly geographically concentrated industries. Again, this is because new immigrants tend to favor destinations where there are ethnic networks created by previous immigrants (Card, 2001; Card and DiNardo, 2000; Peri and Sparber, 2009). A recent paper by Vella and Patel (2007) also shows a concentration of immigrants by location and type of occupation.

In order to capture the degree to which an industry is concentrated within the U.S., we calculate a geographic Gini coefficient for each industry using data on state and industry employment in 2000.[35] Interestingly, the manufacturing sector as a whole is significantly more concentrated than non-manufacturing, with an average Gini of 0.75 compared to 0.72, which bodes well for the validity of the instrument overall. In other words, an immigrant's decision regarding which industry to work in may overlap with their choice of location, strengthening the network effects underlying our IV approach. We therefore take the manufacturing average as our threshold and reproduce the first-stage regression using only those industries with a Gini larger than 0.75, a value that is near the median and so selects nearly 50 percent of the sample.

Table 6 here

The corresponding findings are depicted in Table 6. Comparing the 2SLS results in columns (1) and (2) with the results for the entire sample (in columns 1 and 2 of Table 3), we see that restricting the sample to more concentrated industries increases the estimated,

[34]The details of the empirical analysis and the exact definition of the variables are in the Web Appendix.
[35]These employment data are available for download from the U.S. Bureau of Labor Statistics website.

average impact of immigrants on native employment (from 0.42 to 0.50). This, combined with the relatively larger first-stage coefficient shown in column (2) (to be compared with column 2 in Table 3) constitutes evidence that our immigration instrument is somewhat stronger for spatially concentrated industries and, for these industries, the productivity effect of immigration is also somewhat stronger.

V. Concluding Remarks

We have analyzed the effects of easier offshoring and immigration on the employment share, employment level and task specialization of native workers within the U.S. manufacturing sector from 2000 to 2007. There are very few attempts to combine analyses of immigration and offshoring on labor markets. Analyzing each in isolation ignores the possibility that hiring immigrants or offshoring productive tasks are alternatives that are simultaneously available to producers and, in fact, may compete with one another or with hiring a native worker.

We have modeled and found empirical support for a scenario in which jobs ("tasks") vary in terms of their relative intensity of use of workers' complex skills, while native, immigrant and offshore workers differ systematically in their relative endowments of these skills. When only natives are available, producers will only employ them. When immigrant and offshore workers become increasingly employable efficiency gains can be reaped by hiring them to perform tasks in which they have a comparative advantage, giving native workers the opportunity to specialize in the tasks in which they exhibit their own comparative advantage. If strong enough, the productivity effect associated with this improved task assignment may offset the displacement effect of immigration and offshoring on native workers' employment.

Despite the widely held belief that immigration and offshoring are reducing the job opportunities of U.S. natives, we have found instead that, during our period of observation, manufacturing industries with a larger increase in global exposure (through offshoring and immigration) fared better than those with lagging exposure in terms of native employment growth.

Appendix A - Proof of Proposition 1

Sufficient conditions for the existence of $I_{NO} \in (0,1)$ and $I_{MO} \in (0, I_{NO})$ such that

$$\min[c_D(i), c_M(i), c_O(i)] = \begin{cases} c_M(i), & 0 \leq i < I_{MO} \\ c_O(i), & I_{MO} < i < I_{NO} \\ c_D(i), & I_{NO} < i \leq 1 \end{cases}$$

are that, as i increases from 0 to 1, $c_O(i)$ crosses $c_D(i)$ once and only once and from below in the interval $i \in (0,1)$ and $c_M(i)$ crosses $c_O(i)$ once and only once and from below in the interval $i \in (0, I_{NO})$. The first single-crossing condition holds if $c_O(0) < c_D(0)$, $c_O(1) > c_D(1)$ and $dc_O(i)/di > dc_D(i)/di = 0$. The "marginal offshore task" is then implicitly defined by $c_O(I_{NO}) = c_D(I_{NO})$. Substituting for $c_O(i) = w^* \beta t(i) a_L$ and $c_D(i) = wa_L$ gives (3) and $w = w^* \beta t(I_{NO})$. The second single-crossing condition holds if $c_M(0) < c_O(0)$, $c_M(I_{NO}) > c_O(I_{NO})$ and $dc_M(i)/di > dc_O(i)/di$. The "marginal immigrant task" is then implicitly defined by $c_M(I_{MO}) = c_O(I_{MO})$. Substituting for $c_M(i) = w^* \delta \tau(i) a_L$ and $c_O(i) = w^* \beta t(i) a_L$ gives (4) and $\beta t(I_{MO}) = \delta \tau(I_{MO})$.

Appendix B - Employment levels, Employment Shares and Average Tasks

Given the allocation of tasks in Proposition 1, marginal cost pricing under perfect competition implies that tasks are priced as follows

$$p\left(i\right) = \begin{cases} c_M(i) = w^* \delta \tau(i) a_L & 0 \leq i < I_{MO} \\ c_O(i) = w^* \beta t(i) a_L & I_{MO} \leq i < I_{NO} \\ c_D = wa_L & I_{NO} < i \leq 1 \end{cases}$$

Then, by (1) and (2), the demand for task i is

$$L(i) = \left[\frac{p\left(i\right)}{P_L}\right]^{-\sigma} \left(P_L\right)^{-\frac{1}{1-\alpha}} \left(\alpha p_Y A\right)^{\frac{1}{1-\alpha}} H$$

where P_L is the exact price index of the labor composite, defined as

$$P_L = a_L \left\{ \int_0^{I_{MO}} \left[\delta \tau(i) w^*\right]^{1-\sigma} di + \int_{I_{MO}}^{I_{NO}} \left[\beta t(i) w^*\right]^{1-\sigma} di + (1 - I_{NO}) w^{1-\sigma} \right\}^{\frac{1}{1-\sigma}}$$

Since $i \in [0,1]$, P_L is also the average price (and average marginal cost) of tasks. Using (**??**) we can rewrite it as $P_L = wa_L \Omega(I_{MO}, I_{NO})$ with
(B1)

$$\Omega(I_{MO}, I_{NO}) = \left\{ \int_0^{I_{MO}} \left[\frac{\delta \tau(i)}{\beta t(I_{NO})}\right]^{1-\sigma} di + \int_{I_{MO}}^{I_{NO}} \left[\frac{t(i)}{t(I_{NO})}\right]^{1-\sigma} di + (1 - I_{NO}) \right\}^{\frac{1}{1-\sigma}}$$

This highlights the relationship between P_L and the bundling parameter Ω in Grossman and Rossi-Hansberg (2008), which we encompass as a limit case when σ goes to zero and δ goes to infinity — that is, when tasks are not substitutable and migration is prohibitively difficult. Expression (B1) shows that changes in the migration friction δ and the offshoring friction β that decrease $\Omega(I_{MO}, I_{NO})$ imply improved efficiency in labor usage. This is the source of the productivity effects of immigration and offshoring discussed in Section III.B.

Taking into account the different marginal productivity of the three groups of workers, the amount of labor demanded to perform task i is

$$N\left(i\right)=\begin{cases} a_L\delta\tau(i)L(i) & 0\leq i<I_{MO}\\ a_L\beta t(i)L(i) & I_{MO}\leq i<I_{NO}\\ a_L L(i) & I_{NO}<i\leq 1\end{cases}$$

so that immigrant, offshore and native employment levels are given by

$$\text{(B2)}\qquad \begin{aligned} N_M &= \int_0^{I_{MO}} N\left(i\right)di=\frac{1}{w^*}\left(\frac{P_M}{P_L}\right)^{1-\sigma}\left(P_L\right)^{-\frac{\alpha}{1-\alpha}}B\\ N_O &= \int_{I_{MO}}^{I_{NO}} N\left(i\right)di=\frac{1}{w^*}\left(\frac{P_O}{P_L}\right)^{1-\sigma}\left(P_L\right)^{-\frac{\alpha}{1-\alpha}}B\\ N_D &= \int_{I_{NO}}^{1} N\left(i\right)di=\frac{1}{w}\left(\frac{P_D}{P_L}\right)^{1-\sigma}\left(P_L\right)^{-\frac{\alpha}{1-\alpha}}B \end{aligned}$$

where $B=(\alpha p_Y A)^{\frac{1}{1-\alpha}}H>0$ is a combination of parameters and exogenous variables, and the exact price indices of immigrant, offshore and native tasks are given by
(B3)

$$P_M=a_L\left\{\int_0^{I_{MO}}\left[\delta\tau(i)w^*\right]^{1-\sigma}di\right\}^{\frac{1}{1-\sigma}},\ P_O=a_L\left\{\int_{I_{MO}}^{I_{NO}}\left[\beta t(i)w^*\right]^{1-\sigma}di\right\}^{\frac{1}{1-\sigma}},\ P_D=a_L\left\{\left(1-I_{NO}\right)w^{1-\sigma}\right\}^{\frac{1}{1-\sigma}}$$

Note that N_M is the number of immigrants employed whereas, due to the frictional migration cost, the corresponding number of units of immigrant labor is N_M/δ. Hence, sector employment is $N_L = N_M + N_O + N_D$. The shares of the three groups of workers in sectoral employment are thus

$$\text{(B4)}\qquad \begin{aligned} s_M &= \frac{\left(P_M\right)^{1-\sigma}}{\left(P_M\right)^{1-\sigma}+\left(P_O\right)^{1-\sigma}+\left(P_D\right)^{1-\sigma}\left(w^*/w\right)}\\ s_O &= \frac{\left(P_O\right)^{1-\sigma}}{\left(P_M\right)^{1-\sigma}+\left(P_O\right)^{1-\sigma}+\left(P_D\right)^{1-\sigma}\left(w^*/w\right)}\\ s_D &= \frac{\left(w^*/w\right)\left(P_D\right)^{1-\sigma}}{\left(P_M\right)^{1-\sigma}+\left(P_O\right)^{1-\sigma}+\left(P_D\right)^{1-\sigma}\left(w^*/w\right)} \end{aligned}$$

Finally, the "average task" performed by each group is defined as the employment-weighted average across the corresponding i's:

$$
\text{(B5)} \qquad \begin{aligned}
I_M &= \frac{\int_0^{I_{MO}} iN(i)\,di}{N_M} = \frac{\int_0^{I_{MO}} i\tau(i)^{1-\sigma}di}{\int_0^{I_{MO}} \tau(i)^{1-\sigma}di} \\
I_O &= I_{MO} + \frac{\int_{I_{MO}}^{I_{NO}} iN(i)\,di}{N_O} = I_{MO} + \frac{\int_{I_{MO}}^{I_{NO}} it(i)^{1-\sigma}di}{\int_{I_{MO}}^{I_{NO}} t(i)^{1-\sigma}di} \\
I_D &= I_{NO} + \frac{\int_{I_{NO}}^{1} iN(i)\,di}{N_D} = \frac{I_{NO}+1}{2}
\end{aligned}
$$

*

REFERENCES

Altonji, Joseph G. and David Card. 1991. "The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives." In *Immigration, Trade and the Labor Market*: 201-234. National Bureau of Economic Research, Inc.

Amiti Mary and Shang-Jin Wei. 2005. "Fear of Service Outsourcing: Is It Justified." *Economic Policy*. 20(42): 308-347.

Antecol, Heather, Deborah A. Cobb-Clark and Stephen J. Trejo. 2001. "Immigration Policy and the Skills of Immigrants to Australia, Canada, and the United States." Claremont Colleges Working Papers 2001-26.

Antras, Pol. 2003. "Firms, Contracts, and Trade Structure." *Quarterly Journal of Economics*, 118(4): 1375-1418

Antras, Pol, Luis Garicano and Esteban Rossi-Hansberg. 2006. "Offshoring in a Knowledge Economy." *Quarterly Journal of Economics*, 121(1): 31-77.

Autor, David H. and Lawrence Katz. 1999. "Changes in the Wage Structure and Earnings Inequality." In O. Ashenfelter and D. Card, eds. *Handbook of Labor Economics*, 1463-1555. North-Holland.

Autor, David H., Lawrence Katz and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economics Association Papers and Proceedings*, 96(2): 189-194.

Autor, David H., Levy, Frank and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279-1334.

Barba Navaretti, Giorgio, Giuseppe Bertola and Alessandro Sembenelli. 2008. "Offshoring and Immigrant Employment - Firm-Level Theory and Evidence." Centro Studi Luca d'Agliano Development Studies Working Paper 245.

Bartel, Ann P. 1989. "Where Do the New US Immigrants Live?" *Journal of Labor Economics*, 7(4): 371-391.

Becker, Sascha O., Ekholm, Karolina and Marc-Andreas Muendler. 2009. “Offshoring and the Onshore Composition of Tasks and Skills.” CEPR Discussion Paper 7391.

Blanchard, Emily and Gerald Willmann. 2011. “Trade, Education and the Shrinking Middle Class.” `http://old-hha.asb.dk/nat/philipp/iei/2010/willmann.pdf`.

Blinder, Alan. 2007. “How Many U.S. Jobs Might Be Offshorable?” CEPS Working Paper 142.

Borjas, George J. 2003. “The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market.” *Quarterly Journal of Economics*, 118(4): 1335-1374.

Butcher, Kristin F. and John DiNardo. 2002. “The Immigrant and Native-Born Wage Distributions: Evidence from United States Censuses.” *Industrial and Labor Relations Review*, 56(1): 97-121.

Card, David. 2001. “Immigrant Inflows, Native Outflows, and the Local labor Market Impacts of Higher Immigration.” *Journal of Labor Economics*, 19: 22-64.

Card, David. 2009. “Immigration and Inequality.” *American Economic Review*, 99(2): 1-21.

Card, David and John DiNardo. 2000. “Do Immigrant Inflows Lead to Native Outflows?” *American Economic Review*, 90(2): 360-367.

Chassamboulli, Andri and Palivos, Theodore. 2010. “Give me your Tired, your Poor, so I can Prosper: Immigration in Search Equilibrium.” `http://mpra.ub.uni-muenchen.de/32379/1/12-10.pdf`.

Chiswick, Barry R., Yew Liang Lee and Paul W. Miller. 2005. “Immigrant Earnings: A Longitudinal Analysis.” *Review of Income and Wealth*, 51(4): 485-503.

Costinot, Arnaud. 2009. “An Elementary Theory of Comparative Advantage.” *Econometrica*, 77(4): 1165-1192.

Costinot, Arnaud and Jonathan Vogel. 2010. “Matching and Inequality in the World Economy.” *Journal of Political Economy*, 118: 747-786.

Crinò, Rosario. 2010. “Service Offshoring and White-Collar Employment.” *The Review of Economic Studies*, 77(2): 595-632.

Ebenstein, Avraham, Harrison, Ann, McMillan, Margaret and Shannon Phillips. 2009. “Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys.” NBER Working Paper No. 15107.

Feenstra, Robert and Gordon Hanson. 1996. “Foreign Investment, Outsourcing and Relative Wages.” In *The Political Economy of Trade Policy: Papers in Honor of Jagdish Bhagwati*, ed. R.C. Feenstra, G.M. Grossman and D.A. Irwin. Cambride, MA: MIT Press.

Feenstra, Robert and Gordon Hanson. 1999. “The Impact of Outsourcing and High Technology Capital on Wages: Estimates for the United States 1979-1990.” *Quarterly Journal of Economics.*, 114(3): 907-940.

Feenstra, Robert, Romalis, John and Peter K. Schott. 2002. “U.S. Imports, Exports and Tariff Data.” The Center for International Data, UC Davis.

Goos, Maarten and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistics*, 89(1): 118-133.

Goos, Maarten, Alan Manning and Anna Salomons. 2009. "The Polarization of the European Labor Market." *American Economic Review, Papers and Proceedings*, 99(2): 58-63.

Grossman, Gene. 2004. "The Distribution of Talent and the Pattern and Consequences of International Trade." *Journal of Political Economy*, 112(1): 209-239.

Grossman, Gene and Esteban Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review*, 98(5): 1978-1997.

Grossman, Gene and Giovanni Maggi. 2000. "Diversity and Trade." *American Economic Review*, 90(5): 1255-1275.

Harrison, Ann and Margaret McMillan. 2011. "Offshoring Jobs? Multinational and U.S. Manufacturing Employment." *Review of Economics and Statistics*, 93(3): 857-875

Hendricks, Lutz. 2002. "How Important is Human Capital for Development? Evidence from Immigrant Earnings." *American Economic Review*, 92(1): 198-219.

Hummels, David, Rasmus Jorgenson, Jackob Munch and Chong Xiang. 2010. "Wage and Employment Effects of Outsourcing: Evidence from Danish Matched Worker-Firm Data." `http://128.138.129.98/Economics/seminars/Hummels,%20David.pdf`.

Jensen, Bradford J. and Lori Kletzer. 2007. "Measuring Tradable Services and the Task Content of Offshorable Services Jobs." `http://www.irle-demo.berkeley.edu/events/fall08/kletzer/Kletzer_Job_task_content_080408.pdf`.

Jones, Ronald W. and Henryk Kierzkowski. 1990. "The Role of Services in Production and International Trade: A Theoretical Framework." In *The Political Economy of International Trade: Essays in Honor of Robert E. Baldwin*, R. Jones and A. Kruegers, ed. Oxford: Basil Blackwell.

Kremer, Michael and Keith Maskin. 2006. "Globalization and Inequality." `http://www.economics.harvard.edu/faculty/kremer/files/GlobalizationInequality_Oct06.pdf`.

Levy, Frank and Richard J. Murnane. 2006. "How Computerized Work and Globalization Shape Human Skill Demands." `http://web.mit.edu/ipc/publications/pdf/05-006.pdf`.

Manning, Alan. 2004. "We Can Work it Out: The Impact of Technological Change on the Demand for Low-Skill Workers." *Scottish Journal of Political Economy*, 51: 581-608.

Mataloni, Raymond J. and Daniel R. Yorgason. 2002. "Operations of U.S. Multinational Companies." Survey of Current Business, Bureau of Economic Analysis.

Monte, Ferdinando. 2011. "Skill Bias, Trade and Wage Dispersion." *Journal of International Economics*, 83(8): 202-218.

Ohnsorge, Franziska and Daniel Trefler. 2007. "Sorting It Out: International Trade and Protection With Heterogeneous Workers." *Journal of Political Economy*, 115(5): 868-

892.

Olney, William W. 2012. "Offshoring, Immigration, and the Native Wage Distribution." *Canadian Journal of Economics*, 45(3): 830-856.

Ottaviano Gianmarco I.P. and Giovanni Peri. 2012. "Rethinking The Effect Of Immigration On Wages." *Journal of the European Economic Association*, 10(1): 152-197.

Gianmarco I.P. Ottaviano, Giovanni Peri and Greg C. Wright. 2010. "Immigration, Offshoring and American Jobs." NBER Working Paper 16439.

Peri, Giovanni. 2012. "The Effect Of Immigration On Productivity: Evidence From U.S. States." *The Review of Economics and Statistics*, 94(1): 348-358.

Peri, Giovanni and Chad Sparber. 2009. "Task Specialization, Immigration and Wages." *American Economic Journal*: *Applied Economics*, 1(3): 135-169.

Ruggles, Steven , Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2008). *Integrated Public Use Microdata Series*: Version 3.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor]. http://www.ipums.org.

Sly, Nicholas. 2011. "International Productivity Differences, Trade, and the Distributions of Factor Endowments." Forthcoming in *Review of International Economics*.

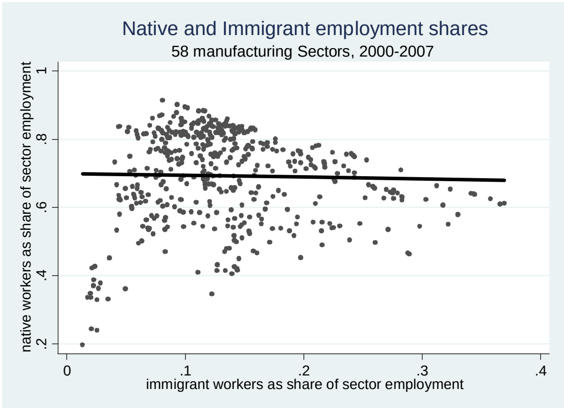
Patel Krishna and Francis Vella. 2007. "Immigrant Networks and Their Implications for Occupational Choice and Wages." IZA Discussion Paper 3217.

Wright, Greg C. 2012. "Revisiting the Employment and Wage Impacts of Offshoring." `http://gregcwright.weebly.com/uploads/8/2/7/5/8275912/offemp_april2012_wright.pdf`.

Yeaple, Stephen. 2005. "A Simple Model of Firm Heterogeneity, International Trade, and Wages." *Journal of International Economics*, 65(1): 1-20.

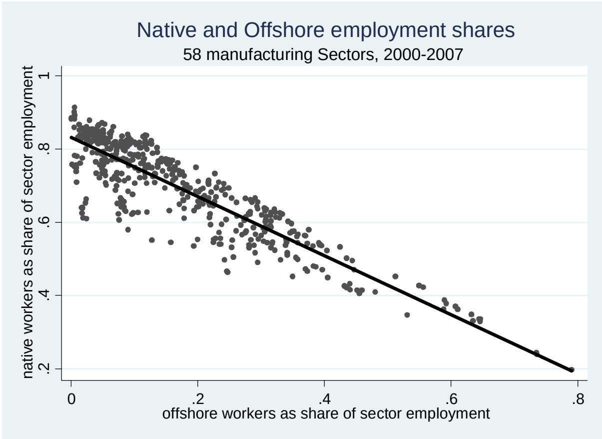
Yeaple, Stephen and Volker Nocke. 2008. "An Assignment Theory of Foreign Direct Investment." *Review of Economic Studies*, 75(2): 529-557.

Figure 1: Shares of Immigrant, Native and Offshore Workers



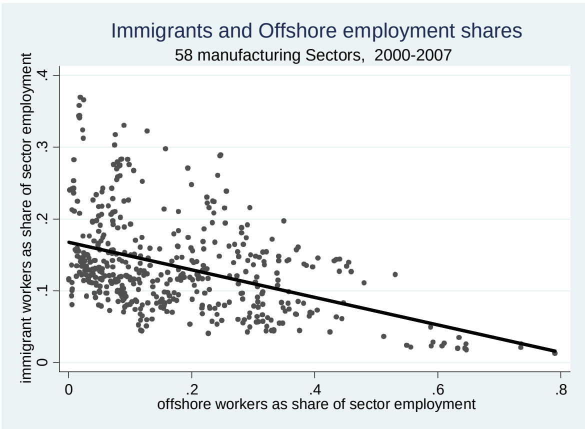
Slope of the regression line: 0.05, Standard error: 0.10

(a)



Slope of the regression line: -0.80, Standard error: 0.02

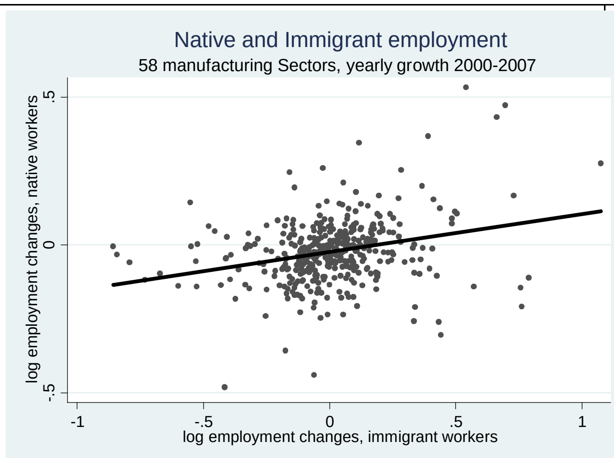
(b)



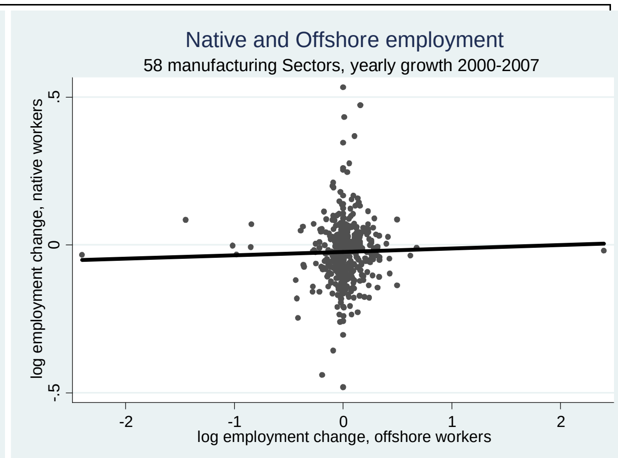
Slope of the regression line: -0.19, Standard error: 0.02

(c)

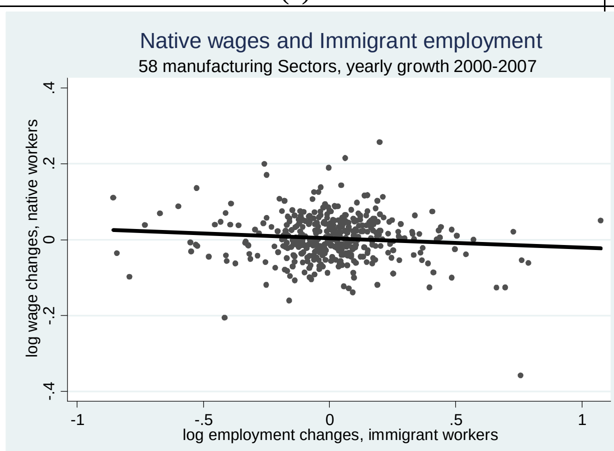
Figure 2: Growth Rates of Employment and Wages



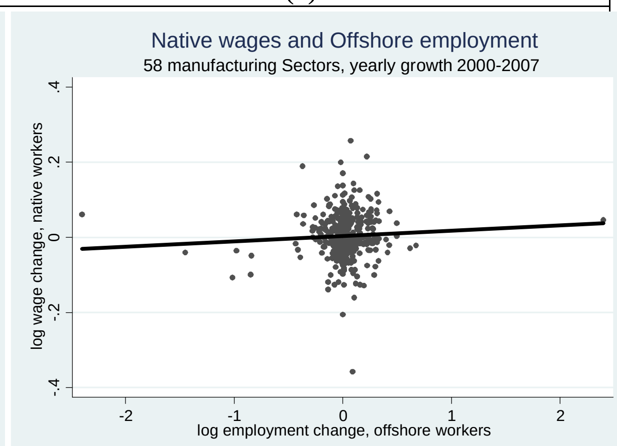
Slope of the regression line: 0.13, Standard error: 0.03
(a)



Slope of the regression line: 0.01, Standard error: 0.01
(b)

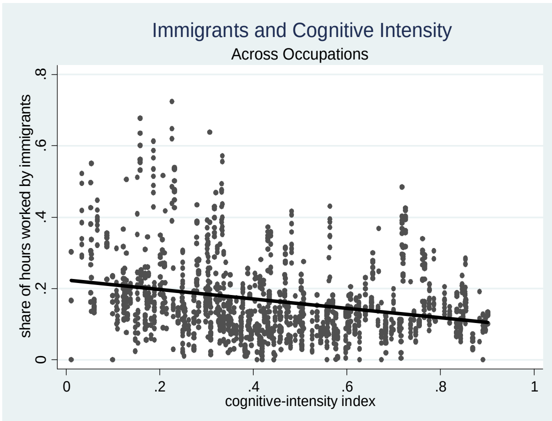


Slope of the regression line: -0.02, Standard error: 0.02
(c)

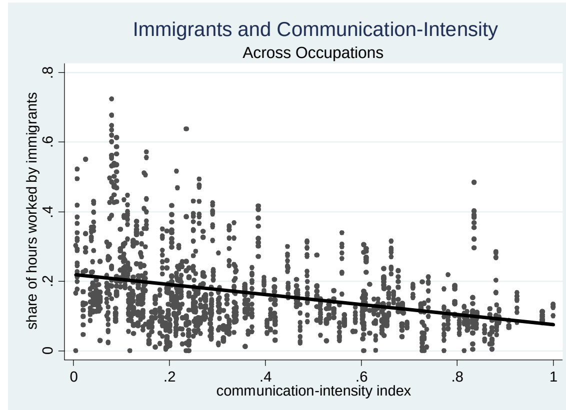


Slope of the regression line 0.014, standard error 0.012
(d)

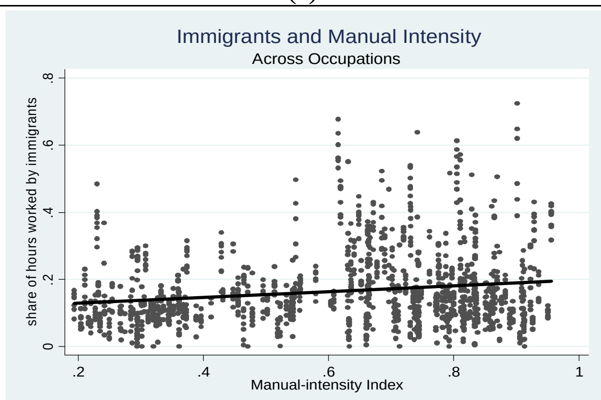
Figure 3: Immigrants and Task Complexity



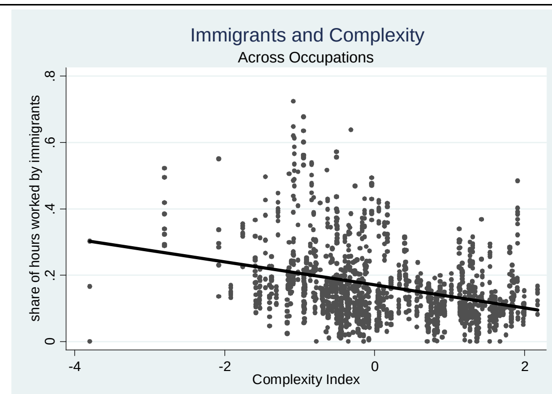
Slope of regression line: -0.13; standard error: 0.01
(a)



Slope of regression line: -0.14; standard error: 0.01
(b)



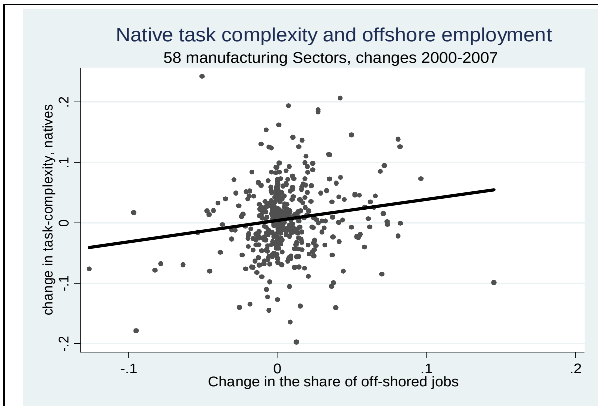
Slope of regression line: 0.087; standard error: 0.01
(c)



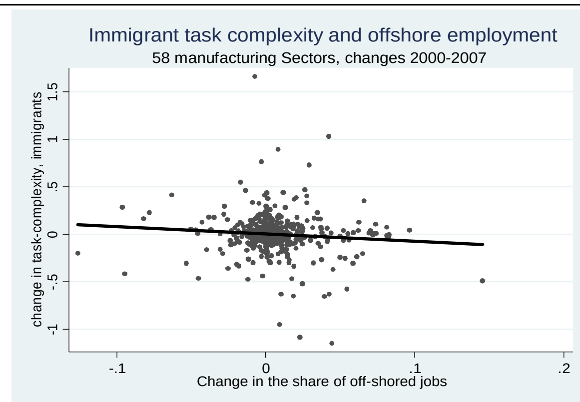
Slope of regression line: -0.034; standard error: 0.002
(d)

Note: Sample is 295 occupations over 2000-2007. Only occupations with over 5000 workers are reported.

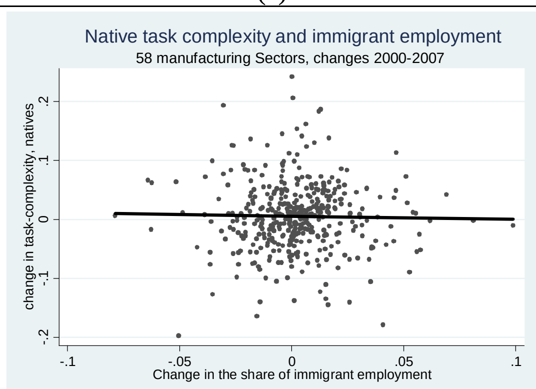
Figure 4: Native Complexity, Immigration and Offshoring (All Workers)



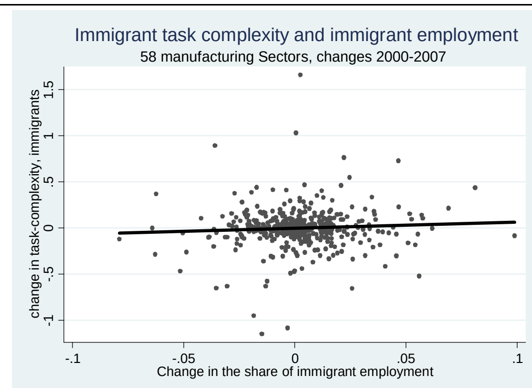
Slope of the regression line: 0.35, standard error: 0.14
(a)



Slope of the regression line: -0.77, standard error: 0.40 (b)



Slope of the regression line: -0.05, standard error: 0.14
(c)



Slope of the regression line: 0.65, standard error: 0.58
(d)

Note: Sample is 295 occupations over 2000-2007. Only occupations with over 5000 workers are reported.

Figure 5: Task Assignment

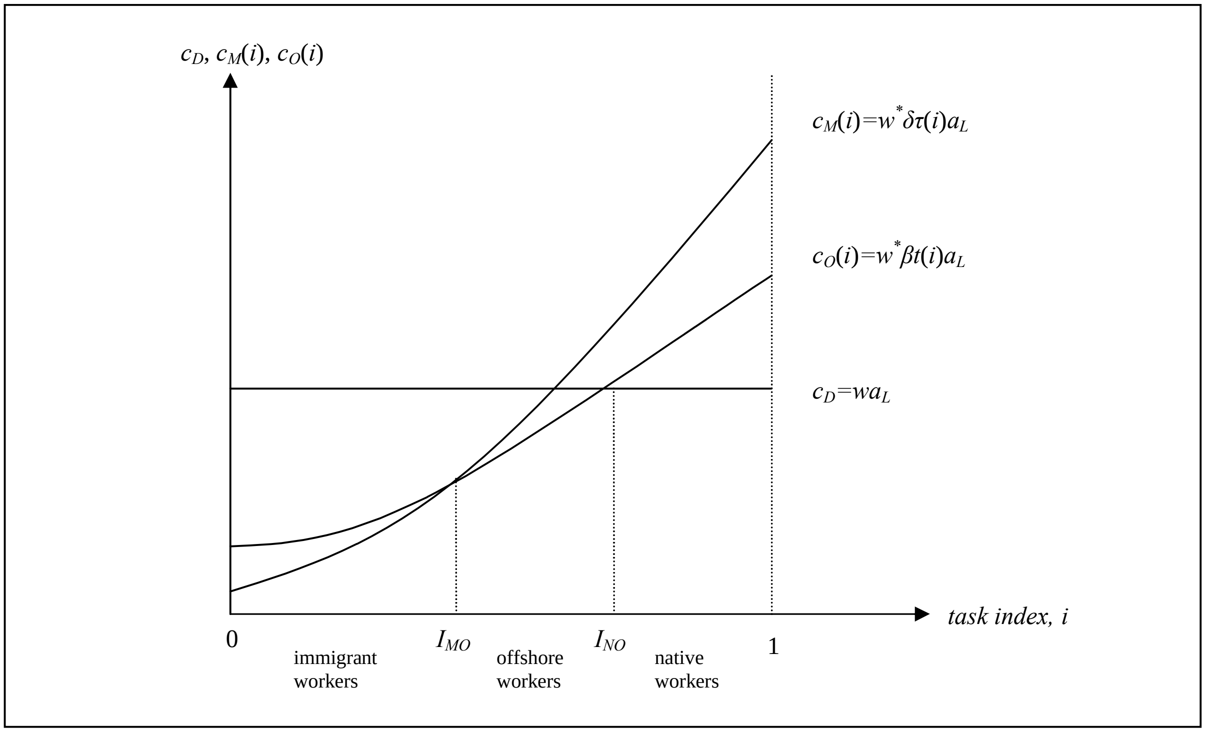


Table 1: Complexity of Native and Immigrant Tasks in Tradable vs. Non-Tradable Industries

Dependent variable is the complexity index for natives	Complexity=ln[(Cognitive + Communication) /Manual]	
	(1)	(2)
	Tradable sectors, 2000-2007	Non Tradable sectors, 2000-2007
Complexity index for the foreign-born	0.04 (0.03)	**0.07**** **(0.01)**
Share of foreign-born	0.01 (0.10)	**0.15**** **(0.06)**
Industry effects	Yes	Yes
Time effects	Yes	Yes
Observations	647	1456

Note: the estimation method is ordinary least squares including industry and time effects. Heteroskedasticity-robust standard errors, clustered at the sector level are reported. **,* significant at the 5, 10 percent level.

Table 2: Effects of Offshoring and Immigration on Employment Shares

	Dependent variable: native share of employment				Dependent variable: immigrant share of employment		Dependent variable: offshore share of employment	
	Method of estimation: 2SLS		Method of estimation: OLS		2SLS	OLS	2SLS	OLS
Specifications	**(1) IV, One instrument**	**(2) IV, One instrument**	**(3) Direct OLS regression**	**(4) Direct OLS regression**	**(5) IV, One instrument**	**(6) Direct OLS regression**	**(7) IV, One instrument**	**(8) Direct OLS regression**
Immigrant share of employment		-0.46 (0.39)					-0.53 (0.39)	
Offshore share of employment	-0.78** (0.07)				-0.21** (0.07)			
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage:	Offshore share of employment	Immigrant share of employment			Offshore share of employment		Immigrant share of employment	
Imputed sector-specific share of immigrants		1.90** (0.48)		-0.91 (1.16)			1.90** (0.48)	-1.03 (0.94)
Sector-specific tariffs	-0.06** (0.01)		0.036* (0.02)		-0.06** (0.08)	0.01** (0.004)		
Number of obs.	464	464	464	464	464	464	464	464
Wald F-stat of first stage	16.6	12.5	NA	NA	16.6	NA	12.5	NA

Note: The dependent variable in each regression is specified at the top of the relative columns. The units of observations are industry by year. All regressions include industry and year effects. Heteroskedasticity-robust standard errors are reported in parenthesis. In the OLS regressions the standard errors are also clustered by industry. **,* significant at the 5, 10 percent level.

Table 3: Effects of Offshoring and Immigration on Employment Levels

	Dependent variable: : ln(native employment)				Dependent variable: ln(immigrant employment)		Dependent variable: ln(offshore employment)	
	Method of Estimation: 2SLS		Method of Estimation: OLS		2SLS	OLS	2SLS	OLS
Specifications	**(1) IV, One instrument**	**(2) IV, One instrument**	**(3) Direct OLS regression**	**(4) Direct OLS regression**	**(5) IV, One instrument**	**(6) Direct OLS regression**	**(7) IV, One instrument**	**(8) Direct OLS regression**
ln(Immigrant employment)		0.42** (0.21)					0.14 (0.43)	
ln(Offshore employment)	-0.11 (0.12)				-0.23 (0.21)			
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage:	ln(Offshore employment)	ln(Immigrant employment)			ln(Offshore employment)		ln(Immigrant employment)	
Imputed sector-specific share of immigrants		14.07** (4.76)		5.83* (3.60)			14.07** (4.76)	2.07 (9.15)
Sector-specific tariffs	-0.032** (0.007)		0.004 (0.008)		-0.032** (0.007)	0.007 (0.010)		
Number of obs.	464	464	464	464	464	464	464	464
F-test of first stage	17.2	8.70	NA	NA	17.2	NA	8.70	NA

Note: The dependent variable in each regression is specified at the top of the relative columns. The units of observations are industry by year. All regressions include industry and year effects. Heteroskedasticity-robust standard errors are reported in parenthesis. In the OLS regressions the standard errors are also clustered by industry. **,* significant at the 5, 10 percent level.

Table 4: Effects of Offshoring and Immigration on Total Employment: The Productivity Effect

	Dependent variable: ln(total employment)			
	Method of Estimation: 2SLS		Method of estimation OLS	
Specifications	**(1) IV, one instrument**	**(2) IV, one instrument**	**(3) Direct OLS regression**	**(4) Direct OLS regression**
Immigrant share of employment		3.86** (1.87)		
Offshore share of employment	1.71** (0.57)			
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	464	464	464	464
First stage:	Offshore share of employment	Immigrant share of employment		
Imputed sector-specific share of immigrants		1.94** (0.55)		7.53** (2.85)
Sector-specific tariffs	-0.06** (0.01)		-0.08 (0.05)	
F-test	16.6	12.5	NA	NA

Note: The dependent variable in each regression is the logarithm of total (native+immigrant+offshore) employment in the sector. The units of observations are industry by year. All regressions include industry and year effects. Heteroskedasticity-robust standard errors are reported in parenthesis. In the OLS regressions the Standard errors are also clustered by industry. **,* significant at the 5, 10 percent level.

Table 5: Effects of Offshoring and Immigration on the Skill Intensity of Native and Immigrant Tasks

	Dependent Variable:					
Specification:	**(1) Complexity Index, Natives**	**(2) Cognitive Index, Natives**	**(3) Communication Index, Natives**	**(4) Non-Manual Index, Natives**	**(5) Complexity Index, Foreign-Born**	**(6) Difference in Complexity Natives-Foreign born**
			2SLS Estimates			
Immigrant share of employment	0.04 (0.66)	0.04 (0.43)	0.12 (0.51)	0.01 (0.22)		
Offshore share of employment	0.64** (0.30)	0.38** (0.18)	0.41** (0.20)	0.26* (0.14)	-0.10 (0.55)	0.75** (0.31)
First stage						
F-statistic	5.10	5.10	5.10	5.10	8.45	8.45
			Direct OLS Estimate			
Imputed sector-specific share of immigrants	-0.72 (0.72)	-0.41 (0.44)	-0.37 (0.55)	-0.31 (0.32)		
Sector-specific tariffs	-0.027** (0.011)	-0.016** (0.007)	-0.018** (0.008)	-0.011** (0.005)	0.04 (0.20)	0.033* (0.02)
Number of observations	464	464	464	464	464	464

Note: The upper part of the table shows the coefficients from the 2SLS estimation using imputed sector-specific share of immigrants and sector-specific tariffs as instrument. The lower part of the table shows the results of a direct regression of the dependent variables on the instruments. The units of observations are industry by year. All regressions include industry fixed-effects. Standard errors are heteroskedasticity robust and clustered at the sector level. **,*= significant at the 5, 10 percent level.

Table 6: Employment Regressions for Geographically Concentrated Industries

	Dependent variable: : ln(native employment)			
	Method of Estimation: 2SLS		**Method of Estimation: OLS**	
Specifications	**(1)** **IV, One instrument**	**(2)** **IV, One instrument**	**(3)** **Direct OLS regression**	**(4)** **Direct OLS regression**
ln(Immigrant employment)		0.50** (0.22)		
ln(Offshore employment)	-0.12 (0.08)			
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
First stage:	ln(Offshore employment)	ln(Immigrant employment)		
Imputed sector-specific share of immigrants		20.90** (8.4)		10.40* (5.40)
Sector-specific tariffs	-0.06** (0.01)		0.007 (0.009)	
Number of obs.	200	200	200	200
F-test of first stage	33.2	6.80	NA	NA

Note: The dependent variable in each regression is the logarithm of native employment. We only include the manufacturing sectors with Gini coefficient of geographic concentration across states larger than 0.75, which is the average for the Gini in manufacturing. Heteroskedasticity-robust standard errors are reported. In specification (3) and (4) standard errors are also clustered at the industry level. **,* significant at the 5, 10 percent level.