CHAPTER 10

Immigration and the Economy of Cities and Regions

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Abstract

In this chapter, we analyze immigration and its effect on urban and regional economies focusing on productivity and labor markets. While immigration policies are typically national, the effects of international migrants are often more easily identified on local economies. The reason is that their settlements are significantly concentrated across cities and regions, relative to natives. Immigrants are different from natives in several economically relevant skills. Their impact on the local economy depends on these skills. We emphasize that to evaluate correctly such impact, we also need to understand and measure the local adjustments produced by the immigrant flow. Workers and firms take advantage of the opportunities brought by immigrants and respond to them trying to maximize their welfare. We present a common conceptual frame to organize our analysis of the local effects of immigration, and we describe several applications. We then discuss the empirical literature that has tried to isolate and identify a

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causal impact of immigrants on the local economies and to estimate the different margins of response and the resulting outcomes for natives of different skill types. We finally survey promising recent avenues for advancing this research.

Keywords

Immigration, Labor markets, Skill complementarities, Innovation, Endogenous technical change, Labor supply, Immigrant enclaves, Firms, Productivity

JEL Classification Codes

Labor: J2, J3, J61; International: F16, F22; Production technique and innovation: O31, O33; Regional: R11, R12

10.1. INTRODUCTION

International migrants to the United States and to other rich countries have grown in number and as share of the population during the last four decades. As of 2010, about 10% of the population in the average OECD country (the club of most economically advanced nations) was foreign born. In the United States, this percentage was 12.9, only slightly above that average. The increase over recent decades of such share was also significant as immigrants comprised only 4.7% of the US population in 1970. While this aggregate number is not negligible, what makes immigration particularly interesting to urban and regional economists is its remarkable concentration in some regions and cities. The United States is a good example of this. Immigrants are more geographically concentrated than natives no matter what geographic unit we choose. We will illustrate this fact with more detailed statistics in the next section. For now, let us just mention that California, the top immigration state, hosts 25% of all US foreign born but only 9% of its natives. New York, the top immigration metropolitan area, hosts 14.5% of all US foreign born but only 5.5% of natives (authors' calculations using the 2010 American Community Survey (ACS; Ruggles et al., 2010)).

As a consequence, native individuals have a very different degree of exposure (in any aspect of their life) to immigrants depending on where they live. Among California residents, in 2011, for every two US-born, there was one foreign born. Hence, it was very likely that the effects of those foreign-born individuals, through their economic and labor market transactions, were felt, in some form, by natives. At the other hand of the spectrum, among West Virginia's residents, for every 99 natives, there was 1 immigrant. This makes it much less likely that those few immigrants produced any noticeable economic or labor market impact on most native West Virginians. Even more extremely, Miami and Los Angeles counted more than 40% of foreign-born residents[1] (almost one

[1] The percentage of foreign-born residents was 62% in Miami and 43% in Los Angeles (authors' calculations using Ruggles et al., 2010).

foreign born for each native) in 2011, while other metropolitan areas (such as Johnstown, PA, and Billings, MT) had less than 1% of foreign-born residents.[2]

The very uneven distribution of immigrants across regions, relative to the native population, makes for a very good "prima facie" setup to study the differential impact of immigration on the local economies. Different geographic areas and the native workers and firms within them have been exposed to very different inflows of immigrants over the last decades. Hence, by appropriately tracking their economic performance (wage and employment of native workers and productivity of firms) subsequent to the inflow of immigrants, we may be able to identify the effects of immigration on these economies.

Certainly, one has to be very careful in drawing causal inference from statistical association. The location of immigrants is not random but is itself the result of decisions that depended on local economic conditions. A booming economy attracts more workers and more firms. If immigrants respond more vigorously to economic incentives than natives (and there is some evidence of this; see, for instance, Cadena and Kovak, 2013), an increase in their share in the population may be a consequence (and not a cause) of regional economic success. Caution is also required in identifying the total economic effect of immigrants by analyzing regions, as those are interconnected: the effects of an inflow of immigrants in one region can spill to others through labor mobility, capital mobility, or trade. Nevertheless, exploiting the massive differences in migrant settlements across regions and cities and correlating those differences with local economic outcomes have been the foundation of the largest part of the empirical studies that have focuses on the local effects of immigrants.[3]

Let us emphasize right away that the features of geographic concentration (and skill concentration, as described below) of immigrants relative to natives are typical not only of the United States but also of most industrialized countries. European cities (such as London, Paris, and Barcelona) have an immigrant density comparable to the top US cities. Our chapter, in fact, will analyze features of immigrants and local economies that can be considered as very general across industrial countries. While we will begin by reviewing several studies that focus on the United States, where this literature originated because of data availability, we will also discuss and analyze many studies and results for other countries, especially in Europe, where immigration flows have been particularly large during the years since 2000, feeding a very contentious policy debate, and where very good administrative data have become available in the recent years, making empirical analysis much more detailed and interesting.

[2] These percentages are calculated from ACS microdata (Ruggles et al., 2010) including all working individuals aged 18–65 not residing in group quarters.

[3] In the 1990s and part of the 2000s, studies using the geographic variation of immigrants to estimate their economic effects were identified as using the "area approach." The more competent of those studies, however, always accounted also for the skill distribution of immigrants across area units not simply their density.

Considering immigrants as one group and focusing only on their uneven geographic distribution cannot by itself provide good insight into their economic impact on natives. Immigrants, in fact, are also distributed differently than natives across other dimensions that we broadly define as "skills." Considering the specific "skill" distribution of immigrants is crucial. For one, it provides us with another dimension of variation to analyze the effect of immigrants. More importantly, it forces us to develop a theoretical approach to analyzing productivity and economic effects of migrants in a context of productive specialization and complementarities across skills. First, we need to identify the more appropriate cells that best correspond to homogeneous skills (or "factors of production"). Then, we need to specify how they are combined in production exhibiting certain patterns of complementarity and substitutability with each other. The immigrant and native distribution across these skill cells and the ability of natives to move across them in response to immigration (as well as to move across geographic units) will be very important factors in determining productivity, wage, and employment effects of immigrants.

There are three dimensions of the native–immigrant difference in skill characteristics that have been used in the literature, leading to somewhat different strategies to identify and analyze the immigrants' effect. First, immigrants differ in their educational composition vis-à-vis natives. They are relatively more represented among very high (PhD degrees) and very low (less than high school diploma) levels of schooling. Second, they differ in their age distribution, as they are overrepresented among young individuals in the labor force (18- to 35-year old). Third, they are employed in some occupations much more than in others with a clear and specific pattern: They are overrepresented in manual–physical-intensive jobs among the less educated and they are overrepresented in science–technology–engineering–math (STEM)-intensive jobs among the highly educated. In contrast, they are relatively rare in white-collar, communication-intensive, bureaucratic types of jobs. This is possibly because their language skills provide them with a comparative disadvantage in those jobs as their physical/manual skills (on one hand) or mathematical/analytic skills (on the other) are more internationally transferrable.

This concentration of immigrants in some skill groups produces three interesting theoretical consequences that we need to consider when analyzing the impact on the native economy. First, the effect on natives will depend on a native's characteristics: individuals with skills and in occupations similar to those where immigrants concentrate will experience their competition more strongly. Individuals in other jobs will experience a beneficial effect or no effect at all, depending on the productive interactions (complementarity) between skills. Second, this uneven concentration will introduce differential incentives for natives to "move" out of their cells. While they may move across local economies toward or away from the areas where immigrants concentrate (depending on their competition or complementarity), they can also move away from the skill cells in which immigrants are concentrated to those skill cells benefiting from immigrants. While workers cannot change their age, they can change their education, occupation, and job specialization, and they typically do over their working career. When exposed to immigration, natives will have economic incentives to specialize, upgrade, and direct their career in order to maximize returns and minimize losses from immigration. Finally, firms are also important players. When faced with a changing concentration of potential workers across skill cells, they may adopt differential technologies or techniques or they may change product combination so as to use more intensely and more efficiently those skills that have become more abundant.

Traditionally, the economic analysis has distinguished between short-run and long-run effects of immigration. However, the so-called short-run effects are mostly a theoretical device to decompose a complex effect. When economists analyze the "short-run effects" of immigrants, they try to isolate the consequences of immigration when all other variables (including the stock of capital, the skill supply of natives, and the technology and productive structure) are fixed. This should be called "partial" effect. It is a way to understand and isolate a specific effect, not a way to forecast what happens, even in the short run. The adjustments in skill supply of natives, the adaptation of technologies and the related capital investments, and the change in product composition described above have typically been associated to the long-run response to immigration. However, bar some exceptional cases, immigration has been a slow and consistent force in the last decades for most countries. It has rarely (if ever) been a temporary 1-year burst followed by slow adjustment. Typically, the yearly inflow of immigrants in countries with fast-growing foreign population has been between 0.3% and 0.6% of the resident population. These inflows have produced significant changes over time, but the horizon to observe these consequences is decades, not years. Hence, the speed of these inflows and their progression and relative predictability imply that the correct perspective is a "long-run" one. Within this time horizon, the described adjustment margins (changes of native skill supply, of capital, of technology, and of output composition) have also played important roles and need to be analyzed as part of the effect of immigration. Let us also add that a focus on the "long-run" consequences of migration implies that the most relevant measure of immigration flows in a country is the change in the stock of foreign born, hence net migration. This implies that short-run temporary flows of migration and return are not central in our chapter. While there is an interesting literature devoted to the selection of returnees and to how this affects the features of remaining migrants (e.g., Abramitzky et al., 2014), we are simply focusing on the characteristic of nonreturning migrants in the long run and their effects on the receiving economies.

The "long-run" nature of the migration phenomenon and the skill characteristics of migrants, at the top and bottom of the receiving-country human capital distribution, imply that at the national level, immigration could have an important role in economic growth and economic inequality. In particular, due to the increase in economic inequality in the United States during the last three to four decades, immigration has been sometimes scrutinized as a potential determinant of it, through its labor market competition effects on less educated natives. Card (2009) and Blau and Kahn (2012) did not find a significant role of immigration in the increase in US inequality during the recent decades. The relatively balanced inflow of immigrants between college-educated and noncollege-educated and the response of local markets and native workers (that we will analyze below) imply a small effect of immigration on native wage (and income) inequality. Also, while some immigrants themselves are at the bottom of the income distribution, their number as share of population is relatively small.[4] Several of the studies at the national level that we will review in Section 10.3.2[5] have quantified the contribution of immigration to inequality in the United States, and none of them has found more than a very small role. Dustmann et al. (2013) considered more directly the effect of immigration on the UK wage distribution and found a mild positive effect on inequality, mainly through an increase in high wages due to complementarity with immigrants.

On the other hand, very limited research exists, at the national level, on immigration and growth. Ortega and Peri (2014) are among the few to tackle the issue of estimating the impact of immigration on average GDP per person and aggregate productivity using cross-country analysis. They use geographic features predicting immigration and control for an array of institutional, cultural, and historical determinants, to isolate the effect of immigration. They find a strong positive effect of the immigrant share on productivity across countries, and they document that this derives in part from more innovation and from other benefits of diversity. Alesina et al. (2013) adopted a similar approach to analyze the effect of "country of birth" diversity on GDP per person and productivity and also found a positive and significant effect. Also promising are those studies analyzing the impact of highly skilled immigrants (scientists and engineers) on average wage and productivity growth in US cities (such as Peri et al., 2014 described in Sections 10.3 and 10.5). The aggregate studies mentioned are interesting and quantitatively useful. However, our approach in this chapter will look in greater detail at mechanisms and models that help us understand the working of immigration on economic activity, productivity, and labor markets. Focusing on local economies and shedding light on those mechanisms have clearly important implications on the role of immigration on aggregate inequality and growth.

After presenting in Section 10.2 some statistics about the distribution of immigrants across geography and skill space, Section 10.3 introduces a rather general "production-function approach" to the economic effects of immigration. We will focus on wage and employment effects of immigrants, and we will also discuss productivity effects that need to be considered as we analyze specialization and choice of technique. The analyzed approaches model the skill interactions across different types of workers in a city

[4] Peri (2013) analyzed directly the impact of immigrants on native poverty rates in the United States during the years 1990–2010, through the labor market competition channel. He found extremely small effects.

[5] See in particular Borjas (2003), Borjas and Katz (2007), and Ottaviano and Peri (2012).

(or region) using a production-function approach. We devote special attention to the nested-CES approach that organizes native and immigrants workers in education, age, and nativity cells and then into production tasks. Variations of this model have been widely used in the recent literature. Using this framework, we derive effects on productivity and wages, and they also produce predictions on changes in specialization, skill supply, and choice of production technology, consequent to immigration-induced changes to the distribution of skills.

Then, Section 10.4 analyzes the empirical strategies used to isolate immigration as an exogenous change in skill supply at the local level. We will consider the potential challenges to identification and the proposed remedies. In particular, the methods based on preexisting settlements and current aggregate inflow by nationality and those focusing on some sudden and large migration shocks or policy changes are considered. Then, in Section 10.5, we review estimates of the effects produced by immigration on local economies in terms of wages and productivity outcomes, and we will pay attention to native responses to immigration and to a general equilibrium effect. The inflow of immigrants, in fact, appears to trigger a mobility response of natives (as immigration changes the relative rewards for them). It turns out that the most significant responses are not represented by net outflows or inflows of natives in geographic areas (what Card and DiNardo, 2000 called the "skating-rink" hypothesis) but by increased mobility across skill cells (specialization, occupation upgrading, and education improvement). This is important because mobility in the skill space affects native wages in a different way than mobility across regions. In particular, if natives move from skills (occupation, tasks, and jobs) that are more substitutable to skills that are more complementary to immigrants' in response to their inflow, this response would increase the native gains from immigration, and those gains can be captured within an economic area. If they instead move out of the area simply to avoid competition, they may not gain from immigrants and the area analysis may miss some of the total effect. Another aspect that we emphasize is that firms may be induced to adopt technology and capital in order to take advantage of immigrant skills. This is even more important in the long run because it may change the productivity of specific skills. We will analyze studies that combine the direct effects and the induced responses (of native workers and firms) to determine the observed productivity and wage outcomes.

Analyzing recent contributions, we think that the differentiated skill cell approach, using variation across regions and cities, is emerging as dominant in the study of immigration to the United States and to other developed countries. Recently, individual-level and firm-level data from different developed countries (mainly in Europe) have also been tackled to analyze these effects. The most interesting European data are from administrative sources and make available to the researcher panels of individuals over time and panel of establishments over time. The ability to identify firm outcomes and the possibility of following individual workers make those data sets able to reveal in more detail the microlevel mechanism of adjustment of local economies to immigration. While several empirical and identification issues still exist when using these data, we think they add very interesting tools to our understanding of the role of immigrants, and in particular, they allow a closer inquiry of the mechanisms at work within labor markets. In Section 10.6, we will analyze the possibilities opened in terms of methods and analysis by the availability of these individual panel data sets, and we also review some recent studies using historical microdata to analyze the productive response to immigrants in historical large migration episodes. Finally, in Section 10.7, we briefly summarize and conclude the chapter.

10.2. IMMIGRANTS' DISTRIBUTION AND NATIVE EXPOSURE

Immigration affects the geographic and the skill distribution of productive resources (workers) in a country. Defining the relevant cells to analyze the economic and productive consequences of immigrants is important. First, however, we describe how the distribution of immigrants in the United States differs on dimensions of geography and skills relative to the distribution of natives. These differences are what create economic opportunities and incentives to implement changes and adjustment by native agents. We use data from the American Community Survey 2011, and we select only individuals who are currently working.[6] A few simple statistics help us to see that the largest variation in native exposure to immigrants is in the geographic dimension, using metropolitan areas as units of analysis. Not only does immigrants' share of employment vary hugely across units, but also immigrants exhibit a much stronger absolute concentration in the top locations than natives do. Then, we analyze the distribution of immigrants and natives across occupations, using the census occupational classification, and finally, we describe the distribution of immigrants across education and age groups. All empirical studies we are aware of use one or more of these dimensions as unit of analysis to identify the productive and labor market effects of immigrants.

The upper part of Table 10.1 shows some simple statistics on the overall concentration of immigrants, relative to natives, across different dimensions. The lower part of Table 10.1 shows instead statistics representing the variation in exposure of natives to immigrants across cells in that dimension. Column 1 of the table considers 284 metropolitan areas as cells, column 2 considers 50 states, column 3 considers 333 occupations, and column 4 uses 7 schooling groups.[7] Finally, column 5 considers 70 education-by-age groups (7 education groups each divided into 10 age bins, for workers between 18 and 65).

[6] Specifically, we consider individuals 18–65 years of age, not living in group quarters who have worked at least a week.

[7] The groups are no diploma, high school diploma, some college, associate degree, college degree, master, and PhD.

Table 10.1 Measures of concentration and exposure native–immigrants for different cell structures

Cell	Metropolitan areas	States	Occupations	Education cells	Education–age cells
Number	284	50	333	7	70
Measures of concentration across cells: relative values immigrant/native					
Foreign/native Herfindahl	3.42	2.76	0.87	0.93	0.99
Foreign/native percentage of population in top unit	2.48	2.74	1.09	1.03	0.98
Foreign/native percentage of population in top 5% of units	1.86	2.07	0.92	N.A.	1.05
Foreign/native percentage of population in top 10% of units	1.60	1.85	0.88	0.94	1.06
Measure of variation in native exposure to immigrants across cells					
(Immigrant per resident) Top 10%/bottom 10%	11.1	6.6	4.3	2.6	5.2
(Immigrant per resident) Top 5%/bottom 5%	17.2	10.3	7.3	N.A.	6.8
(Immigrant per resident) Ratio of largest to smallest	65.1	21.8	63.0	4.6	10.0

Note: All statistics use all US resident individuals, not living in group quarters and working at least 1 week, aged 18–65. The data are from ACS 2011.

The production models that we analyze below consider a stronger direct competition effect of immigrants on natives when they are in the same cell. Hence, the variation in exposure across cells is a crucial dimension to identify the direct competition effect. On the other hand, it is also very important to consider different degrees of interaction between cells and also different ability of natives to move across cells. The more recent empirical studies have been careful in accounting for these cross effects and responses. The interaction between skill cells is typically analyzed within the context of complementarities/substitutability of skills in production, while the interaction across geographic cells is usually considered in the context of the native migration response to immigrants.

The distribution across metropolitan statistical areas (MSAs) shows the strongest difference in concentration of immigrants relative to natives. The Herfindal index of concentration across MSAs, which is calculated as the sum of squared share of total population in each unit, captures the degree of concentration of a population in cells. The Herfindal index of urban population (between 0 and 1) would be close to 1 if most of the urban population (immigrant or native) in the United States were concentrated in the largest metropolitan area. It would be essentially 0 if the urban population was instead equally distributed across metropolitan areas of the same size. The table reports the immigrants–natives ratio of such Herfindal index and implies a 3.5 times larger value for immigrants than for natives denoting a significantly larger concentration of their urban population in the largest metropolitan areas. Similarly (second row), the percentage of immigrant employment in the top metro area is 2.5 times as large as the percentage of natives employed in the top metro area. The percentage of immigrants in the top 5% of metro areas is 1.8 times the percentage of natives in top 5% of metro areas, and immigrants in the top 10% MSAs are 1.6 times the percentage of natives in the top 10% metro areas. The stronger concentration of immigrants across metropolitan areas relative to natives is also shown in Figure 10.1. In that figure, we see that the percentage of total immigrant employment in the top 15 metropolitan areas is significantly larger than that of

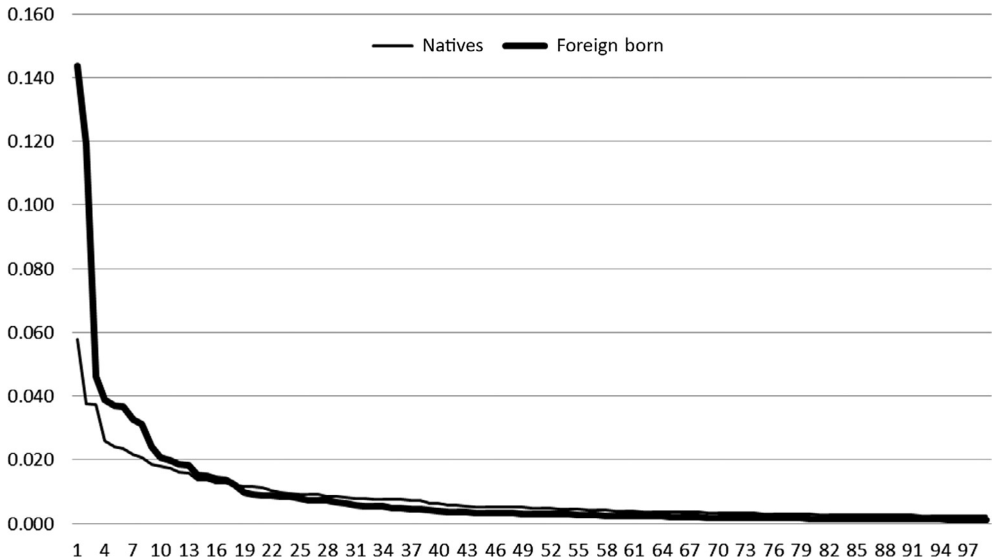

Figure 10.1 Sorted share of urban employment in each of top 100 metro *areas—native and foreign born. Note: The share of employment in each metro area is calculated based on 2011 ACS data, excluding people in group quarters and including only people 18–65 who worked at least 1 week. We consider as urban population is the total population of the top 284 metro areas in the United States.*

natives. When ranking metropolitan areas based on their percentage of total urban employment, the mass of immigrants is strongly shifted toward the very top areas, relative to the mass of natives. A similar pattern of stronger geographic concentration is also revealed in column 2 when we consider states. California, the top immigrant state, had 25% of all US working immigrants but only 9% of all US native workers. Similarly, Figure 10.2 shows much larger concentration of immigrants in the top five states relative to natives.

The lower part of Table 10.1 shows even more interesting statistics. We show the range in the exposure of natives to immigrants as the ratio between the share of foreign born in the most exposed and that of in the least exposed cells. The bottom row is the ratio of the highest exposed cell to the lowest exposed cell; the next row up is the ratio of the cell at the 95 percentile (top 5%) and the one at the fifth. The row above that shows the ratio of the 90–10 percentile. Remarkably, the share of foreign born in the city with the highest concentration (Miami) was 65 times the share in Johnstown (PA), the city with the lowest relative presence of immigrants. Even the 90–10 percentile ratio was a very large, 11. This means that in metropolitan areas with high concentration of immigrants, their density relative to natives was more than 10 times larger than in metropolitan areas with low concentration. Across states, the variation was also remarkable with a top–bottom ratio of almost 22. While these differences are certainly not random, comparing wage, productivity, employment, and other economic outcomes across cells that experience such a drastically different presence of immigrants, if done carefully, could reveal important implications of their presence.

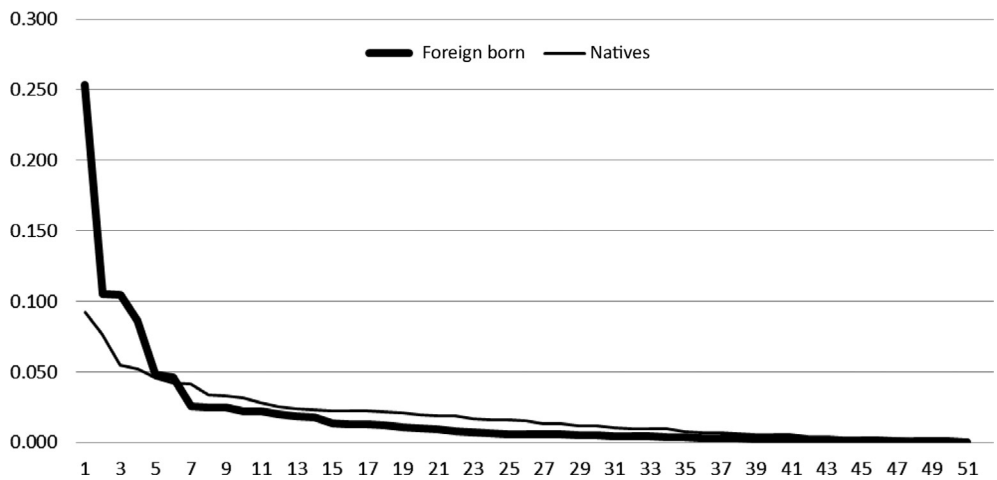

Figure 10.2 Sorted share of total employment in each state—*native and foreign born. Note: The share of employment in each state is calculated based on 2011 ACS data, excluding people in group quarters and including only people 18–65 who worked at least 1 week. We consider 50 US states plus DC (hence 51 units).*

Let us then analyze similar statistics calculated across occupations (column 3) and education and age (columns 4 and 5). In terms of occupations, we notice that immigrants are not more concentrated across them, in absolute terms, than natives are. The indices of relative concentration in the upper part of the table are, in fact, close to 1. However, their distribution across occupations is very different from that of natives, and it generates very different degrees of exposure of natives to immigrants depending on the occupation they are in. The top–bottom ratio is 63 and the 95–5 percentile ratio is 7.3. A native working as "sorter of agricultural products" (the top occupation as share of immigrants) is exposed to a share of immigrants 63 times larger than one working as "funeral director (sic!)" (the occupation with the lowest share of immigrants). Occupations, therefore, as metropolitan areas, vary enormously in the presence of immigrants. Moreover, both dimensions exhibit a significant intercell mobility of native workers over their lifetime, especially when young. Hence, the differential immigration "pressure" across cells may produce a significant response of natives in flowing across cells. This does not imply that they cannot be used as units of analysis of the effects of immigrants, but one certainly needs to account for flows of natives between them as potential response to immigration.

The last two columns show the relative concentration and distribution of immigrants across education and education–age cells. In both dimensions, immigrants and natives have similarly concentrated distributions (ratios are close to 1). Moreover, the educational grouping, as it only includes seven cells that are much larger than those of other grouping, does not exhibit the extreme differences in native–immigrant exposure as the other groups. Even when we consider 70 education–age groups, the range of exposure to immigrants is significantly smaller than for the geographic dimension. Column 5 in Table 10.1 shows a range of exposure of 10 in the top-bottom comparison and of 5 in the 90–10 percentile; both values are well below the corresponding ratio in the geographic units (metropolitan areas and states). An interesting feature of education–age as skill groups is that the intercell mobility of natives in response to immigrants may be significantly smaller than for the geographic-occupation cells. As we will see, the "given" native supply (nationally) within each cell, even as immigrant pressure may vary across them, has contributed to the success of this cell structure in analyzing the effect of immigration.

Let us, finally, emphasize that there is a key economic difference between the geographic and the skill cell units. In the first case, one can treat cells as separate units (in production and as labor markets) and worry later about potential interactions across them because of native mobility or trade of goods and capital. This has been the approach of regional and labor economists, assuming at first independent units (cities and states) and then checking whether the linkages (through internal migration or trade) would affect the findings. In the skill approach, instead, cells are considered as factors interacting within one same production process, and hence, one cannot analyze each cell in isolation. Economists have clearly understood the need to model right away linkages and interactions among them as a first-order concern. The approaches we prefer combine skill cells as factors of production and geographic cells as different production units. It is time to introduce a framework for organizing workers in skill cells and a simple structure to analyze cross cell interactions and potential cross cell mobility.

10.3. THEORETICAL FRAMEWORK: THE SKILL CELLS APPROACH AT THE NATIONAL AND LOCAL LEVEL

10.3.1 Basic framework: Production and labor demand

The commonly used framework to think about the impact of immigrants within the skill cell approach considers an area (typically a region, state, or a city) as producing a homogeneous tradable final good by combining different production skills and physical capital through a production function. This final good (output) is the numeraire, and we can think of the production function of a region as the reduced form of a multigood economy in which different nontradable intermediate goods (and services) each provided by a skill type are combined in the typical final consumption basket (the final output). The simplification is that all local economies produce and consume the same final good, y. They may, however, have different supplies of each intermediate factor (skill) and different techniques in production and hence different marginal productivities and returns to skills.

An alternative framework is one in which individual localities produce a number of different varieties and they partially specialize in the production and trade of varieties. This would generate a Heckscher–Ohlin type of model with a further margin of adjustment to changes in skills due to immigration, represented by changes in the variety composition of production. An increase of a type of skill due to immigrants could be fully absorbed by a change in production composition toward goods intensive in the use of that skill (the so-called Rybczynski effect). However, Lewis (2003) and Card and Lewis (2007), among others, showed that the adjustment in the variety composition of output is not an important margin of adjustment to immigration. This implies that the constant output composition model (the one-good model, used here) does not miss an important margin of adjustment and is a reasonable working model.

For area (region and city) r, the production function of output can be represented as follows:

$$\mathbf{y}_r = \mathbf{F}(\mathbf{A}_{K,r}\mathbf{K}_r, \mathbf{L}(\mathbf{A}_{1,r}\mathbf{L}_{1,r}, \mathbf{A}_{2,r}\mathbf{L}_{2,r}, \ldots, \mathbf{A}_{n,r}\mathbf{L}_{n,r})) \text{ for } r = 1, 2, \ldots, R \tag{10.1}$$

where $\mathbf{L}_{n,r}$ is the amount of factor (skill/task) n used in the production of area r. Similarly, $\mathbf{A}_{n,r}$ is the productivity of factor n in area r. In general, we allow for factor-specific productivity (determined by the chosen technology) to vary across localities (hence the subscript r). Notice that we included the physical capital K (and its productivity $\mathbf{A}_K$) as a factor separable from an aggregate labor factor ($\mathbf{L}$) that, in turn, combines all the skill groups $\mathbf{L}_1, \ldots, \mathbf{L}_n$ and their productivity $\mathbf{A}_1, \ldots, \mathbf{A}_n$. This implies that physical capital is combined with the labor aggregate and has the same degree of substitutability/complementarity with all skill cells. An alternative to this assumption is entertained by Lewis (2013a) who explored the consequences of considering different degrees of complementarity between physical capital and different skill groups. In particular, in the more relevant case of complementarity between capital and college-educated workers, Lewis (2013a) showed that the capital response to immigration of college-educated will attenuate its wage impact.[8] Capital–skill complementarity is an interesting and important avenue to pursue. However, the current literature on regional impact of immigrants mostly relies on the assumption of separability between capital and aggregate labor.[9]

The capital separability assumption, combined with the assumption of long-run mobility of capital and constant long-run returns for capital, implies that we can solve physical capital out of the function to obtain a reduced form:

$$\mathbf{y}_r = \mathbf{f}\left(\mathbf{A}, \boldsymbol{\theta}_{1,r}\mathbf{L}_{1,r}, \boldsymbol{\theta}_{2,r}\mathbf{L}_{2,r}, \ldots, \boldsymbol{\theta}_{n,r}\mathbf{L}_{n,r}\right) \text{ for } r = 1, 2, \ldots, R \tag{10.2}$$

In (10.2), the parameter $\mathbf{A}$ is a combination of parameters including the return and productivity of physical capital and total factor productivity, while the terms $\boldsymbol{\theta}_n$ capture relative productivity of factor (skill) n standardized so that $\sum_n \boldsymbol{\theta}_n = 1$. In the long run, competition among workers and firms ensures that each factor is paid its marginal product. Hence, the compensation to each skill in region r $w_{n,r}$ is as follows:

$$w_{n,r} = \frac{\partial \mathbf{F}}{\partial \mathbf{L}_{n,r}} = \mathbf{f}_n\left(\mathbf{A}, \boldsymbol{\theta}_{1,r}\mathbf{L}_{1,r}, \boldsymbol{\theta}_{2,r}\mathbf{L}_{2,r}, \ldots, \boldsymbol{\theta}_{n,r}\mathbf{L}_{n,r}\right) \tag{10.3}$$

If the reduced form production function is constant return to scale in the labor aggregate, then the sum of compensation to skill equal total output in region r.

10.3.2 Education- and age-based skill cells in a CES production function: The national approach

While early studies (such as Grossman, 1982) experimented with different functional forms for the production function in (10.2), such as the flexible translog specifications, the more recent research on the local (and national) impact of immigrants has focused

[8] This can be shown with the derivative identity, $\frac{d\ln(w_S/w_U)}{d\ln(L_S/L_U)} = \frac{\partial \ln(w_S/w_U)}{\partial \ln(L_S/L_U)} + \frac{\partial \ln(w_S/w_U)}{\partial \ln K}\frac{\partial \ln K}{\partial \ln(L_S/L_U)}$, which says that the total relative wage response to a change in the supply of skilled labor (S) relative to unskilled labor (U) is equal to its partial direct effect—$\frac{\partial \ln(w_S/w_U)}{\partial \ln(L_S/L_U)}$, the (negative of the) inverse elasticity of substitution—plus indirect effects working through the adjustment of capital. Under capital–skill complementarity, both $\frac{\partial \ln(w_S/w_U)}{\partial \ln K}$ and $\frac{\partial \ln K}{\partial \ln(L_S/L_U)}$ are positive, so the adjustment of capital attenuates wage impacts $\left(\frac{d\ln(w_S/w_U)}{d\ln(L_S/L_U)} > \frac{\partial \ln(w_S/w_U)}{\partial \ln(L_S/L_U)}\right)$. When capital is instead assumed separable from labor inputs in production $\frac{\partial \ln(w_S/w_U)}{\partial \ln K} = 0$, so $\frac{d\ln(w_S/w_U)}{d\ln(L_S/L_U)} = \frac{\partial \ln(w_S/w_U)}{\partial \ln(L_S/L_U)}$ (which makes it convenient to make this assumption).

[9] To partial defense of this approach, many of the insights from capital–skill complementarity are recovered in the literature through the introduction of endogenous choice of techniques (hence technology–skill complementarity) that we will review in Section 10.3.6.

on CES and specifically on nested-CES functions. The reason is that the nested CES provides a simple expression of the (log) marginal productivity of each skill as a function of the supply of the same skill, of simple aggregators of other skill supply, and of a small number of parameters. Hence, observing skill supply and compensation (wages) and accounting for the factor aggregators (also easily constructed), one can use (10.3) to estimate empirically the few parameters regulating the response of wages to changes in skill supply.

It is useful to describe in some detail, following Ottaviano and Peri (2012), how the nested-CES approach can be used to estimate important elasticity parameters and to calculate effects of the change in immigrant supply on wages. This approach has been used by several recent empirical papers. The most relevant characteristics used to organize cells in the nested-CES framework have been education levels, age groups (or experience groups), and nativity groups (foreign–native). These have provided the grid to organize workers into cells. Adopting a CES structure, one could represent production function (10.2) with a small number of parameters. And one would be able to estimate those parameters using the whole country as relevant area, simply exploiting the variation of immigrant supply over time and across skill cells.

The cell structure we describe here, originally proposed by Borjas (2003) and Card and Lemieux (2001), has then been followed and enriched by Ottaviano and Peri (2012) and Manacorda et al. (2012) and then followed by other studies after those. All those studies have considered the whole country, rather than local areas, as units of analysis, and hence, we omit the area subscript (r) in this section. One appealing feature of this approach is that considering relatively fixed characteristics (such as age, education, and nativity) and a national market makes the operational assumption that skill supply by natives did not respond to immigration more plausible. In this national approach, the typical assumption is that the supply of skills by natives is totally inelastic (given).

We describe the flexible nested-CES structure that embeds various alternative models studied in the literature, using general notation and allowing for recursive expressions of general results. Consider four characteristics numbered $n=0, \ldots, 3$. Characteristic 0 is common to all workers and defines them as such. Characteristic 1 is education and can be used to partition workers into groups $i(1)=1, \ldots, M_1$ that differ according to educational attainment (e.g., high school dropouts, high school graduates, and college graduates). Then, each of these education groups can itself be partitioned into groups $i(2)=1, \ldots, M_2$ that differ according to characteristic 2, which is age (say, age intervals in the range 18- to 65-year old). Finally, each of those can be partitioned into two groups "natives" and "foreign born" according to characteristic 3, which is "nativity."[10]

[10] Studies that are focused on the diversity of immigrants consider "country of birth" as relevant characteristics and include several countries (or groups) as categories for this partition. See, for instance, Ottaviano and Peri (2005, 2006).

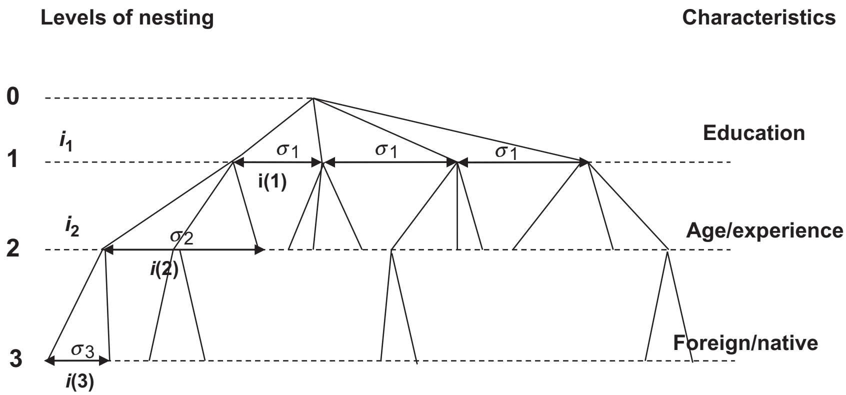

Figure 10.3 General scheme of the CES nests and relative notation education.

This sequential partitioning and its relative notation are illustrated in Figure 10.3. The figure shows how groups are nested into each other with n indexing the nesting level.

The nested-CES structure allows us to define production function (10.2) in the following recursive form. Let us call $i(n)$ a group (cell) of workers defined by common characteristics up to n and define as $L_{i(n)}$ the corresponding factor supply. The CES aggregator at the level n is then defined as

$$L_{i(n)} = \left[\sum_{i(n+1) \in i(n)} \theta_{i(n+1)} \left(L_{i(n+1)} \right)^{\frac{\sigma_{n+1}-1}{\sigma_{n+1}}} \right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}}, \; n = 0, 1, 2, 3 \tag{10.4}$$

where $\theta_{i(n+1)}$ is the relative productivity level of type $i(n)$ standardized so that $\sum_{i(n) \in i(n-1)} [\theta_{i(n)}] = 1$ Any common multiplying productivity factor is absorbed in the TFP parameter $\mathbf{A}$ shown in expression (10.2). Both the parameter $\mathbf{A}$ and $\theta_{i(n+1)}$ depend on exogenous technological factors only. The parameter $\sigma_n > 0$ is the elasticity of substitution between types $i(n)$. Hence, σ_1 is the elasticity of substitution across education group, σ_2 is the elasticity across age groups within education category, and σ_3 is the elasticity between natives and immigrants in the same education–age group. Given the ordering of characteristics and sequential partitioning that leads to less and less heterogeneous groups $i(n)$ as n increases, a reasonable assumption is that $\sigma_3 > \sigma_2 > \sigma_2 > 1$. As type $i(0)$ includes all workers, we can embed the nested structure defined by (10.4) into (10.2) by writing that equation as $\mathbf{y}_i = \mathbf{f}(\mathbf{A}, \mathbf{L}_0)$, where L_0 is the top-level aggregator in the nesting.

Using this structure and notation, we can express the wage of a worker of type $i(3)$, where $i(3)$ indicates a cell for specific values of education, age, and nativity, as the value of her marginal productivity:

$$\ln\left(w_{i(3)}\right) = \ln(A) + \frac{1}{\sigma_1}\ln(L_0) + \ln\theta_{i(1)} - \left(\frac{1}{\sigma_1} - \frac{1}{\sigma_2}\right)\ln L_{i(1)} + \ln\theta_{i(2)}$$
$$-\left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right)\ln L_{i(2)} + \ln\theta_{i(3)} - \frac{1}{\sigma_1}\ln L_{i(3)} \tag{10.5}$$

First, focusing on the last level of nesting and considering native (nat(3))and foreign born (for(3)) sharing the same characteristics of the first two nests, education and experience ($i(2)$ and $i(1)$), Equation (10.5) implies

$$\ln\left(\frac{w_{\text{nat}(3)}}{w_{\text{for}(3)}}\right) = \ln\left(\frac{\theta_{\text{nat}(3)}}{\theta_{\text{for}(3)}}\right) - \frac{1}{\sigma_3}\ln\left(\frac{L_{\text{nat}(3)}}{L_{\text{for}(3)}}\right) \tag{10.6}$$

Therefore, $\frac{1}{\sigma_3}$ the inverse elasticity of substitution between natives and immigrants in the same education–age cell can be estimated from observations on wages and employment levels of natives and immigrants over time, using fixed effects to control for $\ln\left(\frac{\theta_{\text{nat}(3)}}{\theta_{\text{for}(3)}}\right)$. Second, for higher nesting level $m=1$, 2, we can define $w_{i(m)}$ as the average wage of a specific group of workers $i(m)$ sharing characteristics up to m. Then, substituting m instead of 3 as the highest nest level in expression (10.5) gives the profit maximizing relation between $w_{i(m)}$ and $L_{i(m)}$. In this case, using observations over time, the estimation of $\frac{1}{\sigma_m}$ can be achieved by regressing the logarithmic wage of group $i(m)$ on the logarithmic CES aggregate $L_{i(m)}$ with the inclusion of fixed time effects to capture the variation of the aggregate terms $\ln(A)$ and $\ln(L_0)$, when estimating $\frac{1}{\sigma_1}$. In the case of $m=2$, when estimating the elasticity of substitution across age groups, we should also include education by year effects in order to absorb the terms $\ln\theta_{i(1)} - \left(\frac{1}{\sigma_1} - \frac{1}{\sigma_2}\right)\ln L_{i(1)}$ that do not change with characteristic 2 (age).

Once we have estimated the elasticity of substitution between different types of workers at each level of the nest, the wage equation (10.5) can also be used to compute the percentage change in the wage of workers of a certain type j (defined by a specific combination of education–age–nativity) caused by a percentage change in the labor supply of workers of another type i (defined by another combination of characteristics). To show this in a compact way, let us denote by s_i^m the type i's share of labor income among workers exhibiting the same characteristics up to m as that type. Then, we can write the percentage impact of a change in labor supplied by workers of type i on the wage of a worker of type j who share the same characteristics up to m as follows:

$$\frac{\Delta w_j^0/w_j^0}{\Delta L_i/\Delta L_i} = \frac{s_i^0}{\sigma_1} > 0 \text{ for } m=0 \text{ and } \frac{\Delta w_j^m/w_j^m}{\Delta L_i/\Delta L_i} = -\sum_0^{m-1}\left(\frac{s_i^{n+1} - s_i^n}{\sigma_{n+1}}\right) < 0 \text{ for } m=1, 2,\ 3 \tag{10.7}$$

Three remarks are in order. First, an increase in the labor supply of a certain type i causes an increase in the wage of another type j only if the two types differ in terms of characteristic 1 (education in our case) as shown in the first expression of (10.7). In that case, the factors are complements. Second, if the two types share at least characteristic 1, then a rise in the labor supply of i always depresses the wage of j (second expression) as $s_i^{n+1} > s_i^n$ if groups are ordered in increasing level of substitutability. This effect is stronger the larger the number of differentiating characteristics j has in common with i, because this implies more terms in the summation in (10.7). Third, and specific to the effect of immigrants, while the partial effect of immigrants in the same education–experience group as natives is negative, this is only a partial effect. The impact of immigrants in other education–age groups on native wages may be positive and the total effect may therefore be positive. The production function described above allows us to use the easy formulas in (10.7) to calculate the wage impact of immigrants in each education–age group on the wages of natives in each education–age group, once we have the elasticity and the wage shares.

10.3.2.1 Most commonly used nests

Within the general structure described above, the literature based on a nested-CES function has converged toward one (or a few) most commonly used partitions at each level of the nesting. Beginning with the lower level (nativity), most of the literature since Ottaviano and Peri (2012) has allowed two imperfectly substitutable groups of workers: natives and foreign born. There are several reasons for this simple partition. First, even when considering workers with equivalent education and experience, natives and immigrants differ in detailed abilities, motivations, and tastes that may set them apart. Second, in manual and intellectual work, they have culture-specific skills (e.g., cooking, crafting, artistic abilities, and sport talent) and limits (e.g., limited knowledge of the language or culture of the host country), which create comparative advantages in some tasks. Third, due to comparative advantage, migration networks, or historical accidents, immigrants tend to choose different occupations with respect to natives, even for given education and experience levels. Finally, there is no need to impose perfect substitutability between natives and immigrants ex ante as, within the structure proposed, this elasticity can be estimated. While one could envision a larger number of nativity groups, based on areas of origin, the most common studies only separate natives and foreign born.

In terms of the second level of the nest (characteristic 2 is age or experience), the literature has been rather openhanded. Some studies allow 4 or 8 age groups partitioning experience between 0 and 40 years of work (Card and Lemieux, 2001; Borjas, 2003). Others only include two groups (young and old). As it turns out (see Ottaviano and Peri, 2012), this partition and the relative elasticity of substitution are not very relevant in determining wage effects between immigrants and natives and between skilled and unskilled (usually associated with educational differences). In some cases (Peri and Sparber, 2009; Docquier et al., 2011), this level of the nest is omitted altogether, because it does not affect much the consequences of immigrants on native wage distribution.

Finally, and importantly, characteristic 1 determines the grouping according to education. The partition more frequently used in the labor literature is a division into two broad educational characteristics, "high school equivalents," which include individuals up to a high school diploma, and "college equivalents," which include individuals with some tertiary education and a those with college degree. Several papers, most notably Goldin and Katz (2008) and Katz and Murphy (1992) (but others as well[11]), have emphasized that college-educated and high school-educated are hard to substitute and their relative supply, combined with technological progress and an elasticity of substitution around 1.5–2, explains well their relative wage movements in the United States post 1960. The further distinction between high school graduates and high school dropouts does not seem useful to understand relative wages in the United States (see Card, 2009; Ottaviano and Peri, 2012) because those two groups seem close substitutes to each other in production, at least after 1950 (Goldin and Katz, 2008). Hence, we will consider the college–high school partition of education and the foreign–native partition of nativity as the most common features of this approach, with a less clear preference for 2, 4, 8 or even omitting the level altogether, for age–experience groups.

10.3.2.2 Partial and total wage effects of immigrants in the CES model

The nested-CES model described above allows us to distinguish partial and total wage effects of immigrants. The former is the wage impact on native workers due to a change in the supply of immigrants with the same education–age characteristics, while keeping constant the labor supplies of all other workers. This effect has been the main or only coefficient of interest in many "reduced form" approaches that regress native wages on the employment of immigrants in the same skill groups.[12] However, this effect is only an "artificial" partial effect as it misses the entire set of cross effects. The total wage effect, instead, accounts also for the indirect impact of immigration among all groups of workers and is what one would be interested in when analyzing the impact of changes in immigration flows (or immigration policies).

The direct partial wage effect can be estimated by panel regressions of $\ln({w_{j(N)}}^{N-1})$ the logarithmic wage of natives, sharing characteristics up to $N-1$ (namely, education and age) on the supply of immigrants, $\ln L_{i(N)}$, in the same age–education group. Careful econometric specifications (such as Borjas, 2003) control for year-specific effects (to absorb the variation of L_o the labor aggregate over time) and characteristic-by-year-specific effects (to absorb the variation of $L_{i(n)}$ for $n=1$, 2) where characteristics are

[11] Examples are Autor et al. (1998), Krusell et al. (2000), Card and Lemieux (2001), Acemoglu (2002), and Caselli and Coleman (2006), among others.

[12] For instance, in Borjas (2003, sections II–VI) or in Borjas (2006) and in the studies inspired by these seminal papers, the direct partial wage effect of immigration is the main estimated wage effect. Even the recent meta-study by Longhi et al. (2005) considers this partial effect as the relevant estimate across studies.

education and age groups, when running these regression. Using the notation defined above, the resulting partial elasticity can be written as

$$\varepsilon_i^{\mathrm{PART}} = -\left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right) s_i^{N-1} \tag{10.8}$$

The term s_i^{N-1} represents the wage share of immigrants among workers within the same education–age cell as native group i. Note that the direct partial wage effect (10.8) coincides only with the last among the several terms composing the summation in (10.7), which includes both direct and indirect wage effects. This happens because, by construction, the elasticity $\varepsilon_i^{\mathrm{PART}}$ captures only the wage effect of a change in immigrant labor supply operating through the term $\left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right) \ln L_{i(2)}$ in (10.5).

Hence, two important observations are in order. First, $\varepsilon_i^{\mathrm{PART}}$ is negative whenever the elasticity of substitution between age groups, σ_2, is smaller than the substitutability between native and foreign born in the same education–experience group, σ_3. If those elasticities of substitution are close to each other, the partial effect can be 0 or close to 0 (a point emphasized in Peri, 2011 and discussed in Section 10.5). Second, the value and the sign of $\varepsilon_i^{\mathrm{PART}}$ give incomplete information about the overall effect of immigrant supply changes on the wages of domestic workers of type j. Indeed, (10.8) includes only the last term of (10.7). In order to evaluate the total wage effect of immigrants on natives of type j, one has to combine the impacts generated by (10.7) across all the $i(3)$ cells that include foreign-born workers for which $L_{i(3)}$ changes due to immigration. This implies that the total wage effect of immigrants cannot be directly estimated from a regression: one can, however, estimate the elasticities $\sigma_1, \sigma_2, \sigma_3$ and combine them with the income shares in (10.7) and aggregate across all groups for which $L_{i(N)}$ changes due to immigrants.

This detailed analysis of the CES model exemplifies well the importance of recognizing the crucial role of indirect general effects (cross complementarities in this case) in order to capture the total impact of immigrants. We will consider in the next section another important indirect effect of immigrants, namely, their effect on native skill supply.

10.3.3 The area approach and the labor supply response

The nested-CES approach, described in the previous section, can be used at the national level or at the local area level. However, the tenability of the assumption of a fixed skill supply of natives, vis-à-vis changes in the supply of immigrants, is what has moved several researchers to criticize the area approach and prefer a national market one (e.g., Borjas, 1994, 2003; Borjas et al., 1997). They have argued that, while at the national level, the assumption of a rigid labor supply by native workers is tenable, at the local level, mobility of people between cities and regions would cause labor market opportunity differentials to be arbitraged away. Hence, any potential effect of immigrant skills on demand for native skills would be matched by changes in their supply (through internal migration), leaving no effect (or much attenuated effects) on local wages and making cross area wage comparison uninformative.

This criticism is valid. It is not, however, a good reason to abandon the city and regional data that still contain rich variation of immigrant flows and of their labor market effects. First, of all the impact of an exogenous change in foreign born, skills on wages will be uninformative only if native people are perfectly mobile in the long run, and they fully undo the change in skill supply generated by immigrants. Several empirical papers show that this seems hardly to be the case as there is not strong evidence of native internal migratory response to immigrants (Card and DiNardo, 2000; Card, 2001, 2005; Peri and Sparber, 2011a,b). Also, the skill distribution of immigrants seems to affect permanently the skill distribution of a metro area, and it is not undone by differential migration of natives. For instance, as shown in Card (2009) and as reproduced in Figure 10.4 for 283 US metropolitan areas as of 2011, the percentage of high school dropouts in an MSA's labor force is strongly positively correlated with the share of immigrants. This illustrates that cities receiving a large share of immigrants are likely to be permanently affected in their relative skill composition vis-à-vis cities not receiving them. Second, even if perfect (or large) mobility takes place, we simply need to account for it. In particular, we should consider the labor supply of natives at the area level as a potential margin of adjustment to immigration and analyze the impact of immigrants on it. Within the skill cell model sketched above, if we are analyzing two regions, r and s, for each specific skill n, which

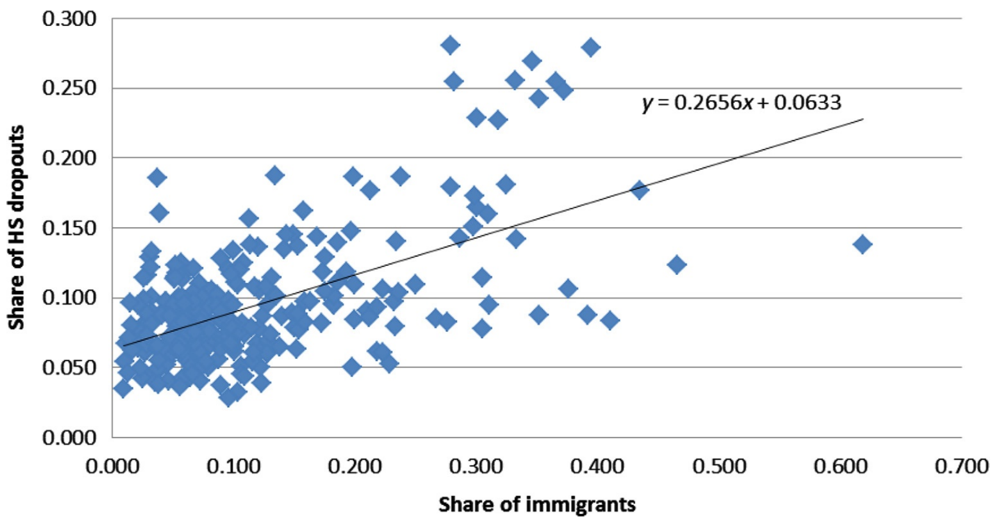

Figure 10.4 Share of immigrants and of dropouts *283 MSA (2011). Note: Authors' calculations based on 2011 ACS data, excluding people in group quarters and including only people 18–65 who worked at least 1 week.*

we can think as an education–age group, we may model the change in native relative supply of that skill between regions r and s (driven by net migration between the two) as

$$\Delta \ln\left(\frac{L_{rn}}{L_{sn}}\right) = \gamma_n \Delta \ln\left(\frac{w_{rn}}{w_{sn}}\right) \text{ for } n = 1, 2, \ldots, N \tag{10.9}$$

This represents a log-linear version of the relative native labor supply of skill n, between areas r and s. The parameter γ_n is the elasticity of relative labor supply capturing the response of interarea migration by native workers of skill n, to wage differentials between the two regions. Namely, an increase in the wage differential will move people toward the high-paying region and change the relative supply of skills in favor of that region. The extreme cases would be represented by $\gamma_n = 0$, when prohibitive moving cost would imply no response to wage differential (vertical labor supply) and by $\gamma_n = \infty$ that would imply wage equalization across areas.

If we observe an *exogenous inflow of immigrants* in a large number of localities (and/or periods of time) and we also observe the native employment (population) and wage change associated to it, for each skill group, we could, in principle, identify the parameters of labor demand and labor supply by solving the sets of Equations (10.2) and (10.9). Using the nested-CES production-function approach, we restrict the number of cross elasticity parameters to estimate, and we can derive log-linear demand functions as (10.3) for each skill, across regions. Then, introducing skill-specific supply would simply add one extra parameter (the elasticity) for each extra equation (log-linear labor supply as in (10.9)). Information on relative changes in native employment (population) and native wages will allow estimation of demand and supply parameters.

An important variation of the supply function described by (10.9) accounts for the fact that the migration response of natives between regions r and s may depend on real rather than nominal relative wages. In particular, the change in local housing price, which several studies have shown to be one of the consequences of immigrants (e.g., Ottaviano and Peri, 2006; Saiz, 2007), can be a separate channel in adjusting relative real wages and hence may affect the supply response of natives. In most cases, however, the housing price (or rent) effect is a common area-level effect and does not vary across skills. It can be due to changes in local amenities (as in Ottaviano and Peri, 2006) or to an upward sloping housing supply (Saiz, 2007), but as long as it affects skill group similarly, it will be absorbed by a common area effect across skills. This approach—identifying skill cell effects in the presence of supply response of natives and allowing for common housing price effects—is followed by Peri (2011), and we will describe his findings in Section 10.5. Peri et al. (2014), on the other hand, use a skill cell approach allowing for skill-supply and (one of the very few cases we know of) skill-specific housing prices to evaluate the demand/supply and productivity effect of STEM immigrants using an exogenous change across US cities due to the introduction of the H1B visa.

Card (2009) used also a skill cell analysis across US cities to show that the employment of natives does not respond much to immigration-driven changes in skill supply and that the estimated labor demand parameters (from a nested CES) are broadly consistent with those estimated at the national level (e.g., in Ottaviano and Peri, 2012). Peri (2013) used a simulation of the same nested-CES education–age skill model across US cities, with nationally estimated parameters, to show that the immigrant inflow to US metropolitan areas during the period 2000–2009 had very small effect on wages of less educated natives (and usually positive effect from complementarity with college-educated immigrants). The area analysis of the impact of immigrants, therefore, has benefited much from a more careful treatment of immigrant skill composition and skill complementarities in production. Accounting for the heterogeneity between immigrants and natives is crucial in finding these complementarity effects.

Let us also notice that some recent papers such as Smith (2012), Hunt (2012), and Jackson (2013) find that immigration may affect the probability that natives stay in school and hence their distribution across age–education cells. We will describe the details in Section 10.5.2. Here, it suffices to say that the impact of immigration, by changing relative returns to each skill cell, pushes natives to respond. They tend to move toward cells that are complements (rather than substitutes) of immigrant skills. The skill cell upgrading, which we will analyze more in detail below, implies that we should not assume fixed native supply of skills even when analyzing national markets.

A simple way to represent the supply response across skill groups of natives is to rewrite (or reinterpret) Equation (10.9) as describing the response of supply across skill groups, rather than regions, to wage differentials. In particular, omitting the regional subscripts and considering two skill cells, n_1 and n_2, we can write

$$\Delta \ln\left(\frac{L_{n1}}{L_{n2}}\right) = \gamma \Delta \ln\left(\frac{w_{n1}}{w_{n2}}\right) \tag{10.10}$$

This relationship can be seen as a basic consequence of a Roy (1951) selection model, in which individuals, given their abilities, choose the skill group that maximizes their returns and respond to changes in relative compensation of those groups. We develop this point further in the next section, when talking about production tasks, but the main working of it is clear already within the skill cell model.

The native population may change its relative supply of skills in response to immigration. Moreover, not accounting for this margin of adjustment, we would underestimate the positive wage effect of immigrants on natives. Think, for instance, of a simple model with two skill levels, high and low, as the one we will introduce below. If an inflow of immigrants in the low-skill cell pushes natives toward the high-skill cell (because its relative compensation increases), then, at the end of the period, fewer natives are exposed to competition and more natives benefit from complementarity from immigrants (assuming the two skills are complementary). If we do not account for this and we evaluate wage gains and losses of natives using the *initial distribution* of natives, we overestimate the competition and underestimate the complementarity effect of immigrants on natives.

10.3.4 Occupations and tasks

The CES model with three levels of nesting (education, age, and nativity) described above is an excellent framework to discuss wage effect of migrants across regions. However, it has two limitations that we address in this section. First, the "age–experience" tier adds complication and number of cells to the model especially in a cross area analysis, but it is not very relevant to understand the impact of immigrants on native wage and their distribution, as shown in Ottaviano and Peri (2012). This is because the largest differences in native–foreign distribution of skills are among education groups and regions rather than across age groups and also because age groups are often close substitutes for each other. Moreover, as experience in the country of origin may have a different labor market value than experience in the destination, a fine partition on this dimension may generate grouping together of rather different natives and immigrant workers. Hence, while allowing individuals of different ages to have different productivity levels, we combine age groups and eliminate the second level of the nest. Second, and more importantly, the described CES nesting assumes a difference between natives' and immigrants' skills, by partitioning them in different groups within the third nest. This way, we can estimate their substitutability, but we do not have a theory of why and how immigrants and natives are different in production for given observable skills. In this section, therefore, we substitute the nativity nest with difference in productivity in performing different tasks, linked to language ability, as the basis of the productive difference between foreign born and natives.

We maintain the top tier of the CES, as above, namely, a partition between two education groups, college and high school equivalents. This partition, we argued in Section 10.5.2, captures fundamental skill differences in production. Within each of those two groups, we include native and foreign born of all ages so that the production function, reintroducing the region index and keeping notation consistent with before, can be written as

$$y_r = A_r\left[(\theta_{\mathrm{CO},r}L_{\mathrm{CO},r})^{\frac{\sigma-1}{\sigma}} + (\theta_{\mathrm{HS},r}L_{\mathrm{HS},r})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \text{ for } r=1,\ldots,R \qquad (10.11)$$

where the factors $L_{\mathrm{CO},r}$ and $L_{\mathrm{HS},r}$ represent employment of college equivalents and high school equivalents, respectively, and the parameters $\theta_{\mathrm{CO},r}$ and $\theta_{\mathrm{HS},r}$ represent their relative productivity and add up to one. The term A_r captures total factor productivity, and σ (>1) represents the elasticity of substitution between them. Within each of these groups, age and detailed education (as well as other attributes) may affect relative productivity. Hence, one can use relative wages to convert workers into "high school" or "college" equivalents. Namely, $L_{HS} = \sum\theta_{HSj}L_{HSj}$ and $L_{CO} = \sum\theta_{COj}S_{COj}$, where the coefficients θ_{nj} are the relative productivity (wages) of workers in subgroup j relative to a "pure" college or high school equivalent. Notice that a two-cell model as (10.11) implies that for the United States as a whole, immigrants did not change much the cell distribution of skills, as it turns out that the immigrant composition between college-educated and noncollege-educated is similar to the native's one.[13] This approach argues that if immigrants affect the wage distribution within each of these two broad skill groups, this is because of different characteristics, not captured by education and age only.

A prominent difference between native and foreign born among high school equivalent is that the second group is highly concentrated in occupations characterized by the use of manual and physical abilities much more intensively than communication and interactive skills. In agriculture, construction, and personal and household services (which are sectors attracting large percentages of immigrants workers), immigrants are builders, sorters, maidens, cooks, and waiters. Rarely are they coordinators, supervisors, or salespersons. In part, this is because of their schooling (no high school degree). However, also controlling for observable characteristics, immigrants with a high school degree or less are disproportionately concentrated in manual jobs. This may be due in part to their worse language skills (Lewis, 2013b), in part to their larger tolerance for (lower disutility from) manual labor (D'Amuri and Peri, 2014).[14] In any case, this type of specialization is typical of less educated immigrants in most rich countries. D'Amuri and Peri (2014) show that this holds also for Europe and it is reasonable to think that immigrants have a comparative advantage and hence specialize in manual jobs.

[13] As of 2011, 31% of US-born workers had a college degree or more, while for foreign born, 29%. The figures are from our calculations on ACS data.

[14] There are several pieces of evidence supporting that language skills drive immigrant comparative advantage. First, in the United States, Lewis (2013b) showed that the elasticity of substitution between natives and subgroups of immigrants with stronger English skills, such as those who arrived at younger ages, is larger than between natives and those with worse English skills (such as those who arrived at older ages). Second, you can find some cross-country evidence in support of this view. You cannot reject that immigrants and natives are perfect substitutes in Puerto Rico (Lewis, 2013b) or Costa Rica (Castillo et al., 2009), where both speak Spanish. Not all of the cross-country evidence is supportive. Amuedo-Dorantes and de La Rica (2011) found, if anything, larger occupational specialization among immigrants in Spain—where a large share of immigrants speak Spanish—than what Peri and Sparber (2009) found in the United States. Another outlier is Manacorda et al. (2012), who found a small elasticity of substitution between immigrants and natives in the United Kingdom. UK immigrants may have particular issues with skills transferability, however, not accounted for in the Manacorda study: while on paper, "high-skill" UK immigrants appear to compete mainly with natives at the lower end of the skill distribution (Dustmann et al., 2013). Future research might do more of these cross-country comparisons of imperfect substitutability, ideally with harmonized methods, although obtaining the wage data to do so would be challenging.

Peri and Sparber (2009) showed this fact and modeled it in a simple way that we describe here. When considering high school-educated equivalents in the two-skill partition model described above, they suggest a further partition based on manual (M) versus communication (C) skills, and they also suggest to nest those two skills within L_{HS} as a lower-level CES aggregate, as follows:

$$L_{\text{HS}} = \left[(\beta M_r)^{\frac{\sigma_{MC}-1}{\sigma_{MC}}} + ((1-\beta)C_r)^{\frac{\sigma_{MC}-1}{\sigma_{MC}}}\right]^{\frac{\sigma_{MC}}{\sigma_{MC}-1}} \tag{10.12}$$

Hence, M_r and C_r are the aggregate amount of manual and communication skills supplied in area r, β captures the relative demand for manual skills, and σ_{MC} represents the elasticity of substitution between manual and communication skills. The relative supply of skills of each individual is derived by O*NET data (from the US Bureau of Labor Statistics) that describe the type of skills used in each occupation and allow a classification between manual (strength, coordination, and manipulation) and communication (spoken and written interactions) tasks. The occupation distribution of natives and immigrants, therefore, determines their supply of manual and communication skills. In particular, the much larger employment of immigrants in manual-intensive occupations reveals that they have a comparative advantage for manual jobs, as they are less proficient than natives in their language skills. We formalize this concept in a simple way.

We assume that natives (N) have efficiency levels μ_N and ξ_N in performing manual and communication tasks, while foreign-born efficiency levels are μ_F and ξ_F. The comparative advantage of foreign born in manual tasks is expressed as $(\mu_F/\xi_F) > (\mu_N/\xi_N)$. Each individual chooses to divide one unit of labor supply (time) into l_j and $(1-l_j)$ units, performing manual and communication tasks, respectively, at a return equal to w_M and w_C per unit of manual and communication service performed. With decreasing returns in performing each type of task, we can write the labor income of individual $j(=F,\ N)$ as

$$w_j = (l_j)^{\delta}\mu_j w_M + (1-l_j)^{\delta}\xi_j w_C \tag{10.13}$$

In (10.13), the amount of effective units of task–service provided is a function of time spent in the task and efficiency in the task as follows: $C_j = (1-l_j)^{\delta}\xi_j$ and $M_j = (l_j)^{\delta}\mu_j$. Assuming $\delta < 1$, the income-maximizing choice of workers implies that each worker type supplies relative tasks C/M as a positive function of her relative ability (ξ_F/μ_F) and of task's relative compensation. In particular, the logarithm of relative supply of communication/manual tasks by workers of nativity $j(=N,\ F)$ in region r is given by

$$\ln\left(\frac{C_{jr}}{M_{jr}}\right) = \frac{1}{1-\delta}\ln\left(\frac{\xi_j}{\mu_j}\right) + \frac{\delta}{1-\delta}\ln\left(\frac{w_{Cr}}{w_{Mr}}\right) \tag{10.14}$$

Expression (10.14) shows that high school natives would have a higher communication/manual relative supply than foreign born ($C_N/M_N > C_F/M_F$) because they have comparative advantages in it $(\xi_N/\mu_N) > (\xi_F/\mu_F)$. It is also easy to show that (10.14) implies that an inflow of immigrants in region r decreases the overall relative supply C/M and, hence, it increases the relative compensation w_{Cr}/w_{Mr}. This improves the wages of occupations using communication skills, and it decreases wages for those occupations using manual skills. Natives who are more concentrated in communication-intensive jobs will mainly benefit from the complementarity effect. Moreover, natives will move their choice of occupations further toward communication-intensive ones as their relative returns (w_{Cr}/w_{Mr}) increase and they have comparative advantages in those.

Let us emphasize that the shift in relative supply by natives obtained taking the difference before and after immigration of Equation (10.14) would be a supply response very similar to the one described in (10.10), except that native reallocation takes place across supplied tasks (manual–communication) rather than across skill groups. Equation (10.14) fully reflects the selection of skill supply of natives, in response to relative compensation, typical of the Roy (1951) model. Hence, high school-educated natives benefit in relative terms, from an inflow of high school-educated immigrants through two channels. First, as they are already more specialized in communication skills, their compensation increases. Second, in response to immigration, they supply more communication skills and those skills are complementary to (and usually better paid than) the manual ones supplied by immigrants. The stronger competition effect is instead experienced by existing immigrants, more specialized in manual-intensive occupations.

In general, the fact that high school equivalent immigrant workers filled manual-intensive jobs that are often at the bottom of the career ladder for natives implies that in locations with large inflows of immigrants, native workers move more rapidly toward communication-intensive and more complex type of jobs. Peri and Sparber (2009) showed this mechanism at work across US states in the period 1960–2000 by estimating a regression as (10.14), using the change in foreign born as exogenous shifter of relative compensation $\frac{w_{Cr}}{w_{Mr}}$, and found a significant response of native relative task supply. D'Amuri and Peri (2014) show a similar push toward more "complex" jobs, when exposed to immigrant competition for European workers. Foged and Peri (2013) identified the same effect in response to non-EU immigrants for Danish workers. Immigrants provide the incentives and the complementary manual factors for natives to specialize in better remunerated communication-intensive job. Those individuals, therefore, move more rapidly out of manual- and physical-intensive occupations. Accounting for this change in relative skill supply of natives is crucial to measure the overall wage effects of immigrants on natives. The upward mobility generated as part of this mechanism shields native wages from competition.

A similar mechanism implying immigrant specialization in the occupation (task) spectrum and subsequent change in the relative skill supply by natives may also take place among college-educated workers. Within that group, immigrants are particularly concentrated in occupations that are STEM-related. The international selection of highly skilled immigrants and the high transferability of mathematical–analytic skills imply that foreign-born immigrants are particularly productive in those skills. Natives, instead, are relatively more specialized in supervisory, managerial, interactive type of occupations, and they further move toward those as more immigrants arrive. Peri and Sparber (2011b) considered such a mechanism of specialization response of natives to college-educated immigrants. Borjas and Doran (forthcoming) showed a similar margin of adjustment in the much smaller field of "mathematician specialization." In response to the large inflow of Russian mathematicians after the collapse of the Soviet Union, US mathematicians moved toward the fields of mathematics that were more complementary and less crowded by Russian mathematicians.

High-skill STEM immigrants may also have a particularly important role in innovation and technological growth, in part, because of their greater connections to the global economy (Saxenian, 2002b).[15] That foreign skilled workers are particularly concentrated in STEM jobs and contribute substantially to patented innovation was shown by Hunt and Gauthier-Loiselle (2010) and Kerr and Lincoln (2010). Peri et al. (2014) look directly at the productive effects of STEM immigrants and find that they generated a positive contribution, localized at the metropolitan area level, to the productivity of college-educated natives. First, they show that in metropolitan areas with large inflow of foreign STEM workers (determined by the change in aggregate H1B visa entry, the main channel of entry of highly educated immigrants), the wage and employment rate of native college-educated workers were substantially higher than in metropolitan areas with small inflows. The use of instrumental variables based on aggregate change in visa and preexisting localization of foreign STEM workers shows that the correlation can be causal. Then, they show that such an increase is only compatible with a significant increase in A_H, the specific productivity of the college-educated equivalents. They also show that A_L, the productivity of high school equivalents, increased as well but not as much as A_H. They emphasize, therefore, that the productivity improvements introduced by STEM (foreign) workers appear to be "skill-biased" in that they increase the productivity of college-educated equivalents more than that of high school equivalents.[16]

The possibility that immigrants may affect productivity through their contributions to technology and science (or through other channels) opens new and very important

[15] Saxenian (1994) had also written about the fact that, in addition to a deep concentration of high-skill workers (including immigrants), institutions and culture that support idea sharing may also be a necessary input into innovation and successful entrepreneurship.

[16] Table 10.2 reports the magnitudes of the effects that they estimate per percentage-point increase of STEM worker employment share.

potential channels through which immigration affects production. Immigration may not only change the supply of foreign skills, inducing a response in the supply of native skills, but also change their productivity A_j by affecting technology, techniques, or efficiency. If this is the case, the overall surplus of immigration can be much larger than calculated before. In particular, increasing the share of STEM or college-educated workers may have positive local externalities on the region. Papers by Ciccone and Peri (2006) and Moretti (2004a,b) have emphasized the importance of productive externalities in US cities from increasing the share of college-educated workers. Those effects go beyond the complementarity effects analyzed above. In particular, local learning and the diffusion of better ideas and of better technologies can be affected by the concentration of college-educated workers, many of whom are foreign born. At least, one paper (Iranzo and Peri, 2009) has directly connected the higher share of college-educated workers in US cities, to a higher share of some immigrants (Indian and Europeans) showing their positive impact on productivity. Another recent paper (Docquier et al., 2011) also emphasizes the potential importance of human capital externalities, driven by immigration in OECD countries, in positively affecting wages. That paper considers OECD countries as units, and it emphasizes the fact that immigration to those countries was prevalently college-biased during the 1990s and 2000s. Adopting a two-tier nested-CES model similar to the one described in Section 10.5.2, but allowing for externalities due to increased share of college-educated workers, that study simulates positive wage effect of immigrants in most countries.

Let us mention, in closing of this section, another way used in a recent paper by Dustmann et al. (2013) of organizing skill cells in a CES model. That study considers workers as belonging to the same skill group if their productivity (wage) is similar. Hence, skills groups are interdecile intervals of the wage distribution. While this requires strong assumptions (such as a unidimensional representation of skills), it proposes to analyze the more direct competition effects of immigrants on natives at a similar level of wage. The paper finds evidence of stronger competition of immigrants with natives of similar wages. It also finds a strong positive effect of immigrants in raising the average native wage, possibly indicating an aggregate productivity (or strong aggregate complementarity) effect. We will focus on potential productivity effects in the next section.

10.3.5 The margin of technological choice

The simple production model of high school and college equivalents, illustrated in Equation (10.11), had widespread diffusion in the literature. One reason for its success is that, when combined with skill-based technological progress, it explains parsimoniously and reasonably well the evolution of relative college–high school wages (e.g., Katz and Murphy, 1992) in the United States during the last four decades. Even more interestingly, Acemoglu (1998, 2002) had argued that the type of technology adopted in a market depends on the relative supply of skills. When one type of skill (say college graduates) becomes more abundant, technologies that increase its productivity (skill-complementary or skill-biased) become more profitable and hence more frequently adopted. The rise in college-educated workers in the United States during the last 40 years can explain, therefore, the adoption of skill-biased technologies that in the long run have increased the productivity of college-educated workers and even increased their wages relative to high school graduates. Against this long-run increase in college education and adoption of skill-biased technology, the fluctuations of relative college–high school supply have then determined the shorter-run change in relative wages.

Notice a very important implication of directed technological change. For a given change in relative supply of skills, the adoption of directed technology, increasing the productivity of the factor whose supply increases more, will attenuate the effect on wages, relative to the case with unchanged technology. This is seen very simply by deriving the relative compensation of skills from (10.11):

$$\frac{w_{\mathrm{CO}}}{w_{\mathrm{HS}}}=\left(\frac{\sigma-1}{\sigma}\right)\frac{A_{\mathrm{CO}}}{A_{\mathrm{HS}}}-\left(\frac{1}{\sigma}\right)\frac{L_{\mathrm{CO}}}{L_{\mathrm{HS}}} \tag{10.15}$$

An increase in the relative supply $\frac{L_{\mathrm{CO}}}{L_{\mathrm{HS}}}$ would reduce the college–high school wage ratio, everything else constant, as long as the two factors are imperfect substitutes. However, if the relative productivity $\frac{A_{\mathrm{CO}}}{A_{\mathrm{HS}}}$ is also positively affected by the relative skill supply, this negative wage effect can be attenuated or even reversed.

Lewis (2011) tested the idea of directed technological adoption at the local (metropolitan area) level when the shift in relative skills is caused by immigration. In particular, in MSAs with a large inflow of less educated immigrants, Lewis (2011) found that firms have fewer economic incentives to adopt techniques that substitute for manual labor (such as automation) and complement human capital relative to metropolitan areas with small inflows of immigrants. Reducing automation and maintaining, instead, techniques that use more efficiently manual and less skilled workers will produce an increase in the relative efficiency $A_{\mathrm{HS}}/A_{\mathrm{CO}}$ and hence could attenuate or eliminate the relative wage effects of an increase in $L_{\mathrm{HS}}/L_{\mathrm{CO}}$. Lewis (2011) was able to identify the adoption of specific mechanization and automation procedures by firms in different metropolitan areas and relate that to the inflow of less educated immigrants. As predicted by the directed technological adoption framework, the study finds that mechanization and automation are faster in metropolitan areas with low immigration and hence lower supply of high school equivalents.

While Lewis (2011) provided evidence on directed technological adoption using microdata, Peri (2012) estimated in a panel of US states the effect of immigration on $\frac{A_{\mathrm{CO}}}{A_{\mathrm{HS}}}$ within an aggregate production function model, which, per (10.15), means imposing a value of σ (the college–noncollege elasticity of substitution) established by the literature. The study finds strong evidence of a negative correlation between the inflow of immigrants and the change in $\frac{A_{\mathrm{CO}}}{A_{\mathrm{HS}}}$, which is consistent with the theory of directed technological change. More details of the empirical approach of this study are in Section 10.5.2.

Overall, the recent literature has emphasized several margins of response to immigration taking place within area economies. A change in relative skills caused by immigrants induces a change in relative skill supply of natives (also characterized as specialization, occupational upgrading, and possibly education upgrading of natives). It may also induce a change in technologies/techniques adopted, which results in a change in relative productivity. Both responses reduce the "competition effect" of immigrants on similarly skilled natives. And they both increase the surplus received by natives as a consequence of immigration. Hence, they can help to explain a smaller negative wage effect of immigrants on wages of comparable natives than predicted by the "partial" effect (everything else equal). We mentioned that the other margins, such as native migration across areas and change in variety composition of output, have been investigated but do not seem to play a major role. While no study accounts explicitly for each margin of adjustment, we will overview the empirical findings on each of them, and we will assess what their combined effect implies on wage and productivity of natives.

10.3.6 Scale externalities, heterogeneity, and search

In the models considered so far, the increase in scale of the local economy due to inflow of immigrants plays no role in productivity and hence wages (because of constant return to scale). The simple increase in density of economic activity due to immigrants (representing simply an increase in the number of worker) and to the fact that they tend to concentrate in cities may have beneficial productivity effects (e.g., Ciccone and Hall, 1996; Greenstone et al., 2010). However, we review here some potential local externalities, from density, that are more specific to immigration. Some recent papers, based on the trade and growth literature, have considered an even finer differentiation of skills between immigrant and natives and among immigrants themselves. Allowing for each country of birth to represent a different skill group (producing a differentiated nontradable intermediate) and combining them in a CES for final production these studies have derived that an index of diversity (fractionalization) of immigrants in the area is positively related with local aggregate productivity (and hence average wages and possibly average rents). In this framework, more immigrants from more countries have a direct positive productivity effect. Ottaviano and Peri (2006) estimated such a model for US metro areas. Alesina et al. (2013) estimated the effect of such country of birth diversity index across countries in the world. Trax et al. (2013) explored this relation at the firm/plant level. Within the production-function context and treating each nationality as a different skill, a more differentiated and larger population of immigrants has positive productivity effects at the local level as it increases the variety of intermediates. There is significant evidence of this positive effect in the mentioned papers, and place of birth is a potentially important dimension of differentiation.[17] However, this research is still at its early stage, and we need a better understanding of the channels through which and the level (firm, area, and sector) at which this "place of birth diversity" effect operates. Certainly, an approach that considers in greater detail the skill differences between immigrants and natives and looks at the microlevel (firm and plant) to identify these effects can shed light on important margins.

Most of the research on the effect of immigrants has focused on their skill differences with natives and has used a competitive approach to labor market equating marginal productivity to wages. This is reasonable in the long run. An interesting new line of research considers instead frictions in labor markets and employer–employee matching that create match-specific surplus. In particular, following the huge success of search models pioneered by Mortensen and Pissarides (1994) to analyze important labor market features, some very recent studies have incorporated immigrants in search and matching models. In this search context, differences between natives and immigrants on the labor supply side (especially in their bargaining power and their outside options) may generate surplus that native workers appropriate. In particular, Chassamboulli and Palivos (2014) show that when immigrants have a worse outside option and/or a lower bargaining power than natives, they will be paid less in equilibrium, even if they have identical productivity as natives. This, in turn, implies that in a market with a larger percentage of immigrants, firms will earn larger average surplus per vacancy filled. Hence, they will create and post more vacancies. If they cannot discriminate natives out of those vacancies, but they can pay different wages, some of these jobs will be filled by natives, and this will increase their employment and also increase their wages (by making their bargaining position stronger).

While the model is somewhat specific, it emphasizes a very general idea. If firms save on their costs by hiring immigrants (who are paid less due to their lower bargaining power), they will appropriate a larger surplus and they will be willing to create more jobs and expand because of that. The new jobs created as a consequence of this profit-seeking expansion will also benefit natives. Hence, differences on the supply side may also result in a "complementarity" of a different kind between natives and immigrants and imply beneficial effects due to stronger job creation when more immigrants are in the labor market. In a similar vein, Chassamboulli and Peri (2014) analyze the effect of different policies aimed at reducing undocumented immigrants, in a search and matching model of the labor market and apply it to the US–Mexico case. This flexible frame allows them to characterize documented and undocumented immigrants as having different outside options and hence to study their job creation effect on the US economy. It also allows

[17] Large part of the gains from trade is predicated on similar type of gains from varieties. See, for instance, Broda and Weinstein (2006).

them to internalize the decision to migrate (from the United States to Mexico) as a search decision and hence analyzes the effect of policies on the incentives to migrate.

Having defined the main frameworks and a unifying approach used in the literature to analyze the economic consequences of immigrants in local economies, we now focus on the empirical implementation and on the issues related to identifying an exogenous change in immigrants and their skill supply.

10.4. EMPIRICAL APPROACHES TO IDENTIFY CAUSAL EFFECTS ON LOCAL ECONOMIES

As summarized in the previous section, the skill cell approach implies that immigration may affect the absolute and relative productivity of skills. However, differential productivity growth (possibly skill-specific) may also attract and select immigrants. The economic conditions in receiving countries are a major motivation for migration (e.g., Clark et al., 2007; Mayda, 2010), and, at least in the United States, evidence suggests that immigrants can be very responsive to different conditions across labor markets (Borjas, 2001; Cadena and Kovak, 2013). This potential endogeneity problem has been addressed with two related strategies: (1) flows, often of refugees, arising from shocks in sending countries (and often flowing to a small number of destinations) and (2) "shift-share"-type instruments that largely take advantage of the autocorrelation in the regional distribution of immigrant flows by origin. Both approaches were pioneered by Card (1990, 2001). A useful recent development is the linking of the "shift-share" instrument to variation driven by actual immigration policies.

The first, "natural experiment" approach was pioneered in Card's (1990) study of the Mariel Boatlift, the influx of about 125,000 Cuban refugees in 1980, on Miami, the largest location in which they settled. There have been several studies since that time using this approach, including Jennifer Hunt's study of repatriates from Algeria to France (1992) and Carrington and Lima's (1996) study of African repatriates to Portugal. Other studies have examined the impact of the refugee flows from the breakup of Yugoslavia (Angrist and Kugler, 2003), among other refugee flows (e.g., Foged and Peri, 2013), and flows that are the result of natural disasters (Kugler and Yuskel, 2008). These studies largely involve immigrants that flow into the lower end of the labor market. Finding similar such events that generate very high-skill immigrant flows is more difficult, but not impossible. Several studies have investigated the impact of the Former Soviet Union (FSU) immigrants to Israel including Friedberg (2001), Lach (2007), and Paserman (2013).[18] The impact of the dismissal of Jewish scientists from Nazi Germany has also received attention (Waldinger, 2012; Moser et al., 2013).

[18] Borjas and Doran (2012) studied the impact of the FSU flows on the academic labor market for mathematicians in the United States.

This approach has at least two challenges. The first challenge is that while a refugee crisis may generate exogenous emigration, the location and occupations taken by refugees may very well be endogenous to economic opportunities in the receiving country. Hence, defining a credible comparison group may be challenging. This is not a trivial problem and not all of the comparisons above necessarily get to credible causal inference.[19] A second challenge for some of these studies, raised in Donald and Lang (2007), is obtaining proper and meaningful inference with a small number of "treatment" cells.[20] Both challenges may have become a bit easier with the spread of Abadie et al.'s (2010) synthetic control technique, which uses data-intensive techniques to construct a matched comparison group and also allows inference by placing the estimates in a distribution of similar structured "placebo" regressions. However, to date, this approach has seen little use in the immigration literature.[21]

An additional concern with this approach is about external validity: studying a group of immigrants that are narrow in type, often to a narrow set of destinations, raises concerns that the results may not generalize to more common types of immigrant flows. Most high-immigration countries have received significant (but not catastrophic) flows for a decade or more, and we are more interested in the effects of those.

A second approach, beginning with Card (2001), parallels Bartik style (1991) of widely used instrument for demand shocks. It essentially predicts flows of immigration in region r based on the lagged locations of similar immigrants.[22] The basic structure of the key "predicted immigration flows" component of the instrument is typically of the form

$$\hat{F}_r = \sum\nolimits_c \left(\text{Lag\_sh}_c^r \times F_c\right)$$

where $\text{Lag\_sh}_c^r = M_c^r / M_c$ is the share of the stock of immigrants, M_c, from source country "c" living in destination area "r" (usually a within-country region or metropolitan area) at

[19] For example, many of the studies that take advantage of the breakup of the FSU use the variation in location of FSU immigrants within Israel across firms (Paserman, 2013) or cities (Lach, 2007). This is likely to be endogenous, and so, it is not clear that these analyses are more credible than OLS. To address this, Friedberg (2001), who used variation across occupations, used occupation prior to arrival as an instrument.

[20] This point is driven home by Angrist and Krueger's (1999) examination of what they call the 1994 "Mariel Boatlift that did not happen" as the Clinton administration blockaded what appeared to be shaping up to be flotilla from Cuba similar in size to the 1980 boatlift. This analysis found a marginal significant positive effect of the nonevent on unemployment rate of blacks (using standard inference techniques that Donald and Lang argue give incorrectly sized tests). There is also the question of whether meaningful inference is even possible with such a small number of cells: Donald and Lang's reestimation of the confidence intervals in Card (1990) suggests that they are uninformative. Even Donald and Lang's approach is made under restrictive assumptions; Conley and Taber (2011) provided a more general procedure for inference in panel data with a small number of treatment cells, which tends to produce even wider confidence intervals.

[21] One example is Bohn et al. (2014).

[22] The idea of using lagged immigrant shares as instrument for current immigration is older, going back to Altonji and Card (1991), but this "shift-share" formulation began with Card (2001).

some point prior to the period of analysis (often the initial period of the analysis), and F_c is the aggregate flows from country c during the periods of study. Note that the formula above can be specialized to skill cells. In that case, F_c would not simply be the total count of immigrants from country c, but instead, the flow of immigrants in a specific skill cell. Often, the constructed variable $\hat{F}_r$ is called the "imputed" inflow of immigrants in area r (and skill cell i, if it is skill-specific). $\hat{F}_r$ is also almost always normalized by some measure of the size of the local economy (or of the cell), such as initial employment so that the final instrument, for areas r and skill cell i, is $Z_{ri} = \hat{F}_{ri}/\mathrm{Emp}_{ri}$ (where Emp_{ri} is initial employment in that area cell).[23]

The basic argument for this instrument's validity begins with the idea that the aggregate component of the instrument is not driven by demand conditions in the destination regions, but rather by conditions in the sending country and possibly by aggregate conditions in the destination country; hence, this is sometimes referred to as the "supply/push" instrument (e.g., Card, 2001). These aggregate flows are apportioned to destination regions by $\mathrm{Lag\_sh}_c^r$, the historical destinations of the same immigrant groups. Mechanically, the strength of the instrument derives from the tendency of new immigrants to choose destinations with existing concentrations of the same ethnicity (Bartel, 1989). The argument for validity rests on the idea that this is driven, rather than by autocorrelation in demand for the labor of that group in a particular location, by labor supply factors like family ties or a preference to settle in a culturally or linguistically familiar environment.[24]

[23] A common approach is to normalize the predicted immigration variable in a way that mirrors the endogenous variable of interest. For example, the endogenous variable in both Card (2009) and Lewis (2011) is the ratio of two different education levels of workers, and so, the predicted immigration expression is calculated separately for high and low education levels (with the same $\mathrm{Lag\_sh}_c^r$, but separate F_cs for high- and low-skill aggregate flows by country), and the final instrument is structured as the ratio of the two in the same way it is in the endogenous variable. Peri et al.'s (2014) endogenous variable is high-skill workers/current employment; the numerator is constructed with predicted immigration, and the denominator is constructed by inflating base year employment by national employment growth. Smith's (2012) independent variable is the growth in the number of immigrants, so he normalizes by a number that imposes that all markets start off at the same fraction immigrant and then grow at the national rate. He also considered alternative versions of the instrument construction, including one that considers the mix of ethnic groups within markets rather than their distribution across markets. The manner in which the predicted immigration variable is normalized may affect the strength of the instrument or the plausibility of the exclusion restriction.

[24] One way to think of this is that an ethnic cluster is a group-specific amenity, an assumption supported with wage and house price data in Gonzalez (1998) for Mexicans in the United States. Additional evidence supporting validity is that a version of this instrument used to predict Mexican flows to particular metro areas in the United States appears uncorrelated with forecasts of employment growth (Card and Lewis, 2007). Lafortune and Tessada (2013) compared the ability of the size of ethnic enclaves and the local occupation mix to predict where immigrants will settle in historical data and find evidence that ethnic networks dominate in most cases.

Note that this approach is not completely independent of the natural experiment approach, which also tends to rely on the historical settlement locations of the immigrant groups under study (when the analysis is regional in nature) such as Cubans to Miami. Indeed, one concern with this instrument is that when destinations and sources are tightly linked—such as Cubans to Miami or Algerians to France—the aggregate flows might be partly driven by regional demand conditions at the destination. Demand conditions in LA and Chicago, for instance, might significantly affect Mexican arrivals to the United States.

One way researchers have attempted to refine this instrument is to try to uncover more exogenous sources of variation in the aggregate component of the instrument. Pugatch and Yang (2011) used rainfall shocks in Mexico as a component of an instrument for Mexican flows to the United States. In their study of the impact of immigration in Malaysia, Ozden and Wagner (2013) used the age structure of the population in the Philippines and Indonesia, two major sending countries, in the instrument, with the idea that migration tends to be concentrated in relatively young age groups.

A very promising recent development is the use of policy variation for the aggregate component of the instrument. In addition to being potentially helpful for addressing the endogeneity problem, this approach makes the estimates more policy-relevant. A number of studies have directly or indirectly used variation in the sometimes restrictive cap on the number of H1-B visas (a high-skill visa issued in the United States) including Peri et al. (2014) and Kerr and Lincoln (2010).[25] Kato and Sparber (2013) examined the aggregate impact of the large drop in the H1-B visa cap after 2003 on the quality of foreign students coming to the United States, using countries that have other visa options as a comparison group.

Much less has been done to make the "shares" ($Lag\_sh^{r}_{c}$) part of the instrument more credibly exogenous beyond using longer time lags.[26] But, again, policy-driven variation has begun to be used: some studies have used the so-called dispersal policies, used in some European countries to give initial, often random, placement of immigrants through public housing. Glitz (2012) used this to study the labor market impact of immigration in Germany. Another example is Damm (2009), who used dispersal policies to study the impact of living an "ethnic enclave" in Denmark at the individual level. Although it is not used directly in their analysis, much of the variation in Foged and Peri (2013)—who studied the effect of non-EU and refugee immigrant share on native wages

[25] Kerr and Lincoln (2010) did not use the "country" (c) element of the instrument described above—they aggregate together all immigrant groups—and estimated a reduced form regression. The H1-B visa cap is not country-specific, but aggregate.

[26] Part of Pugatch and Yang's (2011) variation derives from the historical ties of three major border crossing areas in Mexico to destination markets in the United States via historic railroad routes. Another aspect of the instrument that has not received much attention is the level of detail with which the immigrant groups are constructed, which for practical (small cell size) reasons are often not individual countries but groups of similar countries.

and occupation using variation across Danish municipalities—likely comes from the effect of these dispersal policies.

In the absence of definitive *a priori* grounds for lagged origin shares being random, another approach has been to subject the instrument to various "falsification" tests. One that is often available is to ask if trends in outcomes or treatment are correlated with the instrument prior to the analyzed period. The challenge is that often many of the same patterns of immigration tend to hold prior to the analyzed period, albeit at a lower magnitude. After all, the instrument in fact *exploits* trends in the regional patterns of immigration, so finding zero correlation in a just prior period is not necessarily realistic, but certainly, the correlation should be much weaker for the instrument to be credible. It also helps to be studying a period that begins with a sharp break from prior patterns of immigration, such as Foged and Peri (2013), who examined the impact of immigration from the genesis of large refugee flows to Denmark, in the 1990s.[27] Although harder to come by, when available, examining contemporaneous outcomes that arguably should be unaffected by the treatment is helpful.[28] Although doubts about this approach will likely never totally go away, in the absence of a new approach that captures enough of the variation in immigration to precisely estimate its economy-wide impacts, it seems like that the shift-share instrument will remain a major analysis tool in the near term.

10.5. ESTIMATES OF NATIVE RESPONSES AND EFFECTS ON OUTCOMES

The considerable variation in immigrant density across cells defined by geography or skill categories, as was described in Table 10.1, is potentially useful in estimating immigration's impact on native outcomes. However, as we illustrated in Section 10.3, a challenge in both identifying and understanding the impact of immigration using this variation is that natives may move across these cells in response. This section considers more in detail the empirical estimates of how natives respond to immigration by moving across both geographic locations and skill cells. With that understood, it then turns to organizing the estimates of the impact of immigration on wages, firm productivity, technology choice, and externalities.

[27] The dispersal policy that motivates their approach was in place before their period of study, but Foged and Peri (2013) showed that there was little non-EU immigration to Denmark prior large refugee events in the 1990s (Yugoslavia and Somalia). In their study of native school district choice response to Mexican school-aged arrivals, Cascio and Lewis (2012) examined changes from 1970, which is near the beginning of the large influx of Mexican migrants to California, although Mexican immigration had been rising more slowly for decades before that. Their pretrend test examined changes in the 1960s.

[28] For example, Lewis (2011) examined whether plans for technology adoption (asked in the baseline period) were correlated with later immigration-driven skill mix shocks and found that they were not.

10.5.1 Geographic mobility of natives

The earliest papers that attempted to estimate the impact of immigration, such as Grossman (1982), used variation across geographic space. However, it was not long before the mobility response of natives was raised as a potential confounder of these estimates. Borjas' often-cited review article (Borjas, 1994) argued that estimates of the impact of immigration across space had "no structural interpretation" (p. 1699). In fact, as Equation (10.9) described, a careful approach that allows for native supply mobility response can uncover structural demand parameters, by estimating together wage and employment regressions. Since the time of that review, a considerable literature on the native mobility response to immigration has developed.

Using the "Bartik style" of instrument described in Section 10.4, Card (2001) and Card and DiNardo (2000) found no evidence of any native mobility response across US metropolitan areas to immigrant inflows within broad occupation classes.[29] Borjas (2006) countered with evidence of a native mobility response to immigration, which, sensibly, is increasing in going from large (census divisions) to small (metropolitan areas) geographic units: he found that for every 10 immigrant inflows to a metropolitan area, 6 natives move out.[30] This study differs from the other two in examining responses within relatively narrow (education $\times$ experience) skill cells, in using the observed inflow of immigrants as explanatory variable in an OLS, rather than an IV, approach and in how the mobility response relationship is specified.

Indeed, significant concerns about the specification used in Borjas (2006) are raised in Peri and Sparber (2011a). They argued that because the stock of natives appears both as the dependent variable (native population) and in the denominator of the right-hand-side explanatory variable (immigrants as share of population including natives) in Borjas' specification, estimates may be biased toward finding a negative relationship. Using simulations designed to match aggregate population moments, they confirm that Borjas' approach would tend to find strong evidence of native mobility response even in its absence. Specifically, the authors assume that the change in native population in region $(r) \times$ skill (j) cell, ΔN_{rj}, is linked to foreign arrivals in the cell, ΔF_{rj}, via the structural equation:

$$\Delta N_{rj} = \alpha + \beta \Delta F_{rj} + \varepsilon_{rj}$$

They took random normal draws of ΔF_{rj} and ε_{rj} (and chose α) to match the aggregate mean and standard deviation of the observed data on ΔF_{rj} and ΔN_{rj} across state $\times$ education $\times$ experience cells in the US decennial census since 1960, under varying

[29] Card and Lewis (2007) found a similar lack of native mobility response specifically in response to Mexican inflows.

[30] An older demographic literature also claims to find evidence of "native flight" (e.g., Filer, 1992; Frey, 1995). However, this literature generally does not specify the relationships in a way that is consistent with the recent understanding of how immigration impacts the labor market (described in Section 10.3). In particular, it fails to differentiate by skill category and takes the observed choices of immigrant location as random.

assumptions about β, including $\beta = -1$ (full displacement or "crowding out"), $\beta = 0$ (no displacement) and values up to $\beta = 1$ ("crowding in"). To restate their findings, regardless of the value of β chosen, Borjas' specification (log of native employment on the share of immigrants in employment) finds "evidence" of displacement.[31] Through additional simulations, they also find that the bias in Borjas' specification worsens in the relative variance of ΔN_{jc} compared with ΔF_{jc}, and with the number of cells in the regression, which may help account for how Borjas' estimates vary with geographic scale.

So, what is the specification producing the most reliable estimate of the magnitude of native displacement? Peri and Sparber (2011a) found that the specification used in Card (2007) performs best. In that study, the author regresses $\frac{\Delta L_{rj}}{L_{rj0}}$ on $\frac{\Delta F_{rj}}{L_{rj0}}$, where ΔL_{rj} is the change in and L_{rj0} is the initial size of the labor force (immigrants + natives). Notably, this is similar to specifications used in Card (2001) and Card and DiNardo (2000), and all three studies found little sign of native displacement. In this specification, a coefficient of 1 indicates no displacement: immigration has a one-for-one impact on total skill supply. The authors also point out that, equivalently, one could regress $\frac{\Delta N_{rj}}{L_{rj0}}$ on $\frac{\Delta F_{rj}}{L_{rj0}}$, in which case the coefficient would directly indicate the level of displacement, with a coefficient of 0 implying no displacement.

Peri (2011) further advanced the literature by characterizing the mobility response in terms of the underlying parameters of an aggregate production function. Specifically, it mirrors the CES structure developed and supported in Ottaviano and Peri (2012) and discussed in Section 10.3.2. In such a setup, using Equation (10.5) and taking total differentials with respect to changes in employment of natives and immigrants, one can show that wage growth of native skill group j in local economy r will be

$$\frac{\Delta w_{rj}}{w_{rj0}} = \phi_r + \phi_{r,\,\mathrm{edu}} + \left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3}\right)\frac{\Delta F_{rj}}{L_{rj0}} + \left(\frac{1}{\sigma_2} - \frac{1}{\sigma_3} + \frac{1}{\overline{x}\sigma_3}\right)\frac{\Delta N_{rj}}{L_{rj0}} - \Delta \ln \theta_{rj} \qquad (10.16)$$

where $\overline{x}$ is the native wage bill share; σ_2 and σ_3 are, consistent with the notation of Section 10.3.2, the cross experience cell and immigrant–native elasticities of substitution, respectively; and the rest captures education-specific aggregators and unobserved productivity terms.

The key assumption motivating Peri's (2011) approach is perfect mobility: Natives move to equilibrate wages across labor markets, so $\frac{\Delta w_{rj}}{w_{rj0}}$ is the same in all markets. So Peri (2011) took differences of (10.16) between market r and the rest of the country and denoted with a tilde "~" above a variable such a difference. Then, exploiting full mobility and wage equalization, he set the differenced equation equal to zero and solved for $\widetilde{\frac{\Delta N_{rj}}{L_{rj0}}}$ as a function of $\widetilde{\frac{\Delta F_{rj}}{L_{rj0}}}$. Recall that this is the displacement specification recommended by Peri and Sparber (2011a,b) simulations, but now, the coefficient of that

[31] Borjas also includes an alternative specification meant to reduce this bias, but the authors show that this specification is also strongly biased toward finding evidence of native displacement: again, in all of their simulations, it always finds displacement.

regression is characterized structurally as proportional to $(\sigma_3 - \sigma_2)$, the difference between the elasticity of substitution between native and immigrants and the cross experience elasticity. Comparing California to the rest of the country and using national net arrivals of Central Americans as an instrument for $\frac{\widetilde{\Delta F_{rj}}}{L_{rj0}}$, Peri found little evidence of native mobility response within these skill cells since 1960 (in either OLS or IV), despite the massive and constant inflows of immigrants to California over this period. This can thus be rationalized in the model by $\sigma_2 \approx \sigma_3$. What about his perfect mobility assumption? This is not rejected: Peri (2011) also looks directly at wages and finds no response, which per (10.16) again could be explained by $\sigma_2 \approx \sigma_3$.[32] In plainer terms, the substitution/complementarity structure is such that immigration ends up having little impact on natives' wages within skill cells, providing them no incentive to move out of California in response to immigration. Thus, it simultaneously rationalizes the "zero mobility" finding and explains why immigration appears to have little impact on the wage structure.

A reasonable summary of this literature, then, is that the native mobility response to immigration across geographic space is quite small, an outcome that may be incentive-compatible as the equilibrium effect of immigrants on native wages appears to be small. Nevertheless, the best approach in geographically based studies of immigration's impact is, per (10.9), to allow for the possibility of native mobility response in order to give estimates the proper structural interpretation.

Incidentally, one specification that helps simplify this problem is (when appropriate) to use as the right-hand-side variable the total supply in the relevant skill cells, L_{rj} or a transform of it, and then instrument total changes in skill supply with immigration (or immigration instrument). Put differently, the right-hand-side variable is immigrants + natives, rather than the old approach of treating the size of the immigrant stock itself as the "treatment" variable. In this way, the first stage (regressing labor supply on immigrants by skill across regions) implicitly adjusts for any skill-specific native mobility response and is also a direct indicator of the level of displacement. This approach is, in fact, standard in area studies since Card (2001).[33]

[32] A reasonable question to ask is whether this is consistent with the direct estimates of these parameters in the national data, such as those in Ottaviano and Peri (2012). Peri (2011) asked this as well. Estimates of σ_2 tend to be around 10, while estimates of σ_3 tend to be larger, around 20. Peri argued, however, that existing direct estimates of $1/\sigma_3$ may be biased downward in national regressions by endogeneity. One caveat on this interpretation, which Peri pointed out, is that the regional wage impacts may be small for some other reason, such as some remaining endogeneity (that is, despite having instruments) or adjustments of nonlabor inputs (see Lewis, 2013a).

[33] A nice improvement going forward would be the use of an estimate of the within-skill category imperfect substitutability between immigrants and natives, σ_3, to generate a more general skill group supply measure that allows for such imperfect substitutability, that is, to use $\left(\left[\left(1-\theta_{j,\mathrm{IMM}}\right)N_{rj}\right]^{\frac{\sigma_3-1}{\sigma_3}} + \left[\theta_{j,\mathrm{IMM}}F_{rj}\right]^{\frac{\sigma_3-1}{\sigma_3}}\right)^{\frac{\sigma_3}{\sigma_3-1}}$ in place of $L_{rj} = N_{rj} + F_{rj}$.

10.5.2 Mobility across skill categories

An alternative approach to using variation across geographic space to identify the impact of immigration is to use variation across skill cells over time. As described in Section 10.3.2, this approach was pioneered by Borjas (2003), who described it as a way around the problems of endogeneity of immigrant flows to particular areas and native mobility response. However, depending on one's definition of skill categories, this approach may not be totally immune to native mobility. Indeed, in some cases, such as across occupation, the native mobility response is interesting *per se* in revealing elements of the structure of the labor market. In addition, as was emphasized earlier, estimates that fail to take account of native mobility may lead to an understatement of native gains from immigration.

Native mobility response to immigration across occupations has probably received the most empirical attention. Peri and Sparber (2009) were the first to show that native comparative advantage played a role in this response. Specifically, they test the hypothesis that, among less skilled workers, natives have a comparative advantage in "communication" task-intensive jobs (e.g., sales) and immigrants have a comparative advantage in manual task-intensive jobs (e.g., construction). If so, their model (see Equations 10.12–10.14) has three predictions that they evaluate: (1) Immigration induces natives to shift to more communication-intensive jobs; (2) immigration induces the overall shift to more manual-intensive jobs; and therefore, (3) it raises the relative price of communication tasks. As was mentioned above, they measure task intensity with occupation-level data from O*NET merged to census occupations. To measure the "price" of tasks, they run state time-specific regressions of adjusted occupation-level wages on the average manual and communication intensity of each occupation.[34] They run their analysis across US states over time using 1960–2000 decennial censuses, using both "imputed Mexican immigration" (see Section 10.4) and time-varying functions of the distance to the Mexican border as instruments. They find support for all three predictions, and from the third, they also obtain estimates of the elasticity of substitution between tasks, σ_{MC} in Equation (10.12), which ranges between 0.6 and 1.4. Through simulations, they show that this level of substitutability is of the right order to account for the magnitude of the directly estimated elasticity of substitution between immigrants and natives, σ_3 (per Ottaviano and Peri, 2012).

[34] As is common, they combine several similarly themed O*NET measures into a "percentile" index giving the share of employment with a value at that level or lower. It is worth highlighting at least one unavoidable measurement issue: the occupation-level averages in O*NET are not time-varying, but measured at a single point in time (2000). Although occupational attributes have been measured in other, older surveys including the Dictionary of Occupational Titles, the overlap in the available measures across surveys is basically zero.

A similar pattern emerges among the highly educated: in that skill range, immigration is associated with native shifts toward communication-intensive occupations and away from analytic- or quantitative-intensive occupations, which immigrants tend to specialize in Peri and Sparber (2011b). Both are consistent with comparative advantage driven by natives' superior English language skills (Lewis, 2013b), although other unobserved skill or taste differences might also help rationalize this pattern.

Combining the results of the two Peri and Sparber (2009, 2011b) studies, Foged and Peri (2013) defined job "complexity" as ln((communication + analytical)/manual), using similar O*NET occupation communication, analytic, and manual measures. Taking advantage of the large influx of non-EU immigrants to Denmark since the mid-1990s due to major refugee events (e.g., breakup of Yugoslavia)—and prior to that non-EU immigration to Denmark was trivial—and using the "ethnic enclave" style of instrument, they used detailed firm worker-level data to show that non-EU immigration tends to push both high-skill and low-skill native Danes into more complex jobs, partly through occupational transitions. Since the non-EU immigrants are employed in largely low-skilled occupations, the fact that these gains and occupational transitions occur for both low-skill and high-skill groups (albeit, larger for low-skill groups) is again consistent with gains from specialization. Another nice feature of this study is that the "enclaves" in Denmark were largely the creation of random assignment of the previous small stock of non-EU immigrants due to a dispersal policy that distributed them around the country. Consistent with this, the authors are able to show that there are no significant "pretrends" (1991–1994) in outcomes.

An interesting recent finding is that immigration is not just associated with native specialization across occupations, but more broadly native occupational "upgrading," shifts, that is, to occupations requiring higher skills and granting higher pay. Cattaneo et al. (2013) used rare individual-level panel data for natives in several European countries and found that immigration is associated with the natives of that country moving to higher-skill occupations in order to avoid competition. Foged and Peri (2013) found the same in Denmark. The additional value that comes from the panel-level feature of these studies will be described in Section 10.6.

As was already discussed above, even within narrow occupations, one can sometimes find evidence of specialization. Borjas and Doran (forthcoming) analyze the interesting case of Soviet mathematicians in US departments, following the collapse of the Soviet Union. Soviet mathematicians were particularly concentrated in certain specialties, and these authors show that non-Soviet mathematicians tended to move out of these specialties after the influx.

Other studies, like Borjas (2003) and Ottaviano and Peri (2012), define skill cells in terms of education and (potential) work experience. While it is not possible to move across potential experience cells, there is new evidence that (young) natives may move up education cells in response to low-skill immigration. Using variation across US "commuting zones," which are smaller than metropolitan areas and cover the entire the United States, Smith (2012) showed that youth employment rates are particularly sensitive to immigration, a result that can partly be accounted for by a school enrollment response. Using cross-state variation and carefully accounting for the effect of immigrant children on the school system, Hunt (2012) found that a supply of immigrant adults that pushes up the relative supply of high school dropouts tends to increase the high school completion rates of the native born. Similarly, using cross-state variation and controlling separately for the impact of immigrants as students, Jackson (2013) found that increases in the relative proportion of adult immigrants without a college degree are associated with increases in college enrollment rates of native born.[35] This latter finding also reinforces the consensus that dividing the workforce into two broad categories based on college education is a reasonable first approximation of the labor market (see Section 10.3.4 and Card, 2009).

10.5.3 Immigrant impacts

A very simple two-factor competitive model of the labor market, such as was presented in Equation (10.11), predicts that immigration can raise the average wages of native-born workers (e.g., Borjas, 1999), although there will still be "winners" and "losers" as usual in economics. Note that in this simple, constant return to scale model, the impact of immigration on overall average wages—that is, both immigrants and natives together—is by construction approximately 0. As was discussed above, richer models have been developed that allow for other potential sources of gains from immigration, such as direct impacts on productivity or production technology.

During the past decade, economists have produced many different estimates of the impact of immigration on wages and productivity. The richness of the mechanisms that they have considered has increased as researchers have considered more detailed measures of immigrants' skills and additional outcomes besides wages, including investment and technology choices, and they have considered various sources of complementarities and "spillovers." In Table 10.2, we summarize the estimates in some (but certainly not all) recent studies that try to get to the overall impact of immigrants on productivity of native-born workers. While several studies in the past have focused on the "partial" impact of immigration, that is, on natives within narrow skill cells,[36]—such as in Equation (10.8)—here, we are interested in the general equilibrium impacts of immigration on native productivity and wages, accounting for adjustments, which have been the focus of several studies in the recent decade.

A useful benchmark, reported in the first line of Table 10.2, comes from Ottaviano and Peri (2012), who estimated the elasticity of substitution in a nested-CES production

[35] All of these studies use the "ethnic enclave"/"Bartik style" of instrument.
[36] These studies were summarized in Longhi et al. (2005) and Kerr and Kerr (2011).

Table 10.2 Total productivity effects of immigrants, estimates from the literature

Study	Outcome	Source of variation (cells)	Treatment; instrument	OLS	IV
Ottaviano and Peri (2012)	Native-born average ln(wage)	Education × experience	Actual immigration 1990–2006 (≈10% of pop); N/A simulation	0–0.007	
Ottaviano and Peri (2006)	Native-born average ln(wage)	US metropolitan areas	Diversity of country of birth index (shift-share diversity index)	1.27 (0.27)	0.98 (0.50)
Ottaviano and Peri (2006)	Native-born average ln(wage)	US metropolitan areas	Share foreign born; OLS only	0.57 (0.11)	
Peri (2012)	TFP (residual GSP/worker)	US states	Δimms/pop; ethnic enclave shift share	0.80 (0.39)	1.37 (0.27)
Peri (2012)	Ln(GSP/worker)	US states	Δimms/pop; ethnic enclave shift share	0.62 (0.43)	0.88 (0.25)
Lewis (2011)	Output/worker, manufacturing	US metropolitan areas	HS dropouts/HS graduate; ethnic enclave shift share	−0.14 (0.10)	−0.03 (0.24)
Peri et al. (2014)	Native-born *college* ln(wage)	Metropolitan areas	STEM share of employment; ethnic enclave × change in H1-Bs	4.10 (1.86)	8.03 (3.02)
Peri et al. (2014)	Native-born *noncollege* ln(wage)	Metropolitan areas	STEM share of employment; ethnic enclave × change in H1-Bs	1.16 (1.24)	3.78 (1.75)
Foged and Peri (2013)	Native-born *college* ln(hourly wage)	Metropolitan areas, but within worker and firm	Non-EU imms/pop; ethnic enclave	0.254 (0.121)	0.864 (0.271)
Foged and Peri (2013)	Native-born *noncollege* ln(hourly wage)	Metropolitan areas, but within worker and firm	Non-EU imms/pop; ethnic enclave	0.236 (0.114)	0.460 (0.234)

Trax et al. (2013)	TFP (value-added residual)	Plant (conditional on metro area)	Immigrant diversity index; lagged values of inputs	Manufacture: 0.046(0.027) Service: 0.090(0.042)	Manufacture: 0.310(0.142) Service: 0.033(0.280)
Trax et al. (2013)	TFP (value-added residual)	Region (conditional on plant)	Immigrant diversity index; lagged values of inputs	Manufacture: 0.193(0.101) Service: 0.613(0.168)	Manufacture: 1.617(0.705) Service: 1.187(0.829)
Paserman (2013)	Output/worker, manufacturing	Plant	Share immigrant; OLS only	−0.073 (0.030)	
Paserman (2013)	Output/worker, manufacturing	Three-digit industry	Share immigrant; shift share	−0.028 (0.040)	0.216 (0.554)

function (Equation 10.4) and then used those to simulate the wage impacts of recent immigration on native wages. Depending on the choice of parameters, they found that immigration between 1990 and 2006 (amounting to roughly 10% of the initial workforce) should have raised the wages of the average native-born worker somewhere between 0% and 0.7%. While this model is rich in terms of skill categories—it includes four education groups × eight experience groups and allows for immigrant-native imperfect substitutability within those cells—it may not account for all of the beneficial impacts of immigrant skill diversity, let alone impacts through other mechanisms such as spillovers and native responses.

Ottaviano and Peri (2006) is an early paper suggesting that immigration is associated with higher average wages through a skill diversity mechanism. They found both a general positive association between immigration and wages and, conditional on this, an association with a measure the country diversity of immigrants, a Herfindahl index. Part of this gain may be in the form of cultural amenities, as the index is also associated with higher housing rents (also found in Saiz, 2007). Table 10.2 reports the effect of an increase in the diversity of country of birth index estimated in that article.

Ottaviano and Peri (2006) and Peri (2012) also produced useful "reduced form" benchmarks for the impact of immigration on wages and productivity. The first study estimates that the elasticity of native average wages with respect to immigrant share is 0.57. Since Ottaviano and Peri (2006) used data from 1970 to 1990, we have reestimated a version of what they did using more recent (2000–2010) data. Scatterplots and regression lines are shown in Figure 10.5. We find a native-born wage elasticity with respect to immigrant population share of 0.64 (with a standard error of 0.30) using variation in the percentage change of yearly earnings regressed on changes in share of foreign born across 219 metropolitan areas, weighted by initial population.[37]

Peri (2012) examined productivity. Using gross state product (GSP) data merged to imputed state estimates of capital stock and skill mix, he log-linearized a generalized version of (10.11) (in particular, adding capital as a factor of production) and then regressed each component of the aggregate production function on immigration-driven population change.[38] After imposing an elasticity of substitution between college and noncollege workers of $\sigma = 1.75$ (compatible with consensus estimates, including Katz and Murphy, 1992; other studies include Hamermesh, 1993; Borjas, 2003; Ottaviano and Peri, 2012), he was able to estimate the impact of immigration on TFP. His basic OLS estimate implies that TFP rises 8% for each 10 percentage-point increase in

[37] If one splits employment between college-educated and noncollege-educated, one finds that the positive effect is driven by the college-educated group (elasticity of native college-educated wage to college-educated immigrants share of 0.93, standard error 0.58), while immigration among noncollege-educated has no significant effect on their wages (elasticity of −0.14 with standard error of 0.19).

[38] That is, his "treatment" variable is $\Delta F/\text{Pop}$, where ΔF is the change in the number of foreign-born residents and Pop is population.

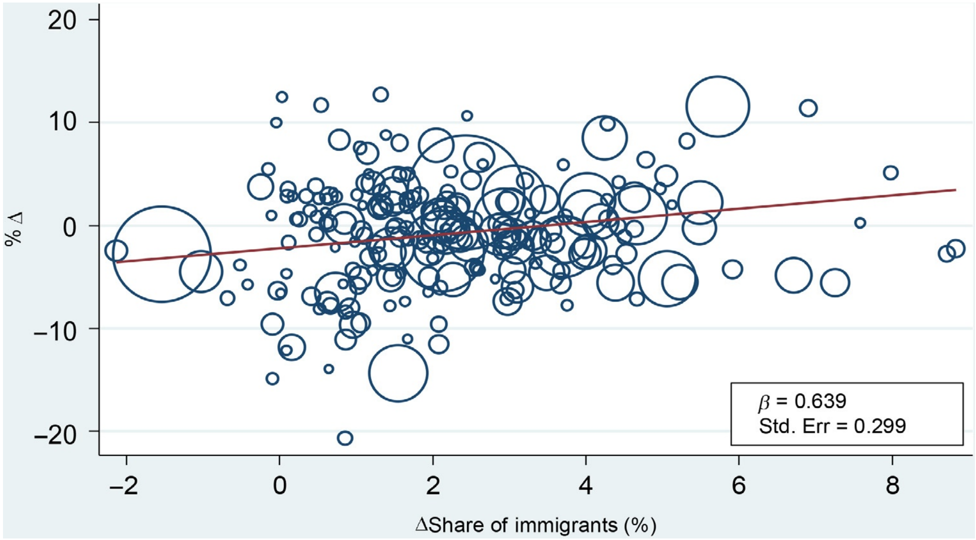

Figure 10.5 Native wages versus immigrant share. US cities 2000–2010. *Note: Each circle represents one of the 219 MSAs (cities). Data are calculated from the 2000 census and 2008–2010 3-year combined American Community Survey. Beta coefficient is from an OLS regression of the percentage change in wages against the change in the immigrant share, and standard errors are corrected for heteroskedasticity. All results are weighted by initial city population in 2000, and thus, the size of circles reflects the city size in 2000.*

immigration-induced population growth. This is confirmed in the 2SLS regression using distance from Mexico interacted with national immigration flows as instruments: his IV estimates are close to 14%. In short, states with a large increase in high school equivalents driven by Mexican immigrants have experienced a very strong relative increase in the productivity/efficiency of that factor in production. Note the critical role of imposing a value of σ to identify TFP impacts, which cannot be separately identified from a direct effect of labor supply otherwise. Reassuringly, although the estimates show some sensitivity to the choice of elasticity, all of the estimates are positive. In addition, the impact on the cruder GSP/worker is roughly the same magnitude (Table 10.2).

It is noteworthy that even the OLS estimates of the reduced from relationship between immigration and average wages in Peri (2012) and in Ottaviano and Peri (2006) are an order of magnitude larger than the simulated impact found in Ottaviano and Peri (2012). While the potential of omitted variable bias is a concern in spite of the 2SLS estimation, the larger measured effects suggest the potential presence of other mechanisms, besides the mechanical changes in observed skill mix, at work in affecting the wages of native-born workers. One mechanism is the working of efficient specialization and upgrades documented in Peri and Sparber (2009, 2011b), Foged and Peri (2013), D'Amuri and Peri (2014), and Cattaneo et al. (2013). Indeed, Peri (2012) provided preliminary support for such a mechanism: controlling for the "communication intensity" of the average native's job—the specialization measure used in Peri and Sparber (2009)—the productivity impact of immigration becomes smaller and statistically insignificant.[39] Another mechanism is a price effect: using a similar cross area approach and ethnic enclave instrument, Cortes (2008) showed that immigration lowers the price of nontraded goods.[40]

As was discussed in Section 10.3.5, firms may also respond to immigration by changing their production technology or, more narrowly, their capital intensity (e.g., Lewis, 2011; Peri, 2012). Peri (2012) showed that immigration (associated with a decrease in the college share of workers) is associated with an increase in the efficiency of high school equivalents in production.[41] Going back to Equation (10.15), this says that immigration lowers both L_{CO}/L_{HS} and A_{CO}/A_{HS}; as (10.15) shows, the latter attenuates any relative wage impacts of immigration due to the shift in L_{CO}/L_{HS}. Equation (10.15) shows the identification problem: impacts of relative labor supply on A_{CO}/A_{HS} are confounded with the direct of labor supply on wages (second term of (10.15)). As before, Peri broke this endogeneity by imposing a value of σ. So, what Peri found, in plainer terms, is that the cross-state impacts on the relative wage of immigration-induced changes in labor mix are smaller than what external estimates of the elasticity of substitution between college and noncollege workers would predict. Qualitatively similar findings are found in Lewis (2003) and Card and Lewis (2007), both of which use variation across metropolitan areas and "ethnic enclave"-style instruments (the latter focuses on the impacts of Mexicans only) and find little relative wage impact of immigration. One strength of the latter two studies is that they account for shifts in industry mix that would occur in a multisector model. These are found to be small, and so, skill mix changes are nearly as large "within industry" as overall. A weakness is that, unlike Peri (2012), they fail to focus on the college/noncollege relative supply, which newer research suggests is the main relative supply measure of interest.

In light of the identification challenge revealed by (10.15), are there some ways to get at the productivity terms or at least their determinants more directly? As was mentioned above, Lewis (2011) looked at the use of automation and capital intensity in the manufacturing sector and found that low-skill immigration reduces it. These changes in production technology and investment might partially account for the impact of

[39] Such evidence should only be taken as preliminary, as it attempts to partial out the impact of an endogenous regressor.

[40] See also Lach (2007).

[41] The finding that changes in skill mix are associated with changes in the skill intensity of production is similar to a cross-country patterns found in Caselli and Coleman (2006) (which did not study immigration).

TFP that Peri (2012) found. However, Lewis did not find any significant association between low-skill immigration and output per worker. The difference in estimated productivity response between Peri (2012) and Lewis (2011) could be a result either of Lewis' narrower focus on the manufacturing sector or of his focus on the high school completion skill margin.[42] A nice direction for future work would be to repeat a study like Lewis (2011) with a focus on the college completion margin.

Immigration may also affect productivity and wages through innovation and possibly through entrepreneurship. A couple of recent studies have focused on immigrants' disproportionate role in patenting and innovation. Hunt and Gauthier-Loiselle (2010) showed that among college graduates, immigrants have much higher patenting rates, which appears to be due to the fact that foreign college graduates have more education and they specialize in larger proportions in scientific and technological fields. Similarly, Brunello et al. (2007) showed that in a regression across US states over time, increases in foreign science PhD density are associated with a greater increase in patent counts than domestic science PhD density. Part of this finding may be due to a spillover from foreign scientists to the innovative productivity of domestic ones: Hunt and Gauthier-Loiselle (2010) found that in a similar panel regression, an increase in foreign college share in a state is associated with an increase in the patenting rate in a state that exceeds what one would expect "mechanically" from the higher patenting rate of immigrants in cross-sectional data. Hunt and Gauthier-Loiselle can only speculate that this is due to "spillovers," however, because the patent count data are not broken out by nativity in their panel data.[43]

To partly address this problem, Kerr and Lincoln (2010) linked the names of patent holders to an ethnic names database, which allows them to divide patent counts, not by nativity, but into "Indian," "Chinese," and "Anglo-Saxon" patents. They studied specifically the role of the US high-skill "H1-B" program, and they took advantage of the fact that most H1-B visa holders are Indian and Chinese, making their ethnic groups a reasonable proxy for nativity.

They used variation across US labor markets. Though they cannot measure the quantity of H1-B holders at a local level, they essentially estimate a "reduced form" version of the ethnic enclave instrument: their right-hand-side variable is the interaction of the

[42] Paserman (2013) also found little sign of a positive association between immigration and productivity using variation at the firm and industry levels in Israel's manufacturing sector. The immigrants in Paserman's study were largely "high-skill" immigrants from the FSU, although many did not end up in high-skill positions.

[43] The cross-sectional data are the National Survey of College Graduates, 2003 wave, while the panel data are tabulations from the US Patent and Trademark Office from 1940 to 2000. Thus, the difference in the timing of the two surveys is one confounder of the apparent difference in the association between immigrants and patenting in the two surveys.

stock of H1-B visas issued nationally with a measure of local "dependence" on H1-B type workers, which is a kind of imputed stock. They found that areas with more H1-B dependence have moderately higher rates of Anglo-Saxon patenting.[44]

While higher patenting rates are associated with higher productivity at the country and sector level (Eaton and Kortum, 1996; Furman et al., 2002), patent counts are only imperfectly related to productive innovations (e.g., Griliches, 1990; Jaffe and Trajtenberg, 2002). So, a complementary approach is to examine the direct relationship between local high-skill share and wages, as Peri et al. (2014) do. Using variation across 219 US metropolitan areas, these authors estimate the relationship between changes in the STEM share of employment— that is, the share in high-tech occupations that they take to represent STEM—and wages. Their identification derives from a version of the ethnic enclave instrument: it is the sum of national changes in the country composition of H1-B immigrants interacted with the lagged size of the foreign STEM workforce in the area. Both their OLS and IV estimates suggest that STEM share is associated with higher wages for college graduates and, to a lower degree, for high school graduates, too.

These studies corroborate influential anecdotal evidence arguing a role for highly skilled engineers and entrepreneurs, especially immigrants (Saxenian, 2002a,b), in innovation and growth (Saxenian, 1994). Indeed, in addition to producing more patents, immigrants have significantly higher rates of entrepreneurship (Hunt, 2011), and immigration is associated with the creation of more small firms (Olney, 2013). Whether this matters for productivity growth is an open question; however, one tantalizing fact is that immigrant-owned businesses seem to be about 12% more productive, on average, than native-owned businesses (Garcia-Perez, 2008).

One final channel by which immigration may affect average productivity—which is related to the trade diversity model described in Section 10.3.5—is by increasing product diversity. di Giovanni et al. (2013) simulated the impact of the increase in-product diversity that comes from an increase in the scale of the economy associated with immigration. They found that it has a substantial positive impact on welfare in many immigrant-receiving developed countries. Empirically, immigration is associated with greater product diversity (Mazzolari and Neumark, 2012), though an increase in place of birth diversity (Ottaviano and Peri, 2005, 2006), rather than a pure scale effect, may account for this fact. Mazzolari and Neumark (2012) found that the strongest association is between immigration and an increase in restaurant diversity; other forms of retail diversity actually decline.

[44] A larger literature uses other (nongeographic) approaches to measuring the impact of immigration on innovation, including the dismissal of Jewish scientists from Nazi Germany (Waldinger, 2012; Moser et al., 2013). This broader literature is reviewed in Kerr (2013). This review also covers the impact of immigrant entrepreneurship.

10.5.4 Summarizing the productivity impacts

Though the number of studies of the direct association between immigration and productivity or wages summarized in Table 10.2 is not large, some interesting patterns emerge that may be helpful in charting a path for future research. The first pattern is that the association seems to be larger for high-skill (e.g., Peri et al., 2014) than low-skill immigrants (Lewis, 2011; Foged and Peri, 2013). The second is that there seems to be an additional impact of "origin diversity" separate from immigration's impact generally (Ottaviano and Peri, 2006; Alesina et al., 2013; Trax et al., 2013). This combined with the fact that the "mechanical" impacts of observed skill mix on the wage structure seem to be small (Ottaviano and Peri, 2012), suggesting that unmeasured skills of immigrants contribute to their productivity impacts, perhaps in part through the sort of specialization directly documented in Peri and Sparber (2009, 2011b). The association with the wages of more educated natives also seems to be stronger (Foged and Peri, 2013; Peri et al., 2014), consistent with a directed technical change story (among others). Immigration may also affect productivity through prices (Lach, 2007; Cortes, 2008), product diversity (Mazzolari and Neumark, 2012; di Giovanni et al., 2013), innovation (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010), or entrepreneurship (Hunt, 2011).

Recently available and richer data—for example, covering firm-level outcomes—may be helpful in uncovering the mechanisms, which rationalize these patterns.[45] We now turn to a discussion of such data and how they are being used.

10.6. RECENT EVOLUTIONS: EMPLOYER–EMPLOYEE PANEL DATA AND HISTORICAL DATA

Two valuable recent developments in the research on the impact of immigration are the use of individual-level panel data and, to be discussed later, the application of similar tools to historical data. The panel data confer several advantages. First, by following individuals over time, panel data allows controls for unobserved sources of heterogeneity. As may have been indirectly evident from the discussion about "displacement effects" in Sections 10.5.1–10.5.2, most of the studies above that employ a cell-based approach do not literally track the same individuals' wages in a cell over time, but rather a representative sample of whoever is in that cell at each point in time.[46] While the potential for immigrants to affect the aggregate quantity of natives in each cell is the first-order concern with this approach (the subject of Sections 10.5.1–10.5.2), even after addressing this

[45] For example, it is notable that the impacts in Table 10.2 seem to be external to the firm (Paserman, 2013; Trax et al., 2013), though, as will be discussed below, firm-level impacts may so far not be as well identified.

[46] The use of repeated, representative cross-sectional sample not necessarily including the same individuals is also sometimes referred to as a "pseudo panel." Note that this description applies to both area studies and "national" approaches to the study of the labor market impact of immigration.

problem, estimates could be biased by more subtle changes in the composition of workers due to selection or attrition from a cell; panel data address such concerns by tracking the same individuals over time. Indeed—and second—such compositional changes may be of direct interest in understanding the labor market dynamics, revealing the dynamics of individual workers' adjustment to immigration.[47] For example, one can estimate the benefits of the type of immigrant–native specialization documented in Peri and Sparber (2009, 2011b) directly, by tracking how individual native workers' productivity changes as they shift across occupations in response to immigration. Third, to the extent that workers are tracked across firms, we can look at outcomes at the level of the firm for the first time. This is a fortuitous feature of the fact that modern panel data often come from a sample of administrative records (social security earnings records), which, for many European countries, is the only reliable source of wage data over a long time frame.[48]

The study by Cattaneo et al. (2013) was mentioned above. They use individual-level panel data to study both the impact of immigration on the wages of native-born workers and the dynamics of adjustment—specifically, the movement of incumbent natives across occupations over time—to immigration. Usefully, their data cover a number of European countries but are from survey data, not from administrative records that identify the firm of employment. They found significant occupation "upgrading" in response to immigration, namely, increased mobility of incumbent natives to jobs associated with higher skills and higher pay. They also found small wage effects on natives. Foged and Peri (2013) had access to a full panel of matched firm-worker data for Denmark from 1991 to 2008.[49] This allows them to study the dynamics of adjustment to immigration and to decompose any impacts into those that occur within a worker-firm match and those due to movements across firms. The focus of that study is on the impact of the non-EU immigration wave that swept over Denmark starting in the mid-1990s, largely due to refugees flows. These immigrants were on average less educated than the native-born

[47] Other studies exist on the dynamics of the response to immigration but observe the adjustment at the aggregate, rather than individual level, including Barcellos (2010), Cohen-Goldner and Paserman (2011), and Murray and Wozniak (2012).

[48] Until recently, European labor force surveys have tended to lack wage data, unlike in the United States, which was a challenge for research on the labor market impact of immigration. Interestingly, the willingness of many European countries to share social security earnings records with researchers now means that European data are of higher quality than those of the United States for many cutting-edge immigration-related research questions. While similar data are now available in the United States in the form of the Longitudinal Employer-Household Dynamics (LEHD) database, access is more difficult, use is more cumbersome, coverage is not as complete, and records are not as detailed when compared with the data available in many European countries. See Kerr et al. (2013) for a description of these data.

[49] Malchow-Moller et al. (2011, 2012) used the same Danish data to analyze the impact of immigrants on firm-specific wages and productivity. However, they do not analyze other outcomes, they do not follow individuals, and their identification strategy is not as convincing.

population, a trait they have in common with the flows analyzed in Peri (2012) and Ottaviano and Peri (2006). Interestingly, the coefficients in all of these studies are a similar order of magnitude despite the richer controls in Foged and Peri (2013)—see Table 10.2. Given the large differences between them, this may simply be a coincidence, but it is nevertheless striking. It would be useful is to apply these methods to similar data in other countries.

Trax et al. (2013) was an early attempt to use German social security data to separately estimate the impact of immigrant diversity (measured in the same manner as in Ottaviano and Peri, 2006) at the plant and region level, using lagged independent variables as instruments. They found effects at both levels, though the effects at the metropolitan area level are much larger in magnitude. At the metro level, they found that a 0.1 unit increase in diversity is associated with 16% higher wages in manufacturing and 18% in services, which is about 50% larger than what Ottaviano and Peri (2006) found. One caveat is that Trax et al.'s instrument set seems dubious, though their metropolitan area results remain similar when adding a more standard ethnic enclave-type instrument. Paserman (2013) also used variation at the firm level interacted with the large inflow of highly educated Russian immigrants to Israel to study the relationship between immigration and productivity at Israel manufacturing firms. He found little to no association in OLS estimates.

Dustmann and Glitz (forthcoming) use German plant-level data from the same source to ask how firms adjust to local immigration-driven changes in skill mix in the manufacturing sector. They find—consistent with the adjustments in production technology that Peri (2012) found at an aggregate level—a surprising level of responsiveness of unit efficiency to regional skill mix changes. In principle, Peri's (2012) result on unit efficiency might have been driven by the composition of firms and industries, rather than a change in production technology *per se*. However, Dustmann and Glitz find that, at least for Germany between 1985 and 1995, 70% or more of the skill mix changes at the region level are passed through to the plant level, despite there being no change in relative wages associated with immigration.[50] This is consistent with fully offsetting changes in unit efficiency (Equation 10.6) due to the adoption of techniques appropriate to the type of skills available. They use standard "ethnic enclave"-type instruments for identification.

Data linking employee characteristics with establishments are harder to come by in the United States. One recent study uses the best available to study the impact of high-skill immigration at the firm (not establishment) level. Kerr et al. (2013) used a subsample of 319 large firms in the so-called LEHD database, which is created from

[50] This figure is for firms that exist over the whole 10-year period. They find that net entry of firms also helps to push the skill mix toward the new level in the region. The authors also find a modest role for changes in product mix in absorbing skill mix changes, though larger than what previous studies had found (including Lewis, 2003).

unemployment insurance records from US states, but which the authors supplement with data from other firm databases (including Compustat).[51] Using a panel regression, the authors find that in response to an influx of young (under age 40), high-wage (above $50,000 in 2008 dollars) immigrants, firms hire more high-wage natives but especially young high-wage native workers. When they estimate using instrumental variables using, among other things, a version of the "ethnic enclave" instrument applied to the firm level, the effect for older native-born workers is often insignificant.[52] Using a simple model of production adapted from Desai et al. (2009), they showed that under some assumptions, this finding is sufficient to show that young immigrants complement young natives.[53] This is not, however, sufficient to demonstrate that these immigrants actually substitute for older workers, but the authors produce some additional inconclusive evidence that these immigrants may actually displace older native-born STEM workers from the firm.[54] If so, the authors argue that this would be inconsistent with the way in which age categories are nested in the CES production structure used in Borjas (2003).

Another interesting recent development is the application of cutting-edge methods to historical data, which allows an investigation of the impact of immigration in the context of much different set of production choices facing firms and potentially differences in market structure. History can thus potentially help reveal how the impact of immigration may depend on context (such as the cultural factors and institutions that Saxenian, 1994 discussed). An additional advantage of historical data is the relative ease of access to business and individual-level data, compared with modern data, in light of the lack of confidentiality concerns.[55] A weakness is often that there is less detail than modern data on things like compensation (wages) and even occupation, and so, researchers are left with the usual challenge of historical research of deriving credible proxies for the desired measures.

Kim (2007) used plant level data taken from 1860 to 1880 (at that time, decennial) US Censuses of Manufactures and ran regressions similar to what are described in Table 10.2—ln(output per worker) and ln(average wages) on immigrant share—using

[51] In order to have their analysis go back to 1995, the authors are limited to firms with a significant presence in 18 US states.

[52] Another instrument interacts the size of the H1-B "cap" with a measures of the firm's H1-B "dependency," for example, the number of "labor conditions applications" (LCA) a firm filed in 2001 per high-wage worker. LCAs are a precursor to hiring a worker on an H1-B visa, among other visa programs. Ghosh and Mayda (2013) used LCA data linked to Compustat to study the impact of H1-Bs at the firm level.

[53] Complementarities between factors are more clearly identified from the cross elasticities of factor prices or output shares (e.g., Lewis, 2013a), but these authors only have data on employment.

[54] If this result holds up, the interesting question would be what happens to these workers, which in principle could be answered with the sort of data that Kerr et al. (2013) were using.

[55] The individual-level records for many historic population and industry censuses, for example, are publicly available.

variation in immigrant share across US counties.[56] The regressions control for industry and state effects but, importantly, not for county fixed effects. In other words, unlike most of the studies in Table 10.2, Kim's results are cross-sectional. He found consistent significant relationships in OLS, with coefficients ranging from 0.5 to 1.5, which are not unlike the estimates in Table 10.2. IV estimates, which use the 1850 share foreign born as an instrument, are similar in magnitude. Kim also showed that immigrant share was associated with larger plants, a proxy for "factory production." This was the important innovation of the era, and it may be partly responsible for these productivity benefits.[57] A serious caveat is the cross-sectional nature of these results. In particular, the author shows that places with more immigrants also were also closer to New York and had better water transportation. These factors would have enabled access to larger markets, which is thought to be a prime driver of the adoption of factory production and productivity gains in this era.[58]

Other recent history papers use variation across US counties but condition on county effects, rather than relying on cross-sectional variation; two studies also use an "enclave" style of instrument. Gonzalez-Velosa et al. (2013) examined the impact on the agricultural sector between 1900 and 1940, using data tabulated from the Census of Agriculture. They found little evidence that immigration affected agricultural productivity but found that immigration may have been mostly accommodated by shifts away from less labor-intensive crops (e.g., wheat) in places where the land could accommodate multiple crops.[59] In places where it could not, immigration is associated with markers of a shift toward more labor-intensive production techniques (from tractors to mules). The latter is consistent with evidence from the natural experiment of the US shutting down immigration in the 1920s (Lew and Cater, 2010).[60]

Lafortune et al. (2014) examine the impact of changes in skill ratios (share literate), induced by immigration, on the manufacturing sector between 1860 and 1940, using data tabulated from the Census of Manufactures to the county or city × industry level. They

[56] Note that the wage data are averaged at the plant level, so the more conceptually appropriate specification average ln(wage) is simply unavailable.

[57] Factory production is believed to be unskilled-labor-intensive compared to the predecessor technology of "artisan" production. Thus, if immigrants raised the relative abundance of unskilled labor, they might have induced adoption of factory production. This specification may oversimplify a bit the role of immigrants, however, many of whom were high skill.

[58] For example, see simulations in Donaldson and Hornbeck (2013) suggesting that market access via waterways access significantly raised local land values. See also Chandler (1977).

[59] The industry mix result contrasts with modern findings that industry mix adjustments play a trivial role in the absorption of immigration-driven skill mix changes (e.g., Lewis, 2003; Card and Lewis, 2007; Gonzalez and Ortega, 2011; Dustmann and Glitz, forthcoming).

[60] Lew and Cater (2010) examined agricultural counties on opposite either side of the Canada–US border during the 1920s, when the United States shut down inflows of foreign workers. This is associated with a sharp uptick in labor-saving tractor use on the US side of the border relative to the Canadian side, on what should be very similar agricultural land.

find a positive association between immigration-induced increases in the skill ratio (that is, using variation from an "enclave" instrument) and wages and productivity, a result that may be compositional only.[61] More interestingly, unskilled immigration is associated with the adoption of more, not less, capital-intensive production techniques between 1860 and 1880. This contrasts sharply with twentieth-century capital–skill complementarity (e.g., Griliches, 1969; Goldin and Katz, 1998; Lewis, 2011) but is consistent with the view that advances in nineteenth-century manufacturing were "deskilling" (e.g., Atack et al., 2004). Thus, the finding is—similar to what Kim (2007) found—unskilled immigration may have induced faster adoption of new production methods in manufacturing in the nineteenth century, though the productivity gains from this may have been much more modest than what Kim found.

10.7. CONCLUSIONS

Across a wide range of settings and research approaches, immigration is associated with higher wages for most native-born workers and with higher productivity, especially when analyzing immigration across geographic areas. This simple fact, which has been subject to a large number of tests but on average has survived, indicates that immigrants represent more than a simple change in total labor supply at the local level. First of all, their skills and occupations are crucial to understand their impact. Second, the responses of native workers, firms, sectors, and potentially local consumers are also important margins to understand the equilibrium effects of migration on local economies. A more careful consideration of these aspects and the development of model-based ways of testing local responses to immigration have been crucial parts of the recent developments in this area of research. While framing the analysis of the effects of immigrants in a model that allows for different skills is very important and allows for a better understanding of complementarities and adjustment margins, it also important to allow for the possibility of productivity effects of immigrants.

The productivity effects of immigration have been found in a variety of European countries and in the United States and measured at the local level (cities or metropolitan areas) up to the country level. The positive impact of immigration on "skill diversity," broadly construed, appears to be a key driving force behind this productivity impact. The adoption of new and efficient technologies in response to this richer set of skills may also be another important force underlying the adjustment. The exact mechanism underlying this impact, however, is still not well pinned down, but evidence suggests that

[61] Their IV estimates are in the range 0.2–0.3, and their skill mix measure is ln(literate workers/illiterate workers). Thus, if literate workers were on the order 20–30% more productive than illiterate workers, these results could be fully accounted for with compositional change. Unfortunately, no data exist to measure the productivity or wages by literacy status at the individual level in this era.

immigration induces natives to specialization in more complex jobs, which complement immigrants' skills and that it induces higher levels of innovation, both of which may contribute to the observed productivity impacts. More research taking advantage of plant- or firm-level data would likely be helpful in achieving a deeper understanding of how the impact of immigration materializes. At the same time, data that follow individuals and firms allow us to identify how these productivity effects diffuse across firms and labor markets and how they interact with firm and workers characteristics to determine winners and losers from these changes.

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