Skilled Immigration, Innovation, and the Wages of Native-Born Americans*

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The paper examines the effects of skilled immigration on wages that can be credited to immigrants' contribution to innovation. Using both individual and state-level datasets from the United States, we find a significant and positive effect of immigration on wages that is attributable to skilled immigrants' contribution to innovation. Our results confirm previous findings that immigrants contribute substantially to the host economy's innovation, which is a major driver of technological progress and productivity growth. When we augment the analysis to an immigration–innovation–wages nexus, the results suggest that as the share of skilled immigrants in a particular skill group increases, the wages of both natives and immigrants in that group also get a positive boost. We also identify evidence in favor of a positive spillover effect of skilled immigrants on a state's wage level of all workers, including those who do not directly contribute to innovation.

Introduction

Does innovation boost wages? What impact does immigration have on native innovation? In this paper, we revisit the immigration–innovation–wages nexus, providing empirical evidence in support of these questions by extending the studies of Hunt and Gauthier-Loiselle (2010) and Hunt (2011). Our interest is in examining the extent to which wage increments in the United States can be credited to immigrants' contributions to innovation. In other words, we provide estimates of the contribution to wage increases that can be attributed to immigrant-led innovation and are measured by patents granted/commercialized and academic performance. Hunt and Gauthier-Loiselle (2010) examined the

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contribution of immigration to innovation. In a subsequent paper, Hunt (2011) investigated the performances of skilled immigrants relative to natives in boosting U.S. productivity. Our research offers a marked extension of these earlier studies, which did not consider the impact of immigrant-driven innovation on wages.

Notwithstanding the existence of a sizeable body of empirical literature on the impact of immigration on wages, the results so far have offered mixed evidence. One line of empirical work that is associated with Borjas and some of his collaborators (Aydemir and Borjas 2007; Borjas, Grogger, and Hanson 2008, 2009) implicitly suggests that native and immigrant workers are perfectly interchangeable. However, a set of recent empirical studies reviewed by Card (2009) indicates that these two types of workers are far from perfect substitutes, even within the same skill group. Peri and Sparber (2011) report that native workers with graduate degrees specialize in occupations that require highly interactive skills, as well as communication skills, while their immigrant counterparts possess quantitative and analytical skills. This heterogeneity in skill levels is more pronounced at the aggregate level of the economy, which makes it more realistic to assume imperfect substitutability between native and migrant workers at an economic level. On the other hand, studies that exploit geographic differences across local labor markets (Altonji and Card 1991; Card 2001; Pischke and Velling 1997) have been criticized for ignoring the tendency for economic conditions to converge across markets.

Our empirical strategy relies on the premise that skilled immigrants' contribution to wages can be attributed to productivity gains from the former's innovation, research, and possibly their entrepreneurial skills and other labor-market effects. A number of papers in the immigration literature have studied the effect of immigration on innovation (e.g., Hunt and Gauthier-Loiselle 2010; Stuen, Mobarak, and Maskus 2012) while others have explored the effect of immigration on wages (e.g., Borjas 2003; Card 2001; Carrasco, Jimeno, and Ortega 2008; De New and Zimmermann 1994; Ottaviano and Peri 2012) or the wage differential between immigrant workers and native workers (e.g., Skuterud and Su 2012; Smith 2006). In contrast to previous research, we addressed the immigration–innovation–wages nexus, an area largely neglected so far, despite its significant policy implications.

The paper contributes to the literature by providing estimates of the natives' wage increases, which can be ascribed to the innovation of skilled immigrants in the United States. We accomplish this by examining two channels in which skilled immigrants could potentially contribute to innovation and wages. First, we analyze the contribution of skilled immigrants to the innovative capacity of individual native skilled workers who are in the same skill group that lead to their wage increments. We carry out this analysis by using individual-level data in an effort to capture the direct effect of skilled immigrants on individual innovative capacity and individual wages. Second, we examine the spillover effect of a state's innovation and technological advance on the wage level of all workers, including those who do not directly contribute to innovation. In particular, we use state-level data to estimate how much a state's wage level is affected by the share of skilled immigrants in the state population through its effect on the state's patenting per capita.

When analyzing individual cases, we first estimate the effect of the share of immigrants in a particular skill group on the workers within that skill group. A skill group is defined by its members' education, occupation, experience, and workplace. Second, we estimated the effect of innovation on wages. To do so, we first assume that much of the effect of skilled immigrants on wages actually comes from their contributions to innovation and research capabilities. Note that, the key to technological progress is rooted in innovation. However, in order to relax the assumption, we account for other effects that immigrants may potentially have on natives' wages. In this situation, we control for the share of immigrants among all workers within a given skill group. Following Borjas (2003), we assume that the direct effect of immigrants on wages is contemporaneous at the national level due to the equalization of economic conditions across geographical regions. However, the indirect effect of innovation is mainly diffused among fellow workers who are employed in the same occupation and are geographically proximate. Therefore, by including a share of immigrants at the national level, we expect the particular share at the skill-group levels to exert some impact on natives' wages only through the innovation channel. Our exercise at the state level is a direct extension of the state-level data analysis by Hunt and Gauthier-Loiselle (2010). These authors used a panel state dataset to estimate the effect of a state's proportion of skilled immigrants in its per capita patenting. We implement the same methodology but take it a step further, which helps us to measure how much this effect is translated into change in the state's wage level. In both analyses, we also account for the potential endogeneity bias that could arise if skilled immigrants' decisions to migrate to a particular part of the United States were based on productivity and innovation. To address this, we adopt an instrumental variable (IV) approach.

We use three main datasets: The National Survey of College Graduates (NSCG) dataset, the 1940–2000 Integrated Public Use Microdata Samples (IPUMS) from the original sources of the U.S. Decennial Census, and the patenting report from the U.S. Patent and Trademark Office (USPTO). Our results reveal a significant positive effect of immigrants on wages that is channeled through innovation as measured by the capability to have patents granted or commercialized. We find that a 1-percentage-point increase in the share of immigrants in a skill group leads to an increase in wages of workers in that skill group in the range of 0.8–1.0 percent through the positive effect on their innovative capacity. Findings from our state-level analysis also suggest a positive spillover effect of skilled immigrants on a state's innovation and technological advancement, which lead to wage increments for all workers in that state. Interestingly, this effect also includes those who do not directly contribute to innovation. Not surprisingly, we find this channel to be quite effective. A 1-percentage-point increase in a state's share of skilled immigrant workers leads to a 7.5 percent increase in the weekly wage for all native workers and a 5.1 percent increase for the low-skilled native workers in that state.

The rest of the paper is organized as follows. The next section offers a brief discussion of related studies on the impact of immigration on labor-market outcomes. Next, we outline the empirical strategy adopted in this paper and then provide a detailed description of the data sources. We then report the results and review the robustness of the results based on alternative estimates. Finally, the last section draws conclusions based on the findings with a note on the directions for future research.

Related Studies

Innovation, which is widely regarded as the driver of technological progress, belongs to the domain of the macroeconomic growth literature, especially in the context of endogenous growth models (Aghion and Howitt 1992; Grossman and Helpman 1991; Howitt 1999; Jones 1995b; Romer 1990). The link between innovation and the number of scientists is also central to the formulation of production function in these models. Jones (1995a) and Ha and Howitt (2007) went to great lengths to empirically examine this relationship. However, even though the share of skilled immigrants in labor markets has been increasing over the past few decades, their contribution to innovation, and thus to technological progress, has received little attention in the extant literature.

One exception is the study by Hunt and Gauthier-Loiselle (2010). They point out that in addition to contributing directly to research, immigrants also take part in technological progress indirectly "through positive spillovers on fellow researchers, the achievement of critical mass in specialized research areas, and the provision of complementary skills such as management and entrepreneurship" (p. 31). However, these positive spillovers can also be offset by negative spillovers or crowding-out effects, which can be associated, for example, with increased competition for university admission and research funding. Borjas (2007) reported little evidence of any crowding-out effect of foreign students for a typical native student in graduate programs but did find a strong negative correlation between increases in the enrollment of white native students and of foreign students, especially at the most elite institutions.

The findings from many of the papers that examined the effects of immigration on innovation are reassuring. The results from Hunt and Gauthier-Loiselle (2010), Stephan and Levin (2001), Chellaraj, Maskus, and Mattoo (2008), and Stuen, Mobarak, and Maskus (2012) reveal that skilled immigrants and doctoral immigrant students contribute significantly to innovation, as measured by a range of different indicators, including patenting, publication and citations in professional journals, and election to science and engineering academies. The results from the analysis of state-level data by Hunt and Gauthier-Loiselle (2010) showed that a 1-percentage-point increase in the share of immigrant college graduates in the population of a state during the period from 1990–2000 increased the patenting per capita in that state by 9–18 percent. The result remains robust even when an IV approach is used to account for possible endogeneity in immigrants' choices of a destination state. Chellaraj, Maskus, and Mattoo (2008) incorporated skilled immigrants in the production function concept as a component of the "idea generation input" and found that an increase in the number of foreign graduate students could lead to a rise in patent applications, university patent grants, and non-university patent grants. Similarly, Stuen, Mobarak, and Maskus (2012) reported that a 10 percent decrease in the foreign share of doctoral students reduced the production of scientific publications and citations in U.S. universities by around 5–6 percent. Kerr and Lincoln (2010) examined the effect of fluctuations in H-1B visa entries. They documented that total innovation could be boosted by granting more H-1B visas, which would have a minimal negative effect, if any, on natives' science and engineering employment and/or patenting opportunities. More recently, Hornung (2014) identified substantial long-term effects of skilled immigrants on the productivity of textile manufactories. That paper used an IV approach to exploit data on skilled immigrants in the religious flight of French Protestants to Prussia in 1685 and Prussian firm-level data from 1802. At a macroeconomic level, Dungan, Fang, and Gunderson (2013) also reported a positive effect of immigration on a number of economic indicators in the host country, including investment and productivity.

Peri (2007)[1] documented that the impact of foreign-born Ph.D. degree holders on the innovation rate is higher than that of those born in the United States. However, this difference could be attributed to the disproportionate employment of immigrants in the research and development (R&D) sectors or perhaps to the better quality of scientist and engineer immigrants. Using

[1] Peri used state panel data but controlled for state and time fixed effects, as well as R&D inputs.

individual-level data from the NSCG, Hunt and Gauthier-Loiselle (2010) found that a college graduate immigrant's contribution to patenting may be at least twice as high as that of their native counterparts. Hunt (2011) also examined the performances of immigrants across different visa types. She found that college graduate immigrants who enter the United States on temporary work or student/trainee visas do better than their native counterparts in patenting and wage earning, while the reverse is true for immigrants who enter as dependents or on other temporary visas.

As an offshoot of the research on labor economics, economists have extensively studied the effects of immigration on host country labor markets, particularly on natives' wages and employment. However, the measured effects vary widely, raising considerable amounts of controversy in research and policy discussions. Most studies that use either a cross-area approach (Card 2001; Card and DiNardo 2000; Friedberg 2001; Lewis 2011) or "natural experiments," such as political developments in the countries of origin (Card 1990), found a small negative or insignificant effect of immigrants on wages. Card (2001) noted that a 10-percentage-point increase in the fraction of immigrants reduces native wages by no more than 1 percentage point. Studies that exploit geographic variations using the correlation between immigration and the changes in native outcomes across cities or regions find less sizable effects (Altonji and Card, 1991) or none at all (Pischke and Velling 1997). Borjas (2003) criticized this approach for ignoring "the strong currents that tend to equalize economic conditions across cities and regions" (p. 1336). Using national-level data, some studies have identified a large and negative impact of immigrants on the wages of less educated native workers (Borjas 2003).

It is important to recognize that an increase in the fraction of the immigrant population will not necessarily raise the supply of low-skilled labor; instead, it may bring a mixed bag of skills, both high and low. The larger the proportion of highly skilled workers, the more likely that an immigration-induced innovation will be triggered, which will lead to technological progress in the long run. With the large-scale immigration inflow in recent decades, a sizeable body of literature has emerged that attempts to measure these labor-market outcomes in host nations. Extending the national approach of Borjas (2003), Ottaviano and Peri (2012) "identify a small but significant degree of imperfect substitutability between native and immigrant workers within the same education-experience group" (p. 155). The authors largely explain this result in terms of imprecise estimates of the elasticity of substitution between workers with at most a high school degree versus workers without a degree. They point out that Borjas's (2003) failure to account for capital adjustment in the short run might have caused such an effect. To remedy the problem, they divided workers into groups of highly educated (at least some college education) and less-educated (high school education) participants. Ottaviano and Peri (2012) found that immigration had a very small long-term effect on the wages of natives without a high school degree and a small positive effect on average native wages from 1990–2006.

Chellaraj, Maskus, and Mattoo (2008) argue that skilled immigrants could foster innovation and thus contribute to gains in future productivity and real wages of the natives. Peri (2012) reported that immigrants increased the total factor productivity growth in the United States. As a caveat, Card (2001), Borjas (2003), and Ottaviano and Peri (2012) do not consider the impact of the potential human capital contained in skilled immigrants or their contribution to the promotion of innovation. Therefore, it is important to understand and identify the channels through which immigrants affect the local labor markets, particularly the natives. In this paper, we argue that innovation is the channel through which immigrants contribute to the local economy.

Empirical Strategy

Our paper is comprised of two main lines of analyses. The first uses individual-level data to estimate the contribution of skilled immigrants to the innovative capacity of native skilled workers who are in the same skill group (as defined by a mix of their educational attainment, work experience, and occupation) and work in the same geographic region; and also to approximate how much this capacity is translated into wage increments of these native skilled workers. In the second approach, we use state-level data to account for any spillover effect of a state's patenting per capita on the wage level of all workers, including those who do not patent. In particular, we estimate how much a state's average wage is affected by the share of skilled immigrants in the state population that are ascribable to the state's patenting per capita. In implementing this aspect, we follow Hunt and Gauthier-Loiselle (2010).

Direct effect on wages of individual innovation. In the context of using individual-level data, our research question can be posed as follows: Is an individual's innovative capacity affected by the proportion of immigrants to natives in respect to the region and the skill group (education, occupation, experience) to which they belong? Assuming that innovators are disproportionally high-skilled individuals, our focus is on a subset of those immigrants and their native counterparts who are relatively well-educated, holding at least college degrees. Using this characterization, we define workers as belonging to the same skill group. We run the following regression to estimate the effect of immigrants on innovation:

$$\Pr(Innovation_{ijklr}) = \alpha + \beta IMS_{jklr} + \delta X_i + \gamma_1 Edu_{ij} + \gamma_2 Occ_{ik} + \gamma_3 Exp_{il} + \gamma_4 \operatorname{Re} g_{ir} + \varepsilon_{ijklr}. \tag{1}$$

The indices, *jklr*, represent individuals with education j (j = 1,. . ., 4), occupation k (k = 1,.., 6), experience l (l = 1, . . ., 8), and area of workplace (the region of residence) r (r = 1,.., 9). Innovation, a dummy variable, is intended to capture the following:

(a) Whether an individual was granted a patent
(b) Whether the patent was commercialized
(c) Whether an individual published a book or journal article or presented a paper at a conference

X represents the demographic variables (age and age squared). *IMS* is the share of skilled immigrants in a specific skill group (individuals with the same education, occupation, experience, and workplace) defined as follows: $M_{ijklr}/(M_{ijklr}+N_{ijklr})$, where M_{ijklr} refers to the number of immigrants in cell (j, k, l, r) and N is the corresponding number of natives (i refers to the individual). In order to account for potential spillover effects on fellow individuals, we group workers by education, occupation, experience, and region of workplace within the United States. *Edu* is an indicator vector for the highest degree achieved; *Occ* is a vector of dummy variables representing fixed effects for occupation. *Exp* is a vector of dummy for years of experience, and *Reg* is the region of workplace of the individual. In the regression, we also added interaction terms for each pair of education, occupation, experience, and state to allow for the possibility of, for example, a particular experience profile for a specific labor market that may differ across schooling groups (interaction of education and experience).[2]

We classify educational attainments into four groups: bachelor's, master's, doctorate, and professional. Occupations are categorized into six major groups: computer and mathematical scientists, life and related scientists, physical and related scientists, social and related scientists, engineers, and other occupations. The use of fixed effects for occupation also addresses potential endogeneity concerns, such as immigrants self-selecting into occupations that offer higher wage growth and patent potential. The same logic applies for fixed effects representing education, states, and experience. We further address the issue by running the regression on a subsample of those with at least a postgraduate

[2] We ran regressions both with and without interaction terms, and the results were similar; therefore, we will only report the results for regressions without interaction terms. These results indicated that there was little effect of immigrants in group *jklr* on other groups and that such a spillover effect was unlikely to dominate the results.

degree and a subsample of those working in the science and engineering sectors. In defining work experience, we follow Borjas (2003) and use effective work experience as a measure of the years of work exposure that are valued in the U.S. labor market. Chiswick and Miller (2009) provide evidence that work experience acquired before emigration has a negative impact on an immigrant's occupational status, which is more pronounced for high-paying occupations due to the limited transferability of skills. We only include individuals who had between 1 and 40 years of experience and classify them into one of the eight experience groups defined in terms of 5-year intervals.

In order to examine the effects of innovation on wages, we run the following equation:

$$\log(w_{ijklr}) = \alpha_1 + \Gamma * Pdtinno_{ijklr} + \theta X_i + \lambda_1 Edu_{ij} + \lambda_2 Occ_{ik} + \lambda_3 Exp_{il} + \lambda_4 \operatorname{Re} g_{ir} + \tau_{ijklr}, \qquad (2)$$

where $\log(w_{jklr})$ denotes the log of wages for individual i who has education j, occupation k, and experience l working in region r. $Pdtinno_{jkl}$ is a measure of innovation for individual i who belongs to education group j, occupation group k, and experience group l. We estimate $Pdtinno_{jkl}$ using the predicted value of innovation from equation (1). As in equation (1), we also tried to capture the interactions between the pairs of education, occupation, and experience.[3] Thus, equations (1) and (2) can be regarded as the first-stage and the second-stage regressions of what we called a two-stage procedure.

The aforementioned estimation strategy is based on the assumption that the share of skilled immigrants in a skill group does not influence natives' wages directly other than through its effects on innovation. To reinforce this assumption, we add another control variable IMS_{jl} to our regressions implied by equations (1) and (2): the share of immigrants in the national total of workers with the same education j and experience l. This addition is to account for other potential effects that immigrants can have on natives' wages. Both IMS_{jl} and IMS_{jklr} explain the imperfect substitutability between different skill groups based on education and experience. As pointed out by Borjas (2003), the effect of immigrants on natives' wages is influenced by the tendency to equalize economic conditions for workers of given skills across U.S. regions that result from interstate flows of labor and capital. Accordingly, we expect the direct effect of immigrants on wages to be present at a national level. Thus, any effect of immigrants on the wages of natives who are in the same skill group is accounted for by

[3] Again, we only report results for regressions without interaction terms because the results for regressions with interaction terms are similar.

IMS_{jl}, except for the indirect effect through innovation, which is transmitted mainly to a fellow in the same occupation and also in geographical proximity. Therefore, by including IMS_{jl} to capture the direct effect of immigrants on wages at the national level, we expect IMS_{jklr} to exert an impact on natives' wages only through the innovation channel.

Our primary interest is in the coefficient Γ, interpreted as measuring the effect of innovation on wages that is attributable to immigration. In the actual estimation, we run an OLS regression in both stages—using equation (1) as the first stage and then using the predicted value of innovation from this stage to estimate equation (2). The standard errors are then corrected to take into account the estimated value of innovation in equation (2).[4] We also cluster the standard errors by skill group (degree, experience, occupation, and workplace) to allow for arbitrary correlations among different types of workers. In addition, we find similar results using two-way clustering by workplace and cluster of degree, experience, and occupation. The regressions are weighted by the survey weights provided in the two datasets. Because the distributions of wages of natives and that of immigrants are very similar, we focus on the mean regression (see Appendix Figure A1). Note that the distribution also does not differ across different groups (e.g., samples of college graduates, postcollege graduates, and scientists and engineers).

We now further address the concern of the potential endogeneity bias arising from an immigrant's choice of destination regions in equation (1). Our use of state fixed effects in the equation should partly address the concern that skilled immigrants are more likely to migrate to states characterized by productivity and innovation. In order to take into account any remaining unobserved factors that could determine the choice of destination state or region in the United States, we follow Hunt and Gauthier-Loiselle's (2010) approach to instrument the share of skilled immigrants (IMS) in the skill group (j, k, l, r) with the predicted share of skilled immigrants in that skill group. In constructing IMS for any skill group, we use regional differences in the shares of immigrants from different regions of origin and the national total of immigrants from that skill group. It is reasonable to assume that immigrants from different regions of origin will choose destinations based on their own preferences. For example, Zavodny (1999) reports that the presence of existing immigrants is

[4] Specifically, we ran the IV regression with the first stage and second stage together in a structural system (by the ivreg2 command in STATA); thus, we can account for the fact that the innovation variable in the second stage is a predicted value from the first stage. We also run a structural system of the zero stage and first stage together (by ivreg2), and the corrected standard errors do not differ much from the uncorrected standard errors.

the primary determinant of the location choice of new immigrants. However, since we use the historical share of both skilled and unskilled immigrants to construct the IV, these preferences are not expected to involve economic factors that might have specifically attracted skilled but not unskilled workers, so that the exclusion requirement is justified. In particular, for a region r, the predicted share of skilled immigrants is calculated as follows:

$$\widehat{IMS}_{jklr} = \frac{\sum_s \frac{IM_{rs}}{IM_s} IMSk_{jkls}}{TotSkill_r},$$

where IM_{rs} is the number of immigrants in region r (both skilled and unskilled) who originated from region s in 1940, IM_s is the national total of immigrants who originated from region s in 1940, $IMSk_s$ is the national total of skilled immigrants in the skill group (j, k, l) from that region of origin in 2000, and $TotSkill_r$ is the predicted total number of skilled workers (both immigrants and natives) of region r in 2000. $TotSkill_r$ is calculated as the product of the national total number of skilled workers in 2000 multiplied by the population of region r as a fraction of the national population in the same year. To account for the fact that there have been numerous shifts in economic activities in the United States across regions since 1940, we also ran a robustness check using the IM_{rs} and IM_s in 1990 instead of 1940.[5] Here, we follow the Hunt and Gauthier-Loiselle (2010) procedure. They use 18 origin regions or countries of origin.[6] In light of the above narrative, we estimate the following zero-stage equation[7] prior to estimating equation (1):

$$IMS_{jklr} = \alpha_0 + \beta_0 \widehat{IMS}_{jklr} + \partial_1 Edu_j + \partial_2 Occ_k + \partial_3 Exp_l + \rho Y_r + \pi IMS_{jl} + \theta_{jklr}, \tag{3}$$

where Y_r is a set of regional-level variables. Thus, we also replace the regional fixed effects in equation (1) with the regional-level variables. Our final estimating equations take the following form (replacing equations (1) and (2)):

$$\begin{aligned}\mathrm{Pa}(Innovation_{ijklr}) = {} & \alpha + \beta * PdtIMS_{jklr} + \delta X_i + \gamma_1 Edu_{ij} + \gamma_2 Occ_{ik} + \gamma_3 Exp_{il} \\ & + \kappa Y_{ir} + \mu IMS_{ijl} + \varepsilon_{ijklr},\end{aligned} \tag{1a}$$

[5] The robustness check results are similar to our main results and are available upon request.

[6] The origin regions/countries are the United Kingdom, Ireland, Italy, Germany, Poland, Russia, Other Europe, Canada, Mexico, Puerto Rico, Cuba, Other Caribbean, Central America, South America, China, India, Other Asia, and Rest of the World.

[7] We will refer to this equation as the zero-stage in order to avoid confusion with equation (1a) as the first stage in the wage equation.

and

$$\log(w_{ijklr}) = \alpha_1 + \Gamma * Pdtinno_{ijklr} + \theta X_i + \lambda_1 Edu_{ij} + \lambda_2 Occ_{ik} + \lambda_3 Exp_{il} + \eta Y_{ir} + \theta IMS_{ijl} + \tau_{ijklr}, \tag{2a}$$

where *PdtIMS* is the predicted share of skilled immigrants obtained from the "zero-stage" regression (equation (2)). Our use of the zero-stage equation is only to address the endogeneity issue in the first-stage equation; thus, the relationship between equations (1) and (2) still applies in the same manner as it holds true between equations (1a) and (2a).[8]

Another potential source of endogeneity lies in the nonrandom nature of selecting skilled immigrants. Because skilled immigrants usually enter the United States under the categories of student or H-1B visas, it is plausible that their innate innovating potential ensures their acceptance by their respective universities or the firms that sponsor their visa applications. In particular, some immigrants may have already obtained a U.S. patent even before emigrating and thus were more likely to be sponsored. To assuage such concerns, we run a robustness check where we restrict our sample of immigrants to only those who entered the United States before 1998. It should be noted that the patent data from the NSCG captures patenting activities since October 1998 only.[9]

Indirect effect of state's patenting per capita on wages. As mentioned earlier, our analysis is a direct extension of the state-level data analysis conducted by Hunt and Gauthier-Loiselle (2010). Hunt and Gauthier-Loiselle (2010) used a panel of state dataset to estimate the effect of a state's proportion of skilled immigrants in per-capita patenting. We adopt the same methodology but take it a step further to measure how much this effect is translated into changes in the state's wage level. To do this, we first estimate the following equation:

$$\Delta \log \text{Patent}_{mt} = \alpha + \beta * \Delta IS_{mt} + \delta \Delta X_{mt} + \gamma Y_{m1940} + \varpi Elect_{m1980} * \mu_t + \mu_t + \pi_m + \Delta\varepsilon_{mt}, \tag{4}$$

where $\Delta \log \text{Patent}_{mt}$ is the change in the logarithm of state *m*'s patenting per capita between the periods (t–1) and t, ΔIS_{mt} is the change in the share of

[8] We ran the IV regression with the first stage and second stage together in a structural system (using the ivreg2 command in STATA); thus, we can account for the fact that the innovation variable in the second stage is a predicted value from the first stage. We did not explicitly account for the fact that the share of immigrants is a predicted value from the zero stage. However, we run a structural system of the zero stage and first stage together (using ivreg2), and the corrected standard errors do not differ greatly from the uncorrected stand errors.

[9] The robustness check results are similar to our main results and are available upon request.

skilled immigrants in the state's total workforce, ΔX_{mt} is changes in the state's characteristics, Y_{m1940} is the state's characteristics in 1940, μ_t are year dummies, and π_m is state dummies.[10] Here, we define skilled immigrants as either all immigrants with at least a bachelor's degree, with at least a master's degree, or those who were working in the science and engineering sectors in separate regressions. We also include an interaction term between the percentages of electrical workers in 1980: $Elect_{m1980}$ and the year dummies to account for the potential effect of the major change to the patent system that occurred between 1980 and 1998 and culminated in a significant increase in patenting in that field (Hunt and Gauthier-Loiselle 2010).

Once again, we need to address the issue of potential endogeneity bias where skilled immigrants might self-select and move to states with positive effects on innovation. Therefore, we instrument the change in the share of skilled immigrants (ΔIS_{mt}) by the predicted change in the share of skilled immigrants. We take into account the regional differences in the shares of immigrants from different regions of origin in 1940 and also the change in the national total of immigrants from those regions of origin. Specifically, our instrument is defined as follows:

$$\widehat{\Delta IS_{mt}} = \frac{\sum_s \frac{IM_{ms}}{IM_s} \Delta IMS_{st}}{Pop_{m(t-1)}},$$

where IM_{ms} is the number of immigrants in state m (both skilled and unskilled) who originated from region s in 1940, IM_s is the national total of immigrants who originated from region s in 1940, ΔIMS_{st} is the change in the national total of skilled immigrants from region of origin s, and $Pop_{m(t\text{-}1)}$ is the state population in period (t–1).

After estimating equation (4) with the share of immigrants instrumented, we estimated the second-stage equation as follows:

$$\Delta\log(w_{mt}) = \alpha_1 + \Gamma * Pdt\Delta\log Patent_{mt} + \delta X_{mt} + \gamma Y_{m1940} + \varpi Elect_{m1980} * \mu_t + \mu_t + \mu_m + \Delta\varepsilon, \tag{5}$$

where w_{mt} is state m's average wage level and $Pdt\Delta\log Patent_{mt}$ is the predicted change in the logarithm of the state's patenting per capita, as estimated from equation (4). To calculate the average wage level, we use the data from

[10] We do not lead patenting by one year from the independent variables as Hunt and Gauthier-Loiselle (2010) do since the dependent variable in our second-stage regression is wage, which is of the same year as the share of skilled immigrants. Our first-stage results are similar and are only slightly larger in magnitude than those from Hunt and Gauthier-Loiselle (2010).

the: (1) full sample of both natives and immigrants or (2) restricted subsample of natives only. We also use the state's average wage of low-skilled workers in addition to the average wage of all workers. Note that this, in fact, is our main variable of interest rather than the general wage level. Also, this variable can better satisfy the exclusion restriction where we consider the change in the share of skilled immigrants as the IV for the state's change in patenting per capita. While any change in the share of skilled immigrants may affect a state's average wage level, especially the average wage of skilled workers, through different channels other than innovation, it is also likely to engender a minimal direct effect on the average wage of low-skilled workers. The main channel through which skilled immigrants affect the average wage of low-skilled workers is by changing the state's overall productivity, which is a direct result of a change in innovative capacity.[11]

Data and Descriptive Statistics

We report summary statistics of individual and state-level variables below. These variables are used in the regression and statistical inference to examine the effects of immigration on innovation on wages.

Individual-level data. The data used in the paper are taken from the 2003 U.S. National Survey of College Graduates (NSCG) by the National Science Foundation.[12] The NSCG data are a random sample of 100,402 respondents from the 2000 Decennial Census long form. The individuals surveyed were living in the United States during the reference week of 1 October 2003, had a bachelor's degree or higher, and were under the age of 76. All respondents who had ever been employed were asked whether they had applied for, been granted, or had commercialized any U.S. patent since October 1998. Thus, the sample does not include any patents that may have been obtained by individuals without a college degree. The respondents were also asked to choose from a set of questions: Whether or not (1) papers they had (co-) authored were presented at regional, national, or international conferences; (2) papers they had (co-) authored had been accepted for publication in refereed professional journals; and/or (3) books

[11] All our state-level regressions are weighted by the state's population, and their standard errors are clustered by state level to allow for serial correlation.

[12] In the previous version of this paper, we included an analysis that used data from the 2000 Integrated Public Use Microdata Series (IPUMS).

or monographs they had (co-) authored had been accepted for publication since October 1998.

We restrict our analysis to male individuals who lived in the United States at the time of the survey, were aged between 25 and 65 years, participated in the labor force, and were not enrolled in school. To measure the share of skilled immigrants in each skill group, we include all individuals who lived in the United States and were between the ages 25 and 65 years. To assess innovation, we include three dummy variables to identify whether the individual had done any of the following during the 5 years prior to the survey: had any patent granted, had any patent commercialized, or published a book or journal article or presented a paper.

Table 1 presents descriptive statistics for the innovation and wage variables computed from the dataset. Following Hunt and Gauthier-Loiselle (2010), we consider three skill categories that are not mutually exclusive: those with at least a college degree, postcollege graduates, and those working in the science and engineering sectors. The average annual and weekly wages show only minor differences between natives and immigrants in all samples. The share of immigrants in the population is higher in the scientist and engineer sample than it is in the samples of either college graduates or postcollege graduates. In all three samples, immigrants appear to be more likely to innovate than their native counterparts. In addition, immigrants have higher average chances of getting patents granted and commercialized. The gap in innovation probability is largest in the postcollege graduate sample and smallest in the sample of scientists and engineers. Of the foreign-born postcollege graduates, 5.9 percent had a patent granted, which is more than double the 2.2 percent of their native counterparts. The gap is much smaller in the sample of scientists and engineers, with 8 percent of immigrants having had a patent granted compared with 5.9 percent of their native counterparts.

State-level data. Our state-level data come from 1940–2000 IPUMS Decennial Censuses and the patenting report from the USPTO. The patenting report displays the number of U.S. patents distributed by the U.S. state of origin and by the calendar year in which the patent is applied for. We use the same series of 1940–1990 patenting data created by Hunt and Gauthier-Loiselle (2010). They merged the electronic data from 1963 onward with a series they obtained from paper records for the 1883–1976 period. For 2000 patenting, we use the data that have been most recently updated by the USPTO. Wages and immigration data come from the IPUMS censuses. Similar to our individual-level data, we restrict our wage sample to male individuals who currently lived in the United States and were aged between 25 and 65 years, participated in the labor force, and were not enrolled in school. For the share of

TABLE 1

Individual-Level Data Descriptive Statistics (NSCG Data)

	College Graduates		Postcollege Graduates		Scientists and Engineers	
	Immigrant	Native	Immigrant	Native	Immigrant	Native
Immigrant share	11.28%		14.67%		19.42%	
No. of observations	8141	32,910	5177	13,887	3812	11,157
Any patent granted	0.0369	0.0165	0.0590	0.0223	0.0802	0.0594
	(0.0021)	(0.0008)	(0.0034)	(0.0013)	(0.0049)	(0.0028)
Any patent commercialized	0.0228	0.0110	0.0337	0.0141	0.0466	0.0378
	(0.0017)	(0.0006)	(0.0025)	(0.0011)	(0.0036)	(0.0023)
Any publication	0.2240	0.1779	0.3537	0.2883	0.2884	0.2325
	(0.0061)	(0.0029)	(0.0090)	(0.0052)	(0.0096)	(0.0058)
Log annual wage	11.0387	11.0288	11.2111	11.1887	11.2053	11.1619
	(0.0136)	(0.0065)	(0.0154)	(0.0100)	(0.0115)	(0.0086)
Log weekly wage	7.1489	7.1300	7.3145	7.3032	7.3062	7.2441
	(0.0142)	(0.0065)	(0.0159)	(0.0100)	(0.0156)	(0.0089)

Note: All statistics are weighted by survey weights and calculated in the sample according to the sample restrictions.

skilled immigrants, we include all individuals (both male and female) who were currently living in the United States and were aged between 25 and 65 years. We also follow Hunt and Gauthier-Loiselle's (2010) practice to drop Alaska and Hawaii from our analysis as data as these two states are not available until 1960.

The descriptive statistics for state-level variables are reported in Table 2. While the annual wages of native male workers were higher and grew faster from 1940 to 2000 than the mean wage level (of both natives and immigrants), the difference is relatively small. The share of skilled workers in the workforce population increased rapidly during the 1940–2000 period and is greater among the immigrant population compared with the natives. In particular, the share of skilled workers among the immigrant workforce increased by about 11–13 percent, while that among the native workforce increased by only 5–7 percent.

Estimation Results

Below we report first the direct effect of innovation on wages using individual-level data. We then use the state-level data to examine the indirect effects of innovation of wages at that level.

Direct effect on the wages of an individual's innovation. We now report the estimated results obtained from individual-level regressions. The estimates

TABLE 2

STATE-LEVEL DATA DESCRIPTIVE STATISTICS (IPUMS AND USPTO DATA)

	1940–2000	1940	2000
No. of observations	343	49	49
Annual wage of male workers (log)	10.5466	9.7323	10.8716
	(0.4070)	(0.2156)	(0.1245)
Annual wage of native male workers (log)	10.5601	9.7339	10.9054
	(0.4178)	(0.2194)	(0.1452)
Annual wage of male workers without a bachelor's degree (log)	10.3632	9.6474	10.5331
	(0.3405)	(0.2314)	(0.0840)
Annual wage of native male workers without a bachelor's degree (log)	10.3819	9.6441	10.5810
	(0.3506)	(0.2311)	(0.0852)
Patents per capita (,00)	0.0237	0.0206	0.0368
	(0.0150)	(0.0151)	(0.0204)
Share of 18–65 population that is:			
Immigrants with at least a bachelor's degree	0.0139	0.0031	0.0329
	(0.0166)	(0.0028)	(0.0224)
Natives with at least a bachelor's degree	0.1212	0.0392	0.1976
	(0.0669)	(0.0088)	(0.0331)
Immigrants with at least a master's degree	0.0061	0.0010	0.0133
	(0.0065)	(0.0009)	(0.0084)
Natives with at least a master's degree	0.0437	0.0101	0.0660
	(0.0251)	(0.0032)	(0.0158)
Immigrants as scientists/engineers	0.0023	0.0005	0.0064
	(0.0030)	(0.0004)	(0.0045)
Natives as scientists/engineers	0.0246	0.0059	0.0271
	(0.0198)	(0.0014)	(0.0074)

NOTES: All statistics are weighted by state population of the census year and calculated in the sample according to the sample restrictions. All data are from IPUMS census data, except for data for patents, which are from USPTO.

obtained from the first stage (equation (1a)) using samples of both natives and immigrants (Tables 3 and 4) display the probability of innovation from the NSCG dataset. The estimates capture the effect of the share of immigrants on the probability of having a patent (1) granted and (2) commercialized. The coefficients corresponding to the immigration share variable, *IMS*, are positive and significant in all samples but are larger in magnitude in the sample of postcollege graduates and also in the sample of scientists and engineers. This trend could be explained by the potentially higher innovative capacity among postcollege graduates and scientists and engineers, compared with those who hold only a bachelor's degree.

The sample of postcollege graduates demonstrates a coefficient of immigration share that is 0.2 with a standard error of 0.04. We interpret this coefficient as being representative of the impact on the innovation probability of the increase in the labor supply due to immigration. The point estimates suggest that an increase of 1 percentage point in the influx of immigrants with at least a master's degree in a skill group is expected to increase the probability of a patent being granted to an individual in that group by 0.2 percentage point and increase the probability of a patent being commercialized by 0.12 percentage point (Tables 3 and 4, column 2). Similarly, an increase of 1 percentage point in the share of immigrants in a skill group in the science and engineering sector would increase the probability of a patent being granted by 0.18 percentage point and the probability of a patent being commercialized by 0.12 percentage point (Tables 3 and 4, column 3). The F-statistics for zero-stages are all above the critical value, signifying that the instruments—the predicted shares of skilled immigrants—are all highly correlated with the share of skilled immigrants in a skill group.

We also use equation (1a) to report the results separately for the sample of native-born participants only. We consider the probability of innovation for natives using the share of immigrants in each group by taking the highest education, occupation, experience, and region of work. The results, which are reported in row 3 of Tables 3 and 4, indicate the presence of positive spillover effects of immigrants on natives' innovation capabilities in all samples of skilled workers. The coefficient of the immigration share is relatively larger than that obtained from combined samples of immigrants and natives. This

TABLE 3

IV Estimates of the Effect on Wages of a Patent Being Granted (Instrumented by Immigration Share)

	College Graduates	Postcollege Graduates	Scientists and Engineers
First Stage (using NSCG): Effects of Immigration on Innovation			
Whole sample	N = 41,041	N = 19,056	N = 14,963
	0.14***	0.20***	0.18***
	(0.023)	(0.040)	(0.044)
Native-only	N = 32,910	N = 13,887	N = 11,157
	0.15***	0.22***	0.23***
	(0.028)	(0.053)	(0.065)
F-stat (zero stage)	839.73	478.01	439.00
Second Stage (NSCG): Effects of (Predicted) Innovation on Wages			
Weekly wage	5.82***	3.95***	5.02***
	(1.31)	(1.20)	(1.54)
F-stat (first stage)	38.21	24.81	15.79
Weekly wage – *natives only*	6.79***	3.71***	3.94***
	(1.74)	(1.40)	(1.46)
F-stat (first stage)	28.23	17.42	12.31

Notes: All regressions include control variables of age, age2, and dummy variables for the highest education level, occupation group, work experience, and regional-level variables. The instrument for the share of skilled immigrants is the predicted share of skilled immigrants in that region, based on the regional difference in the shares of immigrants from different origin regions. All of the regressions are weighted. Robust standard errors, clustered by education level, occupation group, work experience, and workplace, are in parentheses; *** $p < 0.01$.

TABLE 4

IV Estimates of Effect on Wages of a Patent Being Commercialized (Instrumented by Immigration Share)

	College Graduates	Postcollege Graduates	Scientists and Engineers
First Stage (Using NSCG): Effects of Immigration on Innovation			
Whole sample	N = 41,041	N = 19,056	N = 14,963
	0.076***	0.12***	0.12***
	(0.017)	(0.030)	(0.035)
Native-only	N = 32,910	N = 13,887	N = 11,157
	0.085***	0.15***	0.16***
	(0.021)	(0.040)	(0.052)
F-stat (zero stage)	839.73	478.01	439.00
Second Stage (NSCG): Effects of (Predicted) Innovation on Wages			
Weekly wage	10.7***	6.52***	7.50***
	(2.93)	(2.19)	(2.60)
F-stat (first stage)	19.75	16.11	11.01
Weekly wage – *natives only*	11.9***	5.52**	5.69**
	(3.60)	(2.17)	(2.25)
F-stat (first stage)	16.03	13.88	9.05

Notes: All regressions include control variables of age, age2, and dummy variables for the highest education level, occupation group, work experience, and regional-level variables. The instrument for the share of skilled immigrants is the predicted share of skilled immigrants in that region, based on the regional difference in the shares of immigrants from different origin regions. All of the regressions are weighted. Robust standard errors, clustered by education level, occupation group, work experience, and workplace, are in parentheses; *** $p < 0.01$, ** $p < 0.05$.

finding suggests that the spillover effect of immigrants on natives' innovation is larger than that on the immigrants' own innovation probabilities.

We now report our main results: the effects of innovation on wages that can be attributed to immigration. We use the predicted innovation for each group, which is obtained from the first stage (i.e., the regression from equation (1a)), to estimate equation (3). We find that the effects of innovation on individual annual and weekly wages are positive and significant for all samples (Tables 3 and 4).[13] When we assess innovation by measuring the possibility of having a patent granted, the effect is largest in the sample of all college graduates and smallest among those with at least a postcollege degree. On average, a college graduate with a 1-percentage-point higher probability of having a patent granted is expected to experience a weekly wage increase of about 5.82 percent. Put differently, a one-standard-deviation rise (a change of 0.034 percentage point) in the (predicted) probability of a patent being granted would result in a 0.13 percent increase in wages. The respective increase in weekly wages for a postcollege graduate is only 3.95 percent. Thus, skilled workers without

[13] We only reported results for weekly wages here; the results for annual wages were similar and are available upon request.

a postcollege degree seem to benefit more in wages from their innovative capacity than those with a postcollege degree. However the effect of an influx of immigrants with only a bachelor's degree is relatively smaller than that of an influx of immigrants with at least a master's degree or those working in the science and engineering sectors. The effects are similar in the sample of native workers only.

For the whole sample (both immigrant and native workers), a 1-percentage-point increase in the share of immigrants in each skill group translates to an increase in the weekly wage of individuals in that group by about 0.8–0.9 percent. Similarly, in the sample of native workers alone, a 1-percentage-point increase in the share of skilled immigrants translates to a 0.8–1.0 percent increase in the weekly wage of native workers.

Table 4 displays the results for commercialized patents. The results are very similar to those shown in Table 3. Column 2 of Table 4 indicates that a 1-percentage-point increase in immigrant share leads to a rise in the probability of having a commercialized patent by 0.08 percentage point among college graduates and 0.12 percentage-point for both postcollege graduates and scientists and engineers. In turn, these increases lead to a 0.8–0.9 percent rise in wages. The increase is slightly higher at 0.8–1.0 percent in the sample of only native workers. The findings of the positive effects of skilled immigrants on the wages of native skilled workers through increasing the latter's propensity to patent, as measured either by having a patent be granted or commercialized, is in sharp contrast to the result of Card (2001: 23), who found that a 1-percentage-point increase in the fraction of immigrants resulted in reduced native wages. While Card (2001) was dealing with data on low-skilled immigrants, our results present a different scenario because we consider skilled immigrants.

We now consider the effects of immigration on professional advancement, such as writing books or papers for publication or presentation at conferences and the effect of such activity on wages. Immigrants have a higher likelihood of publishing or presenting a paper at a conference in each of the three samples—college, postcollege graduates, and scientists and engineers (Table 1). Table 5 reports the results using the share of immigrants in a given skill group and after controlling for other covariates. The result indicates that in the sample of postcollege graduates, the immigrant share has a negative effect on the publishing or presentation of papers. However, the effect is not statistically significant when we consider the effect on native workers only. Thus, the negative spillover effect of skilled immigrants in academic performance is present only among fellow immigrants, not the natives. Although this negative effect translates to a decrease in wages in the second stage, the F-statistic in the first stage is relatively small (3.98).

In the Appendix (Table A1), we report the results using various controls. The table shows that an increase in the immigration share in one group is

TABLE 5

IV Estimates of the Effect on Wages of Academic Performance (Instrumented by Immigration Share)

	College Graduates	Postcollege Graduates	Scientists and Engineers
First Stage (Using NSCG): Effects of Immigration on Academic Performance			
Whole sample	N = 41,041	N = 19,056	N = 14,963
	–0.057	–0.17**	–0.13
	(0.056)	(0.083)	(0.084)
Native-only	N = 32,910	N = 13,887	N = 11,157
	0.028	–0.10	–0.083
	(0.071)	(0.12)	(0.11)
F-stat (zero stage)	839.73	478.01	439.00
Second Stage (NSCG): Effects of (Predicted) Academic Performance on Wages			
Weekly wage	–14.4	–4.73**	–6.59
	(14.3)	(2.35)	(4.13)
F-stat (first stage)	1.03	3.98	2.53
Weekly wage – *natives only*	35.6	–8.11	–10.8
	(90.5)	(8.97)	(14.7)
F-stat (first stage)	0.16	0.77	0.54

Notes: All regressions include control variables of age, age2, and dummy variables for the highest education level, occupation group, work experience, and regional-level variables. The instrument for the share of skilled immigrants is the predicted share of skilled immigrants in that region, based on the regional difference in the shares of immigrants from different origin regions. All of the regressions are weighted. Robust standard errors, clustered by education level, occupation group, work experience, and workplace, are in parentheses; $^{**}p < 0.05$.

likely to increase publications when considered without any control (column 1). However, when we add a control for education, the effect becomes much smaller (column 3), while the addition of the occupation, as in column (4), renders the coefficient insignificant. This result can be explained by the disproportional representation of immigrants in higher-skill groups and in the science and engineering occupations. Thus, while immigrants might have an advantage over natives in academic performance, this distinction does not appear to have any spillover effect on their fellow workers in the same skill group.

Indirect effect on wages of state's patenting per capita. The state-level analysis considers any spillover effect of a state's patenting per capita on the wage level of all workers, including those who did not patent. We report the results from state-level regressions in Table 6. The first-stage results show a positive and significant effect on a state's patenting per capita on the share of skilled immigrants, defined either as all college graduates or only postcollege graduates.[14] A 1-percentage-point increase in the share of immigrant college

[14] We do not report the results when defining skilled workers as those working as scientists and engineers since the zero-stage coefficient is not significant.

graduates in the workforce led to a 17.5 percent increase in patenting per capita. The effect is larger for postcollege graduates; a 1-percentage-point increase in the share of immigrant postcollege graduates produces a 26.5 percent increase in patenting per capita. The F-test values in the zero stage are all nearly twenty or above. Our estimates are similar to what Hunt and Gauthier-Loiselle (2010) found under their preferred specifications. Their estimated effect ranges from a 12.3 percent to a 17.6 percent increase or from an 18.9 percent to a 27 percent increase in patenting per capita when skilled immigrants are defined as college graduate immigrants or postcollege graduate immigrants, respectively.[15]

In the second stage, we also identify a significant and positive effect of patenting on a state's wage level when patenting per capita is instrumented by

TABLE 6

STATE-LEVEL IV ESTIMATES OF EFFECT OF INNOVATION ON WAGES (INSTRUMENTED BY IMMIGRATION SHARE)

Instrument Variable	Share of College Graduates	Share of Postcollege Graduates
First Stage: Effects of Immigration on Innovation		
	N = 294	N = 294
Log innovation per capita/ skilled immigrant share	17.5***	26.5*
	(5.74)	(14.9)
F-stat (zero stage)	18.88	27.06
Second Stage: Effects of (Predicted) Innovation on Wages		
Wage of all workers (at all education levels)		
Weekly wage	0.40***	0.42**
	(0.091)	(0.20)
Weekly wage – *natives only*	0.43***	0.47**
	(0.095)	(0.21)
F-stat (first stage)	9.29	3.15
Wage of workers without bachelor's degree		
Weekly wage	0.26***	0.17
	(0.081)	(0.16)
Weekly wage – *natives only*	0.29***	0.23
	(0.087)	(0.16)
F-stat (first stage)	9.29	3.15

NOTES: All regressions include regional-level control variables of mean age of workforce population, defense procurement expenses, land area, population in 1940, personal income per capita 1940. The instrument for the share of skilled immigrants is the predicted share of skilled immigrants in that region, based on the regional difference in the shares of immigrants from different origin regions. All of the regressions are weighted. Robust standard errors, clustered by education level, occupation group, work experience, and workplace, are in parentheses; *** $p < 0.01$, ** $p < 0.05$.

[15] Our estimates are not exactly the same as theirs due to our slight difference in specifications that are mentioned in our empirical strategies. One difference is that we do not lead our dependent variable by one year. We also prefer to include state dummies rather than region dummies because the former gives larger F-statistics in the first stage.

the share of immigrant college graduates. The effect is significant on both the mean wage of all workers and that of the low-skilled workers (those without a bachelor's degree). In particular, when patenting per capita increases by 1 percent, the mean weekly wage of all workers also rises by 0.4 percent and the mean weekly wage for native workers increases by 0.43 percent. The effect is smaller for workers who did not have a bachelor's degree; a 1 percent increase in patenting per capita raises the weekly wage by 0.26 percent and the weekly wage of natives alone by 0.29 percent. Thus, a 1-percentage-point increase in the share of immigrant college graduates translates into a 7.5 percent (17.5 percent multiplied by 0.43) increase in the weekly wage of all native workers or a 5.1 percent (17.5 percent multiplied by 0.29) increase in the weekly wage of natives with low skill levels. The smaller effect of skilled immigrants on the wage of low-skilled workers relative to all workers can be explained by the fact that low-skilled workers are less likely to contribute directly to innovation; thus, their wages are only indirectly impacted by the productivity boost caused by an increase in innovation in the state. Moreover, a change in the share of skilled immigrants might have other direct effects on the mean wage of skilled workers and therefore could also impact the mean wage of all workers outside of the indirect channel of innovation. In contrast, innovation alone mostly affects the wages of low-skilled workers.

When patenting per capita is instrumented by the share of immigrant post-college graduates, we find that the effect of patenting per capita is positive and significant on the wages of all workers, including those with high skills, while the effect is positive but insignificant on the wages of low-skilled workers. This finding could have been due to the small F-test (3.15) in the first stage for this group of workers.

Alternative Estimates: Robustness Checks

Our estimates for the individual-level analysis rely on a critical assumption that skilled immigrants do not have any direct effect on wages other than through innovation, which is measured in terms of patents granted, patents commercialized, publications in academic journals, or presentations at professional conferences. This form of assessment is basically the exclusion restriction, which is assumed using the IV estimation method. Unfortunately, such an exclusion restriction is not testable. In our context, the exclusion restriction implies that the coefficient of the immigration share in the wage equation (equation (3)) is equal to zero. Note that the reduced form estimates, which are presented in Tables 6 and 7, do not point to any direct effect of immigration on wages because the effect could run through respective innovation channels.

TABLE 7

Sensitive Estimates of IV Results Using Klein-Vella (Sample of Natives Only)

Effects on Wages of a Patent Being Granted	College Graduates	Postcollege Graduates	Scientists and Engineers
	N = 32,910	N = 13,887	N = 11,157
First Stage: Effects of Immigration on Innovation			
	0.092	0.20***	0.27***
	(0.058)	(0.046)	(0.076)
Second Stage: Effects of (Predicted) Innovation on Wages			
Weekly wage – *natives only*	10.7***	4.12***	3.40***
	(1.68)	(1.14)	(0.69)
Effects on Wages of a Patent Being Commercialized			
	College Graduates	Postcollege Graduates	Scientists and Engineers
First Stage: Effects of Immigration on Innovation			
	0.14***	0.16***	0.21***
	(0.023)	(0.035)	(0.051)
Second Stage: Effects of (Predicted) Innovation on Wages			
Weekly wage – *natives only*	7.29***	5.24***	4.42***
	(1.11)	(1.43)	(0.89)

Notes: All regressions include control variables of age, age2, and dummy variables for the highest education level, occupation group, work experience, and regional-level variables. The instrument for the share of skilled immigrants is the predicted share of skilled immigrants in that region, based on the regional difference in the shares of immigrants from different origin regions. All of the regressions are weighted. Robust standard errors, clustered by education level, occupation group, work experience, and workplace, are in parentheses; ***$p < 0.01$.

Here, we employ some recent advances in the econometric literature, which show that identification can be achieved in the presence of heteroskedasticity even though there are no standard exclusion restrictions available (see Klein and Vella 2009a, 2010; Lewbel 2012; Rigobon 2003).[16] As emphasized by Rigobon (2003), heteroskedasticity can be viewed as a probabilistic shifter, similar to those induced by a more standard instrument satisfying the exclusion restrictions. In this paper, we implement the two-step approach developed by Klein and Vella (2010). In step (1), a generalized least squares (GLS) model is used to estimate equation (1), and the residuals are retrieved to account for heteroskedasticity. In step (2), equation (3) is estimated by taking the residual from step (1) as the selection correction term. The results based on the Klein-Vella method are similar to what we have already found, as reported in Table 7. The coefficients in both the first and second stages are positive and significant, which confirms that an increase in the share of skilled immigrants in the supply of labor has a positive effect on the wages of native workers through innovation. The magnitude of the coefficients differs slightly from our

[16] For recent applications of heteroskedasticity-based identification, see Schaffner (2002), Rigobon (2003), Rigobon and Rodrik (2005), Klein and Vella (2009b), and Millimet and Tchernis (2013).

original estimates at each stage, but the extent to which skilled immigrants impact wages, however, is roughly the same.

Conclusion

In this paper, we consider innovation, as measured by patents, as a possible channel through which immigrants could have a positive effect on wage levels in the host country. We explore two different mechanisms. (1) We examine how skilled immigrants in a particular skill group contribute to the innovative capacity of workers in that group and thus contribute to their wage increments. (2) We estimate the indirect effect of skilled immigrants on a state's wage levels through their contribution to the state's innovation and productivity. In both cases, we identify evidence that skilled immigrants contribute to innovation and wages.

As for the first mechanism, our estimates suggest that a 1-percentage-point increase in the share of immigrants in each skill group is expected to increase the probability of having a patent granted to a native worker in that group by 0.14 of a percentage point in the sample of college graduates. The effect is larger in the sample of postcollege graduates and the sample of scientists and engineers: 0.22 of a percentage point and 0.23 of a percentage point, respectively. This increase in the innovation probability in turn contributes to an increase in the weekly wage in the range of 0.8–1.0 percent. The results are similar when we replace the probability of having a patent granted with the probability of having a patent commercialized.

We also find a positive and significant effect of skilled immigrants on a state's patenting per capita, which can be transmitted to a wage increment in that state. A 1-percentage-point increase in a state's share of immigrant college graduates is correlated with a 17.5 percent increase in the state's patenting per capita. This rise translates to a 7.5 percent increase in the weekly wage for all native workers and a 5.1 percent increase for low-skilled native workers.

In addition to the two innovation measures, we also examine the effects of immigration on wages originating through the likelihood of publications and conference presentations. However, the evidence does not lend support to such a relationship. We do not find a clear link between this probability and wage determination. Such a finding is not surprising because the probability of research and publishing has no material effect on the outcome in the labor market unless it is translated into real technological progress and thereby into a productivity gain. Future research might aim to identify publications or research in particular areas and determine how they translate to specific innovations and lead to technological development. Such work may help to establish a link.

Although this paper does not attempt to find direct links between innovation and economic growth, the positive relationships identified among immigration, innovation, and wages implicitly suggests that immigrants make important contributions to the host country's economic performance, given the generally established role of innovation in growth. Indeed, innovation is the logical prior to technological progress. Therefore, government policies aimed at addressing the immigration issue should give due consideration to the actual and potential contributions made by the immigrants through innovation when evaluating the costs and benefits of immigration into their respective countries. Greenwood and McDowell (2011) examine factors that could affect the skill composition of U.S. immigrants. They find that the U.S. immigration policy has been an important determinant in this respect. For example, lottery programs have tended to draw more skilled immigrants. In contrast, immigrants from countries in the Western Hemisphere were less skilled. This trend occurred during the period when immigrants from these countries were subject to less restrictive entry requirements. Thus, additional measures to encourage positive spillover effects from the innovation propensities of immigrants to natives may boost the entire country's innovative capacity.

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APPENDIX

FIGURE A1

DISTRIBUTION OF WAGES: NSCG SAMPLE

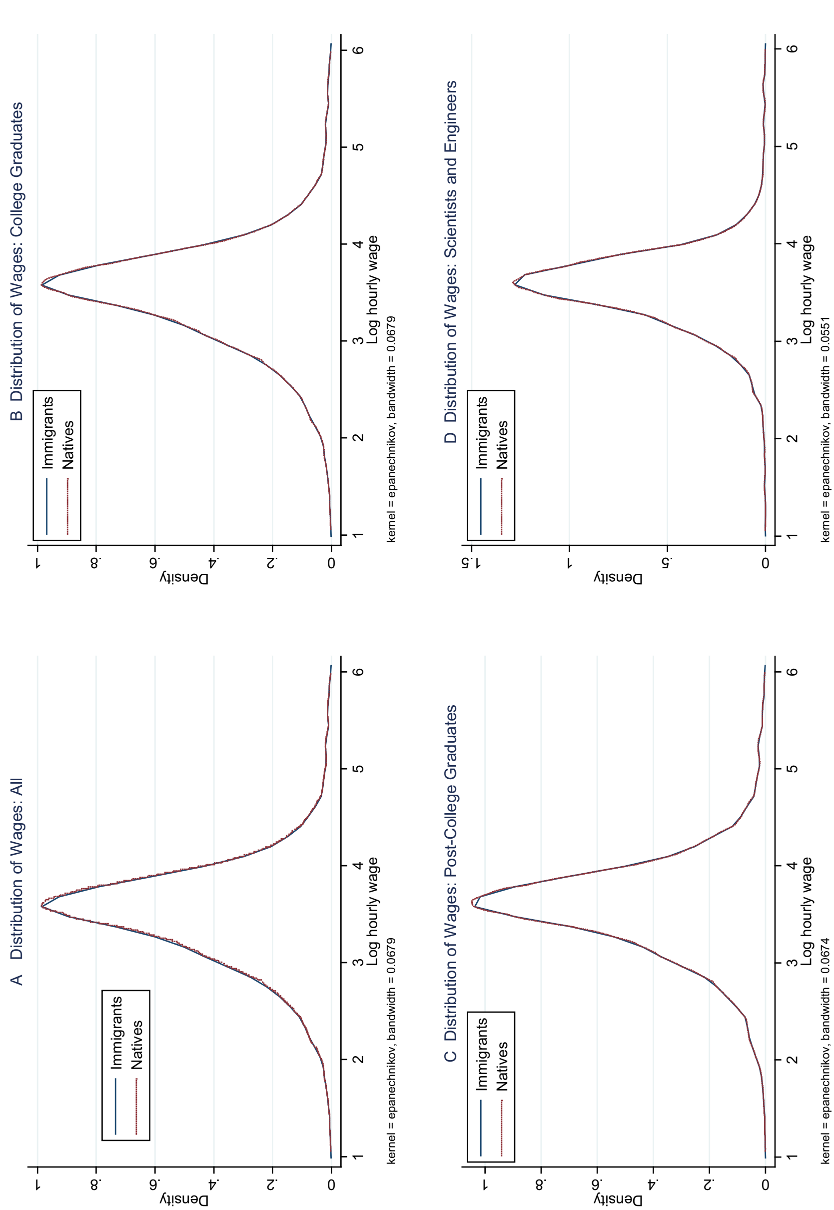

TABLE A1

Effects of Academic Performance on the Wages of Natives: Using Various Controls

Dependent Variables/Independent Variables	(1) No Control	(2) + Age, Age^2	(3) + Education	(4) + Occupation	(5) + Experience	(6) + National Share of Skilled Immigrants
N = 32,910	**Sample of College Graduates**					
Academic performance/immigrant share	0.66***	0.76***	0.17***	0.11*	0.10	0.028
	(0.10)	(0.10)	(0.063)	(0.066)	(0.071)	(0.071)
Weekly wage/academic performance	1.56***	1.97***	6.42**	7.85	8.87	35.6
(second stage)	(0.28)	(0.26)	(2.53)	(4.82)	(6.41)	(90.5)
F-stat (first stage)	41.43	54.20	6.97	2.90	2.04	0.16
N = 13,887	**Sample of Postcollege Graduates**					
Academic performance/immigrant share	0.67***	0.72***	0.12	-0.015	0.0073	–0.10
	(0.12)	(0.13)	(0.086)	(0.11)	(0.12)	(0.12)
Weekly wage/academic performance	0.74**	1.28***	6.84	–52.7	107.4	–8.11
(second stage)	(0.32)	(0.35)	(5.41)	(376.1)	(1710.7)	(8.97)
F-stat (first stage)	30.47	30.62	1.97	0.02	0.00	0.77
N = 11,157	**Sample of Scientists and Engineers**					
Academic performance/immigrant share R^2	0.61***	0.67***	–0.19	0.0074	–0.0030	–0.083
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
Weekly wage/academic performance	0.85***	1.21***	–4.62	101.8	–265.9	–10.8
(2nd stage)	(0.28)	(0.31)	(2.96)	(1513.5)	(10042.6)	(14.7)
F-stat (first stage)	26.61	31.16	2.51	0.00	0.00	0.54

Notes: All of the regressions include regional-level variables, and are weighted. Robust standard errors, clustered by education level, occupation group, working experience, and workplace, are in parentheses; *** $p < 0.01$, ** $p < 0.05$.