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# Task Specialization, Immigration, and Wages\*

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## Abstract

Many workers with low levels of educational attainment immigrated to the United States in recent decades. Large inflows of less educated immigrants would reduce wages paid to comparably-educated native-born workers if the two groups are perfectly substitutable in production. In a simple model exploiting comparative advantage, however, we show that if less educated foreign and native-born workers specialize in performing different tasks, immigration will cause natives to reallocate their task supply, thereby reducing downward wage pressure. We merge occupational task-intensity data from the *O\*NET* dataset with individual Census data across US states from 1960-2000 to demonstrate that foreign-born workers specialize in occupations that require manual and physical labor skills while natives pursue jobs more intensive in communication and language tasks. Immigration induces natives to specialize accordingly. Simulations show that this increased specialization might explain why economic analyses commonly find only modest wage and employment consequences of immigration for less educated native-born workers across US states.

**Key Words:** Immigration, Less-Educated Labor, Manual Tasks, Communication Skills, Comparative Advantages, US States.

**JEL Codes:** F22, J61, J31, R13.

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# 1 Introduction

Immigration has significantly affected the US labor market during the last few decades, particularly increasing the supply of workers with low levels of formal schooling. Economists continue to debate the wage effects of these large inflows on native-born workers. If workers' skills are differentiated solely by their level of educational attainment, and if the production technology and productivity of each type of labor are given, then a large inflow of immigrants with limited schooling should alter the relative scarcity of education groups, increase wages paid to highly-educated natives, and reduce wages paid to less educated ones. Borjas (2003) and Borjas and Katz (2007) adopt this intuitive approach and use US national-level data to argue that immigration reduced real wages paid to native-born workers without a high school degree by four to five percent between 1980 and 2000. Area studies by Card (2001, 2007), Card and Lewis (2007), and Lewis (2005), in contrast, employ city and state level data and find almost no effect of immigration on the wages of less educated native workers.

Ottaviano and Peri (2006 and 2008) emphasize that the effects of immigration depend upon whether native and foreign-born workers with similar observable characteristics are imperfect substitutes in production. They argue that immigrants and natives of comparable educational attainment and experience possess unique skills that lead them to specialize in different occupations, which mitigates natives' wage losses from immigration.<sup>1</sup> We advance this literature by developing a theory and performing empirical analysis to demonstrate *how* native and foreign-born workers are imperfect substitutes in production.

We focus on workers with little educational attainment and argue that less educated native and immigrant workers specialize in differentiated production tasks. Immigrants are likely to have imperfect language (or equivalently, "communication") skills, but they possess physical (or "manual") skills similar to those of native-born workers. Thus, they have a comparative advantage in occupations requiring manual labor tasks, while less educated native-born workers will have an advantage in jobs demanding communication skills. Immigration encourages workers to specialize – less educated natives respond to immigration by leaving physically demanding occupations for language-intensive ones. Importantly, language-intensive tasks tend to earn a comparatively higher return, and those returns are further enhanced by the increased aggregate supply of complementary manual-intensive tasks. Therefore, productivity gains from specialization coupled with the high compensation paid to communication skills together imply that foreign-born workers do not create large adverse consequences for wages paid to less educated natives.

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<sup>1</sup>Manacorda et. al. (2007) and D'Amuri et al. (2008) argue for similar imperfect substitutability between native and immigrant workers in the UK and Germany, respectively. Other important contributions to the literature on immigration and wages include Altonji and Card (1991), Borjas (1994, 1995, 1999, 2003), Borjas, Freeman, and Katz (1997), Butcher and Card (1991), Card (1990), Friedberg and Hunt (1995), Friedberg (2001), and National Research Council (1997).

We begin in Section 2 by describing a simple model of comparative advantage and incomplete specialization of workers. Workers' skill endowments imply that immigration reduces the compensation paid to manual tasks and increases the compensation paid to communication tasks. The complementary nature of the two skills and the reallocation of native workers toward communication tasks favor wages paid to native workers. The effects compensate (in part or entirely) for the depressing effect of immigration on the wage paid to manual tasks.

Section 3 describes the decennial data for the 50 US states (plus the District of Columbia) from 1960 to 2000 and the construction of the variables that we use to test our model. Census occupation codes allow us to merge occupational characteristics with individual-level data from the IPUMS Census microdata (Ruggles et. al. (2005)). To measure the manual and communication skill intensity of occupations, we use the US Department of Labor's *O\*NET* dataset on job task requirements. This dataset measures the importance of several physical (dexterity, coordination, and strength) and language (oral and written comprehension and expression) abilities within each Census occupation code. Data values are based upon experts' recent (post 2000) assessments and therefore reflect the current use of skills across occupations.<sup>2</sup>

The empirical analysis in Section 4 strongly supports key implications of our theory. States with large inflows of less educated immigrants, relative to those with small flows, also experienced i) a greater shift in skill supply among less educated native-born workers toward communication tasks and away from manual ones; ii) a greater decrease in the total supply of communication relative to manual skills; and iii) a greater increase in the compensation paid to communication relative to manual skills. These results are upheld by two stage least squares (2SLS) regressions that instrument for the variation of less educated immigrants across states using two different sets of exogenous variables, both of which exploit the increased level of Mexican immigration as an exogenous supply shift at the state level. The first follows a strategy similar to Card (2001), Card and DiNardo (2000), and Cortes (2008) by using the imputed share of Mexican workers (based upon 1960 state demographics and subsequent national growth rates) as a proxy for the share of less educated immigrants in a state. The second set of instruments interacts decade indicator variables with the distance of a state's center of gravity to the Mexico-US border, its square, and a border dummy.

Section 4 also performs a host of robustness checks to ensure that the results are not spuriously

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<sup>2</sup>Our analysis ignores changes in the task content of occupations over time. Thus, we might underestimate the effect of immigration on task performance of natives by capturing only the part due to reallocation across occupations. In Peri and Sparber (2008c), we use *Dictionary of Occupational Titles (DOT)* and *O\*NET* measures of skill intensity. The *DOT* identifies the intensity of skill use in occupations measured in 1977 and 1991, and therefore accounts for changes over time. Unfortunately, that dataset contains only two measures of manual skills (Eye, Hand, and Foot Coordination and Finger Dexterity) and an imperfect measure of communication abilities (the performance of Direction, Control, and Planning activities) that encompasses many tasks in addition to language skills. Despite the differences between datasets and skill intensity measures, we found remarkably similar and robust results. We refer the reader to Peri and Sparber (2008c) for a more detailed description of analysis and results using *DOT* variables.

driven. We control for possible shifts in the demand for skills, analyze how labor flows affect previous immigrant groups and highly-educated natives, and assess how the effects of immigration vary across demographic groups. The results of these checks again support the implications of our model. Moreover, we briefly demonstrate that the results are not driven by displacement effects, as natives do not respond to immigration by moving to areas with fewer foreign-born workers or by dropping out the labor force – an issue of concern for many area studies in the immigration literature.<sup>3</sup>

Given the positive wage effect of specializing in language-intensive occupations, native-born workers can protect their wages and mitigate losses due to immigration by reallocating their tasks. In Section 5, we use our model and empirical results to calculate the effect of immigration (among workers of all education levels) on average wages paid to native-born employees with a high school degree or less. Task complementarities and increasing specialization among native-born workers imply that the wage impact of immigration on less educated natives, while usually negative, is very small for the US overall. While less educated natives in states receiving a disproportionately large number of less educated immigrants (relative to highly-educated ones) still experience wage losses, the effects are usually small and even positive in some states.

The simulated wage effects for natives and immigrants also allow us to calculate the elasticity of substitution between immigrants and natives implied by our model. We estimate a value between 20 and 47, with an average of 33. These figures are similar to those obtained by Ottaviano and Peri (2008), who instead estimate the inverse elasticity directly by regressing relative immigrant-native wages on relative hours worked at the national level. Hence, the mechanism proposed in our model is able to explain much of the imperfect substitutability more directly estimated in other papers. Altogether, our findings agree in spirit with those of Card (2001), Card and Lewis (2007), and Card (2007) while adding a new dimension and more micro-foundations to the structural framework introduced by Borjas (2003) and refined by Ottaviano and Peri (2008).

## 2 Theoretical Model

We propose a simple general equilibrium model of comparative advantages in task performance to illustrate the effects of immigration on specialization and wages.<sup>4</sup> We briefly describe the model here, and provide more detailed derivations and results in the Appendix. We will test the key qualitative implications of the model in Section 4, and use the production structure

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<sup>3</sup>See Card (2001, 2007), Card and Lewis (2007), Cortes (2006), Lewis (2005), and Ottaviano and Peri (2007) for supporting evidence.

<sup>4</sup>Grossman and Rossi-Hansberg (2006) develop an interesting theory of offshoring that builds upon a process of international task division. Autor and Dorn (2007) use a model of differentiated task performance to analyze the evolution of wages in the 1980s and 1990s related to computer adoption. Those models have features similar to ours.

and empirically-estimated elasticities to evaluate the effects of immigration on wages paid to less educated native-born workers in Section 5.

## 2.1 Production

Consider an open economy (e.g., a US state) that combines two non-tradeable intermediate services,  $Y_H$  and  $Y_L$ , in a *CES* production function to produce a final tradeable consumption good,  $Y$ , according to Equation (1).

$$Y = \left[ \beta Y_L^{\frac{\sigma-1}{\sigma}} + (1 - \beta) Y_H^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (1)$$

The parameter  $\sigma \in (0, \infty)$  measures the elasticity of substitution between  $Y_H$  and  $Y_L$ . The coefficients  $\beta$  and  $(1 - \beta)$  capture the relative productivity of these intermediate services in the production of good  $Y$ . This final consumption good is also the numeraire, so that all prices and wages are expressed in real terms. We assume that it is assembled by perfectly competitive firms that minimize costs and earn no profits. This ensures that the prices of  $Y_L$  and  $Y_H$  (denoted  $P_L$  and  $P_H$ ) are equal to their marginal products.

The two intermediate services are produced by different workers. Low education workers (with total labor supply equal to  $L$ ) produce  $Y_L$ , and high education workers ( $H$ ) produce  $Y_H$ . The symmetric *CES* production function (1) combining the services of more and less educated workers (i.e., those with and without college experience) is widely used in economics.<sup>5</sup> Many immigration papers, in contrast, separate workers into four education groups – high school dropouts, high school degree holders, those with some college experience, and college graduates. However, Ottaviano and Peri (2008) argue that workers with no degree and workers with a high school diploma were close substitutes between 1960 and 2000, as were workers with some college education and those with a college degree. A recent paper by Goldin and Katz (2007) also argues that “high school graduates and dropouts are close substitutes today.” Most of the literature (including Katz and Murphy (1992), Angrist (1995), Johnson (1997), Goldin and Katz (2007) and Ottaviano and Peri (2008)) does find a significant degree of imperfect substitutability between workers with a high school diploma or less and those with some college education or more. Thus, we advocate a two-group *CES* model distinguishing between workers with a high school degree or less and workers with some college education or more.

We add to the framework above by assuming that less educated workers must perform both manual and communication tasks in order to produce  $Y_L$ . Manual tasks require the use of physical skills such as dexterity, body coordination, or strength. Communication tasks such as directing,

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<sup>5</sup>For instance, the literature on cross-country income differences (Acemoglu and Zilibotti (2001), Caselli and Coleman (2006)), technological change (Acemoglu (1998, 2002)), and labor economics (Katz and Murphy (1992), Autor, Katz and Krueger (1997), Card and Lemieux (2001)) all use a production function similar to (1).

managing, and organizing people require mostly language skills. Let less educated workers supply  $M$  units of manual-task inputs and  $C$  units of communication-task inputs in the aggregate.<sup>6</sup> These tasks combine to produce  $Y_L$  according to the *CES* function in Equation (2), where  $\beta_L \in (0, 1)$  captures the relative productivity of manual skills and  $\theta_L \in (0, \infty)$  measures the elasticity of substitution between  $M$  and  $C$ .

$$Y_L = \left[ \beta_L M^{\frac{\theta_L-1}{\theta_L}} + (1 - \beta_L) C^{\frac{\theta_L-1}{\theta_L}} \right]^{\frac{\theta_L}{\theta_L-1}} \quad (2)$$

Since this paper focuses on the market for less educated workers, we make the simplifying assumption that highly-educated workers only perform one “analytical” (or equivalently, “cognitive”) task in the production of  $Y_H$ .<sup>7</sup> Alternatively, one can assume that highly-educated workers provide both analytical and communication skills (and very few physical tasks), that those two skills are highly substitutable, and that their relative supply and returns are not much affected by the presence of less educated immigrants.<sup>8</sup> By standardizing the units of these tasks, we can simply assume that  $Y_H$  is produced according to a linear technology equal to the total supply of highly-educated workers. That is,  $Y_H = H$ .

Competitive labor markets and perfect competition among producers of  $Y_L$  and  $Y_H$  yield the relative task demand function in Equation (3), where  $w_M$  and  $w_C$  denote the compensation (return) paid for one unit of manual and communication task, respectively.

$$\frac{C}{M} = \left( \frac{1 - \beta_L}{\beta_L} \right)^{\theta_L} \left( \frac{w_C}{w_M} \right)^{-\theta_L} \quad (3)$$

## 2.2 Relative Supply of Tasks: Natives and Immigrants

Since each highly-educated worker is identical from a productive point of view, the wage paid to these workers equals the marginal productivity of  $Y_H$  in (1). That is,  $w_H = P_H$ . In contrast, less educated workers are heterogeneous and may differ from each other in their relative task productivity. We consider two types of workers: less educated “domestic” native-born workers ( $D$ ), and less educated “foreign-born” immigrant workers ( $F$ ). We let  $L_j$  (for  $j = D$  or  $F$ ) represent the total labor supply of these groups.

Each less educated worker chooses an occupation and fully allocates one unit of time in order to provide  $\mu_j$  units of manual tasks,  $\zeta_j$  units of communication tasks, or some division between

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<sup>6</sup>We will use capital letters to denote aggregate values, and lower case letter to denote per capita figures, throughout the text.

<sup>7</sup>For a more careful analysis of the interaction between natives and immigrants, and of task-specialization among highly educated workers, see Peri and Sparber (2008b).

<sup>8</sup>We provide empirical evidence in Table 8 that shows the independence between the task supply among highly-educated workers and the inflow of less-educated immigrants.

the two. Native and immigrant workers differ in that the first has a comparative advantage in communication tasks. Mathematically, this implies  $\left(\frac{\zeta_D}{\mu_D}\right) > \left(\frac{\zeta_F}{\mu_F}\right)$ .

Let  $l_j$  be the share of a worker's labor endowment (time) spent performing manual tasks in her occupation, implying that  $1 - l_j$  is the time spent performing communication tasks. A worker's supply of manual task units is  $m_j = (l_j)^\delta \mu_j$ , while her supply of communication task units is  $c_j = (1 - l_j)^\delta \zeta_j$ . The parameter  $\delta \in (0, 1)$  captures the decreasing returns from performing a single task, which implies that no one will fully specialize.

Each worker takes the return paid to tasks ( $w_M$  and  $w_C$ ) as given and chooses an occupation allocating her time between manual and communication tasks to maximize labor income. Labor income is given in Equations (4) and (5) for less educated native and immigrant workers respectively.

$$w_D = (l_D)^\delta \mu_D w_M + (1 - l_D)^\delta \zeta_D w_C. \quad (4)$$

$$w_F = (1 - d) \left[ (l_F)^\delta \mu_F w_M + (1 - l_F)^\delta \zeta_F w_C \right]. \quad (5)$$

These equations sum the income from performing manual and interactive tasks. The productivity in each task is specific to the type of worker ( $F$  or  $D$ ). Notice that in (5) we allow wages of immigrants to be a fraction  $(1 - d) \in [0, 1]$  of their marginal productivity, allowing for some form of discrimination or reduced bargaining power relative to natives. This feature does not affect the relative (or absolute) supply of tasks by immigrants. It only implies that immigrants may earn lower wages than natives do within a given occupation, which is a feature that we allow in the estimation and is supported by the data.

By maximizing wages with respect to  $l_j$  we can identify the equilibrium relative supply of communication versus manual tasks for natives and immigrants. Equation (6), which depends positively on relative task compensation and on the worker's relative efficiency in performing tasks  $\left(\frac{\zeta_j}{\mu_j}\right)$ , describes the relative task supply for natives ( $j = D$ ) and immigrants ( $j = F$ ). Equivalently, Equation (7) expresses this relationship in terms of the relative time spent performing these tasks.

$$\frac{c_j}{m_j} = \left(\frac{w_C}{w_M}\right)^{\frac{\delta}{1-\delta}} \left(\frac{\zeta_j}{\mu_j}\right)^{\frac{1}{1-\delta}} \quad (6)$$

$$\frac{l_j}{1 - l_j} = \left(\frac{\zeta_j w_C}{\mu_j w_M}\right)^{\frac{1}{\delta-1}} \quad (7)$$

Since each occupation requires a unique allocation of time between manual and communication tasks, when a worker chooses an occupation to maximize her wage income, she also reveals her relative efficiency  $\left(\frac{\zeta_j}{\mu_j}\right)$  in task performance. Equations (6) and (7) can therefore be interpreted as describing the occupation choice for a worker of type  $j$  establishing a unique and invertible



relationship between an individual's relative abilities and her occupation.<sup>9</sup> The existence of a continuum of occupations (for values of  $l_j$  between 0 and 1) allows workers to respond continuously to a marginal increase in the relative compensation of communication tasks  $\left(\frac{w_C}{w_M}\right)$  by marginally increasing  $\frac{c_j}{m_j}$  – that is, by moving to an occupation requiring less time devoted to manual tasks,  $l_j$ .

In this simplified model there is no differentiation of abilities within citizenship groups – all native workers are endowed with task efficiency  $(\zeta_D, \mu_D)$ , whereas all foreign-born workers have efficiency  $(\zeta_F, \mu_F)$ . This implies that each native supplies  $(c_D, m_D)$  task units and each immigrant supplies  $(c_F, m_F)$  so that members from each group will choose a common occupation. Each group will choose a new occupation, however, if the relative compensation of tasks changes. Hence in our notation  $j$  represents the worker type as well as her occupation as the second fully reveal the first<sup>10</sup> The aggregate task supply for native and foreign workers will equal the product of individual task supply and total labor supply ( $M_j = L_j m_j$  and  $C_j = L_j c_j$ ). This implies that if we substitute  $\frac{c_j}{m_j}$  with  $\frac{C_j}{M_j}$  (by multiplying numerator and denominator by  $L_j$ ), expression (6) also describes the relative supply of tasks for natives and immigrants.

Equation (8) represents the aggregate relative supply of tasks in the economy obtained by summing the skills provided by each group.

$$\frac{C}{M} = \frac{C_F + C_D}{M_F + M_D} = \phi(f) \cdot \frac{C_F}{M_F} + (1 - \phi(f)) \cdot \frac{C_D}{M_D} \quad (8)$$

The term  $\phi(f) = M_F/(M_F + M_D) \in (0, 1)$  is the share of manual tasks supplied by foreign-born workers, and is a simple monotonically increasing transformation of the foreign-born share of less educated workers<sup>11</sup>,  $f = L_F/(L_F + L_D)$ . Hence, the aggregate relative supply of tasks in the economy is a weighted average of each group's relative supply, and the weights are closely related to the share of each group in employment. Substituting (6) for natives and immigrants in (8) and equating relative supply with relative demand (expressed by (3)) one can solve for the equilibrium relative compensation of tasks:

$$\frac{w_C^*}{w_M^*} = \left(\frac{1 - \beta_L}{\beta_L}\right)^{\frac{(1-\delta)\theta_L}{(1-\delta)\theta_L + \delta}} \left[ \frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right) \right]^{-\frac{1}{(1-\delta)\theta_L + \delta}} \quad (9)$$

The function  $\frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right)$  is a weighted average of the relative skill endowments among natives and

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<sup>9</sup>Empirically, for example, a relative task supply  $\frac{c_j}{m_j}=0.16$  corresponds to the occupation “Assembler of Electrical Equipment.” A relative task supply of 3.12 corresponds to the occupation “Financial Service Salesperson.”

<sup>10</sup>In a model with heterogeneous abilities (as in Peri and Sparber (2008c)) as well as in the empirical implementation, there are workers with different relative ability  $\frac{\zeta_j}{\mu_j}$  choosing different occupations within each group. In that case the index  $j$  can be thought as indexing the worker relative effectiveness as well as their occupation.

<sup>11</sup>Specifically:  $\phi'(f) > 0$ ;  $\phi(0) = 0$  and  $\phi(1) = 1$ .

immigrants, and it represents an aggregate measure of communication relative to manual ability in the economy. More specifically,  $\frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right) = \left[ \phi(f) \cdot \left( \frac{\zeta_F}{\mu_F} \right)^{\frac{1}{1-\delta}} + (1 - \phi(f)) \cdot \left( \frac{\zeta_D}{\mu_D} \right)^{\frac{1}{1-\delta}} \right]^{(1-\delta)}$ . For a given value of the relative skills of natives  $\left( \frac{\zeta_D}{\mu_D} \right)$ , the term  $\frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right)$  depends negatively on  $f$  and positively on  $\frac{\zeta_F}{\mu_F}$  as indicated by the signs in Equation (9). This is intuitive. Due to the assumption that  $\frac{\zeta_F}{\mu_F} < \frac{\zeta_D}{\mu_D}$ , a larger fraction of immigrants decreases the average relative communication skills of the workforce. Similarly, a decrease in the relative communication ability of immigrants  $\left( \frac{\zeta_F}{\mu_F} \right)$  for given share of employment would decrease the average relative communication ability of the workforce.

By substituting the equilibrium wage into the aggregate relative supply for domestic workers, we find their equilibrium relative provision of tasks (Equation (10)). The weighted average of  $\frac{C_D^*}{M_D^*}$  and  $\frac{C_F^*}{M_F^*}$  (according to Equation (8)) identifies the equilibrium aggregate relative provision of tasks in Equation (11).

$$\frac{C_D^*}{M_D^*} = \left( \frac{1 - \beta_L}{\beta_L} \right)^{\frac{\delta \theta_L}{(1-\delta)\theta_L + \delta}} \left( \frac{\zeta_D}{\mu_D} \right)^{\frac{1}{1-\delta}} \left[ \frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right) \right]^{-\frac{1}{(1-\delta)\theta_L + \delta} \frac{\delta}{1-\delta}} \quad (10)$$

$$\frac{C^*}{M^*} = \left( \frac{1 - \beta_L}{\beta_L} \right)^{\frac{\delta \theta_L}{(1-\delta)\theta_L + \delta}} \left[ \frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right) \right]^{\frac{\theta_L}{(1-\delta)\theta_L + \delta}} \quad (11)$$

If we assume that workers also spend their entire wage income to consume  $Y$  in each period (there is no capital in the model so we assume no saving and investment), the equilibrium compensation values  $w_H$ ,  $w_M$ , and  $w_C$  fully determine the income, task supply, and consumption of each agent. Hence, the model is a simple general equilibrium static representation of an economy.

### 2.3 Model Predictions and Empirical Specifications

It is simple and intuitive to perform some comparative static analyses using the equilibrium expressions (9), (10), and (11). In particular, since the average relative ability  $\frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right)$  depends negatively on the share of immigrants in the population ( $f$ ), an increase in that share has three effects. First, the return to communication relative to manual tasks increases (Equation (9)), which in turn implies an increase in the relative supply of communication tasks by natives (Equation (10)) while the aggregate relative supply of communication tasks decreases (Equation (11)). Similarly, since  $\frac{\zeta}{\mu} \left( f, \frac{\zeta_F}{\mu_F} \right)$  depends positively on  $\frac{\zeta_F}{\mu_F}$ , a decrease in that variable produces an increase in the relative return to communication versus manual tasks, an increase in the native relative supply of communication versus manual tasks, and a decrease in the overall relative supply of communication versus manual tasks. Empirically, between 1960 and 2000 the US experienced an

inflow of immigrants with lower  $\frac{\zeta_F}{\mu_F}$  relative to natives.

Figure 1 displays the equilibrium in an economy with native and foreign-born workers, illustrating the effects of an increase in the share of immigrants and/or a decrease in their relative  $\frac{\zeta_F}{\mu_F}$  abilities using relative supply and demand curves. The demand curve is downward sloping and represents relative marginal task productivity as derived from the production function. Comparative advantage dictates that the relative task supply curve among immigrants is to the left of that among domestic workers. Aggregate relative supply (represented by the thickest line in the panel) is a weighted average of the two. The distance of the average supply curve from those of immigrants and domestic workers is proportional to  $\phi(f)$  and  $1 - \phi(f)$ , respectively.

The initial equilibrium relative task compensation  $\left(\ln\left(\frac{w_C^*}{w_M^*}\right)\right)$  and provision  $\left(\ln\left(\frac{C^*}{M^*}\right)\right)$  is denoted by  $E_0$ . The points  $D_0$  and  $F_0$  along the native and immigrant skill-supply curves identify each group's respective initial relative supply of tasks. Either an increase in the foreign-born share of employment or a decrease in  $\frac{\zeta_F}{\mu_F}$  will shift aggregate supply to the left (the latter also shifts the supply curve for immigrants). This implies a new equilibrium,  $E_1$ . The aggregate level of communication versus manual tasks decreases, thus increasing their relative compensation. Natives respond rationally by providing more communication versus manual tasks (a move along their relative skill-supply curve to  $D_1$ ). Hence, a larger share of immigrants among less educated workers (possibly reinforced by a decrease in their relative communication abilities) pushes less educated native workers to further exploit their comparative advantage. The economy experiences (i) An increase in the relative compensation of communication versus manual tasks; (ii) An increase in natives' relative supply of these tasks; and (iii) A decrease in the relative supply of communication versus manual tasks in the aggregate.

In Section 4, we empirically test these three predictions by using decennial (year  $t$ ) US state ( $s$ ) data from 1960-2000. In particular, by log-linearizing the two key equilibrium conditions (10) and (11) we obtain the two linear empirical specifications expressed below.

$$\ln\left(\frac{C_D}{M_D}\right)_{st} = \gamma \cdot f_{st} + \alpha_s^D + \tau_t^D + \varepsilon_{st}^D \quad (12)$$

$$\ln\left(\frac{C}{M}\right)_{st} = \gamma_{TOT} \cdot f_{st} + \alpha_s^{TOT} + \tau_t^{TOT} + \varepsilon_{st}^{TOT} \quad (13)$$

We also invert and log-linearize the relative demand function (3) to obtain a third linear relation given by:

$$\ln\left(\frac{w_C}{w_M}\right)_{st} = -\frac{1}{\theta_L} \cdot \ln\left(\frac{C}{M}\right)_{st} + \alpha_s^w + \tau_t^w + \varepsilon_{st}^w \quad (14)$$

Each regression includes a non correlated zero-mean disturbance term ( $\varepsilon_{st}^D$ ,  $\varepsilon_{st}^{TOT}$ , and  $\varepsilon_{st}^W$ ).

Time fixed effects (respectively as  $\tau_t^D$ ,  $\tau_t^{TOT}$ , and  $\tau_t^w$ ) account for common time-varying technological parameters – the first two capture the terms  $\frac{\delta\theta_L}{(1-\delta)\theta_L+\delta} \ln\left(\frac{1-\beta_L}{\beta_L}\right)$  from Equations (10) and (11), while  $\tau_t^w$  controls for  $\ln\left(\frac{1-\beta_L}{\beta_L}\right)$  from the relative labor demand equation. The state fixed effects in each expression (denoted  $\alpha_s^D$ ,  $\alpha_s^{TOT}$ , and  $\alpha_s^w$ ) account for variation due to unobserved characteristics of the population, including the term  $\frac{1}{1-\delta} \ln\left(\frac{\zeta_D}{\mu_D}\right)$  from (10).

The remaining terms in these log-linearized expressions represent our theoretical model’s central implications. In Equation (12),  $\gamma \equiv -\left(\frac{1}{(1-\delta)\theta_L+\delta}\right) \frac{\delta}{1-\delta} \left(\frac{\partial \ln \frac{\zeta}{f}}{\partial f}\right)$ . The model’s Equation (10) predicts  $\gamma > 0$  because a state’s foreign-born share of less-educated employment ( $f_{st}$ ) causes native workers to increase their relative supply of communication tasks. In Equation (13),  $\gamma_{TOT} \equiv \left(\frac{\theta_L}{(1-\delta)\theta_L+\delta}\right) \left(\frac{\partial \ln \frac{\zeta}{f}}{\partial f}\right)$  is derived from (11), which predicts  $\gamma_{TOT} < 0$  since immigration causes the overall relative supply of these tasks to fall. Finally, we use Equation (14) to estimate the relative wage elasticity,  $\theta_L$ , which is predicted to be positive. This specification rearranges the relative demand function for skills (3) so that  $\ln\left(\frac{C}{M}\right)_{st}$  represents the explanatory variable. Since  $\ln\left(\frac{C}{M}\right)_{st}$  is endogenous, we use the results from our regression of (13) and adopt the share of immigrants,  $f_{st}$ , as an instrument in estimation of (14).

Sections 4.1, 4.2 and 4.3 estimate, respectively (12), (13) and (14). Before showing the results, however, we describe the data and discuss the measures of task supply and task compensation in Section 3.1, and we address important empirical issues (such as the instrumental variable strategy adopted and the construction of sector-specific task demand) in Section 3.2. Readers interested in the results but not in the details of the empirical implementation can skim over Section 3.1, skip Section 3.2, and continue to Section 4.

### 3 Data, Construction of Variables, and Empirical Implementation

This section describes how we construct measures of task supply in order to test the main implications of the model. The IPUMS dataset by Ruggles et. al. (2005) provides individual-level data on personal characteristics, employment, wages, immigration status, and occupation choice. As consistent with the literature, we identify immigrants as those who are born outside of the United States and were not citizens at birth. To focus on the period of rising immigration and to use only Census data we consider decennial years from 1960 to 2000.<sup>12</sup> We include workers who were between 18 and 65 years of age, not residing in group quarters, and who worked at least

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<sup>12</sup>We use the 1% IPUMS sample for the 1960 and 1970 Census data, and the 5% IPUMS sample for 1980, 1990 and 2000.

one week in the year prior to the Census year and at least one hour in the reference week.<sup>13</sup> We also calculate the potential experience of workers assuming that those without a degree started working at age 17, and those with a diploma started at 19. We then eliminate workers with less than one year and more than 45 years of experience. Whenever we construct aggregate or average variables, we weight each individual by his/her personal Census weight, multiplied by the number of hours he/she worked in a year.<sup>14</sup> This allows us to put less weight on part-time workers, and to create variable values reflecting the amount of hourly labor individuals actually supply.

Since the immigrant share of employment varies greatly across US states, we interpret states as labor markets and adopt them as the econometric unit of analysis.<sup>15</sup> One critique of this approach is that states are open economies, so the effects of immigration in one state could spill into others through the migration of natives. Section 4.1.6 notes, however, that most of the literature (including our analysis) finds little to no evidence that, in the long run, natives respond to immigration through interstate migration or by exiting employment. Instead, we provide a new explanation for the observed small wage and employment response to immigration – native-born workers partly protect themselves from competition with immigrants by specializing in language-intensive occupations.

### 3.1 Task Variables

In our theoretical model we argued that individuals of type  $j$  choose occupations that are defined by their manual and communication content. Thus, we can interpret  $j$  not only as representing different individual types, but also as identifying different occupations. For empirical exercises, we do not need data describing the (unobservable) share of time spent performing manual and communication tasks  $(l_j, 1 - l_j)$  or the effectiveness of workers in performing these skills  $(\mu_j$  or  $\zeta_j)$ . Rather, quantitative analysis requires only the effective supply of manual  $(m_j)$  and communicative  $(c_j)$  tasks in each occupation since  $m_j = (l_j)^\delta \mu_j$  and  $c_j = (1 - l_j)^\delta \zeta_j$ . We assume that our task-intensity variables exactly capture this effective task-supply.<sup>16</sup>

By merging occupation-specific task values with individuals across Census years, we are able to obtain these task supply measures for natives and immigrants by education level in each state over time. The US Department of Labor’s *O\*NET* abilities survey provides information on the

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<sup>13</sup>We do not exclude self-employed as long as they report wage income. The exclusion of self-employed did not noticeably change any result (estimates are available upon request).

<sup>14</sup>The number of hours worked in a year equals the number of weeks worked in the year (measured by the IPUMS variable *wkswork2* in 1960 and 1970 and *wkswork1* from 1980-2000) times the number of hours usually worked (*hrswork2* in 1960 and 1970 and *uhrswork* subsequently). As *wkswork2* and *hrswork2* are categorical variables we attribute to each category the median value of the interval.

<sup>15</sup>Also see Card (2001, 2007), Lewis (2005), Card and Lewis (2007), Cortes (2008), and Kugler and Yuksel (2008).

<sup>16</sup>We describe the construction of these variables below, and Table A1 in the Appendix provides  $c_j$  and  $m_j$  values for all occupations  $j$ .

characteristics of occupations.<sup>17</sup> Initiated in 2000, this dataset assigns numerical values to describe the importance of 52 distinct employee abilities (which we refer to as “tasks” or “skills”) required by each SOC (standard occupation classification) occupation. We merge these occupation-specific values to individuals in the 2000 Census using the SOC codes. The arbitrary scale of measurement for the task variables encourages us to convert the values into percentiles. We assume that the 2000 Census is collectively representative of the US workforce, and then re-scale each skill variable so that it equals the percentile score representing the relative importance of that skill among all workers in 2000.<sup>18</sup> Since Census occupation codes vary across years, we then assign these *O\*NET* percentile scores to individuals from 1960 to 2000 using the IPUMS variable *occ1990*, which provides an occupational crosswalk over time. The standardization of skill values between zero and one should facilitate a more intuitive interpretation of their percentage changes over time.<sup>19</sup>

Table 1 lists each of the 52 *O\*NET* variables and organizes them into categories that we use to construct our manual and communication skill supply indices. In our most “basic” (and restrictive) definition of manual skills we average only the variables capturing an occupation’s “Movement and Strength” requirements. As Table 1 shows, those skills can be further divided into “Limb, Hand, and Finger Dexterity,” “Body Coordination and Flexibility,” and “Strength.” Similarly, our basic definition of communication skills includes measures of oral and written expression and comprehension.

Some of our analysis employs “extended” definitions of manual and communication skills so that all of the 52 *O\*NET* variables fall into one of the two categories. In this analysis, we add “Sensory and Perception” abilities (i.e. those using the five senses) to the physical skill group, while we introduce “Cognitive and Analytical” and “Vocal” abilities to the communication skill group. The simplicity of our two-skill dichotomy forces us to make a few somewhat arbitrary choices when trying to fit all the *O\*NET* variables into one of the categories (for instance, cognitive skills do not relate only to language abilities). While we believe that our basic skill definitions more closely manifest the notion of communication and manual skills, the robustness of our empirical results to the use of our extended definitions lends support to our framework of summarizing occupations with just two measures.

To produce the summary statistics in the next section, we calculate the aggregate (US or state-level) supply of manual skills for less educated immigrants ( $M_F$ ), natives ( $M_D$ ), or both groups of workers ( $M$ ) by summing the values of  $m_j$  across individuals.<sup>20</sup> We follow an analogous procedure for aggregate communication skills (creating  $C_F$ ,  $C_D$ , and  $C$ ). Average values for states (or the

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<sup>17</sup>We use version 11.0 of the survey, which is publicly available at <http://www.onetcenter.org/>.

<sup>18</sup>That is, an occupation with a score of 0.02 for a specific skill indicates that only 2% of workers in the US in 2000 were using that skill less often.

<sup>19</sup>See Chiswick and Miller (2007) or Sparber (2008) for alternative uses of *O\*NET* data.

<sup>20</sup>We also weight  $m_j$  by individual sample weights (the IPUMS variable *PERWT*), multiplied by hours worked.

US) are represented by  $m$  or  $c$  (with subscripts if appropriate), and are obtained by dividing the aforementioned aggregate variables by the number of hours worked times the sample weight of the considered population. That is,  $m_D = M_D/L_D$  and  $m_F = M_F/L_F$ , for example.

### 3.1.1 National Trends

This section briefly describes how different occupations rank in their use of physical versus language skills according to the *O\*NET* task variables, and it presents some preliminary trends and correlations. Table 2 lists representative occupations at each decile of the communication versus manual skill intensity ( $\frac{c}{m}$ ) distribution. As we might expect, values are highest among managers, administrators, and clerks, while drivers, electricians, and carpenters score among the lowest (Table A1 in the Appendix provides  $\frac{c_j}{m_j}$  values for all occupations  $j$ ). Table 3 shows the skill intensity for occupations maintaining the most extreme  $\frac{c}{m}$  values (among occupations with more than 25,000 less educated workers in each year). It also reports the change in the foreign-born share of workers with a high school degree or less between 1970 and 2000. One striking fact is that the foreign-born share increased an average of six percentage points between 1970 and 2000 in occupations with high communication versus manual task content, while it gained an average 21 percentage points in those with low  $\frac{c}{m}$  values. As we only include less educated workers in the immigration figures shown in Table 3, the educational distribution of immigrants cannot explain this large difference.

Figure 2 reports the national trend (between 1970 and 2006) in the relative supply of communication versus manual tasks ( $\frac{C}{M}$ ) for less educated natives, recent immigrants (those who have been in the US ten or fewer years), and long-term immigrants (those residing in the US more than ten years).<sup>21</sup> The graph highlights several important stylized facts. First, in accordance with the comparative advantage assumption of Section 2.2, the level of  $\frac{C}{M}$  provided by native workers with a high school degree or less has been higher than that of both recent and long-term immigrants with similar educational attainment. Second, relative skill values are always lowest among new immigrants. In 2006, communication versus manual task provision among natives was 34% higher than for long-term immigrants, and it was almost double that of new immigrants. Third, cross-group disparities have been growing over time. Less educated native workers have increased (if only slightly) their  $\frac{C}{M}$  supply between 1970 and 2006, while values have decreased among foreign-born workers. Altogether, the trends and relationships in Figure 2 do not suggest a common response of natives and immigrants to modified relative demand for skills but rather show increasing specialization of the two groups, consistent with the idea that immigration represented an exogenous change in relative skill supply.

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<sup>21</sup>Since the variable “Year of Immigration” is not available in 1960, we cannot extend this figure back to that year. We provide 2006 American Community Survey (ACS) data for comparison, though it is not part of the empirical analysis.

Figure 3 demonstrates that the (total and recent) immigrant share of less educated workers grew substantially between 1970 and 2006. This, combined with the fact that immigrants’ relative specialization in communication tasks decreased, implies that in aggregate they significantly decreased the overall value of  $\frac{C}{M}$  for the US. If our theory is correct, this should have important ramifications for native-born task supply and wage earnings, which we analyze at the state-level.

### 3.1.2 State-Level Skill Quantities

The empirical analysis of Section 4 assumes that states represent labor markets and can be used to test the implications of our theory in Section 2. To perform the analysis, we must construct state-level skill data for native workers  $\left(\frac{C_D}{M_D}\right)$  in each Census year between 1960 and 2000. Importantly, we must first clean this data of demographic effects. That is, personal characteristics (such as age, education, gender, or race) could affect each state’s task supply and correlate with immigration. Failing to account for this could generate a spurious correlation between the presence of immigrants and the task supply of natives.

To control for personal characteristics, we first regress an individual’s task supply on a set of dummies capturing experience (44 distinct years of experience indicators), education (an indicator for having obtained a high school diploma), gender (a female indicator), and race/ethnicity (six indicators for Black, Hispanic, Native Americans, Chinese, Japanese, and other races). We do these regressions separately for each Census year and  $O^*NET$  variable. Next, we subtract an individual’s predicted task supply from his or her observed value. This residual represents an individual’s skill “cleaned” of demographic effects. We then compute an individual’s total manual and communication task supply by averaging the relevant residuals (i.e., by averaging the cleaned  $O^*NET$  variables belonging to each skill type as defined in Table 1). Finally, we create state-level averages for native workers  $((c_D)_{st}$  and  $(m_D)_{st})$  and their ratio  $\left(\frac{c_D}{m_D} = \frac{C_D}{M_D}\right)$  for each state  $s$  and year  $t$  by weighting each individual by his or her personal weight (and hours worked).<sup>22</sup>

Panel A of Figure 4 plots the immigrant share of less educated workers for a state and year (differenced from the overall 1960-2000 state average) against the relative task supply  $\left(\frac{C_D}{M_D}\right)$  for native workers (also in differences from the overall state average). Panel B simply graphs the immigrant share and relative task supply in levels for 2000. Both figures clearly show a strong and significantly positive relationship between the immigrant share of less educated workers and the communication versus manual skill supply of less educated natives across states. States where the foreign-born presence grew rapidly between 1960 and 2000 were also those in which natives (after controlling for demographic characteristics) shifted their supply more toward communication tasks and away from manual ones. In 2000, there was a strong positive correlation between the level of relative task supply among natives and the share of immigrants. These correlations

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<sup>22</sup>The cleaning procedure eliminates the cross-state variation of skills due to the demographic features of natives. However it maintains the national average skill intensity for the group of natives in each year.



constitute preliminary evidence supporting the prediction of our model that an inflow of less educated immigrants pushes less educated natives to supply more communication skills relative to manual ones.

### 3.1.3 State-Level Skill Compensation

The regression specification in Equation (14) relating relative skill supply to the relative wages paid to those skills encounters an immediate challenge in that the returns to skills  $w_M$  and  $w_C$  are not directly observable. However, the theoretical model suggests that since we know the task content and average wage for each occupation, we can extract a measure of their values. We use two steps to calculate  $w_M$  and  $w_C$  for each state and year. First, we select workers with at most a high school degree and regress, by year, the logarithm of individual real weekly wages<sup>23</sup> on individual experience, education, gender, nativity (US or foreign), and race characteristics, similar to the procedure used to clean the skill data in Section 3.1.2. These regressions also include occupation by state dummies, whose coefficients represent our estimates for the average log-wage,  $\ln(\tilde{w}_{jst})$ , for occupation  $j$ , state  $s$ , and Census year  $t$  after removing individual characteristic effects.<sup>24</sup>

In the second step, we transform  $\ln(\tilde{w}_{jst})$  into levels and regress  $\tilde{w}_{jst}$  on the occupation-specific measures of manual and communication skills (obtained from *O\*NET*) using weighted least squares. We do this using the basic as well as the extended definitions of skills described in Table 1. We then allow the coefficients on the skill variables to vary across states so that they capture the compensation (price) of manual and communication tasks in each state. By separately estimating the second stage regression in Equation (15) for each year, we can identify the state and year-specific wages,  $(w_M)_{st}$  and  $(w_C)_{st}$ , received for supplying manual and communication tasks.

$$\tilde{w}_{jst} = (w_M)_{st} \cdot m_j + (w_C)_{st} \cdot c_j + \varepsilon_{jst} \quad (15)$$

Interpreting  $m_j$  and  $c_j$  as the effective supply of manual tasks in occupation  $j$ , (as expressed in the theoretical model), Equation (15) implements the relationships in (4) and (5) to infer the values of  $w_M$  and  $w_C$  in a market (state) from the occupational wages in that market. The fact that we controlled for nativity in the first stage regression (as well as for other individual characteristics) implies that we allow wages to differ between natives and immigrants by proportional factors (such as the discrimination effect in Equation (5)). In order to obtain coefficients  $\widehat{w}_{Mst}$  and  $\widehat{w}_{Cst}$  that could be interpreted as the weekly compensation of a skill (and therefore always assuming positive values), and in line with our model, we do not include a constant in (15).

Table A2 in the Appendix shows, for each year, the average estimates (at the national level)

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<sup>23</sup>Real weekly wages are calculated by dividing the yearly salary income by the number of weeks worked in the year. The nominal figures are converted into real figures using the CPI-U deflator published by the Bureau of Labor Statistics and available at [www.bls.gov/cpi](http://www.bls.gov/cpi).

<sup>24</sup>Regressions weight each individual by their Census sample weight times hours worked.

of  $\widehat{w}_{Mst}$  and  $\widehat{w}_{Cst}$ , the  $R^2$  values from regressions of (15), and the number of occupation-state observations used in the estimation. The average compensation to communication tasks was larger than the compensation to manual tasks in each year except for 1980. While we observe a drop in the real compensation paid to both tasks between 1980 and 1990 due to the large decrease in real wages of less educated workers, it is clear that since 1980 the premium (wage differential) for communication tasks has increased. Certainly there are other idiosyncratic factors affecting average occupational wages across states, but the model in (15) explains a significant share (30 to 40% in each of the years considered) of the cross-occupation variance in wages. Adopting the extended definitions of manual and communication skills does little to alter the explanatory power of the model in (15), and it does not affect the estimated values of  $\widehat{w}_{Mst}$  and  $\widehat{w}_{Cst}$ .

Figure 5 shows preliminary evidence for another key prediction of our model. The horizontal axis again displays the immigrant share of less educated foreign-born workers in 2000, and the vertical axis records the relative compensation of communication versus manual tasks  $\left(\frac{w_C}{w_M}\right)$  by US state. Consistent with our model, states with a larger immigrant share also have higher  $\left(\frac{w_C}{w_M}\right)$  values (this is what drives natives to alter their skill supply). While Section 4.3 will more formally establish the relationship between immigration and relative task compensation, this preliminary evidence emphasizes that a correlation (in levels) existed in 2000.

## 3.2 Additional Empirical Issues

Our basic empirical specifications in Equations (12), (13) and (14) provide a simplified examination of the theoretical model's predictions. For robustness, the analysis will consider many additional complications as well. These alternatives require further data construction.

### 3.2.1 Instrumental Variables

To establish whether correlation between the foreign-born employment share and native-born (or aggregate) skill use is causal, we need to ensure that the cross-state variation of less educated immigrants is mostly driven by supply shifts. One concern is whether unobserved technology and demand factors, which may differ across states due to variation in sector composition, have simultaneously affected the productivity of (demand for) communicative tasks and attracted immigrants. To establish causality, we use two sets of instruments that build upon the fact that documented and undocumented Mexican immigration has represented a large share of the increase in the less educated foreign-born population beginning in the 1970s. This aggregate inflow was largely independent of state-specific demand shocks and can be exploited as an exogenous supply shift if we can differentiate flows across states.

Our first instrument for the increase in the share of immigrants among less educated workers imputes the proportion of Mexican workers within a state based upon their distribution in 1960

and subsequent national growth rates. This methodology relies upon two facts similarly exploited by Card (2001) and several other analyses of immigration’s effect on state or city economies.<sup>25</sup> First, new immigrants – especially those with little education – tend to move to the same areas in which previous immigrants from their source country live.<sup>26</sup> Second, unlike previous waves of immigration, a large proportion of immigrants between 1960 and 2000 came from Mexico. Together, these facts allow us to use the location preferences of Mexicans as factors affecting the supply of foreign-born workers across states and time that are uncorrelated with state-specific changes in demand (productivity).

First, we record the actual share of Mexicans in the employment of state  $s$  in 1960 ( $MEX_{s,t}$ ), and then assume that the growth rate of the Mexican share of employment between 1960 and year  $t$  was equal across states.<sup>27</sup> Thus, Equation (16) imputes shares in year  $t$ , where  $(1 + g_{MEX})_{1960-t}$  is the growth factor of Mexican-born employment nationwide between 1960 and year  $t$ , and  $(1 + g_{US})_{s,1960-t}$  is the growth factor of US-born workers in state  $s$  between 1960 and year  $t$ . The identification power of the instrument is based on the fact that some states (such as California and Texas) had a larger share of Mexican immigrants in 1960 relative to others. These states will also have larger imputed shares of Mexicans in 1970 through 2000 and, due to the educational composition of this group, will have a larger immigrant share among less educated workers.<sup>28</sup>

$$\widehat{MEX}_{s,t} = MEX_{s,1960} \frac{(1 + g_{MEX})_{1960-t}}{(1 + g_{US})_{s,1960-t}} \quad (16)$$

Our second set of instruments similarly relies upon the exogenous increase in Mexican immigration but is based upon geography. First, we use the formula for geodesic distance to calculate the distance of each state’s population center of gravity (available from the 2000 Census) to its closest section of the Mexican border.<sup>29</sup> Since we already control for state fixed effects in the regressions, we interact the distance variable with four year dummies (from 1970 to 2000). This captures the fact that distance from the border had a larger effect in predicting the inflow of less educated workers in decades with larger Mexican immigration. Second, we also use a Mexican border dummy interacted with decade indicators to capture the fact that border states had larger inflows of Mexican workers due to undocumented border crossings. Since illegal immigrants are less

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<sup>25</sup>Also see Cortes (2008), Lewis (2005), Ottaviano and Peri (2007), and Saiz (2003).

<sup>26</sup>This is due to information networks between immigrants and their country of origin, as well as to the immigration policy of the US. A documented less-educated immigrant is most likely to come to the US to join a family member.

<sup>27</sup>The figures used to impute the Mexican share of employment are not weighted by hours worked.

<sup>28</sup>The analysis in Patel and Vella (2007) also shows evidence of strong “network” effects affecting the supply of immigrants. New immigrants are more likely to settle and work in occupations and areas with a large presence of co-nationals. We do not use the initial occupational distribution to construct the instrument, however, as it is more likely to be affected by demand factors persisting over the decades.

<sup>29</sup>We divide the US-Mexico border into 12 sections and calculate the distance between each center of gravity and each section. Then we choose the shortest distance for each state.

mobile across states, border states have experienced a particularly large exogenous supply-driven increase of less educated immigrant workers. Altogether, our second set of instruments includes both the distance and border variables, each interacted with decade indicators. Essentially, the use of the geographic instruments is equivalent to a difference in difference approach in which the identifying variation stems from differences in the inflow of Mexicans between states close to and far from the border in the post-1980 period (when Mexican migration rose dramatically) relative to previous decades.

### 3.2.2 Technology and Demand Shifts

Our period of analysis is associated with large changes in production technologies, particularly in the diffusion of information technologies and computer adoption. Autor, Levy, and Murnane (2003) demonstrate that this change had a large effect in shifting demand from routine to non-routine tasks. Similarly, the increasing importance of advanced services, the demise of manufacturing, and other sector-shifts might have contributed substantially to differences across states in the demand for manual and communication tasks. State-specific technology and/or sector composition could confound the correlation between immigration and task intensity.

We begin to account for these factors by including the share of workers (with at most a high school degree) who use a computer at work to control for the diffusion of technology across states. This data is available in the October CPS Supplements in 1984 and 1997, and in the September CPS Supplement in 2001. We match the 1984 computer data to the 1980 Census data, the 1997 computer-use data to the 1990 Census, and the 2001 computer data to the 2000 Census. We impute a share of zero for all states in 1960 and 1970 since the personal computer was first introduced in 1981.

Our second control accounts more explicitly for the industrial composition of each state in 1960 and its effect on task demand. We create state-specific indices of communication versus manual task demand driven by each state's industrial composition,  $\left(\frac{C}{M}\right)^{Tech}$ , by assuming that the occupational composition of industries and industry-specific employment shocks are uniform across states. First, we calculate the average physical and language content among all workers for each industry  $i$  in year  $t$  from national data and record the corresponding ratio  $\left(\frac{C}{M}\right)_{i,t}$ . Next, we calculate industry-level national employment growth since 1960,  $g_{i,t}$ . By assuming that industries grew at their national growth rates regardless of the state in which they are located, we can predict the employment share of industries within each state and year,  $\widehat{emp}_{i,s,t}$ . Finally, we calculate a state's level of relative task demand,  $\left(\frac{C}{M}\right)_{s,t}^{Tech}$ , as the average value of each industry's  $\left(\frac{C}{M}\right)_{i,t}$

weighted by the predicted employment shares.

$$\widehat{emp}_{i,s,t} = \frac{Employment_{i,s,1960} \cdot (1 + g_{i,t})}{\sum_{i=1}^{Ind} Employment_{i,s,1960} \cdot (1 + g_{i,t})} \quad (17)$$

$$\left(\frac{C}{M}\right)_{s,t}^{Tech} = \sum_{i=1}^{Ind} \widehat{emp}_{i,s,t} \cdot \left(\frac{C}{M}\right)_{i,t} \quad (18)$$

## 4 Empirical Results

This section uses the empirical specifications in (12), (13) and (14) to formally test the relationships identified by the theoretical model. Section 4.1 assesses the correlation between the foreign-born share of less educated workers and the relative supply of tasks by native workers across states. Section 4.2 tests the effect of immigration on the aggregate supply of relative tasks across states, and Section 4.3 quantifies the effects of immigration on the relative compensation of manual and communication tasks.

### 4.1 The Native-Born Worker Response to Immigration

#### 4.1.1 Immigration and the Relative Task Supply of Natives

We begin by estimating Equation (12) using Least Squares, weighting each observation by employment in the cell (thus accounting for the large variation in labor market size across states) and clustering standard errors by state. This provides a direct test of our theoretical model by determining if  $\gamma$  is positive. We also go beyond this test, however, and ascertain whether immigration has a stronger relationship with the average native-born supply of manual ( $m_D$ ) or communication ( $c_D$ ) tasks by separately estimating Equations (20) and (19).<sup>30</sup>

$$\ln(c_D)_{st} = \alpha_s^C + \tau_t^C + \gamma^C \cdot f_{st} + \varepsilon_{st}^C \quad (19)$$

$$\ln(m_D)_{st} = \alpha_s^M + \tau_t^M + \gamma^M \cdot f_{st} + \varepsilon_{st}^M \quad (20)$$

Table 4 presents the WLS estimates of  $\gamma$ ,  $\gamma^C$ , and  $\gamma^M$  for different samples and different variable definitions.<sup>31</sup> Column (1) uses the basic definitions of manual and language ability involving the average of 19 and 4 *O\*NET* variables, respectively (see Table 1), to construct skill supply. The

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<sup>30</sup>Recall that  $m_D = \frac{M_D}{L_D}$  and  $c_D = \frac{C_D}{L_D}$ .

<sup>31</sup>Note that since  $\ln\left(\frac{C_D}{M_D}\right)_{st} = \ln(c_D)_{st} - \ln(m_D)_{st}$ , it must be also true that  $\gamma = \gamma^C - \gamma^M$ .

remaining columns use alternative definitions of skill supply as indicated by column headers.<sup>32</sup> Each specification uses the full sample of 255 observations (a decennial panel of fifty states plus the District of Columbia from 1960-2000).

Three important results emerge. First, the estimates of  $\gamma$  strongly uphold our theory. The coefficients are positive, between 0.25 and 0.35, and always significant at the 1% confidence level. The estimates in column (1) suggest that a one percentage-point increase in the foreign-born share of less educated workers is associated with a 0.34% increase in the relative supply of communication versus manual tasks among natives. Second, this relative increase is primarily achieved through a rise in the supply of language skills, rather than a fall in natives' supply of physical labor. The estimate of  $\gamma^C$  in Column (1) implies that a one percentage-point increase in the foreign-born share is associated with a significant 0.31% rise in natives' supply of communication tasks, whereas the estimates of  $\gamma^M$  imply that the native supply of manual tasks would only decline by 0.03%, a value not significantly different from 0. Third, the results are robust – the significant correlations generally do not depend upon the different skill definitions used. Not surprisingly, the basic definition is the one producing the strongest and most significant results, while the definition that includes abilities not strictly related to physical and language skills produces the smallest value of  $\gamma$  (still a very significant 0.25). By adding these tangentially-related abilities, the extended index may suffer from larger measurement error, thus producing an attenuation of the estimated effect.

#### 4.1.2 Instrumental Variable Estimation

To argue that our estimates of  $\gamma$  represent the native-born task supply *response* to immigration, the regressions in Table 5 perform the two stage least squares counterparts of columns (1) and (7) of Table 4 by employing the instrumental variables introduced in Section 3.2.1. The first three rows report the two stage least squares estimates of  $\gamma$ ,  $\gamma^C$ , and  $\gamma^M$ , respectively, and the different columns use varied definitions of manual and communication tasks as indicated by column headers. Columns (1) and (2) use the imputed share of Mexicans as an instrument for the foreign-born employment share. Columns (3) and (4) instrument with geographic variables. Columns (5) and (6) use both sets of instruments together.

The two-stage least squares results in Table 5 are extremely robust to the set of instruments used and confirm the OLS conclusions of Table 4. The estimates of  $\gamma$  are always positive and very significant. They now range between 0.33 and 0.38. F-tests reveal that the instruments strongly explain the endogenous variable ( $f_{st}$ ), while regressions using all available instruments pass the test for the over-identifying restrictions.<sup>33</sup>

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<sup>32</sup>The exact variables included in each sub-group can be seen in Table 1.

<sup>33</sup>The value reported in the second to last row is the  $\chi^2$  test statistic under the null hypothesis that none of the instruments appear in the second stage regression. The degrees of freedom are given by the difference between the number of instruments and endogenous variables. We have one endogenous variable and either eight or nine instruments: four distance-decade interactions, four border-decade interactions, and the imputed share of Mexican

Ultimately, we prefer the estimates of Specification (5) since the  $O^*NET$  variables comprising the skill data most closely mirror our communication and language skills of interest. According to those estimates, natives respond to increases in immigration by significantly raising their communication task supply by 0.33% for each one percentage-point increase in the foreign-born share of less educated workers (this figure is similar to those of all other specifications). At the same time, they decrease the supply of manual tasks by 0.04% for each percentage-point increase in the foreign-born share. Note that the magnitude of the communication task response is much bigger than that of the manual response for all specifications. The similarity of the coefficients in Tables 4 and 5, and the fact that the point estimates are slightly larger in the 2SLS regressions, strengthens our conviction that the immigration shock was largely an exogenous shift in the relative supply of skills at the state level to which native workers responded.

### 4.1.3 Controls for Demand Shifts

State-level technology and sector-driven changes in task intensity could confound baseline results. The regressions in Table 6 control for these factors. Regressions (1) and (4) include a variable measuring the intensity of computer use in a state, measured as described in Section 3.2.2. Columns (2) and (5) include a variable imputing a state’s skill-use according to its industrial composition,  $\ln\left(\frac{C}{M}\right)_{s,t}^{Tech}$ , as described in Section 3.2.2. Columns (3) and (6) include both technology variables.

The first row of Table 6 reports the estimate of  $\gamma$ . Our control variables usually have a significant coefficient with the expected sign – computer adoption is associated with a higher provision of communication versus manual tasks among natives, while our constructed sector-driven demand shifts are positively related to the actual changes in relative tasks. Importantly, the inclusion of these variables leaves the estimates of  $\gamma$  extremely significant, and they range between 0.34 and 0.51. When we include both controls, the native task specialization response to immigration seems even stronger than our prior estimates (between 0.44% and 0.51% for a one percentage-point rise in the share of foreign-born labor).

The last two rows of Table 6 decompose the impact of immigration into its effect on the supply of manual and interactive tasks. In all cases the positive impact on the supply of interactive skills (between 0.34 and 0.43) is larger and more significant than the negative effect on physical ones (between -0.08 and 0.00). Altogether, the results of this section continue to provide evidence for increasing task-specialization, even after accounting for the state-specific technological shifts occurring over those decades. The relative supply of communication versus manual skills among natives increases by roughly 0.40% for each one percentage-point increase in the foreign-born share of less educated workers.

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workers. The last row reports the probability of obtaining the observed value of the test statistic or higher under the null. We cannot reject the null at any level of significance, so the assumption of instrument exogeneity stands. See Wooldridge (2002).

#### 4.1.4 Impact on Previous Immigrants and Highly-Educated Natives

Our model’s prediction for the wages of less educated native workers employs two implicit simplifying assumptions. First, we assume long-term immigrants are somewhat similar to new immigrants and different from native workers in that, relative to natives, they also have a comparative advantage in manual tasks. This allows us to group new and long-term immigrants together in our empirical analysis. Second, we assume that highly-educated natives are imperfect substitutes with all less educated workers, and that their relative task supply is not affected by the presence of less educated immigrants. In this section we test the validity of these two assumptions.

Figure 2 shows that while immigrants’ comparative advantage in manual tasks decreases with the duration of US residency (as immigrants become more similar to US-born workers), long-term immigrants still supply more manual versus communication tasks than natives do. This similarity between new and long-term immigrants may be the reason that many authors find a larger effect of immigration on the wages of previous immigrants than on natives (see Card (2001) and Ottaviano and Peri (2008)). In the context of our model, the substitutability of skills among these groups implies that foreign-born workers will experience only a small (if any) reallocation of task supply in response to an inflow of new immigrants. They therefore experience more wage competition with new entrants.

Table 7 reports the estimated coefficients from regressions similar to (12), (19), and (20) but where the dependent variable measures the task supply of less educated long-term (*LT*) immigrants rather than natives. Column (1) shows the WLS estimates, while Columns (2) to (4) show the 2SLS estimates using imputed Mexicans, geographic variables, or both sets of variables as instruments. Though the point-estimates show that long-term immigrants also had a weak tendency to respond to immigration by moving away from manual tasks and into communication tasks, the magnitude of the response is small. Moreover, the large standard errors imply that the estimates are not significant at standard levels of confidence. Thus, the empirics concur with the predictions of our model. Though long-term immigrants are becoming more like natives in their skill use, their response to immigration is small and less significant, making them especially vulnerable to wage competition with new immigrants.

The second simplification adopted in our model is that highly-educated workers (those with some college education) are not closely substitutable with less educated workers. Instead, they perform unique production tasks and constitute a separate input in production. Thus we assume that workers with college experience supply analytical (or cognitive) tasks that are not affected by less educated immigrants.

To justify this assumption, we first note that highly-educated workers supply fewer manual relative to communication tasks than less educated workers do. The average value of the manual supply index for workers with some college education is half of the average among those with a high



school education or less, while the highly-educated supply of communication tasks is double that of less educated workers. Second, we analyze whether the relative supply of analytical versus (oral and written) communication tasks by more-educated natives is in any way affected by the inflow of less educated immigrants. We also test whether the supply of manual tasks by highly-educated natives is affected by immigration.

The results can be seen in Table 8. The dependent variable is the average supply (by state and year) of tasks measured among highly-educated natives, while the explanatory variable is the immigrant share of less educated workers in the state and year. Since the inflow of highly-educated immigrants may affect the task-supply of natives and may be correlated with the inflow of less educated ones, we control for the immigrant share of highly-educated workers as well. Column (1) in Table 4 reports the WLS estimates. Specifications (2) to (4) report the 2SLS estimates using, alternatively, imputed Mexicans and distance from the border (column 2), all geographic variables (column 3), or the two sets of variables together (column 4) as instruments. While the standard errors are large, the regressions clearly indicate that there is no effect of less educated immigration on the relative supply of communication versus analytical tasks among highly-educated natives. They also indicate that immigration does not significantly affect the already small supply of manual tasks among highly-educated natives.

The checks within this section support the simplifying assumptions of our model. Perhaps more importantly, they also show that the large and significant impact of less educated immigrants on task specialization of less educated natives (shown in Table 5) is not the result of a generic positive correlation between immigration in a state and the change in task specialization in that state. Long-term immigrants and highly-educated natives respond much less to immigration among less educated workers by reallocating tasks.

#### 4.1.5 Impact across Demographic Groups

The results in Tables 4-6 assumed a homogenous response among US-born workers with a high school education or less. Our approach, however, allows us to identify the effect of immigration on the task specialization of specific demographic groups of less educated native workers. If  $\gamma$  varies across these groups, then the wage implications of immigration on those groups will vary as well. Table 9 compares estimates of  $\gamma$ ,  $\gamma^C$ , and  $\gamma^M$  for groups bifurcated by race (Column 1), gender (Column 2), age (Column 3), and education (Column 4). For each comparison, “Group 1” represents those earning lower wages (blacks, women, younger workers, and workers without a high school diploma). Except for women, individuals in Group 1 were also more specialized in manual than communication tasks and hence more vulnerable to job competition with immigrants. The first three rows report the 2SLS estimates of  $\gamma$ ,  $\gamma^C$ , and  $\gamma^M$  (using all instruments) for Group 1, and the remaining rows report the same coefficients for Group 2.

Each of the eight native-born groups in Table 9 responds to immigration by shifting their specialization from manual tasks to communication tasks. The shift was significant in six cases, and the increase in supply of communication skills was more significant and larger than the decrease in supply of physical tasks for all eight groups. Interestingly, for each comparison the native group that was more at risk to competition with immigrants (due to a larger reliance upon manual task performance) also exhibited a greater skill response. Men increased their relative skill supply by 0.26% for every percentage-point increase in the foreign-born share, while women only increased theirs by 0.11%. Young workers and those without a high school diploma also significantly shifted their relative supply ( $\gamma = 0.34$ ), while old workers and those with a diploma did not. This is not surprising since young workers have greater occupational mobility (older workers have very low rates of occupational change), and workers with extremely low educational attainment are potentially more threatened by immigrants.

Most strikingly, black workers responded to immigration by changing their relative task specialization three times more than non-black workers did ( $\gamma = 0.63$  versus  $\gamma = 0.20$ ). Blacks were much more specialized in manual tasks in comparison to non-blacks in 1960 and were more susceptible to competition with immigrants. The strong response among blacks in moving toward more language-intensive occupations should, at least in part, have shielded them from large negative wage effects.<sup>34</sup>

#### 4.1.6 Native Employment Response

Our analysis finds that the relative supply of communication versus manual tasks among natives rises in response to increased immigration. We believe that this is likely due to a form of occupational upgrading. One potential alternative, however, is that immigration has simply displaced native workers in physically intensive jobs, leaving only those in language intensive ones. That is, immigrants may have had a negative employment effect on native workers.

Most regional analyses find that immigration generates little to no native employment effect. In a recent note (Peri and Sparber (2008a)), we argue that to obtain an unbiased estimate of the potential displacement effect across states (or any geographical unit), one should perform 2SLS estimation of Equation (21).

$$\left( \frac{\Delta L_D}{L_D + L_F} \right)_{st} = \tau_t + \eta \left( \frac{\Delta L_F}{L_D + L_F} \right)_{st} + \varepsilon_{st} \quad (21)$$

This model regresses the inter-Census change in native employment ( $\Delta L_D$ ) on the change in foreign-born employment ( $\Delta L_F$ ). Effective instruments should avoid “booming region” effects

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<sup>34</sup>We believe that the impact of immigration on sub-groups of American workers – and blacks in particular – is worthy of further analysis. Borjas, Grogger and Hanson (2006) presents an alternative analysis of the effect of immigrants on black workers.

(which would induce positive correlation due to unobserved positive regional shocks). The parameter  $\eta$  then identifies the effect of immigration on native employment. A significantly negative value implies displacement. Using our 1960-2000 state data we estimate a non-significant positive value of  $\eta$  equal to 0.36 (standard error of 0.40) using WLS, and a non-significant positive value of 0.31 (with a standard error of 0.50) using 2SLS and all the instruments from Section 4.1.2.

Several previous studies that use specifications akin to (21) also tend to find zero or small positive effects. Cortes (2008) uses a variant of (21) in levels to analyze the link between immigration and employment of less educated workers across 25 US metropolitan areas between 1980 and 2000. She finds a positive OLS estimate around 0.20 and an IV value near 0.05. Card (2001), who uses population growth in a city-skill group cell as the dependent variable and the inflow rate of immigrants in the same cell as the explanatory variable, always finds positive and sometimes significant effects on the native population (around 0.10). His subsequent IV estimates (using the shift-share instrument to impute the number of immigrants in a cell) often find results similar to those of his OLS regressions. Ottaviano and Peri (2007) aggregate individuals from all skill levels within a state and estimate an impact of immigration on native employment between -0.3 and 0.3 that is never significant (standard errors around 0.3). Card and Lewis (2007) estimate the effect of low skilled Mexican immigrants on native employment. Their Table 6 results find an effect between 0 and 0.5 that is rarely significant. Card's (2007) Specification (2) adopts the total (immigrant and native) change in the less educated population (or employment) as the dependent variable. His estimated coefficient implies a value of  $\eta$  slightly larger than zero.

In sum, previous analyses of immigration have uncovered a puzzling result – immigration simultaneously generates only small wage effects and no employment effects for natives. We believe our article provides an explanation. Native workers adjust through occupation upgrading and task specialization, thereby decreasing their vulnerability to immigration.

## 4.2 Immigration and Total Task Supply

The regression specification in (13) provides a test of the equilibrium condition in (11), which argues for a negative relationship between immigration and aggregate relative supply of communication versus manual tasks in a state. If true, the parameter  $\gamma_{TOT}$  will be negative. (This is the mechanism that alters the relative compensation of tasks and then changes the relative supply among natives as shown above). We can also test, however, whether immigration affects the average amount of communication ( $c$ ) and manual ( $m$ ) tasks supplied in equilibrium by running two separate regressions with  $\ln(c)_{st}$  and  $\ln(m)_{st}$  as dependent variables. Analogous to the specifications in (19) and (20), we call these coefficients  $\gamma_{TOT}^C$  and  $\gamma_{TOT}^M$ . We obtain  $(\frac{C}{M})_{st}$  by aggregating the supply of physical and language skills using the individual supply of tasks among natives and

immigrants.<sup>35</sup>

The first three rows of Table 10 show the parameter estimates of  $\gamma_{TOT}$ ,  $\gamma_{TOT}^C$ , and  $\gamma_{TOT}^M$ . The last three rows show the F-test of significance for the instruments in the first stage and the test of over-identifying restrictions. Manual and communication tasks are measured using varied sets of *O\*NET* variables, with the basic definitions represented in columns 1 and 2. Each WLS (odd columns) and 2SLS (even columns) regression exhibits negative estimates of  $\gamma_{TOT}$ , and they are significant in the majority of the cases. The weaker and less significant estimates, moreover, are those obtained when using the extended and less precise definitions of skills. This confirms the prediction of our model. The point estimate of our preferred specification (column 2) in which the basic skill definitions are applied and all instruments are used implies that a one percentage-point rise in the foreign-born share increases the average supply of manual tasks in the state by 0.05% and decreases the average supply of communication tasks by 0.10%.

### 4.3 Immigration and the Rate of Return to Task Performance

The regression specification in Equation (14) tests the last important condition of our model – obtained from the relative demand for skills – which argues that by increasing the relative supply of skills in a state, immigration reduces their relative rate of return. In this section, we estimate the relative compensation response to a state’s changing task composition. Exogenous shifts in the overall relative supply of physical versus language skills across states identify the coefficient  $\frac{1}{\theta_L}$ , where  $\theta_L$  represents the elasticity of substitution between the tasks. Since exogenous immigration changes will affect the aggregate relative supply of skills, we employ the foreign-born share of workers and its exogenous determinants as instruments in 2SLS specifications.

We acquire estimates for returns paid to communication ( $\widehat{w}_{Mst}$ ) and manual ( $\widehat{w}_{Cst}$ ) tasks by state and year according to the methodology in Section 3.1.3 and then substitute those values into Equation (14) to estimate  $-\frac{1}{\theta_L}$ . Table 11 reports the results as well as their implied elasticity of substitution ( $\theta_L$ ) found using the basic (columns 1 to 4) and extended (columns 5 to 8) task variable definitions. We estimate (14) first by weighted least squares and then with the imputed Mexicans and geographic variables as instruments. The instruments are relatively powerful when used together (F-statistic above 10). The WLS estimates of  $-\frac{1}{\theta_L}$  are around -0.7, while the 2SLS estimates range between -1.4 and -1.5. Each is statistically significant at the 1% level.

Altogether, the 2SLS estimates imply that the share of foreign-born workers significantly increases the relative compensation paid to communication versus manual tasks, thus validating a key mechanism in our model. The 2SLS results in Table 11 suggest that the elasticity of substitution ( $\theta_L$ ) ranges between 0.63 (2SLS estimates) and 1.42 (WLS estimates). Manual and

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<sup>35</sup>We perform separate first-stage regressions for foreign-born workers to calculate skill supplies cleaned of demographic effects similar to the process used for native skill supply discussed in Section 3.1.2.

communication tasks have a significant degree of complementarity. These figures are comparable to commonly estimated values for the elasticity of substitution between labor and capital (usually near 1), or between workers of different education levels ( $\sigma$ , which fall between 1.5 and 2).<sup>36</sup>

## 5 Simulated Effects of Immigration on Real Wages, 1990-2000

Our empirical analysis suggests that to understand the wage implications of immigration, simulations must account for the adjustment in native-born task supply. Hence we can use our model, production parameters (particularly  $\sigma$  and  $\theta_L$ ), and the estimated effect of immigration on native-born task supply to recover the full impact of immigration (at all education levels) on the average wage of natives across US states.

Since the equilibrium prices of factors and intermediate goods are equal to their marginal productivity from (1) and (2), we can derive the change in wages paid to highly-educated workers ( $w_H$ ) in response to immigration (among both high and low education workers) as expressed in Equation (22), where  $\varkappa_H = \left(\frac{w_H H}{Y}\right)$  is the income share paid to highly-educated labor and  $(1 - \varkappa_H)$  is the share paid to less educated labor.

$$\frac{\Delta w_H}{w_H} = \frac{\Delta P_H}{P_H} = -\frac{1}{\sigma} \frac{\Delta H}{H} + \frac{1}{\sigma} \left( \varkappa_H \frac{\Delta H}{H} + (1 - \varkappa_H) \frac{\Delta Y_L}{Y_L} \right) \quad (22)$$

To obtain the effect of immigration on wages paid to less educated natives, however, we must consider two channels. First, we need to obtain values for the percentage change in compensation to manual  $\left(\frac{\Delta w_M}{w_M}\right)$  and communication  $\left(\frac{\Delta w_C}{w_C}\right)$  tasks and then weight those changes by the initial (pre-immigration) average task supply of natives ( $m_D$  and  $c_D$ ).<sup>37</sup> Second, we need to account for the change in the effective supply of natives' manual and communication tasks due to immigration ( $\Delta m_D$  and  $\Delta c_D$ ). The wage impact of this reallocation of tasks equals  $(\Delta m_D) w_M + (\Delta c_D) w_C$ . Altogether, Equation (23) expresses the net effects of total immigration on average wages paid to native-born workers with little educational attainment, highlighting the contribution from these two channels.

$$\frac{\Delta w_D}{w_D} = \underbrace{\frac{\Delta w_M}{w_M} \frac{w_M}{w_D} m_D + \frac{\Delta w_C}{w_C} \frac{w_C}{w_D} c_D}_{\text{First Channel}} + \underbrace{(\Delta m_D) \frac{w_M}{w_D} + (\Delta c_D) \frac{w_C}{w_D}}_{\text{Second Channel}} \quad (23)$$

Importantly, there are two reasons why this model predicts a mitigated wage effect (that may

<sup>36</sup>See Katz and Murphy (1992) or Angrist (1995).

<sup>37</sup>Equations (27) and (28) in the Appendix A report the derived expressions for  $\frac{\Delta w_M}{w_M}$  and  $\frac{\Delta w_C}{w_C}$ . The expressions are affected by inflows of both high and low education labor.

even be positive) when compared to models that assume perfect substitution between natives and immigrants within education groups. First, while the impact on manual compensation  $\left(\frac{\Delta w_M}{w_M}\right)$  due to the increased supply of manual skills from immigrants is negative and larger in absolute value than the impact on  $\frac{\Delta w_C}{w_C}$  (which may be positive for complementarity reasons), it is weighted by the relative task supply of natives. This weight is smaller than the relative supply of the average individual, because the average includes foreign-born workers. Hence, the negative contribution from that term (labeled as “First Channel” in Equation (23)) is smaller for less educated natives than it is for the average less educated worker. Second, the (theoretically and empirically) predicted reallocation of tasks implies that  $\Delta m_D < 0$  and  $\Delta c_D > 0$  so that if the communication task supply response is larger than that of manual tasks, and if  $\frac{w_M}{w_D} < \frac{w_C}{w_D}$  (both conditions are theoretically and empirically true), then the term labeled “Second Channel” in Expression (23) would positively contribute to the average wage paid to domestic less educated workers.

Altogether, Equations (22) and (23) report the wage consequences of immigration on highly-educated and less educated workers after accounting for the effects incurred both within and across education groups. In the next section, we use our model and estimates to simulate the change in wages caused by observed US immigration flows (at all education levels) between 1990 and 2000. First we estimate the effects for highly-educated workers (from Equation (22)). Next we calculate the change in the rate of return to manual and communication tasks (from Equations (27) and (28) in the Appendix), and then combine those results with the estimates of  $\Delta m_D$  and  $\Delta c_D$  in Equation (23) to find the overall effect of immigration on average wages paid to less educated natives.

## 5.1 Effect on the Average less educated US-Born Worker

Table 12 reports the simulated effects of immigrant flows between 1990 and 2000 at the national level (last row) and for the ten states with the highest immigrant share of less educated labor in 2000 (listed alphabetically). The first two columns report the increase in foreign-born employment (as a percentage of 1990 total group employment) among workers with some college education  $\left(\frac{\Delta H_E}{H}\right)$  and those with a high school degree or less  $\left(\frac{\Delta L_E}{L}\right)$ , respectively. Notice that less educated immigration grew more rapidly than more-educated immigration did for all but two reported states (New Jersey and Florida). For Arizona and Texas, growth among less educated foreign workers was more than three times greater than that of their more-educated counterparts. Except for those states, however, immigrant growth disparities were not large. Flows were fairly balanced at the US level, as immigrants increased employment of more-educated workers by 6% and less educated workers by 9%.

Columns (3) through (5) of Table 12 obtain the simulated percentage change in wages paid to highly-educated workers  $\left(\frac{\Delta w_H}{w_H}\right)$ , manual skills  $\left(\frac{\Delta w_M}{w_M}\right)$ , and communication skills  $\left(\frac{\Delta w_C}{w_C}\right)$  caused by

immigration. We assume a value of  $\sigma = 1.75$  that is in the middle of the range of estimates usually found in the literature (1.5–2.0),<sup>38</sup> and we set  $\theta_L = 1$ , a value close to the average of our estimates in Table 11. Since the inflow of highly-educated immigrants was usually smaller than the inflow of less educated ones, the simulated wage effect on people with college experience is usually positive (a gain of 0.6% at the national level). The change in returns to communication versus manual tasks caused by immigration is clearly more important for understanding the effects of immigration on less educated workers. In California, for instance, the compensation to communication skills performed by less educated workers increased by 0.3%, while the compensation paid for manual skills decreased by 8.4%. In Arizona, the return to communication tasks decreased by only 1%, while the wage paid for manual tasks decreased by a whopping 14.2%. Nationally, the return to communication skills increased 1.2%, while the manual return decreased by 2.8%.

The final three columns of Table 12 highlight the ultimate wage consequences of immigration for less educated native-born workers. Column (6) reports the effect on average wages before accounting for any shift in domestic task supply or for differences in the relative supply of tasks. That is, these figures are useful for identifying the counter-factual wage effects identified by models that assume perfect substitutability between native and foreign-born workers of similar educational attainment.<sup>39</sup> Column (8), by comparison, reports the wage effects for less educated natives accounting for the reallocation of tasks following immigration according to Equation (23).<sup>40</sup> Column (7) provides the difference between these values. Thus, this column illustrates the difference between the wage effects estimated in our model of comparative advantage versus a traditional model of homogeneous labor.

By specializing in language skill-intensive occupations, less educated natives reduce wage losses due to immigration. At the national level, specialization causes a reduction in this loss of almost one percentage-point, from an already low value of -1.2% to an ultimate loss of just -0.3%. In states with large immigrant flows (such as California, Arizona, and Nevada), task reallocation reduces the wage loss by around 2.4 percentage-points. Specialization changes the effect of immigration on less educated natives from negative to positive values in two of our reported states.

State-level averages still conceal a large degree of variation in wage effects across occupations. Columns (4) and (5) illustrate that immigration is more likely to harm workers who did not move from physical to language-intensive jobs. For instance, less educated Texas workers in

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<sup>38</sup>See Katz and Murphy (1992), Johnson (1997), and Goldin and Katz (2007).

<sup>39</sup>Note that before accounting for the specialization adjustment, immigration would have caused a wage loss of 1.2% for less-educated workers. As emphasized repeatedly in Ottaviano and Peri (2008), this relatively moderate consequence is due to the roughly balanced flow of immigrants across education groups (after merging the highly substitutable workers with no degree and those with a high school diploma together).

<sup>40</sup>We compute the values of  $\Delta c_D$  and  $\Delta m_D$  by multiplying the change in the foreign-born share of each state between 1990 and 2000 by the average response of communication and manual task supply to immigration found in Column (6) of Table 5 (respectively +0.33 and -0.00). The resulting values are elasticities that, when multiplied by the initial average values of task supply, equal  $\Delta c_D$  and  $\Delta m_D$ .

occupations requiring only manual skills would have lost 8.8% of their wage, while workers in jobs only demanding language skills would have experienced no wage change. This demonstrates that less educated natives who have been able to protect themselves from the negative wage effects of immigration are primarily those who have chosen jobs with higher communication requirements relative to manual requirements, and additionally are those who, due to immigration, were pushed to seek these occupations at higher rates.

## 5.2 Implied Native-Immigrants Elasticity

Though we have emphasized the native-born wage effects of immigration, the figures in column (6) of Table 12 represent the wage consequence for *any* less educated worker who possess skills that are perfectly substitutable with immigrants and who fails to respond to new labor flows by changing occupations. Thus, column (6) also illustrates the change in wages paid to previously established immigrant workers caused by new immigration. By extension, Column (7) can then be interpreted as the percentage change in the relative wage between less educated natives and foreign-born workers. If we divide those values by the percentage change in relative hours worked ( $L_F/L_D$ ), we can obtain the inverse elasticity of substitution between immigrant and native workers implied by our model. This provides a useful benchmark to compare with direct measures of this elasticity, such as those recently provided by Ottaviano and Peri (2008).

The logarithmic (percentage) change in  $L_F/L_D$  across the states listed in Table 12 ranges between 0.33 (33%) in Hawaii and 0.94 (94%) in Arizona, with several values above 0.60 (Texas, the District of Columbia, Illinois, and Nevada). On average, hours worked by less educated immigrants relative to less educated natives increased by 0.60 (60%). The resulting inverse elasticity of substitution between natives and immigrants ranges between 0.021 and 0.051 with an average of 0.03, thus implying an elasticity between 20 and 47 with an average of 33.

Our values are similar to those estimated by Ottaviano and Peri (2008). In particular, their preferred specifications (pooling men and women) report values between 0.024 and 0.047 (significant at the 1% level). Hence, the mechanism illustrated in this paper can explain most of their estimated imperfect substitutability. On the surface, an average inverse elasticity of 0.03 looks small. Given that relative supply has changed by as much as 60 to 90%, however, our estimates suggest a 2 to 3% change in the relative native-immigrant wage that favors natives. This relative effect is large enough to nearly eliminate the potential wage loss among natives, and it implies that less educated foreign-born workers are the ones who experience most of the negative wage consequences of new immigration.



## 6 Conclusions

The effects of immigration on the wages paid to native-born workers with low levels of educational attainment depend upon two critical factors. The first is whether immigrants take jobs similar to those of native workers or instead take different jobs due to inherent comparative advantages between native and foreign-born employees in performing particular productive tasks. The second is whether US-born workers respond to immigration and adjust their occupation choices in order to shield themselves from competition with immigrant labor.

This paper provides a simple theoretical framework and new empirical evidence to analyze these issues. We argue that production combines different labor skills. Immigrants with little educational attainment have a comparative advantage in manual and physical tasks, while natives of similar levels of education have a comparative advantage in communication and language-intensive tasks. Native and foreign-born workers specialize accordingly. When immigration generates large increases in manual task supply, the relative compensation paid to communication skills rises, thereby rewarding natives who progressively move to language-intensive jobs.

Our empirical analysis used *O\*NET* data to measure the task content of occupations in the United States between 1960 and 2000. We find strong evidence supporting the implications of our theoretical model. On average, less educated immigrants supplied more manual relative to communication tasks than natives supplied. In states with large immigrant flows among the less educated labor force, native workers shifted to occupations more intensive in language skills and less intensive in physical ones. However, the total relative supply of communication versus manual tasks is lower in states with high levels of immigration. This implies that immigrants more than compensate for the change in skill supply among natives, and it ensures that manual task-intensive occupations earn lower wages in those states.

Since native-born workers respond to inflows of immigrant labor by specializing in occupations demanding language skills, the relative supply of communication tasks by the average US-born worker has increased significantly in recent decades. As a consequence, immigration-induced wage losses among less educated native workers are significantly smaller than the losses predicted by models in which less educated native and foreign-born labor is perfectly substitutable. In particular, we estimate that immigration only reduced average real wages paid to less educated US-born workers by 0.3% between 1990 and 2000. Without task specialization that loss would have been 1.2%.

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## A Derivation of $\frac{\Delta w_M}{w_M}$ , $\frac{\Delta w_C}{w_C}$ , and $\frac{\Delta Y_L}{Y_L}$

To isolate the effect of immigration on wages, first substitute (2) into the production function (1) and take the derivative with respect to the inputs  $M$ ,  $C$ , and  $H$  to obtain their marginal products.

$$w_M = (\beta_L \beta) Y^{\frac{1}{\sigma}} Y_L^{\left(\frac{1}{\theta_L} - \frac{1}{\sigma}\right)} M^{-\frac{1}{\theta_L}} \quad (24)$$

$$w_C = (1 - \beta_L) \beta Y^{\frac{1}{\sigma}} Y_L^{\left(\frac{1}{\theta_L} - \frac{1}{\sigma}\right)} C^{-\frac{1}{\theta_L}} \quad (25)$$

$$w_H = P_H = (1 - \beta) Y^{\frac{1}{\sigma}} Y_H^{-\frac{1}{\sigma}} \quad (26)$$

Highly-educated workers earn the unit price of the intermediate good they produce. The logarithmic differential of (26) directly measures immigration's effect on highly-educated workers as expressed in (22).

Wages paid to less educated workers are divided into their task components. The first order effect of immigration is equal to the percentage change in the intermediate good price  $P_L$ . Values for  $\left(\frac{\Delta w_M}{w_M}\right)$  and  $\left(\frac{\Delta w_C}{w_C}\right)$  in Equations (27) and (28) are obtainable from logarithmic differentials of (24) and (25).

$$\frac{\Delta w_M}{w_M} = \frac{1}{\sigma} \left( \varkappa_H \frac{\Delta H}{H} + (1 - \varkappa_H) \frac{\Delta Y_L}{Y_L} \right) + \left( \frac{1}{\theta_L} - \frac{1}{\sigma} \right) \frac{\Delta Y_L}{Y_L} - \frac{1}{\theta_L} \frac{\Delta M}{M} \quad (27)$$

$$\frac{\Delta w_C}{w_C} = \frac{1}{\sigma} \left( \varkappa_H \frac{\Delta H}{H} + (1 - \varkappa_H) \frac{\Delta Y_L}{Y_L} \right) + \left( \frac{1}{\theta_L} - \frac{1}{\sigma} \right) \frac{\Delta Y_L}{Y_L} - \frac{1}{\theta_L} \frac{\Delta C}{C} \quad (28)$$

Using Equations (27) and (28) we can express the wage effect for less educated workers at constant specialization by substituting for  $\frac{\Delta w_M}{w_M}$  and  $\frac{\Delta w_C}{w_C}$  and simplifying to obtain Equation (29).<sup>41</sup>

$$\frac{\Delta w_L}{w_L} = \frac{\Delta w_M}{w_M} \frac{w_M}{w_L} m + \frac{\Delta w_C}{w_C} \frac{w_C}{w_L} c = \varkappa_M \frac{\Delta w_M}{w_M} + (1 - \varkappa_M) \frac{\Delta w_C}{w_C} \quad (29)$$

Note that (29) represents the average manual and communication wage effects weighted by their respective initial supplies. The total effect of immigration on the average, native-born, less educated worker accounting for (29) as well as for the effect of changing specialization is given by Equation (23) in the main text.

To derive  $\frac{\Delta Y_L}{Y_L}$ , first note that since  $Y_L$  is produced under perfect competition using services of less educated workers, we know the total income generated in sector  $Y_L$  will be distributed to less

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<sup>41</sup>This can be checked by taking the total logarithmic differential of  $P_L = \beta Y^{\frac{1}{\sigma}} Y_L^{-\frac{1}{\sigma}}$  with respect to  $\frac{\Delta Y_L}{Y_L}$  and  $\frac{\Delta H}{H}$ .

educated workers as in Equation (30).

$$P_L Y_L = w_L L = w_M M + w_C C \quad (30)$$

This allows us to relate changes in the production of  $Y_L$  to small changes in inputs  $M$  and  $C$  as in Equation (34). The formal proof hinges only on constant returns to scale to  $M$  and  $C$  in (2). First, re-write Equation (34) by dividing by  $P_L Y_L$ . Then take the total differential with respect to  $M$  and  $C$  to find Equation (31).

$$\frac{dY_L}{Y_L} = \frac{d\left(\frac{w_M M}{P_L Y_L} + \frac{w_C C}{P_L Y_L}\right)}{dM} dM + \frac{d\left(\frac{w_M M}{P_L Y_L} + \frac{w_C C}{P_L Y_L}\right)}{dC} dC \quad (31)$$

From the definition of wages we know that  $\frac{w_M}{P_L} = \frac{dY_L}{dM}$  and  $\frac{w_C}{P_L} = \frac{dY_L}{dC}$ . Distributing the differentiation with respect to  $M$  and  $C$  we can re-write (31) as in (32).

$$\frac{dY_L}{Y_L} = \frac{w_M M}{P_L Y_L} \frac{dM}{M} + \frac{w_C C}{P_L Y_L} \frac{dC}{C} + \left[ \frac{d\left(\frac{dY_L}{dM}\right)}{dM} \frac{M}{Y_L} + \frac{d\left(\frac{dY_L}{dC}\right)}{dM} \frac{C}{Y_L} \right] dM + \left[ \frac{d\left(\frac{dY_L}{dM}\right)}{dC} \frac{M}{Y_L} + \frac{d\left(\frac{dY_L}{dC}\right)}{dC} \frac{C}{Y_L} \right] dC \quad (32)$$

Due to constant returns to scale of  $M$  and  $C$  in  $Y_L$ , the expression  $\frac{dY_L}{dM} \frac{M}{Y_L} + \frac{dY_L}{dC} \frac{C}{Y_L}$  equals one (Euler Condition). Constant returns also imply that the second derivatives (with respect to  $M$  or  $C$ ), multiplied by the shares  $\frac{M}{Y_L}$  and  $\frac{C}{Y_L}$ , sum to zero. Hence the two terms in brackets equal zero so that (31) reduces to (33).

$$\frac{dY_L}{Y_L} = \frac{w_M M}{P_L Y_L} \frac{dM}{M} + \frac{w_C C}{P_L Y_L} \frac{dC}{C} \quad (33)$$

Finally, we label the term  $\frac{w_M M}{P_L Y_L} = \frac{w_M M}{w_L L}$  as  $\varkappa_M$ , and  $\frac{w_C C}{P_L Y_L} = \frac{w_C C}{w_L L}$  as  $(1 - \varkappa_M)$ . We then use  $\Delta$ , rather than  $d$ , to indicate a small (rather than an infinitesimal) changes to obtain equation (34)

$$\frac{\Delta Y_L}{Y_L} = \frac{w_M \Delta M + w_C \Delta C}{P_L Y_L} = \varkappa_M \frac{\Delta M}{M} + (1 - \varkappa_M) \frac{\Delta C}{C} \quad (34)$$

## Tables and Figures

**Table 1**  
**Skill Types, Sub-Types, and Variables from *O\*NET***

Type of Skill	Definition	Skill Sub-Type	<i>O*NET</i> Variables
<b>Manual (or Physical) Skills</b>	<b>Basic Definition:</b> Movement and Strength	Limb, Hand, and Finger Dexterity	Arm-Hand Steadiness; Manual Dexterity; Finger Dexterity; Control Precision; Multilimb Coordination; Response Orientation; Rate Control; Reaction Time; Wrist-Finger Speed; Speed of Limb Movement
		Body Coordination and Flexibility Strength	Extent Flexibility; Dynamic Flexibility; Gross Body Coordination; Gross Body Equilibrium Static Strength; Explosive Strength; Dynamic Strength; Trunk Strength; Stamina
	<b>Extended Definition:</b> Movement and Strength plus Sensory-Perception Skills	General Perception	Perceptual Speed; Spatial Orientation; Visualization; Selective Attention; Time Sharing
		Visual Perception	Near Vision; Far Vision; Visual Color Discrimination; Night Vision; Peripheral Vision; Depth Perception; Glare Sensitivity
		Hearing Perception	Hearing Sensitivity; Auditory Attention; Sound Localization
<b>Communication (or Language) Skills</b>	<b>Basic Definition:</b> Oral and Written	Oral	Oral Comprehension; Oral Expression
		Written	Written Comprehension; Written Expression
	<b>Extended Definition:</b> Oral and Written plus Cognitive, Analytical, and Vocal Skills	Cognitive and Analytical	Fluency of Ideas; Originality; Problem Sensitivity; Category Flexibility; Mathematical Reasoning; Number Facility; Deductive Reasoning; Inductive Reasoning; Information Ordering; Memorization; Speed of Closure; Flexibility of Closure
		Vocal	Speech Recognition; Speech Clarity

**Note:** *O\*NET* variables are from the *O\*NET* abilities survey available at <http://www.onetcenter.org/>.



**Table 2**  
**Relative Communication/Manual Task Content (Basic Definition) of Representative Occupations**

<b>Occupation</b>	<b>Manual Intensity Index</b>	<b>Communication Intensity Index</b>	<b>c/m Percentile in 2000</b>	<b>Immigrant Share of Occupation, 2000</b>
Financial managers	0.227	0.833	1.00	0.09
Managers and administrators, n.e.c.	0.345	0.686	0.90	0.10
Managers of food-serving and lodging establishment	0.648	0.790	0.80	0.25
Police, detectives, and private investigators	0.794	0.709	0.70	0.04
Retail sales clerks	0.512	0.298	0.60	0.13
Hairdressers and cosmetologists	0.620	0.296	0.50	0.23
Truck, delivery, and tractor drivers	0.877	0.288	0.40	0.12
Carpenters	0.928	0.250	0.31	0.19
Assemblers of electrical equipment	0.677	0.114	0.21	0.23
Textile sewing machine operators	0.731	0.085	0.10	0.45
Drywall installers	0.657	0.003	0.00	0.30

**Note:** Authors' calculations are based upon *O\*NET* task definitions and the 2000 Census. The occupations included in this table are those at each decile of the 2000 distribution when workers are ranked according to their communication versus manual task intensity. The basic manual index represents the average intensity of 19 measures of several physical abilities (listed in Table 1). The basic communication task index represents the average of four measures that capture oral and written expression and comprehension (also listed in Table 1). Both are standardized to be between 0 and 1. The details of their construction are reported in the main text.

**Table 3**  
**Occupations, Relative Task Intensity, and the Foreign-Born Share of Less-Educated Employment**

Occupation	Communication Intensity Index	Manual Intensity Index	C/M Percentile	Change in Foreign-Born Share of Less-Educated Employment 1970-2000
<b>Four Occupations with Highest Communication/Manual Values</b>				
Financial managers	0.83	0.23	0.999	+5.7%
Managers of properties and real estate	0.74	0.21	0.997	+1.8%
Editors and reporters	0.87	0.27	0.991	+12.2%
Operations and systems researchers and analysts	0.64	0.20	0.990	+4.1%
<b>Four Occupations with Lowest Communication/Manual Values</b>				
Vehicle washers and equipment cleaners	0.72	0.72	0.021	+20.6%
Furniture and wood finishers	0.72	0.72	0.021	+13.4%
Roofers and slaters	0.64	0.64	0.020	+26.4%
Drywall installers	0.72	0.72	0.006	+24.2%

**Note:** Authors' calculations based upon *O\*NET* task definitions and Census 1970-2000. The occupations included are those with more than 25,000 employees in each year. Only less-educated wage-earning employees between 18 and 65 years old and not living in group quarters are considered. The basic manual index is constructed averaging 19 measures that capture the intensity of several physical abilities. The basic communication task index is constructed averaging four measures that capture oral and written expression and comprehension. Both are standardized to be between 0 and 1. The details of their construction are reported in the main text.

**Table 4**  
**Impact of Foreign-Born Workers on the Native Supply of Tasks, U.S. States 1960-2000; Least Squares Estimates**  
Workers with a High School Degree or Less, Controlling for Individual Characteristics in the Construction of Aggregate Skills

<i>Explanatory Variable: Foreign-Born Share of Workers with a High School Degree or Less</i>								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Communication Definition:</i>		<i>Basic</i>	<i>Oral</i>	<i>Written</i>	<i>Basic</i>	<i>Extended</i>	<i>Extended</i>	<i>Basic</i>
<i>Manual Definition:</i>		<i>Basic</i>	<i>Limb, Hand, Finger</i>	<i>Body</i>	<i>Strength</i>	<i>Extended</i>	<i>Basic</i>	<i>Extended</i>
Ln( $C_D/M_D$ )	$\gamma$	0.34** (0.05)	0.35** (0.05)	0.34** (0.05)	0.33** (0.05)	0.25** (0.03)	0.28** (0.04)	0.31** (0.04)
Ln( $c_D$ )	$\gamma^C$	0.31** (0.03)	0.31** (0.04)	0.31** (0.04)	0.31** (0.04)	0.25** (0.03)	0.25** (0.03)	0.31** (0.04)
Ln( $m_D$ )	$\gamma^M$	-0.03 (0.02)	-0.04 (0.03)	-0.03 (0.02)	-0.02 (0.02)	-0.00 (0.02)	-0.03 (0.02)	-0.00 (0.02)
Number of Observations		255	255	255	255	255	255	255

**Note:** Each cell contains estimates from a separate regression. The dependent variable in each is indicated in the first column. To construct the average manual  $m_D$  and communication  $c_D$  skill supply by native workers in a state-year, we first run individual regressions of a native's manual (or communication) tasks supply (in each Census year) on age, experience, gender, and race dummies, weighting each observation by hours worked. We then subtract the predicted supply from the observed value. The state average (hours-weighted) of this "cleaned" (residual) supply represents the values  $c_D$  and  $m_D$  after controlling for individual demographic characteristics, and  $C_D/M_D$  is their ratio. The explanatory variable is the immigrant share of less-educated labor hours worked in the state and year. The units of observation in each regression are U.S. states in a Census year (decennial panel of 50 states plus DC from 1960-2000). All regressions include state and year fixed effects. The method of estimation is weighted least squares. Regressions use employment as an analytic weight for each observation, and the standard errors are heteroskedasticity-robust and clustered by state.

\*\* indicates significance at the 1% level \* indicates significance at the 5% level

**Table 5**  
**Impact of Foreign-Born Workers on the Native Supply of Tasks, U.S. States 1960-2000; 2SLS Estimates**  
**Workers with a High School Degree or Less, Controlling for Individual Characteristics in the Construction of Aggregate Skills**

*Explanatory Variable: Foreign-Born Share of Workers with a High School Degree or Less*

		Imputed Mexican Share IVs		Proximity to Mexico IVs		All IVs Together	
		(1)	(2)	(3)	(4)	(5)	(6)
<i>Communication Definition:</i>		<i>Basic</i>	<i>Basic</i>	<i>Basic</i>	<i>Basic</i>	<i>Basic</i>	<i>Basic</i>
<i>Manual Definition:</i>		<i>Basic</i>	<i>Extended</i>	<i>Basic</i>	<i>Extended</i>	<i>Basic</i>	<i>Extended</i>
Ln( $C_D/M_D$ )	$\gamma$	0.36** (0.05)	0.32** (0.05)	0.38** (0.04)	0.33** (0.04)	0.37** (0.05)	0.33** (0.04)
Ln( $c_D$ )	$\gamma^C$	0.32** (0.04)	0.32** (0.04)	0.33** (0.04)	0.33** (0.04)	0.33** (0.05)	0.33** (0.04)
Ln( $m_D$ )	$\gamma^M$	-0.04 (0.03)	0.00 (0.03)	-0.04* (0.02)	-0.00 (0.02)	-0.04** (0.02)	-0.00 (0.02)
<b>First Stage</b>							
Joint F-Test of the Instruments (p-value)		8.02 (0.006)	8.02 (0.006)	21.07 (0.000)	21.07 (0.000)	18.90 (0.00)	18.90 (0.00)
Test of Over-Identifying Restrictions (Specification in First Row)		N.A.	N.A.	11.4	12.7	12.5	13.2
Probability ( $\chi^2 > \text{test}$ ) under the Null of Exogeneity of Instruments		N.A.	N.A.	0.13	0.09	0.14	0.11
Number of Observations		255	255	255	255	255	255

**Note:** Each cell contains estimates from separate regressions. The dependent variable in each is indicated in the first column. The average manual  $m_D$  and communication  $c_D$  skill supply by native workers in a state-year are cleaned in a first-stage regression as described in Table 4. The explanatory variable is the foreign-born share of less-educated labor. The units of observation in each regression are U.S. states in a Census year (decennial panel of 50 states plus DC from 1960-2000). All regressions include state and year fixed effects. The method of estimation is two stage least squares. Specifications (1)-(2) instrument using the imputed share of Mexicans constructed as described in the main text. Specifications (3)-(4) instrument using the distance between the center of gravity of the state and the Mexican border and an indicator for states on the Mexican border, all interacted with four decade dummies. Specifications (5) and (6) use all instrumental variables together. Regressions use employment as an analytic weight for each observation, and the standard errors are heteroskedasticity-robust and clustered by state.

\*\* indicates significance at the 1% level \* indicates significance at the 5% level

**Table 6**

**Impact of Foreign-Born Workers on the Native Supply of Tasks Controlling for Technology and Demand Factors, 2SLS Estimates with All Available Instruments**

<i>Dependent Variable: Relative Task Supply among Domestic Workers, <math>\ln(\text{Communication}_D / \text{Manual}_D)</math></i>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Communication Definition:</i>		<i>Basic</i>			<i>Basic</i>	
<i>Manual Definition:</i>		<i>Basic</i>			<i>Extended</i>	
<b>Explanatory Variables:</b>						
Foreign-Born Share of Less-Educated Employment	0.49** (0.04)	0.38** (0.04)	0.51** (0.04)	0.43** (0.04)	0.34** (0.04)	0.44** (0.04)
Percentage of Workers Using a Computer	0.61** (0.10)		0.62** (0.11)	0.52** (0.08)		0.52** (0.08)
Sector-Driven Communication/Manual Task Demand		0.33 (0.26)	0.33 (0.22)		0.22 (0.25)	0.23 (0.20)
<b>Decomposition of the Effect between Communication and Manual Tasks</b>						
Effect of Foreign-Born Share on $\ln(c_D)$	0.42** (0.04)	0.34** (0.04)	0.43** (0.04)	0.42** (0.04)	0.34** (0.04)	0.43** (0.04)
Effect of Foreign-Born Share on $\ln(m_D)$	-0.07** (0.03)	-0.04** (0.02)	-0.08** (0.03)	-0.01 (0.02)	0.00 (0.03)	-0.01 (0.04)
Number of Observations	255	255	255	255	255	255

**Note:** The top three rows report estimates of the impact of the foreign-born share, percentage of computer users, and industry-driven change in relative task intensity on the relative task supply of natives. The bottom two rows report the effect of immigration on the supply of communication and manual tasks separately. The units of observation in each regression are U.S. states in a Census year (decennial panel of 50 states plus DC from 1960-2000) for a total of 255 observations. All regressions include state and year fixed effects. The method of estimation is two stage least squares. Regressions use employment as an analytic weight for each observation, and the standard errors are heteroskedasticity-robust and clustered by state.

\*\* indicates significance at the 1% level

**Table 7**  
**Impact of Foreign-Born Workers on Long-Term Immigrants' Supply of Tasks**  
Workers with a High School Degree or Less, Controlling for Individual Characteristics in the Construction of Aggregate Skills

<i>Explanatory variable: Foreign-Born Share of Hours Worked among Workers with a High School Degree or Less</i>		(1)	(2)	(3)	(4)
		WLS	2SLS, Imputed Mexican Share IVs	2SLS, Geography IVs	2SLS All IVs
<b>Dependent Variable:</b>	<b>Parameter</b>				
Long-Term Immigrants'	$\gamma$	0.01	0.22	0.22	0.24
	Ln( $C_{LT}/M_{LT}$ )	(0.23)	(0.26)	(0.27)	(0.28)
Long-Term Immigrants'	$\gamma^C$	0.01	0.11	0.11	0.13
	Ln( $c_{LT}$ )	(0.16)	(0.18)	(0.18)	(0.18)
Long-Term Immigrants'	$\gamma^M$	0.01	-0.11	-0.12	-0.11
	Ln( $m_{LT}$ )	(0.07)	(0.10)	(0.11)	(0.10)
Joint F-Test of the Instruments (p-value)		NA	8.16	16.07	14.30
			(0.006)	(0.000)	(0.000)
Number of Observations		204	204	204	204

**Note:** Each cell contains estimates from separate regressions. The dependent variable in each regression is indicated in the first column. The average manual  $m_{LT}$  and communication  $c_{LT}$  skill supply by long-term immigrants in a state-year are calculated by averaging the basic definition of individual skill supply using personal weight times hours worked as weights. The explanatory variable is the foreign-born share of less-educated labor. The units of observation in each regression are U.S. states in a Census year (decennial panel of 50 states plus DC for the period 1970-2000). Year 1960 cannot be used as there is no information on the year of immigration. All regressions include state and year fixed effects.

\*\* indicates significance at the 1% level

**Table 8**  
**Impact of Foreign-Born Workers on the Task Supply of Highly Educated Native-Born Workers, Basic Skill Definitions**  
 Native Workers with Some College Education, Controlling for Individual Characteristics in the Construction of Aggregate Skills

	(1)	(2)	(3)	(4)
	WLS	2SLS, Imputed Mexican Share and Distance IVs	2SLS, Geography IVs	2SLS All IVs
<b>Dependent Variable</b>				
Highly educated Native Workers Ln(Communication/Cognitive)	0.01 (0.04)	0.01 (0.09)	-0.01 (0.07)	-0.01 (0.06)
Highly educated Native Workers Ln(Manual)	-0.24** (0.04)	-0.07 (0.20)	-0.09 (0.16)	-0.12 (0.12)
Joint F-Test of the Instruments (p-value)	na	8.16 (0.006)	16.07 (0.000)	14.30 (0.000)
Number of Observations	255	255	255	255

**Note:** Each cell reports the coefficient from a separate regression. The dependent variable in each regression is defined in the first column. The explanatory variable is the share of immigrants among workers with high school education or less. Each regression controls for the foreign-born share of workers with some college education or more (to avoid spurious correlations) and for state and year fixed effects. The units of observation are 50 U.S. states plus DC in each Census year, 1960-2000. The method of estimation is described in the column header. In each regression we weight observations by the employment in the cell and we report heteroskedasticity-robust standard errors.

\*\* indicates significance at the 1% level

**Table 9**

**Impact of Foreign-Born Workers on the Supply of Tasks among Different Demographic Groups of US-Born Workers  
Workers with a High School Degree or Less, Controlling for Individual Characteristics in the Construction of Aggregate Skills**

*Explanatory Variable: Foreign-Born Share among Workers with a High School Degree or Less*

*Dependent Variables: Basic Definitions of Communication and Manual Skills, Less-Educated Native Workers*

Dependent Variable:	Parameter	Group 1: Blacks Group2: Non-Blacks	Group 1: Women Group 2: Men	Group 1: Young (18-40) Group 2: Old (41-65)	Group 1: No Degree Group 2: High School Degree
<b>2SLS, All Instruments</b>					
Group 1, $Ln(C_D/M_D)$	$\gamma$	0.63** (0.11)	0.11** (0.05)	0.34*** (0.13)	0.34*** (0.07)
Group 1, $Ln(c_D)$	$\gamma^C$	0.50** (0.09)	0.10** (0.03)	0.25** (0.10)	0.28** (0.05)
Group 1, $Ln(m_D)$	$\gamma^M$	-0.13** (0.03)	-0.01 (0.03)	-0.09** (0.04)	-0.06* (0.03)
Group 2, $Ln(C_D/M_D)$	$\gamma$	0.20** (0.10)	0.26** (0.11)	0.11 (0.08)	0.20 (0.14)
Group 2, $Ln(c_D)$	$\gamma^C$	0.15* (0.08)	0.20** (0.10)	0.09 (0.07)	0.15 (0.10)
Group 2, $Ln(\bar{m}_D)$	$\gamma^M$	-0.05 (0.03)	-0.06** (0.02)	-0.02 (0.02)	0.05 (0.04)
Number of Observations		255	255	255	255

**Note:** Each cell contains estimates from separate regressions. The dependent variable is calculated for specific demographic groups. In each comparison, Group 1 earns lower wages than Group 2 does. The average manual  $\bar{c}_D$  and communication  $\bar{m}_D$  skill supply for each group in a state-year are calculated by averaging individual supply using personal weight times hours worked as weights. The units of observation in each regression are U.S. states in a Census year (decennial panel of 50 states plus DC from 1960-2000) for a total of 255 observations. All regressions include state and year fixed effects. The method of estimation is 2SLS using all instruments. Regressions use employment in the cell as an analytic weight for each observation, and the standard errors are heteroskedasticity-robust and clustered by state.

\*\* indicates significance at the 5% level



**Table 10**  
**Impact of Foreign-Born Workers on the Total Supply of Tasks**  
Workers with a High School Degree or Less, Controlling for Individual Characteristics in the Construction of Aggregate Skills

		<i>Explanatory Variable: Foreign-Born Share of Less-Educated Workers</i>							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		OLS	2SLS All Instruments	OLS	2SLS All Instruments	OLS	2SLS All Instruments	OLS	2SLS All Instruments
			<i>Basic</i>		<i>Extended</i>		<i>Extended</i>		<i>Basic</i>
			<i>Basic</i>		<i>Extended</i>		<i>Basic</i>		<i>Extended</i>
Dependent Variable:	Parameter								
All Less Educated Ln(C/M)	$\gamma_{TOT}$	-0.18** (0.04)	-0.15** (0.04)	-0.03 (0.026)	-0.03 (0.03)	-0.07* (0.04)	-0.06 (0.04)	-0.13** (0.03)	-0.11** (0.03)
All Less Educated Ln(c)	$\gamma^C_{TOT}$	-0.12** (0.03)	-0.10** (0.34)	-0.02 (0.029)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.12** (0.03)	-0.09** (0.03)
All Less Educated Ln(m)	$\gamma^M_{TOT}$	0.06** (0.02)	0.05** (0.02)	0.01 (0.015)	0.02 (0.02)	0.06** (0.02)	0.05** (0.02)	0.01 (0.015)	0.02 (0.02)
<b>First Stage</b>									
Joint F-Test of the Instruments (p-value)		NA	18.90*** (0.00)	NA	18.90*** (0.00)	NA	18.90*** (0.00)	NA	18.90*** (0.00)
Test of Over-Identifying Restrictions (Specification in First Row)		NA	9.7	NA	10.1	NA	10.5	NA	10.2
Probability ( $\chi^2 >$ test) under the Null of Exogeneity of Instruments		NA	0.29	NA	0.26	NA	0.24	NA	0.25
Number of Observations		255	255	255	255	255	255	255	255

**Note:** Each cell contains estimates from separate regressions. The dependent variable in each is indicated in the first column. The average manual and communication skill supply by native and immigrant workers in a state-year are cleaned in a first-stage regression that preserves the national average. They are then combined using hours worked by natives and immigrants as weight to produce total skill supply at the state-year level. The explanatory variable is the foreign-born share of less-educated labor. The units of observation in each regression are US states in a Census year (decennial panel of 50 states plus DC from 1960-2000). All regressions include state and year fixed effects. \*\* indicates significance at the 1% level \* indicates significance at the 5% level

**Table 11**  
**Estimates of the Relative Wage Elasticity of Communication versus Manual Tasks**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>OLS</i>	<i>Imputed Mexican Share IVs</i>	<i>Geography IVs</i>	<i>All IVs</i>	<i>OLS</i>	<i>Imputed Mexican Share IVs</i>	<i>Geography IVs</i>	<i>All IVs</i>
<i>Communication Definition:</i>			<i>Basic</i>				<i>Extended</i>	
<i>Manual Definition:</i>			<i>Basic</i>				<i>Extended</i>	
$-1/\theta_L$	-0.75* (0.37)	-1.40** (0.29)	-1.55** (0.26)	-1.58** (0.26)	-0.70* (0.39)	-1.46** (0.41)	-1.55** (0.32)	-1.56** (0.33)
<b>Implied Elasticity of Substitution</b>	<b>1.33</b>	<b>0.71</b>	<b>0.64</b>	<b>0.63</b>	<b>1.42</b>	<b>0.68</b>	<b>0.64</b>	<b>0.64</b>
F-test of Joint Significance of the Instruments	n.a.	2.7	14.5	11.4	n.a.	2.7	14.5	11.4
Observations	255	255	255	255	255	255	255	255

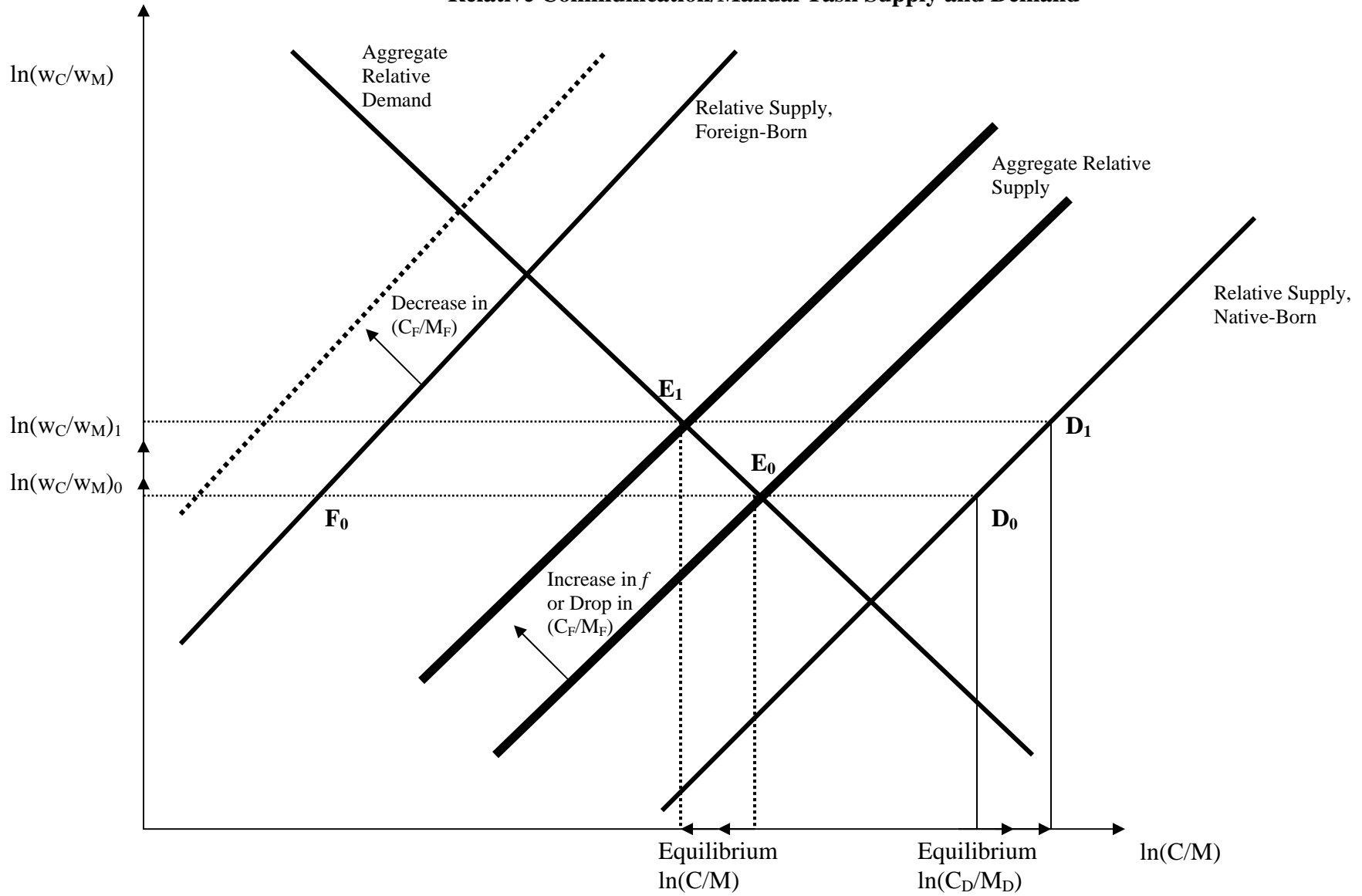
**Note:** The explanatory variable is the negative of the logarithm of the relative supply of communication versus manual tasks among all workers. In Specifications (1) to (4) we use the basic (more strict) definition of communication and manual tasks. In Specifications (5) through (8) we use the extended definitions of tasks. All regressions include state and year fixed effects. Regressions use employment as an analytic weight for each observation, and the standard errors are heteroskedasticity-robust and clustered by state. \*\* indicates significance at the 1%, \* indicates significance at 5%.

**Table 12**  
**The Simulated Effects of Immigration on Native Wages and Task Compensation, 1990-2000**

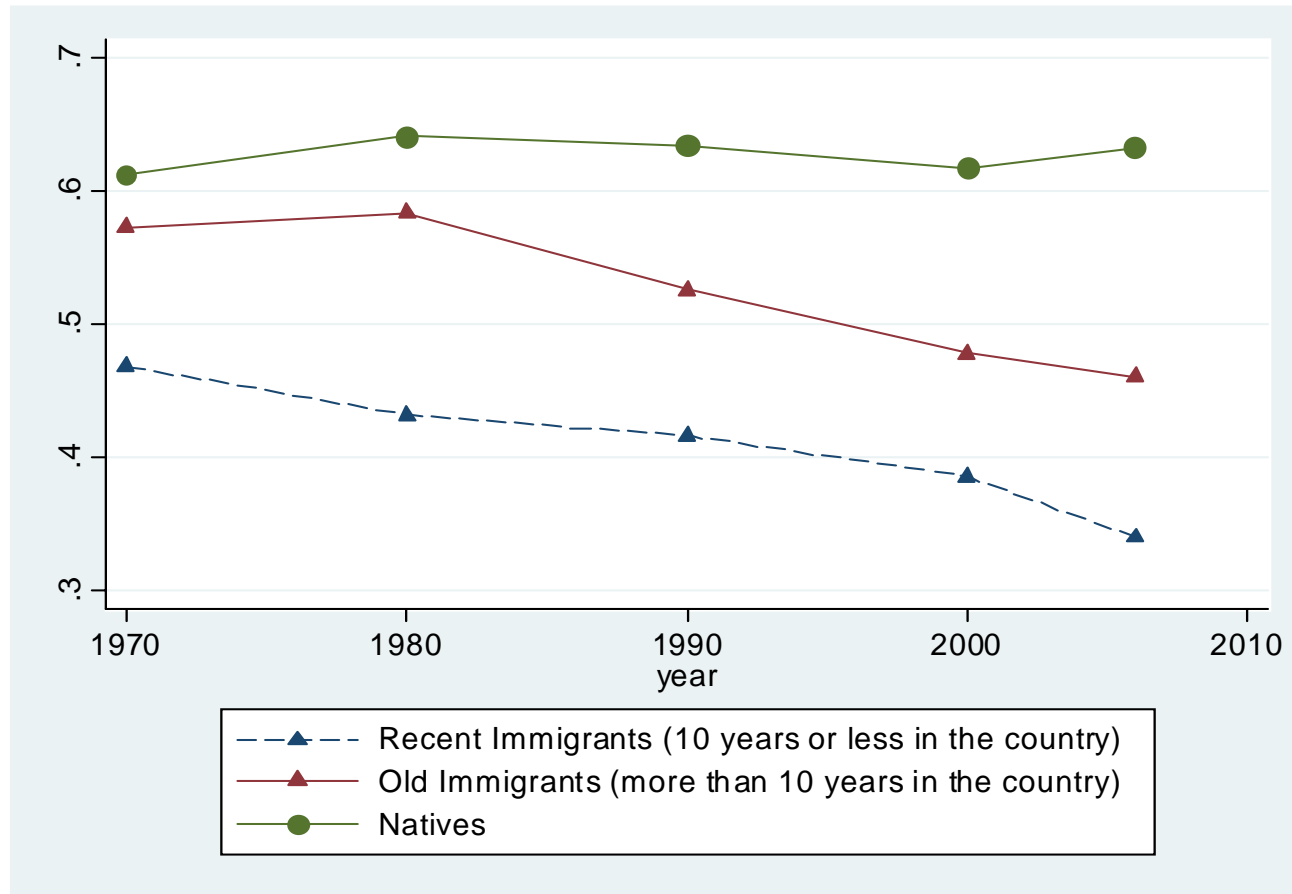
	(1) %Δ Highly- Educated due to Immigration	(2) %Δ Less- Educated due to Immigration	(3) %Δ in Wage Paid to Highly- Educated Workers	(4) %Δ in Manual Task Return	(5) %Δ in Communication Task Return	(6) %Δ in Wage of Less- Educated, Assuming Perfect Native- Immigrant Substitution	(7) %Δ in Wage of Less- Educated due to Task Complemen tarities and Specializati on	(8) %Δ Change in Wage Paid to Less- Educated Natives
Selected States								
<b>Arizona</b>	8%	29%	3.2%	-14.2%	-1.3%	-8.2%	<b>2.5%</b>	<b>-5.7%</b>
<b>California</b>	12%	24%	1.5%	-8.4%	0.3%	-4.5%	<b>2.3%</b>	<b>-2.2%</b>
<b>DC</b>	6%	10%	0.5%	-3.3%	-0.4%	-2.0%	<b>1.9%</b>	<b>-0.1%</b>
<b>Florida</b>	14%	14%	-0.1%	-2.3%	2.8%	0.2%	<b>1.2%</b>	<b>1.4%</b>
<b>Hawaii</b>	7%	8%	0.1%	-3.4%	4.9%	-0.3%	<b>0.9%</b>	<b>0.6%</b>
<b>Illinois</b>	7%	12%	0.8%	-3.5%	0.7%	-1.8%	<b>1.3%</b>	<b>-0.5%</b>
<b>Nevada</b>	16%	34%	3.5%	-12.0%	1.4%	-5.8%	<b>2.2%</b>	<b>-3.6%</b>
<b>New Jersey</b>	13%	10%	-0.6%	-0.4%	3.7%	1.6%	<b>1.3%</b>	<b>2.9%</b>
<b>New York</b>	10%	13%	0.3%	-2.5%	1.1%	-0.7%	<b>1.6%</b>	<b>0.9%</b>
<b>Texas</b>	8%	22%	2.1%	-8.8%	0.0%	-4.8%	<b>1.8%</b>	<b>-3.0%</b>
<b>United States</b>	6%	9%	0.6%	-2.8%	1.2%	-1.2%	<b>0.9%</b>	<b>-0.3%</b>

**Note:** The variables and parameters used in the simulations reported above are described in the text. In particular, we assumed  $\sigma=1.75$  and  $\theta_L=1$ . The ten states chosen are those with highest foreign-born employment shares among less-educated workers in 2000. The parameters used to estimate the change in supply of each task among native workers in response to immigration are the parameters in Column (6) of Table 5, namely  $\gamma^M=0.33$  and  $\gamma^C=-0.00$ .

**Figure 1**  
**Relative Communication/Manual Task Supply and Demand**

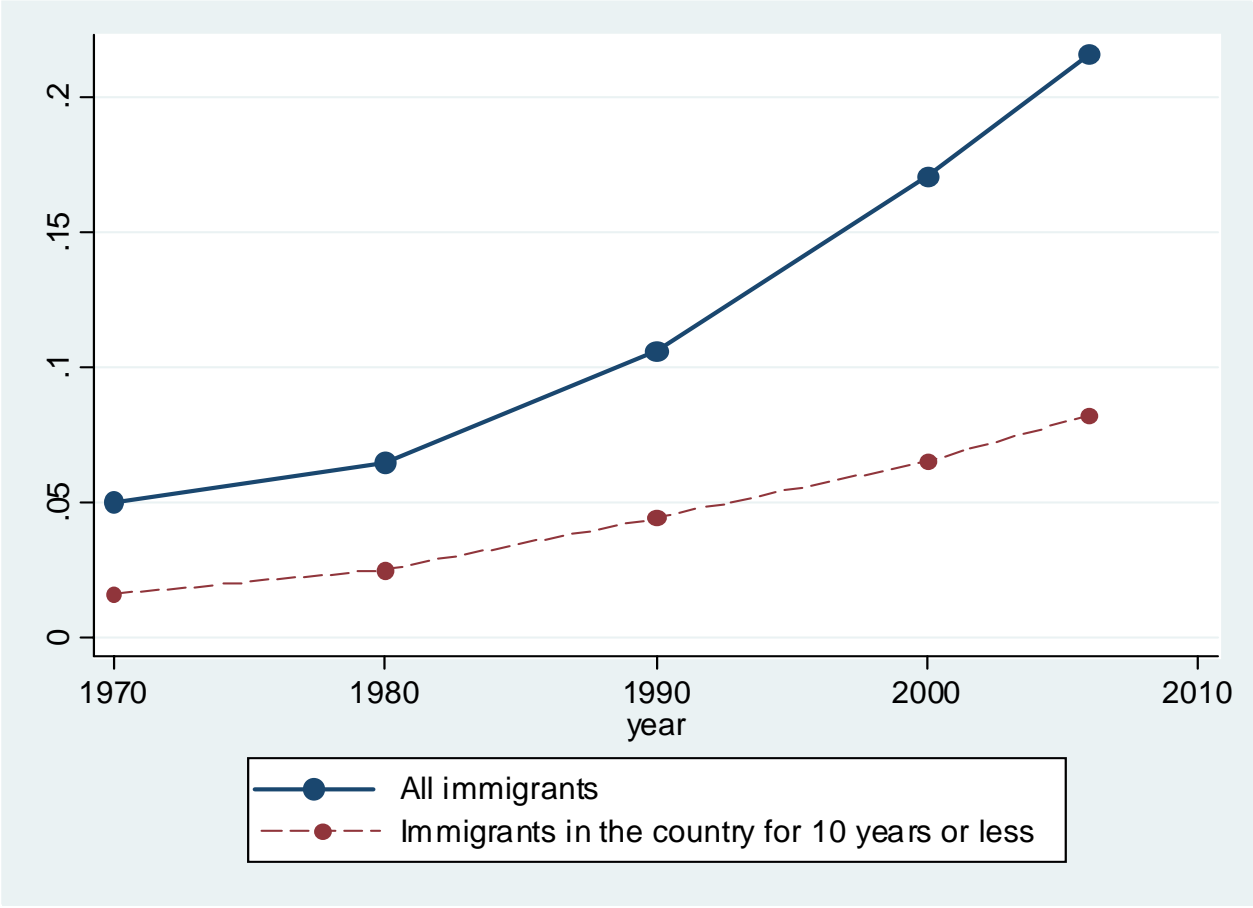


**Figure 2**  
**Communication/Manual Intensity of Natives, Recent Immigrants, and Long-Term Immigrants; US 1970-2000**  
 Workers with a High School Degree or Less Education



Note: The relative C/M supply for the US economy is constructed by aggregating individuals' supply of communication and manual skills, weighted by their hours worked. Natives are individuals with US citizenship at birth, recent immigrants are non-citizens or naturalized citizens who resided in the US for ten or fewer years, long-term immigrants are non-citizens or naturalized citizens who resided in the US for more than years. Source: Ruggles et al. (2005).

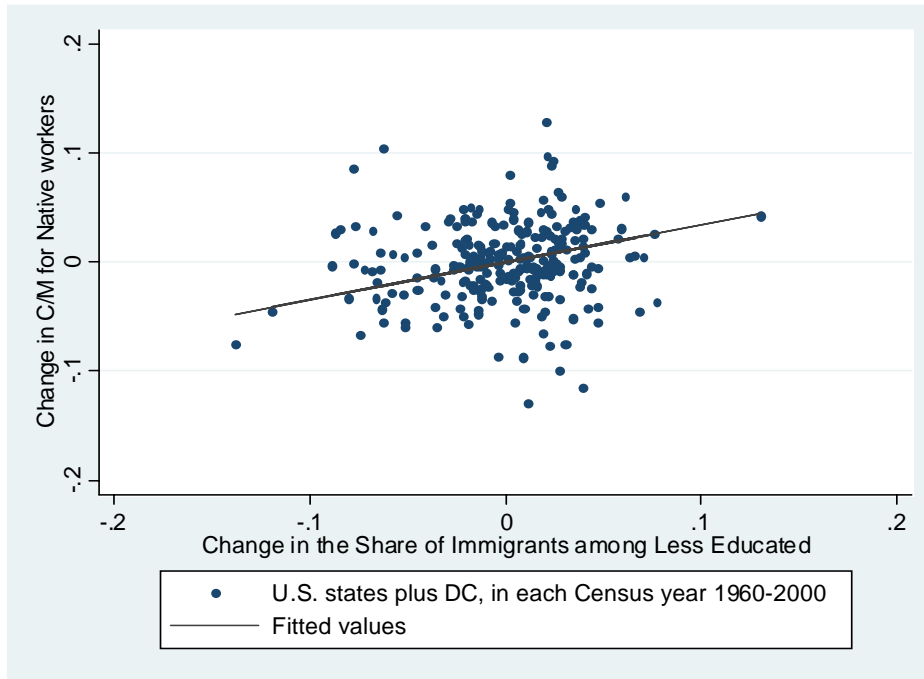
**Figure 3**  
**Foreign-Born Share of Hours Supplied among Workers with a High School Degree or Less Education, 1970-2006**



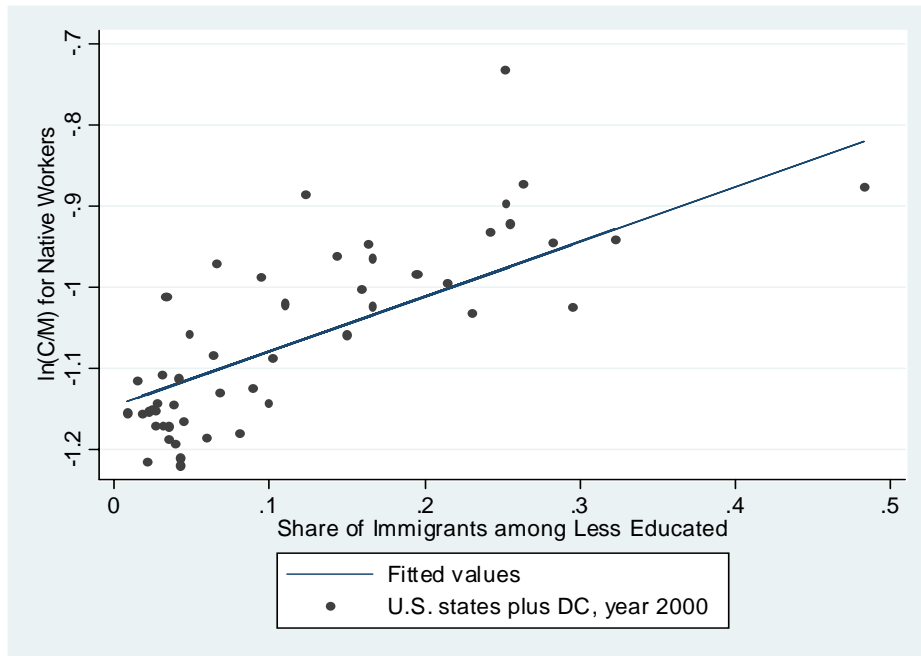
**Note:** Workers are people who worked for at least one week in the representative week and at least one hour in the representative week. Source: Ruggles et al. (2005).

**Figure 4**  
**Share of Immigrants and the Relative C/M Supply of Less-Educated Natives**

**Panel A: In Differences**  
U.S. States, Decade Changes, 1960-2000

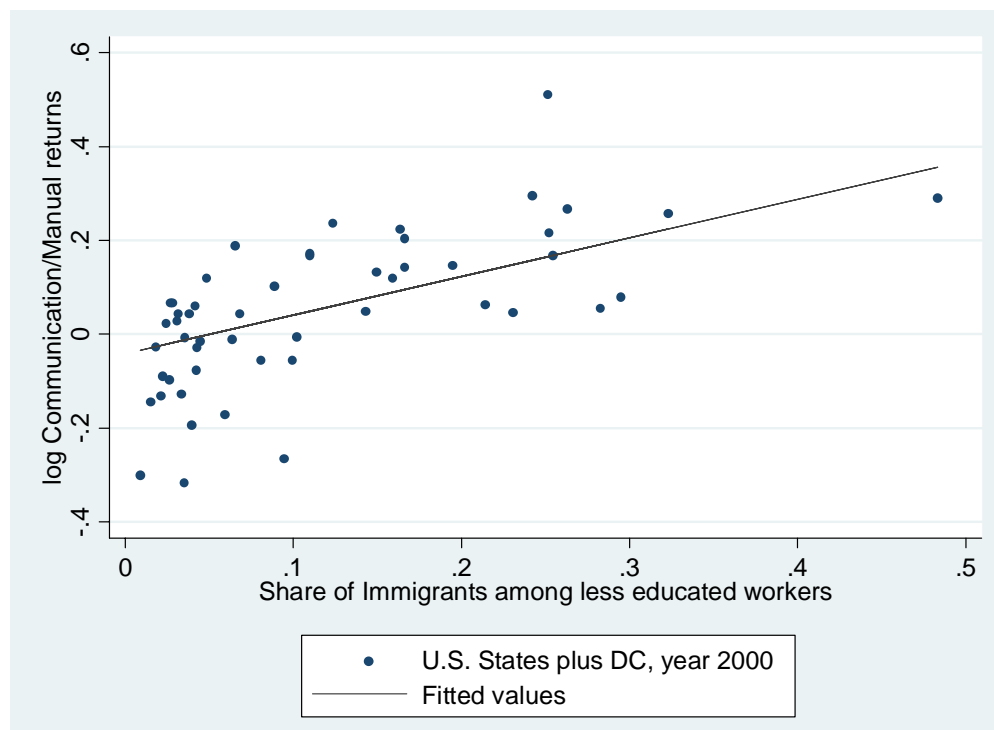


**Panel B: In Levels**  
US states, year 2000



Note: The fitted lines are from a weighted least square regression (weights equal to less-educated employment in the state). Panel A: Slope = 0.34, standard error = 0.04; Panel B: Slope = 0.67 standard error = 0.10.

**Figure 5**  
**Less-Educated Immigrant Share and the Compensation of Communication Relative to Manual Skills across US States, 2000**



**Note:** The relative compensation of Communication and Manual skills is constructed by running a wage regression on less educated workers, controlling for individual characteristics and allowing the compensation of skills to vary across occupation and states (but not within a state across occupations). The detailed description of the procedure is in section 4.3 of the text. The fitted line is from a weighted least squares regression (weights equal to employment of less educated in the state). Slope = 0.82, standard error = 0.13.



**Table A1**  
**Manual (m), Communication (c), & Relative (c/m) Skill Percentiles by Occupation**

<b>Occupation</b>	<b>M</b>	<b>C</b>	<b>C/M</b>	<b>Occupation</b>	<b>M</b>	<b>C</b>	<b>C/M</b>
Psychologists	0.19	0.91	1.00	Purchasing managers, agents & buyers, nec	0.40	0.82	0.90
Management analysts	0.19	0.93	1.00	Computer software developers	0.29	0.61	0.90
Subject instructors (HS/college)	0.22	0.91	1.00	Metallurgical & materials engineers	0.36	0.74	0.90
Atmospheric & space scientists	0.20	0.77	1.00	Geologists	0.34	0.69	0.90
Lawyers	0.23	0.88	1.00	Legal assistants/paralegals/legal support/etc	0.36	0.73	0.90
Judges	0.23	0.88	1.00	Special education teachers	0.39	0.78	0.90
Financial managers	0.23	0.83	1.00	Buyers, wholesale & retail trade	0.31	0.63	0.90
Medical scientists	0.23	0.84	1.00	Managers & administrators, nec	0.35	0.69	0.90
Business & promotion agents	0.24	0.86	1.00	Correspondence & order clerks	0.33	0.66	0.88
Managers of properties & real estate	0.21	0.74	1.00	Air traffic controllers	0.40	0.77	0.88
Physicists & astronomers	0.23	0.76	0.99	Transportation ticket & reservation agents	0.36	0.69	0.88
Legislators	0.30	1.00	0.99	Physicians	0.49	0.93	0.87
Chief executives & public administrators	0.30	1.00	0.99	Material recording/scheduling/planning...	0.34	0.65	0.87
Dietitians & nutritionists	0.23	0.74	0.99	Payroll & timekeeping clerks	0.25	0.47	0.87
Editors & reporters	0.27	0.87	0.99	Pharmacists	0.40	0.76	0.87
Economists, & market/survey researchers	0.21	0.68	0.99	Administrative support jobs, nec	0.34	0.63	0.87
Operations & systems researchers/analysts	0.20	0.64	0.99	Welfare service aides	0.42	0.78	0.87
Management support occupations	0.25	0.80	0.99	Librarians	0.48	0.88	0.86
Actuaries	0.20	0.61	0.99	Computer & peripheral equip operators	0.28	0.52	0.86
Technical writers	0.22	0.69	0.99	Office supervisors	0.54	0.98	0.86
Managers of service organizations, nec	0.29	0.88	0.99	Physicians' assistants	0.38	0.68	0.85
Advertising & related sales jobs	0.29	0.89	0.99	Bookkeepers & accounting/auditing clerks	0.31	0.57	0.85
Aerospace engineer	0.23	0.71	0.99	Dispatchers	0.46	0.83	0.84
Social scientists, nec	0.27	0.82	0.99	Postmasters & mail superintendents	0.31	0.56	0.84
Marketing/advertising mgrs & specialists	0.29	0.84	0.99	Chemists	0.37	0.66	0.84
Insurance sales occupations	0.28	0.81	0.99	Records clerks	0.32	0.56	0.84
Proofreaders	0.21	0.58	0.98	Bank tellers	0.40	0.68	0.84
Writers & authors	0.27	0.77	0.98	Computer systems analysts & scientists	0.36	0.61	0.84
HR & labor relations managers	0.32	0.89	0.98	Statistical clerks	0.31	0.52	0.83
Vocational & educational counselors	0.29	0.80	0.98	Podiatrists	0.53	0.87	0.83
Personnel/HR/training/labor specialists	0.29	0.81	0.98	Agricultural & food scientists	0.32	0.53	0.83
Insurance adjusters/examiners/investigators	0.26	0.69	0.98	Inspectors/compliance officers	0.48	0.78	0.83
Mgrs of medicine & health occupations	0.32	0.86	0.97	Health record tech specialists	0.46	0.74	0.83
Speech therapists	0.35	0.92	0.97	Occupational therapists	0.50	0.80	0.83
Financial services sales occupations	0.29	0.75	0.97	Announcers	0.41	0.65	0.83
Urban & regional planners	0.34	0.88	0.97	Petroleum, mining, & geological engineers	0.38	0.61	0.83
Interviewers, enumerators, & surveyors	0.29	0.74	0.97	Drafters	0.37	0.59	0.83
Eligibility clerks for government programs	0.28	0.71	0.97	Mechanical engineers	0.43	0.67	0.83
Managers in education & related fields	0.33	0.85	0.97	General office clerks	0.35	0.54	0.83
HR clerks, except payroll & timekeepers	0.30	0.77	0.97	Electrical engineer	0.31	0.45	0.82
Sales engineers	0.32	0.82	0.97	Purchasing agents/buyers, of farm products	0.40	0.58	0.82
Secretaries	0.32	0.82	0.97	Non-Horticultural farm managers	0.45	0.64	0.82
Other financial specialists	0.24	0.60	0.94	Primary school teachers	0.50	0.70	0.82
Bill & account collectors	0.29	0.73	0.94	Billing clerks & related financial records	0.27	0.37	0.82
Social workers	0.31	0.76	0.94	Not-elsewhere-classified engineers	0.47	0.65	0.81
Customer service reps, investigators, ...	0.35	0.84	0.94	Mathematicians & mathematical scientists	0.24	0.34	0.81
Real estate sales occupations	0.32	0.76	0.93	Receptionists	0.39	0.53	0.81
Architects	0.34	0.79	0.92	Civil engineers	0.45	0.61	0.80
Clergy & religious workers	0.40	0.91	0.92	Registered nurses	0.66	0.87	0.80
Accountants & auditors	0.32	0.72	0.92	Biological scientists	0.43	0.56	0.80
Hotel clerks	0.35	0.78	0.92	Optical goods workers	0.41	0.52	0.80
Insurance underwriters	0.29	0.62	0.92	Funeral directors	0.51	0.65	0.80
Salespersons, nec	0.33	0.70	0.92	Inspectors of agricultural products	0.61	0.78	0.80
Art/entertainment performers & related	0.38	0.80	0.90	Secondary school teachers	0.58	0.73	0.80
Industrial engineers	0.31	0.64	0.90	Optometrists	0.56	0.70	0.80
Actors, directors, producers	0.40	0.83	0.90	Telephone operators	0.41	0.51	0.80

**Table A1**  
**(Continued)**

<b>Occupation</b>	<b>m</b>	<b>c</b>	<b>c/m</b>	<b>Occupation</b>	<b>m</b>	<b>c</b>	<b>c/m</b>
Licensed practical nurses	0.63	0.77	0.80	Broadcast equipment operators	0.63	0.41	0.61
Food-serving & lodging managers	0.65	0.79	0.80	Surveyors/cartographers/mapping scientists	0.55	0.36	0.61
Supervisors of motor vehicle transportation	0.52	0.63	0.79	Weighers, measurers, & checkers	0.58	0.37	0.61
Library assistants	0.55	0.66	0.79	Public transportation attendants/inspectors	0.66	0.42	0.61
Data entry keyers	0.46	0.53	0.79	Recreation facility attendants	0.51	0.31	0.61
Supervisors of mechanics & repairers	0.74	0.86	0.78	Railroad conductors & yardmasters	0.81	0.49	0.60
Kindergarten & earlier school teachers	0.48	0.54	0.78	Retail sales clerks	0.51	0.30	0.60
File clerks	0.54	0.60	0.78	Dancers	0.75	0.43	0.58
Typists	0.37	0.41	0.78	Art makers: painters, sculptors, crafts, ...	0.53	0.31	0.58
Supervisors of personal service jobs, nec	0.39	0.43	0.78	Fire fighting, prevention, & inspection	0.85	0.48	0.58
Teachers, nec	0.33	0.36	0.78	Pest control occupations	0.83	0.47	0.58
Baggage porters	0.54	0.58	0.77	Shipping & receiving clerks	0.64	0.36	0.57
Guards, watchmen, doorkeepers	0.52	0.56	0.77	Taxi cab drivers & chauffeurs	0.74	0.41	0.57
Production supervisors or foremen	0.60	0.65	0.76	Postal clerks, excluding mail carriers	0.66	0.36	0.56
Power plant operators	0.54	0.57	0.75	Cashiers	0.73	0.38	0.56
Therapists, nec	0.66	0.69	0.75	Elevator installers & repairers	0.84	0.42	0.53
Foresters & conservation scientists	0.65	0.67	0.75	Cooks, variously defined	0.67	0.32	0.53
Chemical technicians	0.50	0.52	0.75	Hairdressers & cosmetologists	0.62	0.30	0.50
Chemical engineers	0.46	0.47	0.74	Motion picture projectionists	0.52	0.25	0.49
Personal service occupations, nec	0.51	0.51	0.74	Repairers of industrial electrical equipment	0.77	0.36	0.49
Construction inspectors	0.66	0.66	0.74	Kitchen workers	0.62	0.28	0.49
Dental assistants	0.65	0.65	0.74	Explosives workers	0.87	0.39	0.49
Health aides, except nursing	0.51	0.51	0.74	Electricians	0.93	0.40	0.49
Supervisors & proprietors of sales jobs	0.50	0.49	0.74	Ushers	0.50	0.22	0.48
Veterinarians	0.74	0.73	0.71	Forge & hammer operators	0.73	0.31	0.48
Supervisors of construction work	0.63	0.61	0.71	Bakers	0.62	0.26	0.48
Archivists & curators	0.46	0.43	0.70	Bus drivers	0.79	0.33	0.48
Respiratory therapists	0.74	0.69	0.70	Crossing guards & bridge tenders	0.59	0.24	0.47
Physical therapists	0.77	0.71	0.70	Winding/twisting textile/apparel operatives	0.82	0.34	0.47
Supervisors of cleaning & building service	0.37	0.34	0.70	Knitters, loopers, & toppers textile op	0.82	0.34	0.47
Clinical laboratory technologies/technicians	0.67	0.62	0.70	Messengers	0.82	0.34	0.47
Health technologists & technicians, nec	0.71	0.65	0.70	Separating/filtering/clarifying machine op	0.82	0.33	0.47
Guides	0.53	0.47	0.70	Animal caretakers except on farms	0.72	0.29	0.47
Police, detectives, & private investigators	0.79	0.71	0.70	Photographers	0.81	0.32	0.46
Door-to-door/street sales & news vendors	0.35	0.31	0.69	Photographic process workers	0.63	0.25	0.46
Designers	0.51	0.45	0.69	Athletes, sports instructors, & officials	0.77	0.30	0.46
Musician or composer	0.41	0.36	0.69	Stock & inventory clerks	0.54	0.21	0.46
Child care workers	0.66	0.58	0.69	Repairers of electrical equipment, nec	0.74	0.29	0.45
Engineering technicians, nec	0.55	0.47	0.68	Barbers	0.56	0.22	0.45
Dentists	0.69	0.58	0.67	Tool & die makers & die setters	0.74	0.29	0.45
Airplane pilots & navigators	0.74	0.59	0.67	Plumbers, pipe fitters, & steamfitters	0.86	0.32	0.45
Recreation workers	0.66	0.52	0.67	Machine operators, nec	0.80	0.29	0.44
Supervisors of agricultural occupations	0.75	0.59	0.67	Dental hygienists	0.66	0.24	0.42
Other law enforcement: sheriffs, bailiffs, ...	0.69	0.53	0.67	Food roasting & baking machine operators	0.76	0.27	0.42
Radiologic tech specialists	0.75	0.58	0.67	Automobile mechanics	0.87	0.30	0.42
Repairers of data processing equipment	0.66	0.51	0.67	Boilermakers	0.87	0.30	0.41
Nursing aides, orderlies, & attendants	0.72	0.55	0.67	Repairers of mechanical controls & valves	0.85	0.30	0.40
Dental laboratory & medical appliance tech	0.64	0.49	0.64	Numerically controlled machine tool op	0.80	0.28	0.40
Biological technicians	0.55	0.42	0.64	Drilling & boring machine operators	0.80	0.27	0.40
Other science technicians	0.61	0.46	0.64	Meter readers	0.80	0.27	0.40
Graders & sorters in manufacturing	0.56	0.40	0.64	Mail clerks, outside of post office	0.67	0.22	0.40
Other health & therapy	0.67	0.48	0.63	Helpers, constructions	0.94	0.32	0.40
Waiter/waitress	0.59	0.41	0.63	Electric power installers & repairers	0.86	0.29	0.40
Protective services, nec	0.58	0.40	0.61	Machinery maintenance occupations	0.79	0.26	0.40
Freight, stock, & materials handlers	0.61	0.42	0.61	Truck, delivery, & tractor drivers	0.88	0.29	0.40
Bartenders	0.67	0.45	0.61	Machinists	0.77	0.25	0.35

**Table A1**  
**(Continued)**

<b>Occupation</b>	<b>m</b>	<b>c</b>	<b>c/m</b>	<b>Occupation</b>	<b>m</b>	<b>c</b>	<b>c/m</b>
Timber, logging, & forestry workers	0.78	0.25	0.34	Assemblers of electrical equipment	0.68	0.11	0.21
Shoe repairers	0.74	0.24	0.34	Plasterers	0.92	0.15	0.19
Mail & paper handlers	0.73	0.23	0.34	Welders & metal cutters	0.75	0.12	0.19
HVAC & refrigeration mechanics	0.85	0.27	0.34	Mixing & blending machine operatives	0.83	0.14	0.18
Insulation workers	0.70	0.22	0.34	Laundry workers	0.66	0.10	0.18
Locksmiths & safe repairers	0.81	0.25	0.34	Structural metal workers	0.89	0.13	0.17
Telecom & line installers & repairers	0.79	0.24	0.34	Other woodworking machine operators	0.78	0.12	0.17
Packers, fillers, & wrappers	0.96	0.29	0.33	Aircraft mechanics	0.86	0.13	0.17
Water & sewage treatment plant operators	0.79	0.24	0.33	Punching & stamping press operatives	0.83	0.12	0.17
Bus, truck, & stationary engine mechanics	0.86	0.26	0.33	Concrete & cement workers	0.85	0.12	0.17
Mail carriers for postal service	0.74	0.22	0.32	Mechanics & repairers, nec	0.84	0.12	0.17
Waiter's assistant	0.66	0.19	0.32	Upholsterers	0.70	0.10	0.16
Drillers of oil wells	0.91	0.27	0.31	Small engine repairers	0.69	0.10	0.16
Rollers, roll hands, & finishers of metal	0.91	0.26	0.31	Housekeepers, maids, butlers, stewards, ...	0.55	0.08	0.16
Glaziers	0.79	0.22	0.31	Slicing & cutting machine operators	0.78	0.10	0.14
Printing machine operators, nec	0.83	0.23	0.31	Painting machine operators	0.81	0.11	0.14
Carpenters	0.93	0.25	0.31	Dressmakers & seamstresses	0.62	0.08	0.13
Railroad brake, coupler, & switch operators	0.86	0.23	0.29	Janitors	0.72	0.09	0.13
Batch food makers	0.69	0.19	0.29	Masons, tilers, & carpet installers	0.86	0.11	0.11
Sales demonstrators / promoters / models	0.44	0.12	0.29	Textile sewing machine operators	0.73	0.09	0.10
Locomotive operators (engineers/firemen)	0.73	0.19	0.29	Butchers & meat cutters	0.81	0.09	0.09
Sheet metal duct installers	0.81	0.22	0.29	Misc material moving occupations	0.69	0.08	0.09
Garage/service station related occupations	0.84	0.22	0.29	Grinding/abrading/buffing/polishing works	0.78	0.08	0.09
Parking lot attendants	0.84	0.22	0.29	Plant & system op, stationary engineers	0.71	0.07	0.09
Heat treating equipment operators	0.91	0.24	0.29	Washing/cleaning/pickling machine op	0.54	0.06	0.09
Office machine operators, nec	0.47	0.12	0.29	Industrial machinery repairers	0.95	0.09	0.09
Auto body repairers	0.91	0.23	0.29	Farm workers	0.90	0.08	0.08
Other plant & system operators	0.63	0.16	0.28	Hand molders & shapers, except jewelers	0.83	0.07	0.07
Crane, derrick, winch, & hoist operators	0.82	0.20	0.28	Gardeners & groundskeepers	0.82	0.07	0.07
Textile cutting machine operators	0.83	0.21	0.28	Drillers of earth	0.95	0.07	0.06
Patternmakers & model makers	0.74	0.18	0.28	Typesetters & compositors	0.61	0.04	0.06
Sawing machine operators & sawyers	0.81	0.20	0.28	Laborers outside construction	0.74	0.05	0.05
Cementing & gluing machining operators	0.92	0.22	0.28	Graders & sorters of agricultural products	0.67	0.04	0.03
Garbage & recyclable material collectors	0.86	0.21	0.28	Molders, & casting machine operators	0.85	0.05	0.03
Paving/surfacing/tamping equipment op	0.88	0.21	0.28	Metal platers	0.65	0.04	0.02
Heavy equipment & farm equipment mech	0.91	0.21	0.28	Helpers, surveyors	0.79	0.05	0.02
Nail/tacking machine operators (wood)	0.88	0.21	0.28	Machine feeders & offbearers	0.91	0.05	0.02
Precision grinders & filers	0.83	0.19	0.27	Vehicle washers & equipment cleaners	0.72	0.04	0.02
Cabinetmakers & bench carpenters	0.94	0.22	0.27	Home appliance & power tool operators	0.63	0.03	0.02
Furnace, kiln, & non-food oven operators	0.84	0.19	0.27	Bookbinders	0.71	0.04	0.02
Lathe, milling, & turning machine op	0.77	0.17	0.27	Other mining occupations	0.84	0.04	0.02
Ship crews & marine engineers	0.68	0.15	0.27	Miners	0.77	0.03	0.02
Millwrights	0.91	0.20	0.27	Shoemaking machine operators	0.63	0.03	0.02
Precision makers, repairers, & smiths	0.66	0.13	0.27	Excavating & loading machine operators	0.76	0.03	0.02
Paper folding machine operators	0.74	0.15	0.27	Engravers	0.70	0.02	0.01
Lay-out workers	0.74	0.14	0.27	Fishers, hunters, & kindred	0.89	0.02	0.01
Wood lathe/routing/planning machine op	0.74	0.14	0.27	Paperhangers	0.71	0.01	0.01
Misc food prep workers	0.81	0.15	0.26	Furniture & wood finishers	0.64	0.01	0.01
Misc textile machine operators	0.66	0.12	0.25	Pressing machine operators (clothing)	0.69	0.01	0.01
Farmers (owners & tenants)	0.77	0.15	0.25	Operating engineers of construction equip	0.71	0.01	0.01
Extruding & forming machine operators	0.89	0.16	0.25	Roofers & slaters	0.72	0.01	0.01
Construction trades, nec	0.79	0.14	0.24	Drywall installers	0.66	0.00	0.00
Painters, construction & maintenance	0.83	0.15	0.24				
Elevator operators	0.83	0.15	0.24				
Packers & packagers by hand	0.65	0.11	0.23				
Construction laborers	0.87	0.15	0.23				

**Table A2**  
**Summary Statistics for the Estimated State-Specific Compensation of Manual and Communication Tasks,**  
**Basic Definitions of Skills**

<b>Year</b>	<b>Average <math>W_M</math></b>	<b>Average <math>W_C</math></b>	<b><math>R^2</math></b>	<b>Observations</b>
1960	519	566	0.41	7738
1970	603	704	0.43	10591
1980	664	617	0.31	15880
1990	547	557	0.38	15607
2000	543	576	0.32	15142

Note: The compensation paid to manual and communication tasks is in 2000 US dollars and corresponds to weekly returns.  $R^2$  comes from Regression (21) when estimated with a constant term.