Immigration Responses to Technological Shocks: Theory and Evidence from the United States*

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Abstract

The changes in technology that took place in the US during the last three decades, mainly due to the introduction of computerization and automation, have been characterized as "routine-substituting." They have reduced demand for routine tasks, but have increased demand for analytical tasks. Indirectly they have also increased the demand for manual and service type of occupations. Little is known about how these changes have impacted immigration, or task specialization between immigrants and natives. In this paper we show that such technological progress has attracted skilled and unskilled immigrants, with the latter group increasingly specialized in manual-service occupations. We also show that this immigration response has helped to reverse the polarization of jobs and wages for natives. We explain these facts with a model of technological progress and endogeous immigration. Simulations show that immigration in the presence of technological change attenuates the drop in routine jobs and the increase in service jobs for natives.

Keywords: Technology, Immigrants, Routine Tasks, Service Jobs

JEL Codes: J15, J24, O15, O33

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1 Introduction

The introduction of information and communication technology, and the accompanying automation and computerization of several tasks of the production process during the last few decades, have produced important effects on US labor markets. First, this type of technological change contributed to the decline of the employment share of workers performing routine-intensive tasks, many of which are now performed by computers (Autor, Levy and Murnane, 2003; Salomon, Goose and Manning, 2010). Second. it may have simultaneously contributed to the increase in the employment share of creative and cognitive-oriented occupations whose productivity and demand were increased by computers. Finally, this phenomenon has been accompanied by the relative stability and possible increase in the employment shares of workers performing manual and non-routine-intensive jobs, in the service sector (see Autor 2011). As routine-intensive occupations tend to be in the middle-range of the earning distribution, while many manual-intensive jobs in services are towards the bottom of the wage range and cognitive intensive jobs cluster at the top, this phenomenon of technological substitution and complementarity has contributed to what has been called "polarization" of the labor market. The employment share of low-paid and high paid jobs have been either stable or expanding, while the middle-range jobs have been shrinking as they are increasingly substituted by machines.

Within this context, we ask two questions about which surprisingly little is known. First, did foreign workers respond to these technological changes and to the labor demand it created by migrating to US labor markets? The focus on immigrants is interesting because this group provides a distribution of skills quite distinct from natives. In particular (see Peri and Sparber 2009), their specialization in manual-intensive service occupations (house-keeping, building, gardening, baby-sitting) may have been particularly responsive to the local routine-substituting technological changes occurring over the last few decades. Moreover as already emphasized by Cadena and Kovak (2016) immigrants, especially the less educated, may have a larger labor response to differential labor demand shocks than native workers at the local level. This was shown to imply differential immigrant-native responses to short-term shocks. Here we analyze whether such different responses were also true for longer-run computer-driven demand shocks.

Second, did the differential inflow of immigrants in local US labor markets affect the extent of technologically-induced employment polarization of natives' jobs? Namely, did the employment impacts of computerization on natives differ in regions with large inflows of immigrants relative to those with low inflows of immigrants? As immigrants tend to specialize in manual service jobs at the bottom of the skill spectrum, and growth in the 1980-2010 period was especially intensive for this segment of the labor market, one could think that it responded to technological changes and potentially produced a complementary effect on natives, reducing their outflow from routine jobs and encouraging their inflow into analytical ones.

In the empirical analysis we first test how immigration responded to computer-intensive technological change. To do this we construct a new measure of computer-driven productivity growth at the local level based on the intensity of computer input growth in local industries. We test the correlation of this measure with measures of routine-substitution as defined by Autor and Dorn, (2013) and we then analyze its correlation with high and low-skilled immigrants. We establish that computerization intensity across local labor markets in the US is strongly associated both with high skilled *and* low skilled immigration over the decades 1980-2010. We also show that the local intensity of computerization is associated with increases in employment for analytical-intensive jobs, decreases in employment of routine jobs, and moderate increases in employment in manual jobs, precisely as predicted by Autor and Dorn (2013). However in areas with large immigration *potential* (proxied by the existing immigrant network) the employment effects of technological change on native workers are attenuated. In these commuting zones we observe a smaller employment growth of manual-intensive jobs for natives and a smaller employment decline in routine intensive job. This is because a larger immigrant supply response fills manual-occupation demand, reducing the displacement of natives from routine to manual. Further, the complementarity between manual and routine jobs raises demand for mid-skills and keeps some natives in routine positions, offsetting some of the polarizing effects of technology. The interesting new implication of this empirical results is that, in the presence of endogenous immigration, the employment- and wage-polarizing effects of computerization on native workers are reversed. Indeed, we see that the majority of service workers contributing to low-end employment polarization are in fact migrants. Conceivably without them mid-skilled natives would be more prone to job and wage losses.

In the second part of the paper, we develop a model that shows more rigorously what framework is needed to produce such effects of technology and endogenous immigration on native polarization. The model extends Autor and Dorn (2013). In that framework the acceleration of routine-substituting progress is the cause of change in demand for routine labor, and the complementarity between goods (routine intensive) and services (non-routine, manual intensive) produces the polarization of employment, with low skilled workers moving from good to service production. In our case we allow for endogenous inflows of immigrants, isolating the low-skilled at first, and then allowing for high-skilled migration as well, and we analyze how the same technological change affects the employment of natives. We compare a case when immigrant supply responds to technological change with a case where no immigrants are allowed to enter, and we obtain the explanation for the key facts of our empirical analysis. In essence immigrant supply and their specialization in manual tasks protects natives from the impact of technology on routine employment, while at the same time raising their wages. Allowing stronger immigrant response reduces the polarization effect of technology on native jobs and wages at the low end of the wage spectrum.

The rest of the paper is as follows. We first review the relevant literature in Section 2. Then in Section 3 we present some empirical facts and regularities. In Section 4 we describe the model and discuss the simulation results. In section 5 we conclude the paper.

2 Literature Review

This paper stands at the intersection of two strands of literature. On one hand it contributes to our understanding of how computerization affected jobs and the polarization of the labor market by exploring less known implications of these phenomena on immigrants' labor supply and tasks. On the other hand it complements the literature on the labor market impacts of immigration, particularly as it has focused on the differences between native and immigrant workers (Ottaviano and Peri 2012), identifying task specialization (Peri and Sparber 2009) and technological adoption (Lewis 2014) as important dimensions.

To explain the poor employment (and wage) growth in the middle of the skill distribution relative to both high and low skilled jobs, especially during the 1990's and 2000's, several recent papers (notably Autor and Dorn 2013, Acemoglu and Autor 2011, and Goos, Salomon and Manning 2013) have shown that computer-intensive technological growth has eroded the demand for routine-jobs. These used to be well paid positions squarely in the middle of the earning distribution. Machines and computers have substituted many of the "routine-tasks" performed by workers. On the other hand they have enhanced the productivity of analytical (also labeled as "cognitive" or "complex") jobs (see Autor 2015 for a detailed explanation of these effects). This contributes to explaining the increase in inequality at the top of the wage distribution. On the other hand computerization has not much affected the physical productivity of manual-intensive jobs in personal services (e.g. cooking, house keeping, baby-sitting, health care, landscaping). However the demand for those services may have increased because they complement the consumption of goods and services produced using computers. Hence, indirectly, computer-driven productivity growth may have also increased demand for manual-intensive service-type jobs. This is the reason for polarization in the low part of the wage spectrum (see Autor and Dorn, 2013).

New in this literature, we extend the analysis of the consequences of computer-driven productivity growth to two new facts. First, related to the work of Kovak and Cadena (2015) and Borjas (2001), who showed larger short-run mobility of immigrants in response to local shocks, we document a strong response of immigrants to computer-driven productivity growth. Particularly interesting is the strong response of *less* skilled immigrants, attracted to areas with fast computer-driven growth. Second, building on the fact that low skilled immigrants supply manual-tasks more intensely than natives, we are the first (to our knowledge) to notice that in areas with high immigration potential, computer driven growth produced less employment transition of native workers from routine to manual jobs, relative to areas with low immigration potential. While the small (and sometimes positive) association of low skilled immigration with employment and wages of native workers has been known for a while (Card 2001, Card 2009, Basso and Peri 2016), we are the first to propose an explanation based on technological growth and specialization. As computer-driven productivity growth has depressed routine-job demand and moved workers from intermediate wage jobs to low paid manual jobs, immigration has pushed in the opposite direction by increasing relative demand for routine jobs performed by natives. Such an attenuating factor may have helped reverse the tendency of less skilled natives to move to lower paid manual jobs.

Finally, our paper complements a series of recent papers that have analyzed the role of high skilled immigrants within the context of innovation and technological change (Bound et al. 2017, Jaimovich and Siu 2017; Waugh 2017). These papers focus on the role of highly skilled immigrants, who are prevalently employed in science and technology, and analyze long-run outcomes in the presence of technological innovation enhanced by high skilled immigrants. These works (especially Bound et al. 2017 and Jaimovich and Siu 2017) also explicitly model the fact that highly skilled immigrants have a strong preference for computer sectors which further enhances innovation. This differentiates them from high skilled natives that may have other high skilled occupations (managerial/non-computer) and produces especially strong effects of immigration on innovation. While we focus on unskilled immigrants, and document a less known complementarity between this group and computer-driven productivity growth, these papers share with our approach the emphasis on the different specialization of immigrants relative to similarly skilled natives, and the benefits that this may generate for natives.

3 Empirical Facts

In this section we present some simple empirical facts and regression results that provide strong support for two regularities at the core of the connection between computerization and immigration. First, areas (commuting zones) with rapid computer adoption due to their industry composition in 1980, attracted a significantly larger number of foreign-born workers as a share of overall employment. This tendency already has been partly documented, as it was known that highly productive urban economies attracted highly educated workers in the 1980-2010 period (e.g. Diamond 2016). Here we show specifically that areas with strong computer-productivity growth attracted *both* high and low educated foreign-born workers. The complementarity of computer adoption and analytical jobs cannot explain the attraction of less skilled immigrants, but another feature of that group can. Unskilled immigrants were significantly more specialized in manual occupations in the service sector, relative to unskilled natives who tended to specialize in routine jobs. Moreover manual tasks supplied by immigrants increased significantly more during this time. Hence, computer-intensive productivity growth that substituted routine tasks and increased demand for manual service tasks attracted disproportionately more immigrants.

Second, analyzing Commuting Zones which experienced high or low immigration, as predicted by the pre-1980 settlement of immigrants, we show that the "polarizing" impacts of routine-substituting computerization on native employment and wages were attenuated in high immigration CZs relative to low immigration zones. In high immigration commuting zones computerization attracted immigrants in manual tasks and attenuated the "downgrading of natives" from routine jobs to manual service ones relative to low immigration CZ's.

3.1 Computerization and Immigration

We first construct a measure that captures the intensity of computerization of local economies (commuting zones) between 1980 and 2010. More precisely we proxy computer-intensive productivity growth, based on the industrial structure of 1980 and industry-productivity growth in computer-intensive sectors between 1980 and 2010. Then we show how that measure is correlated with the routine-intensity of the local economy, the proxy used by Autor and Dorn (2013) to measure the intensity of routine-substitution occurring during the 1980–2010 period. Finally we analyze its correlation with post-1980 immigration across commuting zones to establish whether this measure of computerization is positively associated with inflow of immigrants. We also check that our measure is not correlated to pre-1980 immigration, ruling out spurious correlations due to long-run unobserved trends.

To do so we aggregate US Census microdata as available on IPUMS (Ruggles et al., 2015). We aggregate at the Commuting Zone level, which approximates local labor markets, and encompasses the entire 48 adjoining US states. Our sample is comprised of foreign and US born individuals of working age (between 18 and 65 years old), not residing in group quarters and not enrolled in school.[1] We consider as employed all individuals with a positive number of weeks worked during the previous year. For each of the foreign-born and native groups we define high-skilled workers as those with at least some college education, while low-skilled workers have at most a high school degree or equivalent.

In the spirit of Bartik (1991) we consider the individual composition of commuting zone c as captured by the share of employment in each industry, and we interact these with the national log wage growth for the whole industry, weighted by the computer-intensity of the sector in 1980. The measure captures industry-specific productivity growth and weights it for the computer intensity of the sector in 1980, and then allocates it to a commuting zone in proportion of its employment share across industries. Specifically we construct the following proxy for computer-intensive productivity growth:

$$\text{Computer Growth}_{c,t} = \sum_j \omega_{j,c,1980} * \Delta \log(wage_{j,-c,t}), \tag{1}$$

where $\omega_{j,c,1980} = \frac{empl_{j,c,1980}(\frac{ComputerInput_{j,1980}}{TotInput_{j,1980}})}{\sum_j empl_{j,c,1980}(\frac{ComputerInput_{j,1980}}{TotInput_{j,1980}})}$ and c stands for CZ, t indicates Census year, and j indicates industry. The computer input share in 1980 is taken from the Bureau of Economic Analysis (BEA) Input-Output tables (Table 5.5.4u) and industries are aggregated to match the BEA classification to the Census codification. Our variable differs from a standard Bartik demand shifter in two respects. First, we use the growth of wages (rather than of employment) in a sector, nationally, in order to better capture the increase in labor productivity in the sector.

[1]We define foreign born as those who are born outside the United States and are not US citizens at birth.

Second we weight sectors according to their computer-intensity assuming that productivity growth in those sectors was largely driven by computerization. As in the Bartik measure we allocate such computer-weighted industry specific growth by the employment-share of that industry in the commuting zone. The constructed measure of computer-intensive productivity growth has a strong correlation with the routine-intensity measure used by Autor and Dorn (2013). This is shown in Figure 1, which represents a scatterplot across commuting zones and decades of the routine share of local jobs as defined by Autor and Dorn (horizontal axis) and our computer-productivity growth measure (vertical axis). The positive and strong correlation (t-stat of the linear coefficient is 6.56) indicates that computer productivity growth is correlated with routine-intensity in a commuting zone, and hence with the routine-substituting mechanisms argued by Autor and Dorn (2013). Our measure has the advantage of genuinely capturing the sector-driven computer-intensive productivity growth rather than being a task-based measure.

As a first step, therefore, we test whether our constructed computer-intensive productivity growth is associated with changes in Analytical, Routine and Manual task supplies, and in employment shares of occupations that mainly provide any of these three tasks. To do this we construct two different measures capturing these three types of task supply. The first builds upon previous work that analyzes migration and occupational choices within the task framework (Peri and Sparber, 2009). We construct a set of 330 occupations that are consistently defined across Censuses. Then, we exploit the information contained in the Dictionary of Occupational Titles (DOT) database (US DOL, 1977), which indicates the task performed in each occupation as of 1977. We focus on the indices of analytical, routine and manual tasks, as previously done by Autor et al. (2003) and Autor and Dorn (2013). Differently from them, we reweight each of the three indexes by the 1980 occupational employment to reflect the percentile of each occupation in the distribution of task supplied. Each worker, therefore, has an index that reflects her/his supply of analytical, routine and manual tasks which we can then aggregate by Census year and local labor market.[2] These measures of task supply are exclusively based on the occupational task intensity relative to all other occupations in the economy. And differently from Acemoglu and Autor (2011) and Autor and Dorn (2013), they purely reflect characteristics of the occupations as classified at the beginning of our sample period. In the rest of the analysis we normalize these indices, dividing by the total supply of tasks in each Census year and local labor market to better capture the polarization of occupational shares and the changes in foreign-born and natives specialization.

In their influential work on technological change and occupational tasks, Acemoglu and Autor (2011) suggests it may be preferable to work with occupations directly because task indices, such as those constructed above, may not accurately reflect the actual task structure (Acemoglu and Autor, 2011, page 1078). Thus, we also contruct a second measure of task supply exclusively based on occupational employment shares. Following Autor and Dorn (2013) we categorize occupations into three distinct groups by simply separating managerial / professional / technical, clerical / sales and non-managerial / non-clerical. This partitioning is obtained simply by following the classification of Autor and Dorn (2013), and identifying the occupations that entail the largest use of analytical, routine or manual tasks, respectively. The task-intensity of each group of occupations (managerial, clerical and non-managerial/non-clerical) is reported in Table 1. It shows the high analytical content of managerial occupations, the high routine content of clerical occupations, and the high manual content of non-managerial/non-clerical occupations. The correspondence is of course not exact, but it provides an alternative and simple way of thinking about what analytical and routine jobs actually are. The downside of this approach is that, in an effort to identify occupations that are

[2]Table A1 in the appendix lists the ten occupations with the highest value of each task intensity index. The details of the classification procedure are described in the Data Appendix.

more plausibly affected by "routine-substituting" technological change, we may select occupations only based on anecdotal evidence. Reassuringly, the two methods give very consistent results. This shouldn't come as a surprise given the correlations between the task indexes and the occupation categories presented in Table 1.

Figure 2 and Table 2 use the task supply indexes, our first measure described above, for four groups of workers — low skilled natives, low skilled immigrants, high skilled natives and high skilled immigrants — to establish an important fact. Figure 2 shows the changes in the supply of each type of task in the US labor market by the four groups mentioned above, after standardizing their initial supply to 1 in 1980. Panel (a) shows the changes for low skilled immigrants, Panel (b) for high skilled immigrants, Panel (c) for low skilled natives and Panel (d) for high skilled natives. Table 2 shows the average intensity of each type of task supplied by each of those groups in 1980 and 2010 and the change over the period. One difference between immigrants and natives, especially in the low skilled group, is shown in the table and is clear from panels (a) and (c) of figure 2. Low skilled immigrants supplied significantly more manual tasks relative to natives, and significantly less analytical ones already in 1980. This difference became even larger during the 1980-2010 period when low skilled immigrants increased their supply of manual tasks significantly more than low skilled natives. Even high skilled immigrants increased their manual supply more than high skilled natives. On the other hand immigrant supply or routine tasks was relatively similar to the natives' supply as of 1980 and it declined roughly at the same rate.

Hence, as a group, immigrants produced an increase in the supply of manual tasks relative to routine tasks (and to analytical tasks) especially among less educated workers. This is an important feature differentiating foreign and native low skilled workers and it will play an important role in our story. Related to the significant "manualization" of immigrant jobs relative to natives over the period

1980-2010, there is another interesting stylized fact not very well known or even discussed in the "polarization" literature. Demonstrated in Figure 3, we see that labor polarization at the low end of the skill spectrum is a phenomenon almost exclusively related to *immigrant* employment. The figure shows the percent growth in employment, ranking 330 occupations by their wage percentile in 1980, separately for foreign-born (blue line) and natives (red line). Occupations at the very low end of the 1980 wage percentile distribution (below the 20th percentile), experienced large employment growth over this period (15-20%), but this phenomenon was essentially limited to foreign-born. Native employment growth below the 20th percentile was actually negative. To the contrary, occupations at the high end of the 1980 wage percentile distribution (above the 60-70th percentile) which also experienced significant employment growth (+15%) mainly added native jobs as the employment growth of immigrants in this range was much smaller. Finally the intermediate occupations (between the 30th and the 60th percentile) which did not grow much in terms of employment for either group, still show higher employment growth for natives relative to immigrants. Figure 3 shows, in essence, that the polarization of employment at the low end of the wage distribution was due to immigrant jobs and at the high end to native jobs. And natives did better than immigrants in terms of employment growth in the intermediate wage range. If low-paying manual tasks complement routine-intensive intermediate-tasks, immigrant labor supply responding to computer adoption may have increased the demand of routine tasks and the routine-employment of natives.

In order to use local area variation to test the correlation between computer-intensive productivity change and changes in foreign-born workers, we define the immigration inflow at the commuting zone (CZ) level as the decennial change in the number of foreign-born workers divided by the beginning of decade CZ population, $\Delta Fb_{c,t} = \frac{Fb_{c,t} - Fb_{c,t-10}}{USb_{c,t-10} + Fb_{c,t-10}}$. As suggested by Basso and Peri (2016) and Card and Peri (2016), this measure captures inflows of immigrants relative to the

CZ population at the beginning of the decade, thus avoiding spurious correlations that may arise from endogenous native mobility responses to local labor demand shocks. Specifically we run the following regression:

$$\frac{Fb^h_{c,t} - Fb^h_{c,t-10}}{pop_{c,t-10}} = \beta \text{Computer Growth}_{c,t} + \gamma \text{Immi Shift-share}_{c,t} + \phi^h_{d,t} + \varepsilon^h_{c,t} \quad (2)$$

where h stands for either low-skilled or high-skilled and Computer Growth$_{c,t}$ is the measure of computer-intensive productivity change defined above. Census division-by-time fixed effects ($\phi_{d,t}$) are included in order to control for time-varying demand factors specific to census divisions, and $\varepsilon^h_{c,t}$ are zero-mean random errors specific to the commuting-zone and year. The variable Immi Shift-share$_{c,t}$ is a measure of predicted immigration inflow that exploits pre-existing settlements of immigrants by nationality across US local labor markets. This follows a long tradition in the immigration literature (Altonji and Card, 1991; Card, 2001) and we use the 1970 distribution of immigrants by nationality (n) across CZs, $Fb_{n,c,1970}$, and augment it with the nationwide growth of immigrants of each nationality between 1970 and t, $\frac{Fb_{n,t}}{Fb_{n,1970}}$. The imputed number of immigrants in each CZ would be $F\hat{b}_{c,t} = \sum_c Fb_{n,c,1970} * \frac{Fb_{n,t}}{Fb_{n,1970}}$ and it proxies the change of immigrants at the local level driven by initial composition and changes in aggregate (nationwide) supply of immigrants by nationality. We then construct an imputed change of immigrants $\Delta Fb_{c,t}$ as follows:

$$\Delta \hat{F}b_{c,t} = \frac{F\hat{t}_{c,t} - \widehat{Fb_{c,t-10}}}{USb_{c,t-10} + \widehat{Fb_{c,t-10}}}. \quad (3)$$

This measure, that we call "Immigrant Shift-share", controls for potential "supply side" changes of immigrants, driven by the aggregate increase in migration from some countries. The coefficient on the computer-intensive productivity growth, after controlling for fixed effects and the immigrant shift-share, isolates the response of immigrants to computer technological change.

The estimates of the coefficients β and γ from equation (1) are shown in Table 3. In the first three columns we see the estimates when the change in low-skilled foreign born (those with high school degree or less) is the dependent variable, while columns 4 to 6 show the coefficients for the high skilled change of immigrants. The first row shows the coefficient on the computer-intensive productivity growth (coefficient β) while the second row shows the coefficient on the immigration shift-share (coefficient γ). Columns one and two (five and six) show the coefficients estimated when only one of the two explanatory variables is included, while column three (six) show the estimates when both are included.

Three interesting results emerge. First, both high and low skilled respond positively to the computer-intensive productivity growth. Second, and most interestingly, low skilled immigrants seem even more responsive than high skilled ones. A one percent increase of the productivity variable increases the high skilled immigrant share in the commuting zone by 0.35 percentage points, but it will increase low skilled by 0.76 percentage points. Both effects are very significant and robust. While previous papers had focused on the inflow of high skilled into high productivity cities (e.g., Moretti, 2015; Diamond, 2016), our paper emphasizes that inflows of low skilled immigrants are significantly associated with the computer-driven productivity growth at the local level [3]. Third, our results confirm that the "supply-driven" immigration shift share variable also has a significant effect on immigration of high and low skilled foreign workers. This effect is stronger for low-skilled who are more likely to rely on the location of previous immigrants for information of local opportunities and jobs. We also find that the shift-share variable, usually considered as a more "pure" supply-driven change, has a signif-

[3]Notice that if we construct a simple Bartik measure of productivity growth across commuting zones, not weighting for computer input intensity, such variable is much less correlated with immigration. See Table A2 in the Appendix that includes the standard Bartik and the computer-intensive productivity growth as explanatory variables in regressions of Table 3.

icant correlation with the computer-driven productivity growth: the correlation coefficient weighted by the size of the commuting zone is .18 and is statistically different from zero at .1 percent.[4] This, and the fact that immigrants, including low skilled, respond very strongly to productivity changes introduces a cautionary note on the importance of isolating carefully demand factors when trying to assess the employment and wage effects of immigrants. Here we have explicitly considered the reverse link between computer-intensive technological growth and the change in immigrant employment. What does this link imply for native employment and wages?

3.2 Technological Change, Immigration and Polarization

In order to test empirically that at the local labor market level (CZ) computer-intensive productivity growth was associated with the reduction in routine-employment and with an increase in manual and analytical employment between 1980 and 2010 for US-born workers, we estimate coefficient β in the following regression:

$$\Delta y^k_{c,t} = y^k_{c,t} - y^k_{c,t-10} \quad = \beta \text{Computer Growth}_{c,t} + \phi^k_{d,t} + \Delta\varepsilon^k_{c,t}, \tag{4}$$

where $y^k_{c,t}$ represents the native task supply intensity for each task k (representing analytical-, routine- and manual-intensive tasks) for Commuting Zone c and year t, and the operator Δ captures the difference between census years. We run the regression in differences, thus removing time-invariant unobservable local labor market characteristics. We further control for Census region fixed effects ($\phi^k_{d,t}$), which allow for region-specific time trend in outcomes.

Table 4 reports the estimates of coefficient β from equation (4) above, using the

[4] A regression of the enclave-based predicted immigration share on the computer-intensive labor productivity growth controlling for decade-by-division effects leads to an estimated β of .68, statistically significant at 1 percent.

native employment of analytical, routine and manual occupations, respectively, as dependent variables. Panel B does the same for the share of managerial, clerical and non-managerial/non-clerical occupations as dependent variables. The results are consistent across the two occupational partitions and suggest a significant role of computer-driven technological growth in producing task-demand changes. Computer-intensive productivity growth is positively associated with the share of analytical-intensive and manual-intensive employment, and it is negatively associated with the share of routine-intensive employment. The "polarization" effects are somewhat more extreme when we use managerial (as analytical intensive) and clerical (as routine intensive) occupations, but they are present in each of the two specifications. The computer-intensive productivity growth is therefore associated with the relative shifts in demand for tasks consistent with a decrease in routine demand and an increase in analytical tasks and of manual tasks.

Was the effect of computer-intensive technological growth on task demand of native workers *attenuated* in areas with more robust immigration? In particular, given the specific distribution of task specialization among low skilled immigrants, did labor markets with easier access for immigrants offset part of the shift in relative demand (routine to manual) with increases in immigrant supply? To analyze this question we run the following regression:

$$\Delta y^k_{c,t} = y^k_{c,t} - y^k_{c,t-10} \quad = \beta \mathrm{CG}_{c,t} + \gamma \mathrm{ISS}_{c,t} + \delta(\mathrm{CG}_{c,t} * ISS_{c,t}) + \phi^k_{d,t} + \Delta\varepsilon^k_{c,t}, \quad (5)$$

where we have shortened the variable "Computer Growth" as $CG_{c,t}$ and the "Immigrant Shift-share" as $ISS_{c,t}$. We have then included the interaction of these two terms. As $ISS_{c,t}$ captures the potential exposure to larger supply of immigrants, due to a larger pre-existing network, the *interaction term* captures the impact of larger computer-intensive productivity growth in an environment with potentially larger immigration responses. If immigration attenuates the demand shift driven by technology on natives in the low-range of wages, such interaction should have a positive effect on native routine task supply and clerical employment, and a negative effect on native manual task supply and non-managerial/non-clerical employment. The coefficients on this interaction (as well as those on the main effects) are reported in Table 5. Computer-intensive productivity growth simultaneously attracts immigrants and pushes natives toward manual jobs. Commuting zones with larger exposure to immigration, therefore, experienced the first effect more intensively. Such inflows of immigrants increased the supply manual tasks, attenuating the increase in relative demand of manual tasks for natives. The interaction term shows a negative coefficient on manual tasks of natives (both measured as manual task or non-clerical occupations) and a positive coefficient on the routine tasks of natives (statistically significant when we measure "clerical occupations"). The main effect of computer-intensive productivity growth (row 2, column 1 of the table) is still negative on routine tasks, but the effect is reduced in CZs with large immigration.[5]

If computer-intensive technological growth shifted the relative demand for manual/routine tasks, and immigration attenuated the effects for natives, this should also be captured by occupational wage changes. If employment does not fully respond to demand changes, wages for routine-intensive jobs should decline and those for manual-intensive jobs should increase in areas of fast computer-intensive growth. However, exposure to larger immigrant supply could reverse these wage effects. This is exactly what is reported in Table 6. Computer-intensive productivity growth depressed routine wages, but the effect was attenuated in large-immigration areas, while the rise in manual wages from computer growth was likewise attenu-

[5]Table A3 in the Appendix reports a robustness check in which we include a measure of labor productivity growth constructed similarly to the computer-intensive labor productivity growth that should only capture generic growth in labor productivity: Labor Productivity$_{c,t}$ = $\sum_j$ Empl Sh$_{j,c,1980} * \Delta \log(wage_{j,-c,t})$. The main results are robust to the inclusion of this measure although we loose some precision given the high correlation of the two variables.

ated in the presence of large immigrant inflow[6] (we will discuss how immigration can put upward pressure on wages overall in the next section).

Let's compare two commuting zones, one at the 10th and one at the 90th percentile of the 1980-2010 change in immigrants share distribution: Winston-Salem (NC) and College Station (TX), respectively.[7]. A one percent increase in computer-intensive productivity would increase clerical/sales occupational wages by 1.17 percentage points in College Station relative to Winston-Salem, which corresponds to a 0.21 percent *increase* in College Station and a 0.96 percent *decrease* in Winston-Salem. Similarly, the wages of non-managerial/non-clerical jobs would decrease in College Station relative to Winston-Salem by 1.31 percentage points (which corresponds to a marginal effects difference of -1.14 and 0.17, respectively).

Note that, in combining the insights from Tables 5 and 6, we see something interesting — in high-immigration areas like College Station computerization generates both higher employment *and* higher wages for routine-worker natives, compared with low immigration areas like Winston-Salem. It suggests that immigrants are not merely pushing out natives into routine jobs — they help raise the *demand* for routine jobs and hence attenuate their wage decline. The upshot here is that mid-skilled natives in places like Winston-Salem are predicted to suffer from the de-routinization of technology more strongly because they do not benefit from the attenuating effects of migrant inflows.

When focusing on low skilled immigration it is natural to analyze the impact at low levels of the wage distribution, specifically for routine and manual intensive jobs. It is less clear whether immigration affected polarization at the high end of the wage distribution. On the one hand, migrants with high manual-task ability

[6]Table A4 in the Appendix reports a similar robustness check to the one we performed for task supply and occupational shares. When we include a generic measure of labor productivity growth the sign and magnitude of the main effects hold, but we loose some precision in the estimates.

[7]Winston-Salem increase in immigrant share between 1980 and 2010 was equal to 0.1 percentage point, while it was 15.7 percentage points in College Station.

can raise the demand for jobs requiring analytical task content. On the other hand, immigrants can bring their own analytical skills, raising the supply of analytical workers overall. Table 7 shows the impact of computer-intensive productivity growth and its interaction with immigration intensity on the share of analytical jobs for natives. The interaction effect is not statistically significant and depending on the definition of analytical task supply and managerial occupation share, the point estimate is positive or negative. Hence we do not have clear evidence that immigration affects polarization at the high end in response to technology.[8]

Summarizing the empirical facts of this section we can say the following. (i) We constructed a computer-intensive productivity growth measure for the period 1980-2010, which is negatively correlated with routine-task demand and positively correlated with manual task-demand. (ii) This computer-intensive growth, which we take as a measure of local computer adoption, was strongly associated with immigration of both high and low skilled foreign workers. (iii) In areas of higher immigration the impact of computer-driven productivity growth on routine relative to manual employment was attenuated, as was the effect on routine relative to manual wages.

4 Model

To rationalize these results, we now consider a model in which IT-capital deepening, as a result of lowering computer (capital) prices, drives changes in labor productivities, wages and immigration. A simplified version of this model is discussed in the Appendix section A3 — in this and subsequent sections we lay out the full theory. We begin with a framework similar to Autor and Dorn (2013), and we extend it to include endogenous changes to the supply of labor through

[8]Table A5 reports the robustness check including the generic measure of labor productivity growth. The main effects hold although also our baseline estimate of the interaction term (Table 7) was not statistically different from zero.

immigration, as the inflow of immigrants respond to domestic wage changes. In the model we mainly focus on unskilled immigration — as we show in Table 3, this group has been a very important portion of immigration in the 30 years since 1980, and it is crucial to illustrate the mechanism of comparative advantages and specialization in response to technological change. This will be the focus of our analysis. We also include the possibility of skilled immigration in subsequent discussion, albeit we do not focus on immigrants' ability to innovate and specialize in technological jobs, as some other recent studies have done (e.g. Bound et al. 2016 and Jaimovich and Siu 2016).

The economy consists of two sectors which produce goods, denoted as g, and services, denoted as s. They are imperfectly substitutable in the utility of the representative agent in the economy. For simplicity we solve the social planner's problem (which produces the same result as general equilibrium) and hence we maximize:

$$\left(\rho C_s^{\frac{\sigma-1}{\sigma}} + (1-\rho) C_g^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad , \tag{6}$$

where C_s and C_g are per capita consumption of services and goods, respectively, and ρ is the relative weight placed on services in the representative agent utility function. The parameter $\sigma \leq 1$ determines the elasticity of substitution between goods and services. We will assume throughout that $\sigma > 0$, so that goods and services grossly complement each other in utility.

There are three basic factors of production — IT-capital (K) which we sometimes call "computers" for simplicity, skilled or analytical labor (L_a), and unskilled labor (U). The difference between skilled and unskilled labor is that an individual has to pay an (education/training) cost to be skilled so that she can supply her labor as analytical. This is a simple way of modeling costly human capital acquisition that provides both higher productivity and also greater supply of a different type of task. Capital and skilled labor can only work in goods production (manufacturing). Unskilled labor can be employed in either manufacturing or services. However unskilled workers are heterogeneous and they supply different "ability" levels in performing the "routine" tasks that are needed in manufacturing, and we denote their total supply of these tasks as L_r. They can also supply non-routine (manual) tasks in the service production (whose supply we denote as L_s). Individuals have different relative abilities in routine and service tasks and we will discuss this later. The total effective supply of unskilled workers U, therefore, is split between routine and service supply so that $U = L_r + L_s$.

Consumption of services and goods are subject to the following resource constraints:

$$C_s = Y_s \ , \tag{7}$$

$$C_g = Y_g - p_k K - p_a L_a \ \ , \tag{8}$$

where Y_s is total production of services, Y_g is total production of goods, p_k is the price of computer capital, and p_a is the price of analytical skills. We have standardized the price of the manufacturing good to one. Equation (8) shows that in each period resources, in the form of goods, must be paid to obtain physical and human capital in this economy. Essentially part of the economy income goes each period to investment in human capital and training to upgrade workers from unskilled to skilled. We will also assume that computer capital depreciates completely each period, and so will need to be replenished each period. The price (of physical and human capital) are exogenously given. These prices may be thought of as technological efficiency in converting goods into physical and human capital units. Hence, in a broad sense, they represent the cost of IT capital and schooling. The exogenous decline in the cost of IT capital will be the exogenous technological force at the basis of all the changes that we will analyze. Unskilled service workers produce services with a linear technology and have all the same productivity in those tasks, so that with a standardization of units we can write the production function in the service sector as: $Y_s = L_s$. Goods, instead, are produced according to the following function:

$$Y_g = \left[(\alpha_a L_a)^\beta + X^\beta \right]^{1/\beta} \quad , \tag{9}$$

where

$$X = \left[L_r^\gamma + K^\gamma \right]^{1/\gamma} \quad . \tag{10}$$

Here X is a CES aggregator, composed of routine labor services L_r and physical capital. The elasticity of substitution between analytical labor services and the term X is $1/(1-\beta)$, $\beta < 1$. The elasticity of substitution between routine labor and capital within the composite X is $1/(1-\gamma)$, $\gamma < 1$. We make the key assumptions that routine labor and capital are grossly *substitutable*, which implies $0 > \gamma > 1$. This property is consistent with the fact that IT capital, in the form of increasingly efficient computers, has substituted many routine tasks such as data entry, typing, classifying, book keeping and other similar tasks. We also assume that analytical labor and the capital aggregate are grossly *complementary* , which implies $\beta < 0$, reflecting the higher productivity of analytical and creative abilities when the supply of IT capital increased. We will also assume that $\alpha_a > 1$ to reflect the idea that analytical labor has greater productivity potential than routine labor. All this is already contained in Autor and Dorn (2013).

Labor Amounts

All workers are paid their respective marginal products. The total amount of labor in the economy will be made up of a unitary mass of native workers plus a mass of migrants, mig, that flows into the economy in response to labor productivity and wage growth (more on this below). Native workers are indexed by their routine ability which equals η_i for worker i. We consider this as an endowment distributed in the population as described below. η_i takes on positive values ranging from 0 to ∞. This can be thought, more precisely, as the ability to perform routine tasks relative to the ability to perform manual/service tasks which is common to all workers and standardized to one. We also assume that worker i can "upgrade" her innate ability to an acquired analytical ability, proportional to the initial level, $\phi\eta_i$, where $\phi > 1$ if she expends a lump sum amount of p_a (in units of goods). This price represents a cost of "education" (or training) and our assumptions capture the idea that education will proportionally increase the innate productivity of a worker. Let us emphasize that becoming a skilled (analytical) workers also produces another effect — it provides workers access to a different labor market, specifically that for workers in the manufacturing sector, who supply analytical services. Alternatively, if they remain unskilled, native workers may choose whether to work in service production, or use their routine ability in manufacturing production.

As a consequence of our assumptions there are two relevant ability thresholds for native workers. Specifically, we call η^* the ability level at which a worker would be indifferent between being either a low-skilled manual/service worker or a low-skilled routine worker. For all endowments of $\eta < \eta^*$ workers will prefer to supply manual services to the service sector, as this would provide them a higher compensation. For $\eta > \eta^*$ workers will supply routine services to the goods-producing sector. Let $\hat{\eta}$ instead be the threshold at which a worker would be indifferent between being either a low-skilled routine worker or paying the education cost to become a high-skilled analytical worker. Thus the two thresholds can be characterized by the following conditions:

$$w_r \eta^* = w_s, \tag{11}$$

$$w_a \phi \hat{\eta} - p_a = w_r \hat{\eta}, \tag{12}$$

where w_r, w_s and w_a are the market wages paid to routine, service and analytical workers respectively, and p_a is the training cost to be able to supply analytical labor.

Finally we assume that native workers' ability is distributed as a negative exponential over the interval $[0, \infty]$. The density is given by $f(\eta) = e^{-\eta}$ and the total mass of native labor force is standardized to 1.

We first model the supply and the abilities of immigrants in a very simple way. We focus on a case in which immigrants are all unskilled, and we standardize their ability endowment to be equal among them and low enough that they will always supply manual tasks with a productivity of one (we introduce the possibility of skilled migrants in a later section). This assumption capture the fact that unskilled immigrants are likely to have a higher relative productivity in manual service tasks which are easily transferred across countries (cooking, cleaning, building, gardening) rather than in routine tasks that are more specifically related to manufacturing and working with machines. We assume that unskilled migration is negatively related to a cost of migration p_s^m, and positively related to service wages w_s as immigrants will work in that sector. We assume a simple functional form that implies a log linear supply response to wages as follows:

$$mig = \begin{cases} (1+w_s)^{\epsilon_s} - (1+p_m^s), & \text{if } (1+w_s)^{\epsilon_s} - 1 > p_m^s, \\ 0, & \text{otherwise}, \end{cases} \tag{13}$$

where mig is the mass of unskilled migrants and ϵ_s , $(0 < \epsilon_s < 1)$ governs the extent to which unskilled migrants respond to potential income in the target economy. A low value of ϵ_s could be due to the fact that service wage do not translate linearly into utility for immigrants, while a value of ϵ_s equal to one means that wage earnings translate linearly in their utility and this has a linear effect on their supply. This parameter captures the sensitivity of immigration flows to changes in unskilled wage in the destination country, an elasticity that several papers estimate to be positive and significant (e.g. Mayda, 2010).

Under the assumptions described above the total effective supply (i.e. weighted for units of ability/efficiency) of routine and analytical labor can be written as follows:

$$L_r = \int_{\eta^*}^{\hat{\eta}} \eta e^{-\eta} \partial\eta, \tag{14}$$

$$L_a = \int_{\hat{\eta}}^{\infty} \phi\eta e^{-\eta} \partial\eta. \tag{15}$$

The total mass of unskilled service workers on the other hand is given by

$$L_s = mig + \int_{0}^{\eta^*} e^{-\eta} \partial\eta, \tag{16}$$

where mig is the endogenously determined total mass of unskilled immigrants in the economy. All immigrants here are assumed to be unskilled, and they have an average ability equal to one, so that they only supply service labor in an amount effectively equal to their mass. There will be $1 + mig$ total individuals in the economy between native and foreign-born.

The distribution of potential analytical and routine skills remains fixed in the economy. However, changes in technology will have wage effects. These will then change η^*, $\hat{\eta}$ and mig, and these will cause adjustments in equilibrium labor amounts.

5 Equilibrium Conditions

What characterizes an equilibrium in this simple economy? For exogenously given p_a, p_k, p_m^s and ϵ_s, we must have the demands of each factor (L_a, L_r, L_s and K) equal the respective supply of each. Demand is determined by what each factor provides marginally. These are given below:

$$\frac{\partial Y_g}{\partial K} = \frac{\partial Y_g}{\partial X}\frac{\partial X}{\partial K} = p_k, \tag{17}$$

$$\frac{\partial Y_g}{\partial L_r} = \frac{\partial Y_g}{\partial X}\frac{\partial X}{\partial L_r} = w_r, \tag{18}$$

$$\frac{\partial Y_g}{\partial L_a} = w_a. \tag{19}$$

Furthermore, utility maximization yields us

$$\left(\frac{\rho}{1-\rho}\right)\left(\frac{C_s}{C_g}\right)^{-\frac{1}{\sigma}} = \left(\frac{\rho}{1-\rho}\right)\left(\frac{L_s}{Y_g - p_k K - p_a L_a}\right)^{-\frac{1}{\sigma}} = w_s. \tag{20}$$

The supplies of each labor type will be determined by the threshold levels of human capital — the amount endowed to the person indifferent between routine and service work, and that endowned to the person indifferent between routine and analytical work. These are given by

$$\eta^* = \frac{w_s}{w_r}, \tag{21}$$

$$\hat{\eta} = \frac{p_a}{\phi w_a - w_r}. \tag{22}$$

Finally, solving (14), (15) and (16) allows us to solve for equilibrium amounts of total skilled and unskilled employment:

$$L_r = (\eta^* + 1)\, e^{-\eta^*} - (\hat{\eta} + 1)\, e^{-\hat{\eta}}, \tag{23}$$

$$L_a = \phi\, (\hat{\eta} + 1)\, e^{-\hat{\eta}}, \tag{24}$$

$$L_s = 1 + mig - e^{-\eta^*}. \tag{25}$$

A formal equilibrium is thus given by solving the system of equations (13), (17), (18), (19), (20), (21), (22), (23), (24), and (25) for values of mig, K, w_r, w_a, w_s, η^*, $\hat{\eta}$, L_r, L_a, and L_s.

How might we expect immigration to affect the equilibrium wages and employment levels of natives? As mig rises we might expect unskilled wages w_s to fall as immigrants increase the supply of unskilled service workers (20). This however should also lower η^*, the routine-skill/service threshold for natives (21), which should then generate more native workers choosing routine tasks in manufacturing and hence larger routine supply in the economy (23).

Note that higher levels of services should also raise the relative value of goods in the economy. This should potentially attract additional capital (as the price of capital is exogenously determined), which should then raise the value of analytical skills, which complements this capital in production (19). Note that this also implies that the threshold level of analytical skills in the economy should then fall (22), generating more analytical skills in the economy as well (24).

Of course, migration itself is endogenous in our model. To see if the results suggested above hold when unskilled migration is treated endogenously, we next turn to simulation.

6 Parameter Values and Model Results

In this model we produce one type of exogenous shock to the economy — improvements in technology, represented by exogenous decreases in the price of capital, p_k, each time period. By so doing we can observe the impact of such changes on the flow of unskilled immigration, as well as the general equilibrium effects on native earnings and employment each time period.

Specifically, we simulate technological improvement by exogenously lowering the price of capital, p_k more than 40 percent cumulatively. We decrease p_k from 4 to 2.8 over 30 periods, roughly mimicking the IT-revolution in the US economy from 1980–2010. For unskilled migration, we set $p_m = (1 + w_s)^{\epsilon} - 1$ before any technological progress, so that there is zero migrants to start. For our chosen value of $\epsilon = 0.25$, the cumulative drop in p_k, and our baseline parameter values (described below), this produces a roughly 20 percent cumulative increase in unskilled migration in the baseline case. We both show the evolution of the economy over time, and report cumulative percent changes from period 1 to 30 (baseline case). This roughly mimics the rise in unskilled migrants observed in the United States for the past three decades.

For reasonable parameter values we first must ensure that $\beta < 0$ (X and L_a are grossly complementary), $\gamma > 0$ (K and L_r are grossly substitutable), $\sigma > 0$ (C_g and C_s are grossly complementary in utility), and $\alpha_a > 1$ (analytical labor is more productive than routine labor). Parameters are set to the following: $\alpha_a = 10$, $\beta = -10$, $\gamma = 0.5$, $\rho = 0.1$, $\sigma = 0.5$, $\phi = 2$, $p_a = 0.25$. This parameterization satisfies the above conditions, and it produces relative sizes of the three types of initial labor amounts that match the corresponding relative employment levels around 1980 of what we have defined as analytical, routine and service workers (shown in Table 2).[9]

[9]Specifically, initial labor amounts are $L_a = 0.48$, $L_r = 0.52$, and $L_s = 0.59$. Other combina-

The left-hand-side diagrams in figures A1 through A5 (in the appendix) demonstrate our simulations through 30 periods (the right-hand-side diagrams are cases with both low and high skilled immigration, which we discuss in the next section). We demonstrate three cases. The first case is where $\epsilon = 0$, illustrated with solid blue lines. In this case no immigration is possible. The second case is our baseline where $\epsilon = 0.25$, illustrated with red dashed lines. Here we observe moderate endogenous migration. The final case is where $\epsilon = 0.9$, illustrated with dotted green lines. In this final case we endogenously experience high migration.

From these simulation exercises we discover a number of interesting and informative findings which parallel our empirical findings. We summarize these below:

1) **Technological progress without migration generates employment polarization**. That is, employment for analytical and service workers rises from tech progress, while it falls for routine workers. We demonstrate this in Figure 6. Here we have $\epsilon = 0$ so there is no migration, only exogenous decreases in capital prices. For native workers we observe a rise in analytical employment, a fall in routine employment, and a rise in manual service employment. The latter two effects echo Autor and Dorn (2013).

The rise in analytical work here differs from Autor and Dorn, as they hold this employment level fixed. But this matches quite nicely our empirical findings demonstrated in Table 4. Using either measure of skill level (task-based or occupation-based), we observe computerization increase employment polarization for native workers.

Harder to observe is wage polarization. However, the model also generates greater service wages *relative* to routine wages from technological growth (low-end polarization). It does *not* however generate higher analytical wages relative to rou-

tions of parameter values can generate a similar balance of initial labor amounts. These do not change the qualitative findings of the theory. A fuller description of parameterization is provided in the appendix.

tine wages (high-end polarization). The reason is that here workers can upgrade skills — technological progress generates a higher supply of analytical workers, keeping relative wages between analytical and routine workers fairly consistent. Note of course that any barriers to this skill-upgrading (credit constraints, discriminatory practices, etc.) will create wage polarization at this higher end as well.

2) **Technological progress attracts low-skilled migrants**. This can be seen in the Figure 7. As capital rises due to exogenous capital price declines, it lifts all wages, including those for manual-intensive service workers. This induces more foreign workers to pay the fixed cost p_m to enter the economy and earn $(1+w_s)^{\epsilon_s}-1$. For our illustrated baseline case, where $\epsilon_s = 0.25$, we observe a technologically-induced immigrant inflow of roughly 20 percent of the total original workforce in the simulation. A higher ϵ_s induces even greater migrant inflows from IT-technology growth. This was echoed by the empirical results shown in Table 3 — our empirical proxy for IT technology, Computer Growth, strongly corresponds with low-skilled immigration, even more than with high-skilled immigration.

Thus, both empirically and theoretically, we show that low-skilled migration is a natural concomitant to economic growth. While this implication is straightforward, as long as immigrants respond to local wages, it has important implications for policy. Efforts to staunch the flow of migrants should be careful not to damage the fundamental source of this flow, or else risk productivity improvements more generally.

3) **Immigration tends to reverse the de-routinization of native employment from technological change**. In Figure 8, we observe that while technology hollows out routine employment among native workers (solid blue line), unskilled immigration tends to reverse this by putting downward pressure on η^* (red dashed line). Specifically, in the simulation we see that computerization lowers native employment in routine occupations by roughly 38 percent over 30 periods.

With our baseline case of moderate unskilled migration, computerization lowers native employment in these positions by only 26 percent. With high levels of endogenous migration ($\epsilon_s = 0.9$, green dotted line), the de-routinization of native employment is reversed completely.

Again, our empirical findings lend support to this. We see this in Table 5 by observing the estimated coefficient on the cross-term Computer-Intensive Labor Productivity X Share of Immigration. This is the empirical equivalent of the difference between the blue line and the red dashed line in the simulation graph below — immigration induced by computerization reverses the employment polarization for natives. Given that immigration is itself responding to technological changes, greater openness to migrant inflows should be associated with less de-routinization, even as computerization rises.

4) **Immigration raises the total earnings of routine native workers**. The model demonstrates that immigration tends to increase capital even more given the price level of capital, raising overall production in manufacturing goods. This is an interesting and novel technological spillover from unskilled migration not observable by past partial equilibrium studies. One important implication of this is that any negative wage impact from unskilled migration are mitigated for all natives. For example, without this endogenous technological response from migration, the cumulative earnings curve for unskilled natives with moderate migration (red dotted line in upper-left graph in Figure A5 in Appendix) would slope downward instead of upward. Partial equilibrium analysis misses this ancillary effect from migration.

Figure 9 demonstrates that higher unskilled immigration tends to raise the total earnings of both native routine workers and native analytical workers. Specifically, because immigration produces an extra boost to capital, greater migration partially reverses the negative effect on total earnings for routine workers, and strengthens the positive effect on total earnings for analytical workers. Both wages and employment are raised by migrant flows for natives who employ their mid- or high-level skills.

Empirically, we can observe the impact of immigration on the wages of routine workers in Table 6. Again, we look to the estimated coefficient on the cross term. Here we see that the extra supply of unskilled natives naturally pushes down services wages, but also pushes up routine wages. Combining this with the rise in routine employment documented in Table 5, we see the empirical validation of the theory that the decrease in routine earnings causes by computer technology is attenuated by migration.

5) **Immigration generates skill upgrading among native workers**. With unskilled immigration, some erstwhile routine workers end up paying the fixed cost of schooling to upgrade to become analytical workers ($\hat{\eta}$ falls). We can see this on the left panel of Figure 10 — endogenous migration strengthens the skilling effects of technology for analytical work.

An important implication here is that unskilled immigration can lead natives to upgrade their education, and thus to become more productive in the workforce. This is an idea supported empirically by works such as Hunt (2012).

Note however the possibility that *skilled* migrants accompany these unskilled migrants (the details of how skilled workers enter are provided in the next section). This would generate an extra influx of analytical skills into the economy and thus would tend to push natives back into routine-task occupations. The case with skilled migration along with unskilled migration is demonstrated in the right panel of Figure 10. Here it is clear that the ability of skilled migrants to enter shifts the curves downward (greater skilled immigrants enter even with no unskilled migrants), and also flattens them a bit (greater unskilled migrants are accompanied by more skilled migrants). When considering all migrants, the ultimate employment and wage impacts for analytical natives is then ambiguous. This ambiguity is captured empirically by Table 7.

Overall, the model captures key elements of the empirical findings. Further, we present a simplified version of the model in the Appendix. Though the simpler model abstracts from the polarization aspects of our discussions here, it nonetheless echoes the basic findings we have presented, namely that unskilled migrants help natives upgrade their skills, and thus help bolster their earnings as a result.

Figure 11 provides some intuition regarding our overall results. Here we generate from the model demand and supply schedules for the total supply of unskilled immigration into the economy. Supply curves slope upward — these simply plot equation (13) in $m - w_s$ space. Demand curves slope downward — these simply plot the utility-maximizing values of w_s for given amounts of migrants (see equation 20) and their slope is determined by the fact that at higher costs of service labor people will demand less services. At point A there is no technological progress or any migration. Exogenous decreases in the price of capital, *ceteris paribus*, shifts the demand for migrants to $Demand_2$. This relates to point 2 — lower capital prices will naturally lead to greater unskilled immigration. However, there are also general equilibrium effects with such change. Growth in capital also leads to shifts in native employment, as natives upgrade their skills (points 3 and 5). This produces even greater productivity and capital growth in the economy, shifting demand to $Demand_3$ and fostering more unskilled immigration. Point B demonstrates the full results, where both wages and immigration robustly increase as a consequence of computerization.

6.1 Introducing Skilled Migrants

We can extend the basic analysis described above by also including *skilled* migrants. Now we have both highly skilled (analytical migrants) and unskilled (service migrants). These two groups will be treated separately, and there are no immigrant routine workers. This captures the bi-modality of immigrant skills in the United

States.

Each group must pay a fixed cost to enter the economy. Unskilled immigrants pay p^m, just as before. The immigrant analytical worker on the other hand earns $\eta_m \left[(1+w_a)^{\epsilon_a} - 1\right]$ after paying a fixed cost p_a^m, where η_m is the analytical ability of the skilled *immigrant*, and $0 \leq \epsilon_a < 1$ governs the earnings of the skilled migrant. Note that earnings for the skilled migrant rises with ϵ_a for any $w_a > 0$ — as ϵ_a approaches one, the skilled immigrant earnings approaches that of the skilled native. η_m is distributed in the same way as for native workers. Let $\bar{\eta}$ be the amount of analytical ability held by the immigrant indifferent between staying home or paying the fixed cost to work as an analytical worker here. Then

$$\bar{\eta} \left[(1+w_a)^{\epsilon_a} - 1\right] = p_m^a. \tag{26}$$

Given this, we now have *two* sources of abstract labor:

$$L_a = \int_{\hat{\eta}}^{\infty} \phi \eta e^{-\eta} \partial \eta + \int_{\bar{\eta}}^{\infty} \eta e^{-\eta} \partial \eta. \tag{27}$$

The first term is the total amount of analytical skill supplied by natives; the second term is the total amount of analytical skill supplied by migrants.

Again, we simulate technological improvement by exogenously lowering the price of capital, p_k, by the same amount as before, and look at cases with low and high levels of unskilled migrants. Now, however, we allow for endogenous inflows of skilled migrants as well.[10] Technological changes will then change η^*, $\hat{\eta}$, $\bar{\eta}$ and mig, and these will cause different adjustments in equilibrium labor amounts. In our simulations we now solve equilibrium values for η^*, $\hat{\eta}$, $\bar{\eta}$, L_r, L_a, L_s, K, w_r, w_a, w_s, and mig.

Results from these simulations are illustrated in the right-hand-side panels of Appendix Figures A1 to A5. Here we replicate the simulations for moderate levels

[10] In these cases $\epsilon_a = 0.25$ for all simulations.

of unskilled migration ($\epsilon_s = 0.25$), and high levels of unskilled migration ($\epsilon_s = 0.9$), keeping the scales on the graphs the same for comparability.

From these we may suggest a couple of things:

7) **Endogenous skilled migration attracts greater amounts of capital and unskilled migrants.** We can observe magnified increases in both in the upper-right diagram of Figure A1 (greater mig), and the lower-right diagram of Figure A3 (greater K). Skilled migration complements both capital (through production) and service workers (through utility). As a result greater ease of skilled migration raises the flow of unskilled migration as well as of capital.

8) **Points 1–4 raised above remain consistent with skilled migration.** While quantitative magnitudes may differ, the overall patterns on native employment and wages from unskilled migration remain the same as before. That is, technological growth attracts migrants, these migrants help natives reverse de-routinization, and they boost the overall earnings for mid-skilled natives.

7 Conclusions

In this paper, we provide new empirical evidence, and a theoretical explanation, of the immigration response to computer-driven productivity growth, as well as provide new insights on how the productive specialization of migrants has helped reshape computer-driven polarization.

Empirically, we show that immigration increased in Commuting Zones where computer-intensive growth was stronger between 1980 and 2010. The results hold even when we include a large set of CZs controls. The pull effect was especially strong on low-skilled immigration. Then we show that different intensities of local immigration have affected the extent to which computerization has produced job polarization of employment and wages of natives. CZs that were more likely to attract low-skilled migrants, based on the presence of a large immigrant network in 1980, had smaller declines in routine-intensive employment and wages, and smaller increases in manual-service employment and wages. As a consequence, immigration seem to have slowed job polarization at the low end of the wage distribution. Immigration effects on polarization at the high end of the native skill spectrum are less clear.

We rationalize these facts in a general equilibrium model with three tasks and an exogenous decline in the price of capital. Our main contribution is to augment the traditional model of job polarization with the possibility of an endogenous supply of low-skilled immigrants, who flow in the country in response to higher manual/service wages. Immigrants are different from natives in their larger relative productivity in manual services. The model simulations indicate several novel facts that are in line with the empirical evidence. First, computerization attracts low-skilled migrants, and this in turn tends to attenuate the downgrading of natives from routine to service jobs. Computerization does not produce as strong a polarization of native employment and wages, especially at low skill levels, when immigrants respond to it.

These results have important implications for policy. Growing anti-immigrant sentiments in the US and in Europe occur at the same time as ever increasing labor market polarization. Our model indicates that while immigrants are attracted by technological advances and may compete with natives in manual intensive occupations, their general equilibrium effects on the economy is that of reversing job and wage polarization. Policies aimed at reducing immigration inflows, especially of low skilled, can have the unintended consequences of weakening capital accumulation while simultaneously exacerbating native job and wage polarization. Such policies often allege to assist middle-class Americans; they may do precisely the opposite.

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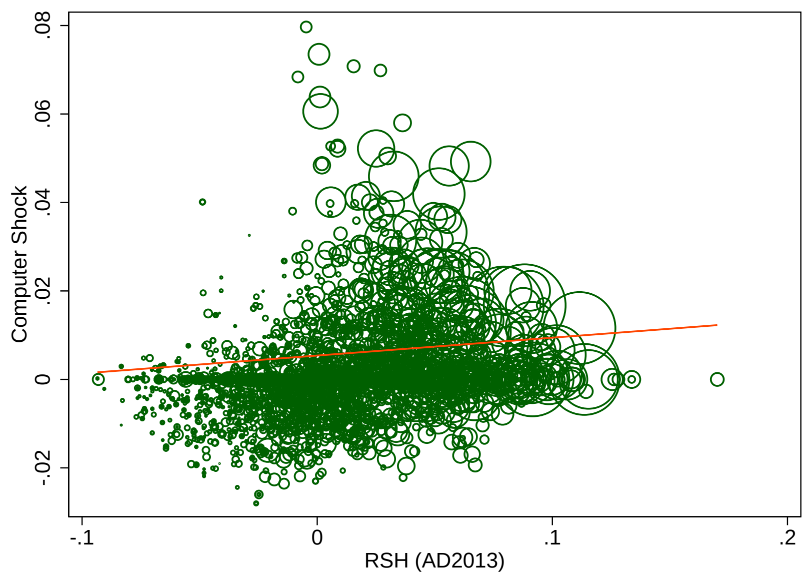
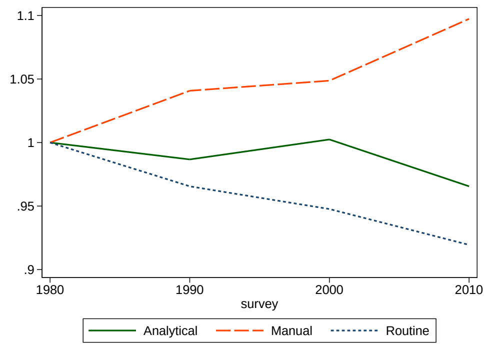
Figures

Figure 1: Correlation *Computer Shock* and AD's *RSH*

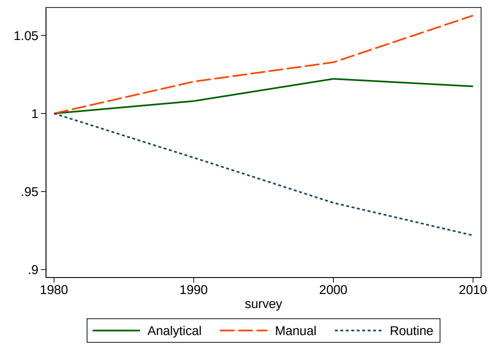


Note: Correlation between the *Computer Shock* measure and the *Routine Share* of Autor and Dorn (2013), controlling for time fixed effects. The regression of coefficient is .081 and it is statistically significant at .01 percent.

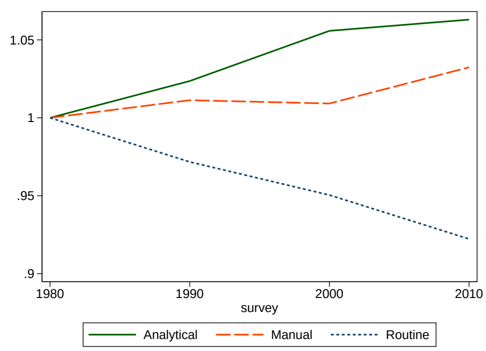
Figure 2: US and Foreign-born Task Supply, 1980-2010



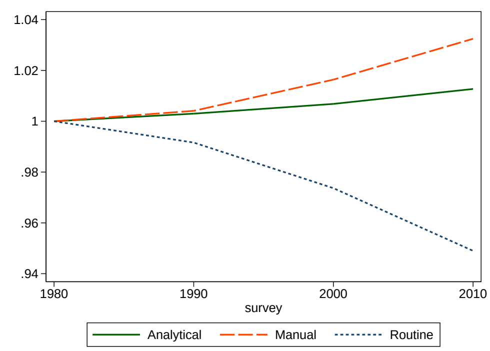
(a) Low-skilled Foreign Born



(b) High-skilled Foreign Born



(c) Low-skilled Natives



(d) High-skilled Natives

Note: panel 2a and 2b plots the task supply of foreign born (as share of total supply) by skill level; panel 2c and 2d plots the same measure for natives.

Figure 3: Smoothed Changes in Foreign-born and Natives' Employment by Skill Percentile 1980-2010

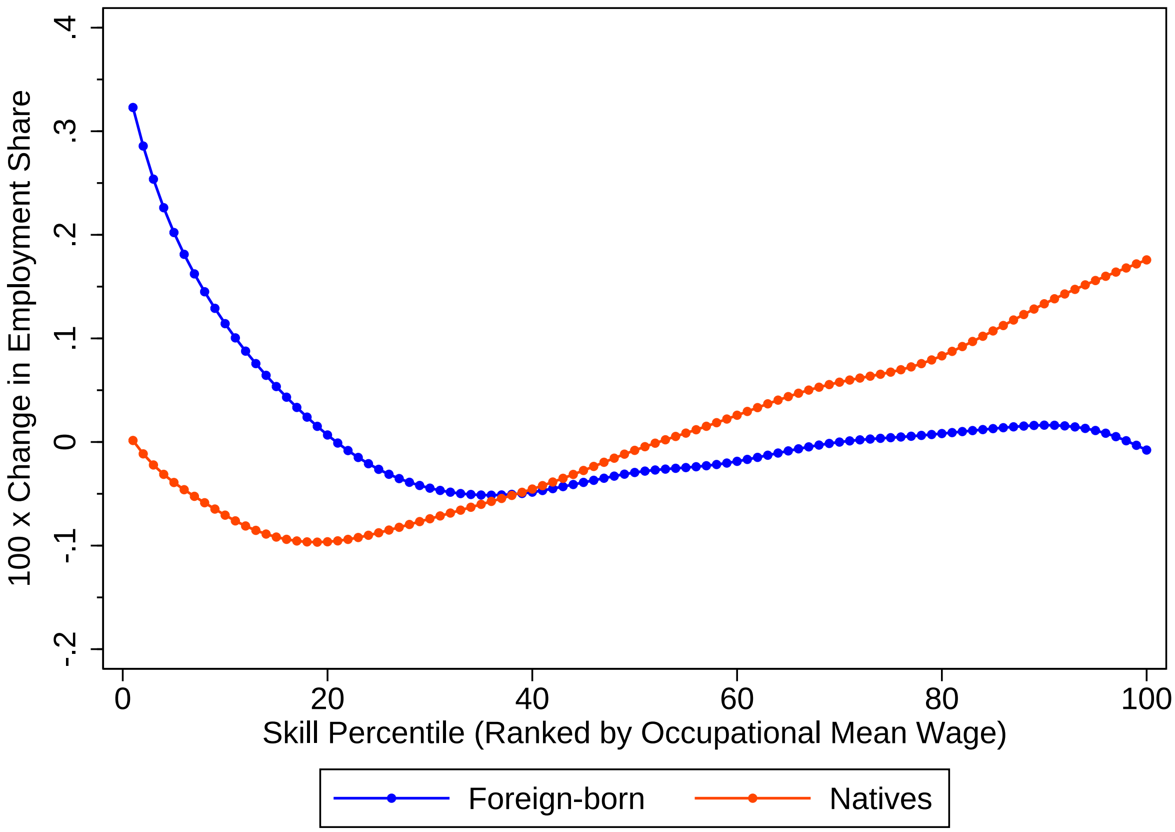
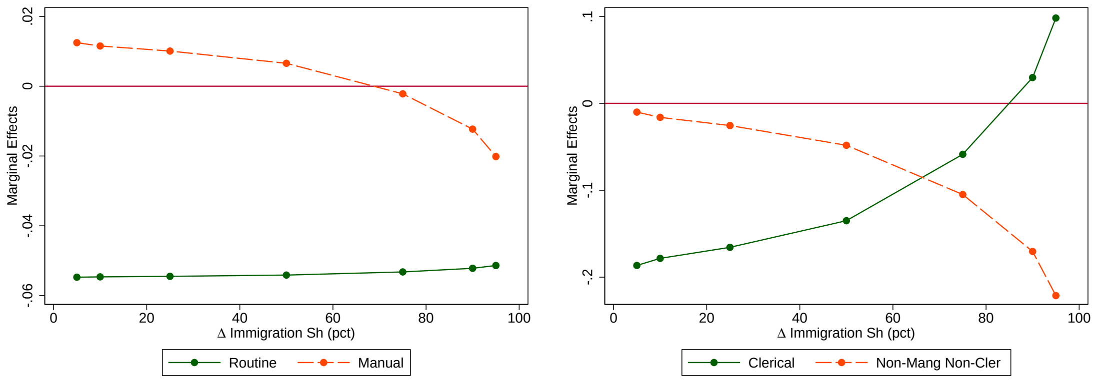


Figure 4: Computer-Intensive Labor Productivity at the Low-End: Marginal Effects Tasks Supply and Occupation Shares

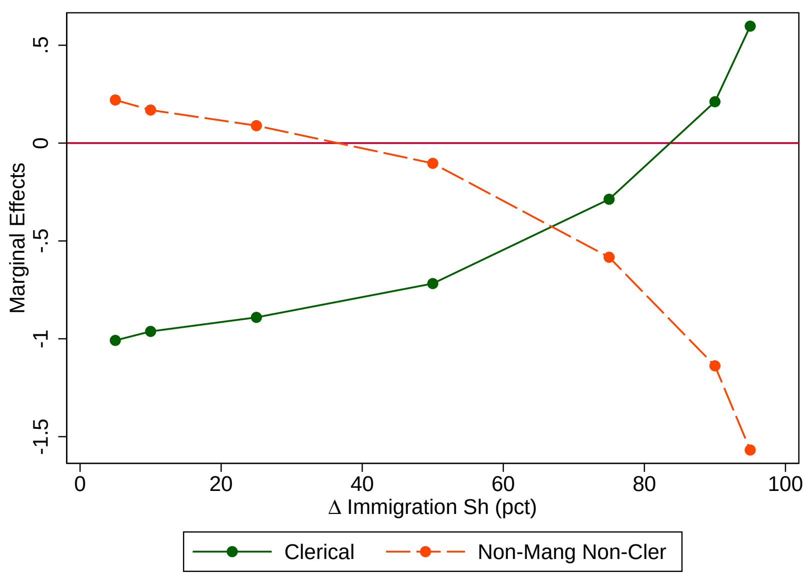


(a) Marginal Effects on Tasks Supply

(b) Marginal Effects on Occupation Shares

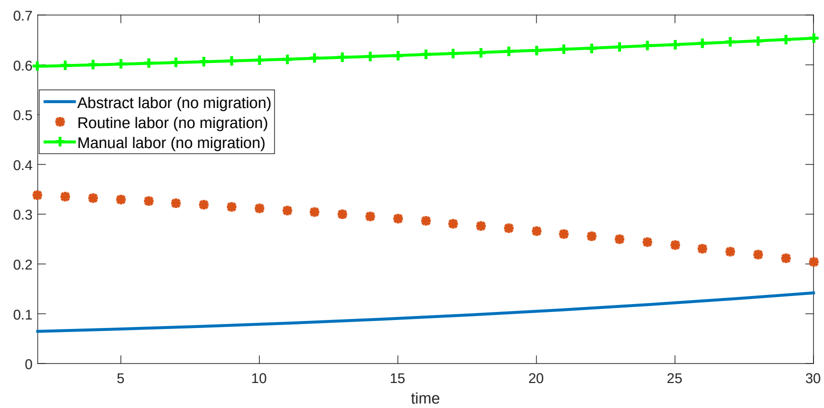
Note: Marginal effects of the Computer-Intensive Labor Productivity measure on task supply and occupation shares at different points of the foreign-born share distribution.

Figure 5: Computer-Intensive Labor Productivity: Marginal Effects on Occupational Wages



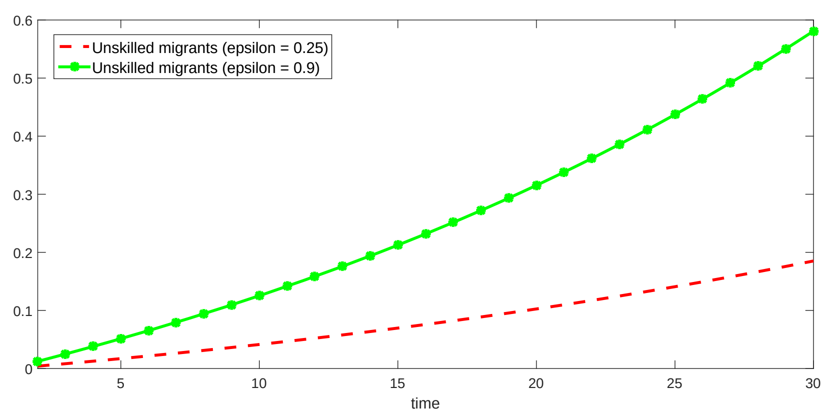
Note: Marginal effects of the Computer-Intensive Labor Productivity measure on occupational wages at different points of the foreign-born share distribution.

Figure 6: Changes in Native Employment Levels from Higher Computerization



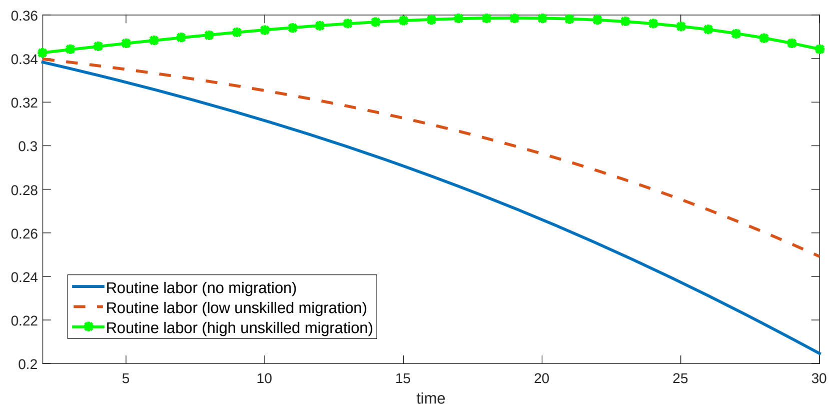
Note: Simulation of model dynamics holding $\varepsilon = 0$.

Figure 7: Changes in Unskilled Migrants from Higher Computerization



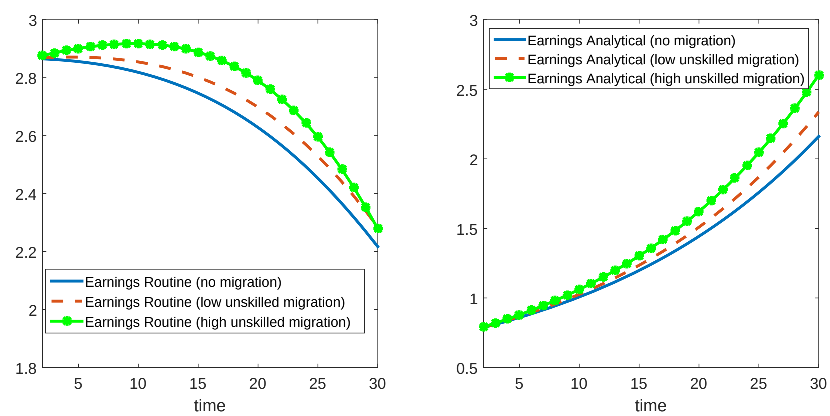
Note: Simulation of model dynamics for $\varepsilon = \{0.25, 0.9\}$.

Figure 8: Changes in Native Routine Employment Levels from Higher Computerization and Immigration



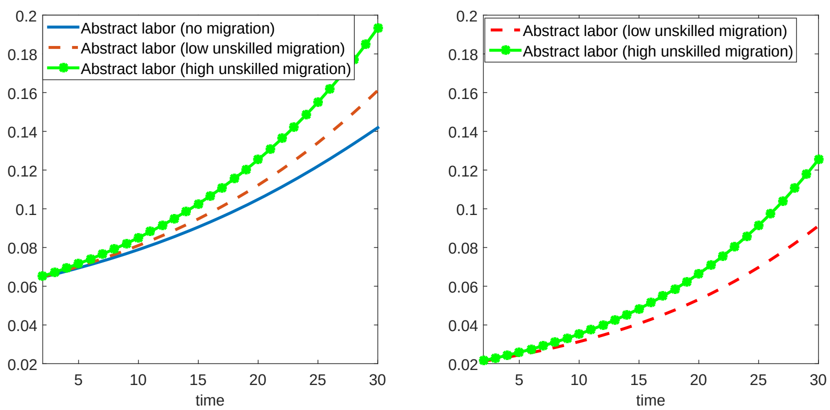
Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$.

Figure 9: Changes in Native Earnings from Higher Computerization and Immigration



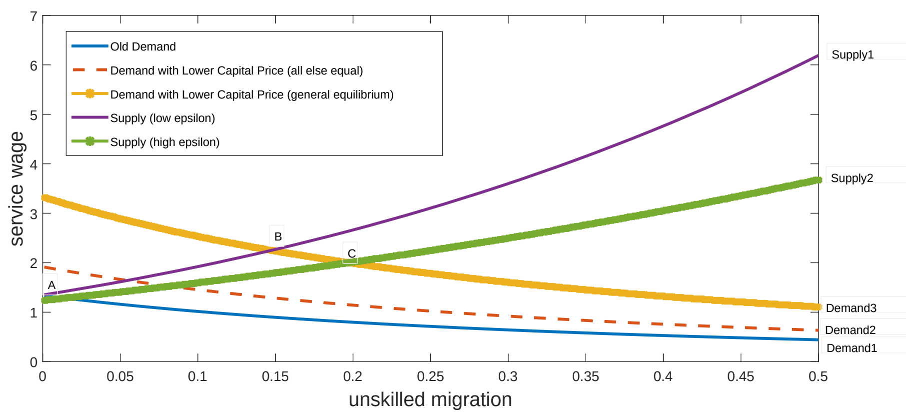
Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$.

Figure 10: Changes in Native Analytical Employment from Higher Computerization and Immigration



Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$.

Figure 11: Representation of the Partial Equilibrium



Note: Partial equilibrium in the service wage-migration space.

Tables

Summary Statistics

Table 1: Occupations and Task Supply in 1980

	Analytical/ Cognitive	**Routine**	**Manual/ Communication**
Managers/prof/tech/finance/public safety	0.81	0.34	0.48
Clerical/retail sales	0.47	0.65	0.22
Non-managerial/Non-clerical	0.32	0.53	0.69
Total Supply	0.49	0.52	0.51
Sh. of Total Supply	0.32	0.34	0.34

Table 2: Foreign-born and Natives' Task Supply: Shares of Total Supply

	Analytical	Manual	Routine	Analytical	Manual	Routine	Analytical	Manual	Routine
Panel A. Foreign-born		*All*			*Low-Skill*			*High-Skill*	
1980	0.292	0.353	0.355	0.230	0.393	0.377	0.397	0.285	0.317
2010	0.313	0.367	0.319	0.222	0.431	0.346	0.404	0.303	0.293
Delta %	7.19	3.97	-10.14	-3.48	9.67	-8.22	1.76	6.32	-7.57
Panel B. Natives		*All*			*Low-Skill*			*High-Skill*	
1980	0.321	0.339	0.340	0.267	0.364	0.368	0.411	0.298	0.292
2010	0.370	0.331	0.299	0.284	0.376	0.34	0.416	0.307	0.277
Delta %	15.26	-2.36	-12.06	6.37	3.30	-7.61	1.22	3.02	-5.14

Main Results

Table 3: Computer-Intensive Labor Productivity and Immigrant Inflows

	Low-Skilled			High-Skilled		
Computer-Intensive Labor Productivity	0.976**		0.762**	0.490**		0.354**
	(0.162)		(0.176)	(0.094)		(0.087)
Sh Immig		0.330*	0.302*		0.225**	0.207**
		(0.144)	(0.138)		(0.051)	(0.050)
Observations	2166	2166	2166	2166	2166	2166

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (2). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 4: Computer-Intensive Labor Productivity and Low-End Job Polarization

	Analytical	Routine	Manual
Panel A			
Computer-Intensive Labor Productivity	0.036*	-0.088**	0.053**
	(0.018)	(0.014)	(0.013)
Obs.	2166	2166	2166
R2	0.6	0.4	0.6
	Managerial Occ	Clerical Occ	Non-Mang Non-Cler
Panel B			
Computer-Intensive Labor Productivity	0.169**	-0.238**	0.069
	(0.046)	(0.053)	(0.046)
Obs.	2166	2166	2166
R2	0.7	0.7	0.7

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (4). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 5: Computer-Intensive Labor Productivity, Low-Skilled Immigration Inflows and Low-End Job Polarization

	Routine	Manual
Panel A		
Computer-Intensive Labor Productivity	0.032	-0.308^{+}
$\times$ Sh Immig (LS)	(0.228)	(0.175)
Computer-Intensive Labor Productivity	-0.055*	0.011
	(0.023)	(0.022)
Sh Immig (LS)	-0.036^{+}	0.069**
	(0.022)	(0.023)
Obs.	2166	2166
R2	0.5	0.5
	Clerical Occ	Non-Mang Non-Cler
Panel B		
Computer-Intensive Labor Productivity	2.686*	-1.992**
$\times$ Sh Immig (LS)	(1.101)	(0.669)
Computer-Intensive Labor Productivity	-0.173^{+}	-0.020
	(0.099)	(0.064)
Sh Immig (LS)	-0.302**	0.264**
	(0.054)	(0.075)
Obs.	2166	2166
R2	0.5	0.6

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 6: Computer-Intensive Labor Productivity, Low-Skilled Immigration Inflows and Low-End Wage Polarization

	Clerical Occ	Non-Mang Non-Cler
Computer-Intensive Labor Productivity	15.152*	-16.877**
× Sh Immig (LS)	(6.092)	(5.033)
Computer-Intensive Labor Productivity	-0.933^{+}	0.137
	(0.549)	(0.465)
Sh Immig (LS)	-1.885**	1.958**
	(0.342)	(0.533)
Obs.	2166	2166
R2	0.5	0.5

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5) where the dependent variable is the change in the occupation log wage. All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 7: Computer-Intensive Labor Productivity, Immigration Inflows and High-End Polarization

	Analytical Task Supply	Manag/Prof Occ Share	Manag/Prof Occ Wages
Computer-Intensive Labor Productivity	0.378	-0.941	-14.072
× Sh Immig	(0.274)	(1.252)	(9.453)
Computer-Intensive Labor Productivity	0.040	0.195^{+}	1.827*
	(0.028)	(0.110)	(0.869)
Sh Immig	-0.046	0.050	1.122
	(0.035)	(0.088)	(0.784)
Obs.	2166	2166	2166
R2	0.6	0.7	0.7

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5): in the first column the dependent variable is the change in the analytical task supply measure; in the second column the dependent variable is the change in the managerial occupations share; finally, in the third column the dependent variable is the change in the managerial log wage occupation. All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Appendix

A1. Empirical Analysis: Robustness Checks

Table A1: Top 10 Occupations by Task Supply Index in 1980

	Occupations	Analytical	Routine	Manual
Panel A. Top Analytical Occupations				
1	Funeral directors	0.990	0.000	0.010
2	Atmospheric and space scientists	0.990	0.000	0.010
3	Writers and authors	0.976	0.000	0.024
4	Dietitians and nutritionists	0.876	0.115	0.009
5	Lawyers	0.847	0.129	0.024
6	Buyers, wholesale and retail trade	0.800	0.057	0.143
7	Bill and account collectors	0.800	0.173	0.027
8	Advertising and related sales jobs	0.798	0.180	0.022
9	Clergy and religious workers	0.771	0.031	0.198
10	Marketing managers	0.760	0.074	0.165
Panel B. Top Routine Occupations				
1	Proofreaders	0.032	0.952	0.016
2	Motion Picture Projectionists	0.156	0.835	0.009
3	Meter readers	0.227	0.760	0.013
4	File clerks	0.118	0.735	0.147
5	Typists	0.156	0.719	0.125
6	Butchers and meat cutters	0.294	0.696	0.010
7	Cashiers	0.248	0.657	0.095
8	Precision grinders and filers	0.133	0.655	0.212
9	Secretaries	0.301	0.654	0.046
10	Payroll and timekeeping clerks	0.340	0.653	0.007
Panel C. Top Manual Occupations				
1	Parking lot attendants	0.000	0.000	1.000
2	Garbage and recyclable material collectors	0.000	0.000	1.000
3	Water transport infrastructure tenders and crossing guards	0.044	0.000	0.956
4	Crossing guards and bridge tenders	0.044	0.000	0.956
5	Law enforcement (e.g., sheriffs, etc.)	0.095	0.036	0.869
6	Bus drivers	0.160	0.008	0.832
7	Housekeepers, maids, butlers, stewards, and lodging quarters cleaners	0.083	0.115	0.802
8	Taxi cab drivers and chauffeurs	0.129	0.073	0.798
9	Waiter/waitress	0.196	0.071	0.732
10	Guards, watchmen, doorkeepers	0.128	0.149	0.723

Table A2: Computer-Intensive Labor Productivity and Immigration Inflows

	Low-Skilled	High-Skilled
Computer-Intensive Labor Productivity	0.710**	0.399**
	(0.210)	(0.120)
Sh Immig	0.300*	0.210**
	(0.136)	(0.051)
Labor Productivity	0.190	-0.169
	(0.364)	(0.248)
Observations	2166	2166

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (2). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A3: Computer-Intensive Labor Productivity, Low-Skilled Immigration Inflows and Low-End Job Polarization

	Routine	Manual
Panel A		
Computer-Intensive Labor Productivity	-0.014	-0.277
$\times$ Sh Immig (LS)	(0.246)	(0.170)
Computer-Intensive Labor Productivity	-0.038	-0.000
	(0.026)	(0.025)
Labor Productivity	-0.064	0.043
	(0.049)	(0.031)
Sh Immig (LS)	-0.031	0.065**
	(0.023)	(0.021)
Obs.	2166	2166
R2	0.5	0.5
	Clerical Occ	Non-Mang Non-Cler
Panel B		
Computer-Intensive Labor Productivity	2.458*	-1.989**
$\times$ Sh Immig (LS)	(1.095)	(0.666)
Computer-Intensive Labor Productivity	-0.091	-0.021
	(0.108)	(0.070)
Labor Productivity	-0.318*	0.004
	(0.161)	(0.126)
Sh Immig (LS)	-0.276**	0.263**
	(0.053)	(0.075)
Obs.	2166	2166
R2	0.5	0.6

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A4: Computer-Intensive Labor Productivity, Low-Skilled Immigration Inflows and Low-End Wage Polarization

	Clerical Occ	Non-Mang Non-Cler
Computer-Intensive Labor Productivity	13.642*	-16.831**
$\times$ Sh Immig (LS)	(5.951)	(5.061)
Computer-Intensive Labor Productivity	-0.390	0.120
	(0.582)	(0.446)
Labor Productivity	-2.102*	0.064
	(0.835)	(0.986)
Sh Immig (LS)	-1.712**	1.953**
	(0.327)	(0.545)
Obs.	2166	2166
R2	0.6	0.5

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

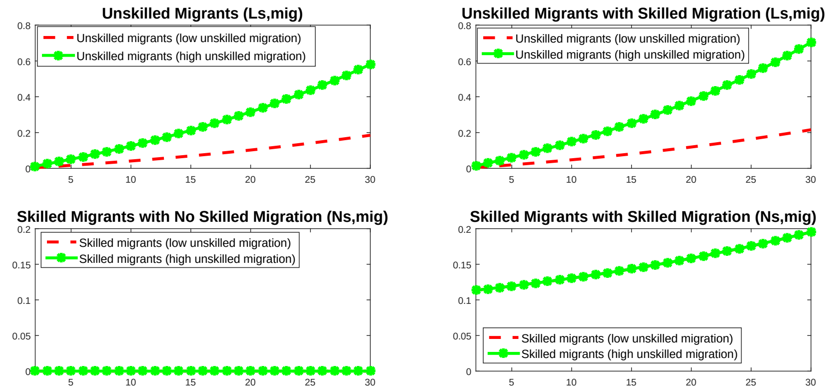
Table A5: Computer-Intensive Labor Productivity, Immigration Inflows and High-End Polarization

	Analytical Task Supply	Manag/Prof Occ Share	Manag/Prof Occ Wages
Computer-Intensive Labor Productivity	0.378	-0.617	-11.531
$\times$ Sh Immig	(0.278)	(1.289)	(9.752)
Computer-Intensive Labor Productivity	0.040	0.107	1.139
	(0.036)	(0.133)	(1.024)
Labor Productivity	-0.000	0.330*	2.584+
	(0.048)	(0.164)	(1.354)
Sh Immig	-0.046	0.012	0.823
	(0.033)	(0.081)	(0.731)
Obs.	2166	2166	2166
R2	0.6	0.7	0.7

Note: Estimated standard errors (in parentheses) are clustered at the state level. Each column reports the βs from equation (5). All the regressions are weighted by the beginning of period population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

A2. Simulation Graphs

Figure 1: Unskilled and Skilled Migration Responses to Higher Computerization



Note: Simulation of model dynamics for $\varepsilon = \{0.25, 0.9\}$ and $\varepsilon_a = \{\}$.

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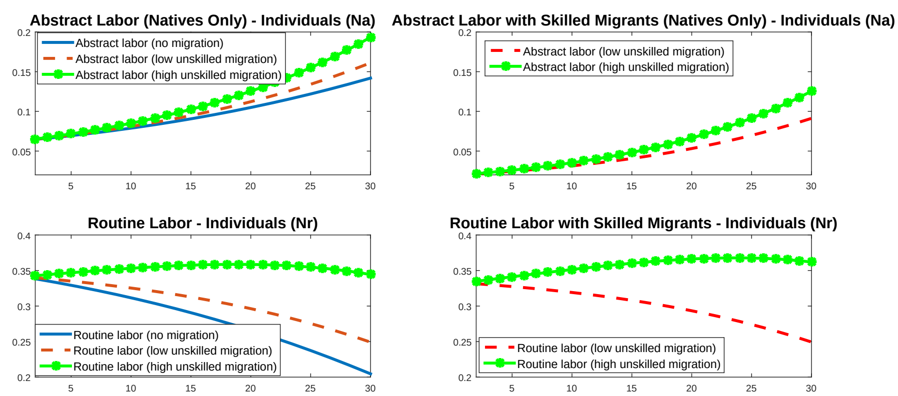
Figure 2: Changes in Native Abstract and Routine Employment from Higher Computerization with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0.25, 0.9\}$ and $\varepsilon_a = \{\}$.

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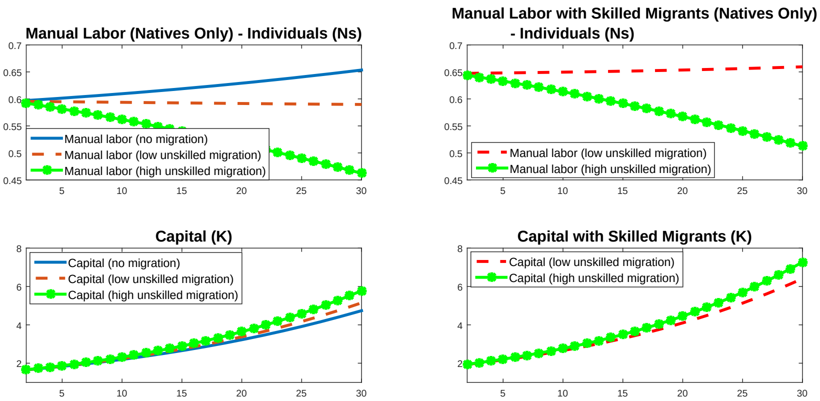
Figure 3: Changes in Native Manual Employment and Capital from Higher Computerization with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$ and $\varepsilon_a = \{\}$.

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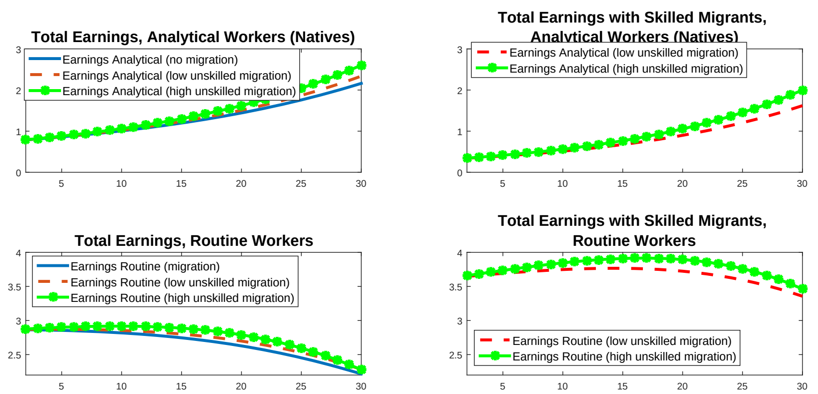
Figure 4: Changes in Native Earnings from Higher Computerization with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$ and $\varepsilon_a = \{\}$.

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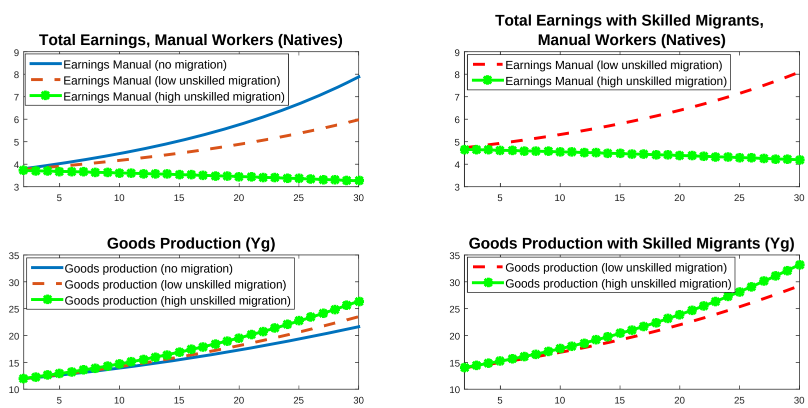
Figure 5: Changes in Native Manual Earnings and Good Production with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0, 0.25, 0.9\}$ and $\varepsilon_a = \{\}$.

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A3. Equilibrium of Simplified Model — Two Forms of Labor and Exogenous Unskilled Migration

In this section we describe a simplified version of the full model. We do this to show some analytical and straight-forward solutions, as well as to demonstrate that our basic findings are consistent even in this more restrictive case.

Consider then the case of just two forms of labor — analytical and manual; there is no routine labor (one can imagine an extreme case where routine labor and capital are perfectly substitutable, with capital the more productive factor. Routine labor then has become completely obsolete.). Utility is still given by:

$$\left(\rho C_s^{\frac{\sigma-1}{\sigma}} + (1-\rho) C_g^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad , \tag{1}$$

and consumption of services and goods have the same forms as before:

$$C_s = Y_s = L_s \quad , \tag{2}$$

$$C_g = Y_g - p_k K - p_a L_a \quad , \tag{3}$$

where Y_s is total production of services, Y_g is total production of manufactured goods, p_k is the price of capital, and p_a is the price of analytical skills. Natives now only have two options: they can be a manual worker, or they can pay p_a to employ their analytical skills in manufacturing. Production in manufacturing here takes the simple Cobb-Douglas form:

$$Y_g = (\alpha_a L_a)^{\alpha} K^{1-\alpha}. \tag{4}$$

Analytical skill is exponentially distributed as before, and total analytical labor is still given by:

$$L_a = \phi \left(\hat{\eta} + 1 \right) e^{-\hat{\eta}}, \tag{5}$$

and the threshold amount of skill ($\hat{\eta}$) is given by equating the return to analytical skilled labor and the return to manual labor for the threshold-individual:

$$w_a \phi \hat{\eta} - p_a = w_s. \tag{6}$$

As usual, labor-types and capital are paid their marginal products. Finally, potential migrants are all unskilled, and contribute to the mass of manual workers. This mass is thus given by

$$L_s = 1 + mig - e^{-\hat{\eta}} \tag{7}$$

Comparative Statics

We wish to understand factors that may lead natives to increase or decrease skills. The wage for these skills is given by

$$w_a = \alpha \left(\alpha_a L_a \right)^{\alpha - 1} K^{1-\alpha}. \tag{8}$$

The price of capital, exogenously given, must equal the marginal productivity of capital:

$$p_k = \left(1 - \alpha \right) \left(\alpha_a L_a \right)^{\alpha} K^{-\alpha}. \tag{9}$$

Combining these and simplifying then gives us

$$w_a = \alpha \left(1 - \alpha \right)^{\frac{1-\alpha}{\alpha}} p_k^{\frac{\alpha-1}{\alpha}}. \tag{10}$$

Right away, we see that the analytical wage is pinned down strictly by the price of capital. As capital prices fall, the return on analytical skills rises. Notice also that this implies *there is no impact from unskilled immigration on analytical wages.* More on this below.

Unskilled immigration on the other hand is predicted to lower the unskilled wage. To see this note that we can rearrange (6), substitute in (10), and get:

$$\hat{\eta} = \frac{(w_s + p_a)\, p_k^{\frac{1-\alpha}{\alpha}}}{\phi\alpha\,(1-\alpha)^{\frac{1-\alpha}{\alpha}}}. \tag{11}$$

We can take this expression and plug it into (7) to solve for w_s:

$$w_s = \frac{-\phi\alpha\,(1-\alpha)^{\frac{1-\alpha}{\alpha}} \ln\left(mig + 1 - L_s\right)}{p_k^{\frac{1-\alpha}{\alpha}}} - p_a \tag{12}$$

Finally, we have some simple comparative statics to suggest.

Proposition 1. $\frac{\partial\hat{\eta}}{\partial p_k} > 0$.

This is clear from equation (11). It means that *falling* capital prices will result in falling levels of $\hat{\eta}$, which means more analytical labor in equilibrium. Capital growth spurs education.

Proposition 2. $\frac{\partial\hat{\eta}}{\partial mig} = \left(\frac{\partial\hat{\eta}}{\partial w_s}\right)\left(\frac{\partial w_s}{\partial mig}\right) < 0$.

The first term being positive is clear from (11); the second term being negative is clear from (12). It means that exogenous increases in unskilled migration results in a falling education threshold, which means more analytical labor in equilibrium. Immigration spurs education.

Proposition 3. $\frac{\partial^2\hat{\eta}}{\partial p_k \partial mig} = \left(\frac{\partial\left(\frac{\partial\hat{\eta}}{\partial p_k}\right)}{\partial w_s}\right)\left(\frac{\partial w_s}{\partial mig}\right) < 0$.

Again, the first term being positive is clear from (11); the second term being negative is clear from (12). This suggests that skill enhancements from technological progress are accelerated with unskilled migration. Technological progress and migration *together* spur education increases even more.

The key takeaway here is that unskilled migration spurs greater human capital accumulation without hurting the earnings of those with human capital. The reason is that the marginal productivity of capital here is pinned down by the price of capital, which is exogenously given. As migrants push natives to higher levels of education, it raises the productivity of capital, which spurs capital growth, pushing analytical wages back up.

Relation to Conclusions from Main Model

So how does the simple theory here compare to the full theory described earlier? This simple model cannot comment on certain points raised by the general theory, since there is no possibility of polarization in this economy, and immigration is treated exogenously. However, it does echo points 3 and 4.

Specifically, immigration is shown to drive natives up the skill distribution, away from manual tasks and toward analytical tasks. Further, we know from the general model that the negative impacts on native wages from migration are mitigated, or even reversed, from the growth in capital that such migration fosters. In this simplified case this suggestion is even more stark. Given (10) skilled wages are altogether unaffected by migration, so we find that the total earnings for skilled natives must rise (greater supply of skills with same wage) with greater migration.

The more generalizable model points to the fact that unskilled immigration is a benefit to middle-income Americans. The simple model here points to something related — unskilled immigration is a benefit to those with at least some skills.

A4. Robustness

Finally, we note that the basic findings of the theory are quite robust to parameterization. Essentially, what we require is that analytical labor and the capital-routine labor aggregate are grossly complementary ($\beta < 0$), routine labor and capital are grossly substitutable ($\gamma > 0$), goods and services are grossly complementary in utility ($\sigma > 0$), and analytical workers are more productive than routine workers in production ($\alpha_a > 1$). Each assumption remains uncontroversial in the literature.

We can however adjust parameters to observe quantitative changes to our baseline results. How our results change, either positively or negatively, are summarized in Table A1. Here we compare our baseline case where $\epsilon = 0.25$ (moderate degree of immigration) illustrated earlier with the same case but with a different parameter value. Among notable observations are the following:

With less complementarity between L_a and X (higher β): Wage growth is less, there is less skill upgrading, and natives do not leave routine jobs as much.

With less substitutability between L_r and K (lower γ): Wage growth is greater, and there is greater skill upgrading, but there is less reversal of polarization at the lower end with immigration.

With more productive analytical workers (higher α_a): All variable changes become more pronounced. Both technological progress and immigration have more beneficial effects for the economy as natives upgrade their skills.

Table A6: Simulation: Robustness to Baseline Parametrization

Variables	**Higher** β	**Lower** γ	**Lower** σ	**Lower** ρ	**Higher** α_a
w_a	-	+	-	+	+
w_r	-	+	-	+	+
w_s	-	+	+	-	+
N_a	-	+	-	+	+
N_r	+	-	-	+	+
$N_{s,natives}$	-	-	+	-	+
K	-	-	-	+	+
Y_g	-	+	-	+	+

Note: "+" suggests a larger cumulative percent change relative to the baseline case with technology and endogenous migration. "-" suggests a smaller cumulative percent change.