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COMPUTERIZATION AND IMMIGRATION:
THEORY AND EVIDENCE FROM THE UNITED STATES

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Computerization and Immigration: 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 the demand for routine tasks, but have increased the demand for analytical tasks. Indirectly they have also increased the demand for manual tasks and service oriented 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 the immigration response has helped to reduce the polarization of employment for natives. We explain these facts with a model of technological progress and endogenous immigration. Simulations show that immigration in the presence of technological change attenuates the drop in routine employment and the increase in service employment for natives.

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1 Introduction

The automation and computerization of several tasks in manufacturing 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, as those were increasingly performed by computers (Autor, Levy and Murnane, 2003; Goos, Manning and Salomon, 2014). Second, it simultaneously contributed to the increase in the employment shares of cognitive-intensive 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 are towards the bottom and cognitive intensive jobs cluster at the top, this phenomenon has contributed to what has been called "polarization" of the labor market.

Within this context, we ask two sets of questions about which very little is known. First, did foreign workers respond to these shifts in labor demand more than native workers, so that the share of immigrant workers increased, especially in the faster growing segments of the labor market? And once established in the United States, did immigrants concentrate in those labor markets where computerization occurred at faster rates? The focus on immigrants is interesting because they exhibit a distribution of skills quite distinct from natives. They specialize, particularly the less educated among them, in manual-intensive service occupations[1] (such as house-keeping, building, gardening, baby-sitting) and their supply may have been particularly responsive to these routine-substituting technological changes. Moreover as already emphasized by Cadena and Kovak (2016), less educated immigrants seem to respond more to differential labor demand shocks than native workers at the local level. This was shown for short-term shocks; here we analyze whether this was true for long-run technology-driven demand changes.

Second, did the differential inflow of immigrants in local US labor markets affect the

[1] See Peri and Sparber (2009).

extent of employment polarization of natives? Namely, did the employment impact of computerization on natives differ in areas 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 instead encouraging their inflow into analytical ones.

In the empirical analysis we first test how immigration responded to what we call "*computer-intensive productivity growth*." Computer intensity is the use of computer/machines/IT in production, which we measure as the computer share in inputs at the sector level. Then we interact such intensity measured in 1980 with the labor productivity growth of the sector during the period 1990–2010. The larger is the computer intensity and productivity growth of the sector, the larger is the index value for that sector. Hence this index captures for each sector the part of productivity growth positively associated with computer intensity. We then construct a local labor market measure of this index by weighting the index in each sector by the 1980 employment share of the sector. This is a novel way to capture the fact that a locality with a large employment share in sectors that had high computer-related productivity growth were likely subject to larger changes in occupational and productive structure and hence in skill demand. Sometimes, for compactness, we simply call this variable "computerization." To validate our novel measure, we test its correlation with the existing proxy used to measure the predicted intensity of local computerization, namely the measure of local routine-intensity as defined by Autor and Dorn (2013). We then analyze its correlation with employment changes for high- and low-skilled immigrants. We establish that computerization intensity across local labor markets in the US is strongly associated with both 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, as predicted by Autor and Dorn (2013). However, novel to this paper, we find that in areas with large immigration *potential* (proxied by the pre-existing immigrant network) the employment effects of technological change on native workers are attenuated. In these Commuting Zones (CZs), we observe smaller employment growth of manual-intensive jobs for natives, and smaller employment declines in routine intensive jobs for natives. This is because a larger immigrant supply response fills manual-occupation demand, reducing the displacement of natives from routine to manual and hence reducing their "downgrading." 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 attenuated. Indeed, we see that the majority of service workers contributing to low-end employment polarization are in fact migrants, and their presence generates more local demand for routine, mid-skilled jobs. Conceivably without them mid-skilled natives would be more prone to employment 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 computerization and endogenous immigration on native polarization. The model extends Autor and Dorn (2013). In that framework the acceleration of computerization 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. The crucial novelty of our model is that we allow for endogenous inflows of immigrants, focusing on the low-skilled ones.[2] We then analyze how computerization affects the employment of natives. We compare a baseline case when immigrant supply responds moderately to computerization with a case where no immigrants are allowed in the country. These comparisons provide a reasonable quantitative explanation for the key findings of our empirical analysis. Immigrant supply and their specialization in manual tasks attenuates the negative impact of technology on routine employment of natives, while at the same time raises the demand for analytical tasks. Allowing stronger immigrant response would reduce further the polarization effect of computerization on native jobs and wages at the low end of the wage spectrum.

The rest of the paper proceeds as follows. We review the relevant literature in Section

[2]In an extension we allow also immigration of high skilled immigrants

2. Then in Section 3 we present some empirical facts and estimate some correlations across local labor markets. In Section 4 we develop a model that provides intuition for the main findings and we 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 from immigrants' labor supply and task specialization. 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, 2013) 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 during the 1990's and 2000's, several recent papers (notably Autor and Dorn, 2013; Acemoglu and Autor, 2011; and Goos, Salomon and Manning, 2014; Acemoglu and Restrepo, 2017) 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 helps explain the increase in inequality at the top of the wage distribution. Finally computerization has not much affected the physical productivity of manual-intensive jobs in services (e.g. cooking, house keeping, baby-sitting, health care, food, landscaping). However, the demand for those services may have increased because they complement the consumption of goods and services produced using computers. Hence, computer-driven productivity growth increased the demand for manual-intensive service-type jobs. This is the reason for polarization in the lower part of the wage spectrum (see Autor and Dorn, 2013). [3]

[3] A recent paper by Cerina et al. (2017) argues that women are the main driver of both low and high-end

New in this literature, we extend the analysis of the consequences of computer-driven productivity growth on two dimensions. First, relative to findings in Cadena and Kovak (2016) and Borjas (2003), who show larger short-run responses of immigrants to local labor demand shocks, and we document a strong response of immigrants to computer-driven productivity growth at the Commuting Zone level. 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 (as captured by pre-existing immigrant networks). While the small (and sometimes positive) association of low skilled immigration with employment and wages of native workers has been known for some time (Card, 2001; Card, 2009; Basso and Peri, 2015), 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.

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 studies (especially Bound et al., 2017; and Jaimovich and Siu, 2017) also explicitly model the fact that highly skilled immigrants have a strong preference for occupations in the computer sector which further enhances innovation. While we focus on unskilled immigrants, and document a less known complementarity between computerization and this group, these papers share with our approach the emphasis on the different specialization of immigrants

polarization. Our work is complementary to Cerina et al., in that we look at the importance of low-skilled immigrants in driving the growth in service occupations, and we analyze how, in turn, this affects native occupational upgrading.

relative to similarly educated natives, and the benefits that this may generate for natives.[4]

Finally, our paper is further related to, but substantially differs from, the literature on directed skill-biased technical change (Galor and Moav; 2000, Acemoglu, 1998, 2002; Acemoglu and Restrepo, 2016). While recent and valuable contributions in this literature indicate that the abundance of low-skilled migrants induces a delay in the adoption of machinery and innovation (Lewis, 2011; Clemens et al., 2017), we highlight two important channels previously overlooked by this literature. First, we document that immigration responds endogenously to the adoption of technology on top of supply-driven immigrant inflows. Second, we highlight the role of immigration in determining occupational and skill upgrading when both technology adoption and immigration are present.

3 Empirical Facts

In this section we present some simple empirical facts and regression results that provide strong support for two regularities. First, labor markets (Commuting Zones) with intense computerization 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-intensive productivity change attracted *both* high and low educated foreign-born workers. The complementarity of computerization and analytical jobs cannot explain the inflow 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 low skilled immigrants.

[4] Llull (2017) adds the education and labor participation adjustment margins to the more traditional literature on the effects of immigration on natives wages and employment using a more structural approach. With respect to this paper, we focus on technological advancements, its interplay with immigration and their effects on job and wage polarization.

Second, analyzing Commuting Zones (CZs) which experienced high or low immigration, as predicted by the pre-1980 network of immigrants, we show that the "polarizing" impacts of 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 this response attenuated the "downgrading of natives" from routine jobs to manual service ones relative to low immigration CZs.

3.1 Computerization and Immigration

We first construct a measure of "computer-intensive productivity growth" ' of local economies (Commuting Zones) between 1980 and 2010. More precisely we first proxy computer-intensive productivity growth for each sector during 1980–2010 and then, based on the industrial structure of a commuting zone in 1980, we calculate this measure at the local level. Then we show how this 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 inflows of immigrants. We also check that our measure is not correlated to pre-1980 immigration, ruling out spurious correlations due to long-run unobserved and persistent trends.

The data we use are the 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.[5] 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.

Somewhat following Bartik (1991) we use the shares of employment in each industry in Commuting Zone c and we interact these with the national log wage growth for the whole

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

industry, weighted by the computer-intensity (share of computer in inputs) of the sector in 1980. The measure captures the industry-specific productivity growth interacted with the computer intensity of the sector in 1980, and then allocated to a Commuting Zone in proportion of its 1980 employment share across industries. Technically, the computer-intensive productivity growth (CIPG) is calculated as:

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

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 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 labor productivity (rather than of employment) in a sector, nationally, in order to better capture the increase in labor productivity in the sector. Second we weight sectors by their computer-intensity to capture the part of productivity growth associated to computer use and hence 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 labor 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 the CIPG measure (vertical axis). The positive and strong correlation (t-stat of the linear coefficient is 6.56) indicates that computer-intensive 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 the indexes of analytical, routine and manual task specialization, 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 specialization. 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 indexes of analytical, routine and manual tasks, as previously done by Autor et al. (2003) and Autor and Dorn (2013). Each of the three indexes represents the percentile of each occupation in the distribution of occupations ranked by task in 1980. Each worker, therefore, has an index that reflects her/his specialization in analytical, routine and manual tasks, which we can then be aggregated by Census year and local labor market.[6] These indexes of task specialization are exclusively based on the occupational task intensity relative to all other occupations in the economy. And differently from Acemoglu and Autor (2011) 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 indexes, dividing by the total supply of tasks in each Census year and local labor market to better capture the changes in the polarization of foreign-born and natives' specialization.

Acemoglu and Autor (2011) suggests it may be preferable to work with occupations directly because task indexes, such as those constructed above, may not accurately reflect the actual task structure (Acemoglu and Autor, 2011, page 1078). Thus, we also look directly at occupational employment shares. Following Autor and Dorn (2013) we categorize occupations into three distinct groups by simply aggregating managerial, professional and technical occupations, routine occupations (mainly clerical, sales, precision production and machine operators) and non-managerial/non-routine occupation (personal services, construction, mechanics and agricultural workers). 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

[6]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.

occupations (managerial, routine and non-managerial/non-routine) is reported in Table 1. It shows the high analytical content of managerial occupations, the high routine content of routine occupations, and the high manual content of services/construction/transportation 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 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 and the correlations between the task indexes and the occupation categories presented in Table 1 are high.

Figure 2 and Table 2 use the task specialization 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 value 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 index 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 are specialized significantly more in manual tasks relative to natives, and significantly less in analytical ones already in 1980. This difference became even larger during the 1980–2010 period when the index of manual tasks increased significantly more for low skilled immigrants than for low skilled natives. Even high skilled immigrants increased their manual specialization more than high skilled natives. On the other hand, immigrant specialization in routine tasks was relatively similar to the natives' one as of 1980 and it declined roughly at the same rate.

Hence, as a group, immigrants' specialization in manual tasks increased 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. As firstly noted by Mandelman and Zlate (2014), and 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.[7] 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 attenuated the decline in demand of routine tasks and in routine-employment of natives.

In order to use local area variation to test the correlation between computer-intensive productivity growth and changes in foreign-born workers, we define the immigration inflow at the Commuting Zone 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 (2015) and Card and Peri (2016), this measure captures inflows of im-

[7]Mandelman and Zlate (2014) develop a three-country dynamic stochastic general equilibrium model in which polarization is attenuated by low-skilled undocumented immigrants. We see this valuable work as complementary to ours as they reach similar conclusions despite substantial differences: first, their driver for polarization is off-shoring and not automation contrary to the empirical evidence (Autor, Levy and Murnane, 2003; Goos, Manning and Salomons, 2014); second, they model immigration as high-school dropouts illegal immigration inflows from Mexico only; and third, they provide limited empirical evidence consistent with their claims and assumptions.

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

$$\frac{Fb^s_{c,t} - Fb^s_{c,t-10}}{pop^s_{c,t-10}} = \beta \text{CIPG}_{c,t} + \gamma \Delta \hat{F} b_{c,t} + \phi^s_{d,t} + \Delta \varepsilon^s_{c,t}, \tag{2}$$

where s stands for either low-skilled or high-skilled and $\text{CIPG}_{c,t}$ is the measure of computer-intensive productivity growth 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 $\varepsilon^s_{c,t}$ are zero-mean random errors specific to the Commuting Zone and year. The variable $\Delta \hat{F} b_{c,t}$ is a measure of predicted immigration inflow that exploits pre-existing settlements of immigrants by nationality across US local labor markets. It captures a supply-driven push of immigrants. 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 $F\hat{b}_{c,t} = \sum_n Fb_{n,c,1970} * \frac{Fb_{n,t}}{Fb_{n,1970}}$ 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:

$$\Delta \hat{F} b_{c,t} = \frac{F\hat{b}_{c,t} - F\widehat{b_{c,t-10}}}{USb_{c,t-10} + F\widehat{b_{c,t-10}}} \tag{3}$$

This measure, which 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 change in high-skilled foreign born. 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 (four and five) 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 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 the low skilled immigrant share by 0.76 percentage points. Both effects are very statistically significant and robust. While previous papers had focused on the inflow of high skilled into high productivity cities (e.g., Moretti, 2013; Diamond, 2016), our paper emphasizes that inflows of low skilled immigrants are significantly associated with computer-driven productivity growth at the local level.[8] 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.

3.2 Native Polarization

In order to test empirically that at the local labor market level 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:

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

where $y^k_{c,t}$ represents the native specialization intensity for each task k (representing alternatively analytical-, routine- and manual-intensive) for Commuting Zone c and year t, and the operator Δ captures the difference between census years. We run the regression in dif-

[8]Notice that if we construct a simple Bartik measure of productivity growth across Commuting Zones, such a variable is much less correlated with immigration than CIPG. See Table A4 in the Appendix that includes the standard Bartik and the CIPG as explanatory variables in regressions of Table 3. Moreover, CIPG does not systematically predict the 1950–1980 immigration inflows (see Table A8 in the Appendix) confirming that it is not correlated with other unobserved and persistent factors affecting immigrant demand.

ferences, thus removing time-invariant unobservable local labor market characteristics. We further control for Census division-by-time fixed effects ($\phi^k_{d,t}$), which capture region and time specific shocks.

Table 4, Panel A reports the estimates of coefficient β from equation (4) above, using the native employment of analytical, routine and manual indexes, respectively, as dependent variables. Panel B does the same for the share of managerial/professional, clerical/sales/operators and services/construction/transportation occupations as dependent variables. The results are consistent across the two occupational partitions and suggest a significant role of CIPG 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.

Was the effect of CIPG 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? As it could be already inferred from Figure 3, job market polarization among natives is less pronounced at the low-end. Table 5 reports the changes of occupational employment shares among natives between 1980 and 2010. Managerial and professional occupations, whose task specialization is prevalently analytical, increased their share by 7.6 percentage points between 1980 and 2010. In the same period, the employment shares of clerical and machine operator (prevalently routine) and non-managerial/non-routine (prevalently manual) occupations decreased by 10.6 and 2.4 percentage points, respectively.

To further analyze this question we run the following regression:

$$\Delta y^k_{c,t} = y^k_{c,t} - y^k_{c,t-10} = \beta \mathrm{CIPG}_{c,t} + \gamma \Delta \hat{F}b_{c,t} + \delta(\mathrm{CIPG}_{c,t} * \Delta \hat{F}b_{c,t}) + \phi^k_{d,t} + \Delta\varepsilon^k_{c,t} \qquad (5)$$

where we have shortened the variable computer-intensive labor productivity growth as $CIPG_{c,t}$

and the predicted immigrant inflows (or "Immigrant Shift-share") as $\Delta\hat{F}b_{c,t}$. We have then included the interaction of these two terms. As $\Delta\hat{F}b_{c,t}$ 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 inflows. If immigration attenuates the demand shift driven by CIPG on natives in the low-range of wages, such interaction should have a positive effect on native routine task specialization and clerical employment, and a negative effect on native manual task specialization and non-managerial/non-clerical employment. The coefficients on this interaction (as well as those on the main effects) are reported in Table 6. Computer-intensive productivity growth simultaneously attracts immigrants and pushes workers toward manual jobs. Commuting zones with larger exposure to immigration, therefore, experienced the first effect more intensively. Such inflows of immigrants increased the supply of 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").[9] 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.[10]

If employment does not fully respond to the relative demand changes described above, 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 should attenuate these wage effects on natives. This is exactly what is reported in Table 7. 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 attenuated in the presence of large immigrant inflow (we will discuss how immigration can put upward pressure on wages overall in the next section).[11]

[9] Figure A1 in the Appendix reports the marginal effects of the computer-intensive productivity measure on task specialization and occupational shares over the distribution of the 1980-2010 changes in the low-skilled immigration share.

[10] Table A5 in the Appendix reports a robustness check in which we include a Bartik-type labor productivity growth: 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.

[11] Table A6 in the Appendix reports a similar robustness check to the one we performed for task special-

To give an idea of the magnitude of these effects, let's compare two commuting zones, one at the 10th percentile and one at the 90th percentile of the 1980–2010 change in immigrant share distribution: Winston-Salem (NC) and College Station (TX), respectively.[12] 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 services/construction/transportation 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).[13]

Note that, in combining the insights from Tables 6 and 7, 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 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 8 shows the impact of computer-intensive productivity growth and its interaction with immigration intensity on the share of analytical jobs and on the wage for natives. The interaction effect is not statistically significant for employment (first two columns) and depending on the definition of analytical task

ization 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.

[12]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.

[13]Figure A2 in the Appendix reports the marginal effects of the computer-intensive productivity measure on occupational wages over the distribution of the 1980-2010 changes in the low-skilled immigration share.

specialization and managerial occupation share, the point estimate is positive or negative. The interaction on native wages for Manager-professionals is negative and borderline significant. The evidence on how immigration affects polarization at the high end in response to technology is thus not very clear.[14]

Summarizing the empirical findings 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 computerization of production, 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 computer-capital deepening, as a result of lowering its price, drives changes in labor productivities, wages and immigration. A simplified version of this model is discussed in the Appendix section A4 — 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 immigration, as the inflow of immigrants respond to domestic wage changes. In the model we mainly focus on unskilled immigration. This group has been a very important portion of immigration in the 30 years since 1980, and as we show in the previous section, it seems crucial to the mechanism of comparative advantages and specialization in response to technological change. This will be the focus of our analysis. We include the possibility of skilled immigration in subsequent discussion, although 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., 2017 and Jaimovich and Siu, 2017).

[14] Table A7 report the robustness checks including the generic measure of labor productivity growth. The main effects hold although the estimates of the interaction term are often not statistically significant at conventional levels.

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:

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

subject to the constraints discussed below. Here 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. [15]

There are three basic factors of production — "computer 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. As the cost of training is paid every period and we are implicitly assuming that skills are fully used in the production of a final good, one can think of a model as representing infinitely lived households, with successive generations of people with independent skills and education. This is a simple way of modeling costly human capital acquisition. Computer 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 (service) tasks in the service production (whose supply we denote as L_s). Individuals have different relative abilities in routine 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:

[15] This is an important assumption, adopted also in Autor and Dorn (2013), justified by the fact that goods and services are quite differentiated from each other.

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

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

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 total income in the economy 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 the technological efficiency of converting goods into physical and human capital units. Hence, in a broad sense, they represent the cost of computer capital and schooling. The exogenous decline in the cost of computer 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 computer 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 computer 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 computer 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 and Skill 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 the process of education/training for worker i is equivalent to an "upgrade" of her endowment-ability to an acquired level, proportional to the initial level, $\phi\eta_i$. The parameter $\phi > 1$ is the proportional increase in productivity due to training if she expends a lump sum amount of p_a (in units of goods) in training. 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 labor 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 $f(\eta) = \lambda e^{-\lambda \eta}$, where $\lambda > 0$, and the total mass of native labor force is standardized to 1.

A key novelty of our model is to introduce an immigration response to wages and to allow immigrants to supply abilities that are different from those of natives. We 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 captures 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, and more related to communication-oriented tasks. We assume that unskilled migration is negatively related to a cost of migration p_s^m, and positively related to service wages w_s in the economy, as unskilled immigrants can only work in that sector. Note that p_s^m can include the wages earned by the migrant in their country of origin — in this case it can be interpreted as an opportunity cost of migrating. Such costs are not a function of changes in the host economy, and so we treat p_s^m as exogenous. We assume a simple functional form that implies a log linear supply response to wages, which is qualitatively in line with a simple model of immigration choice, such as Grogger and Hanson (2011). The reduced form immigration equation is 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, ($\epsilon_s > 0$) governs the extent to which unskilled migrants respond to potential income in the host economy. A low value of ϵ_s can mean that service wages do not translate into much utility for immigrants, while a high value of ϵ_s suggests that wage earnings translate strongly into utility and this would then have a strong effect on their labor 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). It will be determined by a combination of the distribution of unobserved skills of immigrants, and by immigration policies.

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:

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

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

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

$$L_s = mig + \int_0^{\eta^*} \lambda e^{-\lambda \eta} d\eta, \tag{16}$$

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.

4.1 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:

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

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

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

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.

What are the channels for 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, also lowers η^*, the routine-skill/service threshold for natives (21), which then generates a larger number of native workers choosing routine tasks in manufacturing increasing the routine supply in the economy (23).

Note that higher levels of services should also raise the relative value of goods in the economy. Such an effect can be considered as the "demand effect" of immigrants, who produce more services but they also contribute to the demand of complementary goods. And this effect attracts 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), to the advantage of native workers. 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.

4.2 Parameter Values and Model Simulation

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.[16] 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 $\epsilon = 30$, the cumulative drop in p_k, and our baseline parameter values (described below), this produces a roughly 6.5 percent cumulative increase in unskilled labor due to migration. 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 immigrants as share of the population observed in the United States for the past three decades (as described, for instance in Chapter 2-3 of Borjas 2014).

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: $\alpha_a = 1.75$, $\beta = -10$, $\gamma = 0.5$, $\rho = 0.5$, $\sigma = 0.5$, $\phi = 2$, $p_a = 0.25$, $\lambda = 0.05$. 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).[17]

[16] In the simulation one period can correspond to one year.

[17] Specifically, initial shares of native employment are $N_a = 0.27$, $N_r = 0.35$, and $N_s = 0.38$. Other combinations 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.

We demonstrate both the directional changes in the model diagrammatically, and the we show quantitative magnitudes of changes in tables. Figures 4 to 8 and the left-hand-side diagrams in Figures A3 through A7 (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). Table A9 displays the magnitudes of these changes. We demonstrate two basic cases. The first case is where $\epsilon = 0$, illustrated with solid blue lines. In this case no immigration takes place as computerization occurs. The second case is our baseline where $\epsilon = 30$, illustrated with red dashed lines. Here we observe moderate endogenous migration of a magnitude roughly consistent with the U.S.'s experience during the three decades of 1980–2010 and computerization in the form of the decrease in price of capital.

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 labor market polarization**. That is technological progress produces an increase in employment for analytical and service workers while it produces a decline of employment for routine workers. We demonstrate this in Figure 4. 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 (cumulatively equal to 14 percent of employment), a fall in routine employment (by 21 percent), and a rise in manual service employment (by 9.6 percent). 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.

The model also generates wage polarization. This is clear from Table A9 — wages for analytical labor rises relative to routine labor. And wages for service labor also rise relative to routine labor. We thus see that computer capital growth in the model produces the kind of polarization observed in the United States over the last few decades.

2) **Technological progress attracts low-skilled migrants**. This can be seen in Figure

5. 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 cost p_m to enter the economy and earn $(1 + w_s)^{\epsilon_s} - 1$. For our illustrated baseline case, where $\epsilon_s = 30$, we observe a technologically-induced immigrant inflow of roughly 6.5 percent of the total original workforce in the simulation. This finding matches the empirical results shown in Table 3 — our empirical proxy of computer intensive productivity growth, strongly correlates 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 6, 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 21 percent over 30 periods. With our baseline case of moderate unskilled migration, computerization lowers native employment in these positions by only 14 percent.

Again, our empirical findings lend support to this, both in terms of direction and magnitude. We see this in Table 6 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 of Figure 6 — 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 somewhat mitigated for all natives. Partial equilibrium analysis misses this ancillary effect from migration.

Figure 7 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 7. Again, we look to the estimated coefficient on the cross term. Here we see that the extra supply of unskilled immigrants naturally pushes down services wages, but also pushes up routine wages. Combining this with the rise in routine employment documented in Table 6, 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 in Figure 8 — 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 (2016).

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 upper right panel of Figure A4. 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 even 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 8 in which the effect of openness to immigration interacted with CIPG is not found to be statistically significant.

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 9 provides some intuition regarding our overall results. Here we generate from the model demand and supply schedules for unskilled immigration into the economy. The horizontal axis shows immigrants as share of the population. 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.

4.3 Introducing Skilled Migrants

We extend the basic analysis described above by including *skilled* migrants on top of 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 who, as shown for instance in Peri (2016), are particularly concentrated among less educated manual workers and highly educated professionals in cognitive-intensive jobs.

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. Notice that we allow skilled immigrants to have different moving cost relative to unskilled, which is possibly due to their higher adaptability (if migrants are heterogeneous) or their higher options to remain in touch with the country of origin. This is a plausible and general assumption and adopted by Grogger and Hanson (2011) among others. Also 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:

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

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.[18] 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 A3 to A7 where we replicate the simulations for no entry of unskilled migrants

[18] In these cases $\epsilon_a = 1.5$ for all simulations.

($\epsilon_s = 0$), and baseline levels of unskilled migration ($\epsilon_s = 30$), keeping the scales across graphs the same for comparability.

As we can observe in the right side diagram of Figure A3, the initial economy is composed of a sizable group of skilled migrants, and this group rises as computer capital grows over time. From simulations of this case, we can suggest a number of other propositions:

7) **Endogenous skilled migration attracts greater amounts of unskilled migrants and capital.** We can observe magnified increases in both the left diagram of Figure A3 (greater mig), and the lower-right diagram of Figure A5 (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.

Given that the inclusion of skilled migrants magnifies the rise of both computer capital and unskilled migrants, one might wonder if the earlier suggestions of the model hold in this case.

8) **Points 2–5 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. First, technological growth attracts unskilled migrants. In fact, this growth creates an even greater attraction, as skilled migrants flow in as well, and these workers further complement unskilled workers. Next, unskilled migrants help natives reverse de-routinization. We can observe this in the bottom diagrams of Figure A4. While the flow of skilled workers tends to shift up routine-labor supply, unskilled migration still partially reverses the outflow of natives from routine jobs.

It is also still the case that unskilled immigration raises the earnings for routine and analytical native workers (right side diagrams in Figure A6), and that unskilled immigration helps natives upgrade to analytical tasks (upper right diagram of Figure A4). Note however that the inclusion of skilled migrants shift these curves down. If migrants include both skilled and unskilled workers, the *net* impact of these migrants on native earnings and skills can be ambiguous, as suggested by our empirical results in Table 8.

5 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 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 for natives. As a consequence, immigration seem to have slowed native 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, and with heterogeneity in productivity of low skilled workers. 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 produces a weaker 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 along with 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 for natives. This is because they complement native skills and because they increase demand for goods produced. 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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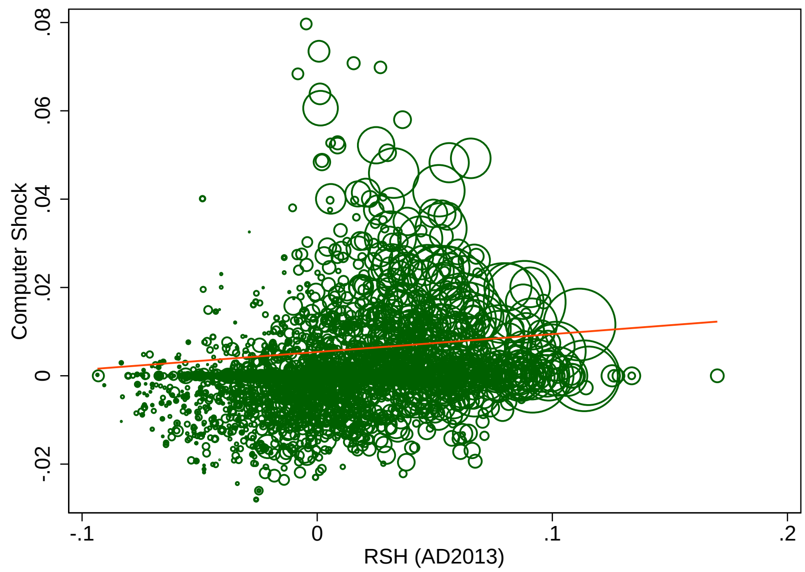
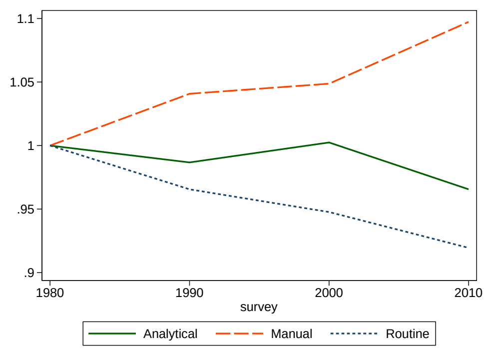
Figures

Figure 1: Correlation: Computer-Intensive Productivity Growth and AD's *RSH*

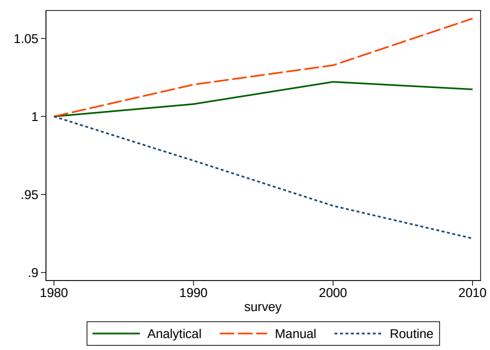


Note: Correlation between the Computer-Intensive Productivity Growth measure and the *Routine Share* of Autor and Dorn (2013), controlling for time fixed effects. The regression of coefficient is .081 and it is statistically significant at .01 percent.

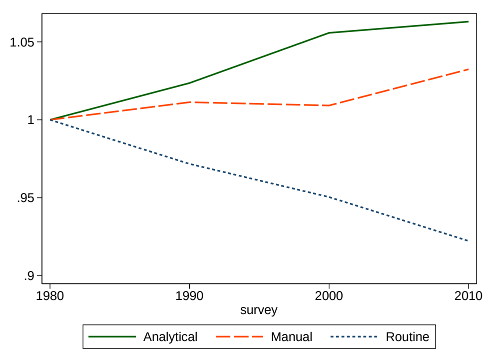
Figure 2: US and Foreign-born Task Supply, 1980-2010



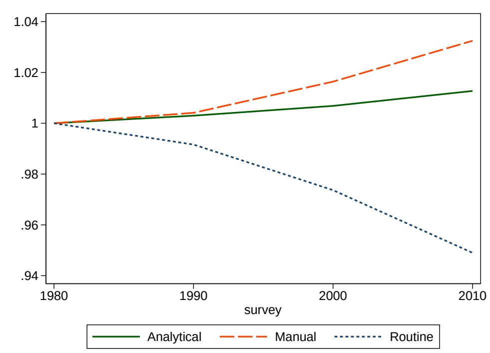
(a) Low-skilled Foreign Born



(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

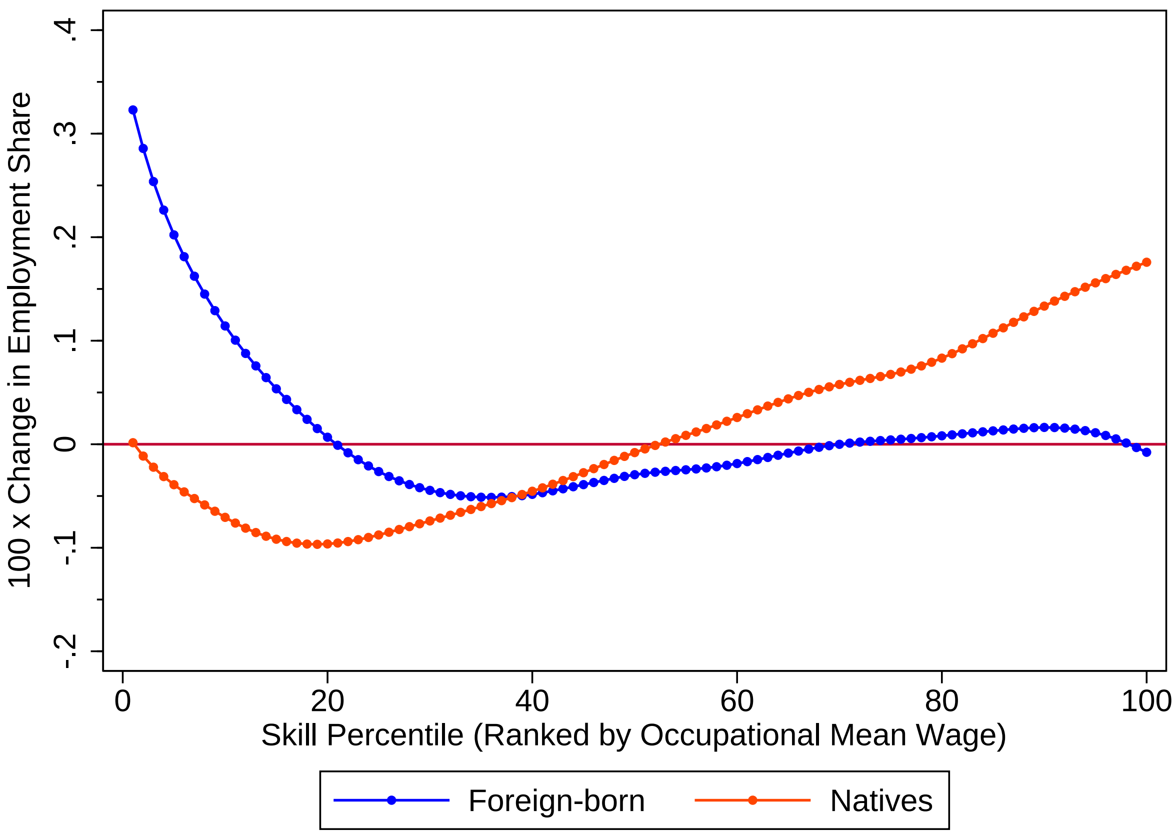
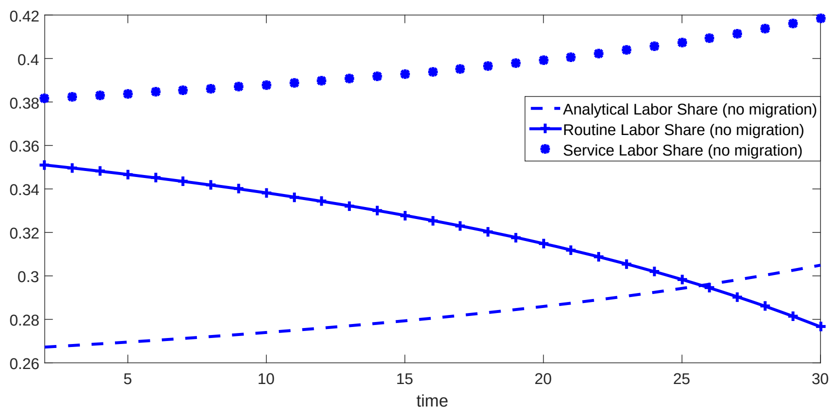
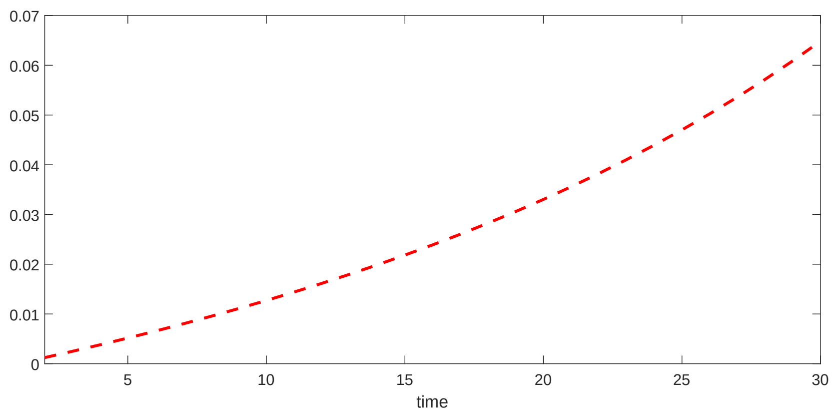


Figure 4: Changes in Native Employment Levels from Higher Computerization



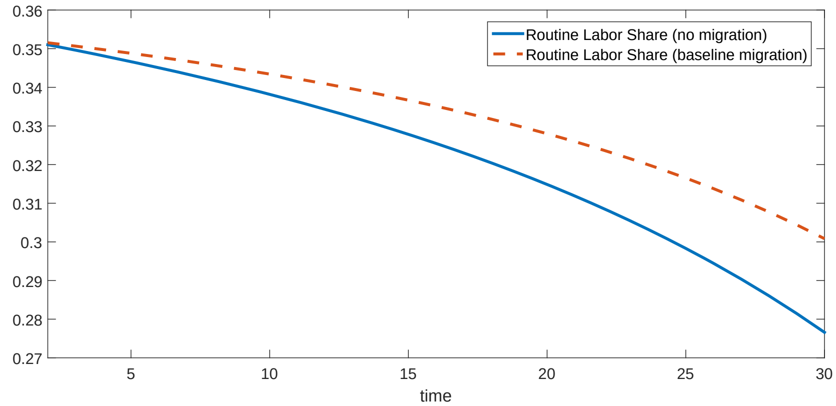
Note: Simulation of model dynamics holding $\varepsilon = 0$.

Figure 5: Changes in Unskilled Migrants from Higher Computerization



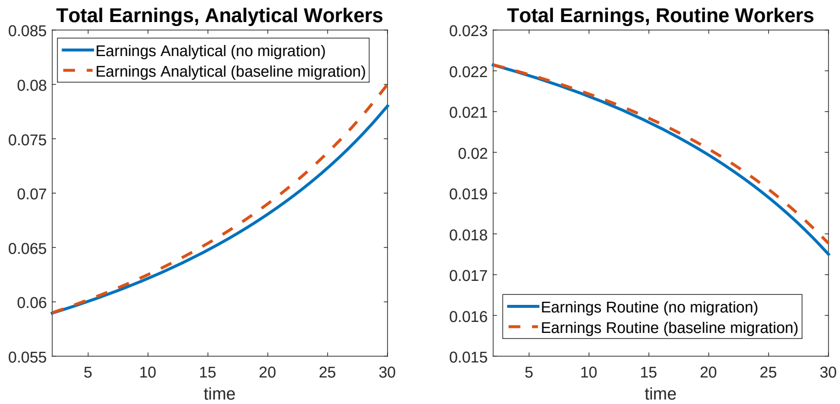
Note: Simulation of model dynamics for $\varepsilon = \{30\}$.

Figure 6: Changes in Native Routine Employment Levels from Higher Computerization and Immigration



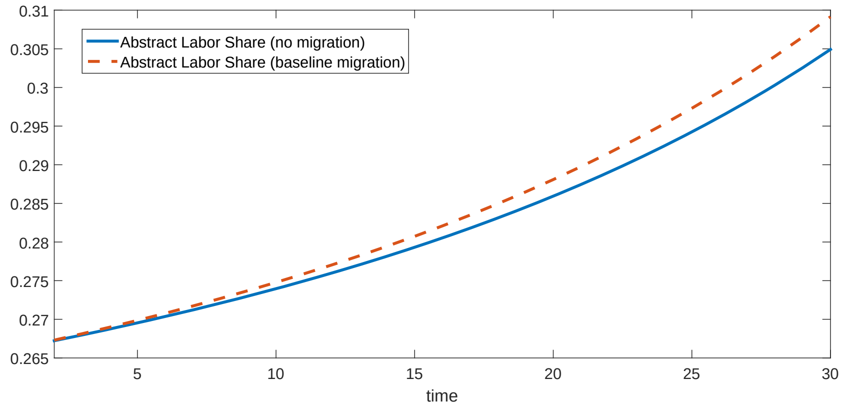
Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$.

Figure 7: Changes in Native Earnings from Higher Computerization and Immigration



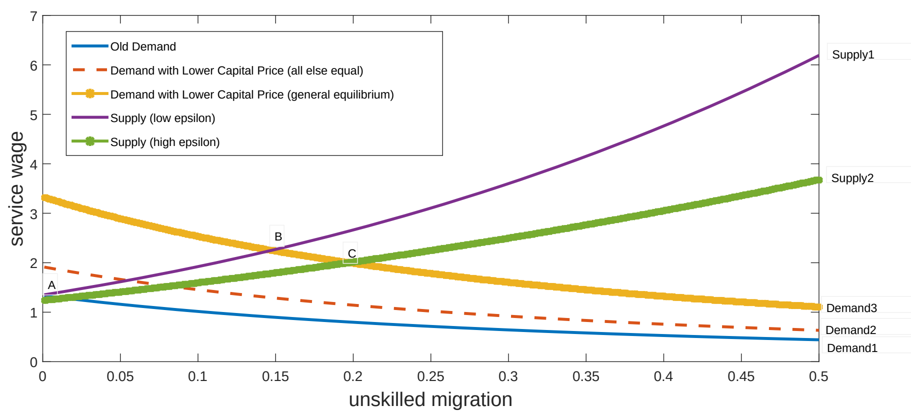
Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$.

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



Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$.

Figure 9: Representation of the Partial Equilibrium



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

Tables

Summary Statistics

Table 1: Average Task Specialization by Occupation in 1980

	Analytical/ Cognitive	Routine	Manual/ Communication
Managers/prof/tech	0.807	.343	0.478
Clerical/sales/operators	0.415	0.664	0.358
Services/construct/transp	0.322	0.451	0.737
Average Specialization	0.493	0.505	0.517
% of Total	32%	34%	34%

Table 2: Foreign-born and Natives' Task Specialization Indexes (Shares)

	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

Table 3: Computer-Intensive Productivity Growth and Immigrant Inflows

	Low-Skilled			High-Skilled		
Computer-Intensive Productivity Growth	1.035**		0.778**	0.579**		0.411**
	(0.179)		(0.140)	(0.100)		(0.096)
Sh Immig		0.373**	0.340**		0.244**	0.225**
		(0.084)	(0.079)		(0.031)	(0.030)
Observations	2166	2166	2166	2166	2166	2166

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (2). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 4: Computer-Intensive Productivity Growth and Job Polarization

Panel A: Task Specialization Indexes			
	Analytical	Routine	Manual
Computer-Intensive Productivity Growth	0.042*	-0.097**	0.055**
	(0.018)	(0.016)	(0.012)
Obs.	2166	2166	2166
R2	0.6	0.4	0.5
Panel B: Occupation Shares			
	Managers/prof/ tech	Clerical/sales/ operators	Services/construct/ transp
Computer-Intensive Productivity Growth	0.181**	-0.199**	0.018
	(0.050)	(0.044)	(0.032)
Obs.	2166	2166	2166
R2	0.7	0.6	0.6

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (4). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 5: Occupational Employment Shares among Natives

Prevalently	Managers/prof/tech *Analytical/Cognitive*	Clerical/sales/operators *Routine*	Services/construct/transp *Manual*
1980	0.257	0.409	0.315
1990	0.318	0.359	0.290
2000	0.319	0.348	0.281
2010	0.333	0.303	0.291
Delta	0.076	-0.106	-0.024

Table 6: Computer-Intensive Productivity Growth, Low-Skilled Immigration Inflows and Low-End Job Polarization

Panel A: Task Specialization Indexes		
	Routine	Manual
Computer-Intensive Productivity Growth × Sh Immig (LS)	0.074	-0.143
	(0.128)	(0.106)
Computer-Intensive Productivity Growth	-0.055**	0.013
	(0.017)	(0.018)
Sh Immig (LS)	-0.044**	0.050**
	(0.017)	(0.013)
Obs.	2166	2166
R2	0.5	0.5
Panel B: Occupation Shares		
	Clerical/sales/ operators	Services/construct/ transp
Computer-Intensive Productivity Growth × Sh Immig (LS)	1.067+	-0.166
	(0.622)	(0.284)
Computer-Intensive Productivity Growth	-0.230**	0.054
	(0.083)	(0.046)
Sh Immig (LS)	-0.065	-0.018
	(0.062)	(0.040)
Obs.	2166	2166
R2	0.6	0.6

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (5). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 7: Computer-Intensive Productivity Growth, Low-Skilled Immigration Inflows and Low-End Wage Polarization

	Clerical/sales/ operators	Services/construct/ transp
Computer-Intensive Productivity Growth	3.740	-3.771*
× Sh Immig (LS)	(3.351)	(1.812)
Computer-Intensive Productivity Growth	-1.230**	0.568*
	(0.471)	(0.285)
Sh Immig (LS)	-0.289	0.086
	(0.363)	(0.265)
Obs.	2166	2166
R2	0.7	0.6

Note: Estimated standard errors (in parentheses) are clustered at the CZ 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 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table 8: Computer-Intensive Productivity Growth, Immigration Inflows and High-End Polarization

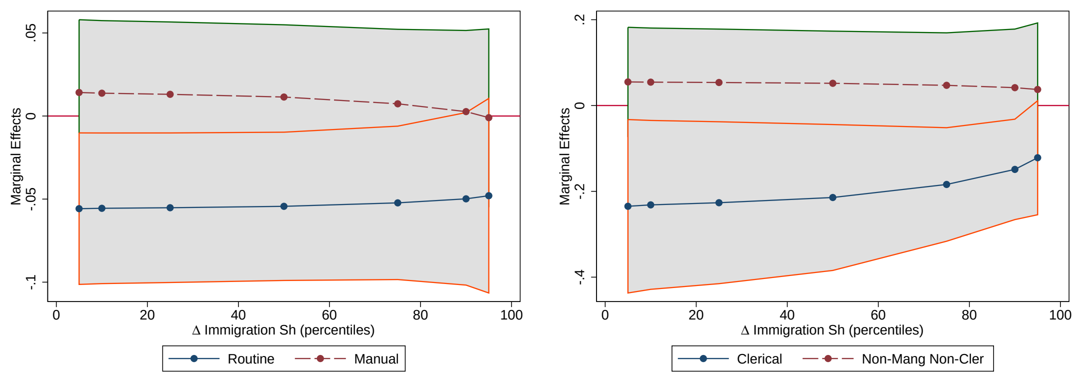
	Analytical Task Index	Manag/Prof Occ Share	Manag/Prof Occ Wages
Computer-Intensive Productivity Growth ×	0.103	-1.345	-16.223*
Sh Immig	(0.219)	(0.923)	(7.512)
Computer-Intensive Productivity Growth	0.042^{+}	0.180*	1.726**
	(0.022)	(0.076)	(0.605)
Sh Immig	-0.009	0.127	1.613*
	(0.025)	(0.082)	(0.728)
Obs.	2166	2166	2166
R2	0.6	0.7	0.7

Note: Estimated standard errors (in parentheses) are clustered at the CZ 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 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Appendix

A1. Empirical Analysis: Additional Figures

Figure A1: Computer-Intensive Productivity Growth: Marginal Effects Tasks Supply and Occupation Shares

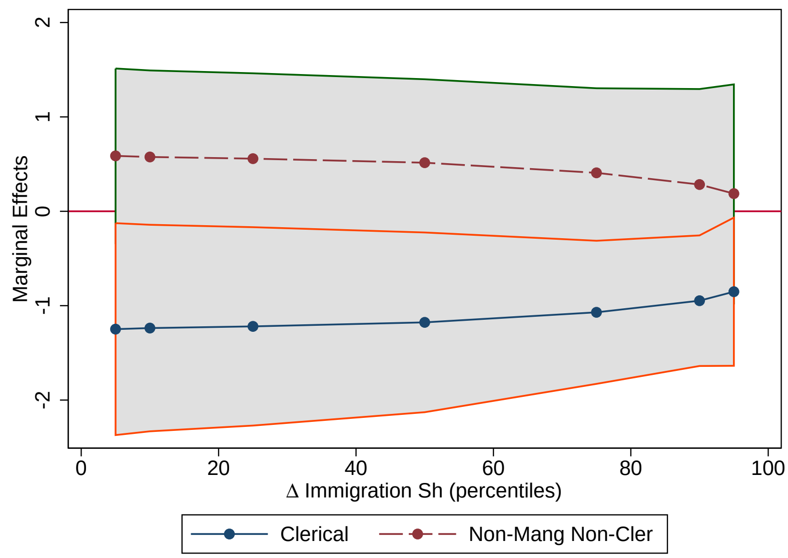


(a) Tasks Specialization

(b) Occupational Shares

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

Figure A2: Computer-Intensive Productivity Growth: Marginal Effects on Occupational Wages



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

A2. Empirical Analysis: Additional Tables and 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: Top 10 Commuting Zone by Computer-Intensive Productivity Growth Growth, 1980-2010

	Commuting Zone	**State**	**Computer-Intensive Labor Productivity**
1.	Rochester	NY	.219
2.	Union	NY	.210
3.	Poughkeepsie	NY	.205
4.	San Jose	CA	.182
5.	Lexington-Fayette	KY	.171
6.	Elmira	NY	.166
7.	Fort Collins	CO	.159
8.	Minneapolis	MN	.158
9.	Boston	MA	.151
10.	Raleigh	NC	.145

Note: The table lists the top 10 CZs in terms of the Computer-Intensive Productivity Growth Growth measure in the period 1980-2010. The lists include local labor markets that are either location of large universities (Rochester, Boston, Minneapolis, Raleigh, Fort Collins, San Jose) or hosts headquarters and production centers of technology corporations (Poughkeepsie: IBM; Fort Collins: HP, Intel, AMD, among others; Lexington: Xerox, Lexmark, IBM, Lockheed-Martin among others) or both.

Table A3: Top Industries by Use of Computer Inputs as of 1980

	Industry	**Computer Share of Inputs**
1.	Computer and electronic products	.386
2.	Other transportation equipment	.097
3.	Broadcasting and telecommunications	.093
4.	Computer systems design and related services	.089
5.	Federal general government	.075
6.	Data processing, internet publishing, and other information services	.071
7.	Administrative and support services	.034
8.	Electrical equipment, appliances, and components	.028
9.	Management of companies and enterprises	.028
10.	Miscellaneous professional, scientific, and technical services	.026

Note: The table lists the top 10 industries by use of 'Computer and electronic products' inputs (over total inputs) as of 1980. The data come from the Bureau of Economic Analysis Input-Output Tables.

Table A4: Computer-Intensive Productivity Growth and Immigration Inflows

	Low-Skilled	High-Skilled
Computer-Intensive Productivity Growth	0.692**	0.416**
	(0.151)	(0.106)
Sh Immig	0.335**	0.225**
	(0.077)	(0.031)
Labor Productivity	0.338	-0.019
	(0.292)	(0.149)
Observations	2166	2166

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (2). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A5: Computer-Intensive Productivity Growth, Low-Skilled Immigration Inflows and Low-End Job Polarization

	Routine	Manual
Panel A		
Computer-Intensive Productivity Growth × Sh Immig (LS)	0.044	-0.118
	(0.132)	(0.115)
Sh Immig (LS)	-0.040*	0.047**
	(0.017)	(0.013)
Labor Productivity	-0.050	0.043
	(0.040)	(0.026)
Computer-Intensive Productivity Growth	-0.043*	0.003
	(0.019)	(0.020)
Obs.	2166	2166
R2	0.5	0.5
	Clerical/sales/ operators	Services/construct/ transp
Panel B		
Computer-Intensive Productivity Growth × Sh Immig (LS)	0.952	-0.233
	(0.617)	(0.280)
Sh Immig (LS)	-0.051	-0.010
	(0.062)	(0.044)
Labor Productivity	-0.195	-0.113
	(0.127)	(0.089)
Computer-Intensive Productivity Growth	-0.183*	0.081+
	(0.088)	(0.046)
Obs.	2166	2166
R2	0.6	0.6

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (5). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A6: Computer-Intensive Productivity Growth, Low-Skilled Immigration Inflows and Low-End Wage Polarization

	Clerical/sales/ operators	Services/construct/ transp
Computer-Intensive Productivity Growth × Sh Immig (LS)	2.899	-4.218*
	(3.296)	(1.896)
Sh Immig (LS)	-0.188	0.140
	(0.361)	(0.287)
Labor Productivity	-1.415+	-0.752
	(0.771)	(0.577)
Computer-Intensive Productivity Growth	-0.891+	0.749**
	(0.504)	(0.288)
Obs.	2166	2166
R2	0.7	0.6

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (5). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A7: Computer-Intensive Productivity Growth, Immigration Inflows and High-End Polarization

	Analytical Task	Manag/Prof Occ Share	Manag/Prof Occ Wages
Computer-Intensive Productivity Growth	0.107	-1.040	-13.945*
× Sh Immig	(0.224)	(0.855)	(6.929)
Sh Immig	-0.010	0.090	1.336*
	(0.025)	(0.073)	(0.665)
Labor Productivity	0.004	0.338**	2.523*
	(0.040)	(0.123)	(1.005)
Computer-Intensive Productivity Growth	0.041	0.098	1.107+
	(0.027)	(0.085)	(0.642)
Obs.	2166	2166	2166
R2	0.6	0.7	0.7

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (5). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

Table A8: Computer-Intensive Productivity Growth and Immigrant Inflows 1950-1980

	Low-Skilled			High-Skilled		
Computer-Intensive Productivity	0.142^{**}		0.058	0.115^{**}		0.039
Growth (1980-2010)	(0.054)		(0.041)	(0.034)		(0.029)
Sh Immig (1980-2010)		0.069^{**}	0.067^{**}		0.063^{**}	0.062^{**}
		(0.018)	(0.018)		(0.015)	(0.015)
Observations	1444	1444	1444	1444	1444	1444

Note: Estimated standard errors (in parentheses) are clustered at the CZ level. Each column reports the βs from equation (2). All the regressions are weighted by the 1980 CZ share of national population and include division-by-year fixed effects.
**, *, + indicate significance at 1-percent, 5-percent and 10-percent level, respectively.

A3. Simulation Tables

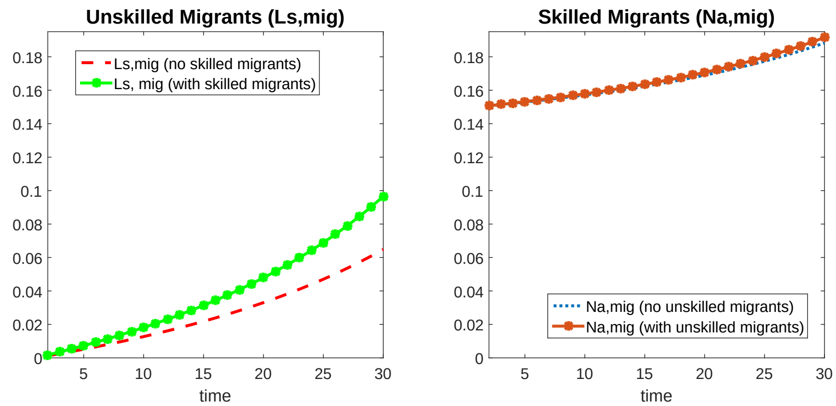
Table A9: Simulation Results - Baseline Parametrization

Variables	**No Migration**	**Migration Baseline**
$\%\Delta population$	0	**6.5**
$\%\Delta N_a$	14.1	**15.7**
$\%\Delta N_r$	-21.2	**-14.4**
$\%\Delta N_{s,natives}$	9.6	**2.3**
$\%\Delta w_a$	9.6	**10.2**
$\%\Delta w_r$	1.7	**-0.9**
$\%\Delta w_s$	14.7	**2.1**
$\%\Delta K$	272.0	**274.5**
$\%\Delta Y_g$	21.8	**24.2**
$\%\Delta earnings_{natives}$	18.9	**18.2**

Note: Baseline parameters set to the following: $\gamma = 0.5$, $\beta = -10$, $\sigma = 0.5$, $\rho = 0.5$, $\alpha_a = 1.75$, $p_a = 0.25$, $p_m = 0.5$, $\phi = 2$, $\epsilon_s = 30$. This produces initial employment levels of $N_a = 0.27$, $N_r = 0.35$, and $N_s = 0.38$. Furthermore, changes in values for p_a, p_m and between 0.1 and 1 keep changes in quantities close to baseline results.

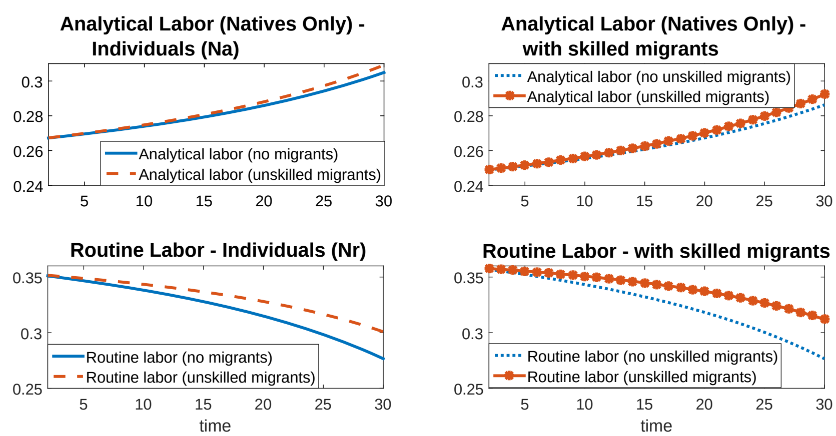
A4. Simulation Graphs

Figure A3: Unskilled and Skilled Migration Responses to Higher Computerization



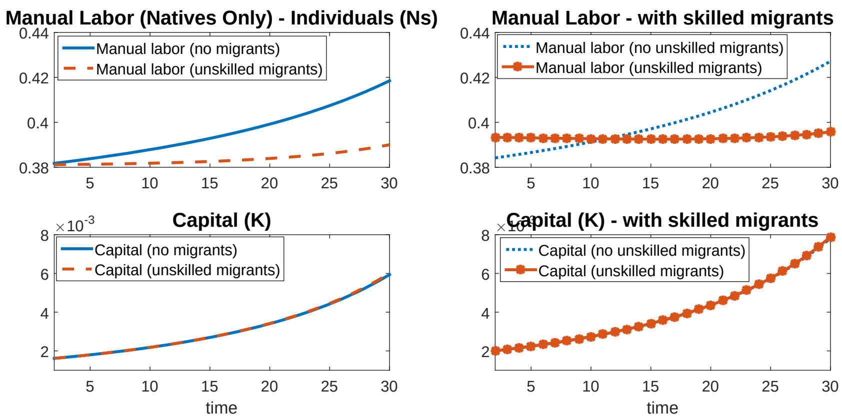
Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$ and $\varepsilon_a = 1.5$.

Figure A4: Changes in Native Abstract and Routine Employment from Higher Computerization with and without Skilled Migrants



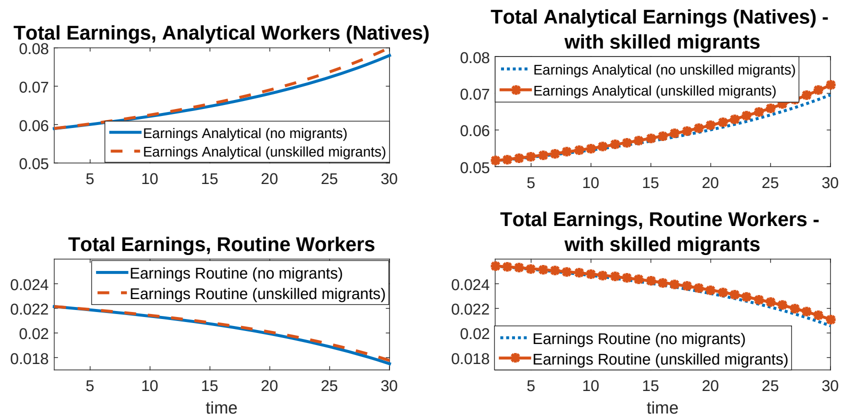
Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$ and $\varepsilon_a = 1.5$.

Figure A5: Changes in Native Manual Employment and Capital from Higher Computerization with and without Skilled Migrants



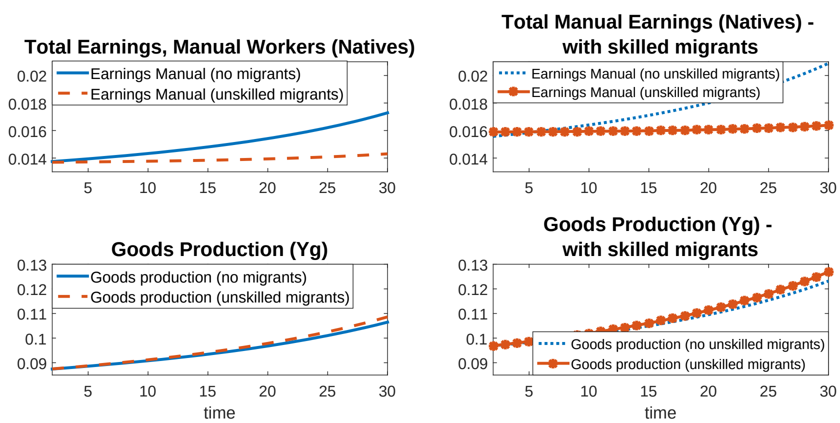
Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$ and $\varepsilon_a = 1.5$.

Figure A6: Changes in Native Earnings from Higher Computerization with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$ and $\varepsilon_a = 1.5$.

Figure A7: Changes in Native Manual Earnings and Goods Production with and without Skilled Migrants



Note: Simulation of model dynamics for $\varepsilon = \{0, 30\}$ and $\varepsilon_a = 1.5$.

A5. 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:

$$\left(\rho C_s^{\frac{\sigma-1}{\sigma}} + (1-\rho) C_g^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad , \tag{A1}$$

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

$$C_s = Y_s = L_s \quad , \tag{A2}$$

$$C_g = Y_g - p_k K - p_a L_a \quad , \tag{A3}$$

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:

$$Y_g = (\alpha_a L_a)^{\alpha} K^{1-\alpha}. \tag{A4}$$

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

$$L_a = \phi\left(\hat{\eta}+1\right)e^{-\hat{\eta}}, \tag{A5}$$

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:

$$w_a\phi\hat{\eta} - p_a = w_s. \tag{A6}$$

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

$$L_s = 1 + mig - e^{-\hat{\eta}} \tag{A7}$$

Comparative Statics

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

$$w_a = \alpha\left(\alpha_a L_a\right)^{\alpha-1} K^{1-\alpha}. \tag{A8}$$

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

$$p_k = \left(1-\alpha\right)\left(\alpha_a L_a\right)^{\alpha} K^{-\alpha}. \tag{A9}$$

Combining these and simplifying then gives us

$$w_a = \alpha\left(1-\alpha\right)^{\frac{1-\alpha}{\alpha}} p_k^{\frac{\alpha-1}{\alpha}}. \tag{A10}$$

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 (A6), substitute in (A10), and get:

$$\hat{\eta} = \frac{(w_s + p_a)\, p_k^{\frac{1-\alpha}{\alpha}}}{\phi\alpha\,(1-\alpha)^{\frac{1-\alpha}{\alpha}}}. \tag{A11}$$

We can take this expression and plug it into (A7) to solve for w_s:

$$w_s = \frac{-\phi\alpha\,(1-\alpha)^{\frac{1-\alpha}{\alpha}} \ln\left(mig + 1 - L_s\right)}{p_k^{\frac{1-\alpha}{\alpha}}} - p_a \tag{A12}$$

Finally, we have some simple comparative statics to suggest.

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

This is clear from equation (A11). 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 (A11); the second term being negative is clear from (A12). 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 (A11); the second term being negative is clear from (A12). 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 – 5.

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 (A10) 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.

A6. Model 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 Tables A10–A11. Here we compare our baseline case where $\epsilon = 30$ illustrated earlier with the same case but with a different parameter value. Each parameter change creates a change both to the initial values of the variables ("shift") and to their growth paths as computer capital growth occurs ("over time").

Table A10: Simulation Results - Robustness: Changes in Parameter Values (I)

Variables	$\beta = -5$ shift	$\beta = -5$ over time	$\gamma = 0.75$ shift	$\gamma = 0.75$ over time	$\sigma = 0.25$ shift	$\sigma = 0.25$ over time
$\%\Delta population$	-	**6.0**	-	**1.4**	-	**2.7**
$\%\Delta N_a$	-14.7	**14.9**	-4.1	**7.9**	5.9	**14.9**
$\%\Delta N_r$	20.1	**-11.9**	5.5	**-5.7**	41.6	**-11.3**
$\%\Delta N_{s,natives}$	-8.3	**1.7**	-2.2	**1.8**	-42.5	**6.5**
$\%\Delta w_a$	-9.8	**27.1**	-4.5	**4.2**	2.6	**9.9**
$\%\Delta w_r$	-5.3	**0.4**	-11.7	**-1.7**	-6.8	**-4.3**
$\%\Delta w_s$	-15.2	**2.6**	-14.2	**0.6**	-52.0	**2.8**
$\%\Delta K$	-92.2	**126.3**	-17.3	**1743.8**	-2.1	**255.7**

Table A11: Simulation Results - Robustness: Changes in Parameter Values (II)

Variables	$\phi = 2.5$ shift	$\phi = 2.5$ over time	$\alpha = 2.5$ shift	$\alpha = 2.5$ over time
$\%\Delta population$	-	**12.5**	-	**17.3**
$\%\Delta N_a$	0.1	**24.4**	-0.6	**30.0**
$\%\Delta N_r$	1.7	**-15.1**	0.5	**-15.6**
$\%\Delta N_{s,natives}$	-1.6	**-2.9**	-0.03	**-6.5**
$\%\Delta w_a$	-14.4	**16.5**	11.1	**21.0**
$\%\Delta w_r$	42.3	**5.3**	69.5	**10.1**
$\%\Delta w_s$	39.4	**1.5**	69.5	**1.1**
$\%\Delta K$	104.2	**287.4**	189.4	**303.8**

B. Data Appendix

The data used to construct our dependent and independent variables are drawn from the US Census public use microdata as available from IPUMS (Ruggles et al. 2015) and the US Bureau of Economic Analysis Input-Output Tables. We use Census microdata from 1950, 1970 (aggregating two 1% metropolitan area samples), 1980, 1990 and 2000 (5% samples), as well as the 2009-2011 American Community Survey, which creates a 3% sample around 2010 that we use for that year. We include in our sample all individuals age 18-65 not residing in group quarters and not enrolled in school. We define employed an individual who worked a positive amount of hours and had positive income from wages in the previous year, excluding thus self-employed and unpaid family workers. Wages are measured as the logarithm of weekly wages that we define as the total income from wages divided by weeks worked in the previous year. All the dollar amounts are expressed in $ as of 2010 adjusted using the BLS CPI-U All Items. The samples are weighted by the product of the Census personal weight.

We define foreign born, or immigrants, all the individuals who are born abroad (outside US territories), including those who become naturalized citizens. We define low-skilled workers (or "high school or less") as those with either 12 completed years of schooling and/or a high school or equivalent diploma, and as high-skilled workers (or "college or more") those with at least one year of college or more. Following Autor and Dorn (2013), we define occupations based on the IPUMS variable OCC1990, aggregating the classification in order to construct a consistent set for the entire sample period. We construct the three group of occupations, managerial/professional/technicians, clerical/sales/operators, and services/construct/transp, further aggregating up the occupations following Autor and Dorn (2013). To construct the task specialization measure we match each of the 330 occupation categories to the intensity of manual, routine and analytical tasks performed on the job as described by the 1977 BLS Dictionary of Occupational Titles (Autor and Dorn, 2013). We directly use these measures to construct three indexes of task specialization which represent the percentiles of each occupation in the distribution of occupations ranked by task in 1980 (weighted by 1980 occupational employment). Each worker, therefore, has an index that reflects her specialization in analytical, routine and manual tasks, which we then aggregate by Census year and Commuting Zone. Table A1 lists the ten occupations with the highest value of each task intensity index as of 1980.

We use as main geographical unit of analysis 722 Commuting Zones that encompass the 48 adjoining US states, thus dropping Alaska and Hawaii. Commuting Zones are clusters of counties that are characterized by strong within-cluster and weak between-cluster commuting ties, thus capturing the boundaries of local labor markets (Tolbert and Sizer, 1996; Autor and Dorn, 2013; Basso and Peri, 2016). In order to match the geographic information contained in the IPUMS data (SEA in the 1950 Census, County Group in the 1970 and 1980 Census, PUMA in the 1990 and 2000 Census, and in the 2009-2011 ACS) to Commuting Zones we use the crosswalk developed by Autor and Dorn (2013) (as available on David Dorn's website, http://www.ddorn.net/data.htm). Hence we multiply the person weights described above with an adjustment factor that accounts for the fraction of a

SEA/County Group/PUMA that maps to a given Commuting Zone.

The proxy for computerization that we adopt measures the growth in labor productivity overweighing the importance computer and electronic products as inputs and exploiting the heterogeneity in the US local labor market industrial structure. Using the Census IPUMS microdata, we calculate the share of employment in each industry and Commuting Zone in 1980. We interact its numerator with the share of "Computer and electronic products" as share of overall inputs of the sector in 1980 measured from the Bureau of Economic Analysis BEA Input-Output (I-O) Use Tables (and we normalize the denominator by the overall use "Computer and electronic products" as share of inputs in the local economy). In order to match the BEA industrial definition with that of IPUMS, we first aggregate the IPUMS variable IND1990 in order to create a consistent set of industries across Census years. Then, following the definition of industries in the I-O Tables provided by the BEA, we match the industries to IND1990. Finally, we interact the newly constructed weights, $\omega_{j,c,1980}$, with the decennial change in the national log wage for the industry (i.e., in the entire set of CZs, but its own CZ level). The computer-intensive productivity growth (CIPG) for each CZ c and Census year t is thus calculated as follows:

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

where industries are indexed by j and $\omega_{j,c,1980} = \frac{empl_{j,c,1980}(\frac{ComputerInput_{j,1980}}{TotInput_{j,1980}})}{\sum_j empl_{j,c,1980}(\frac{ComputerInput_{j,1980}}{TotInput_{j,1980}})}$. In words, the measure captures the industry-specific productivity growth interacted with the computer intensity of the industry in 1980, and then allocated to a Commuting Zone in proportion of its 1980 employment share across industries.