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ABSTRACT

How Do Low-Skilled Immigrants Adjust to Chinese Import Shocks? Evidence Using English Language Proficiency*

This paper examines the link between trade-induced changes in local labor market opportunities and English language fluency rates among low-skilled immigrants in the United States. Many of the production-based manufacturing jobs lost in recent years due to Chinese import competition did not require strong English-speaking skills while many of the jobs in expanding industries, mostly in the service sector, did. Consistent with responses to these changing labor market opportunities, we find that a $1,000 increase in import exposure per worker in a local area led to an increase in the share of low-skilled immigrants speaking English very well in that area by about half a percentage point. As evidence that at least part of this is a result of actual improvements in English language speaking abilities, we show that low-skilled immigrants in trade-impacted areas became especially likely to be enrolled in school compared to similarly low-skilled natives. However, while we find little support for selective domestic migration in response to trade shocks, we present evidence suggesting that new immigrants arriving from abroad choose where to settle based either on their English fluency or their ability to learn English. Regardless of whether low-skilled immigrants respond to trade shocks via actual improvements in English fluency or migration choices, our results suggest that immigrants help to equilibrate labor markets, an implication we find evidence for in the data.

JEL Classification: J15, J61, J24, F16

Keywords: immigrants, language fluency, import competition, immigrant assimilation

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1 Introduction

Most economists agree that while international trade results in aggregate welfare gains, these gains as well as some losses are unevenly distributed. Suggestive of large welfare losses for certain people, Autor, Dorn, and Hanson (2013) find sizeable decreases in employment in the manufacturing sector in local areas specializing in industries competing with Chinese imports. The long-run welfare impacts of these job losses, however, depend on the ability of workers to move into expanding markets either by changing sectors of employment or geographic locations. Autor et al. (2013) find little evidence of such adjustments within the general population. However, we examine the impact of Chinese import competition on a population that may, on the one hand, be especially vulnerable to manufacturing job loss given their often-poor English-speaking skills, but on the other hand, may be more adaptable than the general population: low-skilled immigrants. Specifically, we examine whether, on average, the share of low-skilled immigrants speaking English very well increased in areas that were more affected by the large increases in Chinese import competition around the turn of the century. We also consider whether any such changes are likely to have been driven by actual improvements in English speaking abilities or selective migration into or out of local areas based on language abilities. We then explore whether immigrants help equilibrate labor markets by testing whether the native-born in areas with more low-skilled immigrants had relatively better labor market outcomes in response to trade shocks.

While in 1991, the share of total U.S. spending on Chinese goods was a little over half a percent, this figure rose more than seven-fold by the year 2007 (Autor et al. 2013) and has continued to grow since then (authors' own calculations).[1] This has led to large reductions in U.S.

[1] Data on U.S. imports from China by year are available on the U.S. Census website (https://www.census.gov/foreign-trade/balance/c5700.html). Deflating the 2018 values to 2007 dollars using the Personal Consumption Expenditures (PCE) price index, we calculate that net imports from China increased 38 percent between 2007 and 2018.

manufacturing employment. More generally, because of input-output linkages as well as other local general equilibrium effects, Chinese imports have decreased overall U.S. job growth (Acemoğlu et al. 2016). People living in areas with more Chinese-import induced job losses have received more transfer payments for unemployment, disability, retirement and healthcare (Autor et al. 2013), have experienced worsening physical and mental health (McManus and Schaur 2016), and have higher mortality rates (Pierce and Schott 2020). Other evidence also points to declines in marriage (Autor, Dorn, and Hanson 2019), increases in out of wedlock births (Autor et al. 2019), and increases in political polarization (Autor, Dorn, Hanson, and Majlesi 2020).

The degree to which employment losses in certain manufacturing industries result in overall declines in welfare depends on workers' abilities to reallocate themselves either to different jobs—jobs that often require acquiring new skills—or to different locations. Greenland and Lopresti (2016) find large increases in U.S. high school graduation rates in local labor markets most negatively affected by import competition. This result is consistent with a model in which high school students compare opportunity costs of staying in school to the expected future benefits of a high school degree and make decisions accordingly; Chinese import competition decreases the opportunity costs and increases the expected benefits of a high school degree. We contribute to this literature by examining the impact of import exposure on the human capital investments of low-skilled immigrants, focusing on English fluency.

We also explore whether low-skilled immigrants make migration decisions based on the returns to their skills in different locations. While Autor et al. (2013) do not find evidence of migration responses to local Chinese import shocks, Greenland, Lopresti, and McHenry (2019) show that the local labor markets most exposed to trade shocks experienced a relative reduction in population growth over the following decade. We contribute to this literature by studying whether low-skilled immigrants make migration choices based on Chinese import exposure in different U.S. locations in conjunction with their own levels of English fluency.

Low-skilled immigrants may be especially susceptible to the negative consequences of trade shocks because their limited English-speaking abilities can make moving to growing sectors, many of which are in the service industry, especially difficult. The reason immigrants are highly represented in the manufacturing sector (Andersson et al. 2014) may be that production work does not require the English fluency of a native speaker. Production workers typically do not communicate with customers and clients, and given the repetitive nature of many manufacturing jobs, effective communication with managers and coworkers may not be very important. In fact, even rudimentary English-speaking abilities may not be necessary if immigrants are able to segregate into plants employing mainly speakers of their native language. While there is considerable evidence that immigrants who are better able to speak the host country's language earn higher wages (e.g., Bleakley and Chin 2004), the returns to host country language skills depend on a worker's occupation and in some occupations, can be close to zero (Berman, Lang and Siniver 2003).

Immigrants with limited English proficiency may respond to the loss of manufacturing jobs by improving their English skills. Workers displaced from manufacturing jobs typically find reemployment in low wage service jobs (Autor and Dorn 2013; Goos, Manning and Salomons 2014) which often require the use of English on the job. Even the threat of job loss in the manufacturing sector may induce some immigrants to enroll in formal English classes or take other active steps to improve their English. Perhaps more importantly, when low-skilled immigrants lose their jobs in the manufacturing sector, they may take jobs in sectors requiring their use of English on-the-job. The increased exposure to the language is likely to increase fluency even without any active investments.

While immigrants with weak English-speaking skills may find it more difficult to move into sectors requiring English fluency within the same local geographic area, they may find it easier, compared to natives, to move to U.S. locations with less manufacturing job loss. Indeed, Cadena and Kovak (2016) show that low-skilled Mexico-born immigrants were more likely than low-skilled natives to migrate within the U.S. in response to Great Recession-induced labor market shocks. In addition, low-skilled immigrants with limited English-speaking abilities may choose not to settle in affected areas when they first arrive in the United States or simply return to their home countries in response to poor local labor market conditions.

We start by examining whether, on average, English language proficiency among immigrants remaining in areas most affected by Chinese import exposure improved relative to those in areas less hard hit. Using data from the 1990-2000 Censuses as well as 2006-2008 American Community Surveys, we show that for every $1,000 increase in import exposure per worker in the U.S., the share of low-skilled immigrants speaking English very well increased by about half of a percentage point, a magnitude comparable to the associated decline in manufacturing employment (Autor et al. 2013). Conducting a pre-shock placebo analysis, we show that this relationship is not likely to be coincidental. Large decreases in the share of employed low-skilled immigrants working in occupations not requiring English speaking skills point to labor demand shocks as drivers of our main findings. Our tests for heterogeneity reveal that our baseline results are mainly driven by white non-Hispanics. They also suggest that immigrants with a solid base level of English proficiency, immigrants with relatively higher educational attainment, and immigrants who have been in the U.S. for less than ten years respond more strongly to Chinese import competition than immigrants in other groups.

We then turn to examining whether the relationship between Chinese import exposure and English-speaking abilities of low-skilled immigrants is mainly a result of actual improvements in English language proficiency or selective migration. Because our data do not allow us to follow the same immigrants over time, we cannot show conclusively that English-speaking abilities of individuals improved in response to changes in Chinese import competition. However, we do show that the low-skilled immigrants in our sample living in areas with more import competition are more likely to be enrolled in school than those in areas that are less affected. In fact, in terms of school enrollment, low-skilled immigrants are more responsive to import exposure than are low-skilled natives despite the fact that on average, natives are more likely to be in school. Given that English proficiency is likely to improve while taking classes regardless of what is being taught, we interpret these school enrollment results as suggestive of low-skilled immigrants responding to manufacturing job loss with actual improvements in English language fluency as well as other forms of general human capital.

To explore how large a role selective migration may play in driving our baseline estimates, we start by simply looking at the impact of trade exposure on low-skilled immigrant population changes at the local level. Mirroring the results in Autor et al. (2013), we find no statistically significant populations shifts, a result that may mask language-based selective migration if the number of English-fluent in-migrants approximates the number of out-migrants with poor English skills. To address this issue, we explore the relationship between Chinese import exposure and changes in characteristics of people that are difficult or impossible to change. We do not find any statistically significant impacts in terms of educational attainment, age, and years in the U.S.—characteristics we would expect to change along with language fluency if our results were mostly driven by migration patterns.

Next, we examine internal migration decisions more directly by using answers to survey questions on residence one or five (depending on the survey year) years prior to the survey. Keeping in our sample only immigrants who were living in the U.S. in the years prior to the survey, we can link individuals either to trade exposure in their current residence or to trade exposure in their previous residence. Interestingly, immigrants who were living in areas harder hit by Chinese import exposure in the years prior to the survey were actually less likely to migrate out than those in less hard-hit areas, a result suggesting that people in the hardest hit areas did not have the financial resources to migrate. When considering where migrants go, we also find smaller shares of recently arrived internal migrants in areas with more trade exposure, but the change is statistically insignificant. These estimates suggest that internal migration patterns do not seem to be a first order driver of our language results.

We then explore whether our baseline findings may be driven by initial settlement choices of new immigrant arrivers by examining impacts separately by years in the U.S. Given that it takes time to become fluent in a language, a finding of strong effects of Chinese import exposure on language fluency among those who arrived within the year prior to the survey might be interpreted as evidence of selective migration. We find statistically insignificant and rather small impacts for the very recent arrivers suggesting that our results are not solely driven by initial settlement decisions. However, while estimates are strongest for those in the U.S. between two and nine years, there is no evidence of English language improvements for immigrants who have lived in the U.S. for ten or more years. Moreover, when separating the sample based on where people were living five years (or one year in the ACS) prior to the survey, estimates are strongest among those who were previously living abroad. Together, these results may point to a role of selective settlement patterns of new immigrants to the U.S., perhaps based on the ability to learn English as opposed to language skills acquired before migration. However, our results are also consistent with import-induced language acquisition if the largest improvements in English fluency are most likely in the first few years after arriving.

Irrespective of whether low-skilled immigrants are more likely than natives to respond to labor market shocks via human capital investments or migration decisions, their responses are likely to help equilibrate labor markets. To explore this hypothesis, we compare the labor market outcomes of low-skilled natives in areas with initially small numbers of low-skilled immigrants to those in areas with initially larger numbers of low-skilled immigrants. We show that low-skilled natives in areas with initially fewer low-skilled immigrants had worse labor market outcomes in response to Chinese import exposure than those in areas with more low-skilled immigrants. We interpret this result as evidence that immigrants indeed help to equilibrate labor markets.

The remainder of the paper is organized as follows. Section 2 presents background and motivation for the study. Section 3 describes the data and our measurement of key variables. Section 4 describes our empirical approach, and section 5 presents our baseline empirical results. Section 6 examines whether our baseline results are likely to be driven by actual improvements in English fluency or selective migration, section 7 examines whether immigrants help equilibrate labor markets, and section 8 concludes.

2 Background

2.1 Human Capital Investment Responses to Changes in Labor Market Returns to Skill

Existing evidence suggests that people increase their investments in skills that become more highly valued in their local labor markets. Weinstein (2020) uses three exogenous market shocks to show that in universities in areas more exposed to sectoral shocks, the number of majors in sectorrelevant fields increases. In a developing country context, Millett and Oster (2013) find that increases in high-skill IT service jobs in India promote school enrollment. Clingingsmith (2014) shows that the expansion of the manufacturing sector in India during the 20th century increased bilingualism and reduced district level language heterogeneity. We contribute to this literature by considering a low-skilled population in a developed country context.

Language skills are an important form of host country-specific human capital for immigrants. While previous studies have shown a positive association between language skills and earnings (e.g. Arendt et al. 2020; Angrist and Lavy 1997; Bleakley and Chin 2004; and Dustmann and van Soest 2002), there is considerable variation in the extent to which immigrants become fluent in the host country language even after spending many years in the host country.[2] Much of the literature on language acquisition focuses on factors making learning a new language easier, for example, age at arrival (Bleakley and Chin 2004), the similarity between an immigrant's native language and the host country language (Adsera and Chiswick 2007), or the availability of high quality language courses (Arendt et al. 2020; Lochmann et al. 2019). Our paper considers whether increases in the labor market returns to learning the host country language influence immigrants' fluency in the host country language.

Because workers in the manufacturing sector are mainly engaged in routine manual work (Autor 2010), communication skills may not be as important in this sector. Managers are able to communicate instructions without requiring complex language and work within teams is probably not necessary. Most of the workers within manufacturing, those involved in production, do not often communicate with customers. Consistent with the idea that English language proficiency is

[2] About 9% of the U.S. population can be considered Limited English Proficient (LEP), and approximately 21% speak a language other than English at home (Zong and Batalova 2017). In the year 2012, more than 37 percent of immigrants living in the U.S. for 30 years or more were not able to speak English "very well" (Gambino, Acosta, and Grieco 2014).

less important for manufacturing workers, Chiswick and Miller (2010) show that workers in low-skilled occupations, such as production, transportation, and material moving occupations, have a distribution of English language importance scores skewed towards the left, while service and sales occupations have a relatively high mean score for the importance of English language fluency. Moreover, Arendt et al. (2020) show that in response to a reform expanding and improving early language classes to refugees in Denmark, refugees became increasingly likely to have occupations requiring relatively more communicative tasks.

According to related research (Autor and Dorn 2013, Autor et al. 2015), technological change has made social skills more highly rewarded in the labor market than routine physical skills. Consistent with the hypothesis that natives have a comparative advantage in jobs requiring social skills, Song (2020) shows that native-immigrant wage gaps widened more in metropolitan areas that were more strongly impacted by computerization.[3] In our paper, we consider whether Chinese import exposure in a local area led to changes in the English fluency of low-skilled immigrants living in that area.

2.2 Migration Responses to Labor Market Shocks

In addition to the literature on human capital investments, our paper also contributes to a literature on the impact of local labor market changes on migration. Domestic migration rates in the U.S. have fallen quite dramatically in the past few decades (Molloy, Smith, and Wozniak 2011), and the seminal work of Autor et al. (2013) suggests little to no migration responses to Chinese import

[3] In related work, Furtado and Song (2015) show that immigrants' labor market returns to marriage to a native have increased over the years. They suggest that this is because technological change and globalization have increased the returns to English skills and knowledge of U.S. culture, skills that immigrants married to natives are more likely to have.

exposure.[4] Analyses of data from other countries also point to minimal migration responses to local trade shocks (see Erten et al. (2019) for evidence from South Africa; Topalova (2010) for evidence from India; and Dix-Carneiro and Kovak (2017; 2019) for evidence from Brazil). However, the low-skilled immigrants in our sample may be more mobile than the general population. Cadena and Kovak (2016) find that low-skilled Mexican-born immigrants were more responsive to Great Recession-induced local labor market shocks than were natives. Schündeln (2014) finds similar results using data on immigrants in Germany.

In addition to internal migration, immigrants are also likely to make initial within-U.S. settlement decisions based on labor market conditions. It is well known that emigration is negatively related to unemployment at the destination (Hatton and Williamson 2009). Villarreal (2014) shows that when there are negative labor demand shocks in sectors that typically employ Mexicans, Mexican migration to the U.S. decreases. Given this evidence, it seems plausible that if appropriate jobs are scarce in the U.S. cities where potential migrants may go, then they may simply choose to stay in their home countries. This could induce a correlation between import exposure in a city and the number, as well as characteristics (including English fluency), of low skilled immigrants in that city.

It is also possible that immigrants who had been in the U.S. for several years may return to their home countries in response to unfavorable labor market conditions. In practice, there is little evidence of much return migration in response to the Great Recession (Passel, Cohn and Gonzalez-Barrera 2012; Rendall, Brownell, and Kups 2011; Van Hook and Zhang 2011; Fix et al. 2009), and so we might not expect much return migration in response to Chinese import exposure.

[4] In contrast, taking a more long-term view, Greenland et al. (2019) show that local labor markets most exposed to trade shocks experienced a relative reduction in population growth over the following decade. Hakobyan and McLaren (2016) also find NAFTA-induced migration responses to labor market changes but only among those with less than a high school degree.

Migration responses to trade-induced shocks are not in themselves sufficient to generate increases in English fluency rates in trade exposed areas. For this to happen, English-fluent workers must be relatively more likely to remain in (or more likely to migrate to) import-affected areas than workers with more limited English skill. In practice, however, it may be those who are most comfortable speaking English that are able to leave their families and ethnic communities in trade-impacted areas in search for better labor market opportunities elsewhere. After all, other evidence has shown that in general, it is those with more education that are more mobile (Molloy et al. 2011; Notowidigdo 2020).[5] Moreover, newly arrived immigrants with limited English proficiencies may be forced to live near family and friend within the U.S. despite better labor market opportunities elsewhere (Munshi 2003).

To conclude, it is possible for us to observe increases in language proficiency rates among low-skilled immigrants in areas more exposed to Chinese import competition even if individual immigrants do not become better English speakers. However, this would only happen if immigrants with limited English-speaking ability migrated out of or did not migrate to areas that were most affected by import shocks. While there are papers suggesting that low-skilled workers do respond to labor market shocks (Wilson 2020; Cadena and Kovak 2016), most of the literature finds that low-skill workers are much less likely to move than high skill workers (Molloy et al. 2011; Notowidigdo 2020).

3 Data

[5] Although in general, low-skilled workers are less likely to migrate domestically in response to economic opportunities than high-skill workers (Molloy et al. 2011; Notowidigdo 2020), low-skilled immigrants are especially responsive (Cadena and Kovak 2016, Schündeln 2014). Notowidigdo (2020) suggests that eligibility for means tested public assistance programs during economic downturns is one important explanation for why low-skilled workers in general are less mobile than high skill-workers. Because the low-skilled immigrants in our sample are often not eligible for these programs, they may be more mobile than their native-born counterparts.

3.1 Main Sample

Our data come from the five percent state samples of data in 1980, 1990 and 2000 U.S. Censuses as well as the 3-year one percent sample of the American Community Survey (ACS) data from 2006 to 2008 all drawn from the U.S Census Integrated Public Use Micro Samples (IPUMS (Ruggles et al. 2018)); the 1980 data is used only to construct our instrumental variable. These data are particularly well suited for this study because they contain information on immigrants' English proficiency and the large sample sizes allow us to create accurate measures of demographic characteristics within commuting zones for relatively small populations.[6]

Our main sample consists of immigrants between the ages of 18 and 65, from non-English speaking countries,[7] who arrived in the U.S. after turning 18 and who have completed at most a high school degree—those with any college attendance (even less than a year) are dropped from the sample. This last requirement is to ensure that we do not include in our sample international students who have not yet completed their college degrees. We also drop those immigrants who report speaking only English since for them, English is likely their native language despite their being born abroad. Our justification for dropping childhood immigrants is that they are typically fluent in English by the time they join the labor market (Bleakley and Chin 2004). We restrict our sample to low-skill immigrants because they are more likely to work in production within the manufacturing sector. They are also less likely to have been fluent in English before coming to the United States making them more sensitive to changes in U.S. industrial structure. For constructing all of the variables in our analysis, we keep only individuals living in the mainland United States.

[6] We do not use more recent data given Bloom et al.'s (2019) finding that the impacts of Chinese imports disappeared after 2007.

[7] English speaking countries are defined as countries where more than half the recent adult immigrants speak English at home (Bleakley and Chin 2004). Countries with English as an official language are also excluded from the sample. Puerto Rico is classified as a non-English speaking country. Details regarding the origin countries used in our analysis can be found in Appendix Table A1.

Because our analysis relies on making comparisons across geographic areas, we drop individuals without detailed geographic information.

Our measure of English proficiency is based on answers to the survey question: "How well does this person speak English?" The question has four possible responses: "very well," "well," "not well", and "not at all." Following Bleakley and Chin (2004), we create an English fluency dummy variable equal to one for immigrants speaking English "very well" and zero otherwise.[8]

The primary goal of this paper is to study how low-skilled immigrants respond to industrial structure changes in local labor markets. Following Autor et al. (2013), we measure labor markets using commuting zones (CZs)—areas resembling Metropolitan Statistical Areas (MSAs) in that they are created so that most inhabitants live and work within the same area but differing in that they cover the entire United States including rural areas. Using the method discussed in Autor and Dorn (2013), we map individuals in the Census and ACS samples to 1990 commuting zones based on their Public Use Microdata Areas (PUMAs).[9] By the 1990 definitions of commuting zones that we use, there are 741 commuting zones in the U.S. and 722 in the U.S. mainland. Just as in Autor et al. (2013), although we start with the individual-level data from the IPUMS, we eventually aggregate the data to the commuting-zone year level.[10]

[8] Because this information is self-reported (or reported by the household member filling out the survey), the English-speaking ability variable may suffer from measurement error. Different people might have different answers to the English-speaking ability question even holding constant actual English-speaking ability. We note, however, that while classical measurement error in a dependent variable will yield more imprecise estimates, they will not be biased. A more problematic concern is that people systematically report better English skills in areas with more import exposure. We expect, however, that when workers are expected to use more advanced-level English on the job, they will perceive their English skills to be less adequate. This would make it more difficult for us to detect improvements in English skills. Also placating concerns is a literature showing that self-assessed oral proficiency tends to be a reliable measure of actual oral skills (see Ma and Winke (2019) and references therein).

[9] A complication with the cross-walk is that some PUMAs span multiple commuting zones. In these cases, we duplicate individual observations in the original data, one for each potential commuting zone a person in a PUMA may be in, and then we adjust the person weights based on the share of the population of the PUMA that resides in the different commuting zones.

[10] There are six small population CZs not included in our sample because there were no low-skilled immigrants sampled in these commuting zones. Of those six, four are in South Dakota, one is in Arkansas, and one is in Minnesota. We use 716 commuting zones in our baseline sample.

3.2 Measuring Chinese Import Shocks to Local Areas

To measure Chinese import exposure in each CZ, we follow Autor et al. (2013) in interacting the change in U.S. imports from China in each industry with the share of workers in that commuting zone working in that industry and then summing this across all industries in the commuting zone. More specifically,

$$\Delta IPW_{zt}^{u} = \sum_{j} \frac{L_{zjt}}{L_{zt}} \frac{\Delta M_{ucjt}}{L_{ujt}} \quad (1)$$

where ΔM_{ucjt} is the change in the dollar value of imports in industry *j* to the U.S., *u*, from China, *c*, in a ten-year or equivalent period, L_{ujt} is the start of period employment in industry *j* in the entire U.S., L_{it} is the start of period employment in CZ *z*, and L_{zjt} is the start of period employment in industry *j* in CZ *z*. Thus, the variation in ΔIPW_{zt}^{u} stems from differences by CZ in start-of-period industrial structures.[11]

3.3 Descriptive Statistics

Our data is aggregated to the CZ-year level. Our main variables are constructed as decadal differences, 1990-2000 and 2000-2007. Table 1 presents descriptive statistics of the 1432 cells in our data (716 commuting zones multiplied by the two decadal differences) separated by whether the changes in import exposure are above or below the median change in import exposure in the sample. As can be seen from the table, the share of low-skilled immigrants who speak English very well generally decreased by about four percentage points in this time period, but the decrease was smaller in magnitude in commuting zones with larger increases in Chinese import exposure.

[11] We use the variable constructed in Autor et al. (2013) and made available on David Dorn's website. To construct the variable, Autor et al. (2013) use data on imports from the United Nations Commodity Trade Statistics.

Table 1 also presents descriptive statistics on start of period commuting zone characteristics, again separated by whether the commuting zone experienced above or below median changes in Chinese import exposure in the ten years following that base period. As can be seen from the table, the low-skilled immigrants in high exposure commuting zones are less likely to have high school degrees, are more likely to be Hispanic, less likely to be Asian, and are significantly more likely to be employed in manufacturing. The table also presents start of period descriptive statistics for the general working age population of the commuting zones (not just the low-skilled immigrants in our sample). Relationships mirror those for the low-skilled immigrants: In CZs with larger increases in import exposure, the share of the working age population employed in manufacturing is higher. These commuting zones also have a slightly larger share of the population with college degrees.[12]

4 Empirical Approach

To identify the impact of changes in industrial structure on the English language fluency of immigrants, we exploit variation across commuting zones in exposure to Chinese import competition. Following Autor et al. (2013), our baseline empirical specification is a stacked first difference model of the form,

$$\Delta ENG_{zt} = \alpha \Delta IPW_{zt}^{u} + W_{zt}\beta_1 + X_{zt}\beta_2 + \gamma_t + \varepsilon_{zt} \quad (2)$$

where the dependent variable, ΔENG_{zt} is the decadal change between year *t* and year *t+1* in the share of low-skilled immigrants in CZ *z* that speak English very well. The right-hand side variable of interest, ΔIPW_{zt}^{u}, measures the change in Chinese import exposure in commuting zone *z* again

[12] While we constructed our own aggregate characteristics for the low-skilled immigrants in our baseline model, the data on working age population characteristics (namely, the share of the commuting zone workforce employed in manufacturing, the share of the working age (16-64) population that has a college education, and the share employed among working age female workers) were obtained from David Dorn's website.

between the year *t* and *t+1*.

The vector, W_{zt} , contains a set of demographic characteristics of commuting zone *z* measured at the start of decade. These include characteristics like share of the working age population that is college educated and share female in the labor market, but also the share of the commuting zone workforce employed in manufacturing at the start of the period. The latter is an especially important control variable for our analysis because commuting zones may be strongly affected by Chinese imports both because they have more people employed in the manufacturing sector and because the particular manufacturing industries in those commuting zones are in direct competition with Chinese imports. Commuting zones with larger manufacturing sectors may be very different commuting zones focusing in other industries and so the characteristics of people in the manufacturing-centric commuting zones may have evolved over time for reasons unrelated to Chinese import competition (for example, technological change). By controlling for base period share of the workforce employed in manufacturing, we are implicitly comparing the evolution of English-speaking abilities of immigrants residing in commuting zones with very similar initial industrial structures but with some facing more competition from imports from China than others. The vector, X_{zt} , controls for characteristics of the low-skilled immigrant population in the commuting zone, including the share with a high school degree, average age, average years in the U.S., share female, and the shares of different races.

Because the model is estimated in first differences, we have two observations for each commuting zone: one for the difference between 1990 and 2000 and the other for the difference between 2000 and 2007. Each observation is weighted by the start of period CZ population. To allow for differences across decades in changes of English-speaking abilities of immigrants across the entire U.S., we include decade fixed effects, γ_t, which we estimate by including a dummy variable equal to one for commuting zone differences between 2000 and 2007. Finally, ε_{zt} is an error term. As in Autor et al. (2013), standard errors are clustered at the state level throughout. We note that the estimates from a first difference model of this type tend to be similar to those from a more traditional three period fixed effects model but with less restrictive assumptions made on the error term (see Autor et al. 2013, footnote 26).

If changes in our measure of import exposure across commuting zones arise mostly from supply shocks in China, then we might interpret our estimated α as the impact of imports-induced job losses in a commuting zone on the English language fluency of immigrants in that commuting zone. A potential concern with this estimation strategy is that the changes in CZ import competition are instead driven by U.S. demand shocks. For example, if people in the U.S. start demanding more smartphones, then China would export more smartphones to the U.S., but at the same time, U.S.-based smartphone manufacturers would also produce more smartphones. If this is true, commuting zones with more smartphone production may even have better labor market opportunities than those specializing in other industries, despite the fact that they are exposed to more Chinese import competition. Thus, demand-induced changes in Chinese exports will attenuate our estimates of the impact of import exposure.

To address this issue, we follow Autor et al. (2013) in instrumenting for Chinese import exposure with a variable constructed from changes in Chinese imports to other developed countries, namely, Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland:

$$\Delta IPW_{zt}^{o} = \sum_j \frac{L_{zjt-1}}{L_{ujt-1}} \frac{\Delta M_{ocjt}}{L_{zt-1}} \quad (3)$$

where ΔM_{ocjt} is the change in imports from China to the eight other high-income countries. These changes are driven by Chinese supply-side factors as well as demand-side factors specific to those other countries. If the demand-side factors in these other developed countries are rather idiosyncratic, i.e., not correlated with U.S. demand, then the IV strategy will identify the impact of Chinese import exposure stemming solely from improvements in Chinese productivity and openness to trade.[13] If this is the case, we expect our IV estimates to be larger in magnitude than our ordinary least squares (OLS) estimates.

Another source of potential bias with our import exposure measure (equation 1) is that contemporaneous employment may be affected by anticipated trade exposure in the future. To address this issue, equation (3) differs from equation (2) in that the start-of-period employment levels are replaced with employment levels from the prior decade. Using lagged employment decreases simultaneity bias.

5 Empirical Results

5.1 Baseline Findings

Table 2 displays our baseline results. Controlling only for period fixed effects, column 1 shows that the share of low-skilled immigrants speaking English very well increases in local areas with more exposure to Chinese import competition. In column (2), controls for base period low-skilled immigrant characteristics are added to the model, and this results in a slight increase in the magnitude of the estimate of interest. As can be seen in column 3, the magnitude of the estimated impact of import exposure remains almost the same when state fixed effects and base period manufacturing share are added to the model. Column 4 presents results when base period share of the commuting zone working age population that has a college degree and share female in the labor force are added as controls to the model. Our estimate of interest decreases again but not

[13] Using a gravity-based measurement of import exposure, Autor et al. (2013) present evidence suggesting that correlated import demand shocks across countries are not important drivers of results.

substantially.

Next, we turn to the IV analysis. Column 6 shows that the IV is positively associated with Chinese import exposure, and the F statistic of 53.7 points to a strong first stage. The two stage least squares estimate in column 5 suggests that for every $1,000 increase in import exposure per worker, the share of low-skilled immigrants in the commuting speaking English very well increased by 0.47 percentage points. For comparison, this same increase in import exposure reduces manufacturing employment per working-age population by 0.60 percentage points (Autor et al. 2013). As expected, the IV estimates are larger in magnitude than the corresponding OLS estimates in column 4 suggesting that U.S. demand shocks may be attenuating the OLS estimates, but the difference is not very large. We note, however, that it is certainly possible for demand shocks in other countries (used to create our IV) to be correlated with demand shocks in the U.S.; this would attenuate even our IV estimates.

A more worrisome issue arises if the IV is correlated with commuting zone level characteristics associated with improvements in English proficiency for reasons unrelated to Chinese import exposure or even industrial structure more broadly. To address this concern, we regress *past* changes in English proficiency of immigrants on *future* changes in Chinese import exposure. If, for example, Chinese import competition and English language fluency of immigrants in a commuting zone were both increasing over time but Chinese import exposure was not causing the changes in English proficiency, then we would expect to estimate a positive coefficient on future changes in Chinese import exposure. If instead, our baseline estimates reflect causal relationships, we should see no statistically significant impacts. Results from this placebo regression are shown in Appendix Table A2. The change in import exposure from 2000 to 2007 in a commuting zone has no statistically significant impact on the change in English fluency among immigrants from 1990 to 2000 in that commuting zone. In fact, the estimate has a negative sign.

Finally, for further evidence that the changes in English fluency we observe are driven by labor market shocks, we look at occupational changes among the employed low-skilled immigrants in our sample. Mirroring the results in Autor et al. (2013), the estimate in column 1 of Table 3 suggests that, just like the general population, low-skilled immigrants become less likely to work in the manufacturing sector in places harder hit by Chinese import competition.[14] The estimate in column 2 of Table 3 points to an increase in the share of the low-skilled immigrant population working in the service sector in commuting zones experiencing more trade shocks. While the service sector estimate is not statistically significant, it is clear from comparing the estimates in columns 1 and 2 of Table 3 that in commuting zones harder hit by Chinese import competition, workers become relatively more likely to work in the service sector than in the manufacturing sector.

Next, we look more carefully at whether Chinese import competition pushes low-skilled immigrants into jobs requiring more English skills and out of jobs that do not require much communication. To examine this issue, we gather data from the U.S. Department of Labor's O*NET survey on the importance of oral abilities (specifically, oral expression and oral comprehension) in different occupations. Following Peri and Sparber's (2009) broad technique, we classify occupations based on the importance of oral abilities for success on the job.[15] We then

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[14] Appendix Table A3 presents estimates of this model using progressively smaller samples. In column 1, we start by using a sample of the entire employed working age population. Column 2 shows estimates constructed using a sample consisting of only the native born, column 3 uses a sample of low-skilled natives, and column 4 shows estimates constructed using a sample of low-skilled immigrants from non-English speaking countries. The point estimates are consistently negative across the different samples. Interestingly, the estimate of the impact of Chinese import competition has the largest magnitude when constructed using low-skilled immigrants from non-English speaking countries. The estimate in column 4 of Appendix Table A3 is larger in magnitude than the estimate in column 1 of Table 3 because in the appendix table, we keep just employed workers in the sample while we use the entire working age population in constructing Table 3.

[15] The O*NET dataset provides a measure of importance of different abilities for success in each occupation ranging from one to five (1 signifying "not important" and 5 signifying "extremely important"). We merge these occupation-

construct for each commuting zone-year cell in our sample, the share of employed low-skill immigrants who work in occupations that require strong oral skills (top quartile) as well as the share working in occupations that only require weak oral skills (bottom quartile). Finally, we estimate models of the form in equation (1) using the share of low-skilled immigrant workers in an occupation requiring strong (shown in column 3) or weak (shown in column 4) spoken English skills as the dependent variables.

The positive estimate in column 3 of Table 3 might suggest that Chinese import shocks pull low-skilled immigrants into occupations requiring very strong English skills, but the estimate is not statistically significant. However, the results in column 4 of Table 3 show that trade exposure pushes low-skilled immigrants out of occupations that require only very weak oral expression and comprehension skills; the estimated coefficient on trade exposure is negative and statistically significant. These findings not only provide support for our hypothesis that the language fluency changes we estimated in our baseline regressions are driven by labor market changes, but they also alleviate any potential concerns about whether the self-reported measure of English fluency that we use is an appropriate measure of actual English fluency.[16]

5.2 Heterogeneity in Impacts of Chinese Import Exposure on English Fluency

specific numerical measures of the importance of oral abilities into a sample of workers drawn from a 2007-2011 ACS sample. Following Peri and Sparber (2009), we then create a variable measuring the relative importance of abilities. For example, an occupation with an oral ability score of 0.10 implies that only 10 percent of workers in 2007-2011 worked in an occupation where oral abilities were less important than in their occupation. We then merge these percentile scores to the low-skilled immigrant individuals in our 1990 U.S. Census, 2000 U.S. Census, and 2006 to 2008 ACS samples by occupation. This is complicated by the fact that O*NET contains 840 occupations classified using the standard occupation classification (SOC), while Census and ACS data classify only 324 possible occupations in the OCC1990 variable. To address this issue, we take the average score if multiple O*NET occupations matched with one OCC1990 occupation. We then take the average of the rescaled scores for the two oral abilities (expression and comprehension) as the oral score.

[16] Also using O*NET data, Arendt et al. (2020) show that refugees to Denmark who completed more hours of language classes take jobs that require more language skills, pointing to a link between knowledge of the host country language and immigrants' abilities to take jobs requiring language skills.

As a first step towards understanding the main drivers of our baseline results, we examine which immigrants are most affected by changes in import competition. We start by testing for heterogeneity by level of English fluency. For ease of comparison, in column 1 of Panel A in Table 4, we simply reproduce our baseline estimates using changes in the share of immigrants speaking English very well as the dependent variable. In column 2 of the same panel, we replace the dependent variable with changes in the share of immigrants speaking English either well or very well, thereby decreasing the threshold for fluency. While 17 percent of our sample speaks English very well, 42 percent speak it well or very well. Chinese imports do not have a statistically significant impact on improvements in English fluency as measured by the share of speakers with abilities above this lower threshold. In the last column, results are shown for an even lower threshold and again, no statistically significant impacts. We conclude from this analysis that any language-based changes resulting from Chinese imports occur at the top of the English-speaking distribution. This is certainly consistent with average or above average English speakers who have lost their manufacturing jobs taking jobs in the service sector and then improving their English further with the extra practice, but these estimates alone cannot rule out selective migration at the top of the English-speaking distribution driving results.

In Panel B of Table 4, we conduct the analysis separately by race, and results suggest that our findings are driven by whites.[17,18] Finally, in Panel C, we separate the sample by education.

[17] Approximately 70 percent of the non-Hispanic white group is from Europe. Poland, Italy, Russia, Germany, Yugoslavia and Portugal are the top 6 source countries. Details can be found in Appendix Figure A1.

[18] The number of observations in column 1 differs from the number in the baseline sample because there were 212 commuting zone-year cells with zero low-skilled white immigrants in them. Recall that our dependent variable is the decadal change in the language abilities of immigrants in the commuting zone. If there are no immigrants with a particular characteristic (like race) in the initial IPUMS sample in either the base year or the end year, we are not able to calculate a difference and so the commuting zone-year observation is dropped in our aggregate analysis. While this issue results in differences in the number of observations across groups, it is not likely to result in large differences in coefficient estimates because the dropped cells tend to have very small populations and we weight our observations (the commuting zone-year cells) by the start year population of the commuting zone.

To create the estimates in columns 1 and 2, we separate our baseline sample of immigrants with no more than a high school degree into a group with less than a high school degree (column 1) and another with a high school degree (column 2). Estimated impacts are stronger for those with a high school degree, perhaps because high school graduates are better equipped to learn a new language (Arendt et al. 2020) or because they are more likely to move in response to labor market opportunities elsewhere. In the following section, we examine these possibilities more carefully.

6 Mechanisms: English Proficiency Improvements vs. Selective Migration

In response to trade-induced manufacturing job losses, do the English-speaking abilities of immigrants actually improve or is it that the least English proficient immigrants leave (or do not move to) the hardest hit areas? We are not able to perfectly distinguish between these mechanisms, both of which may be occurring at the same time. Instead, we present evidence suggesting that English learning is driving at least part of our estimates and that selective internal migration does not seem to be playing an important role.

For evidence of actual learning, without actual measures of within-person changes in English proficiency, we look to other investments in human capital that are likely to be correlated with improved English skills. Specifically, we consider the impact of Chinese import exposure on the likelihood that low-skilled immigrants, who are age 18 or above and who have never been enrolled in college, are enrolled in school. We note that our measure of school enrollment only includes schooling which leads to a high school diploma or a college degree; English as a Second Language (ESL) classes would not be counted in this measure. Also, because we drop from the sample even those who attended college for less than a year, our enrollment measure is not picking up college attendance. However, we believe that participation in GED classes, for example, improves English speaking abilities of immigrants regardless of the subjects being taught.

Column 1 of Table 5 shows that Chinese import exposure increases the likelihood that low-skilled immigrants in the commuting zone are enrolled in school. For comparison, we also consider the same model but run on a sample of low-skilled native-born individuals. Consistent with Greenland and Lopresti's (2016) findings that high school graduation rates increase in areas with more Chinese import exposure, we do estimate a positive and statistically significant impact of import exposure on the likelihood that natives are enrolled in school, but the magnitude of the impact is substantially smaller for natives than it is for immigrants. While it is theoretically possible that the immigrants enrolling in school are not the same individuals improving their English skills, these results still imply that low-skilled immigrants are more likely than comparable natives to make active investment in the skills that are being more rewarded in labor markets affected by trade.

Even if low-skilled immigrants are more likely to improve their English skills if they happen to be in areas harder hit by Chinese import shocks, this does not rule out a role for selective migration. After all, it may be the immigrants who were planning to enroll in school that move to (or do not move out of) commuting zones with more import exposure. Following Autor et al. (2013) and Cadena and Kovak (2016), we start exploring this issue by examining whether Chinese import competition leads to commuting zone population changes. Estimating our baseline model (equation 1), including the controls for low-skilled immigrant characteristics as well as a control for lagged low-skilled immigrant population change $\Delta \ln\ (Population_{zt-1})$,[19] but substituting our language-based dependent variable with changes in log low-skilled immigrant population counts,

[19] Following Monras (2018) and Greenland et al. (2019), we add the lagged population control to address the concern that population growth tends to be quite persistent over time.

we find no statistically significant evidence of changes in the low-skilled immigrant population in response to Chinese import competition (column 1, in Panel A of Table 6), and strangely the estimate is positive.

It may be difficult to interpret these results given that if the population changes, the average characteristics of low-skilled immigrants remaining in the commuting zone would likely change, and so it is unclear whether we should control for these characteristics (vector X in equation 2) in the model. Column 1 in Panel B of Table 6 shows results from a model controlling for baseline characteristics of the entire commuting zone (that is, including natives as well as high-skilled immigrants, vector W in equation 2) but not including characteristics of the low-skilled immigrants in our sample. In line with Autor et al. (2013) but contrary to Cadena and Kovak (2016), again we find no evidence of population changes.[20] The estimate has a positive sign but is very small and statistically insignificant.

While these results are certainly not indicative of strong general migration responses, selective migration may still be behind our baseline results if the number of poor English speakers leaving areas with more trade exposure approximates the number of fluent English speakers coming to these areas.[21] In columns 2 and 3 of Table 6 (both panels), the point estimates point to

[20] Consistent with the findings in Cadena and Kovak (2016), our preferred point estimate (column 1 of Panel B) is negative. The main difference between our estimate and that in their paper is that their estimate is not statistically significant while ours is. This may be because responses to Chinese import exposure are fundamentally different from responses to the Great Recession. It may also be because we use commuting zones, which include cities as well as rural areas, while they only use cities. Another potential explanation for the discrepancy is that Cadena and Kovak (2016) focus only on Mexican low-skilled immigrants while we consider all low-skilled immigrants. The authors write that they focus on Mexicans not because they find “strong evidence against” mobility of other groups but because Mexicans “exhibit the strongest and most precisely estimated mobility responses among the foreign born (footnote 1, Cadena and Kovak 2016).

[21] This seems unlikely given previous research showing that Chinese import-exposed areas suffer job losses in all sectors, not just manufacturing, because of general equilibrium effects (Acemoğlu et al. 2016). On the other hand, Bloom et al. (2019) find little evidence that Chinese import competition led to net job losses, but instead show that it simply reallocated jobs from manufacturing to services. This is unlikely, however, to impact the low-skilled immigrants in our sample because the new service sector jobs were in research, management, and resale (i.e. high skill jobs) in high human capital areas (Bloom et al. 2019). Hakobyan and McLaren (2016) found evidence of decreased wage growth in areas affected by NAFTA even among service-sector workers.

increases in the population of fluent English speakers and decreases in the population of poor English speakers, but the estimates are not statistically significant. Moreover, the coefficient signs may be explained by actual language improvements as opposed to migration. After all, when an immigrant becomes fluent in English, then even without anyone moving, the number of fluent English speakers increases by one and the number of poor English speakers decreases by one. To explore this further, in column 4, we show changes in the number of low-skilled immigrants from English speaking countries, a population not included in our baseline sample because they are likely to have arrived in the U.S. already proficient in English. The point estimates are negative in both panels and statistically significant in Panel A. This suggests that, if anything, those already proficient in English are relatively more likely to leave, not move to, commuting zones hard hit by trade shocks.

For further analysis of selective migration, in Table 7 we examine the relationship between import exposure and characteristics that are either impossible or at least difficult for a person to change. If the results in Table 2 are mostly driven by migration choices, then we would expect to see increases in the share of low-skilled immigrants with (difficult to change) characteristics that tend to be correlated with better English skills, for example, more schooling and years in the United States. On the other hand, if they are driven by actual improvements in English fluency as opposed to migration, we should see no impacts on these characteristics. Column 1 of Table 7 shows that there is no statistically significant relationship between Chinese import exposure and the share of low-skilled immigrants in the commuting zone with a high school degree. The estimate is small but is actually negative which is not what we would have expected if the more educated, and therefore more likely to be fluent, immigrants were moving to import-exposed commuting zones. Column 2 of Table 7 shows the same basic relationship when considering years in the U.S. instead of high school graduation. Similarly, there does not appear to be any relationship between trade exposure and the age distribution of low-skilled immigrants; the estimate in column 3 is negative, small in magnitude, and statistically insignificant.

Columns 4 through 8 consider the relationship between Chinese import competition and the racial composition of low-skilled immigrants in the commuting zone. Column 4 and 5 show that there are no statistically significant changes in the case of non-Hispanic blacks and Asians. Interestingly, the estimates are substantially larger in these models but they remain statistically insignificant in the case of Hispanics (column 6) and non-Hispanic whites (column 7). Strangely, column 8 shows the share of low-skilled immigrants who are "other races" increases and the estimate is statistically significant. Also, column 9 shows that the share of low-skilled immigrants in a commuting zone who are female decreases quite substantially in response to increased import exposure.[22] These findings may be interpreted as evidence that there are some population changes as a results of trade exposure, but given the statistically insignificant estimates of effects on the other composition measures, especially those that are likely to be correlated with English fluency, the overall results in Table 7 do not make a strong case for migration being a primary driver of English fluency improvements in commuting zones with more exposure to Chinese import competition.

Next, we consider internal migration more directly by limiting our baseline sample of low-skilled immigrants to those who were living the U.S. either five years prior to the survey (in the 1990 and 2000 Censuses) or one year prior to the survey (in the 2006-2008 ACS sample). The Census and ACS surveys collect information on previous PUMA of residence and with this

[22] In Appendix Table A4, we conduct the baseline analysis separately by gender. Although females are more likely to speak English very well than males, the estimated coefficient on trade is not statistically significant in the female sample. Interestingly, the point estimates are very similar to each other in the male and female samples.

information, we can assign people to both their previous and current commuting zones.[23] We then label individuals as migrants if their current commuting zone is not the same as their previous commuting zone.[24] We start by examining whether the low-skilled immigrants in our sample of people already living in the U.S. in the year(s) prior to the survey are more likely to leave commuting zones hard hit by Chinese imports. To do this, we match our trade exposure and other commuting zone characteristics to individuals based on their previous commuting zone instead of their current commuting zone. We then estimate a model with the same right-hand side variables as equation 1 (using previous commuting zone characteristics) but with the change in the share of movers from that previous commuting zone as the dependent variable.[25]

The estimate, shown in column 1 of Panel A in Table 8, suggests that immigrants living in commuting zones with more exposure to Chinese import competition are actually less likely to leave these commuting zones than those living in areas with less exposure. This is consistent with the point estimates in Dix-Carneiro and Kovak (2019) showing that people in areas of Brazil hardest hit by changes in tariffs were the least likely to move, but the authors warn against making

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[23] Historical PUMA is a 3-digit variable instead of a 5-digit variable that is used in the PUMA to CZ cross-walk file. A detailed explanation of how we conducted the match can be found in the Data Appendix.

[24] As discussed previously, this process is rather complicated for those in PUMAs that span multiple commuting zones. This issue is addressed by duplicating individual observations in the original data, one for each potential commuting zone a person in a PUMA may be in, and then adjusting the person weights based on the probabilities that they live in each of the potential commuting zones. For our migration analysis, we duplicate observations again (even the already duplicated observations) when people's previous PUMAs also span multiple commuting zones. Using this technique, an observation of an individual currently and previously living in a PUMA spanning, for example, two potential commuting zones would be duplicated to four observations (given the 2 x 2 = 4 possible combinations of commuting zones) with the weights on the four observations summing to one. This technique addresses the possibility that a person can remain in the same PUMA but still move between commuting zones, but it also overestimates the number of cross-commuting zone migrants. Because the duplicate observations receive little weight, they are unlikely to impact results. In Appendix Table A5 we show that these results are not sensitive to assigning all people living in the same PUMA in the two years to be non-migrants. Instead of making duplicates, we also tried randomly allocating each individual to a CZ based on their PUMA. Results estimated using this technique, available upon request, are consistent with those presented in our tables.

[25] This estimation procedure is not ideal because, for example, we are using changes in trade exposure in a commuting zone between 1990 and 2000 to explain the difference between the share of commuting zone leavers between 1985 and 1990 and the share of leavers between 1995 and 2000. If exposure to Chinese import competition changes gradually through time, our results are still likely to be informative about migration responses even though the timing does not line up perfectly. In any case, this issue is likely to attenuate our results.

strong conclusions based on these results given the lack of statistical significance. In columns 2 and 3, we separate the sample based on English fluency. The negative impact is larger in the sample of immigrants who speak English very well, a result consistent with the idea that immigrants who are proficient in English (or are able to become proficient as a result of the shock) face less pressure to leave the hardest hit commuting zones. However, the estimates are only statistically different from each other at the 10 percent level. Moreover, because the estimates are negative in both samples, we do not view internal migration patterns as a major driver of our baseline results.

Next, we consider where domestic migrants go. Following Erten et al. (2019), we examine whether those currently living in commuting zones with more exposure to Chinese import competition are less likely to be recent arrivers. The point estimate in column 1 of Panel B in Table 8 suggests that people are less likely to migrate to commuting zones with more trade exposure, but the estimate is not statistically significant. As shown in Columns 2 and 3 in Panel B, estimates remain negative and statistically insignificant when the analysis is done separately by English fluency. They are also of practically the same magnitude suggesting that immigrants in general are not moving to hardest hit commuting zones, regardless of English fluency.

Taken together, the results in Table 8 do not point to internal migration as a major driver of the positive relationship between trade exposure and English fluency rates. However, it is possible that initial settlement decisions of new arrivers to the U.S. can explain the pattern. To explore this possibility, we return to our full sample of low-skilled immigrants, including those who were not in the U.S. one or five years prior to the survey, and then separate the sample based on years in the country. If our baseline results are mostly driven by how English fluency influences where immigrants choose to settle upon arrival, then we would expect a strong relationship between trade exposure and English fluency rates even among immigrants arriving in the in the previous year. On the other hand, if our results are driven mostly by people learning to speak better English, we would not expect to see impacts on the most recent arrivers. Presumably, they would not have had enough time to improve their English.

Results, shown in Table 9, show that there is no statistically significant impact of trade exposure on English fluency rates of immigrants who have been in the U.S. for a year or less, but there are strong and statistically significant impacts on those who have been in the U.S. between two and five years (column 2) or between six and nine years (column 3). Interestingly though, there is again no statistically significant impact on English fluency rates of immigrants who have been in the U.S. for ten or more years, and the point estimate is practically zero. Given that our baseline sample consists only of immigrants who arrived in the U.S. at age 18 or above, even the youngest immigrants in our sample of those who have been in the U.S. for more than ten years are 28 years old at the time of the survey. Our inability to detect impacts on this group may simply reflect how difficult it is for older people to learn a new language (Hartshorne, Tenenbaum, and Pinker 2018).

It is also possible, however, that our baseline results are driven by selective return migration, and immigrants in the U.S. for more than ten years are simply less likely to return to their home countries in response to poor labor market opportunities in their commuting zones. We do not believe that selective return migration is a major driver of our results in light of the extensive literature showing that immigrants did not return to their home countries during the Great Recession (Fix et al. 2009, Passel and Cohn 2009, Rendall et al. 2011). Unfortunately, however, it is difficult for us to test for return migration using our own data because we have only repeated cross-sections, and immigrants who return to their home countries simply do not appear in our data.

For further evidence that migration choices among newly arrived immigrants from abroad may be important drivers of our results, we also conduct the baseline analysis (estimating equation 2) separately by where people were living five years (in the 1990 and 2000 censuses) or one year (in the 2006-2008 ACS survey) prior to the survey: in the same house, in a different house but the same state, in a different state, or abroad. As can be seen in Table 10, only for the low-skilled immigrants who recently arrived from abroad (within the past year or five years) is the relationship between Chinese import exposure and the share of low-skilled immigrants speaking English very well statistically significant (see column 4). We note, however, that newly arrived immigrants have the most incentive to make language improvement investments, and because they tend to be young, they may also be better able to learn a new language. The point estimate is also quite large in the sample of state movers, but caution is required in interpreting this result given that it is statistically insignificant.

7 Equilibrating Labor Markets

While it is certainly interesting to consider the mechanisms driving the relationship between Chinse import exposure and the share of low-skilled immigrants in the commuting zone who speak English very well, for the purposes of equilibrating the labor market, the mechanisms do not matter. Regardless of whether low-skilled immigrants are responding to import-induced labor market changes by adjusting their skill set or by migrating to where their skills are more highly rewarded, the natives, who may not be as willing or able to make these types of changes, will benefit. In other words, were it not for the skill investments or migration decisions made by immigrants, the wage and employment consequences of import exposure on natives may have been much worse.

Exploiting geographic variation in local labor demand conditions during the Great Recession, Cadena and Kovak (2016) find that low-skilled Mexicans' location choices were more responsive to local labor shocks than were low-skilled natives. They also show that natives living in areas with larger Mexican populations experienced less recession-induced job loss than natives in areas with fewer Mexicans (Cadena and Kovak 2016). In a similar vein, Basso, Peri, and Rahman (2020) also present evidence suggesting that immigrants have protected natives from job and wage polarization resulting from technological change.

We consider how immigrants attenuate natives' employment and job losses as a result of Chinese import competition. Specifically, we compare the employment and wage impacts of Chinese import exposure on low-skilled natives depending on whether they live in commuting zones with large initial populations of low-skilled immigrants. If immigrants indeed help equilibrate the labor market, regardless of whether it is via migration or skill-upgrading, then we would expect fewer negative impacts in the areas with more immigrants.

Table 11 presents evidence that this is indeed the case when considering both employment (Panel A) and wages (Panel B). Panel A shows that although the estimates of the impact of Chinese import exposure on employment of low-skilled native are statistically insignificant in commuting with above mean shares of low-skilled immigrants, the point estimate in the below mean sample (column 1) is larger in magnitude than the estimate in the above mean sample (column 2). Column 3 shows that the difference between these two samples is statistically significant at the five percent level. Panel B shows that in commuting zones with below-mean shares of low-skilled immigrants, increases in import exposure leads to statistically significant decreases in weekly wages of low-skilled natives (column 1) while in commuting zones with above-median shares of low-skilled immigrants, import exposure has a statistically insignificant smaller estimated impact on native wages (column 2). While the difference between the two estimates in this model are not statistically significant, we view these results as broadly consistent with immigrants' roles in equilibrating labor markets. Taken together, our results are very much in line with the conclusions of Cadena and Kovak (2016) that the harmful impacts of economic downturns on natives are smaller in areas with more immigrants. While their analysis focused on the internal migration mechanism driving this relationship, we show that language acquisition and perhaps language-selective migration are likely to be additional important mechanisms.

8 Conclusion

This paper examines the relationship between Chinese import competition in an area and low-skilled immigrants' language skills in that area. Our results suggest that for every $1,000 increase in import exposure per worker, the share of low-skilled immigrants who speak English very well increases about half of a percentage point. This result is driven by whites, those with a high school degree, those who have been in the U.S. for ten years or less, and those who most likely start with a fairly advanced level of English proficiency.

These findings may be driven by actual improvements in immigrants' English-speaking abilities, either via active investments in English classes or more passive on-the-job learning, or by selective migration into or out of trade hit areas based on English proficiency. Because our data do not allow us to track individuals over time, we cannot perfectly distinguish between these two broad mechanisms. However, we do show that low-skilled immigrants in trade-impacted areas are more likely to be enrolled in school than their native-born counterparts providing some evidence of actual acquisition of new skills. While we do not find evidence implying a large language-selective internal migration response to Chinese import competition, our results do suggest that settlement decisions of new migrants from abroad seem responsive to either immigrant language abilities before migration or perhaps their ability to learn the language within the first few years after arriving.

Regardless of whether our findings are driven by actual English language learning or selective migration, they provide further support for an often-ignored potential benefit of low-skilled immigration to natives: Because immigrants tend to be more responsive to labor market shocks than natives, they can dampen negative impacts of labor market shocks to specific local areas by helping to equilibrate local labor markets. This finding should help inform policy makers considering more open immigration policies.

Our results also imply that even people who are the most negatively affected by trade can and often do make investments that may actually improve their long run outcomes. Perhaps instead of discouraging trade, policymakers may consider facilitating these investments. There is growing evidence that intense host country language classes increase employment prospects for refugees (Arendt et al. 2020; Lochmann, Rapaport, and Speciale 2019). Our work implies that employment prospects themselves can reinforce host country language proficiency leading to multiplier effects of English language proficiency. In addition to any benefits to the immigrants themselves, improved language skills of immigrants can yield productive social interactions with natives potentially improving welfare overall.

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Data Appendix: PUMA and MIGPUMA Matching with 1990 Commuting Zones

Following Autor et al. (2013), we create 1990 commuting zone characteristics using information on Public Use Microdata Areas (PUMA) available in the IPUMS samples of the 1990 Census, 2000 Census and the 2006-2008 ACS. In the raw data, PUMAs take a 5-digit numeric value which can identify a unique PUMA when used together with a state code. Joining the code for state with the code for PUMA produces a six-digit code. For example, the 01801 PUMA in Louisiana (state code 22) becomes 221801.

In the 2006-2011 ACS data, three PUMAs in Louisiana: 221801, 221802, and 221905 are all coded as 297777. This is because, after Hurricane Katrina, each of these three PUMAs no longer had a large enough population to be listed as separate PUMAs. All of the three PUMAs above belong to Commuting Zone (CZ) 3300, and so we manually recoded PUMA 297777 to 221801 in our 2006-2008 sample.

In producing Table 8, we use information on current residence PUMA as well as prior PUMA of residence (five years prior in 1990 and 2000 and one year prior in the ACS data). While current residence PUMA is reported with a five-digit code, previous PUMAs (called MIGPUMAs in the IPUMS) are reported with only a three-digit code. So, for example, a person’s current residence PUMA would be listed as 00300 in the survey but if someone lived in that same PUMA five years prior to the survey, the reported PUMA of residence five years prior to the survey would be 003. Similarly, PUMA 00801 at the time of the survey would be coded 008 if listed as a PUMA of residence five years prior to the survey. To make PUMAs and MIGPUMAs comparable, we first make the 3-digit MIGPUMA a 5-digit value by multiplying it by 100 (and so MIGPUMA 003 would become 00300 and MIGPUMA 008 would become 00800). We then put together this newly created variable with the state code to create a six-digit prior PUMA code (e.g., PUMA 00300 in

Louisiana becomes 220300). We then verified in the crosswalk files that most of the PUMAs with the same leftmost three digits are also located in the same CZ. For example, four PUMAs in Louisiana, 221901, 221902, 221903, and 221904 (again, 22 is the state code for Louisiana) are all in CZ 3300. So, for those PUMAs whose codes do not end with 0, we recode their transferred 5-digit MIGPUMAs by adding 1 to them. For example, if people lived in the four Louisiana PUMAs 221901, 221902, 221903, and 221904 five years ago, MIGPUMA will report 019, multiplying MIGPUMA with 100 and then merging in the state code will give us 221900. By adding 1, we get 221901 as the PUMA they lived in five years ago. Even though these residents may not have lived Louisiana PUMA 221901 five years prior to the survey, they all lived in the CZ 3300 according to the crosswalk files. Thus, our imputation will not cause measurement error since the geographic unit in our analysis is CZ.

More specifically, in 1990, all of the PUMAs with the same leftmost three digits are located in the same CZ. However, in 2000, there are 7 exceptions: 80100, 80500, 170100, 171100, 182000, 422000, and 422800. As shown in the table below, we cannot identify the CZ based on the adjusted MIGPUMA. For example, if people report a MIGPUMA of 80100, we know they lived in PUMAs 80101, 80102 or 80103, but we cannot not know which CZ they lived in. thus, we drop observations with these seven MIGPUMAs. Since less than 0.1% of our sample are dropped (287 out of 310227 omitted in 2000 data, around 0.0925%), our results are not likely to be affected by this.

MIGPUMA	PUMA	CZ	Afactor
80100	80101	36401	0.389
	80101	35201	0.031
	80101	28800	0.127
	80101	28704	0.016
	80101	28702	0.438
	80102	28800	1

	80103	35201	1
80500	80501	28502	0.276
	80501	34805	0.45
	80501	28503	0.229
	80501	28501	0.045
	80502	28502	1
170100	170101	23801	0.068
	170101	23200	0.209
	170101	24400	0.723
	170102	23801	1
	170103	23801	1
	171101	24701	1
171100	171102	24701	0.742
	171102	25500	0.258
182000	182001	14000	1
	182002	14000	0.035
	182002	14200	0.965
422000	422001	16400	0.84
	422001	16300	0.16
	422002	16300	1
422800	422801	19200	0.812
	422801	17400	0.188
	422802	17400	1

In 2005-2011 ACS data, "MIGPUMA1" reports a 5-digit code which indicates the PUMA people lived in one year prior to the survey. However, these 5-digit codes are not exactly the same as the 5-digit PUMA codes that are used in the cross-walk files. For example, in the ACS data, if people lived in one of the following California (state code: 6) PUMAs: 61401, 61402, 61501, …, 61506, their reported MIGPUMA1 is "61490". However, PUMA "61490" does not exist in the PUMA to CZ cross-walk file provided on David Dorn's website, and so "MIGPUMA1" cannot be directly used to match with CZs. The IPUMs website does provide a table describing the relationships between 2000 PUMAs and migration PUMAs. Using this table, we first transfer those 5-digit MIGPUMA1 codes to the 3-digit MIGPUMA codes, then we make the adjustment exactly as what we did in 2000 census data. Those who lived in Louisiana PUMA 297777 (i.e., 221801, 221802, and 221905) are recoded to 221801. Also, those with MIGPUMA 80100, 80500, 170100, 171100, 182000, 422000, and 422800 are dropped from the sample because their MIGPUMAs match with multiple PUMAs. This amounted to dropping 21 observations out of 75,618 (0.028%) in the 2006 ACS, 22 observations out of 77,208 (0.028%;) in the 2007 ACS, and 22 out of 74,709 (0.029%) in the 2008 ACS.

Table 1: Descriptive Statistics

	Change in Import Exposure in CZ		
	Below Median	At or Above Median	Total Sample
	(1)	(2)	(3)
Change imports from China to US / worker	1.05	2.16	1.84
	(0.57)	(1.59)	(1.47)
Among low skilled immigrant population			
Change in percentage speaking English very well	-5.46	-3.77	-4.26
	(5.20)	(4.02)	(4.46)
Average age$_{-1}$	40.80	41.14	41.04
	(2.91)	(2.90)	(2.91)
Average years in the US$_{-1}$	12.64	13.04	12.92
	(2.45)	(2.22)	(2.29)
Percent female$_{-1}$	49.92	50.52	50.35
	(6.23)	(4.64)	(5.15)
Percent with high school degree$_{-1}$	30.57	27.84	28.63
	(11.06)	(8.13)	(9.15)
Percent non-Hispanic white$_{-1}$	14.01	14.59	14.42
	(12.75)	(12.79)	(12.78)
Percent non-Hispanic black$_{-1}$	2.49	1.96	2.12
	(3.86)	(3.13)	(3.37)
Percent Asian$_{-1}$	17.22	11.92	13.45
	(12.91)	(8.41)	(10.20)
Percent Hispanic$_{-1}$	64.37	70.29	68.58
	(20.53)	(16.42)	(17.90)
Percent married$_{-1}$	62.51	61.70	61.93
	(6.93)	(5.08)	(5.68)
Percent of immigrants employed in	10.20	15.99	14.33
manufacturing$_{-1}$	(5.07)	(5.85)	(6.22)
Among whole commuting zone population			
Percentage employed in manufacturing$_{-1}$	11.52	17.43	15.73
	(5.23)	(5.68)	(6.16)
Percentage of employment among women$_{-1}$	62.40	62.40	62.40
	(6.22)	(4.70)	(5.18)
Percentage of college-educated population$_{-1}$	53.35	52.13	52.48
	(7.61)	(6.11)	(6.60)
Number of observations	716	716	1432

Note: Statistics in column 1 are based on the 716 CZs that are below the median level of changes in import exposure per worker in each period. Statistics in column 2 are based on the 716 CZs that are above the median level of changes in import exposure per worker in each period. Percent and means are reported at the beginning of each period. All statistics are weighted by the start-of-period CZ share of the national low-skilled immigrant population. Standard deviations are reported in parentheses.

Table 2: Baseline Regressions

Dependent Variable:	Change in Share Speaking English Very Well					Change in imports from China to US / worker
	OLS	OLS	OLS	OLS	IV	First Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Imports from China to US/ Worker	0.405***	0.446***	0.440***	0.373**	0.465**	
	(0.122)	(0.133)	(0.122)	(0.150)	(0.229)	
Δ Imports from China to Other Countries / Worker						0.547***
						(0.075)
Constant	-4.547***	-35.577***	-41.636***	-49.481***	-48.841***	-1.855
	(0.379)	(5.312)	(9.522)	(12.557)	(12.279)	(2.428)
Observations	1,432	1,432	1,432	1,432	1,432	1,432
R-squared	0.014	0.170	0.288	0.293	0.292	0.735
Low skilled immigrant controls	N	Y	Y	Y	Y	Y
Whole population controls	N	N	N	Y	Y	Y
State FE	N	N	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Dependent variable mean (levels, not changes)	17.13	17.13	17.13	17.13	17.13	1.839
F statistic first stage						53.72

Notes: N=1,432 (716 × 2 time periods). The sample consists of immigrants between the ages of 18 and 65, from non-English speaking countries, who arrived in the US after turning age 18 and who have completed at most a high school degree. See Table 1 for a description of the control variables used in columns 2-6. The IV regression includes the full vector of controls from column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national low-skilled immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Impact of Chinese Imports on Employment in Different Occupations

Dependent variable:	Change in Share Employed in Corresponding Occupations			
Sample:	Manufacturing Sector Occupations	Service Sector Occupations	High Oral Requirement Occupations (Top 25%)	Low Oral Requirement Occupations (Bottom 25%)
	(1)	(2)	(3)	(4)
Δ Import from China to US / Worker	-0.610**	0.179	0.041	-0.818***
	(0.283)	(0.286)	(0.146)	(0.272)
Observations	1,394	1,394	1,394	1,394
R-squared	0.326	0.368	0.311	0.162
Average Dependent Variable (Levels)	24.20	26.14	12.79	46.57
F	53.57	53.57	53.57	53.57

Notes: These IV regression includes the full vector of controls from Table 2 column (4). See Table 1 for description of variables we use as controls. All regressions include a dummy for the 2000-2007 period. Oral requirements for occupations obtained from O*NET data. See footnote 14 in the text for more details. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Heterogeneity of Impacts of Chinese Import Exposure

Panel A: Heterogeneity by Measure of English Fluency

Dependent Variable:	Change in Share Speaking English …		
	Very Well	Well or Very Well	(Regardless of How Well)
Δ Imports from China to US/ Worker	0.465**	0.114	0.253
	(0.229)	(0.421)	(0.184)
Observations	1,432	1,432	1,432
Average Dependent Variable (Levels)	17.13	42.18	78.69
F	53.72	53.72	53.72

Panel B: Heterogeneity by Race

Dependent variable:	Change in Share Speaking English Very Well			
Sample:	White	Black	Asian	Hispanic
Δ Imports from China to US/ Worker	3.204***	0.280	0.543	0.331*
	(1.196)	(2.427)	(0.545)	(0.177)
Observations	1,220	158	1,242	1,288
R-squared	0.146	0.323	0.101	0.150
Average Dependent Variable (Levels)	32.80	29.20	12.79	14.02
F	42.17	20.77	124.7	39.81

Panel C: Heterogeneity by Completed Schooling

Dependent variable:	Change in Share Speaking English Very Well	
Sample:	< High School	High School
Δ Imports from China to US/ Worker	0.191	1.142***
	(0.198)	(0.432)
Observations	1,384	1,384
R-squared	0.258	0.240
Average Dependent Variable (Levels)	13.07	27.33
F	48.29	68.04

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of Chinese Imports on School Enrollment of Low Skilled Immigrants and Natives

Dependent variable:	Change in Share Enrolled in School	
Sample:	Low Skilled Immigrants	Low Skilled Natives
	(1)	(2)
Δ Imports from China to US/ Worker	0.521***	0.191***
	(0.147)	(0.070)
Observations	1,432	1,444
R-squared	0.327	0.337
Average Dependent Variable (Levels)	5.826	7.033
F	53.72	39.88

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Impact of Chinese Imports on Population

Dependent variable:	Change in log of Low-Skilled Immigrant Population × 100			
Sample:	All	Do Not Speak English Very Well	Speak English Very Well	Immigrants from English-speaking Countries
	(1)	(2)	(3)	(4)
Panel A: Full Set of Controls				
Δ Imports from China to US/ Worker	0.472	-0.074	1.858	-3.544*
	(0.979)	(0.947)	(2.019)	(1.978)
Observations	1,428	1,366	1,360	1,318
R-squared	0.670	0.665	0.465	0.377
Average Dependent Variable (Levels)	1199	1188	994.4	976.8
F	54.23	54.42	39.08	15.56
Panel B: Omitting Controls for Low-Skilled Immigrant Characteristics				
Δ Imports from China to US/ Worker	0.028	-0.499	2.754	-1.960
	(1.807)	(2.032)	(2.153)	(2.285)
Observations	1,428	1,366	1,360	1,318
R-squared	0.652	0.644	0.453	0.365
Average Dependent Variable (Levels)	1199	1188	994.4	976.8
F	63.13	62.06	45.10	14.82

Notes: See Table 1 for description of variables. The IV regression in Panel A includes the full vector of controls from Table 2 column (4) along with an additional control for lagged population growth. Low skilled immigrant characteristics are not included as controls in Panel B. All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. Column 4 considers the impact of imports on the population of low-skilled immigrants from English-speaking countries. These immigrants are not included in the baseline sample. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Impact of Chinese Imports on Changes in Demographic Composition

Dependent variable:	Δ Share with High School Degree	Δ Average Years in the US	Δ Average Age	Δ Share Non-Hispanic Black	Δ Share Asian	Δ Share Hispanic	Δ Share Non-Hispanic White	Δ Share Other Races	Δ Share Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Imports from China to US / Worker	-0.054	-0.072	-0.099	-0.052	0.012	-0.452	0.280	0.212*	-0.383***
	(0.267)	(0.062)	(0.072)	(0.062)	(0.275)	(0.523)	(0.325)	(0.110)	(0.148)
Observations	1,432	1,432	1,432	1,432	1,432	1,432	1,432	1,432	1,432
R-squared	0.676	0.784	0.747	0.337	0.434	0.503	0.594	0.670	0.403
Average Dependent Variable (Levels)	28.63	12.92	41.04	2.117	13.45	68.58	14.42	1.434	50.35
F	54.13	53.72	54.56	52.86	52.86	52.86	52.86	52.86	51.93

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls as well as the fixed effects from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Impact of Chinese Imports on Migration between Commuting Zones

Sample:	All	Do Not Speak English Very Well	Speak English Very Well
	(1)	(2)	(3)
Panel A			
Dependent variable:	Change in Share Migrated Out of Previous CZs		
Δ Imports from China to US/ Worker	-0.873***	-0.838***	-1.465***
	(0.317)	(0.289)	(0.477)
Test for Equality of Estimates (p Value)		0.073	
Observations	1,444	1,392	1,360
R-squared	0.598	0.575	0.416
Average Dependent Variable (Levels)	11.02	10.76	12.03
F	76.23	80.83	48.25
Panel B			
Dependent variable:	Change in Share Migrated to Current CZs		
Δ Imports from China to US/ Worker	-0.948	-1.000	-1.071
	(0.757)	(0.697)	(1.029)
Test for Equality of Estimates (p Value)		0.891	
Observations	1,432	1,376	1,344
R-squared	0.543	0.535	0.388
Average Dependent Variable (Levels)	11.07	10.82	12.11
F	65.01	69.97	40.21

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). P values of tests for equality between estimates reported in columns 2 and 3 are reported. All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 Impact of Chinese Imports on Immigrants with Different Years in the US

Dependent variable:	Change in Share Speaking English Very Well			
Sample:	Years in the US <=1	Years in the US 2-5	Years in the US 6-9	Years in the US >=10
	(1)	(2)	(3)	(4)
Δ Imports from China to US/ Worker	0.346	0.727*	1.082***	0.014
	(0.696)	(0.388)	(0.253)	(0.313)
Observations	1,098	1,066	1,020	1,396
R-squared	0.145	0.138	0.131	0.322
Average Dependent Variable (Levels)	11.94	13.02	14.84	20.79
F	26.42	30.89	47.21	82.20

Notes: Years in the US were reported in interval in 1990, the smallest imputed value is 1.5 years, these observations are included in column (1). See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Heterogeneity by Recent Migration History

Sample:	Same House	Migrated within Same State	Migrated from Different State	Migrated from Abroad
	(1)	(2)	(3)	(4)
Dependent variable:	Change in Share Speaking English Very Well			
Δ Imports from China to US/ Worker	0.193	0.147	2.646	1.435**
	(0.234)	(0.341)	(1.797)	(0.648)
Observations	1,388	1,214	926	1,048
R-squared	0.401	0.171	0.069	0.203
Average Dependent Variable (Levels)	20.36	16.58	20.84	11.15
F	95.90	55.41	18.71	27.99

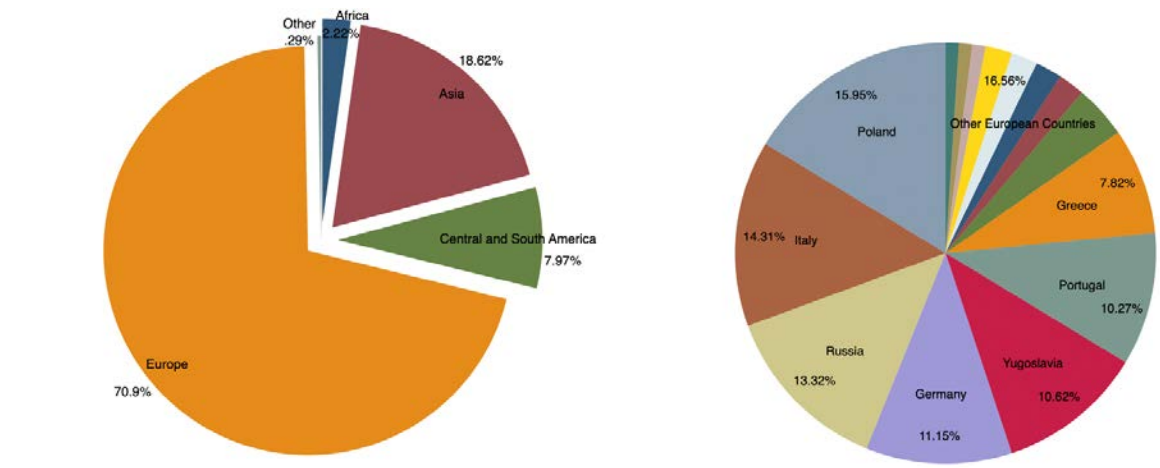
Notes: See Table 1 for description of variables. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Low Skilled Immigrants Equilibrating Labor Markets

	(1)	(2)	(3)
	Share Low-Skilled Immigrant below Mean in Base Period	Share Low-Skilled Immigrant above Mean in Base Period	Difference
Panel A:			
Dependent variable: Change in log of employed population × 100			
Dependent variable sample: Low-skilled working age natives			
Δ Imports from China to US/ Worker	-1.247**	-0.698	1.918**
	(0.552)	(1.179)	(0.834)
Observations	1,048	395	1,443
R-squared	0.285	0.778	0.563
Average Dependent Variable	980.1	1001	985.8
F	32.08	11.27	10.39
Panel B:			
Dependent variable: Change in log of weekly wage × 100			
Dependent variable sample: Low-skilled working age natives			
Δ Imports from China to US/ Worker	-0.722**	0.070	0.005
	(0.298)	(1.171)	(0.545)
Observations	1,048	395	1,443
R-squared	0.509	0.554	0.480
Average Dependent Variable	640.1	645.3	641.5
F	31.13	9.958	9.636

Notes: See Table 1 for description of variables. The IV regression includes the full vector of controls from Table 2 column (4). In panel B, we only include those who worked full-time full-year in the previous year, not in unpaid jobs. All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by start-of-period CZ share of the national immigrant population. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Figure A1: Source Countries of Non-Hispanic White Immigrants in the US



Note: The sample consists of only non-Hispanic white immigrants between the ages of 18 and 65, from non-English speaking countries, who arrived in the US after turning age 18 and who have completed at most a high school degree. All statistics are weighted using the IPUMS-provided personal weights.

Appendix A1: Immigrants by Country of Birth

Rank by N	Country	N	Share of total N	Rank by N	Country	N	Share of total N
1	Mexico	443863	43.72	32	Romania	3732	0.37
2	El Salvador	42991	4.23	33	Ukraine	3646	0.36
3	Cuba	39810	3.92	34	Lebanon	3467	0.34
4	Vietnam	38064	3.75	35	Spain	3455	0.34
5	Puerto Rico	34308	3.38	36	Israel/Palestine	3261	0.32
6	China	32490	3.20	37	Iraq	3027	0.30
7	Dominican Rep.	27507	2.71	38	Hungary	2924	0.29
8	Guatemala	25070	2.47	39	Costa Rica	2842	0.28
9	Italy	24150	2.38	40	Panama	2837	0.28
10	Korea	19630	1.93	41	France	2777	0.27
11	Colombia	19187	1.89	42	Bosnia	2761	0.27
12	Poland	17282	1.70	43	South Korea	2708	0.27
13	Haiti	16856	1.66	44	Chile	2644	0.26
14	Honduras	13384	1.32	45	Turkey	2353	0.23
15	Portugal	12974	1.28	46	Africa, ns/nec	2123	0.21
16	Ecuador	12214	1.20	47	Czechoslovakia	1873	0.18
17	Greece	10492	1.03	48	Syria	1823	0.18
18	Germany	9152	0.90	49	USSR, ns	1785	0.18
19	Laos	9021	0.89	50	Azores	1755	0.17
20	Peru	8895	0.88	51	Egypt/United Arab Rep.	1739	0.17
21	West Germany	8669	0.85	52	Venezuela	1735	0.17
22	Nicaragua	8635	0.85	53	Netherlands	1675	0.16
23	Japan	8335	0.82	54	Bolivia	1493	0.15
24	Cambodia (Kampuchea)	6704	0.66	55	Uruguay	1468	0.14
25	Yugoslavia	6640	0.65	56	Jordan	1396	0.14
26	Brazil	6638	0.65	57	Cape Verde	1278	0.13
27	Iran	5784	0.57	58	Indonesia	1270	0.13
28	Other USSR/Russia	4714	0.46	59	Afghanistan	1231	0.12
29	Taiwan	4605	0.45	60	Albania	1230	0.12
30	Argentina	4497	0.44		Subtotal, top 60 countries	992,835	97.79
31	Thailand	3966	0.39		Subtotal, other countries	22,386	2.21
					Total non-English speaking obs	1,015,221	100.00

Note: Data drawn from the 5 percent samples of the 1990 and 2000 U.S. Census as well as the 2006-2008 ACS sample Our sample includes immigrants between the ages of 18 to 65 who arrived in the US after age 18, have completed at most a high school degree, and do not speak English only. Statistics in this table are not weighted. In constructing this table, we use the detailed birthplace codes from the IPUMS, and “n.s.” denotes not specified.

Appendix Table A2: Placebo Regression, Regressing Past Changes in Language Fluency on Future Changes in Import Exposure

Dependent variable:	Change in Share Speaking English Very Well$_t$
Δ Imports from China to US/ Worker$_{t+1}$	-0.625
	(0.449)
Observations	716
R-squared	0.572
Average Dependent Variable (Levels)	37.26
F	25.74

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A3: Impact of Chinese Imports on Manufacturing Employment

Dependent variable:	Change in Share Employed in Manufacturing			
Sample:	All Skilled Sample	All Skilled Native	Low Skilled Native	Low Skilled Immigrants Non-English Countries
	(1)	(2)	(3)	(4)
Δ Imports from China to US/ Worker	-0.378***	-0.318***	-0.506***	-0.769***
	(0.064)	(0.066)	(0.093)	(0.212)
Observations	1,444	1,444	1,444	1,414
R-squared	0.512	0.537	0.523	0.324
Average Dependent Variable (Levels)	9.703	9.168	14.98	24.11
F	40.29	39.65	39.52	61.76

Notes: See Table 1 for description of variables. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A4: Heterogeneity by Gender

Dependent variable:	Change in Share Speaking English Very Well	
	(1)	(2)
Sample:	Males	Females
Δ Imports from China to US/ Worker	0.488**	0.471
	(0.199)	(0.331)
Observations	1,334	1,414
R-squared	0.162	0.293
Average Dependent Variable (Levels)	16.94	17.30
F	43	68.51

Notes: See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A5: Migration between Commuting Zones: People living in the same PUMA Treated as Non-Migrants

	(1)	(2)	(3)
Sample:	All Immigrants from non-English Countries	Do Not Speak English Very Well	Speak English Very Well
Panel A			
Dependent variable:	Change in Share Migrated Out of Previous CZs		
Δ Imports from China to US/ Worker	-0.449	-0.384	-1.238***
	(0.452)	(0.473)	(0.475)
Observations	1,444	1,392	1,360
R-squared	0.576	0.567	0.438
Average Dependent Variable (Levels)	9.793	9.638	10.43
F	76.23	80.83	48.25
Panel B			
Dependent variable:	Change in Share Migrated to Current CZs		
Δ Imports from China to US/ Worker	-0.604	-0.643	-0.851
	(0.648)	(0.574)	(0.979)
Observations	1,432	1,376	1,344
R-squared	0.577	0.577	0.430
Average Dependent Variable (Levels)	9.852	9.691	10.52
F	65.01	69.97	40.21

Notes: People living in the same PUMA has been treated as non-migrators in this table. See Table 1 for description of variables and sample. The IV regression includes the full vector of controls from Table 2 column (4). All regressions include a dummy for the 2000-2007 period. Robust standard errors are clustered at the state level. Stacked first difference models are weighted by the start-of-period CZ share of the national immigrant population. *** p<0.01, ** p<0.05, * p<0.1.