The University of Texas at Austin
Department of Economics

November 14th, 2019

Dear Search Committee,

I am writing to apply for the tenure-track position of Assistant Professor in the College of Agriculture and Life Sciences at the Texas A&M University. I am currently completing my doctoral degree in the Department of Economics at the University of Texas at Austin. I expect to receive my Ph.D. in May 2020, with my emphasis in Applied Microeconomics. My career goal is to work at an elite university where I can continue to conduct high-quality research while teaching and mentoring a diverse group of undergraduates. I am a great fit for the Assistant Professor at the Texas A&M University. I believe my research agenda dovetails well with the Department's existing strengths in empirical research and I believe my work would further the missions of the Department and University.

My research interests are labor economics, public finance, health economics and finance. My graduate research focuses on important topics of trade policy changes. In my dissertation, supervised by Professor Stephen Trejo, I analyze the role of immigrants in adjusting the US labor market which is adversely impacted by China import competition. My study shows that the labor mobility of immigrants works as a new mechanism through which the US local labor market adjusts to the China trade shocks: I have been invited to present my job market paper at 2020 American Economic Association meetings in San Diego, Immigration Paper Session. For another research, "Gender Inequality in the US Manufacturing Sector: Evidence from Chinese Import Competition", I have been invited to present my work at conferences and seminars in the US and China.

I am enclosing my job market paper, curriculum vitae, statements of teaching and research interests, teaching evaluations and contacts of my referees. Letters of recommendation will arrive under separate cover. If you require any additional materials or information, I am happy to supply it. I will be attending the AEA meeting in San Diego in January. I can be reached via e-mail at chanyu@utexas.edu or via phone at (+1) 518-428-6667. I maintain a professional website at www.chan-yu.com.

Thank you for reviewing my application, and I look forward to hearing from you soon.

Sincerely,

Chan Yu
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University of Texas at Austin
2225 Speedway
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CHAN YU

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EDUCATION

Ph.D. Candidate, Economics, University of Texas at Austin, May 2020 (Expected)
Dissertation Title: *'The Role of Immigrants in the US Labor Market and Chinese Import Competition*"
M.S., Economics, University of Texas at Austin, 2017
M.S., Economics, University of Illinois at Urbana-Champaign, May, 2015
B.S., Finance & B.E., Printing Engineering, Wuhan University, 2009-2013

REFERENCES

Stephen J. Trejo (Chair)
Department of Economics
University of Texas at Austin
512-475-8512
trejo@austin.utexas.edu

Sandra E. Black
Department of Economics and International and Public Affairs
Columbia University
212-854-3676
sblack@columbia.edu

Richard Murphy
Department of Economics
University of Texas at Austin
512-475-8525
richard.murphy@austin.utexas.edu

TEACHING AND RESEARCH FIELDS

Fields: Labor Economics, Public Finance, Health Economics, Finance
Sub-Fields: Trade and Inequality

HONORS, SCHOLARSHIPS, AND FELLOWSHIPS

October, 2019	Southern Economic Association, Graduate Student Award
Summer, 2019	University of Texas at Austin, Graduate Student Fellowship
2018–2019	Department Travel Funds
March, 2019	Travel Fund, China Economic Society
October, 2012	Italian Technology Awards for College Students, Italian Printing Association
March, 2012	National Innovative Research Awards

RESEARCH EXPERIENCE AND OTHER EMPLOYMENT

2018 – Present	University of Texas at Austin, Department of Economics, Research Assistant to Professor Vasiliki Skreta
2017 – 2018	Center for Education Research and Policy Studies, Research Associate
Winter, 2017	University of Texas at Austin, Department of Economics, Research Assistant to Professor Sandra Black
2009 – 2011	University of Illinois at Urbana-Champaign, Department of Economics

Research Assistant to Professor Stephen Parente

TEACHING EXPERIENCE

Spring, 2019	Education Economics, Department of Economics, University of Texas at Austin, Teaching Assistant for Professor Richard Murphy
Fall, 2018	Federal Tax Policy, Department of Economics, University of Texas at Austin, Teaching Assistant for Professor Dayanand Manoli
Summer, 2018	Managerial Microeconomics/Macroeconomics (MBA), McCombs Business School University of Texas at Austin, Teaching Assistant for Professor Michael Saddler
Spring, 2017	Macroeconomics Theory, Real Analysis, Department of Economics, University of Texas at Austin, Teaching Assistant for Professor Anastasia Zervou
Summer, 2017	Financial Economics, University of Texas at Austin, Teaching Assistant for Professor Patrick Van Horn
Fall, 2017	Econometrics, Department of Economics, University of Texas at Austin, Teaching Assistant for Professor Haiqing Xu
Summer, 2016	Real Analysis (Master), Department of Economics, University of Texas at Austin, Teaching Assistant for Kirk Blazek
Spring, 2016	Introduction to Microeconomics, Department of Economics, University of Texas at Austin, Teaching Assistant for Stephanie Houghton
Fall, 2016	Macroeconomics Theory, Department of Economics, University of Texas at Austin, Teaching Assistant for Tara Sinclair
Spring, 2016	Introduction to Econometrics, Department of Economics, University of Texas at Austin, Teaching Assistant for Stephen Donald
Fall, 2015	Economic Statistics, Department of Economics, University of Texas at Austin, Teaching Assistant for Valerie Bencivenga

PROFESSIONAL ACTIVITIES

Conferences:

January, 2020	American Economic Association Meetings, San Diego, Individual Paper Session (Job Market Paper)
November, 2019	Southern Economic Association, Graduate Student Session (Job Market Paper)
September, 2019	STATA Texas Microeconomics Conference, Austin, TX, Poster Session (Job Market Paper)
June, 2019	Wuhan University, Economics and Management, Econometric Society Asian Meeting (Xiamen University) "Gender Inequality in the US Manufacturing Sector: Evidence from Chinese Import Competition"
May, 2019	Midwest International Trade Conference, Indiana University, "Gender Inequality in the US Manufacturing Sector: Evidence from Chinese Import Competition"
March, 2019	China Economics Society North America Meeting, Kansas University, "Gender Inequality in the US Manufacturing Sector: Evidence from Chinese Import Competition"

WORKING PAPERS

"The Role of Immigrants in the US Labor Market and Chinese Import Competition" *(Job Market Paper)*

I propose a new mechanism through which a local labor market adjusts to Chinese import competition: the labor mobility of immigrants. I find a larger mobility response of immigrants than natives to Chinese import competition. A $1000 (around 26 percent) increase in import exposure per worker leads to a 2.6 percent decline in the immigrant population whereas a 0.5 percent insignificant decline in the native population. Additionally, I show that immigrant mobility lessens the negative effects of trade shocks on the employment and wages for immobile natives. Natives in places with more immigrants experience smaller declines in employment and wage rates compared to natives in places with fewer immigrants.

“Gender Inequality in the US Manufacturing Sector: Evidence from Chinese Import Competition”

This paper highlights the role of age in analyzing the effects of trade shocks on gender inequality. China trade shocks adversely impact workers in manufacturing, and the country's negative employment and wage effects are felt most strongly by female workers over 40 without a college education. A $1000 increase in the import exposure per worker leads to approximately 0.57 percentage point decline in manufacturing employment for low-skilled older women, but only 0.26 percentage point decline for low-skilled older men. The main cause of the rising gender inequality is the labor market attachment due to motherhood rather than employer's discrimination or gender difference in industry employment. By examining the effects of gender inequality across areas with different job tenure gaps, I find that the increasing gender inequality of Chinese import competition is entirely from areas with large job tenure gaps prior to the trade shock. This finding suggests that the gender difference in labor market experience might explain why trade shocks generate differential labor impacts for men and women in manufacturing.

“Does Farm Credit Crisis Worsen Off Infant Birth Outcome? "

In this paper, I examine the impact of the 1980s’ farm credit crisis in the Midwest on infant birth outcomes by exploiting the county-level variations in pre-period agricultural loans. By conducting a Difference-in-Differences approach, I find that counties with more pre-existing farmland loans (per acre) experienced worse infant health outcomes after the crisis exploded in 1980. A $100 dollar increase in farmland loan per acre raises the low birth weight rate by around 0.4 percentage points and reduces the birth weight by 19 grams. Moreover, counties that had purchased more farmlands prior to the shock are associated with greater reductions in farm earnings, higher delinquency rates and more bank failures. This implies that infant health outcomes are worse off when families face a tightening credit constraint.

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REFERENCES

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Please contact the surrogate Jolie (phd-econ@austin.utexas.edu) for letter requests.

Thanks

THE UNIVERSITY OF TEXAS AT AUSTIN

OFFICE OF THE REGISTRAR, MAIN BLDG. ROOM 1, AUSTIN, TX 78712-1157, (512) 475-7575

FICE CODE: 3658 IPEDS CODE: 228778 ATP CODE: 6882 ACT CODE: 4240

OFFICIAL TRANSCRIPT

NAME: YU, CHAN STUDENT ID: XXX-XX-7295 DATE: 09/11/19
DOB: 11/02/91 PAGE: 1

DEGREES AWARDED BY THE UNIVERSITY OF TEXAS AT AUSTIN:

DEGREE: MASTER OF SCIENCE IN ECONOMICS
DATE: AUGUST 14, 2017
MAJOR: ECONOMICS

ATTENDED: WUHAN UNIVERSITY FALL 2009 SPRING 2013
DEGREE AWARDED: B E SPRING 2013

ATTENDED: UNIVERSITY OF ILLINOIS URBANA CHAMPAIGN FALL 2013 SPRING 2015
DEGREE AWARDED: M S SPRING 2015

COURSEWORK UNDERTAKEN AT THE UNIVERSITY OF TEXAS AT AUSTIN

FALL SEMESTER 2015 GRADUATE SCHOOL

ECO	385D	MATH FOR ECONOMISTS	3.0	A
ECO	386C	MICROECONOMICS I	3.0	A-
ECO	387C	MACROECONOMICS I	3.0	A

HRS UNDERTAKEN 9 HRS PASSED 9 GPA HRS 9 GR PTS 35.01 GPA 3.8900

SPRING SEMESTER 2016 GRADUATE SCHOOL

FIN	395	3-ASSET PRICING THEORY	3.0	A-
ECO	386D	MICROECONOMICS II	3.0	A
ECO	387D	MACROECONOMICS II	3.0	B+

HRS UNDERTAKEN 9 HRS PASSED 9 GPA HRS 9 GR PTS 33.00 GPA 3.6666

FALL SEMESTER 2016 GRADUATE SCHOOL

FIN	395	5-CORPORATE FINANCE-PHD	3.0	B+
ECO	385K	1-INTRO TO LABOR ECONOMICS	3.0	A-
ECO	388D	ECONOMETRICS II	3.0	A

HRS UNDERTAKEN 9 HRS PASSED 9 GPA HRS 9 GR PTS 33.00 GPA 3.6666

SPRING SEMESTER 2017 GRADUATE SCHOOL

ECO	384H	PUBLIC SECTOR MICROECONOMICS	3.0	A
ECO	385K	2-TOPICS IN LABOR ECONOMICS	3.0	A
ECO	386E	HEALTH ECONOMICS	3.0	A

HRS UNDERTAKEN 9 HRS PASSED 9 GPA HRS 9 GR PTS 36.00 GPA 4.0000

SUMMER SEMESTER 2017 GRADUATE SCHOOL

ECO	F386E	SEMINAR IN ADV MICROECONOMICS	3.0	A

HRS UNDERTAKEN 3 HRS PASSED 3 GPA HRS 3 GR PTS 12.00 GPA 4.0000

FALL SEMESTER 2017 GRADUATE SCHOOL

ECO	384H	SEMINAR IN PUBLIC FINANCE	3.0	A
ECO	386E	RESEARCH SEMINAR: ADV MICRO	3.0	A
ECO	387M	WRITING SEMINAR IN ECONOMICS	3.0	A

HRS UNDERTAKEN 9 HRS PASSED 9 GPA HRS 9 GR PTS 36.00 GPA 4.0000

SPRING SEMESTER 2018 GRADUATE SCHOOL

ECO	387E	RESEARCH SEMINAR: ADV MACRO	3.0	A
ECO	387M	WRITING SEMINAR IN ECONOMICS	3.0	B
ECO	388E	RESEARCH SEMINAR: ADV METRICS	3.0	A

MORE WORK ON NEXT PAGE

Mark Simpson, University Registrar

*** ISSUED TO STUDENT ***

THE UNIVERSITY OF TEXAS AT AUSTIN

OFFICE OF THE REGISTRAR, MAIN BLDG. ROOM 1, AUSTIN, TX 78712-1157, (512) 475-7575

FICE CODE: 3658   IPEDS CODE: 228778   ATP CODE: 6882   ACT CODE: 4240

OFFICIAL TRANSCRIPT

NAME: YU, CHAN   STUDENT ID: XXX-XX-7295   DATE: 09/11/19
DOB: 11/02/91   PAGE: 2

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CONTINUE  SPRING SEMESTER 2018      GRADUATE SCHOOL
          HRS UNDERTAKEN 9    HRS PASSED 9    GPA HRS 9    GR PTS   33.00   GPA 3.6666

          SUMMER SEMESTER 2018      GRADUATE SCHOOL
               ECO F386E  RESEARCH SEMINAR: ADV MICRO                 3.0  A
          HRS UNDERTAKEN 3    HRS PASSED 3    GPA HRS 3    GR PTS   12.00   GPA 4.0000

          FALL SEMESTER 2018        GRADUATE SCHOOL
               ECO  386E  RESEARCH SEMINAR: ADV MICRO                 3.0  A
               ECO  387E  RESEARCH SEMINAR: ADV MACRO                 3.0  A
               ECO  387M  WRITING SEMINAR IN ECONOMICS                3.0  A
          HRS UNDERTAKEN 9    HRS PASSED 9    GPA HRS 9    GR PTS   36.00   GPA 4.0000

          SPRING SEMESTER 2019      GRADUATE SCHOOL
               ECO  380P  INTERNSHIP IN ECONOMICS                     3.0  CR
               ECO  387M  WRITING SEMINAR IN ECONOMICS                3.0  A
               ECO  388E  RESEARCH SEMINAR: ADV METRICS               3.0  A
          HRS UNDERTAKEN 9    HRS PASSED 9    GPA HRS 6    GR PTS   24.00   GPA 4.0000

               CUMULATIVE TOTALS EARNED AS A GRADUATE STUDENT AT U.T. AUSTIN
          HRS UNDERTAKEN 78   HRS PASSED 78   GPA HRS 75   GR PTS  290.01   GPA 3.8668

          THIS TRANSCRIPT IS BEING ISSUED PRIOR TO THE END OF THE SEMESTER.
          COURSES LISTED BELOW ARE IN PROGRESS.  ANY GRADES THAT APPEAR ARE
          NOT INCLUDED IN COMPUTATION OF THE GRADE POINT AVERAGE OR
          SCHOLASTIC STATUS.  A POUND SIGN INDICATES NO FINAL GRADE HAS
          BEEN ASSIGNED.

          FALL SEMESTER 2019        GRADUATE SCHOOL
               ECO  386E  RESEARCH SEMINAR: ADV MICRO                 3.0  #
               ECO  387M  WRITING SEMINAR IN ECONOMICS                3.0  #
               ECO  388E  RESEARCH SEMINAR: ADV METRICS               3.0  #

                         ***   E N D   O F   T R A N S C R I P T   ***

          TSI STATUS INFORMATION

          TSI AREA  TSI STATUS       EXPLANATION
          ALL       EXEMPT           DEGREE HOLDER

          TEC 51.907 UNDERGRADUATE COURSE DROP COUNTER: X
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Mark Simpson, University Registrar

*** ISSUED TO STUDENT ***

This official transcript is printed on security paper and does not require a raised seal.

THE UNIVERSITY OF TEXAS AT AUSTIN
Office of the Registrar

SEMESTERS, SESSIONS, AND TERMS: An academic year consists of consecutive fall and spring semesters and the following summer session. A semester normally is about sixteen weeks long. The summer session comprises a first term (f) and a second term (s) each six weeks in duration; work also is offered on a nine-week basis (n) and a whole-session or twelve-week basis (w). The same academic credit is given for a course whether it is taken in the long session or the summer session.

ACADEMIC CREDIT: The unit of measure for academic credit is the semester hour. Most courses meet three hours a week in the long-session semester and have a credit value of three semester hours. The same courses meet for seven and one-half hours a week in a six-week summer term and have a credit value of three semester hours. For students enrolled in graduate programs, GPA hours and hours-passed reflect only those graduate-level courses (excluding thesis, dissertation, report, and treatise) and certain in-residence upper-division undergraduate courses taken while the student was enrolled in the Graduate School. Upper-division undergraduate courses taken in the fall of 1999 through the summer session of 2008 are not included.

COURSE NUMBERING SYSTEM: Courses are designated by a three-digit number or a three-digit number with a capital letter affixed. The first digit in the course number indicates the value of the course: 001-099 indicates zero credit value; 101-199 indicates one semester hour credit; 201-299 indicates two semester hours credit; 301-399 indicates three semester hours credit; and so on. The last two digits indicate the rank of the course: 01-19 indicates lower-division rank; 20-79 indicates upper-division rank; and 80-99 indicates graduate rank.

All courses in the School of Law and some courses in the College of Pharmacy are considered professional rank.

Two courses with the same abbreviation and the same last two digits may not both be counted for credit by a student unless the two digits are followed by a capital letter. Some courses may be repeated for credit. Those courses are indicated in the University's catalogs.

PREFIXES AND SUFFIXES: The suffix letters A, B, and X, Y, Z indicate that a part of the course was given. A suffix of A or B divides the course into two parts; X, Y, or Z divides the course into three parts. In each case, the semester-hour credit given for the course is reduced accordingly.

The prefix letters f, s, n, and w indicate the terms of the summer session (see above) in which the course was offered: f indicates first term; s indicates second term; n indicates nine-week session; and w indicates whole session.

For grading systems used prior to 1979, contact the Office of the Registrar.

GRADE		GRADE PTS PER SEM HR
	1979-1980 through 2004-2005	
A	EXCELLENT	4
B	ABOVE AVERAGE	3
C	AVERAGE	2
D	PASS	1
F	FAILURE	0
I	PERMANENT INCOMPLETE (effective fall 1997)	na[1]
X	TEMPORARY DELAY OF FINAL COURSE GRADE	na[1]
CR	CREDIT	na[1]
NC	NO CREDIT	na[1]
*	COURSE IS CONTINUING	na[1]
Q	OFFICIALLY DROPPED THE COURSE	na[1]
W	OFFICIALLY WITHDREW FROM THE UNIVERSITY	na[1]
#	COURSE GRADE NOT REPORTED BY FACULTY	na[1]
S	SATISFACTORY (DEV courses only)	na[1]
U	UNSATISFACTORY (DEV courses only)	na[1]
	2005-2006 to the present	
A	EXCELLENT[3]	4.00
A-		3.67
B+		3.33
B	ABOVE AVERAGE[3]	3.00
B-		2.67
C+		2.33
C	AVERAGE[3]	2.00
C-		1.67
D+		1.33
D		1.00
D-	PASS[3]	0.67
F	FAILURE[3]	0.00
I	PERMANENT INCOMPLETE	na[1]
X	TEMPORARY DELAY OF FINAL COURSE GRADE	na[1]
CR	CREDIT	na[1]
NC	NO CREDIT	na[1]
*	COURSE IS CONTINUING	na[1]
Q	OFFICIALLY DROPPED THE COURSE	na[1]
W	OFFICIALLY WITHDREW FROM THE UNIVERSITY	na[1]
#	COURSE GRADE NOT REPORTED BY FACULTY	na[1]
S	SATISFACTORY (DEV courses only)	na[1]
U	UNSATISFACTORY (DEV courses only)	na[1]

Through the summer session of 2009, plus and minus grades are reserved for graduate, graduate business, and law students enrolled in graduate-level, non-law courses. Beginning fall of 2009, plus and minus grades are valid for all students.

A course dropped by the twelfth class day of a long-session semester (fourth class day of a summer session term) is not entered on the permanent academic record.
Prior to fall 1981, NC grades did not appear on the transcript.

SCHOOL OF LAW

Prior to 1990-1991

The School of Law employed a numeric grading system with the following alpha equivalents:

85 - 100	A
75 - 84	B
65 - 74	C
60 - 64	D
BELOW 60	F

1990-1991 - Present

Letter Grade	Grade Points Per Sem Hr.[2]
A+	4.3
A	4.0
A-	3.7
B+	3.3
B	3.0
B-	2.7
C+	2.3
C	2.0
D	1.7
F	1.3

1. na = not applicable to gpa calculation
2. Official grade point averages are not calculated for students in the School of Law.
3. Grade interpretation is applicable to undergraduate students.

NRTRP2 09/01/2009

The Role of Immigrants in the US Labor Market and Chinese Import Competition*

Chan Yu†

November 13, 2019

Most Recent Draft Here

Abstract

I propose a new mechanism through which a local labor market adjusts to China trade shocks: the labor mobility of immigrants. I find a larger mobility response of immigrants than natives to China trade shocks. A $1000 (around 26 percent) increase in import exposure per worker leads to a 2.6 percent decline in the immigrant population whereas a 0.5 percent insignificant decline in the native population. Importantly, I show that immigrant mobility lessens the negative effects of trade shocks on the employment and wages for immobile natives. Natives in places with more immigrants experience smaller declines in employment and wage rates compared to natives in places with fewer immigrants. A ten percentage point increase in the share of the immigrant population reduces the negative impact of trade shocks on native employment by around 0.2 percentage points.

Keywords: Trade, Immigrants, Geographic Mobility, Manufacturing
JEL Codes: F16, J23, J31, J71, L60, R12

*I am grateful to Steve Trejo, Sandra Black, Gerald Oettinger, Manuela Angelucci, Richard Murphy, Brendan Kline as well as seminar participants at the University of Texas at Austin for helpful comments and feedback.

†Chan Yu: Graduate Student (PhD Candidate), Department of Economics, The University of Texas at Austin, 2225 Speedway, BRB 1.116, C3100, Austin, Texas 78712. (email: chanyu@utexas.edu); Phone: 518-428-6667. This is a preliminary draft. Please do not cite or distribute without permission of the author.

1 Introduction

Conventional trade literature emphasizes that trade policy changes can increase geographic inequality of labor outcomes (Autor, 2018; Goldberg and Pavcnik, 2016). Local labor markets that are specialized in tradable sectors will be more impacted by trade shocks. Theoretically, perfect labor mobility facilitates adjustment of the local labor supply so that employment and wage effects from trade shocks can dissipate (Blanchard et al., 1992). A series of empirical studies exploring the relationship between labor mobility and trade liberalization finds negligible effects of trade shocks on labor mobility within developed countries such as the United States (Autor et al., 2013; McLaren and Hakobyan, 2012). These studies seem to confirm the declining internal migration rates in the United States since the 1980s (Molloy et al., 2011; Ottaviano and Peri, 2012). Due to a lack of geographic labor mobility, the impacts of trade shocks on the US labor market tend to be localized and last for a long period (David, 2018; Pierce and Schott, 2016; Autor et al., 2013; Topalova, 2010).

Finding a weak labor mobility effect on the overall population does not mean that there are no labor mobility responses by particular groups of workers. As the most mobile workforce, immigrants increase labor flows to the US labor market (Borjas, 2001).[1] The mobility of immigrants helps to adjust the local labor supply to trade shocks and reach equilibrium. Through immigrant mobility, regional employment and wage inequalities arising from trade shocks can be reduced. So far, there is scant empirical evidence regarding how immigrants respond to trade shocks.[2] In this paper, I provide the first evidence of how immigrants respond to Chinese import competition in the US labor market and attempt to answer two questions. First, do immigrants leave areas that are highly impacted by trade shocks? Second, does the mobility of immigrants mitigate native employment and wage outcomes that are negatively impacted by China trade shocks?

[1]Immigrants are defined as individuals who are born outside the United States. I also regard Puerto Ricans as immigrants because they are born outside the US and move frequently between the US and Puerto Rico.

[2]As far as I know, most empirical research focuses on studying the overall population mobility. See David (2018) and Greenland, Lopresti, and McHenry (2019).

Understanding the immigrant mobility response may uncover the mechanism of geographic labor mobility through which the regional divergence in employment and wages induced by trade shocks can be reduced. Also, this study is informative for the design of future immigration policy to achieve more positive labor market outcomes for natives (Clemens et al., 2018). While much of the literature studies the impact of immigration on natives, there is less clear evidence about the relationship between immigration and native outcomes when economic conditions change (Peri, 2010). During an economic downturn, local labor markets may have limited capacity to absorb the supply of immigrants. If immigrants are immobile, then the existence of immigrants will generate negative impacts on natives and thus hurt local welfare (Bonin et al., 2008). Policy intervention to restrict immigration could prevent the adverse impacts on natives. However, if immigrants play an effective role in adjusting the local labor market by moving, then policies restricting immigration might not be optimal.

To assess the role that immigrants play when trade shocks occur, I focus on China trade shocks from 1990 to 2007. The unexpected rise of China in the manufacturing sector generated enormous impacts on the US labor market during those two decades (Autor et al., 2016).[3] Following Autor, Dorn, and Hanson (2013), this paper uses the same methodology of Bartik Instrument approach at the commuting zone level as the main specification (Bartik, 1991). The main sources of variation in Chinese import competition across commuting zones are the commuting-zone industry specialization and the national import growth for each industry.[4] To address the concern that increasing import demand for Chinese imports may arise from industry-specific demand shocks that also impact local population growth (Wilson, 2016), the import growth in the US is instrumented by the import growth in other developed countries. Using a gravity model, I further show that the import growth in the

[3] From 1990 to 2007, the share of US manufacturing imports from China grew from 7% to 25% and thus China became the major trading partner with the US. Source: UN Comtrade Database.

[4] Following Autor, Dorn and Hanson (2013), this paper basically assumes zero import growth in the nonmanufacturing sector. The tradable sector is the manufacturing sector and all manufacturing industries have at least one tradable industry in this paper.

other developed countries is exogenous to the US labor market.[5]

My results for population changes reveal that immigrants are sensitive to China trade shocks by decreasing the likelihood of residing in areas with larger import exposure. Consistent with prior studies, I find weak evidence that natives' location choices are sensitive to China trade shocks. With a $1000 increase (approximately 26 percent increase in 1990-2007) in import exposure per worker, the immigrant population is significantly reduced by 2.6 percent while the native population is reduced by only 0.5 percent and also the population effect for natives is statistically insignificant.[6] I also find a larger response by the non-college-educated immigrant population possibly because low-skilled workers are concentrated in the manufacturing sector and are therefore disproportionately impacted by the trade shocks.

Previous studies have found that new immigrants are less attached to the local labor market (Borjas, 2001). Consistent with previous studies, I find that mobility response is more pronounced among relatively new immigrants who have resided in the US for fewer than ten years. A $1000 increase in the import exposure per worker reduces the population of immigrants with fewer than five years in the US by around 7.6 percent. The same increase in the import exposure reduces the population of immigrants with five to ten years in the US by 4.4 percent (with a $1000 import exposure increase). Immigrants who have spent more than ten years in the US are less responsive to trade shocks and are as immobile as natives.[7]

To illustrate what factors result in a lower migration cost for new immigrants, I further examine the changes of population by age, gender, home-ownership and marital status. Since recently arrived immigrants after 1990 are from certain source countries and possess different

[5] Following Autor, Dorn, and Hanson (2013), I construct a gravity model which limits the variation in the instrumental variable to China specific factors (growing comparative advantage and falling trading costs) between the US and China and show that the estimates are robust.

[6] Autor, Dorn and Hanson (2013) finds approximately 0.355 decline in the overall population with a $1000 increase in Chinese import exposure per worker. However, the native population effect is statistically insignificant.

[7] Using the Migration Sample from Census, I also find that the significant declining new immigrant population by the trade shocks is driven by both a decreasing in-migration rate and an increasing out-migration rate. This implies that the trade shock reduces the likelihood of new immigrants residing in areas with more import exposure.

characteristics compared to natives, it might be that new immigrants respond more than natives to trade shocks because new immigrants are younger, more likely to be single and house renters compared to established immigrants and natives. However, I find little heterogeneity in new immigrant population responses to China trade shocks across demographic groups.[8] Also, within each group, immigrant population changes remain statistically distinguishable from native population changes, implying that these observable characteristics might play weak roles in explaining why immigrants are more responsive.

I conduct a series of robustness exercises by controlling for local labor market characteristics, state linear trends, using a broad set of alternative import exposure measures. My results are all insensitive and stable. I further test whether the commuting-zone import exposure is picking up the effects of other local economic factors on local population growth by performing a pre-period analysis. I find that the pre-period population growth weakly correlates with the future import exposure. This pre-period analysis demonstrates that the import exposure is not likely contaminated by other local economic factors, which adds credibility to my identification strategy.

I then turn to the second question: does the mobility of immigrants mitigate the effects of China trade shocks on native labor outcomes? To identify the impact of the mobility of immigrants on native outcomes, I compare the native employment and wage effects of China import competition across areas with different foreign-born populations. Since areas with more immigrants would lose more of the immigrant population and therefore adjust the local labor supply to a greater extent, natives in high-immigration areas would be more insulated from China trade shocks. To test this hypothesis, I modify the model from Autor, Dorn, and Hanson (2013) and add the interaction between the import exposure and the initial foreign-born share in 1990 into the baseline model.

A potential concern is that areas with many immigrants may experience different labor market condition changes than areas with few immigrants. To eliminate this concern, I

[8] I also look at responses by immigrant groups by English-speaking fluency and citizenship. I still find no heterogeneity effects of trade shocks across groups with different language skills and citizenship statuses.

adopt a past settlement instrumental variable approach developed by Card (2009). Since new immigrants tend to locate in the same areas as earlier immigrants from the same country, one can use the geographic distribution of earlier immigrants to predict the distribution of new immigrants. The instrumental variable is obtained by interacting the earlier local immigrant composition with the national immigrant inflows from different sending countries.[9] The rationale behind this instrumental variable is that the national immigrant inflows are less correlated with the local economic condition changes.

The estimates from models that use and do not use the past-settlement instrumental variable show consistent results. Natives experience smaller declines in employment and wages from the trade shock if they reside in areas with more immigrants. A ten percentage point increase in the immigrant population share leads to an approximately 0.2 percentage points significant increase in the native employment rate. Controlling for the local commuting zone linear trend, I find that my results remain statistically significant and positive. A back-of-envelope calculation implies that immigrants reduce the impact of trade shocks on the low-skilled native employment in high-immigration areas by around 35 percent.

This paper complements previous work by Autor, Dorn, and Hanson (2013), but provides the first empirical evidence to show an immigrant mobility mechanism that the local labor market may rely on to adjust to trade shocks. Autor, Dorn and Hanson (2013) examine the entire population's mobility response to Chinese import competition but finds little evidence of such mobility. I find a significant labor mobility effect among immigrants, which is consistent with prior immigration literature emphasizing that immigrants are more sensitive to economic condition changes (Cadena and Kovak, 2016; Borjas, 2001). Greenland, Lopresti, and McHenry (2019) study a different trade policy change: the elimination of trade uncertainty due to the granting of Permanent Normal Trade Relations to China in 2001 on the internal migration rate. They find that the internal migration responds at a lag of seven or more years. However, they do not conduct separate analyses for immigrants and natives,

[9] I choose 1970 as the baseline year for immigrant composition.

who may respond differently to trade shocks. Moreover, finding less negative native employment and wage effects from China trade shocks in areas with more immigrants in this study is important and informative for future immigration policy regarding the contribution made by immigrants to local labor market.

My study also contributes to a stream of literature on immigrant mobility and economic condition changes. Finding an exogenous economic shock remains an identification challenge in this literature. Cadena and Kovak (2016) study the Great Recession and find a positive relationship between employment and immigrant population responses. They find that the immigrant population increases more in cities with higher employment growth. Here I use an exogenous trade shock resulting from China's rise in manufacturing that negatively impacts the US labor market. While Cadena and Kovak (2016) find that the established Mexican-born population is the most responsive group, my results show that the mobility effect results from new immigrants rather than established ones. The possible explanation for the difference between our results is that two studies focus on different times of immigration. I study the time period from 1990 to 2007, when the immigrant population grew sharply, while they focus on a time when immigration slowed down (Massey, 2012).

The rest of the paper proceeds as follows. In the next section, I describe the main data set and measures used in this paper. In Section 3, I discuss the baseline model and assumptions for the main identification strategy. Section 4 shows estimates for population growth, the heterogeneous effects. In Section 5, I discuss if immigrant's mobility improves native labor outcomes using the past settlement IV approach. Section 6 shows the in- and out-migration effects. Section 7 concludes.

2 Data and Measures

2.1 Data Set

I mainly use U.S. Census decennial data set for the period 1990, 2000 and pooled American Community Survey (ACS) from 2005 to 2007 to indicate the year 2007.[10] When conducting a pre-period analysis, I use the 1970 and 1980 Census. My definition of workers are individuals aged at 16-64 who worked last year and do not live in any group quarter.[11] Immigrants are those individuals born outside the United States. The immigrant sample also includes people born outside the US maindland as people from territories might behave similarly as immigrants considering the fact that people born in the territories frequently travel back and forth (Ramos, 1992). Among foreign-born population, I distinguish new immigrants who arrived in the US within the last than ten years from those who arrived more than ten years ago.

My outcomes of interests include population growth, employment and wages of natives and immigrants. In the wage sample, I only include workers who are employed and are not self-employed. I exclude workers from family owned business.[12] Hourly wage rates are obtained by the annual wage rates divided by the total annual working hours.[13]

The basic unit of analysis is at the commuting zone level. One issue with previous immigration studies using Metropolitan Statistical Area (MSA) level is that metropolitan area boundaries might change over time. However, studying the labor mobility at the commuting zone level improves the accuracy of measuring population flows as the commuting zone covers the entire United States and do not change over time. There are 722 commuting zones in my main sample. When constructing the population and labor outcomes at the commuting zone level, I convert aggregated outcomes at Census defined Public Use Micro

[10] I use the year before 2008 to avoid any confounding effects from the Great Recession.

[11] Following Autor, Dorn and Hanson, working-age population in this paper refers to workers. My estimates are robust to using 16-64 working-age population.

[12] Workers with zero wages work in family-owned business. I exclude these individuals in my sample.

[13] The total annual working hours are the product of the usually weekly hours and the number of weeks worked last year.

Area (PUMA) to the commuting zone level.[14] Some commuting zones have extremely large or small immigrant population, such as San Francisco. However, excluding these geographic outliers does not affect my estimates.

The import growth data comes from the United Nation Comtrade dataset and is available since 1991. UN Comtrade dataset provides import and export volumes (dollars) at the country-product level. The imported products are recorded using a 6-digit Harmonized System. I aggregate the product-level imports to the four-digit SIC industry level and there are 397 manufacturing industries in all. For constructing the initial industry specialization, I use the County Business Pattern dataset (CBP) in year 1980, 1990 and 2000. The CBP dataset records the number of employees at the establishment by county-industry level. I then aggregate total number of workers at the county-industry level to the commuting zone-industry level.

I use 1980, 1990, 2000 Census migration sample to separately analyze the impacts of Chinese import competition on in- and out-migration rates. In the Census migration sample, individuals' geographic locations five years ago or one year ago (in ACS) are provided at the level of Public Use Microdata Area (MIGPUMA). Therefore, it allows me to separate movers from stayers in the migration sample by looking at whether one lives in the same commuting zones. To study in-migration and out-migration changes, I convert migration rates at the MIGPUMA level to the commuting zone level.[15]

2.2 Import Exposure Measure

Ideally, to measure the import exposure at the local commuting zone level, one would like to use the commuting-zone level import growth from China. Unfortunately, information about the commuting-zone level import is usually not available. For this reason, I construct the commuting zone-level import competition following Autor, Dorn and Hanson (2013) who

[14]David Dorn provides the crosswalk on his website,https://www.ddorn.net/data.htm.

[15]MIGPUMA is slightly different than PUMA in the way that MIGPUMA only provides detailed three digits of the 5-digit PUMA code. This is not a concern when my unit of observation is at the commuting zone level as PUMAs that differ only in fourth and fifth digits are in the same commuting zone.

distribute the national-level import growth from China to the local region based on the initial industry specialization of each region.

Since China has its comparative advantage in producing labor-intensive products such as textile, apparel and leather, it causes higher amount of import exposures to the US manufacturing sectors using cheap labor. Across different manufacturing industries, the import growth varies. Also, depending on the initial industry specialization of a local labor market, areas that are highly-specialized in sectors where China has higher growth will be more impacted than other areas. Therefore, the variation of import competition is determined by two factors: the industry-specific import growth at the national level and the initial industry specialization at the commuting zone level.

The industry specialization is constructed via the share of all workers that are employed in a specific manufacturing industry. Then the commuting-zone level import competition is a given by the product of the local-level industrial specialization and the observed import growth and is shown as below:

$$\Delta IPW_{it}^{us} = \sum_j \frac{L_{ijt}}{L_{it}} \frac{\Delta Import_{jt}^{us}}{L_{jt}} \tag{1}$$

where j indexes for the industry j.[16] i is the commuting zone. L_{ijt} is the employment in the manufacturing industry j at the commuting zone i at period t. L_{jt} is the U.S. employment in the manufacturing industry j at period t. $\Delta Import_{jt}^{us}$ is further weighted by the total employment in the industry j. $\frac{L_{ijt}}{L_{it}}$ is the region i's specialization of industry j at the initial period of a decade. All employments in equation (1) uses County Business Pattern (CBP) data[17]. As one can see in Figure 1, the import exposure is concentrated in certain areas such as Atlantic, East North and East South Central regions. To account for any specific regional trends which may lead to population changes, I add twelve census

[16]All tradable sectors are within the manufacturing sector.

[17]Different than Census survey dataset, CBP provides detailed information on all employments, firm size and payroll for each establishment by county and industry level (NAICS). In the baseline model, I use CBP data. In later section, when measuring separate import exposure, I use Census survey data to construct the industry specialization because CBP data does not break employments into demographic groups.

division dummies in all regressions.

The measure in equation (1) does not consider a role for exports from the U.S. to China. International trade theory tells us the productivity growth or falling trade cost in China may affect the local labor market in the US by changing the export supply in US as well: increasing export supply from US to China will lead to wage growth in US. However, the size of import greatly exceeds the export so that the impact from export change should be not as significant as the import change. Based on some facts, the trade balance for goods and service in US has shown a deficit since the 1980s. In the robustness section, I will use alternative import exposure measures by using the net import growth.

3 Identification Strategy

One identification challenge in prior trade studies is that trade policy changes are usually endogenously determined. For instance, the export growth in Mexico and Central America is driven by the product demand change of their trading partner - US, rather than the changing conditions in those countries. Studies using tariff reduction also face a issue that the tariff imposed on specific industry by a government is correlated with the market condition in that country. China's growth has the advantage to avoid these identification issues. The dramatic growth in China in the 1990s and 2000s is driven by a series of reforms initiated by the China government and were not anticipated by the western countries.[18] Between 1990-2007, the share of US imports of manufacturing goods from China grew from 7% to 25%, which generated tremendous impacts on the US manufacturing sector.[19]

Following Autor, Dorn, and Hanson (2013), the baseline model is a two-period stacked difference model (1990-2000, 2000-2007). The dependent and main explanatory variables are

[18] Before 1978, Chinese domestic production was not adjusted by the market demand but under the control of its government, which generated a lot of inefficiency and distortion. However, a series of new reforms led by the new chairman-Deng Xiao Ping, aiming to develop "socialism with Chinese characteristics", transformed Chinese economy from highly centralized economy to market-oriented type and promoted the growth of China's productivity since then.

[19] In 1990, around 20% immigrant workers and 17% native workers are concentrated in the manufacturing sector in the US.

in change not in level to reflect changes of local labor demands when China shocks hit in.[20] The stacked difference model takes the form as below:

$$\Delta LogN_{it} = \beta \Delta IPW_{it}^{us} + X_{it} + \gamma_t + e_{it} \tag{2}$$

The main outcomes are the log native and immigrant population change of a decade. γ_t controls for decade fixed effects. X_{it} includes a set of commuting-zone variables at the initial period to control local labor market characteristics that correlate with the import exposure measure and might also affect migrations: the share of manufacturing employment, share of foreign-born population, share of population with college education, routine employment share and offshoring.

The share of manufacturing employment controls for underlying trends in the manufacturing sector (see also Section 4). Since most areas that are highly specialized in manufacturing are big cities that attract immigrants, the estimates of population changes could be biased upward if manufacturing concentration is omitted. Previous immigration studies show that immigrants are more likely to move into the same areas where earlier immigrants went (Card and Lewis, 2007; Cadena and Kovak, 2016). To account for ethnic enclaves, I control for the share of foreign-born population at the initial period (1990 and 2000) of a decade.

I also control for the skill composition of workers across local labor markets by adding the percentage of population with at least college degree. Finally, the share of employment in routine related occupations and offshorability created by Autor, Dorn, and Hanson (2013) are used to absorb the negative labor impact of automation and offshoring activities on the low-skilled workers.[21]

[20] Another reason mentioned by Autor, Dorn and Hanson (2013) is that the two period stacked difference model imposes less restrictive assumption than three period fixed effect model in level.

[21] Routine related occupations are jobs such as white collar positions whose job tasks involve routine information processing and blue collar production occupations involve repetitive motion and monitoring tasks. The offshorability index is from zero to ten which measures how likely the occupations require neither proximity to a specific work-site nor face-to-face contact with US workers.

3.1 Instrumental Variable

One concern about estimating equation (2) by OLS is that the observed import growth in the US (ΔIPW_{it}^{us}) may be correlated with unobserved productivity shocks that also affect people's moving decisions (Kearney and Wilson, 2018). For instance, the import demand for clothing from China may result from a local labor demand in the apparel sector that will increase the labor demand for low-skilled workers.[22] As a result, my estimates of population changes can be positively biased.

China's growth in manufacturing generates large impacts in both the US and other European countries.[23] Therefore, the import growth in the US is highly correlated with the import growth in the other developed countries.[24] One could use the Chinese import growth in other developed countries other than US to instrument for the observed import growth in the US from China. The way to construct the predicted import exposure measure is as below:

$$\Delta IPW_{it}^{oth} = \sum_j \frac{L_{ijt-1}}{L_{it-1}} \frac{\Delta Import_{jt}^{oth}}{L_{jt}} \tag{3}$$

where $\frac{L_{ijt-1}}{L_{it-1}}$ is the local industry specialization of workers in the manufacturing sector at the initial period of the *previous* decade t-1 (1980 and 1990). The purpose of using the previous decade's industry share is to avoid the reverse causality resulting from the impacts of China trade shocks on the employment of workers in the manufacturing industries.

For the IV approach to be valid, I need to assume that import growths in the US and other highly developed countries are only driven by internal factors in China (falling trade costs or rising comparative advantage), not by any industry-specific shocks that take place worldwide. For instance, if the computer bubble in early 2000s increases the global demands

[22] China has the most comparative advantage in apparel related products.

[23] Here the eight European countries are those countries with similar trading environment as the US. They are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. (Autor et al., 2013)

[24] The correlation between import growth in the USA and import growth in eight highly developed countries from 1990 to 2007 is around 0.93.

towards computer equipment and accessories, then the predicted import exposure measure will generate a positive bias in the estimates as the shock in the computer sector also positively impacts the US labor market. I will test the validity of the IV assumption using a gravity model which will be discussed in Section 6.1 Another threat to the identification strategy is that industry shares entering into equation (1) and (3) might correlate with local labor market characteristics, which will render the instrument variable invalid. I did two relevant analyses in Section 4 to examine whether industry shares correlate with local economic conditions by performing a pre-period analysis.

4 Results

4.1 Graphical Analysis

Before presenting the estimated results, I used a raw data set to analyze the impact of Chinese import competition on population changes. As discussed in Section 3, highly concentrated areas in manufacturing generally attract immigrants. I demonstrate this by first dividing the 722 commuting zones into ten decile groups ranked by the manufacturing concentration of employment in 1990. For each commuting zone decile group, I calculated the average native and immigrant population changes and drew the relationship between the manufacturing concentration and population changes.

As shown in the top graph in Figure 2, the immigrant population increases in commuting-zones highly concentrated in manufacturing. Further, the positive relationship in Figure 2 indicates a strong trend of the immigrant population growth with manufacturing concentration. Since areas highly-exposed to trade shocks are specialized in manufacturing, it is important to control the manufacturing concentration in order to absorb the effects of manufacturing trends on population changes. I control for the manufacturing concentration of employment in the regression and obtain the residual parts of population changes.

In addition, I find evidence showing that residual immigrant population change decreases further in highly-exposed areas. In the bottom graph of Figure 2, the X-axis shows the decile groups of commuting zones ranked by the average import exposure per worker from 1990 to 2007. The Y-axis shows changes in residual native and immigrant population after controlling for the manufacturing concentration. Therefore, I control for the initial manufacturing concentration of employment in all specifications in this paper.

4.2 Main Results

I begin the formal analysis by studying the effects of import growth from China between 1990 and 2007 on native and immigrant population changes. The dependent variables are log population changes of native and immigrant workers between 1990-2000 and 2000-2007. By estimating the 2SLS model specified in equation (1) and (2), the main results are reported in Table 2 and discussed in further detail below.

In the odd columns of Table 2, I only control for the census division, decade fixed effects and initial share of manufacturing employment. The census division dummies absorb the region-specific trends in population changes. Based on the previous graphical analysis shown in Figure 2, I add the initial share of manufacturing employment to absorb the manufacturing concentration effect on immigrant population growth. Further, I find a larger decline in the immigrant population compared to the native population. With a $1000 increase in import exposure per worker, the immigrant population decreases significantly by 2.504 percent but the native population only decreases modestly by 0.636 percent (Column (1) and column (3)). The second row of Table 2 shows the coefficients on the manufacturing concentration of employment. The positive and significant coefficients in column (3) imply strong growing trends in the immigrant population in areas that are highly concentrated in manufacturing.

In the even columns of Table 2, I further control for several other commuting-zone characteristics. The share of foreign-born population and the fraction of that population with college education in the initial period of a decade are included to account for the observable labor market characteristic differences that could independently impact native and immigrant population growth. Additionally, I add two important variables to account for the effects of automation and offshoring activities, which could occur simultaneously with the trade shocks and impact the US labor market as well. The method of measuring the routine task and offshorability index is the same as Autor, Dorn and Hanson (2013).[25] Overall, I find my main results robust to the add-ins of commuting-zone observables.[26]

After including the controls of commuting-zone characteristics, I find that a $1000 increase in import exposure per worker decreases the immigrant population by 2.643 percent but the native population only by 0.483 percent (column (2) and (4)). An alternative way to interpret the estimates is that one interquartile range of increase in import exposure per worker leads to a 5.44 percent decrease in the immigrant population ((2.49-0.43)$\times$2.643) but only a 0.99 percent decrease in the native population.[27]

I continue my analysis by looking at how the immigrant population's response to the trade shock varies with the number of years in the US. By comparing the population change of new immigrants who have spent fewer than ten years in the US with that of established immigrants who have spent more than ten years, I find that new immigrants respond more to trade shocks. Column (6) and (8) show that a $1000 increase in import exposure per worker decreases the new immigrant population by 5.30 percent. However, for established immigrants, the estimated decline is only 1.26 percent and statistically insignificant.

The remaining rows of Table 2 show the coefficients of other main controls in the same regression. The negative and significant coefficients of the foreign-born population share imply that immigrants respond more in areas with a higher number of foreign-born populations at the start of the period. An increase in the share of foreign-born population by one

[25]Following Autor, Dorn and Hanson (2013), I use the share of employment in routine task occupations as an indicator for automation. The offshorability index is a standardized measure to describe how closely an occupation requires face-to-face communication.

[26]A stricter test of the robustness is to control for the economic growth at the commuting zone level by adding 722 dummies in the main specification. The results are robust to adding the 722 dummies. However, the preciseness of estimates decreases after controlling for commuting zone trends in economic growth. However, this exercise may bring in the issue of perfect collinearity between the import exposure measure and commuting zone dummies when there are only two time periods.

[27]The import exposure at 25th and 75th percentile is 0.43 and 2.49 (kUSD).

percent decreases the immigrant population by an additional 0.841 percent. Moreover, the positive coefficient of the offshorability index implies that offshoring activities could increase the immigrant population growth, since offshoring decreases the labor demand for routine jobs but increases the demand for manual jobs where low-skilled immigrant workers are likely to be employed (Mahutga et al., 2018).

One may notice that the coefficient of routine employment share in Table 2 is significantly negative, implying a strong negative correlation between automation and population growth. Furthermore, areas more vulnerable to technology-related changes (automation) also experience greater declines in the immigrant population.[28] It is possible that areas highly-exposed to trade shocks are likely to increase their investment in technology and accelerate the automation process in the manufacturing sector. However, automation does not fully absorb the effects of trade shocks on the immigrant population because the estimates for the immigrant population slightly change once control for routine employment share.

In addition, I compare the OLS with 2SLS estimates in Table 3 to see whether the OLS estimates are positively biased by unobserved industry demand shocks. The OLS estimates are smaller in magnitude compared to the 2SLS estimates. As such, finding a weaker population effect for the OLS model suggests that positive industry demand shocks are likely to occur (see discussion in Section 3.1). If local labor markets that increase the import demand for Chinese products also attract workers to move in due to a positive industry demand shock, a positive bias will be generated in my estimates. Therefore, I will use the 2SLS model has been used as the preferred identification strategy for the rest of the analyses. Overall, both models produce consistent results and reach the same conclusion that immigrants respond more to China trade shocks compared to natives through greater

[28] Automation tends to decrease routine-jobs and increase demand for manual-jobs where unskilled immigrants are most likely to be employed (Basso et al., 2017), some high immigration cities such as Las Vegas and El Paso experience larger automation shocks than other areas. Therefore, low-skilled immigrants might still be disproportionately impacted by automation. On average, automation may generate a negative impact on low-skilled immigrants. Source:https://www.iseapublish.com/index.php/2017/05/03/future-job-automation-to-hit-hardest-in-low-wage-metropolitan-areas-like-las-vegas-orlando-and-riverside-san-bernardino/

decline in their populations in areas highly-exposed to the shock. Moreover, the effects are more pronounced among newly arrived immigrants who have spent fewer than ten years in the US.

4.3 Immigrant Mobility by Year of Immigration

Finding a larger population response among new immigrants rather than established immigrants is consistent with the hypothesis that the more recently arrived immigrants are new entrants to the US labor market. Consequently, compared to natives and established immigrants who have more local affiliations and networks within the current environment, new immigrants are less attached to the local labor market and therefore more flexible to move.

If less attachment was the main factor driving new immigrants to be more mobile than natives and established immigrants when China trade shock occurred, one may have expected to see a larger population response among immigrants with fewer years in the US. Although Table 2 compares the population change of new immigrants with that of established immigrants by dividing the entire immigrant population into two groups, the ten-year interval of immigration year measure is too broad. Hence, I examine the immigrant population response within five years following the immigration instead. Table 4 shows the results by estimating the same 2SLS model specified in equations (1) and (2). In each column, I have included the full set of controls as shown in Table 2.

Table 4 tells a striking story of a more negative relationship between Chinese import exposure and the population change for immigrants with fewer years in the US. The point estimates in columns (4) and (6) suggest that the more recent immigrants are more responsive to China trade shocks. Evidently, the population of immigrants with spent fewer than five years in the US is reduced by 7.639 percent with a \$1000 increase in import exposure per worker. In contrast, the estimated population change for immigrants who have stayed in the US between five and ten years is 4.425 percent with a \$1000 increase in import exposure per worker.[29] I further repeat the specification in Panel A of Table 4 for the population with at least some college education and the population with high school education and less and show the estimates in panels B and C.

The different immigrant responses to trade shocks by years of arrival cannot be explained by skill composition. As shown in Panel B and C, within each education group, immigrants with fewer than five years in the US are still the most responsive group. It is noticed that Chinese import competition generates a substantially larger decline in the non-college-educated immigrant population, and a smaller decline in the college-educated immigrant population. As can be seen in panels B and C of Table 4, a \$1000 increase in import exposure per worker leads to a 6.702 percent decline in the new immigrant population with no college education. However, the same amount of Chinese import exposure leads to a decline of only 1.819 percent decline in the established immigrant population with no college education. Therefore, it is reasonable to find a larger population response among low-skilled immigrants with no college education because China trade shocks hits the manufacturing sector the hardest, which has a high concentration of low-skilled immigrant workers.

Furthermore, I divide the immigrant sample on a two-year interval of the immigration year. Figure 3 shows a similar result compared to Table 4. Each point in Figure 3 shows the estimated population change to the import exposure for immigrants whose year of arrival falls under a given interval. To observe when natives and immigrants have the converging mobility responses, I draw a horizontal reference line and mark the estimated native population change by China trade shocks (0.483 percentage points).[30] The most recently arrived immigrants have the largest declines in the population. Consistent with the results in Table 4, with more years of immigration, the immigrant population change converges with its native population change.The results align with the hypothesis in Borjas's theoretical framework (Borjas, 2001): new immigrants are sensitive to changes in economic condition because they have a lower

[29] A simple test of the difference between coefficients in column (4) and column (5) finds that the difference is statistically distinguishable.

[30] The average native population change to China trade shock is estimated to be 0.483 percentage points with \$1000 increase in the import exposure. See Table 2.

migration cost than natives. New immigrants are more sensitive to trade shocks and behave as arbitrageurs in the labor market.

4.4 Heterogeneous Effects

Recent immigrants mainly come from Mexico and Central America with a lower level of education than immigrants who arrived in the US in an earlier decades. Additionally, new immigrants tend to be young, single and house-renters (Table A.1). Do these observable characteristics explain why new immigrants are more responsive than natives and established immigrants to trade shocks? This section explores the heterogeneous effects across workers from different demographic groups. I re-estimate the specification in Table 4 for the Mexican-born and other foreign-born populations, the population between 16-39 and 40-64 years of age, and the population with different home-ownership and marital status. Overall, I find little heterogeneous effects across different groups.

I first focus on whether the mobility response of immigrants was from certain sending countries by breaking immigrants into different gender-nativity groups, as seen in columns (2), (3), (5) and (6) of Table A.2, Chinese import exposure generates similar declines in the Mexican-born and other foreign-born population. Furthermore, both Mexican and other foreign-born population changes are statistically distinguishable from native population change. As such, by breaking workers by age, home-ownership and marital status, I did not find any differential impact on population changes across different groups (see Table A.3). Within each demographic group, the estimated population changes between native and immigrant workers remains statistically different. After controlling for demographic characteristics, I still see larger responses to trade shocks among immigrants compared to natives, which rules out the possibility that the observable characteristics of newly arrived immigrants can fully explain why they are more responsive to trade shocks than established immigrants.

4.5 Pre-period Analysis

Recall that one important source of variation in the Chinese import exposure measure is the commuting-zone industry specialization (Autor et al., 2013). Consequently, the validity of the Bartik instrument in my model greatly depends on the exogeneity of the local level industry specialization. If the local industry specialization correlates with other economic factors that affect population growth, then the measure of Chinese import exposure would be problematic as it captures the effects of local economic condition changes rather than the Chinese trade shock. In order to reduce this concern, I conduct a pre-period exercise to see if there was any population response before China trade shocks occurred. In order to accomplish the above, I regress the past population changes in the 1970s and 1980s on the future average import growth between 1990-2007.[31] Figures 4 and 5 compare the reduced-form population changes in the post- and pre-period.[32] The flat slope in Figure 5 shows a weak relationship between the pre-period population change and the future import exposure.

Further, Table 5 shows the results by regressing past population changes on the average import growth between 1990-2007. Although there is a positive significant change in immigrant population between 1970-1980,in the immediate decade (1980-1990) prior to China's rise, the population effect by future Chinese import competition is quite weak. In other words, the trends in population growth are almost similar across areas with different future import growth. This exercise reduces the potential concern that other factors correlating with the local industry specialization might drive immigrants to move and therefore confound the main estimates for population changes in this paper.

[31]Since China trade shock grew over time, the import exposure measure is not a time-constant variable. I take the average import exposure between 1990 to 2007 to represent the future import exposure .

[32]Since the OLS reduced form plots in Figure 4 and 5 are crowded and informative, I show a binned scatter plot to visualize the relationship between change in log populations and change in predicted import exposure in Appendix Figure A.1, using *binscatter* command in STATA.

4.6 Additional Outcomes

Prior literature on the local labor market suggests that wages of immobile workers are more vulnerable to the local labor demand (Topel, 1986). If immigrants are the only group responsive to the trade shock and have reduced the likelihood of staying in areas more exposed to the shock, do they achieve better outcomes compared to natives who are immobile? I estimate the baseline model in equation (2) by using employment to populations and log hourly wages as dependent outcomes.

Table 6 suggests that immigrants experienced larger declines in their employment to population than natives under the impact of the China's trade shock. However, the estimated employment effects for immigrants are imprecisely measured. For the wage effects, the hypothesis that natives and immigrants suffer the same wage reductions due to trade shocks cannot be rejected despite large standard errors in immigrant wages.

5 Immigrant Mobility and Native Labor Outcomes

Having established that immigrants, especially those who have spent fewer years in the US, are more sensitive to China's trade shocks, the next question is: what is the role of immigrant mobility in a local economy impacted by China trade shocks. Does the mobility of the immigrant population absorb the adverse impact of China trade shocks on natives? Prior studies suggest that immigrants and natives are imperfect substitutes, but less-educated immigrants and natives are close to perfect substitutes (Card, 2009).[33] Accordingly, when immigrants move out or choose not move into a highly-exposed labor market,[34] the local labor supply is reduced. Therefore, the mobility of immigrants facilitates the local labor market adjustment to China's import growth and may benefit the immobile natives. In this

[33]David Card (2009) uses an IV approach to show the inverse elasticity of substitution between less-educated immigrants and natives at the state level is approximately 40 and implies that less-educated immigrants are perfect substitutes to natives.

[34]Up till now, I have not separate the inflows from the outflows of immigrants. The estimated population change only tells us the net immigrant flows, in Section 6.2, I will discuss the channel of in-migration and out-migration.

section, I demonstrate how the mobility of immigrants mitigates negative labor outcomes among natives when natives face increasing import growth from China.

Ideally, in order to identify the impact of immigrant mobility induced by the trade shock on native outcomes, one needs to compare the estimated native outcomes with a counterfactual world where immigrants did not move in response to China trade shocks.[35] However, an identification issue arises when one uses the estimated immigrant mobility to the import exposure as an explanatory variable, since both outcome variables (employment and wage changes of natives) and the explanatory variable (estimated population changes of immigrants) are functions of Chinese import competition.[36] Therefore, in order to avoid the aforementioned, instead of comparing areas with different immigrant mobility response to China trade shocks, I demonstrate how native labor outcomes differ across regions with different shares of the foreign-born population. Furthermore, studying the share of foreign-born population provides a more concrete way for policymakers to regulate immigration across areas exposed to the trade shocks.

In order to estimate the smoothing effects of immigrants' mobility on native labor outcomes impacted by China trade shocks, I specify a model by adding an interaction term of the foreign-born population share in 1990 with the import exposure measure ΔIPW and show the model as shown in equation (4). If we take a closer look at how immigrants are geographically distributed in the US, shown in Figure 6, areas with larger shares of the foreign-born population do not fully overlap with areas highly-exposed to trade shocks.[37] This lack of geographical overlap allows for the identification of immigration on native outcomes that are impacted by the trade shocks.

[35] $\Delta L_{it} = \beta_1 \Delta IPW_{it} \times \Delta\widehat{\text{Immigrants}}_{it} + \beta_2 \Delta IPW_{it} + \beta_3 \Delta\widehat{\text{Immigrants}}_{it} + X_{it} + \gamma_t$. $\Delta\widehat{\text{Immigrants}}_{it}$ is the estimated immigrant mobility effect of Chinese import competition.

[36] Autor et al., (2013) finds that Chinese import competition generates a significant negative impact on the overall employment to population.This specification runs into identification issue because it is the same as using ΔIPW as an instrumental variable for immigrant population changes.

[37] On average, the correlation between the foreign-born population and the import exposure measure is -0.1.

$$\Delta L_{it} = \beta_1 \Delta IPW_{it} \times \frac{M_{i,90}}{P_{i,90}} + \beta_2 \Delta IPW_{it} + \beta_3 \frac{M_{i,90}}{P_{i,90}} + X_{it} + \gamma_t \quad (4)$$

The main outcome of interest, ΔL_{it}, is native employment to population rate and log hourly wages at the commuting zone level. The share of foreign-born population is calculated using the total number of immigrants ($M_{i,90}$) in the commuting zone i in 1990 divided by the total population ($P_{i,90}$) in the commuting zone i in 1990.

In equation (4),in addition to the main controls shown in Table 2, I add several other variables to address a potential concern when comparing native outcomes in areas with different immigrants.[38] First, I add the representation ratio of immigrants in the manufacturing sector to control for the industry segregation. Natives living in areas with large fractions of foreign-born population may work in different industries than immigrants and could be less vulnerable to China trade shocks. Second, I control for the share of immigrants and natives employed in manual occupations.[39] Due to a lack of language skill and the existence of cultural barriers, immigrants usually perform manual tasks while natives are more likely to perform non-manual tasks that are less impacted by the shocks (Autor et al., 2015). It could be the case that natives from areas with more immigrants perform non-manual tasks less impacted by China trade shocks. Furthermore, I add the share of immigrants and natives with at least some college education into the specification to control for the positive externality generated by high-skilled immigrants (Peri, 2016).[40]. Finally, I include the population size to absorb the density of economic activity that may have impacted the native labor outcomes.

[38] My results are very robust to adding or dropping these variables.

[39] Manual occupations include machine operators, transportation, construction and service.

[40] In previous specifications, I also control for the share of population with college education. However, I did not separate immigrants and natives. My results are also robust to controlling for the share of people with college education within the nativity group.

5.1 IV Approach from Immigrants' Past Settlement

According to prior studies, areas with more immigrants may experience different local labor demand changes relative to areas with fewer immigrants. If the share of foreign-born population correlates with local labor demand changes, estimates of immigration on native outcomes may pick up the effects of unobservables on native labor outcomes. Here I use a shift-share approach developed by Card (2009) to reduce the endogeneity concern about using the initial foreign-born population share in equation (4). The rationale behind this approach is that new immigrants reside in the same areas as the previous ones from the same country, so the past settlement of immigrants can thus be used to predict the observed immigrant population in the current period. The instrument is constructed by interacting the immigrant composition at the local level interacting with the national immigrant inflows from the same sending countries. Since the national immigrant inflow is weakly correlated with local economic activities, using immigrant inflow at the national level from different sending countries, the shift-share approach overcomes the identification threat that the local-level immigrant population might correlate with the local labor market condition.[41] The equation below illustrates how the instrument is constructed.

$$\frac{M_{i,90}}{P_{i,90}}^{Predict} = \sum_k \frac{M_{ik,70}}{M_{k,70}} \times \frac{M_{k,90}}{P_{i,90}} \tag{5}$$

Where $\frac{M_{i,90}}{P_{i,90}}^{Predict}$ is the past-settlement instrument. $M_{k,90}$ is the number of immigrants from the sending country k in 1990 and $P_{i,90}$ is the total population in the commuting zone i in 1990. k indexes for the sending country. $\frac{M_{ik,70}}{M_{k,70}}$ is the share of immigrants in the commuting zone i that are from country k in 1970. The reason behind choosing 1970 and not 1980 or 1990 as the base year is that Mexicans constituted a large proportion of immigrants in the 1980s and 1990s. They tend to cluster in areas with higher economic growth. Therefore, the

[41] The Mexican-born population might reside in certain areas such as California and Texas. One potential concern is that using the national-level Mexican population may still result in the endogeneity concern. However, an exercise excluding the Mexican-born population does not change my results.

foreign-born share may pick up the effects of other economic factors on native outcomes.

A 2SLS model with three instrument variables (past settlement instrument, the predicted import exposure, and an interaction term of the two), it involves three equations in the first stage, the results of which are shown in Figure 7 and Table 6.

$$\Delta IPW_{us} \times \frac{M_{i,90}}{P_{i,90}} = \Delta IPW_{it}^{oth} \times \frac{M_{i,90}}{P_{i,90}}^{Predict} + \Delta IPW_{it}^{oth} + \frac{M_{i,90}}{P_{i,90}}^{Predict} + X_{it} + \gamma_t \tag{6}$$

$$\Delta IPW_{us} = \Delta IPW_{it}^{oth} \times \frac{M_{i,90}}{P_{i,90}}^{Predict} + \Delta IPW_{it}^{oth} + \frac{M_{i,90}}{P_{i,90}}^{Predict} + X_{it} + \gamma_t \tag{7}$$

$$\frac{M_{i,90}}{P_{i,90}} = \Delta IPW_{it}^{oth} \times \frac{M_{i,90}}{P_{i,90}}^{Predict} + \Delta IPW_{it}^{oth} + \frac{M_{i,90}}{P_{i,90}}^{Predict} + X_{it} + \gamma_t \tag{8}$$

Figure 7 and Table 7 display the first stage results by estimating equation (6) and (8). All instrumental variables in the model have strong predictive power.[42] Panel A in Table 7 shows a strong correlation of the predicted interaction term with the observed interaction term between Chinese import exposure and the foreign-born population. As such, holding the import exposure to be constant, a one percent increase in the predicted foreign-born population share using the past settlement instrument will lead to a 0.782 percent increase in the observed foreign-born population share. Importantly, the statistically significant coefficients on the diagonal cells of Table 7 suggest a well-identified first stage, in the sense that the main variations in the instruments only come through the correspondingly endogenous variables.

Table 8 reports the 2SLS estimated effects of immigration on native employment and wages impacted by the trade shock via estimating equation (4). I find a strong evidence of the smoothing effect of immigration on native employment outcomes that are negatively

[42]F-statistics of first stage for the interaction term is 29.55 and 12.74 for the share of foreign-born population. The F-statistic report is generated using *estat first stage* command in STATA.

impacted by China trade shocks. The first row of Table 8 shows that the coefficients of the interaction term for native employment outcomes are all statistically positive, implying that the effects of China trade shocks on native employment are less negative in areas with more foreign-born population. With a ten percentage point increase in foreign-born population share, there is approximately 0.21 percentage point increase in low-skilled native employment (0.021×10).[43] The estimates for wage effects are much weaker, still showing that hourly wage effects of trade shocks on the low-skilled natives are less negative in areas with more immigrants.[44] A back-of-envelope calculation suggests that immigrants on average reduce the size of the impact of trade shocks on low-skilled native employment in areas with foreign-born population above the median level by around 35 percent.[45] The results not using the past-settlement IV are shown in column (5)-(8). I find my estimates are similar in models applying and not applying the past-settlement IV.[46]

One potential concern is that immigrants may cluster in areas with lower import exposure at the start of the period. If this is so, the coefficients of interaction term specified in equation (4) may be caused by nonlinear effects of the import exposure on native outcomes. I conduct a robustness exercise by adding a square term of the import exposure in the equation (4) to control for the non-linear effects of trade shocks on native outcomes. The estimates in Table 8 are stable and rule out the possibility of the non-linear effects of the trade shocks on native outcomes. According to Figure 6, areas highly-exposed to China trade shocks seem to

[43]The difference in foreign-born population share in 75th percentile and 25th percentile is around 4.03 percent. With one percentage point increase in the share of foreign-born population in 1990, I find that high-skilled native employment increases by 0.007 percentage points and the low-skilled native employment increases by 0.021 percentage points.

[44]Wage effects require more more problematic as it is estimated via a selected group of workers who are fully employed. If natives who stay are those have high potentials and less affected by immigrants, then it is difficult to observe a significant positive effect on wages.

[45]I divide the full sample into high- and low-immigration samples based on the median level of foreign-born population in 1990 which is 4.07%. Increasing the share of foreign-born population from low-immigration area to high-immigration area would reduce the impacts of trade shocks on the low-skilled native employment by 0.351 percentage points (0.021×12.34). Also, the estimated impact of trade shocks on low-skilled native employment is -0.738 percentage points in areas with no immigrants. Thus, immigrants reduce the negative effects of trade shocks on low-skilled native employment in high-immigration areas by approximately 35%.

[46]A robustness exercise by controlling for the 722 commuting zone dummies in the model shows consistent estimates. Though the magnitudes of coefficients increase compared to the ones in Table 8, it is mainly driven by the increasing standard errors. Thus, I use it only for a robustness exercise examination.

have fewer foreign-born populations. In fact, the average correlation between the change of Chinese import exposure (1990-2007) and the 1990's foreign-born population share is -0.1.[47]

Previous studies point out that native women, especially black women, have the most direct competition with immigrants because they are highly concentrated in industries with a high proportion of immigrants (Altonji and Card, 1991). Therefore, when immigrants leave the local labor markets due to Chinese import competition, low-skilled black women should benefit more. To see this, I break natives into different gender-race groups, and I control for the initial female worker employment to take out different female labor demand changes across regions. Table 9 shows the estimated native employment effects by gender-race group. Although the standard errors are large, the point estimate suggests that low-skilled black women indeed face greater employment effects of immigration compared to other group of workers (column (3)). Holding Chinese import exposure per worker to be the same, a ten percent increase in the share of foreign-born population raises low-skilled black female employment by around 0.82 percentage points, with only 0.16 percentage points for low-skilled black male employment.

6 Additional Empirical Evidence

6.1 Alternative Measures

When constructing the import competition measure, I mainly use the observed US imports from China. This section provides additional robustness analyses using a broad set of alternative measures developed by Autor, Dorn, and Hanson (2013) in import exposure that accounts for the export sector, international competition, and intermediate inputs. Overall,

[47]For instance, in a quadratic case, the increasing import exposure decreases the native employment and wage rates. However, the subsequent increase in the import exposure will reduce the negative impacts of the trade shocks on native outcomes if the relationship between native outcomes and Chinese import competition is non-linear. I provide a simple analysis of the non-linear effects of Chinese import competition on native employment and wage outcomes by adding a square term of the import exposure measure on the right hand side of equation (4). Instead of interacting the import exposure with the foreign-born share, I interact the import exposure with itself. I find my estimates in Table 8 remain statistically significant.

the estimates in Table 10 are robust to changing to other measures.

Panel A shows the baseline result which is the same as Table 4. Panels B and F substitute the main import exposure measure with alternative import exposure measures. Panel B shows the case of the Chinese import competition affecting the US manufacturing sector in the international market. The increasing Chinese trade shocks also impedes the selling of US products to other countries and indirectly impact the US labor markets. For this purpose, I add the total imports from China to other countries to account for the international competition. In Panel C, I exclude the intermediate inputs, because the decrease in their price may raise the manufacturing productivity and generate positive effects in some manufacturing sectors.

Panel D uses the net imports by subtracting the US exports from the imports. Since the export growth from the US to China could increase the employment and lead to wage growths in the manufacturing industries that rely heavily on export, one may need to consider the net effects of imports and exports. In panel E, I use a gravity-based approach developed by Autor, Dorn, and Hanson (2013) to see if there is a strong correlation between import growth across countries. The idea behind this gravity-based approach is to control for the industry fixed effects; the residual part of import growth only reflects the factors of China's falling trading costs or increasing comparative advantage. The results estimated via the gravity-based approach are consistent with the baseline results. Lastly, I consider a factor content model. Since the US is more abundant in capital than labor source, workers from sectors that are capital-intensive utilize the capital factor should be less impacted by trade liberalization as Chinese trade shocks do not decrease the demand for the capital-intensive goods (equipment). In the factor content model, I basically weigh the import exposure using the employment per dollar value of gross shipments at the national level to account for the labor factor in net imports. The results of Panel F are consistent with the baseline findings. Although the result for the low-skilled immigrant population becomes insignificant after controlling for factor content, the population decline of newly arrived immigrants remains statistically negative.

6.2 In- and Out-Migration

There are three possible channels through which the net immigrant population decreases with the increasing import competition: first, fewer immigrants enter the highly-exposed areas; second, more immigrants move out of highly-exposed areas; and third, both in- and out-migration rates of highly-exposed areas are impacted. While prior studies have found that the in-migration rate is usually more responsive to economic conditions change than the out-migration rate in the US, there is less empirical work to show that internal migration change could work through out-migration rate change (Monras, 2018). People are reluctant to move because they are strongly tied to their current locations by their houses, family members and local amenities. However, newly arrived immigrants are flexible to moving. In this section, I provide further analysis of the in-migration and out-migration rate and China import competition to discover the main channel.

I use the Census migration sample for 1980, 1990 and 2000 to construct migration rates. Since the ACS data set only reports the current residential location for the last year, I limit my analysis to 1980-2000 to avoid inconsistent estimates from different migration sample. One limitation of this analysis is that it does not account for return migration rates because Census does not keep track of movers who return to their home countries. Therefore, the in-and out- migration rates only include movers who move within the US. Following Cadena and Kovak (2016), I define the migration rate as flow of immigrants or natives across origin as well as destination locations as follows:

$$\text{In Migration}_{it} = \frac{I_{it}}{N_{it-1}} \tag{9}$$

$$\text{Out Migration}_{it} = \frac{O_{it}}{N_{it-1}} \tag{10}$$

Where I_{it} denotes the number of movers (move between $t-1$ to t) whose destination location is commuting zone i at time t, O_{it} denotes the number of movers whose origin location is commuting zone i at time $t-1$, and N_{it-1} is the total population at initial period $t-1$.

One issue of the Census migration data set is that it asked for the respondents' origin places only five years ago. However, the Census conducts a survey every ten years, which means that there is no information of commuting-zone population for 1975, 1985, and 1995. I impute the population during these years by subtracting the current population with the five-year net population flows from the migration sample.

A descriptive statistic for the in- and out-migration rate of the five year period is shown in Table A.4. Over time, there was a slight decline in both in- and out- migration rates for natives from 1980 to 2000. The in- and out- migration rates are consistent with those measured by Molloy, Smith, and Wozniak (2011). In addition, I find migration rates to be higher among new immigrants than the other group in row (3).

The relationship between population growth and in- and out-migration rates are as follows:

$$\Delta \log \mathrm{N}_{it} = \frac{N_{it} - N_{it-1}}{N_{it-1}} = \frac{I_{it}}{N_{it-1}} - \frac{O_{it}}{N_{it-1}} \tag{11}$$

where N_{it} is the total number of workers living in the commuting zone i at Census year t. The population change consists of two components: in- and out-migration rates. Subsequently, I estimate the effect of Chinese import competition on in- and out-migration rates to see which component plays a major role in the population change of immigrants.

$$log \frac{I_{it}}{N_{it-1}} = \beta_I IPW_{it} + Z_i + \gamma_t + e_{it} \tag{12}$$

$$log \frac{O_{it}}{N_{it-1}} = \beta_O IPW_{it} + Z_i + \gamma_t + e_{it} \tag{13}$$

The level-model above controls for the commuting zone fixed effects. The import exposure in 1980 and 1990 is assumed to be zero because China started to rise in the late 1980s.

The estimates of in-and out-migration rate changes are reported in Table A.4. Similarly, I find that low-skilled new immigrants are the most sensitive group to Chinese import competition with a significant decrease in in-migration and out-migration. On average, Chinese import competition decreased the in-migration rate by 4.36 percent (0.44×9.91) and increased the out-migration rate by 3.66 percent (0.44×8.32) between 1980-2000 for new immigrants.[48] Interestingly, as shown in column (3), the magnitude of the in-migration coefficient is approximately equal to the out-migration estimate for low-skilled newly arrived immigrants. This is plausible as immigrants who moved out from high exposed areas are the same group of workers who moved into less exposed areas. As such, I find similar but weaker in- and out-migration changes in established immigrants. For natives, I did not find any significant change in migration rates because natives generally do not move in response to China trade shocks. For high-skilled workers, the effect of China trade shocks on both the in-migration and the out-migration rate is weak.

7 Conclusion

Geographic labor mobility is an important channel for a country to absorb asymmetric labor demand shocks. With lower geographic mobility, it takes a longer time for the labor market to reach an equilibrium. This is because labor force mobility equilibrates local labor markets by sorting labor into the most growing regions. Prior trade studies find little evidence that geographic mobility responds to China trade shocks. In this paper, I provide the first empirical evidence to show that the mobility provided by immigrants could work as a mechanism for adjusting the local labor market when trade shocks occur.

By distinguishing immigrants from natives, I find robust evidence that immigrants are responsive to China trade shocks. The immigrant mobility is almost five times as large

[48] The average import exposure in level is 0.44 kUSD from 1980-2000.

as the native mobility in response to China trade shocks. Most of the mobility effects are concentrated among recently arrived immigrants as new immigrants have fewer local affiliations compared to natives and established immigrants. As immigrants have more years in the US and develop more local affiliations, immigrants behave more likely to natives and more reluctant to move.

The findings have important implications that go beyond the fact that immigrants are more mobile than natives in response to trade shocks. The mobility of immigrants adjusts the local labor market which lessens the adverse impacts of China trade shocks on native labor outcomes. In areas with the same level of import exposure but more immigrants, natives suffer less adverse effects from China trade shocks. This finding is informative for future immigration policy regarding to the empirical contributions of immigrants.

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Table 1: Summary Statistics

1990-2007:	Low Sample	High Sample	Full Sample
ΔImports from China	2.16	5.00	3.77
to US/worker	(1.39)	(2.84)	(2.71)
Percentage of employment	13.66	22.17	18.47
in manufacturing at t-1 (%)	(5.72)	(8.36)	(8.45)
Percentage of foreign-born	12.04	12.69	12.41
at t-1 (%)	(10.15)	(12.97)	(11.83)
Percentage of population	52.13	49.66	50.74
with college at t-1 (%)	(7.45)	(6.69)	(8.26)
Percentage of employment	31.80	32.24	32.05
in routine occupations at t-1	(2.84)	(2.43)	(2.63)
Average offshorability	0.03	0.06	0.05
index at t-1	(0.51)	(0.48)	(0.49)
ΔLog native	6.03	4.72	5.29
population (100×log pts)	(6.39)	(7.86)	(8.12)
ΔLog immigrant	41.49	40.51	40.93
population (100×log pts)	(24.86)	(31.29)	(28.66)
ΔLog new immigrant	42.56	44.39	43.60
population (100×log pts)	(43.17)	(57.37)	(51.66)
Number of commuting zones	361	361	722
Obs	722	722	1444

Notes: Data source is from Census 1990 and 2000 as well as three-year data of 2007 American Community Survey. Δimports from China to US/Worker is the main measure of Chinese import exposure, ΔIPW in equation (1). Statistics are weighted using the commuting zone share of national population at the initial period in each decade. Percentage of employment in routine occupation and offshorability index are two measures created by Autor and Dorn (2013). The full sample is split into high and low sample based on the median-level import exposure from 1990 to 2007 (3.24 kUSD). Each sample includes 722 observations (361 commuting zones × 2 periods).

Table 2: Chinese Import Exposure and Population Changes: 2SLS Estimates

Dependent variable: change in log working-age pop (100×log pts)

	Natives	Natives	Immigrants	Immigrants	New Immigrants	New Immigrants	Established Immigrants	Established Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	-0.636	-0.483	-2.504***	-2.643***	-6.034***	-5.299***	-0.583	-1.260
to US/worker	(0.631)	(0.507)	(0.853)	(1.008)	(1.512)	(1.215)	(0.799)	(1.081)
Percentage of employment	0.017	-0.095	0.790***	0.606**	1.878***	1.055***	0.266	0.389*
in manufacturing	(0.070)	(0.068)	(0.192)	(0.236)	(0.277)	(0.307)	(0.163)	(0.217)
Percentage of employment		-0.330		-0.927		-2.329**		-0.606
in routine occupations		(0.280)		(0.667)		(0.984)		(0.675)
Offshorability		2.251		24.668***		39.792***		19.060***
index		(1.683)		(5.337)		(8.220)		(5.147)
Share of foreign-born		-0.149***		-0.841***		-1.762***		-0.373**
population		(0.049)		(0.158)		(0.238)		(0.150)
Share of population		-0.127		-0.412*		-1.191***		-0.103
with college		(0.126)		(0.226)		(0.301)		(0.221)
Full Controls	No	Yes	No	Yes	No	Yes	No	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1444	1444	1444	1444	1441	1441	1444	1444

Note: N=1444 (2 periods × 722 commuting zones). The even columns show the results when fully controlling for the initial commuting zone characteristics in manufacturing concentration of employment, population share of college education, routine occupation index, offshorability and share of foreign-born population. I control for this initial share of manufacturing employment in all regressions in Table A1 to absorb the underlying manufacturing trend effect which positively bias my estimates. The positive significant coefficients of the initial manufacturing employment share suggest that there is a general trend of increasing immigrant workers in local labor markets that are concentrated in the manufacturing sector. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3: **Chinese Import Exposure and Population Changes: OLS and 2SLS Estimates**

Dependent variable: change in log working-age pop (100×log pts)

	Natives		Immigrants		New Immigrants		Established Immigrants	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.239	-0.483	-1.008**	-2.643***	-2.563***	-5.299***	-0.078	-1.260
to US/worker	(0.180)	(0.507)	(0.425)	(1.008)	(0.758)	(1.215)	(0.528)	(1.081)
Percentage of employment	-0.180*	-0.095	0.412*	0.606***	0.731**	1.055***	0.250	0.389*
in manufacturing	(0.095)	(0.068)	(0.234)	(0.236)	(0.316)	(0.307)	(0.204)	(0.217)
Full Controls	No	Yes	No	Yes	No	Yes	No	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1444	1444	1444	1444	1441	1441	1444	1444

Note: This table compares the OLS with 2SLS estimates for population changes of different worker groups to Chinese import competition. Odd columns report the OLS estimates and even columns report the 2SLS results. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4: Impact of Chinese Import Exposure on Population Changes: 2SLS Estimates

Dependent variable: change in log working-age pop (100×log pts)

	1990-2007 stacked first differences					
				Year of Immigration		
	All	Natives	Immigrants	< 5 Years	5-10 Years	>= 10 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-0.315	-0.483	-2.643***	-7.639***	-4.425***	-1.166
to US/worker	(0.546)	(0.507)	(1.008)	(1.805)	(1.419)	(1.149)
Panel B. High School and below						
ΔImports from China	-0.572	-0.978*	-3.335***	-10.657***	-4.534***	-1.640
to US/worker	(0.623)	(0.518)	(1.181)	(2.307)	(1.603)	(1.412)
Panel C.Some College and above						
ΔImports from China	-0.246	-0.358	-1.712	-4.634**	-3.574*	-0.615
to US/worker	(0.515)	(0.517)	(1.046)	(2.132)	(1.932)	(1.152)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: N=1444 (2 periods × 722 commuting zones) except that 16 and 15 commuting zones do not have any immigrants living in the US fewer than 5 years and between 5 to 10 years. Results are robust to dropping those commuting zones. Column (1) shows the results for the entire population. Column (2) and column (3) show the estimated native population and immigrant population changes. By breaking the immigrant population by the number of years living in the US, column (4) shows the estimated population change for immigrants living in the US fewer than five years prior to the survey; column (5) shows the results for immigrants living in the US more than five years but fewer than ten years. The last column shows the results for established immigrants living in the US more than ten years. All regressions include full controls of manufacturing employment share, foreign-born population share, share of population with college education, routine employment share, offshorability, census division dummies and decade fixed effects. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: **Future Chinese Import Exposure and Preperiod Population Changes, 1970-1990: 2SLS Estimates**

Dependent variable: change in log working-age pop (100×log pts)

	1970-1980			1980-1990		
	Natives	Immigrants	New Immigrants	Natives	Immigrants	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
Δ Future Imports from	0.882	2.289	-1.765	-0.349	-0.003	0.497
China to US per worker	(0.989)	(1.935)	(3.182)	(0.594)	(1.103)	(1.617)
Panel B. High School and below						
Δ Future Imports from	1.872	5.316***	-0.478	0.734	0.032	-1.496
China to US per worker	(1.170)	(1.919)	(3.394)	(0.775)	(1.415)	(2.169)
Panel C.Some College and above						
Δ Future Imports from	1.402	-0.853	-4.210	0.328	1.104	1.901
China to US per worker	(1.002)	(2.558)	(4.946)	(0.695)	(1.081)	(2.063)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	No	No	No	No	No	No
Obs	722	722	722	722	722	722

Notes: This Table shows preperiod effects using population changes in previous decades as dependent variables. The Δ Future Imports from China to US/worker equals to the average Δ imports from China between 1990-2007. Column (1)-(3) uses the population change from 1970 to 1980 as dependent variables. Column (4)-(6) uses the population change from 1980 to 1990 as dependent variables. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: Impacts of Chinese Import Exposure on Employment and Wages, 1990-2007: 2SLS Estimates

Dependent variable: change in employment to population (%pts) and log hourly wage (100×log pts)

	Employment			Hourly Wage		
	Natives	Immigrants	New Immigrants	Natives	Immigrants	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-0.249***	-0.688***	-0.710**	-0.534***	-0.785*	-0.218
to US/worker	(0.055)	(0.230)	(0.300)	(0.173)	(0.432)	(0.594)
Panel B. High School and below						
ΔImports from China	-0.390***	-1.040***	-1.233***	-0.549***	-1.127**	-0.267
to US/worker	(0.104)	(0.281)	(0.421)	(0.194)	(0.476)	(0.811)
Panel C.Some College and above						
ΔImports from China	-0.211***	-0.404*	-0.163	-0.518**	-0.443	-0.169
to US/worker	(0.050)	(0.245)	(0.310)	(0.209)	(0.491)	(0.962)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This shows the impact of Chinese import exposure on labor outcomes by estimating the equation (2). Panel A shows the estimated employment and wages effects for all workers, panel B shows the estimated effects for workers without college education and panel C shows the estimated effects for workers with college and above education. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: Chinese Import Exposure and Past Settlement-Two IVs: First Stages of 2SLS Estimates, 1990-2007

	ΔImports from China to US/worker × $Share_{90}$	ΔImports from China to US/worker × $Share_{90}$	$Share_{90}$
	(1)	(2)	(3)
Instrumented by:			
Δ Predicted imports from China	0.782***	-0.005	0.009
to US/worker × Predicted $Share_{90}$	(0.254)	(0.005)	(0.034)
ΔPredicted imports from China	0.092	0.667***	0.307
to US/worker	(1.827)	0.110)	(0.209)
Predicted $Share_{90}$	-0.274	0.013	0.592***
	(0.312)	(0.009)	(0.076)
R square	0.814	0.585	0.853
Full Controls	Yes	Yes	Yes
Obs	1444	1444	1444

Notes: This table shows the first stage results of using the past-settlement instrument variable strategy. $Share_{90}$ is the share of foreign-born population share in 1990 and Predicted $Share_{90}$ is the past settlement IV specified in equation (5). Column (1) shows the first stage by estimating equation (6); column (2) and (3) shows results by estimating equation (7) and (8). All regressions include full controls as Table 2 and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: Chinese Import Exposure, Native Outcomes and Immigrant Mobility: 2SLS Estimates 1990-2007

Dependent variable: change in employment to population (%pts) and log hourly wage (100×log pts)

	Past-Settlment IV				No-Past Settlement IV			
	Employment		Hourly Wage		Employment		Hourly Wage	
	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.007**	0.021***	-0.002	0.012	0.008***	0.017***	0.002	0.027***
to US/worker × Share_{90}	(0.003)	(0.006)	(0.016)	(0.016)	(0.002)	(0.005)	(0.011)	(0.007)
ΔImports from China	-0.314***	-0.738***	-0.499	-0.734**	-0.102***	-0.229***	-0.191*	-0.430***
to US/worker	(0.096)	(0.201)	(0.358)	(0.368)	(0.031)	(0.041)	(0.110)	(0.105)
Share_{90}	-0.026	0.011	0.089	-0.333**	-0.033**	-0.081***	-0.003	-0.191***
	(0.032)	(0.063)	(0.197)	(0.167)	(0.012)	(0.021)	(0.062)	(0.055)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past Settlement IV	Yes	Yes	Yes	Yes	No	No	No	No
Obs	1444	1444	1444	1444	1444	1444	1444	1444

Notes: Dependent variables are changes of employment to population and log hourly wages for natives. The odd columns show the estimated results for low-skilled workers who do not have any college education. The even columns show the estimated results for high-skilled workers who have at least some college education. All regressions include full controls. Column (5)-(8) show the estimates using initial share of foreign-born population not the predicted one from past settlement IV. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 9: Chinese Import Exposure, Native Outcomes and Immigrant Mobility by Gender and Race: 2SLS Estimates 1990-2007

Dependent variable: change in employment status as percentage of working-age pop (%pts)

	Low Skill				High Skill			
	White Men	White Women	Black Men	Black Women	White Men	White Women	Black Men	Black Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.061**	0.047*	0.016	0.082	0.010	0.020	0.057	0.004
to US/worker × Share_{90}	(0.025)	(0.026)	(0.037)	(0.052)	(0.026)	(0.028)	(0.037)	(0.031)
ΔImports from China	-1.342**	-1.003*	-0.872	-2.285**	-0.329	-0.479	-0.754	-0.042
to US/worker	(0.614)	(0.542)	(0.812)	(1.127)	(0.242)	(0.291)	(0.564)	(0.524)
Share_{90}	0.441*	0.381*	0.320	0.980*	-0.320	-0.284	-0.015	-0.599**
	(0.246)	(0.227)	(0.335)	(0.516)	(0.200)	(0.232)	(0.413)	(0.271)
Observations	1444	1444	1305	1239	1444	1444	1313	1251
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

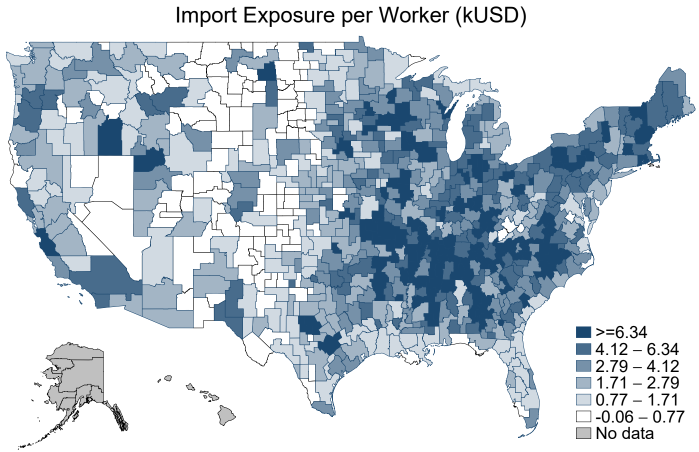
Notes: Column (1)-(4) show the estimated employment effect for low-skilled gender-race specific workers who do not have any college education. Column (5)-(8) show the estimated employment effect for high-skilled gender-race specific workers who have at least some college education. The data sample does not include other race group. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 10: Alternative Import Exposure Measures and Population Changes, 1990-2007: 2SLS Estimates

	Natives		Immigrants		New Immigrants		Established Immigrants	
	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Baseline Results:								
ΔImports from China	-0.358	-0.978**	-1.712	-3.335***	-3.657**	-6.762***	-0.698	-1.819
to US/worker	(0.518)	(0.518)	(1.046)	(1.181)	(1.379)	(1.449)	(1.107)	(1.303)
Panel B. Domestic plus international exposure:								
Δglobal imports from	-0.297	-0.717*	-1.493*	-2.935***	-2.908**	-5.406***	-0.733	-1.852*
China to US/worker	(0.440)	(0.429)	(0.876)	(0.923)	(1.162)	(1.240)	(0.954)	(1.061)
Panel C. Exposure to final goods and intermediate inputs:								
Δglobal imports from	0.034	-0.519	-1.696*	-2.100*	-2.974**	-3.959**	-1.051	-1.574
China to US/worker	(0.470)	(0.557)	(1.024)	(1.151)	(1.315)	(1.724)	(1.198)	(1.198)
Panel D. Net Chinese imports per worker:								
Δglobal imports from	-0.052	-0.517	-1.719**	-1.814*	-2.638**	-3.602**	-1.168	-1.160
China to US/worker	(0.361)	(0.467)	(0.840)	(1.047)	(1.165)	(1.528)	(0.958)	(1.045)
Panel E. Gravity residual:								
Δglobal imports from	-0.044	-0.307	-0.744*	-1.836***	-1.347**	-3.668***	-0.416	-0.770
China to US/worker	(0.170)	(0.187)	(0.420)	(0.615)	(0.635)	(1.081)	(0.513)	(0.491)
Panel F. Factor content of net Chinese imports per worker:								
Δglobal imports from	-0.086	-0.945*	-1.878**	-1.703	-4.043***	-4.773***	-0.735	-0.359
China to US/worker	(0.400)	(0.545)	(0.894)	(1.337)	(1.359)	(1.602)	(0.881)	(1.244)

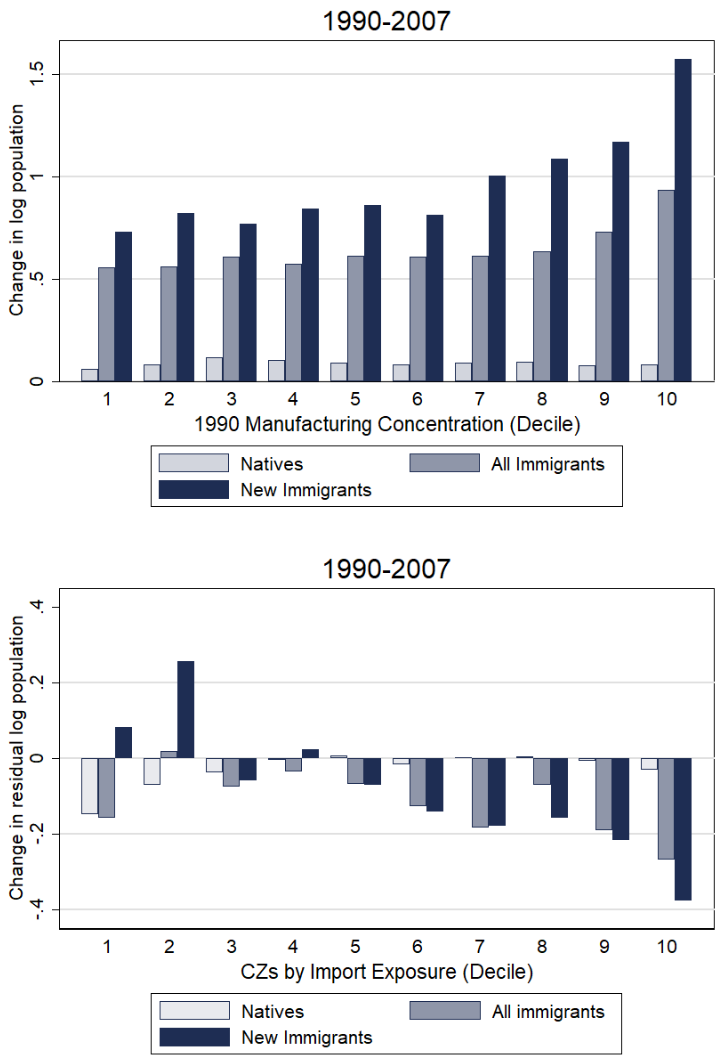
Note: Table 10 examines the robustness of results in Table 4 by using different import exposure measures following Autor, Dorn, and Hanson (2013). Panel A displays the main results in Table 4. Panel B add import growth in other countries from China to account for foreign competition in the international market. Panel C excludes import goods that are intermediate inputs when measuring the import growth. Panel D uses the net export by subtracting US exports from US imports. Panel E uses the residuals of the import exposure after controlling country and industry fixed effects based on a gravity approach method. Panel F uses a factor content weight to account for labor intensity in net imports. All regressions include all controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 1: Geographic Variation in Chinese Import Exposure, 1990-2007



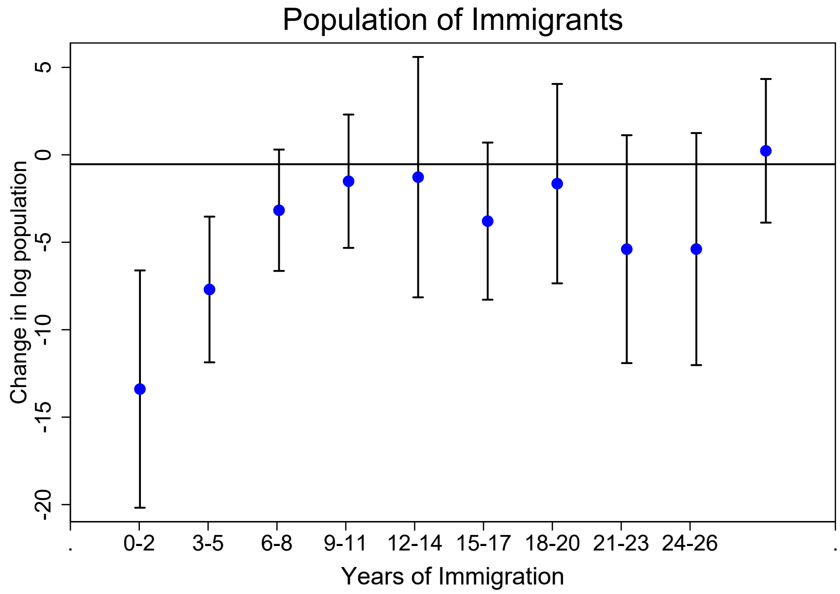
Note: N=722. The top figure shows the geographic variation in ithe Chinese mport exposure (ΔIPW, kUSD).

Figure 2: Change of log population and Manufacturing Concentration, Chinese Import Exposure, 1990-2007



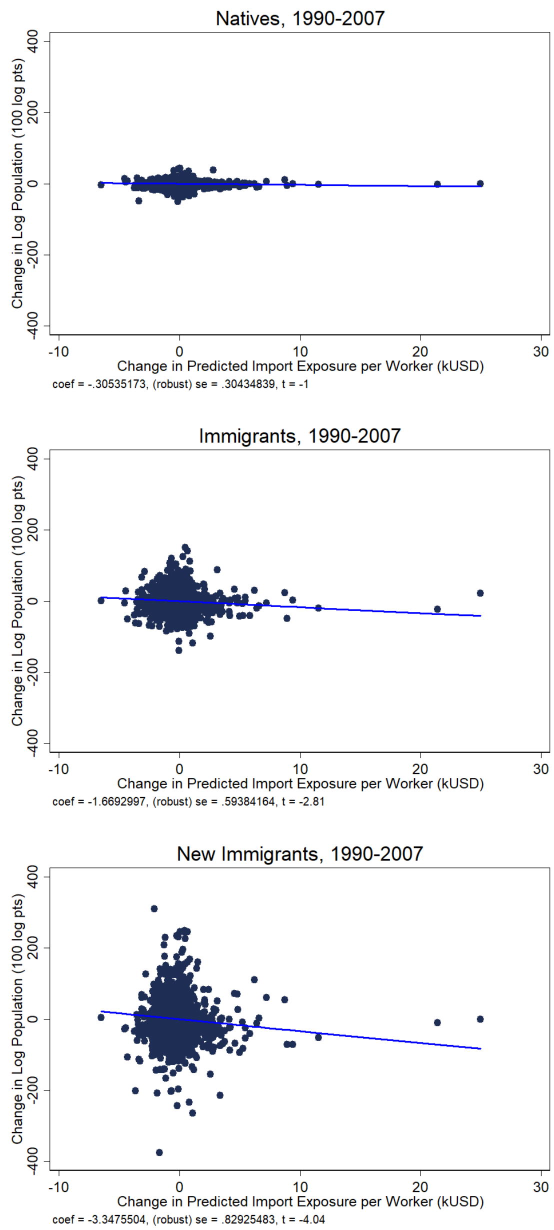
Note: N=722. The top figure shows the relationship between the manufacturing concentration in 1990 and change in log population between 1990-2007. I divide the 722 commuting zones into ten decile groups based on the 1990's manufacturing concentration. The bottom figure shows how the residual change of log population varies by import exposure per worker. The residual change of population is obtained by regressing the change of log population on the manufacturing concentration of employment at the initial period, census division and time dummies.

Figure 3: Estimated Change of Immigrant Population by Detailed Year of Immigration (100×log pts)



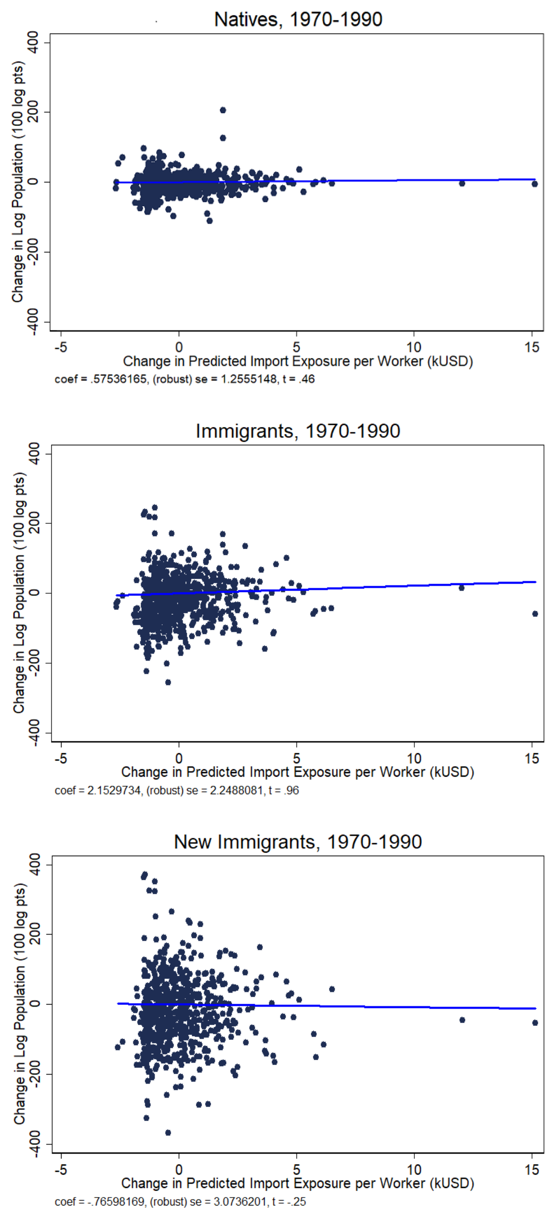
Note: N=722. The y-axis shows the estimated population changes of Chinese import competition from 1990 to 2007 by year of immigration. X-axis shows the year of immigration at a two-year interval. The reference line is the point estimate of native population change to the China import exposure which is -0.483. All regressions include full controls as ones in Table 2.

Figure 4: Reduced Form Estimates of Population Changes by Nativity Group, 1990-2007 (100×log pts)



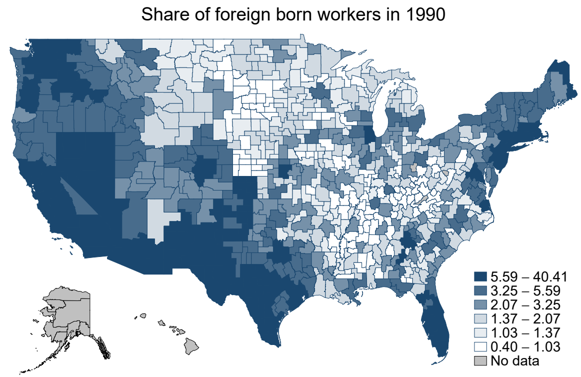
Note: N=1444. X axis shows the change in the predicted import exposure. using the average change of import exposure from 1990 to 2007. Y-axis shows the change of log population of different nativity groups. Regressions in Figure 4 add full controls of the initial commuting zone characteristics in manufacturing concentration of employment, population share of college education, routine occupation index, offshorability and share of foreign-born population as Table 2. Models are weighted using initial share of national population at the commuting zone level in each decade.

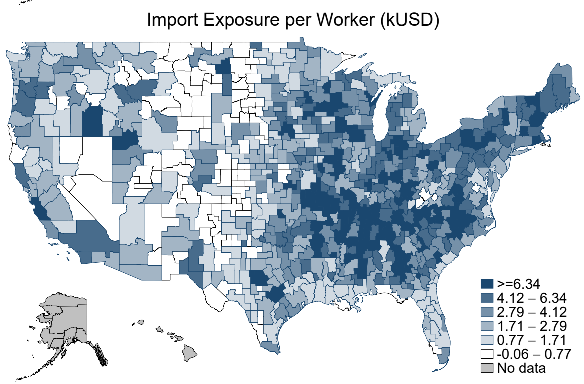
Figure 5: Preperiod Estimates of Population Changes by Nativity Group, 1970-1990 (100×log pts)



Note: N=722. This figure plots the correlation between pre-period population changes (1970-1990) and the average future import exposure. The average future import exposure is obtained by averaging Chinese import exposure from 1990 to 2007. Regressions in Figure 5 add census division dummies and decade fixed effects. Models are weighted using initial share of national population at commuting zone level in each decade.

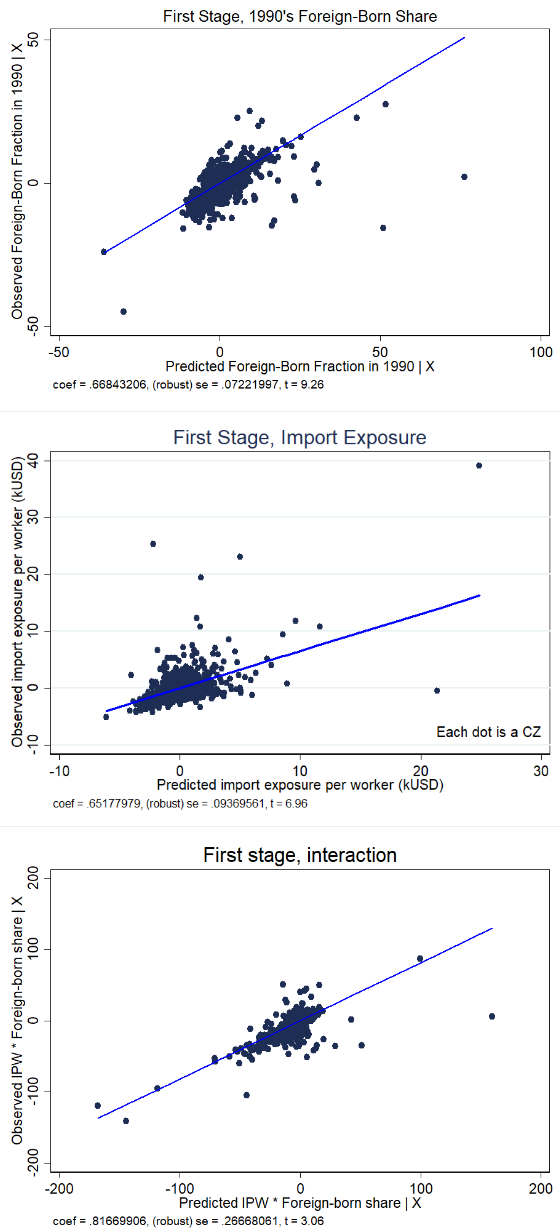
Figure 6: Geographic Variation in Foreign-Born Population (%), 1990





Note: The top figure shows the geographic variation in the foreign-born population in 1990.

Figure 7: Smoothing Effects of Immigrants, First Stages



Note: N=1444. The top figure shows the relationship between the observed foreign-born share and the predicted foreign-born using the past-settlement in equation (7). The middle figure shows the reduced form estimate of the observed import exposure, ΔIPW. The bottom figure shows the first stage result of the interaction term between ΔIPW and 1990's foreign-born share. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at commuting zone level in each decade.

Table A.1: Characteristics of Natives and Immigrants in 1990

	Natives	Immigrants	New Immigrants
Mean Values	(1)	(2)	(3)
Age	38.3	38.1	32.8
Share of Female Population	32.5 %	33.5%	30.6 %
Percentage of Singles	20.1 %	17.2%	24.8 %
Share of Homeowners	73.97 %	63.48 %	42.32 %
Obs	1,408,687	121,328	45,053

Note: This table shows the mean values of demographic characteristics for native, immigrant and new immigrant workers in 1990.

Table A.2: Population Changes of Mexican and Other-Foreign Born: 2SLS Estimates

Dependent variable: change in log working-age pop (100×log pts)

	Men			Women		
New Immigrants	All	Mexican	Other Foreign-born	All	Mexican	Other Foreign-born
	(1)	(2)	(3)	(4)	(5)	
Panel A. All						
ΔImports from China	-5.502***	-6.931***	-5.679***	-4.783***	-4.993	-3.664***
to US/worker	(1.448)	(2.633)	(1.723)	(1.202)	(4.388)	(1.304)
Observations	1426	1147	1404	1432	967	1424
Panel B. High School and below						
ΔImports from China	-6.091***	-7.918***	-8.625***	-6.505***	-4.766	-6.905***
to US/worker	(1.879)	(2.763)	(2.195)	(1.751)	(4.494)	(2.557)
Observations	1384	1118	1295	1380	929	1294
Panel C.Some College and above						
ΔImports from China	-4.026**	2.400	-2.843	-3.615**	-7.347	-2.215
to US/worker	(1.879)	(6.272)	(2.107)	(1.771)	(5.896)	(1.731)
Observations	1365	752	1340	1355	542	1341
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table explores the effects of Chinese import competition on population changes of Mexican and other foreign-born who arrive in the US fewer than ten years. All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.3: Heterogeneious Effects of Chinese Import Exposure on Population Changes across Groups: 2SLS Estimates

Dependent variable: change in log population (100×log pts)

	Age		Home-Ownership		Marriage	
	16-39	40-64	Owner	Renter	Married	Single
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Natives						
ΔImports from China	-0.550	-0.314	-0.514	-0.466	-0.475	-0.508
to US/worker	(0.711)	(0.379)	(0.616)	(0.524)	(0.416)	(0.612)
Panel B. Immigrants						
ΔImports from China	-3.151***	-1.789***	-2.146*	-3.828***	-2.209**	-4.595***
to US/worker	(1.002)	(1.106)	(1.301)	(1.214)	(1.014)	(1.354)
Panel C.New Immigrants						
ΔImports from China	-5.325***	-5.708**	-2.913***	-3.325**	-2.304**	-5.397***
to US/worker	(1.259)	(1.662)	(1.324)	(1.693)	(1.130)	(1.871)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Column (1)-(2) divides workers based on age group; column (3)-(4) show estimates of home-ownership status. Owners are workers who own a house and renters are those who rent an apartment or house. Married sample consists of individuals who have ever married (include divorced and widow). All regressions include full controls and eight census division dummies. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

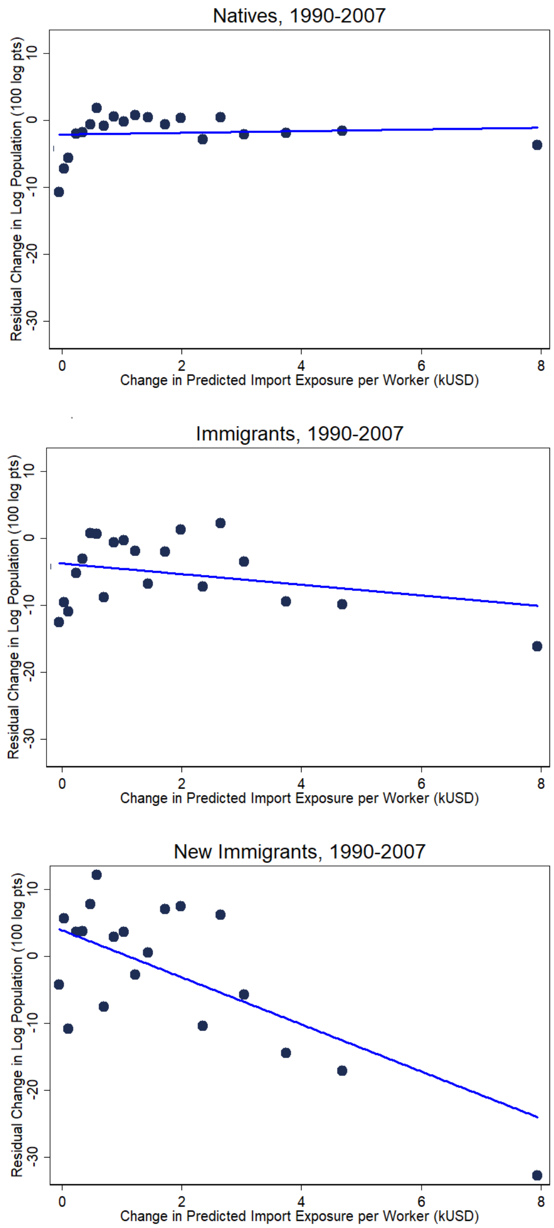
Table A.4: Chinese Import Exposure and In-Migration, Out-Migration, 1980-2000: 2SLS Estimates

Dependent variable: log Migration rates (log pts)

	Low Skill			High Skill		
	Natives	Early	New Immigrants	Natives	Early	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. In-Migration						
imports from China	0.535	-3.669	-9.909*	0.216	2.032	-0.568
China to US per worker	(1.260)	(3.147)	(5.360)	(1.126)	(2.481)	(3.636)
Panel B.Out-Migration						
imports from China	0.737	6.008**	8.321*	-1.097*	-1.632	-1.887
China to US per worker	(1.048)	(3.160)	(4.975)	(0.580)	(1.666)	(2.760)
Panel C.Net Migration						
imports from China	-0.202	-9.289**	-17.069**	1.313	-4.048	2.489
China to US per worker	(1.598)	(4.154)	(8.852)	(1.267)	(2.819)	(5.317)
State Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
the commuting zone FE	Yes	Yes	Yes	Yes	Yes	Yes

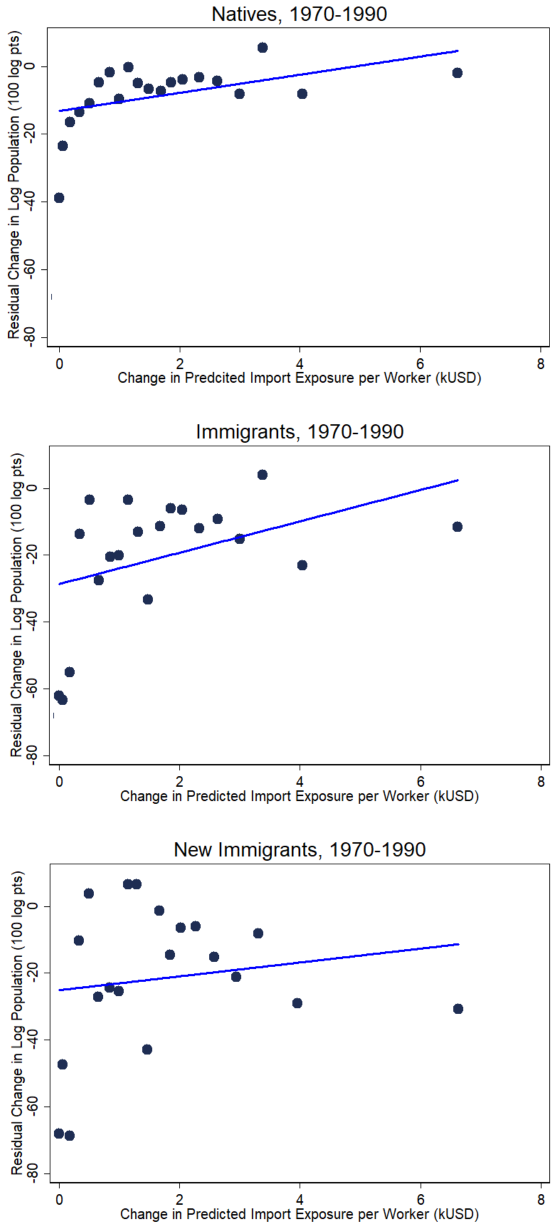
Note: N=537. This table uses the level of log in-migration, log out-migration or log net-migration as dependent variables. Migration rates are constructed from migration sample of 1980, 1990 and 2000 Census data. Estimates are obtained by regressing log migration rates on imports level from 1980-2000 (equation 12-13). Net migration rate is obtained by subtracting log out-migration rate from log in-migration rate. I control for the state linear trend, commuting zone fixed effects and census year fixed effects. I drop those commuting zones with no inflow or outflow of newly arrived immigrants. I did not include immigrants who were abroad five years ago. Models are weighted using initial share of national population at the commuting zone level in each decade. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure A.1: Binned Scatterplot: Reduced Form Estimates of Population Changes by Nativity Group, 1990-2007 (100×log pts)



Note: N=1444. This figure shows the binned scatter plot of Figure 4. X axis shows the change in the predicted import exposure that is obtained by averaging the change of import exposure from 1990 to 2007. Y-axis shows the residual changes in log population across groups that are obtained by regressing the change in log population on the full set of controls as Table 2.

Figure A.2: Binned Scatterplot: Preperiod Estimates of Population Changes by Nativity Group, 1970-1990 (100×log pts)



Note: N=722. This figure shows the binned scatter plot of Figure 5. X axis shows the change in the predicted future import exposure by averaging the import exposure from 1990 to 2007. Y-axis shows the pre-period residual changes in log population across groups that are obtained by regressing the change in log population from 1970 to 1990 on the census division dummies.