Fiscal Impact, Immigration and Productivity

Bhargavi Sakthivel

Dissertation submitted for the degree of Doctor of Philosophy in Economics at The London School of Economics and Political Science

November 2021

Declaration

I certify that this thesis is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 28,330 words.

Statement of conjoint work

I confirm that Chapter 2 was jointly co-authored with Dr Thummim Cho, LSE and Dr Yosub Jung, Harvard. I contributed to 90% of the data analysis and at least 60% of the overall paper.

Statement of inclusion of previous work

I can confirm that a preliminary version of Chapter 3 was the result of research that I conducted in the Masters in Research degree that I undertook at the London School of Economics in 2017.

Abstract

Public and political concerns over the effects of immigration on the U.S. public finances heighten during recessions. The first chapter estimates the changes to the fiscal impact of immigration over the business cycle (2006 - 2018). I focus on the extensive margin - "how much more likely are immigrants to make and receive transfers from the government", and the intensive margin - "how much do immigrants contribute to the government balances". The likelihood that an immigrant receives individual benefits decreases (pro-cyclical) relative to a native during a downturn. The difference in the net contributions between immigrants and natives is consistently positive and increases post-2012. These dynamic changes over the business cycle are due to variations in the immigrant composition since immigrants are more likely to be positively selected during recessions.

The second chapter proposes a simple way to address the endogeneity problem in tax multiplier studies. The endogeneity arises because lawmakers propose tax cuts in anticipation of a slowing economy, making it difficult to identify the causal impact of tax changes on aggregate output. Since only the legislated tax changes directly impact the economy, proposed tax changes that ultimately fail to become law can serve as a proxy for the unobserved output expectations of lawmakers. Using this proxy method and novel data on failed tax proposals, we obtain a tax multiplier of around -0.46 to -2.06 for the United States from 1975 to 2017.

The final chapter studies the extent of the productivity gains in the IT-intensive manufacturing sector between 1980 and 2009. I use the methodology of Young (2014) to estimate the elasticity of average worker efficacy and changing labour allocations (+1.4) and use that to remeasure total factor productivity growth. The revised productivity measures provide some evidence that the lack of observed productivity gains is caused by the changing labour shares.

Acknowledgements

I owe a debt of gratitude to my supervisor Dr Ethan Ilzetzki for guiding me through the journey of the PhD. Ethan's generous and patient support has greatly improved my research and his unwavering assistance especially during the pandemic was priceless. I am also grateful to Dr Thummim Cho and Dr Yosub Jung for always believing in me. I am also thankful to Professor Alwyn Young whose supervision at the beginning of my career as a researcher has been extremely valuable.

I am grateful to many other faculty members at LSE including Rachel Ngai, Alan Manning, Francesco Caselli, Wouter den Haan, Benjamin Moll, Shengxing Zhang and many others. Their supportive comments and feedback during various meetings and seminars played an important role in my PhD journey.

I would also like to thank Dr Ana Damas De Matos without whose help and generosity I could not have written Chapter 1. I am indebted to her for taking the time to discuss the data, programs and provide valuable feedback on the chapter.

Parts of the dissertation were presented at different stages at the following seminars and conferences from which I got valuable feedback: the ASSA (AEA) Annual Meeting (Atlanta, 2019), the Center For Macroeconomics (CFM) Student Seminars, the Labour Markets Workshop at the LSE and the various student-led seminars.

I would like to thank the professional services staff at the LSE, especially Mark Wilbor, Emma Taverner and Anna Watmuff, for their patient and outstanding administrative support.

A big thank you to all my MRes and PhD colleagues, who have helped me by brainstorming ideas and sharing lunches and breaks, especially to Yue Yuan, Tillman Hoenig, Nicolas Chanut, Nikita Singh and Derek Pillai.

Finally, this thesis would not have been possible without the steady and unconditional love and support provided to me by my entire family, especially my parents and my husband Dilip Nalla. I owe them everything for their unconditional trust and endless patience.

Contents

List of Figures

List of Tables

Chapter 1

1 The Fiscal Impact of Immigrants in the U.S. Business Cycle Implications and Immigration Compositions

1.1 Introduction

In recent times, the economic, social and political narrative has focused on studying whether immigrants are net contributors or a burden to public finances (OECD, 2021, Chojnicki et al., 2018, Blau et Mackie, 2017, Dustmann et al., 2014). The integration of migrants and their potential fiscal costs has gained considerable traction and become a matter of great importance to policymakers and citizens alike. According to the 2017 survey conducted by the Ipsos Institute, 56% of American adults aged 16-64, agreed with the statement that Immigration has placed too much pressure on public services in their country. Moreover, policymakers respond to public concern regarding immigration by changing immigration policies or decreasing welfare allowances for immigrants. On August 12, 2019, Ken Cuccinelli, the then acting director of the U.S. Citizenship and Immigration Services said "Give me your tired and your poor who can stand on their own two feet and who will not become a public charge" modifying an original Emma Lazarus poem that adorns the pedestal of the Statue of Liberty. This public charge rule which was enforced from February 2020 until March 2021, essentially denies Lawful Permanent Resident status to poorer immigrants who have received certain public benefits for at least 12 months, further emphasising the growing political interest in determining the fiscal impacts of immigrants.

This paper studies the fiscal impact of immigrants in the United States between 2006 and 2018. The objectives of this paper are to estimate the fiscal impact for each nativity-age-education subgroup for every year and identify how demographic compositions affect the fiscal impact over a business cycle. I do this by (a) estimating the demographic and cyclical differences in the likelihood of making and receiving transfers from the government and by (b) measuring the fiscal ratio[1] for nativity-age-education subgroups over time, to discern which subgroups are net contributors or net benefiters and how immigrants and natives with the same demographics, differ, from a fiscal standpoint. I find that the trend and cyclical changes in immigrant composition can explain the changes in the extensive and intensive margins of the fiscal impact between natives and immigrants.

This paper utilises a static accounting approach to estimate the fiscal impact of immigrants but has a dynamic component since it assesses the impact over a long horizon using homogeneous data and standard assumptions. Several papers in the recent past have utilised this static-long horizon approach since this method eliminates the need to compute the hypothetical life cycle contributions of immigrants or their descendants[2]. The most recent paper in this literature, using the static-long horizon approach is OECD (2021)[3] which focuses on comparing the fiscal impact of immigration across OECD countries.

Existing literature finds that demographic differences such as age, education, origin country, recency of arrival and second-generation, fundamentally drive the differences in fiscal impact. Blau and Mackie (2017) conduct a dynamic life cycle analysis in the U.S. from 1994-2013 and focus heavily on the generational aspects of immigration. They find that second-generational immigrants outperform natives and first-generation immigrants, a difference which is mainly driven by variation in age profiles. In contrast, this paper focuses on how changes to fundamental differences such as age and education profiles affect the fiscal impact over a business cycle. Moreover, this paper focuses on cyclical trends[4] and extends the analysis by estimating the differential probability of

[1]The fiscal ratio is defined as the share of the total government revenues (or contributions) divided by the share of the total government expenditures (or benefits).

[2]Preston (2014) provides a more comprehensive comparison between the static and dynamic approaches

[3]I contributed to the empirical analysis of this chapter for U.S. and Canada

[4]Blau and Mackie (2017) also focus on questions such as how the attribution of public goods affects the fiscal impact and study the differential effect on state vs central government. The sensitivity analysis in this paper considers the public goods and second-generation questions, however, I do not have detailed enough data to look at the different levels of government.

natives and immigrants in the U.S. for the first time.

Dustman and Frattini (2014) conduct a likelihood estimation analysis between natives and immigrants in the UK controlling for demographic characteristics and find that origin and time of arrival play an important role in estimating the fiscal impact of immigrants. Focusing on the U.S., Lee and Miller (1997) found that descendants of immigrants have a strong positive fiscal impact irrespective of their parents' fiscal impact which becomes positive only for the highly educated. Storesletten (2000) and Chojnicki et al. (2011) also use dynamic models to estimate the fiscal impact and focus on the importance of education and age respectively in reducing transfer payments.

The results of this paper match the findings of past research and contribute to the literature by (i) extending the net fiscal impact of immigrants in the U.S. beyond 2012 up to 2018, a period that hasn't previously been studied before and one that experienced a significant shift in the education levels of working-age immigrants, (ii) estimating the differential likelihood between natives and immigrants in making and receiving government transfers over a business cycle and (iii) providing a detailed breakdown of the net fiscal impact of immigrants across demographics and time by each item of the government balance, thus providing additional insights on the differential utilisation of transfers and welfare eligibility.

The main findings of this paper can be summarised as follows.

Extensive Margin: Immigrants were 11% less likely to receive individual benefits (which account for 83% of the total Social Protection benefits expenditure) such as sickness and disability, old age, survivor and unemployment benefits compared to natives but were 12% more likely to receive household benefits (which accounts for the remaining 17% of the total Social Protection benefits expenditure) such as family, children, housing or social exclusion benefits. Contrary to negative public opinion, the gap in probabilities between immigrants and natives increased during the recessionary years and followed a pro-cyclical pattern (-0.7% to 0.3%) for individual benefits. For the household benefits the differential probabilities were smaller and counter-cyclical (-0.1% to 0.3%) relative to 2006. Immigrants were also far less likely to contribute to government revenues than natives (-1.2% to 0%), although the difference in likelihood decreased post-2012. Across age-education subgroups, the sign of the likelihood remains the same although the magnitude differs. The young adult highly educated population are most likely to make contributions while the 65+ old age population are most likely to receive benefits.

Intensive Margin: In the baseline scenario, the fiscal ratio of immigrants was 7% more than natives over the 2006-2018 time period indicating their relative better fiscal position. The fiscal position of immigrants relative to natives improved considerably post-2012, reaching a high in 2016 when the fiscal ratio of immigrants became 14% greater than the natives. Working-age adults (25-65) who had at least a bachelor degree contributed nearly 1.5 to 2 times the amount of benefits they received, although their net contributions were less relative to natives with comparable socio-economic standings. On the other hand, although the aged population received the largest amount of benefits making them net benefiters, the immigrants received far fewer benefits than the comparable native making them relatively lesser burdens on the government.

Thus, regarding social protection benefits, fewer (more) immigrants receive a fewer (greater) amount of individual (household) benefits. And although fewer immigrants made fewer contributions relative to natives, the overall fiscal position of immigrants consistently remained better than the natives, even experiencing an improvement post-2012. The cyclical variations in the differential probabilities and changes to the fiscal ratio can be explained by the favourable age and educational shift in the immigrant composition post the Great Recession since different subgroups differentially utilise benefits and make contributions. The magnitude of the fiscal impact also differs depending on the origin and recency of arrival of the immigrant, although these differences are predominantly driven by demographic profiles.

Sensitivity analyses are conducted by modifying the assumptions on pure public goods, estimating the second-generation of immigrants born in the U.S. separately, including the children of immigrants as well as looking at the detailed breakdown of benefits and contributions. Having immigrants contribute towards pure public goods such as defence systems, saved the U.S native an estimated 3.23 trillion dollars in taxes during this period[5]. Most immigrants from the OECD except the low-skilled and 15-25 age group, contribute 15% more than their comparable natives. The results are similar for the second-generation whose net contributions relative to both the natives (third+ generation) and the first-generation immigrants are much larger. Regarding recency, only the highly skilled young adult population contribute more than they receive but only the aged 65+ population do better than their comparable natives.

Consistent with past research, this paper finds that immigrants have a small and negative fiscal impact (-1.5% to -0.2% of GDP) which increased in magnitude only during the years of the Great Recession and its recovery and even then, the fiscal impact was significantly smaller than the natives, even after accounting for population size. It follows, that relative to natives, immigrants have a more favourable fiscal ratio, although the magnitude depends on their socio-economic characteristics and the economic conditions at any given point in time. Given that the U.S. has consistently maintained a fiscal deficit over this period, neither natives nor immigrants have a positive fiscal impact, although on aggregate the fiscal ratio of immigrants has consistently been higher than natives, with the gap increasing considerably post-2012. While the general trend of immigrants during the 21^{st} century has witnessed an increase in age and educational levels, the Great Recession experienced a reduction in immigrant inflow among all subgroups except for the elderly high-educated immigrant population, who instead experienced an increased inflow. In the appendix, I use an augmented selection model to show that migration costs that vary with age and skill could explain this idiosyncratic deviation. This paper also focuses specifically on this sub-population, since high-skilled immigrants are net contributors who become net benefiters after retirement. In fact, I find that

[5]The baseline scenario allocates the burden of paying for pure public goods on both natives and immigrants. Also known as the average cost method, this assumes that the spending on pure public goods rises with population and the change is non-zero, so the cost of these expenditures need to be allocated to the entire population proportionally.

the increase in age profiles of immigrants relative to natives is partially responsible for the improvement of the immigrant's net fiscal position post-2012. Thus, overall this paper identifies the demographics of the immigrant population coupled with the business cycle implications as essential components of the fiscal impact of immigration in the United States.

The next section details the framework utilised to estimate the fiscal impact and the methodology. Section three introduces the data while discussing the patterns of U.S. immigration and establishing the assumptions made. Section four reports and discusses the results, section five lists the sensitivity analysis and section six concludes the paper.

1.2 Methodology

There are essentially two aspects to analysing the fiscal impact of immigration- the extensive and intensive margins.

Firstly, since most negative sentiments regarding immigrants are concerned with immigrants taking away benefits from natives, it would be useful to understand if immigrants are indeed more or less likely to utilise the welfare system compared to native-borns. The differential probability, between natives and immigrants of paying taxes and receiving benefits, can be estimated in a manner similar to Dustmann and Frattini (2014). However, since public sentiments peak during recessions, I further estimate the cyclical differences in immigrant composition and fiscal behaviour by evaluating the changes to the differential probabilities over the business cycle.

Secondly, I estimate the fiscal impact of immigration which is done by allocating every individual their estimated contributions and estimated benefits including public services rendered. This is a top-down accounting approach in which all items of expenditure and revenue of the general government (federal and state) balances are attributed to every individual in the population. Then aggregating by natives and immigrants gives us the net fiscal impact of each group. The advantage of this approach is that after attributing the items of the public budget, we can aggregate the individuals to any subgroup we want allowing for a study of natives vs immigrants by socio-economic subgroups.

This requires very rich data both at the national level and at the individual survey level, both of which are detailed in the data section below. The methodology followed in this paper which is used to attribute the national budget items to individuals is closest to the methodology used by OECD (2021). However, before the fiscal impact can be estimated, several assumptions need to be made regarding how each item in the government budget should be attributed. Further assumptions regarding who constitutes an immigrant and how to deal with items such as education or defence are important questions that will be addressed next.

It should be explicitly stated here that this paper will only look at the direct effect of immigrants on fiscal balances and does not consider the indirect implications of immigration which includes the effects on wages of natives, productivity and economic growth which have been very well documented by several illustrious studies (Card, 1990, 2001; Altonji and Card, 1991; Borjas, 2003, Manacorda et al., 2012, Ottaviano and Peri, 2012). Although generally the effects of immigrants on the native's wages have been found to be very low, the fact that there are policy changes as a result of immigration may impact natives and immigrants alike, however, this paper does not study these general equilibrium effects and only looks at the direct effect.

1.2.1 Conceptual assumptions

Defining an Immigrant An immigrant[6] is defined as any person who was born outside the borders of the country but resides in the host country for at least one year. This definition does not include individuals who are born abroad to American parents as well as individuals who move to the U.S. and obtain American citizenship later in life. This definition includes students, temporary workers and refugees or asylum

[6] In the rest of the paper, the terms immigrant and foreign-born are used interchangeably, although immigrant as defined in this section, is the intended objective.

seekers, although, despite the weighting of the sample, there are some concerns that these groups may be under-represented in the CPS.

Another essential point of contention lies in the classification of children below 15, who are born in the U.S. to foreign-born individuals. This paper's baseline results categorise them as native-borns. This is chosen to be the baseline specification since these children will grow up and become taxpayers and net contributors which will be counted towards the fiscal contributions of native-borns.

However, since there are reasons to believe that they would be in a different country if their parent(s) had not migrated, alternate specifications where the second-generation children are classified as foreign-born are explored. This is an important consideration since children are generally expensive to the country they live in due to their education and health costs, both of which are subsidised in the United States. In order to account for the grown-up U.S.-born individuals with foreign-born parent(s) since they may also be living in a different country if not for their parent(s)' migration, alternate specifications will include second-generation of all ages. This alternate specification can be considered an upper bound since the net fiscal impact of the second-generation overall is identified to be stronger than that of their parents (Blau and Mackie, 2017).

Furthermore, in line with most static accounting studies, this paper will not make any assumptions about the savings on education costs of immigrants who migrated as working adults which makes the baseline results, a lower bound on the net fiscal impact of immigrants. This is primarily due to the static nature of this accounting exercise, data restrictions and the need for assumptions regarding average costs of an adults education, which could be potentially estimated with historical data and assumptions about future immigration patterns.

Public goods Expenditure on public goods is a large share of the government's expenditures (with a slight decrease from 45% in 2006 to 40% in 2018) because of which determining how to attribute these expenditures between natives and immigrants is of huge importance.

Public goods can be divided into two categories - pure and congestible public goods. Congestible public goods are publicly provided goods whose availability and quality are affected by an increase in population since the higher population will result in higher costs of provision. i.e. they are rival in consumption. This includes public infrastructure, administration and services such as police stations, water, public transport etc. Most studies assume that the costs of these goods are directly proportional to the adult population and thus attribute them equally across the entire adult population. While the ideal scenario would be to measure the marginal cost of providing these services to a new immigrant and attribute it to them, measuring the marginal cost is not something that can be easily done. So, the common economic assumption here is that the average cost of providing public goods and services is equal to the marginal cost. Then, the government's expenditure on congestible public goods is attributed per capita irrespective of the country of birth of the individual.

Pure public goods are typically defined as public goods that are not rival in consumption. The marginal costs of spending on pure public goods are assumed to be zero and do not change with the population. On the one hand, the inflow of immigrants should not change the government's expenditure on pure public goods such as defence services or interest on public debt, which causes many studies to apportion pure public goods to the native-born only (Rowthorn, 2014; 2008). Nevertheless, others argue that defence spending tends to grow proportionally with GDP and since the entire population benefit from the internal and external security provided by such expenditure, it is sensible to attribute it to the entire population in a welfare type approach. The baseline results assume this welfare type approach wherein both pure and congestible public goods are attributed per capita to both natives and immigrants who are 15 years or older. However, an alternate specification does consider the marginal cost scenario where pure public goods are attributed to only native adults.

The baseline scenario wherein all public goods are attributed per capita to both natives and immigrants once again acts as a lower bound to the immigrant's fiscal impact since attributing it completely to natives will only increase the net contribution of immigrants. Given the size of the government's expenditure on public goods in the United States, having immigrant's share the costs of these spendings provides the natives with substantial savings every year.

While there may be other subcategories of the public good expenditures which are specifically targeted at a sub-population such as immigrant integration programs, community development projects or language training, inability to identify either the expenditure on each of these programs or lack of data on specifications of the participants makes it difficult to attribute the expenditure accurately. Instead, all public goods expenditure will be attributed equally to the adult population.

In a similar vein, the government's revenue from sales, grants and others are also attributed per capita over the entire adult population including immigrants. The government's revenue from capital taxes (inheritance taxes) is attributed per capita to all natives and immigrants aged 70 and above.

1.2.2 Estimations

Probability of utilising benefits and making contributions The first estimation deals with identifying whether immigrants are more likely than natives to receive benefits or make contributions and whether this differential probability between immigrants and natives changes over the business cycle. The business cycle aspect of this analysis provides a deeper understanding of whether immigrants are more dependent than natives during a recession or not. Further, by studying sub-groups with similar socio-economic characteristics, a more realistic comparison can be drawn between natives and immigrants.

An individual is considered as having received individual benefits if they report receiving either of the following benefits- sickness and disability benefits, old age benefits and survivor benefits or unemployment benefits in the CPS[7]. Household

[7]Old age benefits include social security, supplemental security and veteran payments in addition to pension. All benefits are defined in Appendix section 1.6.3.

benefits are benefits that are generally provided to a household. So any adult (15 years or older) that was part of a household that received family and children benefits, social exclusion benefits, housing rent subsidies or lived in public housing was considered to receive household benefits. Thus the unit of analysis is always an individual even when discussing household benefits. An individual is considered to be receiving overall benefits if the individual receives either an individual benefit or a household benefit. An individual is considered to make contributions if they reported paying any type of direct taxes or making social security contributions. Thus four main indicator variables are constructed which identify the adults who receive (1) individual benefits, (2) household benefits, (3) overall benefits and (4) makes contributions. In later analysis, we also construct indicators for each type of benefit and contribution to understand what is driving the changes.

Suppose the binary indicator variable is given by y_{it}, then there exists a random variable $y{*}_{it}$ such that the probability that $y_{it} = 1$ is equal to the probability that $y{*}_{it} > 0$. Then, a simple probability model can be implemented:

$$y{*}_{it} = \alpha + \beta D_{it} + X_{it}\gamma + \delta T_t + \epsilon \tag{1}$$

where the dependent variable y_{it} corresponds to the per capita benefits or contributions, D_i is the dummy variable that identifies nativity, T_t corresponds to year dummies and X_{it} corresponds to gender dummies, education dummies, age group dummies and interaction terms of nativity and year and interaction terms of age and education. Assuming $\epsilon \sim N(0,1)$ implies that the above is a probit model.

The object of interest is the difference in probability between a native and immigrant which is given by the marginal effects $\partial Pr(y_{it} = 1|T_t, X_{it})/\partial D_{it}$. This differential probability is estimated at the mean value of time dummy T_t and the mean value of the characteristics X_{it} of the natives and reported in section 1.4.1. By conditioning on time, the aggregate changes in welfare laws or automatic stabilisation due to economic conditions are accounted for. Further, by conditioning on socio-economic characteristics, the differences in probability between the two groups become more factual than counter-factual.

To study the effect over time, the marginal effects $\partial Pr(y_{it} = 1|X_{it})/\partial T_t$ (difference in probability between T_t and 2006) is estimated for natives and immigrants, treating each as a separate sample. Once again, conditioning on a variety of socio-economic characteristics such as gender, age and education allows for a more accurate comparison between the two groups.

Estimating the fiscal impact Each item in the general government's revenue and expenditures is apportioned to every individual based on a variety of assumptions which are explicitly stated in section 1.6.3. Information regarding all possible benefits and contributions that were reported by individuals in the micro surveys is used to match the items of expenditures and revenues in the national accounts data, where possible. A methodology very similar to that employed by OECD (2021) is employed to apportion these items to each individual. For some items such as Health, the National Health expenditure is apportioned as per the age and gender specific data from the U.S. Centers for Medicare & Medicaid Services (CMS). Similarly, each level of education is apportioned based on the age of the individual and using survey responses of adults who report being in school or college. Household disposable incomes, constructed from reported income and reported transfers and taxes, are used to identify levels of indirect taxes by assuming that a household's consumption basket is directly proportional to their disposable incomes.

The final unit of apportioning is at the individual level so all reported survey measures are annualised, individualised and appropriately corrected such that the total sum of each item across the population adds up to the total expenditure/revenue in the general government accounts. The broadest level of comparison is done between natives and immigrants. The total expenditure/revenue attributed to each individual is summed up for all natives and immigrants to identify the total expenditure/revenue that is attributed to each group. A deeper analysis is carried between subgroups divided based on age group and education across each year. As table 1 shows the age group divisions are based on the behaviour patterns of individuals. So individuals aged 0-15 are labelled as children, 15-25 are young adults who may be in transition between securing education and working. The main working-age population is 25-55 years of age. Adults between 55-65 are in the transition stage between working and retiring which leaves us with adults of 65 years and above as the old age population. The 15 years and older population can be further sub-divided based on their level of education. Education up to lower secondary (or grade 9 in the U.S. system) is classified as low education. Medium level of education includes all individuals who had some upper secondary education, graduated high school or had some college experience that did not result in a degree. High-skilled individuals are those that received either an associate/bachelor degree or higher. The same age-education divisions are maintained when studying the fiscal impacts of natives vs immigrants from different origins (OECD vs non-OECD) or immigrants based on recency of arrival (within 10 years of the survey vs longer). Alternate specifications also look at first-generation vs second-generation vs third-generation (natives) within the same age-education framework.

Throughout the 21^{st} century, the United States has maintained a fiscal deficit. Defined as total revenue minus total expenditure, a negative fiscal balance implies that the net contributions of an average individual are likely to be negative since the government is spending more on its welfare system and public goods relative to the contributions that it receives. To see this, we can divide the fiscal balance defined as general government revenue minus expenditure, into each revenue and expenditure item attributed by sub-population.

$$\begin{aligned} B &= R - X \\ &= \sum_i R^i - \sum_j X^j \\ &= \sum_p (\sum_i R^i_p - \sum_j X^j_p) \end{aligned} \tag{2}$$

where R_i and X_j correspond to the revenues and expenditure from each item i and j of the national account revenues and expenditures respectively and p corresponds to the sub-populations based on nativity, age and education.

Since net contributions do not control for the fiscal deficit and population sizes, an alternate preferred measure called the fiscal ratio is used. The fiscal ratio is defined as the total contributions to government revenue divided by the total benefits received from government expenditures for each sub-population.

$$FR_p = \frac{\sum_i R_p^i * 100}{\sum_j X_p^j} \tag{3}$$

A fiscal ratio above 100, implies that the subgroup p contributed more in dollars relative to the benefits that they received and vice versa. The fiscal ratio of some sub-populations, for example, the highly educated working-age population, can be nearly 200% in some years. Comparing the fiscal ratios of two subgroups can provide a clearer picture regarding the relative net contributions. The fiscal ratio also accounts for the size of the population since the fiscal ratio *per capita* of any sub-population will equal the fiscal ratio of that sub-population as both revenue and expenditures will be divided by the same number of individuals.

To compare the foreign-borns with the natives, the relative fiscal ratio (RFR) is thus used. This is defined as the fiscal ratio of the foreign-born sub-population p, divided by the fiscal ratio of the natives sub-population p with the same socio-economic characteristics.

$$RFR_p = \frac{FR_p^{fb}}{FR_p^{nb}} \tag{4}$$

So irrespective of the level of deficit in the country. A relative fiscal ratio greater than 1 implies that the foreign-born sub-population has a better fiscal position relative to the native sub-population. Thus when looking at the 65+ aged population, despite the fact that both the native-born and foreign-born subgroups are net-benefiters and typically have a fiscal ratio lower than 100, a relative fiscal ratio greater than unity indicates that the foreign-born are a smaller burden on the government relative to the natives with the same socio-economic characteristics. In the following sections, the fiscal ratio (in percentage terms) and the relative fiscal ratio are often used when comparing different subgroups although net contributions in dollars are also provided for the aggregate native and foreign-born populations.

1.3 Data

The main micro survey which is used to identify the demographic populations, as well as the benefits and transfers reported by the individuals is the Current Population Survey (CPS) of the United States. This is a monthly household survey jointly conducted by the U.S. Census Bureau and the Bureau of Labor Statistics to over 65,000 households. This paper uses the Annual Social and Economic Supplement (ASEC) of the CPS survey downloaded via IPUMS. This survey contains detailed information on the demographic, economic and social data such as country of birth, year of arrival to the United States (within a 2-3 year band), labour income including wages, length of unemployment if any, education level and detailed self-reported information on household income, social benefits, contributions, taxes, transfers and health care. This information is used both in the probability differential analysis as well as in the estimation of the fiscal impact.

The data on the general government expenditures and revenue which is used in the fiscal ratio estimation is taken from the OECD statistical tables. The categorisation of government expenditures is based on the OECD's Classification of the Functions of Government (COFOG) and is supplemented by the OECD's Education at a Glance, 2020 (EAG) and Social Protection Expenditure detailed datasets. The revenue data from the OECD statistical tabes is supplemented by data from the National Income and Product Accounts (NIPA) Tables published by the Bureau of Economic Analysis (BEA). Appendix section 1.6.3 details each item and its sources.

1.3.1 Population characteristics

The CPS creates weights for each observation such that the dataset, on the whole, mimics the U.S. population. The weights are created using an inverse probability of selection and accounts for various inconsistencies, including sample errors and behavioural causes such that the weighted resultant demographic breakdown is representative of population statistics. All the data described in the next sections make use of the weighted sample to represent the real U.S. population.

Immigration Trends Since the Immigration and Nationality Act of 1965 which equalised immigration policies irrespective of country of origin, the number of immigrants entering the United States rose dramatically. The trend has continued during the 21^{st} century despite the dip in the years immediately following the 2007-08 Great Recession. Table 2 shows the total population of the U.S. and the percentage breakdown of natives and foreign-born by their country of origin and recency of arrival into the U.S.

The total population has grown by 9.3% from 297 million individuals in 2006 to over 324 million individuals in 2018. During the same time, the immigrant population had grown nearly 22.5% from 41 million to over 50 million. i.e. in these 15 years, immigrants had become 15.5% of the total population which is a 1.7 percentage point (p.p.) increase from 2006. The Great Recession in 2007-08, characterised by the loss of economic opportunities, was the only period when immigrants, as a percentage of the total population decreased.

The business cycle has clear implications on the decision of immigrants to immigrate to the U.S. and remain in the country. The foreign-born population that arrived more than 10 years ago has been growing steadily from 8.42% to 11.04% between 2006-18. In contrast, in 2018, the percentage of immigrants who had immigrated within the past decade was only 4.48% of the 2018 population. This is 1.09% or 2 million less than the number of immigrants who had migrated between 1997 and 2007. Thus, although the number of immigrants has been growing, there has been a slowdown in the arrival of new immigrants post-2007 which continued at least until 2015. Column 5 of Table 2 shows the percentage of immigrants that arrived in the last 3 years. It was only in 2018 that recent immigrants were 2.4% of the total population, a percentage that was previously seen in 2006. This can also be seen in figure 1 which shows the total foreign-born population in the U.S. between 2006 and 2018 and includes a quadratic fit of the immigrant population that arrived in the last three years. Although the trend of total immigrants only sees a dent in 2008 with 6.67 million fewer immigrants, it is clear from the recent immigrant curve that the arrival of immigrants has only just returned to early 2000 levels. Thus immigrants, including those who had been in the U.S. for longer than 10 years emigrated out of the U.S. during the Great Recession and it was only when the economy began improving that the arrival of new (or returning) immigrants picked up once more.

The last two columns of table 2 classify the immigrant population by country of origin. On average the population of immigrants from non-OECD countries is 4 times more than those from OECD countries. Further, the immigrant population from OECD countries has been slowly declining over time although a slight reversal can be seen in the last few years. In 2018, only 8 million of the 50 million immigrants were from developed OECD countries.

Age and Education There has also been a clear shift in demographics in terms of age and education for both the native and immigrant populations. Table 3 lists the share of children, old age individuals, low-skilled and high-skilled by nativity over time.

The share of children has consistently decreased over time, particularly for immigrants and that too for those from non-OECD countries. On the other hand, the ageing of the population is visible as the share of the total population over 55 years of age increased by over 6% to 29.15% in 2018. By 2013, there was a larger share of 55+ among the immigrants than the natives. Among the immigrants, 30.36% or nearly 15.3 million were over the age of 55 in 2018. This was only 21.39% or 8.8 million in 2006.

The split by the country of origin is particularly interesting since, in 2018, over a third of immigrants from the OECD countries were over 55 versus 17.8% of immigrants from non-OECD countries. Overall, the number of old age immigrants from non-OECD countries in the U.S. has almost doubled between 2006 and 2018 while the shift has been less subtle among OECD immigrants which have always had a high percentage of older individuals.

Both recent and not-recent immigrants have experienced an increase in the population of the 55+. In 2018, 31% of the immigrants who have been in the U.S. for at least 10 years are over 55 years old. Given that most immigrants migrate when they are young adults, a very small fraction of recent migrants are over 55 years of age. In 2006, 7% of recent immigrants were over 55 while this was 10.7% in 2018. A little over half of them belong in the 55-65 age group with only 4.7% over 65 years of age.

The exact shifts in the distribution can be seen in figure 2. The solid lines represent the native population, the dashed lines the immigrant population and the dotted lines the recent immigrants - those who entered the U.S. in the last ten years. The average age (represented by vertical lines) of the immigrants is consistently higher than that of the natives. This is primarily because of the low population of children among immigrants. Moreover, the ageing of the natives and immigrant population can be observed since the average age of immigrants increased by 4.5 years from 40.4 to 44.9 between 2006 and 2018 while the average age of natives rose as well, but by less, from 35.8 to 37.7 years.

Even the average age of recent immigrants has increased from 30.4 years to 32.5 years between 2006 and 2018 which shows that in addition to the ageing of the existing immigrant population in the U.S., there has also been an increase in the immigration of the older population during this time period. This could be due to a variety of reasons including the overall ageing of the world population, elderly parents of working-age naturalised citizens immigrating to be with family and highly skilled immigrants immigrating for work opportunities. Irrespective of the reason, a larger share of immigrants or 1.4 million additional immigrants aged 55+ are now choosing to retire in the United States which has direct implications on the immigrants' fiscal impact since the elderly are typically beneficiaries of the U.S. welfare system.

Most recent immigrants belong to the young working-age population. However, between 2006 and 2018, the recent immigrant distribution has become flatter. While nearly 1.5% of total immigrants who immigrated in the last 10 years were 30 years old in 2006, this was less than 1% in 2018.

The shift in the educational attainment of immigrants has also been incredible. There has been a significant decline in the population of low-skilled individuals among all populations, but the shift was most apparent among immigrants from non-OECD countries. The percentage of low-skilled non-OECD originating immigrants in the U.S. decreased from 24.5% in 2006 to 18.6% in 2018. Among immigrants from OECD countries, the percentage of low-skilled halved from 10.6 to 5.8%. Simultaneously, the percentage of high-skilled has been steadily increasing with time. In 2018, half the immigrants from OECD were high-skilled whereas this was 35.4% of the immigrants from non-OECD countries.

The shift in educational qualifications among immigrants is also primarily striking due to the changing demographics of new immigrants - recent immigrants are much more educated. Recent immigrants with low levels of education decreased from 22% to 11% over the 12 year time period whereas the recent immigrants with high levels of education increased from 25% to 38%. Figure 3 shows the ratio of high-skilled to medium and low-skilled natives and immigrants (including recent immigrants) aged 25 and above, over time. It is particularly interesting to note that the ratio of high to medium and low-skilled for recent immigrants over 25 years of age has exceeded the ratio for natives since 2014. By 2018, 38% of immigrants have at least an associate or bachelor degree versus 33% natives. However, although the low-skilled immigrant population has declined during this time, in 2018, there were still 7.7 p.p. more low-skilled recent immigrants than low-skilled natives.

In a distinctive change relative to the late 1900s, the current immigrant population in the U.S. is composed of a significantly higher-skilled population than in the past. Moreover, both the existing immigrant population as well as the general trend of recent immigrants is skewed towards the older population. Recent immigration has seen a slowdown caused primarily due to the Great Recession and most of this decrease has been in the working-age population. Recent immigration from the OECD has also decreased and instead there has been a relatively higher influx of immigrants from non-OECD countries. Overall, the trend of immigration is seeing a slow shift towards the higher-skilled and the older population which has multiple fiscal implications which will be discussed in the next sections.

The Great Recession The economic downturn which originated in late 2007 in the U.S., and then quickly spread across the world, affecting the economy and labour markets everywhere, influenced immigration greatly. In the U.S., as unemployment levels increased, consumption and output declined and income inequality grew rapidly, the total immigrant population also declined for the first time in the 21^{st} century by 0.7 million people. The recession officially lasted until June 2009, although recovery unofficially continued until 2016. The U.S. government responded with a \$152 billion and a \$787 billion fiscal response in 2008 and 2009 respectively which included tax cuts and government spendings planned for the entire decade. The enormous fiscal deficit in 2009 was a consequence of these fiscal policies in addition to the automatic stabilisers in play. Thus, the downturn combined with the sizeable welfare support raises the question about what role immigration played during the Great Recession.

Figure 4 shows the changes in the population of immigrants by age and education over time. The ratio of high-skilled to low and medium-skilled is increasing for both the working-age and the old age populations. As previously discussed, among the working-age population, the number of low-skilled immigrants is decreasing over time while the number of high-skilled is rising. The ratio of high-skilled to low-and-medium-skilled more than doubles post-2012 stemming from the faster decline among the low-skilled working-age population. Among the old age population, the high-skilled population is rising although the low-skilled population remains more or less constant.

In 2008, the number of immigrants in the U.S. decreased by 0.7 million, however, the decrease was not the same across all subgroups (see figure 5). The working-age population, which have the highest overall share experienced a 7% decline. Similarly, the number of old age immigrants who are medium-skilled also declined. What is surprising however is the slight increase in the low-skilled working-age immigrant population (0.9%), low-skilled old age immigrant population (2.1%), and the larger increase in the high-skilled old age immigrant population (7.7%).

While the uptick for the low-skilled is small enough to be explained by data limitations, the increase in the high-skilled old age population cannot be ignored. The ageing of the existing U.S. population is one major reason but the selective increase among high-skilled suggests that the old age immigrant population preferred to stay back in the U.S. only if they are high-skilled. In fact, the increase was 18% for recent high-skilled 55+ immigrants vs a -15.9% for the medium-skilled. One simple explanation could be that the increase in the high-skilled old age immigrant population is being driven by the trend. Immigrants arriving in the U.S. are older and better educated, thus an individual immigrating to the U.S. during a recession is more likely to belong to this category. Another reason for old age immigration is the family reunification policy whereby, elderly parents of naturalised children immigrate to the U.S. high-skilled individuals, who are likely to have high-skilled parents would most likely be able to support their parents, especially in a recession. Furthermore, applying for benefits and accessing social welfare is easier for old age immigrants with English speaking abilities and legal status in the U.S. In fact, eligibility requirements need at least 10 years of working experience for an immigrant to qualify for social security. Thus, old age immigrants who have been in the U.S. for 10 years and are well assimilated into society are more likely to receive health and welfare benefits and thus more likely to stay back in the U.S. instead of returning to their home countries (Vega 2013).

A similar change occurred in 2018 when the total number of immigrants increased by only 0.19 million (see figure 1). This was possibly due to the zero-tolerance policy of the Trump administration which placed strict restrictions on unlawful entry and banned immigration from certain Muslim-majority countries. The limited entry of immigrants implied a stark change in the composition of incoming immigrants. Figure 4 shows how the ratio of high-to-low-skilled immigrants jumps up for the working-age population. This shift in the socio-economic characteristics of the immigrants in 2018, drastically affects the fiscal impact of immigrants even though economic growth remained the same during this time.

1.3.2 Benefits and contributions

Benefits refer to the Social Protection benefits and as described before can be divided into individual benefits and household benefits. The quantity utilised and eligibility to receive these benefits varies by sub-population. As Table 4 shows, immigrants receive fewer overall benefits and make fewer contributions on average. Also, the average overall benefits increase substantially with age, particularly among the 65+ population. Furthermore, the differences between native-born and foreign-born also increase with age with old age natives receiving a lot more benefits on average.

However, observing the breakdown between individual and household provides further insights into the utilisation behaviour of different age groups. Young adults utilise more of the household benefits. This is driven by the fact that the young adults may need to support small children or are socially marginalised and therefore they utilise a lot more of the family and children benefits. Similarly, older individuals generally receive much larger individual benefits which are particularly driven by the old age benefits[8]. While natives get higher overall benefits on average, foreign-borns receive more household benefits on average, a fact that remains true across all education levels. The relatively large size of individual benefits relative to household benefits for older populations results in higher overall average benefits for natives. For younger populations, this difference is marginal since these age groups receive

[8] This doesn't include health benefits which would increase the averages by much more

very little individual benefits.

There are wide variations within education levels as well. Among the younger population, the individuals with low education receive nearly three times more benefits whereas the reverse is true for the 65+ population - the individuals with high levels of education receive more benefits, nearly double. Average contributions increase with education across all age groups. The increase is sharpest among the 25-55 and 55-65 age groups whose high-skilled workers contribute the most on average. The 65+ low-skilled contribute the least overall. Immigrants across all age groups and education levels, contribute less than their native counterparts on average.

The working-age population receives a fraction of benefits relative to the ageing population. Furthermore, although the highly skilled working-age population receive less than $1000 in benefits on average, the highly skilled old age native and immigrant population receive close to $25,000 and $17,000 on average. Meanwhile, the difference between the age groups for the low-skilled is much lower since the low-skilled old age receive nearly half the average benefits received by a high-skilled.

Average contributions between the working-age population and the old age group, actually decreased by over 1000 dollars for the low-skilled natives and increased by $400 for the low-skilled immigrants whereas the average contributions for the high-skilled natives decreased by $5000 for both natives and immigrants. Only considering social protection benefits and household contributions, high-skilled working-age immigrants hold the best possible fiscal position although the same population will require larger support from the welfare system as they age and reach retirement. This graph does not include other forms of benefits and contributions such as health, education, public goods, etc.

Social protection benefits are created with the intention of protecting individuals from falling into poverty. Thus, average benefits would be expected to increase during recessionary periods and drop during booms. Figure 6 shows that the average benefits of recent immigrants, as a percentage of GDP, are countercyclical as expected. Average benefits as a percentage of GDP received by immigrants is consistently lower than that of natives. Post the Great Recession, the average benefits by GDP for immigrants have returned to pre-recession levels while that of the natives remain at higher levels.

Average contributions by GDP on the other hand for recent immigrants are procyclical with individuals making lower social security payments and lower direct tax payments during recessions. Average contributions by GDP made by immigrants are consistently lower than that of natives, however, the gap has been lessening with time. This could be due to the changing composition of the recent immigrant population which has a higher percentage of the high-skilled and a lower percentage of the low-skilled, post-2012. In fact, the difference in average contributions by GDP has dropped by 50% in this time frame.

1.3.3 National Accounts

The data on general government expenditure and benefits are disaggregated based on the OECD statistical tables and the U.S. Bureau of Economic Analysis, NIPA tables as defined in table 5. Public goods including Defence and Public Debt are the main channels of government expenditure. Apart from that, Health and Education have the highest weights of general government expenditure. Among the social protection expenditure items, old age and survivors have the largest weight at 67%. Family and children, housing and social exclusion which are usually classified as household benefits are only 17% of the total Social Protection benefits and are responsible for only a little over 1 percent of the GDP. On the other side of the government balance sheet, income tax (direct tax) is the largest source of government revenue, followed by indirect taxes (tax on products and production) and social contributions.

Table 5 also shows the changes in government expenditure and revenue over time. In 2009 and the years immediately following the great recession, government expenditure increased (as a percent of GDP) across all items. The increase in the expenditure on Health however has continued to increase, reflecting the demands from the ageing population and health care reforms. By 2018, the general government expenditure by

GDP remains higher than the 2006 numbers. Only expenditure on other public goods[9] and expenditure on Education decreased during this time.

The decrease in revenues by GDP during the recession years is primarily driven by lower income taxes. All the other categories remain constant over time such that all changes to government revenue are primarily driven by changes to income taxes. Medicare contributions, which is a subset of Employee social contribution has been steadily growing at par with economic growth, and by 2018, it stands at 0.5% of the U.S. GDP. Property taxes which is a part of the indirect taxes are a significant source of revenues at 2.7% of the GDP. The dip in employee contributions in 2011 and 2012 relative to employer contributions is due to a change in policy when the Social Security payroll tax rate was reduced for employees and the self-employed temporarily.

1.4 Results

In this section, I expand on the empirical results regarding the impact of immigrants on the fiscal balance. First, I report results on the differential probability of receiving benefits and making contributions between natives and immigrants across demographics. Changes to immigration compositions provide valuable insights into the cyclical trends. Next, I report the results from the estimation of the fiscal impact of immigrants, notably the fiscal ratios of the different sub-populations and the relative fiscal ratio of immigrants to natives. Aggregate results, i.e. differences between natives and immigrants are listed first, followed by results by nativity-age-education. Results for immigrants based on recency of arrival and origin or arrival are also reported for some of the analyses. Finally, the sensitivity analysis which includes the generational results and fiscal ratios based on alternate assumptions are reported.

[9]Other public goods are general public services (minus debt), public order and safety, economic affairs and housing and community development

1.4.1 Probability distribution

The probability of receiving a specific benefit from the government varies greatly on the age and education of the individual. As discussed in section 1.3, the older population receive greater individual benefits while the younger population receive greater household benefits on average. Thus it is useful to study the probability of receiving individual and household benefits separately.

Similar to Dustman and Frattinni (2014), two regressions are conducted. The first set of results reported in Table 6 (columns 1 and 2) condition on the time dummies and can be interpreted to account for all the time variations in the receipts of benefits and contribution transfers. Column 1 reports the weighted averaged difference between individuals and natives, conditioning on yearly variations and column 2 reports the predicted probability of natives in receiving benefits or making contributions. The second regression's results are reported in the same table 6 columns 3 and 4. This regression conditions on the individual's age and gender structure, in addition to time, such that the differential probability in column 3 is a comparison between immigrants and natives of the same demographic characteristics.

Immigrants are less likely to receive individual benefits and more likely to receive household benefits. The probability of immigrants receiving any type of individual benefits is 21.96% less than natives when accounting for yearly variations. However, the difference drops to 10.45% when the same age and gender structure is maintained between natives and immigrants. In contrast, immigrants are more likely to receive all types of household benefits by 19%, which drops to 12% when the age and gender structure is taken into account. Thus, it is not surprising to see that the differential probability of immigrants in the receipt of overall benefits changes signs across the two regressions from immigrants receiving 2.9% less to immigrants receiving 4.75% more when conditioning on demographic characteristics.

Among the individual benefits, the old age benefits which are responsible for 67% of the overall social protection benefit expenditure, is the most commonly used benefit with 95% of natives receiving it. Immigrants are 2.4% less likely to receive this benefit. Interestingly, once the age and gender structure are accounted for, the difference in unemployment benefits falls from 18% less than natives to a less than a 1% difference. Among household benefits, family and children benefits are the most popular, and immigrants are 10% more likely to receive this. Immigrants, particularly the vulnerable subgroups, receive 14% more social exclusion benefits (which account for only 7% of the total social protection expenditure).

Immigrants are less likely to make contributions than natives. Although the majority of individuals contribute via taxes or social security, Immigrants are less likely to make contributions relative to natives by approximately 7%[10]. The only difference between the employer contribution and household contributions is that household contributions include direct income taxes in addition to social security contributions. So it is interesting to note, that immigrants make 4% more contributions when considering only social security but this reduces to 6% less than natives when taxes are also involved. Property taxes show the greatest disparity - immigrants are 18% less likely to pay property taxes, which is unsurprising since immigrants are less likely to own houses.

Differential probability between natives and immigrants of receiving and making transfers differs by demographics. Table 7 provides the differential probability (immigrant - native) for the different demographic categories. The predicted probability of natives which is the estimated marginal effects measured at the mean value of all other regressors are reported in parenthesis below the differential probability. The probit regression results reported also condition on the educational classification of the U.S. population, interacted with the age classification. The base results remain close to the previous results. Immigrants receive 11.6% less individual benefits, 12.2% more household benefits which results in 2.1% more benefits overall and contribute 4.3% less. Immigrants who arrived in the U.S. less than 10 years ago are 16.6% less likely to receive individual benefits and

[10]Overall contributions here include social security payments, income taxes and property taxes.

only 10.5% more likely to receive household benefits. i.e. recent immigrants are less likely to be a burden on the welfare system in terms of receiving benefits compared to immigrants who have been in the U.S. for more than 10 years. However, they are 8.7% less likely to make contributions. Immigrants from the OECD are the least different from the natives. They receive 5.1% less individual benefits and make 1.9% fewer contributions.

Table 7 also reports the probability differential of natives and immigrants that belong to a specific age and education bracket. The predicted probability of receiving individual benefits is 90% for the old age natives, the predicted probability for the younger population (15-25) is 5% in contrast. [1.] *The weighted average difference between immigrants and natives in receiving individual benefits is highest for the old age population- 14.2% less for those between 55-65 and 11% less for the highly skilled 65+; and among the low-skilled working-age population - 10%.* For household benefits, the opposite is true as the younger population is more likely to receive benefits (61.2%) although there is a wide difference depending on educational qualifications. The older population is far less likely to receive household benefits, with only 8% of the high-skilled as recipients. [2.] *The relative immigrant population is likely to receive 10% more household benefits than the natives among all subgroups except the high-skilled, where the difference is about 5-7% instead.*

Overall benefits are highest among the older population, but the difference in probability between immigrants and natives is positive and highest among the working-age population at about 3%. Thus, the difference in probability between natives and immigrants within subgroups is fairly small (seldom exceeds 10%). So, the immigrant's likelihood of receiving benefits is predominantly driven by their age and education composition. The shift in immigration patterns towards older high-skilled immigrants would suggest that overall, more immigrants are likely to receive individual benefits in the future, although this number may be fewer relative to natives.

The likelihood of making contributions is highest among the highly skilled working-age natives, and immigrants in all age and education categories are less likely than natives to make contributions. [3.] *The weighted average difference in probability of making contributions between immigrants and natives is least among the highly skilled, 2% for the working-age high-skilled and 4% for the highly skilled 65+.* The difference is highest at 8% for the low-skilled population. So a shift in immigration trend towards the highly skilled will positively benefit the fiscal position of immigrants in the future.

The differential probability changes over the cycle. Negative sentiments and concerns over whether immigrants are burdens on the public system rise during recessions. This makes it valuable to study if immigrants are more or less likely to depend on the welfare system during downturns. Table 8 lists the predicted probability in the base year 2006 for natives and immigrants. The differential probability is -11.3% and +12.3% for individual and household benefits respectively.

Figure 7 shows that the changes in the differential probability, relative to 2006 is pro-cyclical for individual benefits and counter-cyclical for household benefits. Specifically, the differential probability of receiving individual benefits in 2009 changes by 0.7 p.p. from -11.3% to -12%. By 2017, the differential probability changes by 0.3 p.p to -11%. Since between 2006 and 2018, variations in the predicted probability of natives was limited to ± 2 p.p., the 0.7 p.p decrease in differential probability is sizeable. Inversely, the differential probability of receiving household benefits increases during the recessionary years by 0.3 p.p to 12.6% and decreases in 2017 to 12.2%. The variations in household benefits are small and more sticky since this category has access to public housing and subsidy on housing.

Most of these dynamic changes in the differential probability can be explained by the changes in immigrant composition. We already know that (a.) there was a shift towards the old age population and that (b.) the relative population of the working-age high-skilled to low-skilled has seen a substantial increase, particularly post-2012 (see figure 4). The continuous increase, even during the recession, in the old age immigrant population can explain the increase in differential probability since this subgroup has the largest differential probability relative to natives (see [1]). The subsequent decrease in the differential probability of individual benefits and the increase in household benefits post-2012 can be attributed to the relative decrease of the low-skilled working-age population (see [1] and [2]).

More intuitively, during a recession, immigrants who require benefits such as sickness, old age or unemployment benefits may be in need of healthcare or must have lost their jobs. Since immigrants can choose to leave the country and moreover since for many immigrants their visas are dependent on their working abilities, these immigrants may choose to migrate back to their source countries. The immigrants including the old age immigrants who stay behind may choose to do so because they are more secure with sufficient income or network support and thus are less likely to utilise benefits (see figure 8a).

The differential probability of making contributions is 3.8% less for the immigrant population in 2006. There is some evidence of cyclicality as the differential changes post the Great Recession to 5% in 2011 and then becomes 4.4% in 2017 (see figure 8b). The reversal in the direction of dynamic change of the differential probability intensifies post-2012 which coincides with the decrease of the low-skilled working-age populations. This change in the immigrant composition can explain the dynamic change since the differential probability of making contributions is -8% for the low-skilled and about -3% for the high-skilled (see [3]).

Clearly, the shift in distributions of the immigrant population relative to age and educational qualifications impact the likelihood of receiving different types of benefits and contributions. However even though the differential probability of individual benefits of an immigrant versus native is pro-cyclical, the average individual benefits received definitely increased during the recession. Similarly, although, the differential probability of making contributions decreased relative to 2006, the actual gap in dollars between the average contributions made by natives and immigrants halved by 2018. Section 1.4.2 reports the fiscal ratio of the overall immigrant population and subgroups, and evaluates the net fiscal impact of immigrants relative to natives and over the business cycle. Section 1.4.3 looks into distributional differences and details the differences in the intensive margin for the social protection benefits and contributions discussed in this section.

1.4.2 Fiscal impact estimates

Aggregate Results. The fiscal balance has predominantly been negative over the 21^{st} century. The years immediately post the Great Recession witnessed large negative deficits which decreased in magnitude post-2012, only to worsen again in 2018. Thus, as reported in table 9 the overall net contribution to the fiscal balance ranges between -1897 billion (-13.13% of GDP) in 2009 and -461 billion (-3.33% of GDP) in 2006. In those years, the contribution by the natives ranged between -1670 billion (-11.56% of GDP) and -425 billion (-3.08% of GDP) respectively while the contribution by immigrants ranged between -226 billion (-1.57% of GDP) and -36 billion (-0.26% of GDP) respectively.

While, for a number of years, the contribution of immigrants in percent of GDP lay between $\pm 0.5\%$, in the years immediately post the Great Recession, the contribution to the fiscal balance by the immigrants was nearly 1.5% for 3 consecutive years. Despite the high negative contribution to GDP, the immigrant population was never solely responsible for the fiscal deficit. The native's contribution to GDP was always larger in magnitude and of the same sign as that of the immigrants. This is not surprising considering that the immigrant population is a small fraction of the total U.S. population.

One useful measure which removes the population size effect thus allowing for better comparisons between the native and immigrant populations is the fiscal ratio also reported in table 9. The fiscal ratio (as defined in section 1.2.2) is less than 100 across the entire time period, implying that the overall contributions of the group to the general government accounts is less than the overall benefits received. The fiscal ratio ranges from a minimum of 69% in 2009 to a maximum of 90% in 2006 for the natives and from a minimum of 73.38% in 2009 to a maximum of 95.84% in 2015.

The difference in the fiscal ratio between immigrants and natives is

positive and increasing. Immigrants appear to have a better fiscal position than natives between 2006 and 2018. As figure 11a shows, although the fiscal ratio declined for both groups by 20 p.p. because of the Great Recession, the fiscal ratio of the immigrants increased much faster than that of the natives, even exceeding the 2006 ratio before declining in 2018. Overall by the end of the decade, the difference between the fiscal ratio of immigrants and the fiscal ratio of natives had increased substantially.

Crucially, the decomposition of the net contributions by the immigrant's origin country discloses an important observation. Immigrants from OECD countries have a substantially larger fiscal ratio relative to immigrants from non-OECD countries. In fact, apart from the recessionary years, the fiscal ratio of OECD immigrants was greater than 100 which implies that these immigrants were contributing more in social security contribution and taxes relative to the social protection and public good benefits that they were receiving. Even in 2009, the OECD immigrants had a fiscal ratio of 84% and the non-OECD immigrants had a fiscal ratio of 70.6%, which is higher than the fiscal ratio of natives at 69%.

Decomposing the net contributions by recency also has essential implications. Immigrants who arrived in the U.S. more than 10 years ago, consistently have a larger fiscal ratio relative to immigrants who arrived in the U.S. less than 10 years ago. In 2006, the not-recent immigrants had a fiscal ratio of 101.4% whereas the recent immigrants had a fiscal ratio of only 82.3% which is much lower than the fiscal ratio of natives at 90.3%. In contrast, in 2015, the fiscal ratio of not-recent was almost 100% whereas the fiscal ratio of recent immigrants was at 86.3% which is nearly the same as the fiscal ratio of natives at 86.5%. By 2017, even recent immigrants had a fiscal ratio higher than that of the natives.

An alternate way of measuring the fiscal impact is by estimating the net contributions per capita (see Appendix 1.6.4), thus accounting for the difference in the size of the native and immigrant populations. As with the other measures, the net contributions per capita of natives is highly negative throughout the time period, decreasing to a maximum of -6381 USD in 2009. the immigrants had a net contribution per capita of -5332 USD in the same year, although they quickly bounced back to 2006 levels by 2015, which was something that the natives did not manage. The net contributions per capita of the OECD immigrants was positive during non-recessionary years while the immigrants from non-OECD countries consistently had negative net contributions per capita, although the magnitude was smaller than that of the natives. The net contribution per capita of recent immigrants is also negative but relative to natives the measure is found to be more (less) negative than that of the natives before (after) 2012, reflecting the change in immigrant composition and behaviour. The net contribution per capita for not-recent immigrants is much smaller and in 2006, it was positive at 240 USD. Thus, in the years immediately post the Great Recession, immigrants arriving to the U.S. were receiving more benefits than previously.

Finally, the last measure used is the net contribution per resident which partitions the average contribution per capita between the natives and immigrants[11]. In 2009, the average net contribution per capita for the entire population was -6233 USD. This can be attributed as -5489 USD per resident to the natives and -744 USD to the immigrants. This implies that in 2009 the immigrant's accounted for 11.9% of the fiscal balance which was still far less than their share of the total population, 14%. The immigrant position which worsened in 2009, recovered very well until 2017 before declining once again.

The changing demographic composition of the immigrant population is partially responsible for the differences in the fiscal position of the immigrants. Apart from the ageing of the immigrant population, the characteristics of the immigrants who are consciously making the decision to migrate to the U.S. is changing with the economic situation and the immigration and social security policies in the country.

Age plays a major role since the very young and the old population are generally net benefiters while the working-age population contribute

[11] This measure is defined in Appendix 1.6.4 and was first defined in Chojnicki et al (2018)

the most. As figure 9a shows, benefits per capita is highest for those below the age of 20 and above the age of 60. The former is driven by public education benefits with a maximum fiscal flow of 17,500 USD for 15-year-olds, while the latter is at over 30,000 USD for the 70+ age group and is driven by health care, old age and sickness benefits (which encompasses social security, supplemental security income and Medicare benefits). Children below the age of 15 do not contribute anything to the national accounts and so, the contributions per capita spike up at the age of 15 and increase slowly reaching a maximum of 25000 USD around the age of 40 before declining once again. The speed of decline in contributions per capita increases post the age of 60, stabilising at 11000 USD.

Moreover, the individualised benefits per capita have been slowly increasing over time such that an average individual in 2018 received 4700 USD more benefits relative to an average individual in 2006 (see figure 9b). This increase was driven by the 60+ population due to the rise in old age and sickness benefits. Similarly, the individualised contributions have also been increasing over time such that an average individual in 2018 contributed 3500 USD more than an average individual in 2006.

The Fiscal Ratio differs by age and education. Socio-economic characteristics of the immigrants, as well as yearly variations, drive the fiscal impact of immigrants in the United States. The Relative Fiscal Ratio measure (RFR: as defined in section 1.2.2) can be used to compare the fiscal ratio (FR) of natives and immigrants across various socio-economic sub-populations over time. Table 10 lists the FR and RFR of the natives and immigrants divided into various sub-populations by age and educational qualifications.

Both natives and immigrants who are highly educated and belong to the working-age population of 25-55 or transitioning to the retirement age group of 55-65 are net contributors with a fiscal ratio above 100. Although the magnitude decreases from more than 200% in 2006 to 150% in 2012 for the 25-55 age group, it remains that on average, highly educated working-age individuals contribute much more than they receive in benefits and public goods and services. In addition, natives who are medium-skilled are also net contributors during the non-recessionary years. This is the only subgroup where the natives are net contributors while the immigrants are net benefiters.

Overall, education plays a large role. For the population over 25 years of age, the highly educated have a larger fiscal ratio than the low-skilled within each age bracket. This is different for individuals between the age of 15 and 25 since many highly educated individuals of this age bracket may still be studying and therefore utilising education benefits. Thus a native in 2006 who is highly educated on average contributes 30% of what they receive if they are between 15 and 25 years of age whereas they contribute 225% of what they receive if they are between the ages of 25 and 55.

The highly educated 15-25 aged population and the low educated 65+ older population have the lowest fiscal ratios at around 20% and 25% respectively in 2009. The fiscal ratio for the same groups was much higher by 2018, with a greater growth for immigrants in the highly educated older population than in the low educated young population. This coincides with an increase in the population of highly educated 65+ and a decrease in the population of low educated 15-25-year-old immigrants.

Relative Fiscal Ratio between natives and immigrants differs across age groups. Although it is the working-age population who contribute the most even among immigrants, the sub-population with the best relative fiscal ratio is the 55-65 and 65+. Apart from the highly educated 55-65-year-olds, the rest of the sub-population are net benefiters, however, since the natives in each sub-population receive relatively more benefits than the immigrants, the relative fiscal ratio for 65+ in all the years and 55-65 for most non-recessionary years is greater than 1. The relative fiscal ratio for the 65+, particularly the low and medium educated, also experiences an increase in the years immediately following the Great Recession. This is driven by the fact that natives were more likely to be eligible or were better able to access the benefits during the economic recession relative to the immigrants. The low educated 65+ had the highest RFR at 1.4 in 2012 while the young and working-age immigrants have the worst fiscal positions relative to immigrants. The young 15-25 highly educated have the least RFR at 0.6 in the year 2018.

The rise in the fiscal ratio of immigrants relative to natives (see figure 11a), can be explained in part by the changing demographics. The share of the highly educated older immigrant population (55+, H) who have a better fiscal position relative to similar natives (RFR>1) has been increasing in the U.S. while the share of the low educated working-age population (25-55, L) who have a poorer fiscal position than the natives (RFR<1) has been decreasing in the 2010s. Thus, in addition to the economic situation and returns to skills in the U.S., the immigration and fiscal policies play an important role in determining the type of immigrants entering the country and consequently the fiscal position of these immigrants.

1.4.3 Decomposing benefits and contributions

Government policies improving access to health care or social protection play an integral role in determining the fiscal position of immigrants. Since a new policy or law that selectively affects a specific category of government accounts will have differential effects depending on the socio-economic characteristics of the population, it is useful to look into the decomposition of the individualised and household benefits and overall contributions.

As table 11 shows the per capita health benefits, per capita old age and per capita survivor benefits increase with age. The health benefits of an individual aged 65+ are five times that of an individual 15-25 years old on average. Education benefits are highest for those between 15-25 years of age and for working-age highly educated individuals. Sickness benefits vary, although it is highest for the 55-65 year population. Household benefits are highest for the young and low-skilled populations.

The relative fiscal ratio for each item i defined as the per capita expenditure of that item on the foreign-born divided by the per capita expenditure on the natives is given in table 11. The RFR varies widely across the different socio-economic subgroups.

$$RFR_i = \frac{X^i_{fb}}{X^i_{nb}} \tag{5}$$

As expected, the RFR for health is close to 1 since the apportioning of healthcare depends on the age distributions of immigrants and natives. The RFR for education is greater than 1 for all except the low-skilled working-age population. This is unsurprising since most low-skilled immigrants of the working-age have already studied in their source country and therefore are unlikely to utilise the public education system in the U.S. On the other hand, a substantial group of immigrants enter the U.S. to pursue higher education which can explain why the high-skilled immigrants receive more benefits per capita relative to the natives. The per capita individualised benefits for sickness, old age and survivors is consistently lower for immigrants than natives across all subgroups. However, the RFR is lowest among the young and the low-skilled suggesting that immigrants from these groups may have the least access or eligibility to these benefits. Unemployment benefits are more even between natives and immigrants of most groups. Only the medium and high-skilled working-age population have an RFR substantially less than 1 (0.66 and 0.83 respectively) which could be driven by the fact that skilled working-age immigrants are more likely to migrate for economic reasons thus making it unlikely that they would require unemployment benefits. Moreover, immigrants without a job can choose to leave the country and return to their source country.

For most sub-populations, household benefits per capita, have an RFR greater than 1. This is particularly true for the older immigrant population who receive 3.37 times the amount of family benefits that the natives receive. However, as noted before, the per capita household benefits are very small. For example, the 65+ immigrant population only receive 98 USD per capita in family benefits. In the other extreme, the low and medium-skilled working-age immigrant population are the only ones to receive less housing benefits than the natives.

Table 12 shows that the average per capita contributions are highest for the high-skilled working-age population, followed by the 55-65 aged individuals. The per capita indirect and household social contributions are lowest among the low educated working-age population while the per capita employer social contributions are lowest among the

65+ old population for both natives and immigrants.

Immigrants consistently underperform relative to natives. Employer social contribution is the only field wherein immigrants have an RFR greater than 1. This is true for the low-skilled working-age population and for the older 65+ population. Interestingly household contributions are lowest for low-skilled working-age immigrants, relative to natives with an RFR of 0.48. Since the social contributions (given by employer contributions) for this subgroup show that immigrants contribute more, the low RFR in household contributions implies that the immigrants pay far less in direct income taxes relative to natives. For every group except the high-skilled working-age population, the RFR of household contributions is lower than the RFR of employer contributions which suggests that the immigrants generally pay fewer taxes on average relative to natives.

While the above explains the immigrant's per capita benefits relative to the native, as seen from the differential probabilities of natives and immigrants, depending on the economic conditions, the share of immigrants and natives who are beneficiaries will vary. Thus, per capita benefits may vary drastically from per recipient benefits. In other words, measuring the per recipient benefits can help answer the question - does an immigrant beneficiary receive the same dollar amount of benefits as a native beneficiary?

Table 13 lists the relative fiscal ratio of per capita benefits in column 1 (for the 15+ population), the relative share of immigrants to natives who receive non-zero benefits in column 3 and the RFR per recipient in column 4 (see Appendix 1.6.5). Column 2 lists the relative share of relevant sub-populations[12]. For all individual benefits, the RFR per recipient is greater than the RFR per capita which implies that the per capita measure underestimates the dollar amount of benefits utilised by immigrants who do utilise benefits. For example, the RFR per capita of unemployment is 0.9 which implies that immigrants on average receive 90% of the average unemployment benefits received

[12]Old age benefits are only considered for individuals 60 and older while unemployment benefits are considered for individuals between 15 and 64 years.

by a native. The share of the 15-64 population in the total population of immigrants is only a little larger than that of natives so we can ignore the size effect. However, only 43% of the immigrants receive unemployment benefits relative to natives. As discussed before this may be because most immigrants without employment can choose to leave the country. However, this implies that the immigrants who do receive unemployment benefits, receive two times the amount of unemployment benefits that native recipients receive.

Family and social exclusion benefits are the only benefits where the RFR per recipient is less than RFR per capita. This is driven by the greater fraction of immigrant recipients relative to native recipients. A larger fraction of immigrants receive these household benefits than natives and so per recipient, the family and social exclusion benefits are nearly the same for an immigrant and a native (1.05 and 1.02 respectively).

Distribution of benefits and contributions The Relative Fiscal ratio of benefits per capita can be defined as the difference in the per capita total benefits of an immigrant relative to a native. In 2016, this was 0.79 implying that an average immigrant receives 21% fewer benefits than an average native.

$$RFR_{benefit} = \frac{\sum_i X^i_{fb}}{\sum_i X^i_{nb}} \tag{6}$$

Table 14 shows how the differences in per capita benefits for each of the different items add up to the total difference in total benefits per capita. The differences in total benefits depend on not only the relative fiscal ratio per benefit but also on the share of each of these items in the native's budget (Details in Appendix 1.6.6). i.e. the 21% difference in using benefits can be divided between all the individualised and household benefits. This table continues with the baseline assumption that public goods are attributed equally to natives and immigrants such that they do not contribute to these benefit differences.

Health, education and old age are the largest components of the native's budget. Education and old age benefits per capita of an immigrant are less than 50% of the benefits per capita received by a native so together they can explain 16% of the differences between immigrants and natives. The remaining differences are driven by health (4%), sickness and survivors (1% each). As expected, family and social exclusion are two items of government expenditure where the immigrants receive more benefits than natives and so this constitutes a 1% difference each in the opposite direction. Figure 10a shows this decomposition of benefits across time.

A key observation that can be made is that immigrants across all years receive fewer benefits relative to a native. This lower expenditure per capita on immigrants is driven by lower education and old age benefits. The difference is the least in 2012 when immigrants receive 18.5% fewer benefits than natives. This was brought about by higher expenditure on education, old age, survivor and household benefits to immigrants. Thus, immigrants who are less likely than natives to receive individual benefits, also receive lesser benefits per capita in 2012. In contrast, immigrants who are more likely than natives to receive household benefits also received more dollar benefits per capita. However, since household benefits are a small fraction of the expenditure budget, the effects of the individual benefits dominate.

A similar decomposition exercise can be conducted for the contributions to government revenue (see figure 10b). Immigrants contribute 14.5% less than natives on average. This ranges from 10.6% in 2016 to 17.7% in 2007. The years following the recession witnessed the greatest difference between the natives and immigrants in terms of per capita contributions, although these differences decreased post-2012. Household social contributions which include direct taxes were the largest source of difference between natives and immigrants as on average, contributing to 10.5% of the total difference between natives and immigrants. Post-2012, payment of taxes by natives and immigrants became more similar, although even at its lowest, it was the largest component contributing to differences in the per capita contributions.

1.4.4 Sensitivity Analysis

This section looks at alternate specifications of the main results listed above.

Apportioning public goods As discussed before, this literature has seen a lot of studies discussing the apportioning of public goods. Essentially, this paper assumes an average cost scenario as its baseline assumption where public goods (pure and congestible) are attributed to all adults above 15 equally irrespective of their country of birth. Figure 11a maps the fiscal ratio and relative fiscal ratio (RFR) between 2004 and 2018 under this assumption. The RFR clearly increases over time reflecting on the improving fiscal position of immigrants in the U.S.

The marginal cost scenario assumes that the natives would have been responsible for the pure public goods expenditure irrespective of the arrival of immigrants in the country and so with a marginal cost of zero, pure public goods are only apportioned to the native adults. Figure 11b shows the fiscal ratios and relative fiscal ratios under this assumption. Notably and as expected, the fiscal ratio of immigrants who are no longer paying for pure public goods is significantly higher than before while the fiscal ratio of natives is lower (since they are paying for the entire pure public goods). Thus, the RFR is much larger than in the average cost scenario. However, post the recession, the RFR decreases a little and does not increase, unlike the average cost RFR.

The differences in the trend of the RFR are driven by the fact that the fiscal ratio of immigrants in the average cost scenario returns to and exceeds its pre-recession levels while this does not happen with the marginal cost scenario. Moreover this disproportionate increase in the fiscal ratio of immigrants in the average cost scenario occurs in spite of the decrease in the share of expenditure in pure public goods post-2012. Thus, when immigrants are responsible for pure public goods, their fiscal ratio decreases but by less in the years post-2012 demonstrating that their fiscal position involving benefits and contributions, excluding public goods, has actually improved over time.

Country of origin and recency of arrival Table 15 reports the fiscal ratios and relative fiscal ratio of immigrant groups based on their origin - OECD or non-OECD countries, and their recency of arrival in the U.S. In general, natives of the working-age with medium and high education and 55-65-year-olds are net contributors while all other natives are net benefiters. However, only the high-skilled working-age population remained net contributors during the recessionary years. Also, the fiscal ratios across all groups decrease due to the Great Recession and improve gradually post-2012.

Immigrants from developed OECD countries generally perform even better than natives of the corresponding sub-populations. Only the young (15-25) and low educated working-age (25-55, L) perform at the same level as natives, although even these sub-populations have higher fiscal ratios in 2018. Thus, as seen by the RFR in the second column, immigrants from OECD countries either perform as well or better than natives.

On the other hand, only immigrants from non-OECD countries belonging to the highly educated working-age population are net contributors. However, the fiscal ratios of most sub-populations are lower than that of the natives (and consequently the OECD immigrants). Only the 65+ old population have an RFR that is greater than 1 and as net benefiters this implies that the immigrants from non-OECD countries receive fewer benefits than their native counterparts.

The immigrants who arrived in the U.S. within 10 years (recent immigrants) have a fiscal position very similar to that described above for the non-OECD immigrants. Only working-age highly educated are net contributors and only the 65+ population outperform natives with an RFR greater than 1 due to receiving fewer benefits. However, the RFR for recent immigrants of the working-age population is the lowest at approximately 0.7. This is driven by education and household benefits. The education benefits are consumed by the younger age structure of immigrants who are more likely to pursue higher education especially among the high-skilled and the household benefits by other immigrants who are more likely to have children in their household and a relatively weaker economic status compared to the native-born.

Immigrants who have been in the U.S. for more than 10 years outperform natives in both the 25-55, H and 65+ sub-populations. Thus, immigrants from the working-age and highly educated are more likely to become net contributors if they stay in the U.S. long enough. The older population (65+) do better than the natives irrespective of their length of stay in the U.S. In fact, recent immigrants outperform not-recent immigrants in this sub-population. However, for all other subgroups, the immigrants' fiscal position improves the longer they are in the U.S., particularly among the medium-skilled working-age population and the 55-65-year-olds.

Second-generation So far the second-generation adults and children have been treated as natives since they were born in the United States. But due to the arguments put forth in the Methodology section, treating this group separately and estimating their fiscal ratio could be useful. Generally, studies have found that second-generation adults contribute much more than the first-generation.

Table 16 reports the fiscal ratio and RFR for the different sub-populations based on their generational status. First-generation individuals are the same as the immigrants considered in the paper so far. Second-generation are U.S.-born individuals to one or more immigrant parents. Third+ generation are all other native-born individuals. Thus, the results of first-generation are identical to the results of immigrants. The second-generation population which has been growing slowly over the time period is 11.6% of the total population on average. Thus, the results for the third+ generation, which corresponds to 84% of the natives (as defined by country of birth) or 74% of the total population, is nearly identical to the results of natives.

The key takeaway from this table is that the second-generational adults hold a better fiscal position across most sub-populations relative to the first-generation. However, the 65+ old population first-generation holds a better fiscal position than their second-generation counterparts. Another key observation is that apart from the young and low educated working-age population, individuals born to immigrants hold a far better fiscal position than the third-generation, especially during recessions. Observe the fiscal ratio of working-age high educated individuals, during the recession, the second-generation outperformed the third-generation (195% vs 170%) before returning to the same fiscal levels as the third-generation by 2015 (187% vs 186%).

Clearly including the second-generation as part of the first-generation can significantly change the interpretation of the fiscal impact of immigrants. The next table 17 reports the fiscal ratio for each social protection benefit and contributions for the baseline specification and the second-generation specification in an effort to identify the cause and magnitude of these differences.

The fiscal ratio per capita of total benefits[13] increases from 0.96 to 1.13 as soon as the U.S.-born children of foreign-born parents are counted as immigrants. This is because children are net benefiters and including them as immigrants will increase the per capita benefit in health and education. In fact, the per capita education benefits of immigrants in the baseline which was 56% of the natives, increases to 131% of natives in the SG 15- specification. Health per capita also increases from 102% to 119%. None of the other benefits and contributions change since they are apportioned to the adult 15+ population. The fiscal ratio per capita of total contributions in both scenarios was 1.09 which suggests that immigrants contribute more than natives overall[14]. This is mainly driven by sales, grants etc. (which is evenly apportioned per adult), indirect taxes (not including property taxes) and employer contributions.

On including the entire second-generation population (SG All scenario), children and adults, as immigrants, the fiscal ratios of most benefits decreased. Only education per capita benefits and the survivor benefits increase although education benefits per capita increased by less than the SG 15- scenario. Overall, the total benefits per capita decreased relative to the baseline scenario from 0.96 to 0.92. i.e. Under the assumption that second-generation should be considered immigrants since they may not be in the U.S. if not for their parents, the government expenditure on

[13]This measure differs from the previously defined fiscal ratio per capita since this measure includes the under 15 population.

[14]In most results above, the total contributions fiscal ratio had the opposite sign. This difference is because previously the per capita measures were constructed for the 15+ population. In this table the per capita includes children.

immigrants in terms of benefits is less than their expenditure on the third+ generation. However, the government revenue from immigrants also decreases relative to third+ generation if the second-generation are counted as immigrants. This suggests that although second-generation immigrants mostly receive fewer benefits, they are also less likely to contribute to government balances on average.

1.5 Conclusion

The impact of immigration on fiscal balances is widely scrutinised. However, subjective assumptions combined with measurement challenges imply that proclaiming a singular objective figure as the immigrant's fiscal impact would be preliminary and misleading. Socio-economic differences heavily influence the fiscal impact of immigrants and natives. Working-age highly educated immigrants who are net contributors, become net benefiters when old. Moreover, the old age immigrants despite being net benefiters have a more favourable fiscal position relative to natives. In general, immigrants on aggregate hold a better fiscal position than natives, although their net fiscal impact is in the same direction but considerably smaller than that of natives.

The business cycle differences for an immigrant appears to go beyond automatic stabiliser effects and depends instead on the characteristics of the immigrants in the country. As illustrated in appendix section 1.6.1, a simple self-selection model that allows the choice to migrate to depend on age, skill levels and the welfare system can explain some of the unusual trends in immigration. Across the cycle, I find that immigrants' contributions consistently fall below the natives' although there is considerable variation in the likelihood and quantity of benefits received. In general, fewer immigrants receive (make) fewer benefits (contributions) during a recession.

Modifications to fiscal policy and immigration laws both have immediate short-term and long-term effects on immigration and its fiscal impact. Future research can focus on identifying the fiscal impact in counterfactual exercises such as changes to the eligibility criteria of welfare schemes or the legalisation of illegal immigrants by using the fiscal ratio of each type of benefit and contribution discussed in this paper. Subsequent research could also focus on predicting the fiscal impact of immigrants over their lifetimes by applying the current findings to a life-cycle analysis that also takes the country's debt cycle into consideration.

1.6 Appendices

1.6.1 Augmented Selection Model

Changes to immigrant composition fundamentally affect the estimated fiscal impact of immigrants. Thus, the general trends towards an increase in the age and educational status of recent and overall immigrants and cyclical changes due to economic fluctuations have important fiscal implications. In this section, I describe a simple selection model based on Borjas (1987) that uses age and skill based migration selection to explain the data observations from section 1.3 and support the empirical analysis that follows.

The model detailed below describes the important role of age and education in determining an immigrant's decision to migrate. Changes to immigration law or fiscal policy can alter potential income and living standards in the U.S. and directly impact migration decisions. This model uses variation in migration costs due to age and skill to explain general immigration trends as well as the idiosyncratic increase in highly educated old aged immigrants during the Great Recession.

Chiquiar and Hanson (2005) introduce the effect of skill on migration costs by arguing that for a variety of reasons including higher fixed costs for moving, complicated paperwork and borrowing rates, highly educated individuals might find it cheaper to relocate. Thus, the migrant's decision to leave the source country can be shown to depend on returns to skill and inequality in the country. In line with Borjas (1991), they show that there is a negative selection when migration costs are assumed constant but there can be both positive and negative selection when migration costs are decreasing with skill.

In a similar vein, the migrant's age can play a crucial factor in the migrant's decision to relocate. Primarily, older migrants are considered as a vulnerable population and so face extremely high costs to migrate. Compared to immigrants who moved in their early ages, older migrants face a myriad of challenges such as language ability, weak ties to social institutions and difficulty in assimilating with the natives and society, all of which have negative bearings on their abilities to become naturalised citizens (Population Reference Bureau, 2013). Thus older immigrants who do end up migrating tend to be healthier, wealthier and smarter (Wilmoth, 2012). Further, low-income elderly immigrants are less likely to utilise health care arrangements in the U.S. either due to preferences or lack of access. Given that health benefits are a major concern for the elderly, an increase in accessibility or dollar amount of benefits for the older generation can effectively decrease migration costs and change migration decisions.

In the U.S in 2016, 68% of immigrants entered the U.S. on family-sponsored visas and 12% of immigrants entered with employer-sponsored visas (U.S. Department of Homeland Security). Thus, in addition to wages determined by labour markets, migration costs that determine the overall welfare of immigrants such as network support, welfare eligibility, health care, schooling etc. are important considerations for a potential migrant.

Since the 2000s the incoming migrant population has seen a rise of high-skilled workers and a decrease in low-skilled workers even from developing countries which was a marked change compared to the migration demographics in the 90s. The negative selection story of the 1990s cannot possibly explain this shift. A variety of observable and unobservable factors including network effects, the development of Latin America and Asia, the returns to skill as well as the relative social contributions program in the U.S. played an important role in this transformation.

Building on a simple selection model, any potential migrant with a skill level measured by years of schooling s and age a faces the following wage equation in their source country where μ_0^a corresponds to the average wage in the country for an individual with that set of age characteristics:

$$ln\ w_0 = \mu_0^a + \delta_0 s \tag{7}$$

The number of years in school directly increases the wage which is measured by the return to schooling variable δ_0. This model assumes an average wage based on the age profile for each country since the lifetime wage profile is popularly considered to have a concave/hump-shape. In addition to direct income, the average wage μ_0^a can also be interpreted as containing information on the welfare support. This is particularly relevant to the old age immigrants since they may have retired already and could be migrating on a family-sponsored visa.

If an individual migrates to the United States, they will face a similar equation that determines the wage.

$$ln\ w_1 = \mu_1^a + \delta_1 s \tag{8}$$

Here μ_1^a corresponds to the average wage in the U.S. for someone with age a and δ_1 measures the returns to skill or schooling of skill s. The relationship between δ_0 and δ_1 depends on the skill scarcity of the source country relative to the U.S. If the source country has high returns to skills, such as Mexico, then $\delta_0 > \delta_1$ but the reverse may be true for highly developed countries.

In usual fashion, assume C to be migrant costs. Then $\pi = C/w_0$ is migrant costs in time equivalent units which are measured in the number of labours hours. The higher the initial wages, the lower are the individual's migration costs. Since a highly skilled worker earns more than a low-skilled worker, the high-skilled worker will face lower migration costs. Similarly, wages and age have an inverse U relationship, so migration costs are the lowest for a middle-aged immigrant (approximately 45 years of age[15]) . In addition, the older the person is, the more difficult it becomes for them to uproot their entire lives and relocate. Moreover, if they have limited English proficiency or are not very well educated, they may face more difficulty in landing a job or integrating with society, suitably taking advantage of health care and other benefits. On the other hand, young adults may also face higher costs of migration since they may not have the necessary educational qualifications and ability to qualify for benefits.

[15]This is based on the CPS data which shows that individuals around 50 years of age have the highest average wages. Moreover, the results from section 1.4.2 show that immigrants around 45 years of age contribute the most and utilise the least amount of benefits suggesting that they have the least requirements for government or network support.

Thus migration costs can be represented as follows:

$$ln\ \pi = \mu_\pi - \delta_s s + \delta_a |a - \bar{a}| \tag{9}$$

where any individual aged higher or lower than $\bar{a}$ faces higher migration costs. μ_π is the average relocation costs for an individual which can include psychic costs, travel and visa application expenses. δ_s measures the value of an additional year of schooling on decreasing migration costs while δ_a quantifies the increase in costs for a young person and an elderly person. These costs could be further affected by the availability and accessibility to benefits in the host country.

An individual will make the decision to migrate if

$$ln(w_1) > ln(w_0 + C) \quad \equiv ln(w_1) > ln(w_0) + \frac{C}{w_0} \tag{10}$$

$$\equiv ln(w_1) - \pi > ln(w_0) \tag{11}$$

Figure 12 combines equations 7, 8 and 9 to identify the skill support of immigrants of age 'a' who make the decision to migrate. The net income for the individual in the source country is given by a linear line with a slope equal to the return to skill. The net income for the individual in the host country takes the migration costs into account resulting in a quadratic curve. An individual aged $a = \bar{a}$ has the least migration costs due to age. If this individual is from a country with lower levels of schooling or skill development, there is positive selection, wherein people with skills above s_L choose to migrate and others stay back. If this individual is from a country with high levels of schooling or skill, there is negative selection wherein individuals with skills lower than s_H migrate and those with skills greater than s_H do not (Chiquiar and Hanson, 2005).

For any individual older than or younger than $\bar{a}$, the migration costs increase. This can be seen as a downward shift of the net income of the immigrant in the host country (the dotted line in figure 12). This implies that in a country with positive selection, only individuals at the higher end of the skill spectrum choose to migrate since the skill level determining the decision increases from s_L to s'_L. Similarly, in a country with negative selection, only individuals at the lower end of the spectrum migrate[16].

Model implications

Proposition 1: The incentives to migrate are highest for the middle-aged working population. Every individual has an incentive to migrate if equation 11 holds. The difference in incentives between a person aged a and the optimal aged individual of age $\bar{a}$ is given by the '*Age Incentive*': $I_a = -e^{\mu_\pi - \delta_s s}[e^{\delta_a |a-\bar{a}|} - 1] < 0$[17]. This difference in incentives is negative indicating that an older or younger person has fewer incentives to migrate due to increased migration costs. This is the downward shift in the curve in figure 12. Furthermore, the further away from the optimal age, the lower are the incentives to migrate since $\partial I_a / \partial a = -\delta_a e^{-\delta_s s + \delta_a |a-\bar{a}|} < 0$. So for any individual with some given schooling level, which we assume to denote both observable and unobservable skills, the incentives to migrate decreases on either side of $\bar{a}$.

Proposition 2: The decrease in *Age Incentives* is more pronounced among the low-skilled. This is because the age incentives to migrate becomes less negative with skill since $\partial I_a / \partial s = \delta_s s e^{-\delta_s s}[e^{\delta_a |a-\bar{a}|} - 1] > 0$. Thus a low-skilled old (young) age individual will have lower incentives to migrate than a high-skilled old (young) age individual. Logically, the higher-skilled individuals may find it easier to deal with migration costs and so will face lower differences in age incentives. This is consistent with the idea that the older population and the younger population who are generally dependants may face high migration costs but the more highly skilled they are, the easier it may be for them to migrate. Moreover the high-skilled find it easier to assimilate into society, apply for jobs and benefits.

[16]Figure 12 assumes $\delta_0 > \delta_1$, which corresponds to source countries with skill scarcity and high returns to schooling compared to the U.S. But assuming the latter $\delta_1 > \delta_0$ will result in a single crossing denoting that only positive selection can occur from such source countries. Both cases of positive and negative selection are discussed.

[17]This requires the assumption that differences in wages across ages is the same in both countries: $\mu_1^a - \mu_0^a = \mu_1^{\bar{a}} - \mu_0^{\bar{a}}$. This is a less strict assumption than assuming a single average wage that doesn't vary with age in each country.

In the rest of this section, to ensure that the interpretation remains tractable, I will focus on the older population, although the same argument will apply to those younger than $\bar{a}$. A consequence of the above proposition is that the older migrant population on average will have higher levels of schooling than the working-age population simply due to the asymmetry caused by the decrease in age incentives. For an older population, the lower bound increases much more than the decrease in the upper bound $|\triangle s_L| > |\triangle s_H|$[18]. So assuming that the population density is evenly spread out across the age groups, the older population on average would have higher levels of schooling.

So policies designed to decrease migration costs including better transportation, accessible community health services, improved network support etc. such that δ_a decreases, will benefit the lower-skilled more than the high-skilled.

Consider two individuals of the same age who differ only by the level of their schooling or skill. Normalising the skill level of the low-skilled individual to $s = 0$, without loss of generality we can write that the difference in incentives to migrate between the two is given by the '*Skill Incentive*': $I_s = (\delta_1 - \delta_0)s - e^{\mu_\pi + \delta_a|a-\bar{a}|}[e^{-\delta_s s} - 1]$ which can be positive or negative. I_s is always positive if the U.S. has greater returns to schooling: $\delta_1 > \delta_0$, but if the source country has higher returns to schooling: $\delta_0 > \delta_1$, then I_s is only greater than zero if the decrease in migration costs because of skill exceeds the difference in the return to skill between the countries. This is given by: $e^{\mu_\pi + \delta_a|a-\bar{a}|}[1 - e^{-\delta_s s}] > (\delta_0 - \delta_1)s$.

Proposition 3: The age distribution of high-skilled immigrants is more dispersed than the age distribution of low-skilled immigrants if and only if '*Skill Incentives*' are positive. This statement follows from the definition of Skill incentives since $I_s > 0$ implies that a high-skilled has a greater incentive to migrate across all ages (a$\neq \bar{a}$). Thus, there will be a greater number of migrants at the young

[18] The decision to migrate is marked by the bounds s_L and s_H. The individuals at the bounds are indifferent between migrating and face the equation $\mu_0 + \delta_0 s = \mu_1 + \delta_1 s - e^{\mu_\pi - \delta_s s + \delta_a|a-\bar{a}|}$.

Differentiating with respect to a, $\frac{\partial s}{\partial a} = -\frac{\delta_a e^{\mu_\pi - \delta_s s + \delta_a|a-\bar{a}|}}{\delta_0 - \delta_1 - \delta_s e^{\mu_\pi - \delta_s s + \delta_a|a-\bar{a}|}}$.

Using the fact that $\partial s_L/\partial a > 0$ and $\partial s_H/\partial a < 0$, we can rewrite the above to get $\frac{\partial s_L/\partial a}{\partial s_H/\partial a} > 1$

and old ages who are high-skilled than low-skilled. The inverse becomes true when the Skill incentives are negative. Changes to the parameters of the migration costs can change the sign of the skill incentive (from negative to positive) and cause an increase in the concentration of high-skilled immigrants even among the older population.

This can be clearly seen in figure 13 which shows the migration decision across a support of age groups for individuals with high skills $s > 0$ (dotted lines) and individuals with low skill denoted here as a skill of zero $s = 0$ (solid lines) under the assumption that skill incentives are positive. The points of intersection between the net income in the source country (horizontal line) and the net income in the host country minus migration costs (curve) determines the cut-off ages for migration. high-skilled individuals will now migrate if their age is between a'_Y and a'_O while for a low-skilled worker, the age of migration lies between a_Y and a_O[19] The age spectrum for the high-skilled are much wider than the spectrum for the low-skilled, indicating that individuals with higher skills can migrate even if they are significantly older or younger than optimal.

Moreover, $\partial I_s/\partial a = -\delta_a e^{\mu_\pi + \delta_a|a-\bar{a}|}[e^{-\delta_s s} - 1] > 0$ implying that that this increase in incentives to migrate increases more for an individual further away from the optimal age. If 'Skill Incentives' are negative, then this incentive to migrate becomes less negative for an individual who is further away from the optimal age. Thus, with positive 'skill incentives', a lower-skilled individual is more likely to belong to the middle-aged population while the young and the aged are more likely to have high-skilled individuals.

High-skilled old age immigrants during 2008.

The economic situation of a country is crucial in determining the influx of immigrants since wage prospects will decrease in a recession. The Great Recession saw a sharp decline in the incoming immigrant population across all ages and skills except for the

[19] The cut-off ages for the high-skilled are more widespread than that of the low-skilled only if $[1 - e^{-\delta_s S}] > \dfrac{(\delta_0 - \delta_1)s}{(\mu_1 - \mu_0)} >$ which holds when $I_s > 0$ for the low-skilled.

high-skilled 55+ population (see discussion on figure 5 in section 1.3.1). The decrease in μ_1[20] due to the Great Recession will result in a downward shift of the U.S. wage equation, which will decrease the incentives to migrate for all individuals.

A recession originating in the U.S. will negatively impact the migration decision of most immigrants, particularly the young and the elderly population and within these age groups, the low-skilled. Although the high-skilled may be the least affected depending on the age support, skill levels and average wages, they are unlikely to experience any increases in the incentives to migrate. Thus, the explanation for the increase in the high-skilled old age (55+) immigrant population in the U.S. during the Great Recession is not obvious even after accounting for the ageing of the existing population. One explanation for this increase can be attributed to lower migration costs specifically for the older high-skilled population. Since the high-skilled old age immigrants receive the most benefits on average relative to any other immigrant subgroup (see table 4), the decrease in migration costs (δ_a) is most likely to be largest for this population.

Figure 14 shows the migration decision of a high-skilled individual older than the optimal age. The Great Recession which was accompanied by a decrease in average income (μ_1 to μ_1') shifts the net income equation of the U.S. downwards, from the black line to the red line, such that immigrants between the ages of a_O^0 and a_O^1 choose to no longer migrate.

However, eligibility and access to increased benefits could result in a decrease to migration costs (δ_a to δ_a') which can shift the net income equation upwards. If the decrease in migration costs are large enough, then as figure 14 shows, despite the recession, older immigrants will choose to migrate. All individuals below the age of a_O^2, which includes those aged a_O^0 and older, now choose to migrate.

[20]This is under the assumption that the decrease in wage prospects in the U.S. is greater than in the host country ($\Delta\mu_1 > \Delta\mu_0$) which is true for most countries in 2008 since the Recession originated in the U.S. This equivalently implies that μ_1 is decreasing while μ_0 remains unchanged.

1.6.2 Figures and Tables

Table 1: Definition of Nativity, Education and age groups

Sub-populations	Details
Nativity	
Native	Born inside the U.S.
foreign-born	Born outside the U.S.
Origin	OECD
	Non-OECD
Recency	Entered U.S. within 10 years
	More than 10 years
Education	
Low	Upto lower secondary
Medium	Upper secondary to some college
High	Associate/Bachelor degree or higher
Age	
0-15	Children
15-25	Young adults transitioning to working
25-55	working-age population
55-65	Transitioning to retirement
65+	Old age population

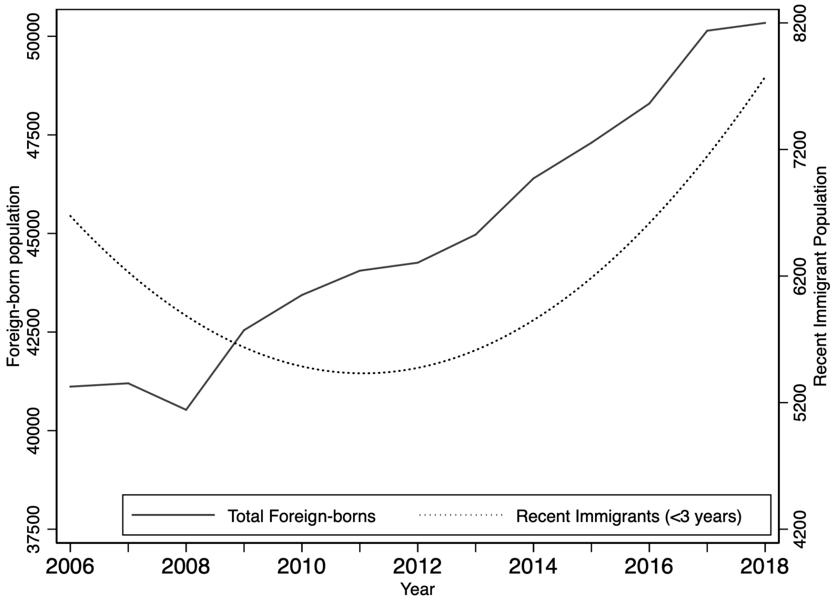
Notes: The OECD category under Origin includes the following countries: Canada, Puerto Rico, U.S. Virgin Islands, Bermuda, Chile, Colombia, Denmark, Finland, Iceland, Norway, Sweden, England, Scotland, Wales, U.K, Ireland, N. Ireland, Belgium, France, Netherlands, Switzerland, Greece, Italy, Portugal, Spain, Austria, Czechoslavakia, Slovakia, Czech Republic, Germany, Hungary, Poland, Estonia, Latvia, Lithuania, Japan, South Korea, Israel, Australia, New Zealand. Non-OECD includes all other countries. Education levels are the highest level of education attained by the individual at the time of the survey.

Table 2: Population composition of immigrants (CPS)

	Total			FB by Recency			FB by Origin	
Year	population	NB	FB	<3 yrs	<10 yrs	>10 yrs	OECD	Non-OECD
2006	296824000	86.15	13.85	2.38	5.43	8.42	2.64	11.21
2007	299105728	86.23	13.77	1.84	5.57	8.20	2.61	11.17
2008	301482816	86.56	13.44	2.13	4.99	8.46	2.50	10.95
2009	304281696	86.02	13.98	1.70	5.55	8.43	2.57	11.41
2010	306553216	85.83	14.17	2.01	4.92	9.25	2.62	11.55
2011	308827264	85.73	14.27	1.56	5.09	9.17	2.62	11.64
2012	311116160	85.77	14.23	1.87	4.29	9.94	2.49	11.73
2013	313413344	85.65	14.35	1.58	4.69	9.65	2.39	11.96
2014	316167936	85.33	14.67	2.01	4.33	10.35	2.42	12.26
2015	318868480	85.17	14.83	1.90	4.84	10.00	2.55	12.29
2016	320372000	84.93	15.07	2.30	4.42	10.66	2.56	12.52
2017	323156096	84.48	15.52	2.02	4.76	10.75	2.59	12.93
2018	324355840	84.48	15.52	2.41	4.48	11.04	2.54	12.98

Notes: This table reports the total population in the United States over the 2006-2018 time period. Columns 3-9 are in percentage terms of the total population for each year. NB denotes native-borns and FB-denotes Foreign-borns or immigrants. Column 5-7 lists the percentage of immigrants who arrived in the United States less than 3 years before, less than 10 years before and more than 10 years before the survey was held. The last two columns correspond to the origin country of the immigrant. OECD corresponds to all the developed countries of the OECD and Non-OECD to all the rest.

Figure 1: Immigration distribution by recency (in 1000s)



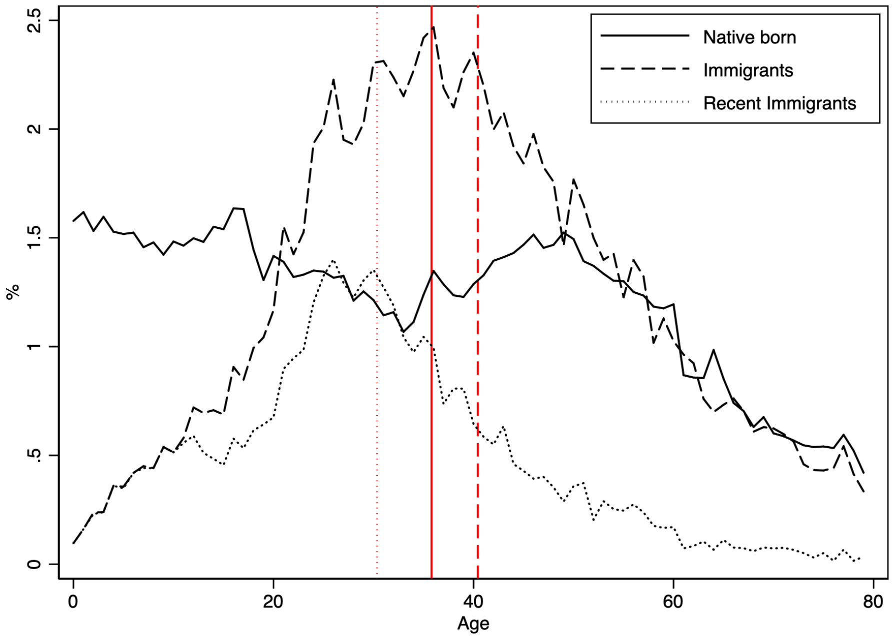
Notes: This figure shows the total immigrant population and the number of recent immigrants. Recent immigrants are identified as immigrants who arrived in the last three years. A quadratic fit of the data has been shown here to emphasise on the trend rather than the data coding limitations.

Table 3: Population composition by age and education (CPS)

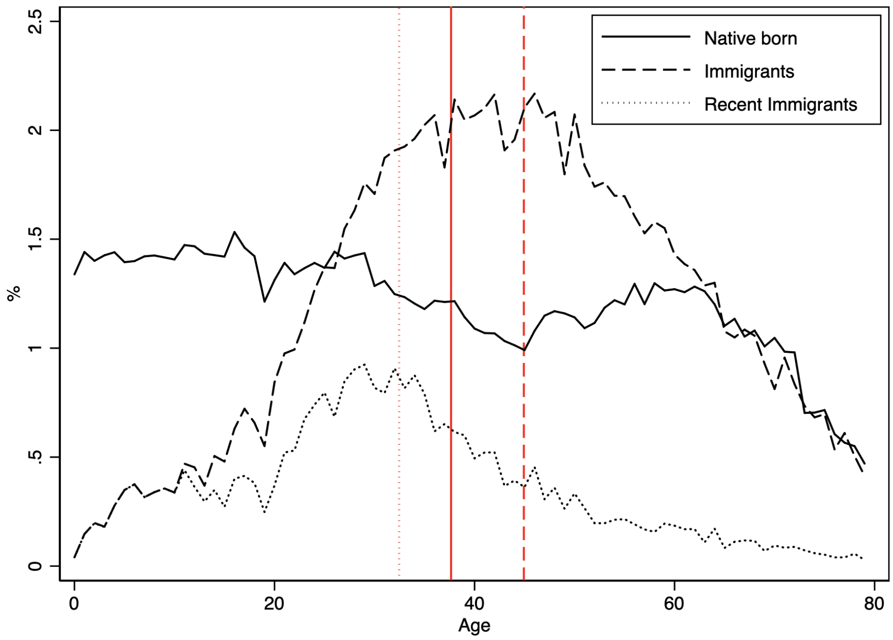
	2006	2009	2012	2015	2018
Total Population (millions)	297	304	311	319	324
Share of immigrants	13.85	13.98	14.23	14.83	15.52
OECD	2.64	2.57	2.49	2.55	2.54
non-OECD	11.21	11.41	11.73	12.29	12.98
Recent (<=10 years)	5.43	5.55	4.29	4.84	4.48
Not-recent (>10 years)	8.42	8.43	9.94	10.00	11.04
Share of 0-15					
In % of total pop	20.48	20.10	19.64	19.12	18.74
in % of native pop	22.73	22.48	22.12	21.67	21.31
in % of immigrants	6.52	5.51	4.66	4.48	4.71
in % of OECD	6.64	5.17	5.85	5.61	5.89
in % of non-OECD	6.49	5.59	4.41	4.25	4.48
Share of 55+					
In % of total pop	22.99	24.62	26.29	27.81	29.15
in % of native pop	23.24	24.74	26.37	27.69	28.93
in % of immigrants	21.39	23.84	25.80	28.51	30.36
in % of OECD	36.60	37.51	39.07	40.39	40.46
in % of non-OECD	17.81	20.75	22.99	26.05	28.38
in % of recent immigrants	7.04	8.68	8.84	9.92	10.69
in % of not-recent immigrants	30.64	33.82	33.12	37.50	38.35
Share of low-skilled					
In % of total pop	7.66	6.91	6.46	6.06	5.58
in % of native pop	5.37	4.71	4.31	3.94	3.57
in % of immigrants	21.92	20.42	19.45	18.23	16.52
in % of OECD	10.64	10.06	8.08	6.74	5.75
in % of non-OECD	24.57	22.76	21.86	20.61	18.63
in % of recent immigrants	22.27	20.92	17.98	14.58	11.22
in % of not-recent immigrants	21.69	20.10	20.08	20.00	18.68
Share of high-skilled					
In % of total pop	25.79	27.12	29.17	30.91	33.33
in % of native pop	25.34	26.49	28.59	30.24	32.52
in % of immigrants	28.60	31.03	32.69	34.80	37.72
in % of OECD	37.35	39.04	41.69	44.43	49.47
in % of non-OECD	26.54	29.22	30.78	32.80	35.42
in % of recent immigrants	24.51	26.68	30.36	34.32	38.08
in % of not-recent immigrants	31.23	33.89	33.70	35.02	37.58

Notes: This table lists the age and education breakdown of the total population, natives and immigrants, who are further divided based on country of origin and recency of arrival.

Figure 2: Age distribution over time



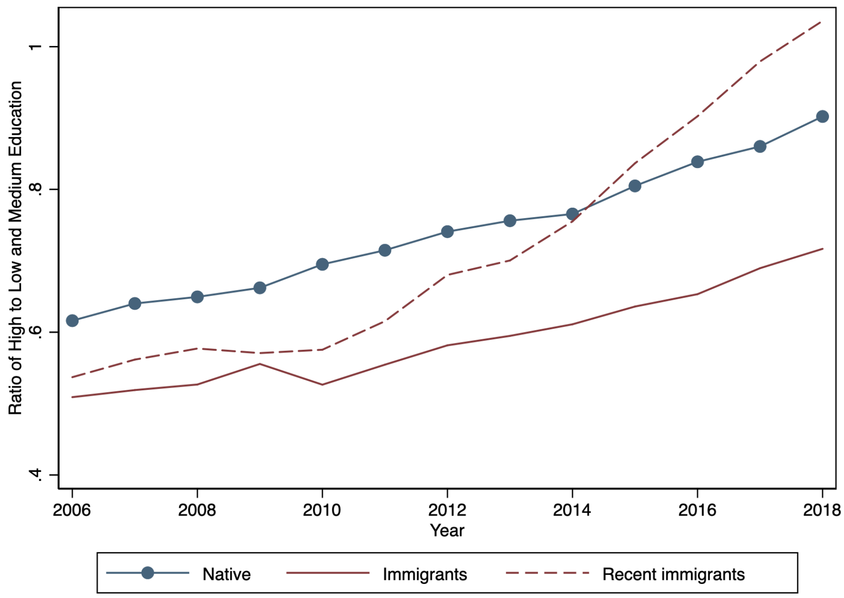
(a) 2006



(b) 2018

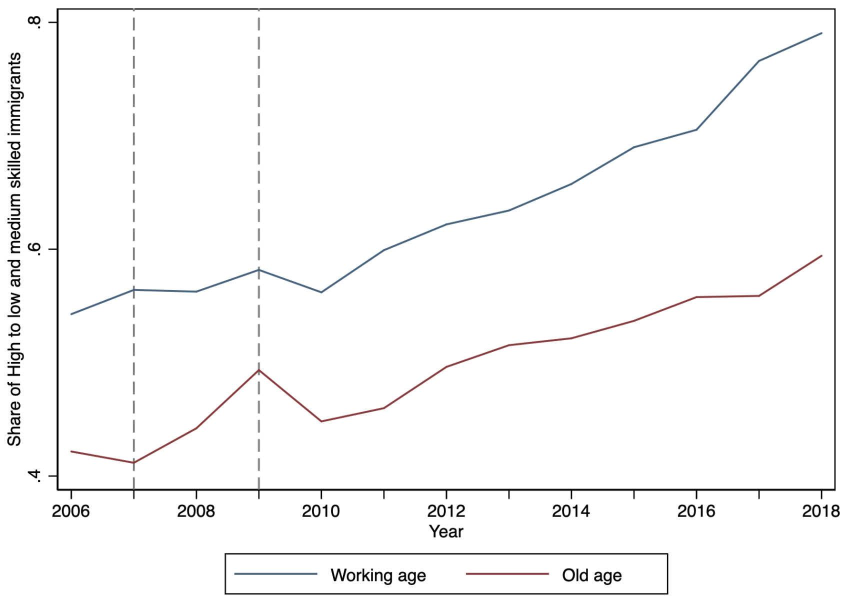
Notes: This figure maps the age distribution of the native population and immigrant population for 2006 and 2018. The age distribution of recent immigrants is as a percentage of total immigrants. The average age (identified by the vertical lines) of the natives increased from 35.8 to 37.7 while the average age of immigrants (recent immigrants<10 years) increased from 40.4 (30.4) to 44.9 (32.5) years from 2006 to 2018

Figure 3: Education distribution by nativity over time



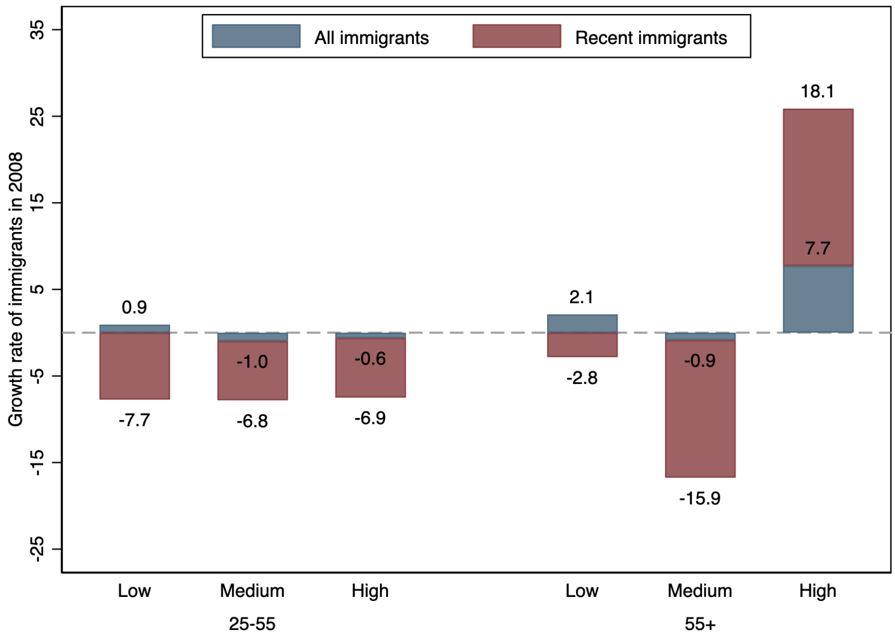
Notes: This figure shows the ratio of high-skilled to low and medium-skilled individuals for the natives, immigrants and recent immigrants (who arrived less than 10 years ago). This figure only considers individuals aged 25 years and above.

Figure 4: Population of immigrants by age and education over time



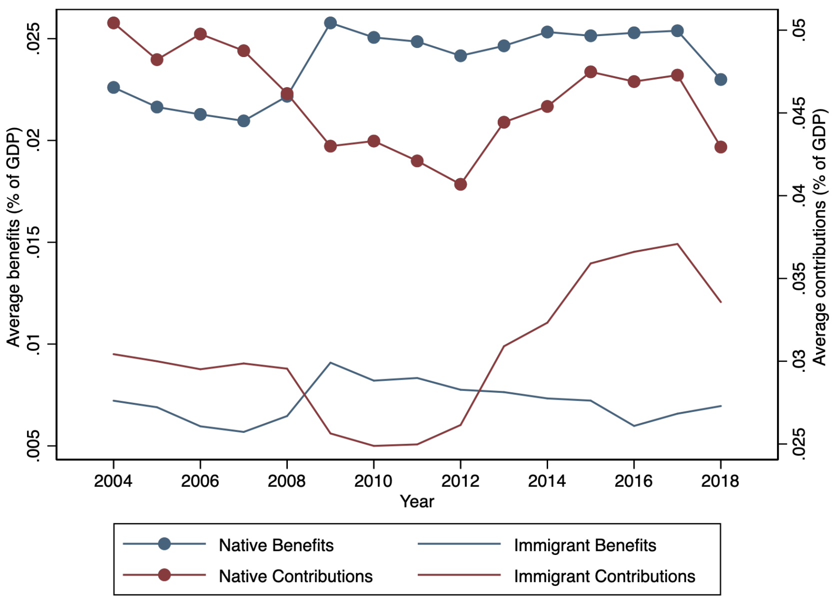
Notes: This figure shows the ratio of high-skilled to low and medium-skilled for the working-age (25-55) and old age (55+) immigrants over time. The vertical lines mark the beginning and end of The Great Recession.

Figure 5: Growth rate of age-education-recency immigrant sub-populations in 2008



Notes: This figure highlights the growth rate of recent immigrants (<10 years) and all immigrants by age-education sub-categories in 2008. The total immigrant population decreased by 1.6% (0.7 million) in 2008.

Figure 6: Average benefits and contributions of recent immigrants over time



Notes: This figure shows the average overall benefits and average contributions (as a percentage of GDP) of natives and recent immigrants (those who arrived within the last ten years), over time.

Table 4: Average benefits and contributions per sub-population

Age	Edu	Nativity	Benefits Overall	Benefits Individual	Benefits Household	Contributions
All	All	Native	3867.11	3477.74	389.37	7197.41
		Foreign-born	2856.51	2137.37	719.14	5834.23
15-25	L	Native	1124.43	27.58	1096.86	4462.34
		Foreign-born	1214.53	28.05	1186.48	2229.85
	M	Native	724.09	81.27	642.82	4650.82
		Foreign-born	824.48	51.88	772.60	3014.37
	H	Native	319.68	105.65	214.03	6774.51
		Foreign-born	309.56	57.96	251.61	5446.95
25-55	L	Native	1550.48	380.53	1169.95	2165.80
		Foreign-born	1713.18	199.99	1513.20	1225.15
	M	Native	1316.23	449.05	867.18	5207.78
		Foreign-born	1345.47	250.11	1095.36	3486.11
	H	Native	830.39	352.52	477.87	12563.87
		Foreign-born	744.56	223.97	520.58	11821.17
55-65	L	Native	4823.24	4332.39	490.85	2020.16
		Foreign-born	2462.39	1896.05	566.34	2189.41
	M	Native	4494.85	4287.25	207.60	5964.30
		Foreign-born	2568.89	2257.40	311.49	4881.88
	H	Native	5035.21	4943.23	91.99	13535.66
		Foreign-born	2610.38	2449.41	160.97	11658.60
65+	L	Native	13420.86	13226.09	194.78	1089.24
		Foreign-born	9120.81	8698.00	422.81	1630.57
	M	Native	17272.07	17182.81	89.26	2633.05
		Foreign-born	12534.86	12326.42	208.44	2750.91
	H	Native	25420.97	25377.39	43.58	7263.91
		Foreign-born	17327.49	17189.90	137.60	7295.82

Notes: This table reports the average amount of benefits and contributions per sub-population. Individual benefits includes sickness, disability, old age (which includes social security and supplemental security income), survivor income and unemployment benefits. Household benefits includes family and children and social exclusion benefits. Overall benefits includes all of the above and contributions correspond to employee contributions such as direct taxes and social security contributions.

Table 5: National Accounts (% of GDP)

Year	2006	2009	2012	2015	2018
Expenditure	36.7	43.3	40.2	37.9	37.8
Health	7.4	8.7	8.7	9.1	9.3
Education	6.2	6.8	6.3	6.1	5.9
Sickness and disability	0.8	1.0	1.0	0.9	0.8
Old age and Survivors	4.5	5.5	5.3	5.5	5.5
Family and children	0.6	0.6	0.5	0.5	0.5
Unemployment	0.2	0.7	0.4	0.1	0.1
Housing and social exclusion	0.7	0.9	0.9	0.8	0.7
Public Debt	1.6	1.3	1.4	1.2	1.6
Defence	3.9	4.6	4.2	3.3	3.2
Other public goods	14.7	17.8	15.8	13.7	13.5
Revenue	33.3	30.1	31.0	33.3	31.6
Income Tax	13.0	9.4	11.4	12.9	11.6
Employee social contribution	3.4	3.5	2.7	3.5	3.6
Capital Tax	0.2	0.2	0.1	0.1	0.1
Employer social contribution	3.3	3.2	3.2	3.2	3.1
Tax on products and production	7.2	7.1	7.0	7.0	7.0
Other revenue	6.2	6.7	6.5	6.7	6.3

Notes: This table lists the main categories of the U.S. general government expenditures and revenue as a percentage of GDP.

Table 6: Probability of various items of benefits and contributions

	All immigrants			
	Differential Probability	Probability of natives	Differential Probability	Probability of natives
Sickness and disability	-0.0015***	0.0069	-0.0030***	0.0073
Old age benefits	-0.0239***	0.9546	-0.0240***	0.9546
Survivor benefits	-0.0054***	0.0102	-0.0039***	0.0062
Unemployment benefits	-0.1773***	0.3818	-0.0075***	0.0269
Individual benefits	-0.2196***	0.4394	-0.1045***	0.2339
Family and children	0.1587***	0.2574	0.1069***	0.2920
Social exclusion	0.1643***	0.1572	0.1363***	0.1930
House subsidy	0.0045***	0.0362	0.0110***	0.0334
Household benefits	0.1905***	0.3434	0.1223***	0.3101
Overall benefits	-0.0293***	0.7154	0.0475***	0.6517
Employer contributions	0.0307***	0.8553	0.0443***	0.8627
Household contributions	-0.0721***	0.8490	-0.0639***	0.8214
Property taxes	-0.2484***	0.7124	-0.1796***	0.7150
Overall contributions	-0.0740***	0.9266	-0.0671***	0.9093
Year	Yes		Yes	
Age	No		Yes	
Education	No		Yes	
Sex	No		Yes	
Immigrant*Year	Yes		No	
Age*Education	No		Yes	

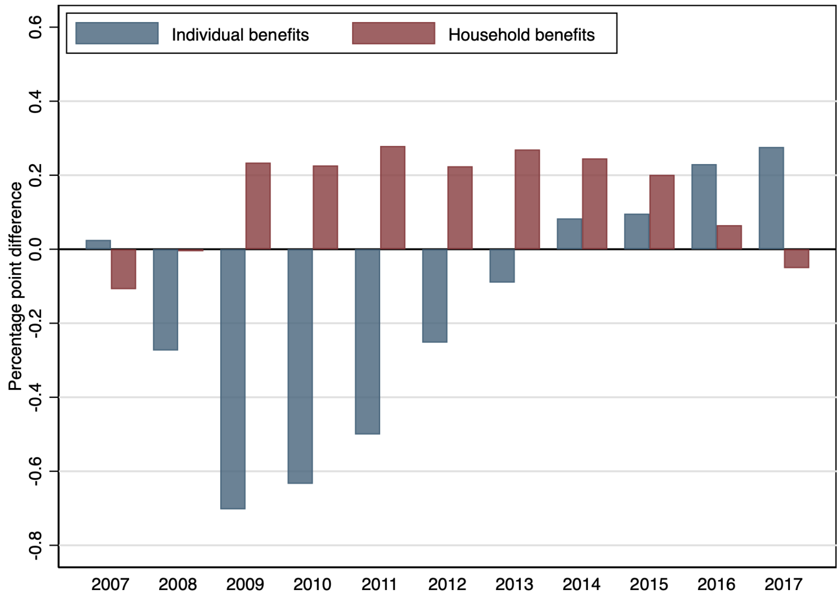
Notes: This table provides the predicted probability of natives and the differential of immigrants from natives for two separate linear probability regressions for each type of benefit and contribution as defined in the Data section 1.3.2. *** Denotes significance at 1%

Table 7: Probability of receiving benefits and making contributions by subgroups

	Benefits			Contributions
	Individual	Household	Overall	
By immigrant population				
All	-0.116***	0.122***	0.021***	-0.043***
	(0.236)	(0.310)	(0.650)	(0.914)
Recent	-0.166***	0.105***	0.017***	-0.087***
	(0.232)	(0.302)	(0.646)	(0.915)
OECD	-0.051***	0.006***	-0.031***	-0.019***
	(0.241)	(0.297)	(0.649)	(0.916)
By Age and Education				
15-25	-0.030***	0.101***	0.028***	-0.056***
	(0.049)	(0.612)	(0.633)	(0.882)
25-55, L	-0.098***	0.0875***	0.021***	-0.080***
	(0.197)	(0.705)	(0.788)	(0.779)
25-55, M	-0.078***	0.104***	0.028***	-0.056***
	(0.146)	(0.577)	(0.642)	(0.882)
25-55, H	-0.046***	0.110***	0.030***	-0.022***
	(0.077)	(0.459)	(0.510)	(0.969)
55-65	-0.142***	0.092***	0.030***	-0.037***
	(0.339)	(0.230)	(0.467)	(0.937)
65+, L	-0.094**	0.102***	0.010***	-0.085***
	(0.909)	(0.299)	(0.929)	(0.753)
65+, M	-0.086***	0.070***	0.010***	-0.064***
	(0.919)	(0.137)	(0.929)	(0.856)
65+, H	-0.109**	0.050***	0.014***	-0.042***
	(0.882)	(0.082)	(0.883)	(0.925)

Notes: This table lists the differential probability of immigrants from natives in receiving individual, household and overall benefit as well as in making contribution as defined in the section 1.3.2. The predicted probability of natives for every probit regression is provided in parenthesis below the differential probability. This is the estimated marginal effect from the probit model which estimated at the mean value of all other regressors. The regressions by immigrant population were conditioned on the following regressors: Year (2004-2019), Age, a dummy variable split into the five categories, Education, a dummy divided into three categories defined in the section 1.2.2, Gender and interactions terms between the Age and Education dummies, and between the Year and Immigrant status dummies. The regressions by Age and Education include the Year dummy, interacted with the Immigrant status dummy, Gender dummy and the dummy variable with the 8 categories of Age and Education listed above. *** Denotes significance at 1%

Figure 7: Differential probability of receiving individual and household benefits over time



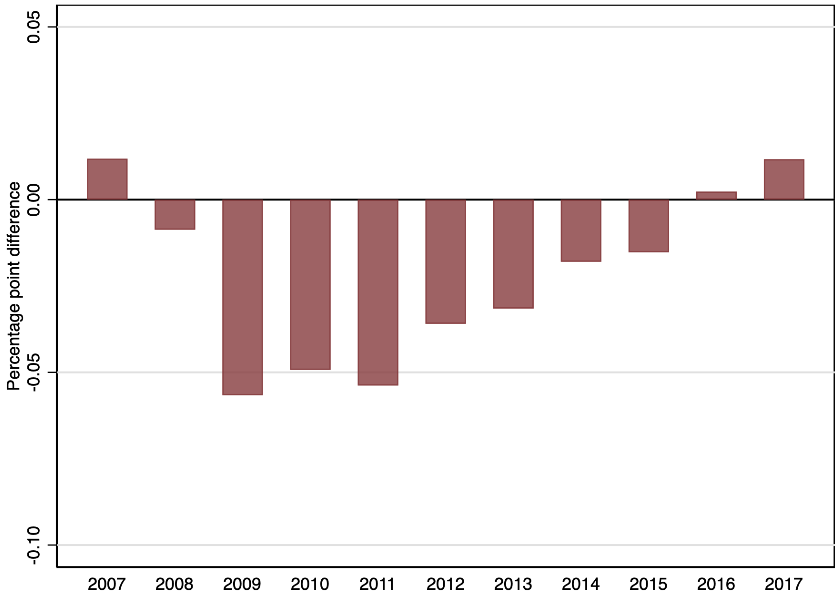
Notes: The figures above graph the differential probability of an immigrant (vs a native) relative to the base year 2006. (a) shows the differential probability of individual and household benefits separately while (b) shows the differential probability of overall contributions. All the estimated marginal effects were significant at a 1% level.

Table 8: Predicted probability of receiving benefits and making contributions in 2006

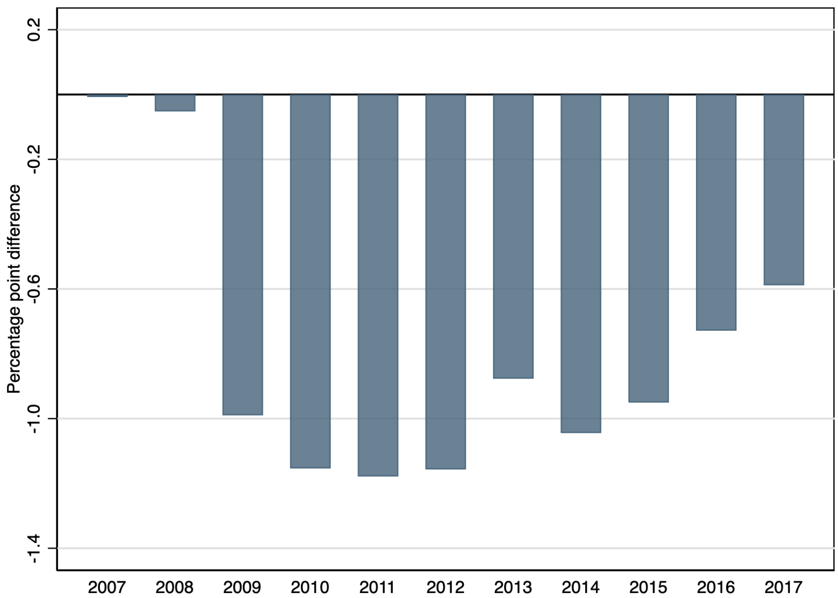
	Benefits			Contribution
2006	Individual	Household	Overall	
Natives	22.9%	29.9%	63.7%	93.4%
Immigrants	11.6%	42.2%	65.9%	89.6%

Notes: This table provides the underlying base outcomes shown in figures 7, 8a and 8b, i.e. the predicted probability of natives and immigrants in receiving individual, household and overall benefits and making contributions of the base year 2006.

Figure 8: Differential probability of receiving benefits and making contributions over time



(a) Overall benefits



(b) Contributions

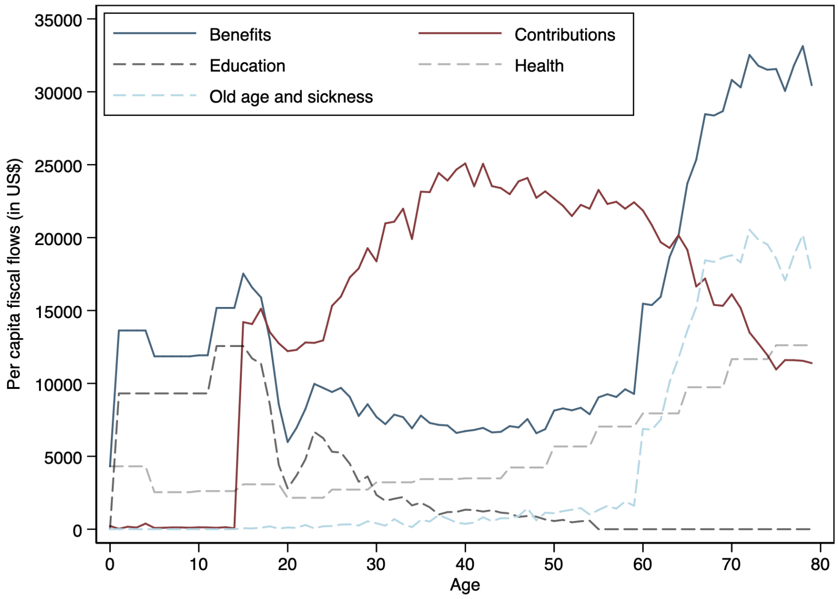
Notes: The figures above graph the differential probability of an immigrant (vs a native) relative to the base year 2006. (a) shows the differential probability of individual and household benefits separately while (b) shows the differential probability of overall contributions. All the estimated marginal effects were significant at a 1% level.

Table 9: Net contribution to fiscal balances

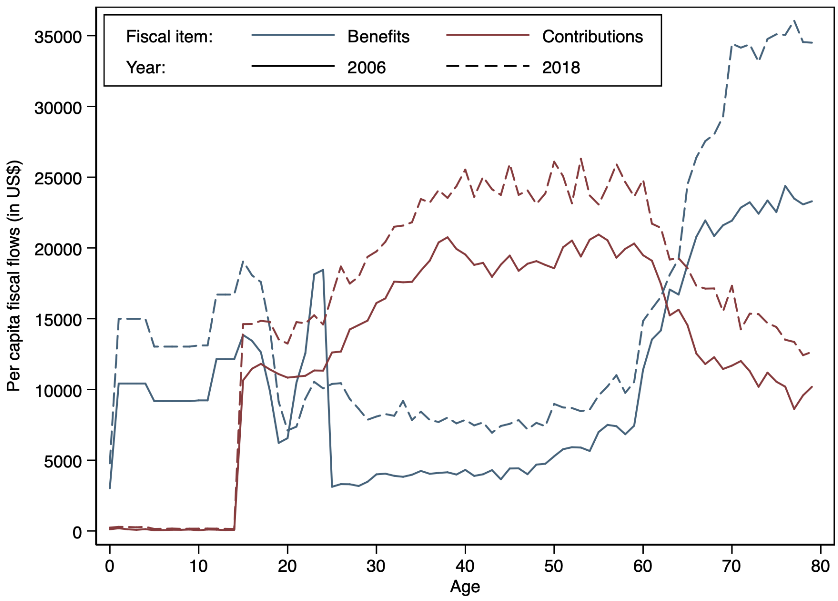
	2006	2009	2012	2015	2018
	Overall contribution (in billions)				
Fiscal balance	-461	-1897	-1493	-837	-1283
Natives	-425	-1670	-1308	-795	-1163
Immigrants	-36	-226	-186	-42	-119
	Contribution (percent of GDP)				
Fiscal balance	-3.33	-13.13	-9.22	-4.59	-6.22
Natives	-3.08	-11.56	-8.07	-4.36	-5.64
Immigrants	-0.26	-1.57	-1.15	-0.23	-0.58
	Fiscal ratio (in %)				
Natives	90.32	69.07	76.61	86.52	82.41
Immigrants	94.73	73.38	79.93	95.84	89.88
OECD	103.24	84.13	91.93	106.40	102.66
Non-OECD	92.29	70.64	76.99	93.29	87.12
Recent	82.33	64.88	70.85	86.30	83.67
Not-recent	101.36	78.06	83.33	99.89	92.21
	Net contribution per capita (in USD)				
Natives	-1662	-6381	-4901	-2928	-4245
Immigrants	-866	-5322	-4192	-889	-2373
OECD	622	-3492	-1891	1551	701
Non-OECD	-1216	-5735	-4681	-1394	-2949
Recent	-2580	-6286	-5510	-2674	-3468
Not-recent	240	-4688	-3624	-24	-1897
	Net contribution per resident (in USD)				
Natives	-1432	-5489	-4203	-2494	-3586
Immigrants	-120	-744	-596	-132	- 368

Notes: Author's calculations using the Apportioning criteria described in Appendix section 1.6.3 under the baseline scenario. The fiscal ratio estimation is done using the baseline assumption that all public goods are apportioned equally between the adult population of the U.S. irrespective of the country of birth. Please see section 1.6.4 for definitions of net contribution per capita and per resident.

Figure 9: Fiscal flows per capita across age



(a) 2015



(b) 2006 vs 2018

Notes: This figure graphs the fiscal flows per capita across the various age groups. The sub figure 9a, shows the net fiscal flows per capita in the year 2015 for the entire U.S. population. Sub figure 9b shows net fiscal flows per capita of benefits and contributions for the years 2006 and 2018. The fiscal flows for total benefits includes all the individualised benefits such as education, health and all social protection benefits. The fiscal flows for total contributions includes all the individualised contributions (this includes all contributions except sales, grants and others). The fiscal flows of education, health and old age and sickness are individually depicted in sub figure 9a.

Table 10: Relative fiscal ratio (base)

Age	Education	Nativity	Fiscal Ratio (%) 2006	2009	2012	2015	2018	Relative fiscal ratio (FB/NB) 2006	2009	2012	2015	2018
15-25	L	Native	61.7	50.4	56.2	69.0	64.8					
		Foreign-born	52.3	41.5	49.6	56.2	55.1	0.8	0.8	0.9	0.8	0.9
	M	Native	93.5	69.7	79.3	93.0	89.8					
		Foreign-born	75.4	55.3	62.2	75.6	76.6	0.8	0.8	0.8	0.8	0.9
	H	Native	29.2	23.8	61.4	69.1	73.0					
		Foreign-born	20.9	17.2	41.6	46.2	45.0	0.7	0.7	0.7	0.7	0.6
25-55	L	Native	72.9	51.5	56.4	71.1	72.5					
		Foreign-born	65.9	45.6	49.6	66.8	61.3	0.9	0.9	0.9	0.9	0.8
	M	Native	**121.9**	87.9	95.5	**116.0**	**108.6**					
		Foreign-born	99.6	71.4	75.7	94.1	88.7	0.8	0.8	0.8	0.8	0.8
	H	Native	**224.5**	**172.3**	**155.9**	**185.9**	**171.3**					
		Foreign-born	**213.1**	**159.3**	**149.1**	**175.2**	**162.3**	0.9	0.9	1.0	0.9	0.9
55-65	L	Native	55.5	36.8	50.4	51.4	53.1					
		Foreign-born	59.4	43.8	49.2	57.7	53.7	**1.1**	**1.2**	1.0	**1.1**	**1.0**
	M	Native	90.7	70.2	78.1	84.7	86.1					
		Foreign-born	93.5	70.5	72.8	85.0	78.8	**1.0**	**1.0**	0.9	**1.0**	0.9
	H	Native	**155.8**	**116.7**	**139.4**	**151.8**	**145.7**					
		Foreign-born	**156.1**	**128.6**	**119.0**	**160.7**	**145.7**	**1.0**	**1.1**	0.9	**1.1**	**1.0**
65 +	L	Native	33.2	25.2	25.9	32.6	30.8					
		Foreign-born	40.5	33.1	36.4	40.1	32.5	**1.2**	**1.3**	**1.4**	**1.2**	**1.1**
	M	Native	40.8	31.7	34.6	37.0	37.0					
		Foreign-born	42.4	40.6	39.4	44.3	41.1	**1.0**	**1.3**	**1.1**	**1.2**	**1.1**
	H	Native	54.9	44.6	51.6	53.9	52.9					
		Foreign-born	67.0	52.9	62.0	68.5	61.6	**1.2**	**1.2**	**1.2**	**1.3**	**1.2**

Notes: This table displays the fiscal ratio (FR) and Relative Fiscal Ratio (RFR) of the different populations of natives and immigrants, The Age and Education sub-divisions are defined in section 1.2.2. This table only shows the baseline specification and the details of measuring the FR and RFR are detailed in section 1.2.2 and in Appendix section 1.6.3. Bold font: The fiscal ratios that are greater than 100 indicating a net contributing sub-population. The relative fiscal ratios that are greater than 1 indicating a sub-population in which immigrants hold a better fiscal position.

Table 11: Breakdown by benefits

Age	Education	Nativity	Health	Education	Sickness	Old age	Survivors	Unemployment	Family	Housing	Social exclusion
Per capita benefits											
15 - 25	All	Native	2274	8766	74	0	43	54	385	192	506
		Foreign-born	2173	9194	27	0	13	50	403	207	650
25-55	L	Native	3399	161	872	0	87	217	522	389	1046
		Foreign-born	3302	39	225	0	8	204	809	203	1229
	M	Native	3321	81	664	0	113	364	535	190	631
		Foreign-born	3244	93	277	0	48	241	680	178	795
	H	Native	3280	1620	454	0	194	238	447	43	174
		Foreign-born	3250	1965	222	0	69	197	440	68	238
55 - 65	All	Native	6461	0	1516	3228	514	274	68	111	155
		Foreign-born	6444	0	965	1495	217	272	148	170	267
65 +	All	Native	10570	0	510	15660	1308	0	28	149	82
		Foreign-born	10464	0	412	10231	650	0	93	365	242
Relative Fiscal Ratio											
15 - 25	All	Native									
		Foreign-born	0.96	1.05	0.37	0.00	0.31	0.91	1.05	1.08	1.29
25-55	L	Native									
		Foreign-born	0.97	0.24	0.26	0.00	0.09	0.94	1.55	0.52	1.18
	M	Native									
		Foreign-born	0.98	1.16	0.42	0.00	0.43	0.66	1.27	0.94	1.26
	H	Native									
		Foreign-born	0.99	1.21	0.49	0.00	0.35	0.83	0.98	1.59	1.37
55 - 65	All	Native									
		Foreign-born	1.00	-	0.64	0.46	0.42	0.99	2.18	1.53	1.73
65 +	All	Native									
		Foreign-born	0.99	-	0.81	0.65	0.50	-	3.37	2.46	2.94

Notes: This table reports the average benefits per capita (in USD) used by each sub-population for each type of benefit during 2006-2018. Apportioning criteria are detailed in section 1.6.3. The bottom section of the table measures the relative fiscal ratio for each benefit of each sub-population.

Table 12: Breakdown by contributions

Age	Education	Nativity	Indirect tax	Household contributions	Employer contributions
Per capita revenue					
15 - 25	All	Native	3557	6808	1668
		Foreign-born	2730	4354	1344
25-55	L	Native	2455	3660	1140
		Foreign-born	2392	1746	1278
	M	Native	3864	7500	2070
		Foreign-born	3320	4916	1784
	H	Native	6475	17687	3440
		Foreign-born	6059	16504	3213
55 - 65	All	Native	5128	12905	2291
		Foreign-born	4418	9665	2006
65 +	All	Native	4481	6052	723
		Foreign-born	4054	5687	912
Relative Fiscal Ratio					
15 - 25	All	Native			
		Foreign-born	0.77	0.64	0.81
25-55	L	Native			
		Foreign-born	0.97	0.48	1.12
	M	Native			
		Foreign-born	0.86	0.66	0.86
	H	Native			
		Foreign-born	0.94	0.93	0.93
55 - 65	All	Native			
		Foreign-born	0.86	0.75	0.88
65 +	All	Native			
		Foreign-born	0.90	0.94	1.26

Notes: This table reports the average contributions per capita (in USD) used by each sub-population for each type of contribution during 2006-2018. Apportioning criteria are detailed in section 1.6.3. The bottom section of the table measures the relative fiscal ratio for each benefit of each sub-population. Household contributions include direct taxes and Medicare contributions unlike employer contributions which only consider social security contributions. Indirect tax includes property taxes in addition to VAT.

Table 13: Benefits breakdown

RFR (FB/NB) in 2016	(1)	(2)	(3)	(4)
	Per capita (15+)		Non-zero benefit	Per recipient
Survivors	0.31		0.38	0.82
Sickness	0.47		0.56	0.84
Family	1.47		1.40	1.05
Housing	1.23		0.91	1.35
Social exclusion	1.64		1.61	1.02
	Per capita (15+)	Share of 60+	Non-zero benefit	Per recipient
Old age	0.48	0.80	0.99	0.60
	Per capita (15+)	Share of 15-64	Non-zero benefit	Per recipient
Unemployment	0.90	1.05	0.43	2.01

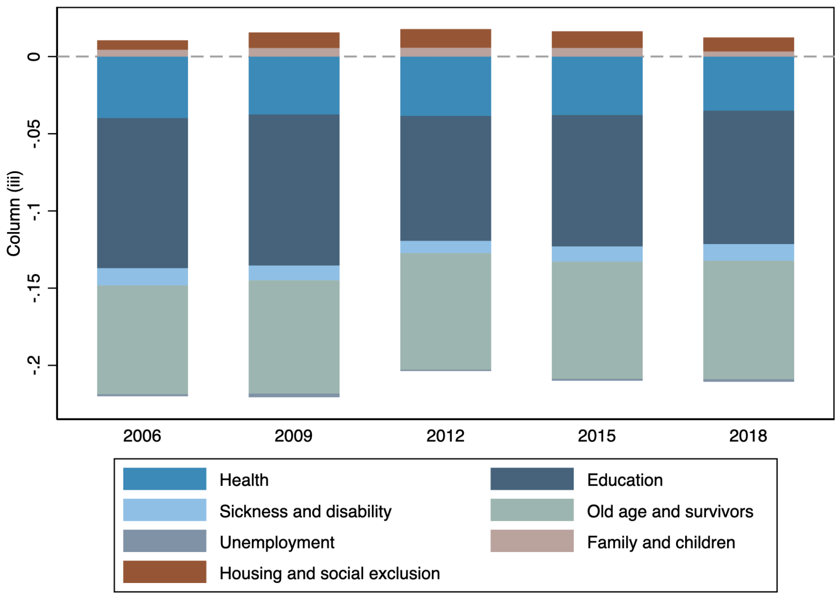
Notes: This table displays the RFR per capita in 2016 for each type of individual benefit (column 1), the relative share of non-zero beneficiaries (column 3) and the RFR per recipient (column 4). See section 1.6.5 for the detailed definition. Example: immigrants receive almost half the old age benefits as natives (1), but there are less 60+ immigrants than natives (2) although the share of 60+ who receive non-zero benefits are the same for immigrants and natives (3), so in reality the average immigrant recipient receives 60% of the old age benefits that an average native recipient would receive. (1) = (2)*(3)*(4)

Table 14: Distribution of benefits relative to native

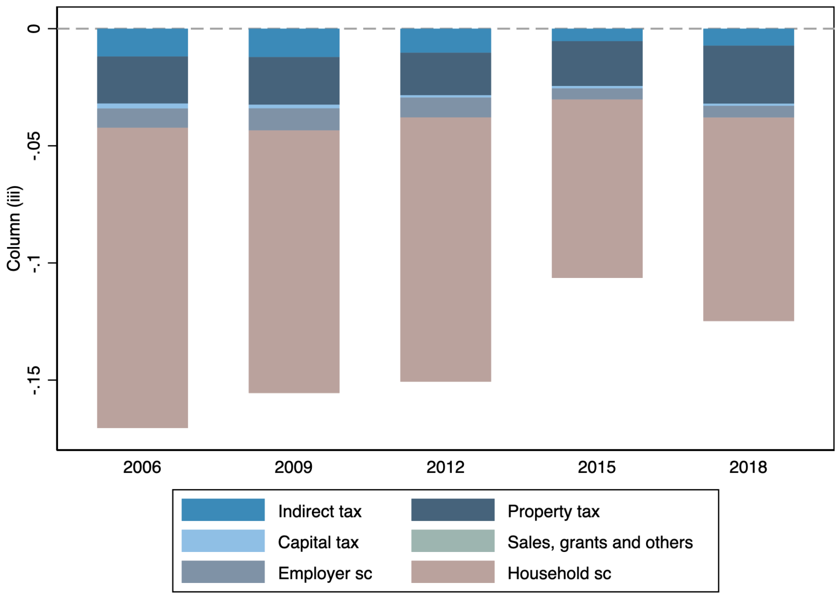
2016	Share in native's budget	Ratio pc	((ii) -1) *(i)
	(i)	(ii)	(iii)
Health	0.24	0.84	-0.04
Education	0.17	0.46	-0.09
Sickness	0.02	0.47	-0.01
Old age	0.14	0.49	-0.07
Survivors	0.01	0.31	-0.01
Unemployment	0.00	0.95	0.00
Family	0.01	1.47	0.01
House allowance	0.00	1.23	0.00
Social exclusion	0.01	1.64	0.01
			-0.21

Notes: This table reports the differences in per capita benefits for each of the different items, the share of each benefit in the native's budget and the difference in total benefits per capita. The shares in column (i) do not add up to 1 since public goods (assumption of marginal cost allocation) accounts for the missing 0.38. See section 1.6.6 for more details.

Figure 10: Decomposition of per capita differences (fb/nb) across time



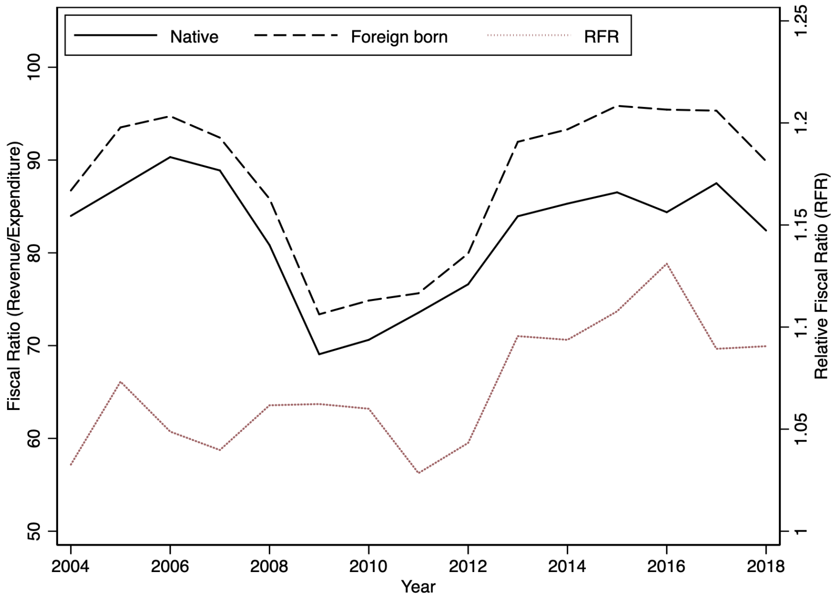
(a) Benefits



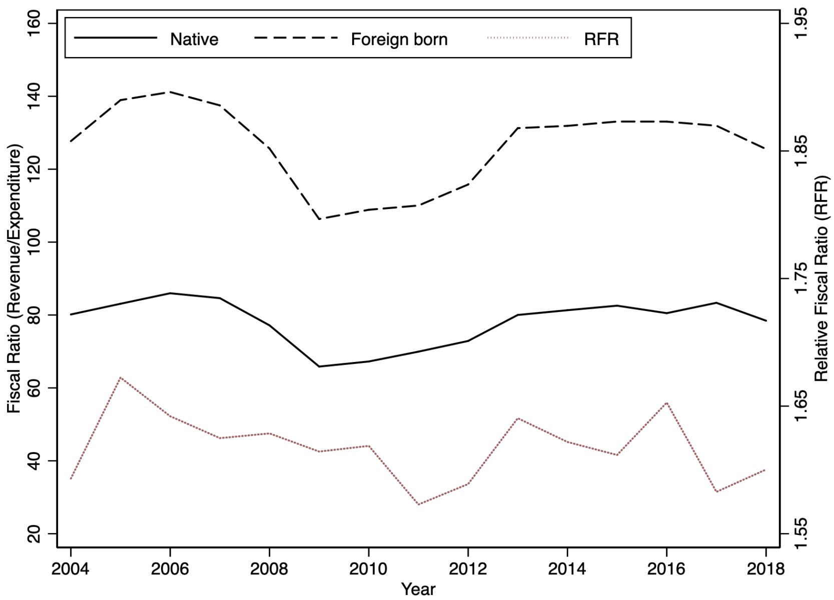
(b) Contributions

Notes: This figure shows the decomposition of the differences in benefits per capita between immigrants and natives over time, as detailed in Appendix 1.6.6. For items above the zero line, immigrants receive (give) more benefits (contributions) and vice versa.

Figure 11: Fiscal ratio of foreign-born over native over time



(a) Average cost scenario



(b) Marginal cost scenario

Notes: This figure shows the fiscal ratio of natives and immigrants (left axis) and the relative fiscal ratio denoted by the red line (right axis) under two scenarios. The average cost scenario attributes the pure public goods expenditure equally to adult natives and immigrants. The marginal cost scenario assumes that the marginal cost of pure public goods expenditure on an additional immigrant is zero and so attributes the expenditure entirely on adult natives.

Table 15: Fiscal ratio by country of origin and arrival date

	Age, Edu	Fiscal Ratio (%)					Relative fiscal ratio (FB/NB)				
		2006	2009	2012	2015	2018	2006	2009	2012	2015	2018
Natives	15-25	70	54	72	85	82					
	25-55, L	73	51	56	71	72					
	25-55, M	**122**	88	96	**116**	**108**					
	25-55, H	**225**	**172**	**156**	**186**	**171**					
	55-65	**115**	89	**104**	**113**	**112**					
	65+	44	35	40	44	44					
OECD	15-25	58	53	69	92	**106**	0.8	1.0	1.0	**1.1**	**1.3**
	25-55, L	75	45	52	67	88	**1.0**	0.9	0.9	0.9	**1.2**
	25-55, M	**131**	94	99	**119**	**123**	**1.1**	**1.1**	**1.0**	**1.0**	**1.1**
	25-55, H	**245**	**177**	**179**	**215**	**199**	**1.1**	**1.0**	**1.1**	**1.2**	**1.2**
	55-65	**120**	**103**	**101**	**129**	**120**	**1.1**	**1.2**	1.0	**1.1**	**1.1**
	65+	44	42	46	48	45	**1.0**	**1.2**	**1.2**	**1.1**	**1.0**
Non-OECD	15-25	51	38	53	61	58	0.7	0.7	0.7	0.7	0.7
	25-55, L	65	46	50	67	61	0.9	0.9	0.9	0.9	0.8
	25-55, M	94	67	72	90	84	0.8	0.8	0.8	0.8	0.8
	25-55, H	**204**	**155**	**142**	**166**	**154**	0.9	0.9	0.9	0.9	0.9
	55-65	**102**	79	80	**102**	96	0.9	0.9	0.8	0.9	0.9
	65+	52	43	46	54	48	**1.2**	**1.2**	**1.1**	**1.2**	**1.1**
Recent	15-25	51	38	51	59	57	0.7	0.7	0.7	0.7	0.7
	25-55, L	67	44	49	65	63	0.9	0.9	0.9	0.9	0.9
	25-55, M	90	65	70	87	84	0.7	0.7	0.7	0.8	0.8
	25-55, H	**181**	**145**	**117**	**139**	**134**	0.8	0.8	0.7	0.7	0.8
	55-65	90	74	75	80	88	0.8	0.8	0.7	0.7	0.8
	65+	53	47	52	57	46	**1.2**	**1.3**	**1.3**	**1.3**	**1.1**
Not-recent	15-25	54	43	60	74	76	0.8	0.8	0.8	0.9	0.9
	25-55, L	65	47	50	68	61	0.9	0.9	0.9	0.9	0.8
	25-55, M	**105**	75	78	97	90	0.9	0.9	0.8	0.8	0.8
	25-55, H	**233**	**169**	**167**	**203**	**181**	**1.0**	1.0	**1.1**	**1.1**	**1.1**
	55-65	**110**	86	86	**111**	**102**	1.0	1.0	0.8	1.0	0.9
	65+	48	42	45	52	47	**1.1**	**1.2**	**1.1**	**1.2**	**1.1**

Notes: This table displays the fiscal ratio (FR) and Relative Fiscal Ratio (RFR) of the different populations of natives and immigrants, by origin and recency. The Age and Education sub-divisions are defined in section 1.2.2. This table only shows the baseline specification and the details of measuring the FR and RFR are detailed in section 1.2.2 and in Appendix section 1.6.3. The list of countries belonging to the developed OECD and non-OECD group is defined in the introduction. Recent immigrants refers to all immigrants who arrived in the U.S. within 10 years of the survey and not-recent refers to all others. Bold font: The fiscal ratios that are greater than 100 indicating a net contributing sub-population. The relative fiscal ratios that are greater than 1 indicating a sub-population in which immigrants hold a better fiscal position.

Table 16: Fiscal ratio by generation

		Fiscal Ratio					Relative fiscal ratio (FB/NB)				
Generation	Age, Edu	2006	2009	2012	2015	2018	2006	2009	2012	2015	2018
Third +	15-25	71	56	75	88	85					
	25-55, L	73	52	57	70	72					
	25-55, M	**122**	88	96	**116**	**109**					
	25-55, H	**223**	**170**	**155**	**186**	**171**					
	55-65	**114**	88	**103**	**112**	**110**					
	65+	44	35	40	44	43					
Second	15-25	62	44	62	74	71	0.9	0.8	0.8	0.8	0.8
	25-55, L	70	47	55	78	73	1.0	0.9	1.0	**1.1**	**1.0**
	25-55, M	**123**	92	93	**116**	**103**	**1.0**	**1.0**	1.0	1.0	0.9
	25-55, H	**237**	**195**	**163**	**187**	**170**	**1.1**	**1.1**	**1.0**	**1.0**	1.0
	55-65	**119**	97	**112**	**121**	**138**	**1.0**	**1.1**	**1.1**	**1.1**	**1.3**
	65+	45	36	42	44	49	**1.0**	**1.0**	**1.1**	**1.0**	**1.1**
First	15-25	52	40	55	65	65	0.7	0.7	0.7	0.7	0.8
	25-55, L	66	46	50	67	61	0.9	0.9	0.9	1.0	0.9
	25-55, M	100	71	76	94	89	0.8	0.8	0.8	0.8	0.8
	25-55, H	**213**	**159**	**149**	**175**	**162**	1.0	0.9	1.0	0.9	0.9
	55-65	**107**	85	84	**107**	**100**	0.9	1.0	0.8	1.0	0.9
	65+	49	42	46	52	47	**1.1**	**1.2**	**1.2**	**1.2**	**1.1**

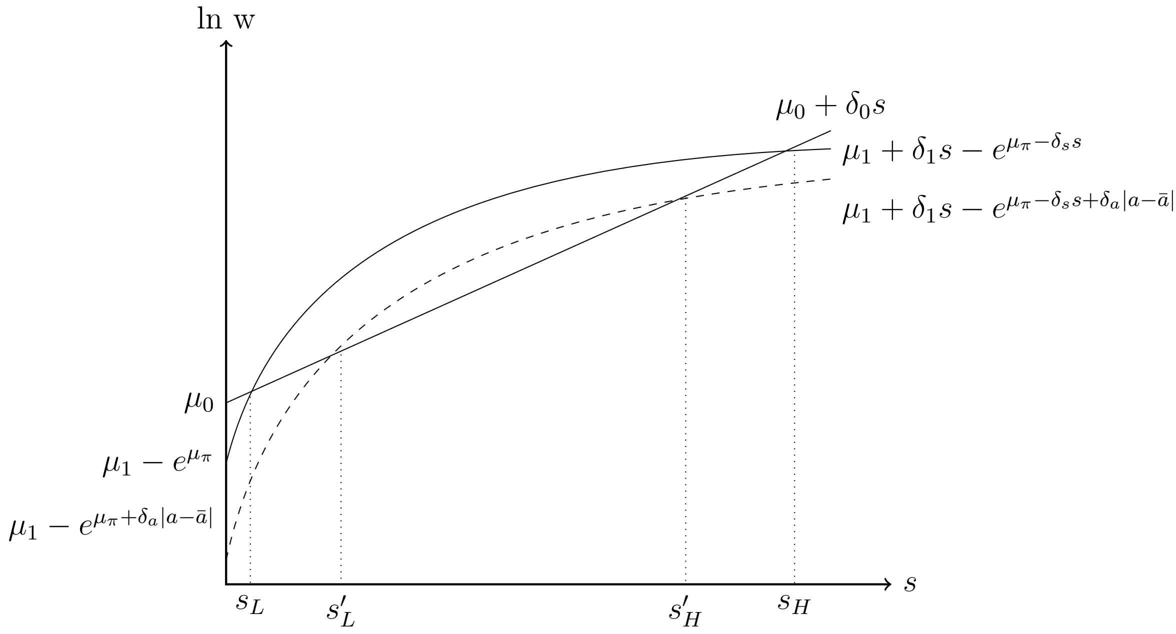
Notes: This table reports the fiscal ratio (FR) and Relative Fiscal Ratio (RFR) of the different generational populations. second-generation includes all individuals born in the U.S. to one or more immigrant parents. The Age and Education sub-divisions are defined in section 1.2.2. This table only shows the baseline specification and the details of measuring the FR and RFR are detailed in section 1.2.2 and in Appendix section 1.6.3. Bold font: The fiscal ratios that are greater than 100 indicating a net contributing sub-population. The relative fiscal ratios that are greater than 1 indicating a sub-population in which immigrants hold a better fiscal position.

Table 17: Fiscal ratio per capita in 2016

	Baseline	SG 15-	SG All
Health	1.02	1.19	0.91
Education	0.56	1.31	1.10
Sickness	— 0.57 —		0.44
Old age	— 0.59 —		0.59
Survivors	— 0.38 —		0.50
Unemployment	— 1.15 —		0.92
Family and children	— 1.78 —		1.42
House allowance	— 1.50 —		1.22
Social exclusion	— 1.99 —		1.53
Total benefits	0.96	1.13	0.92
Indirect taxes	— 1.15 —		0.96
Property tax	— 0.98 —		0.87
Capital tax	— 0.91 —		0.81
Household contribution	— 0.98 —		0.87
Employer contribution	— 1.16 —		0.94
Sales, grants etc.	— 1.21 —		1.00
Total contributions	— 1.09 —		0.91

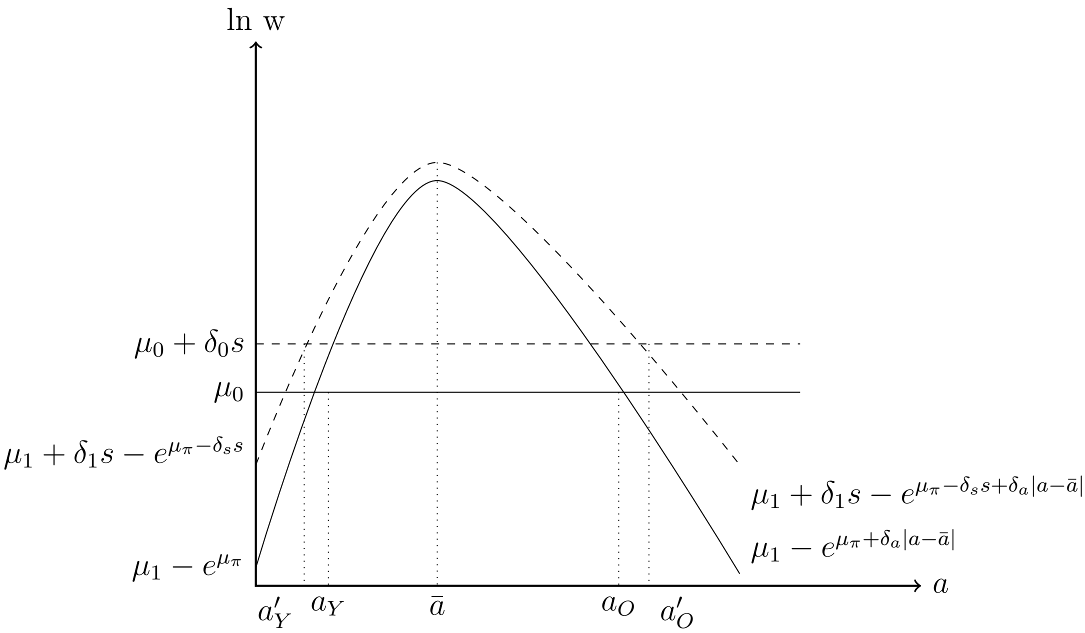
Notes: This table reports the fiscal ratio per capita (FR) for each individual benefit and contribution (immigrant/native). The baseline specification reports the foreign-born to native-born fiscal ratios, the second-generation specification is divided into two alternate specifications, one which only considers children less than 15 years as second-generation and one which considers all individuals with one or more immigrant parents. SG 15- considers children born to two foreign-born parents as an immigrant and divides the benefits and contributions of children born to one foreign-born parent equally between natives and immigrants. SG All considers all individuals born to one or more foreign-born parents as an immigrant. Total benefits includes public goods which is apportioned equally to all adults.

Figure 12: Migration decision based on age



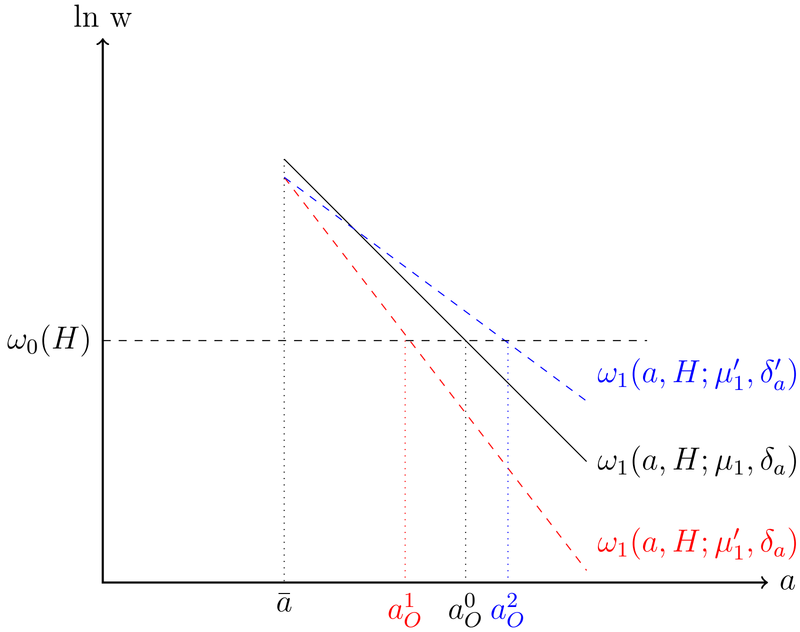
Notes: This figure graphs the wage equations which inform the migration decision of individuals aged $\bar{a}$ and older or younger individuals aged $a \neq \bar{a}$ across all skill levels.

Figure 13: Migration decision for individuals with different skills



Notes: This figure graphs the wage equations which inform the migration decision of individuals with high skill level $s > 0$ and individuals with low skills, identified here as $s = 0$ across all age groups. This figure also assumes that $I_s > 0$

Figure 14: Old high-skilled individuals incentives to migrate during a recession



Notes: This figure graphs the wage equations of a high-skilled elderly individual. The black line is the baseline. The red line shows the impact of the recession via a decrease in average wage and the blue line shows how lower migration costs will affect the wage equation and thus the migration decision.

1.6.3 Apportion criteria to determine the fiscal ratio

Each expenditure and revenue item from the general government accounts is apportioned to each subgroup of immigrants and the native-borns using several data sources and specific assumptions which are listed below. All items from the general government's revenues and expenditures are apportioned to the populations as represented by the Current Population Survey in each year.

- Expenditure: The OECD's Classification of the Functions of Government (COFOG) is adopted to identify each item of the U.S. general government's expenditures. The CPS survey responses are used to identify the benefits received by the population.
  - *Public goods*, both pure (COFOG items General public services and Defence) and congestible (COFOG items Public order and safety, Economic affairs and Housing and Community Development) are apportioned per capita to all individuals aged 15 and over, native-born and immigrants. Pure public goods are apportioned to only native-born individuals aged 15 and over in an alternate specification
  - *Health* expenditure is apportioned to the population using age and gender specific National Health Expenditure data from the U.S. Centers for Medicare & Medicaid Services (CMS).
  - *Education* expenditure is apportioned separately depending on the level of education. Information about the expenditures by levels of education was obtained from the Education at a Glance (EAG) 2020, OECD publication[21][22]. Information about the ages of the individuals that study

[21] Missing data on expenditures at each level of education was missing for the years 2004, 2006, 2007 and 2018 and so data from the other years was used to linearly extrapolate for the missing years. For secondary and tertiary education, due to a lack of trend in change in educational expenditure post 2014, the average ratio split across the different education levels was calculated and used to populate the expenditures in 2018.

[22] Since the sum of the SOCX categories is lower than the COFOG sum by 20%, the shares of each sub-category are readjusted so as to match the COFOG total expenditure on Education

at each level is determined by the National Center for Education Statistics (NCES).

    * Pre-primary and primary education expenditure is apportioned per capita to all children, immigrants and native-born, aged 0 to 11.
    * Secondary education expenditure is apportioned per capita to children aged 10-14 and to individuals aged 15 and over who declare in the CPS to be studying at secondary level (high school or lower).
    * Post-secondary non-tertiary and tertiary education expenditure is apportioned per capita to all individuals who are reported as per the CPS to be studying at some college level for the former and at an associate degree or higher for tertiary education.
    * Information on the CPS on school/college attendance was only available for ages 16-24 before 2012 and for ages 16-54 from 2013 onwards.

- The apportionment of all *social protection benefits* is based on estimates from the CPS data. Information on the expenditure breakdown across the different social protection COFOG categories was estimated using the OECD's Social expenditure detailed data of the U.S. (SOCX- U.S. country data)[23].

    * Sickness and disability benefits, old age and survivor benefits, unemployment benefits are all available at an individual level. Private benefits from a non-governmental source are not included.
    * Old age benefits includes Supplemental security income, social security benefits, pension and veteran payments from the general government.
    * Old age benefits are applied for individuals 60 and above while unemployment benefits are applied for those between 15 and 64 years of age.

[23]Since the sum of the SOCX categories is greater than the COFOG sum by 25%, the shares of each sub-category are readjusted so as to match the COFOG total expenditure on Social Protection

    * However, family and children benefits and social assistance benefits are only available at a household level. Thus, the household benefits are divided by the number of adults (15+) in the household and attributed to them equally.
    * Family and children benefits include the market value of school lunches, child tax credit and additional child tax credit as well as public assistance of types TANF and ADTC. Social assistance benefits include other types of public assistance, market value of food stamps and earned income tax credit.
    * Regarding housing benefits, any individual that reports living in public housing *or* paying lower rents due to government subsidies is considered to receive housing benefits, which is coded as a dummy variable.
    * The average benefits are calculated for each subgroup (by origin, age and education), for each type of benefit every year. The average benefits are then readjusted such that the total benefits add up to the total amount of the item in the government's expenditure (similar to Chojnicki et al, 2018).

- Revenue: Each category of the U.S. general government's revenues are identified based on the OECD classification and augmented by the National Income and Product Accounts (NIPA) Tables from the Bureau of Economic Analysis (BEA) government website. The CPS survey responses are used to identify the taxes, levies and contributions declared by the population.
  - *Household social contributions* (not including Medicare contributions) which is made up of direct taxes and employee social contributions (revenue item identified from NIPA Table 3.6) is apportioned based on the declared taxes and social contributions of households. This includes the federal income taxes, state taxes, federal retirement payroll deduction and social security retirement payroll deduction (FICA). Since these items are available at a

household level, the yearly declared contributions are evenly divided across the adult population and attributed to them.

- *Employer social contributions* (not including unemployment insurance) (revenue item identified from NIPA Table 3.6) is apportioned based on the reported amounts of the employee social contributions - Social security retirement payroll deduction (FICA) in the CPS surveys. However, since the employee rates were decreased by 2 pp in 2011 and 2012, this adjustment was made to reflect the real employer contribution rates.
- The attribution for all of the above is done similar to the social protection benefits attribution. The averages of each subgroup are readjusted such that the total contributions sum up to the corresponding item in the government's revenue.
- *Medicare contributions* (revenue item identified from NIPA Table 3.6) is a subset of household contributions. However, the revenue from medicare contributions in the government revenue is treated differently. The contributions are attributed based on the age and gender specific National Health Expenditure data from the U.S. Centers for Medicare & Medicaid Services (CMS), to all individuals who reported having Medicare.
- *Employers unemployment insurance contributions* (revenue item identified from NIPA Table 3.6), which is a subset of employers social contributions, are made by employers at a flat rate which is independent of the employee's incomes. So, irrespective of origin or socio-economic characteristics, this revenue item is allocated to all individuals above 15 who pay social contributions (FICA>0)
- *Capital taxes* revenue is apportioned to all individuals aged 70 and over, irrespective of the country of origin.
- Revenue from *indirect taxes* (which includes taxes on products such as VAT, imports and others, taxes on production such as land, use of fixed

assets, payroll, professional licenses, etc. but does not include property taxes) is apportioned based on the disposable income which is calculated as the total household income minus direct taxes, transfers and contributions[24]. Disposable income which is at a household level is converted to an individual level using the OECD Square root equivalence scale. Once the mean disposable income is determined for each subgroup the apportioning of the indirect tax revenue is similar to the method employed for household social contributions. This estimation assumes that both immigrants and native-borns have the same consumption baskets such that their total consumption expenditures are linear in disposable income.

– *Property tax* revenue which is a subset of indirect taxes is apportioned by using the declared amount of property taxes in the CPS which is annualised and individualised before being attributed to each individual in a method similar to the household social contributions. This revenue item is identified as a ratio of total indirect taxes from NIPA Table 3.5.

– *Sales, grants and others* are apportioned per capita to all individuals aged 15 and over, native-born and immigrants.

1.6.4 Net contribution per capita and per resident

The net contribution per capita c^p_{pc} is defined as the total revenue minus total expenditures attributed to the population p divided by its population.

$$c^p_{pc} = \frac{(\sum_i R^i_p - \sum_j X^j_p)}{n_p} \tag{12}$$

But due to variation in the immigrant population and changes in demographics of the U.S., it may be better to study the net contribution per resident since it does a

[24]Disposable income is calculated as reported household income minus reported direct taxes and household social contributions as defined above minus child care paid while working minus child support paid minus health insurance premium minus Medical out of pocket expenditures. Some of these items are not available in the CPS surveys prior to 2011.

better job in preserving the population size (Chojnicki et al, 2018).

$$c_{pr}^{p} = c_{pc}^{p} * \frac{n_p}{\sum_p n_p} \tag{13}$$

1.6.5 The relative fiscal ratio of beneficiaries

The fiscal ratio defined in per capita terms can be misleading if the percentage of beneficiaries are different for natives and immigrants. Thus the relative fiscal ratio per capita RFR_i^{pc} can be rewritten as the relative fiscal ratio of item i per recipient RFR_i^{pr} times the relative ratio of beneficiaries to population RRR_i.

$$\begin{aligned} RFR_i^{pc} &= \frac{X_{fb}^i}{P_{fb}} * \frac{P_{nb}}{X_{nb}^i} \\ &= \frac{X_{fb}^i}{P_{Rfb}} * \frac{P_{Rnb}}{X_{nb}^i} * \frac{P_{Rfb}}{P_{fb}} * \frac{P_{nb}}{P_{Rnb}} \\ &= RFR_i^{pr} * RRR_i \end{aligned} \tag{14}$$

where X^i is the amount of expenditure of item i which is apportioned to an individual. P_{Rnb} and P_{Rfb} are the total number of native-borns and foreign-borns who receive benefits and P_{nb} and P_{fb} are the total number of native-borns and foreign-borns in the population. A similar fiscal ratio per recipient can be determined for each item of the government revenue.

1.6.6 Distribution of benefits and contributions at the individual level

Immigrants and natives on average receive different quantities of benefits and contributions. For example, in 2016, immigrants received 21 percentage less benefits as compared to natives on average but this difference in amount of benefits received varies vastly across the types of benefits. In 2016, immigrants also received 47% more family and children benefits as compared to natives in 2016 but these benefits are a very small share of the total benefits that a native receives (1%). So in order to compare the differential composition of the benefits (and contributions) weighted by their share in the National accounts, we use the following method.

The fiscal balance defined as the Government revenue minus expenditures, can be further divided into the revenues and expenditures attributed to the natives and immigrants.

$$\begin{aligned} B &= R - X \\ &= (R_N - X_N) + (R_F - X_F) \\ &= N + F \end{aligned} \tag{15}$$

Each of the balances attributed to immigrants and natives can be further subdivided into the type of benefits and contributions, such that $\sum_i N_i = N, \sum_i F_i = F$, where each i corresponds to an item of the general government accounts such as old age benefits. Then, the expenditure (or revenue) attributed to each individual foreign-born on average can be defined as the total expenditure (or revenue) of item attributed to the foreign-borns divided by its population $f_i = \dfrac{F_i}{P_F}$. $n_i = \dfrac{N_i}{P_N}$ has a similar definition.

So in order to understand which benefits (or contributions) immigrants receive (make) more relative to the natives, we can estimate the percentage difference between the total expenditure (or revenues) attributed to a foreign-born and the total expenditure (or revenues) attributed to a native individual, which can then be rewritten as follows:

$$\begin{aligned} \frac{\sum_i f_i}{\sum_i n_i} - 1 &= \sum_i \frac{f_i - n_i}{\sum_i n_i} \\ &= \sum_i \left(\frac{f_i - n_i}{n_i}\right) * \frac{n_i}{\sum_i n_i} \end{aligned} \tag{16}$$

The first term on the right hand side is the percentage difference of an item i between a foreign-born and native and the second term is the share of the item in the native's consumption basket. So even if immigrants receive more family benefits, the fact that they receive significantly less health and education benefits which make up larger shares of the native's budget explains why immigrants were overall receiving fewer benefits relative to natives.

Chapter 2

2 The Impact of Tax Changes on the Macroeconomy: A New Approach Using Failed Tax Changes

2.1 Introduction

The magnitude and extent to which tax changes impact the aggregate economy is a widely studied question in macroeconomics. Despite this, estimating the causal impact of tax changes on the aggregate output has remained a challenge due to endogeneity concerns in econometric analyses. Since lawmakers tend to propose and legislate a tax cut in anticipation of slower output growth, tax changes are positively correlated with the output growth expectations of lawmakers which are unobserved by the econometrician. If this endogeneity is not addressed, the econometric analysis will result in an upward bias in the estimated impact of tax changes on the economy.

In this paper, we propose addressing the endogeneity in tax multiplier studies by using a newly constructed time series of *failed* tax changes - tax changes considered by Congress that ultimately fail to become law - as a proxy for the unobserved output expectations of lawmakers. Our approach is motivated by the finding that legislative bills aimed at stabilizing output are often delayed or fail entirely due to political reasons (e.g., Chappell and Keech (1986), Alesina and Drazen (1991), Alesina and Rosenthal (1994), Poterba (1994), Fatás and Mihov (2003)). If a substantial fraction of stabilizing tax proposals fail to pass for political reasons, then even the time series of failed tax changes is likely to have a positive correlation with the output expectations that affect legislated taxes. Moreover, unlike legislated taxes, failed taxes by definition cannot affect output directly[25]. Hence, in a tax multiplier study that regresses future output growth on legislated tax changes, including the failed tax change variable helps

[25]There may be anticipatory effects where the proposed tax changes cause individuals to change their behaviour thereby indirectly affecting output, but since 75% of the failed tax changes remain in discussion in Congress for less than a quarter, we ignore the anticipatory effects for now.

absorb the effect of the unobserved output expectations without affecting the causal relationship between legislated tax changes and output.

To illustrate our approach, we collect data on both legislated and failed tax revenue changes in the United States from 1975 to 2017. Among the 420 tax bills which have revenue estimates from the Joint Committee on Taxation, 103 bills (25%) eventually get legislated and 317 bills (75%) fail to become law. From these, we obtain our quarterly measures of legislated and failed tax revenue changes.

Consistent with our assumption that failed tax changes reflect the output expectations of lawmakers, the failed tax changes indeed predict future GDP growth. This is evidenced by a positive coefficient when regressing real GDP growth on contemporaneous and lagged failed tax changes over 8 quarters. This regression mimics the conventional time-series tax multiplier regression and we find that a 1% increase in the failed tax change as a fraction of GDP is associated with a 1.3% increase in the GDP growth over the next 8 quarters. Since failed tax changes do not affect GDP directly, this large "failed tax multiplier" of around 1.3 reflects that more tax cuts (increases) are proposed in anticipation of a slower (faster) output growth. Furthermore, we find that failed tax changes contain information about future output growth orthogonal to other potential predictors of output growth. That is, failed tax changes positively predict future GDP growth after controlling for lagged GDP growth and various survey forecasts.

Moving onto our main empirical approach, we illustrate how the failed tax variable helps correct the tax multiplier. We find that a naive regression that does not address endogeneity implies a positive tax multiplier of around 0.7. This small but positive value suggests that the endogeneity of lawmakers legislating more tax cuts in anticipation of a slowing economy overwhelms the potential direct effect of tax cuts stimulating the economy. On the other hand, once we control for failed tax changes as a proxy for the anticipated output growth, the legislated tax multiplier falls to around -0.9, which we argue is more likely to capture the causal effect of legislated tax changes on output. We also find this tax revenue estimate to be reasonably robust. Regardless of alternative specifications and data constructions, we obtain a tax multiplier of around -0.46 to -2.06.

To summarize, our contribution is to propose a simple proxy approach to dealing with the endogeneity issue in fiscal multiplier studies and to illustrate the approach in the context of tax multipliers. Other types of fiscal policy also have historical data on both the legislated and failed changes, so one can apply the proxy variable method to obtain the correct fiscal multiplier in other settings.

Related literature Our paper belongs to the large literature proposing alternative ways to obtain the correct fiscal multiplier.[26] Although various approaches have been proposed, we do not view this literature as crowded given the importance of estimating the correct fiscal multiplier and the wide range of the estimates found in the literature.

The structural VAR approach identifies the tax multiplier by imposing additional structures on the evolution of the economy.[27] For example, Blanchard and Perotti (2002) use elasticities inferred from institutional information about tax and transfer systems and assume that discretionary fiscal policy takes longer than one quarter to respond to news about the economy. Mountford and Uhlig (2002) impose restrictions on the sign of impulse responses. However, the structural VAR approach can be sensitive to the structural assumptions (Caldara and Kamps, 2012) and to assumptions about the implementation lag in the policy variable (Martens and Ravn (2010) and Favero and Giavazzi (2012)). The simple fiscal VAR has also been extended to incorporate key country characteristics that fiscal shocks depend on, such as the level of development, exchange rate regime, openness to trade, and public indebtedness (Ilzetzki, Mendoza, and Végh (2010)) and debt dynamics analysis (Ilzetzki, 2011).

The narrative approach identifies the principal motivation for policy actions from presidential speeches and Congressional reports to distinguish between "exogenous" and "endogenous" actions. Using this approach, Romer and Romer (2010) and Cloyne

[26] The literature is too large to list here in a satisfactory manner. Ramey (2011a) is a recent survey paper on the topic.

[27] Examples are Perotti (1999), Fatas and Mihov (2001), Blanchard and Perotti (2002), and Mountford and Uhlig (2002) among others.

(2013) obtain a large GDP tax multiplier of around -2.5 to -3 in the U.S. and the U.K., respectively, whereas Ramey (2009) and Perotti (2012) obtain much smaller multipliers. The narrative approach is a departure from the earlier studies which focused on correcting for the relationship between output and revenues and the behavior of government spending to obtain an unbiased estimate of the tax multiplier (Romer and Romer, 2010). However, the narrative approach tends to be time-consuming and subjective.

Others combine the VAR and narrative approaches or suggest an entirely new approach. Martens and Ravn (2014) use narrative measures as proxies for structural shocks to total tax revenues in an SVAR. Ramey and Shapiro (1998) and Ramey (2011b) use defensive spendings due to war events to gauge the government spending multiplier. Barro and Redlick (2011) use marginal tax rates series to estimate a tax multiplier but instrument the variation using the Romer-Romer tax dataset and find a negative multiplier of -1.1. However, they find that the "tax revenue" multiplier is negligible due to the substitution effect. Some others use the cross-sectional variation in fiscal shocks to identify their effect on macroeconomic variables (e.g., Johnson, Parker, and Souleles (2006), Chodorow-Reich, Feiveson, Liscow, and Woolston (2012), Parker Souleles, Johnson, and McClelland (2013), and Chodorow-Reich (2018) among others).

Some papers focus on reconciling the differences in the SVAR and narrative measures with the premise that the difference arises from either the identification assumptions of the SVAR or from the assumed reduced-form transmission mechanisms. Charhour, Schmitt-Grohe, and Uribe (2012) however reject this hypothesis and suggest instead that the observed differences are due to either both models failing to identify the same tax shocks or due to small-sample uncertainty. Favero and Giavazzi (2012) aim to reconcile the difference between Romer and Romer (2010) and Blanchard and Perotti (1991) by including narrative shocks in a VAR model. They create an encompassing model where the Romer-Romer taxes appear as a limited information approach since while it directly identifies tax shocks, it omits other sources of information that are included in the VAR approach. Perotti (2011) counters this by claiming that the Favero and Giavazzi (2012) multiplier is biased towards zero since the discretionary component of tax will have different effects compared to the automatic response of tax revenues to macroeconomic variables. Leeper, Walker, and Yang (2008) on the other hand argue that even the most creative identification schemes in a fiscal VAR cannot extract economically meaningful shocks to taxes because of the existence of the non-invertible moving average component in the equilibrium time series that results in biased tax multipliers. Furthermore, even narrative approaches that aim to identify fiscal foresight ex-ante will only be successful depending on the degree to which forecasted revenue changes reflect exogenous changes in taxes and the relative volatility of the random components of tax decisions.

Our approach is appealing in multiple ways. Unlike the structural VAR approach, we do not rely heavily on the structural assumption regarding the evolution of the economy. The assumption we do impose is that all tax proposals - legislated or failed - carry some information about the lawmakers' expectations of future economic activities. We test the validity of this assumption. Unlike the narrative approach, our method has less room for subjectivity and can be implemented quickly. The weakness of our approach is the assumption that the failed actions are determined by similar variables that determine the legislated actions. However, one can address this issue by presenting evidence consistent with the assumption as we do, based on the GDP predictability evidence.

2.2 The framework

We use a simple econometric model to describe why a naive regression of the output growth on the legislated tax changes is biased and how using failed tax changes solves this issue.

Endogeneity of legislated tax changes. We begin by highlighting how the endogeneity of legislated tax changes leads to a bias in the tax multiplier estimation. Suppose that the data-generating process for output growth at time $t+1$ is

$$\Delta Y_{t+1} = \beta \Delta T_t + g_t + \epsilon^Y_{t+1}, \tag{17}$$

where ΔT_t measures the change in legislated tax revenue, g_t is the deviation in the economic agent's expectation of the output growth from the stationary level of growth, and ϵ^Y_{t+1} measures other shocks to the economy that are independent of everything else. Importantly, the legislated tax revenue change at time t follows the data generating process,

$$\Delta T_t = f(g_t) + \epsilon^T_t, \tag{18}$$

where ϵ^T_t is a measurement error that is independent of everything else. If lawmakers legislate tax cuts when anticipating a recession, then $\frac{df}{dg} > 0$. For simplicity, we suppose $f(g) = \gamma_1 g_t$, where $\gamma_1 > 0$.

The problem is that the econometrician does not observe g_t. Hence, a naive tax multiplier regression estimates the following model:

$$\Delta Y_{t+1} = b \Delta T_t + e^Y_{t+1} \tag{19}$$

This leads to a bias $b > \beta$ because $Cov(\Delta T_t, g_t) > 0$. Intuitively, if lawmakers anticipate a recession and legislate tax cuts, then a naive econometrician observes a low output growth after tax cuts and erroneously conclude that tax cuts reduce the future economic growth.

Failed tax changes as a proxy for g_t. Our approach is to use additional information contained in changes in failed tax revenues. Because failed tax revenue changes do not become law, they do not directly enter into the data generating process for the output growth. Instead, they load on g_t. Specifically, we assume that the failed tax revenue change at time t follows the following data generating process:

$$\Delta U_t = h(g_t) + \epsilon_t^U \tag{20}$$

where ϵ_t^U is a measurement error that is independent of everything else. If lawmakers propose tax cuts when anticipating a recession, then $\frac{dh}{dg} > 0$. For simplicity, we assume linearity $h(g) = \gamma_2 g_t$.

We model $f(g_t)$ and $h(g_t)$ separately because a legislated tax bill may have more components than a failed tax bill. For example, lawmakers may add "pork barrel" components - components that help their constituents for political reasons- into a tax bill as the bill goes through the legislative process (e.g., passing the House, resolving the difference between the House and the Senate). In this case, since a legislated tax bill goes through more steps in the legislative process than a failed tax bill, we would expect $f(g) > h(g)$ for the same g.

Solving for g_t, we have

$$g_t = \frac{\Delta U_t - \epsilon_t^U}{\gamma_2} \tag{21}$$

Plugging g_t into the output growth data generating process, we have

$$\begin{aligned} \Delta Y_{t+1} &= \beta \Delta T_t + \tfrac{\Delta U_t - \epsilon_t^U}{\gamma_2} + \epsilon_{t+1}^Y \\ &= \beta \Delta T_t + \tfrac{\Delta U_t}{\gamma_2} + (\epsilon_{t+1}^Y - \tfrac{\epsilon_t^U}{\gamma_2}) \end{aligned} \tag{22}$$

Because ϵ_{t+1}^Y and ϵ_t^U are independent of everything else, we can correctly estimate the tax multiplier β now.

2.3 Data

Legislated and failed tax revenue changes. We collect data on revenue estimates for tax proposals in the U.S. during the period 1975-2017. We begin with the universe of revenue estimates available on the Joint Committee on Taxation (JCT) website since the JCT provides revenue estimates for all tax proposals (bills) considered by Congress since July 1974. To obtain revenue estimates for tax proposals, we apply two criteria. First, we require that the title of the revenue estimate document contains the bill identifier information (e.g., House bill "H.R. 4”). This discards revenue estimates that are not specific to any specific tax bill (e.g., an overview of tax expenditures in a given year). Second, we require that the document contains a table with the revenue estimates to minimize errors in the digitization process. We have widened our dataset and incorporated a few revenue estimates that were available only in text form into our analysis[28]. This leaves us with 816 JCT revenue estimates on 517 distinct tax bills. Some tax bills have multiple JCT estimates since Congress may revise the proposal as the bill progresses through the legislative rounds. Excluding 127 bills with zero revenue estimates and taking the latest revenue estimate, we obtain 420 proposed tax changes.[29] Figure 15 summarizes these 420 proposed tax changes by the last congressional action on the bill. We find that the number of bills that do not pass either of the chambers of the Congress, those that pass at least one chamber but fails to pass the other chamber, and those that successfully become law make up 48%, 27%, and 25% of all proposed tax changes.

By matching tax revenue estimates with legislative records on the U.S. Congress website, we obtain the dates when the bill was last considered in Congress. For legislated bills, this is the day when the bill was legislated, and for failed tax bills, this is the date when the bill was last discussed in Congress. However, we need to

[28]However, we concede that there may be other revenue estimates that may have been missed in the digitization process.

[29]If there are multiple JCT revenue estimate documents for the latest date associated with the bill, we assume that they are estimates for different provisions of the bill and take a sum over those estimates. We show in our robustness section that taking an average leads to similar results.

find the actual and supposed implementation date of the tax change for the legislated and failed bills. Mertens and Ravn (2008) report that the median lag between the legislation date and the implementation date is 6 quarters. Assuming a similar lag, we add 4 and 6 quarters to the last record date to obtain the implementation quarter for legislated and failed tax changes, respectively. That is, we assume a "legislation lag" (the time it would have taken for a failed tax to pass) of 2 quarters and an "implementation lag" (the time it would have taken for a legislated tax to be implemented) of 4 quarters. However, we consider alternative lags and find that our numbers do not change significantly. Following Romer and Romer (2010), we focus on the effect of the initial change in the tax policy. We do this by constructing our series based on JCT's estimate of tax revenue change to the first year of implementation[30], assuming that the tax revenue changes in the following years merely reflect the continuation of the same policy change[31].

By aggregating all the tax changes in a given quarter and dividing the resulting sum by nominal GDP, we obtain the time series of legislated and failed tax changes. These are plotted in the figure 16 series plot. Both legislated and failed tax change proposals tend to be sparse and smaller in magnitude between 1985 and 2000, whereas they are more frequent before 1985 and after 2001 although they are predominantly negative in the second half of the sample. Although this is consistent with having more tax cut proposals around economic downturns, it could also lead the two tax change series to act as a (-1 times) dummy variable on the time period 1985-2000[32]. This could result in a bias if the GDP growth rate has slowed down over time or was low following the financial crisis of 2008-2009. We address this concern in two ways. First, we include a dummy variable for the time period 1985-2000, which we interact with the control variable, thereby using only the variation within each half of the sample. Second, we

[30]We include a robustness check which includes the tax revenue estimate for the second year

[31]We allocate this tax revenue change in the first year to the supposed quarter of implementation although we do a robustness check with involves spreading the tax revenue change across different quarters.

[32]One reason for the sparse tax changes in the 1990s is the rule we apply to obtain JCT tax revenue estimates. Some of the large tax proposals in the 1990s did not have accompanying JCT tax revenue estimates in a table format, making it difficult to digitize the information.

also repeat our regressions using the pre-crisis sample of 1975-2007 and report it as one of our robustness specifications.

Macroeconomic variables. The following data are from the National Income and Product Accounts: Nominal GDP from Table 1.1.5, Real GDP from Table 1.1.3 (Index : 2012=100), Price Indices for GDP from Table 1.1.4 and Government spending from Table 3.1. Government Current Receipts and Expenditures. All of these are provided in billions of dollars and are seasonally adjusted at annual rates. The data on the three-year bond rate are from the Board of Governors of the Federal Reserve System, series H15/H15/RIFLGFCY03_N.M. All the above data were last revised on October 26, 2018.

GDP forecast data. In the next section, we evaluate the ability of failed tax changes to predict output growth beyond survey forecasts. The forecast variables we look at are from the Survey of Professional Forecasters (SPF), the Livingstone Survey (Livingstone), the Survey of Consumers (SC) and Fed Staff's Greenbooks (Greenbooks). Apart from the Survey of Consumers which uses the level value of real GDP, all the other datasets provide the growth rates of the real GDP forecasts. Data is available from 1975 to 2018 for all except the Survey of Consumers and the Fed Staff's Greenbooks. While the Survey of Consumers misses data from 1975 and is only available from 1978, the Fed Staff's Greenbooks provide data only until 2012. Another key distinction is that while most of the forecast variables are available at a quarterly rate, the Livingstone forecasts are available only at a semi-annual rate[33].

2.4 Failed tax changes as a proxy for unobserved growth expectations

In this section, we provide evidence consistent with our conjecture that failed tax changes are positively correlated with the unobserved output expectations. If failed

[33] The forecast data from the Survey of Consumers is available at a monthly rate and was transformed into a quarterly forecast.

tax changes load positively on output expectations that are on average correct and if failed tax changes cannot affect future output directly, we would expect the multiplier on failed tax changes to be positive.

To check this, we regress real GDP growth on the contemporaneous and lagged failed tax changes (up to 8 quarters) to infer the coefficients on those tax changes over the time period 1975-2017:

$$\Delta Y_t = \alpha + \sum_{i=0}^{8} \beta_i \Delta U_{t-i} + \epsilon_t \tag{23}$$

where ΔY_t denotes real GDP growth in quarter t and ΔU_{t-i} denotes the failed tax change in quarter $t - i$. In other words, the cumulative GDP response $\sum_{i=0}^{8} \beta_i$ represents the "failed tax multiplier" coming purely from failed tax changes being positively correlated with the lawmakers' expectations of future GDP growth and not from any causal effect on GDP.

Figure 17 shows that the failed tax multiplier is positive. That is, output growth tends to be faster (slower) following failed proposals to increase (cut) taxes. Moreover, the magnitude of the multiplier is large. A one-percentage increase in the failed tax change proposals as a fraction of GDP is associated with around 1.3 percentage point (pp) increase in the GDP growth rate over the next 8 quarters following the supposed implementation. This suggests that failed tax increases (cuts) tend to be proposed in anticipation of higher (lower) output growth rate, consistent with the premise of our proxy approach.

Table 18 shows that the finding is robust to controlling for other potential predictors of output growth and to alternative assumptions about the number of quarters it would have taken for the failed tax proposals to be implemented. This suggests that the output expectations of lawmakers contained in failed tax change proposals are not fully captured by other time-series variables. It is also reassuring that the results are not sensitive to the assumption about the number of quarters between the last congressional action on failed tax bills and the supposed date of implementation.

2.5 The legislated tax multiplier

Using failed tax changes as a proxy for the growth expectations of lawmakers, we show how the proxy variable addresses the endogeneity problem in tax multiplier studies. In all analyses, the baseline specification is 4 quarters' implementation lag (the lag between legislation and implementation) and 2 quarters' legislation lag (the time it would have taken for a failed tax bill to pass).

2.5.1 The naive multiplier

We begin by estimating the naive multiplier. This is useful in highlighting the presence of endogeneity in a tax multiplier regression and serves as a benchmark for the next subsection when we address the endogeneity problem with a proxy variable. To do this, we regress real GDP growth on the contemporaneous and lagged legislated tax changes (up to 8 quarters) as well as lagged GDP growth to infer the coefficients on the tax changes:

$$\Delta Y_t = \alpha + \sum_{i=0}^{8} \beta_i \Delta T_{t-i} + \sum_{j=1}^{8} \eta_j \Delta Y_{t-j} + \epsilon_t \tag{24}$$

where ΔT_{t-i} denotes the legislated tax changes in quarter $t-i$.

Figure 18 shows that the naive tax multiplier is slightly positive (0.66) rather than negative for the baseline sample of 1975-2017, contrary to the notion that a tax increase (cut) has a contractionary (expansionary) effect on GDP.[34] This points to the endogeneity problem that motivates our study. Even if legislated tax changes have a negative causal effect on future output, they are likely to be positively correlated with the component of future output observed by lawmakers, leading to an upward bias. The conclusion is similar when we include a structural break dummy for the time period 1985-2000. In this case, we get a small negative naive multiplier of -0.03.

[34] In the specification without lagged GDP, the "tax multiplier" would simply be the sum of the betas $\sum_{i=1}^{8} \beta_i$. For the specification with lagged GDP, the tax multiplier is the dynamic tax multiplier that accounts for the feedback effect between ΔT and ΔY as in Romer and Romer (2010). The multiplier represents the effect of the legislated tax change on GDP 8 quarters or 2 years after legislation

2.5.2 The proxy variable approach

We offer a simple remedy to the endogeneity problem illustrated above. Since failed tax changes are also likely to be positively correlated with the output expectations of lawmakers, one can include failed tax changes as a proxy variable for those unobserved expectations:

$$\Delta Y_t = \alpha + \sum_{i=0}^{8} \beta_i \Delta T_{t-i} + \sum_{j=0}^{8} \gamma_j \Delta U_{t-j} + \sum_{k=1}^{8} \eta_k \Delta Y_{t-k} + \epsilon_t \tag{25}$$

As explained in section 2.2, this corrects for the bias arising from the omitted variable if failed tax changes have a non-zero loading on the unobserved growth expectations, even if the loading is different from that of legislated tax changes.

Figure 19 shows that the tax multiplier on legislated tax changes is now negative and significant at -0.88 as opposed to 0.66 in the naive approach. This is more in line with the notion that the causal effect of tax changes on GDP is negative. This suggests that the positive correlation between legislated tax changes and output expectations is now absorbed by failed tax changes, leaving the coefficients on legislated tax changes to only reflect the causal effect on future output. In terms of the magnitude, cutting tax revenues by 1% in the legislated tax change as a fraction of GDP is associated with around 0.9pp increase in the GDP growth rate over the next 8 quarters. The conclusion is again similar in the alternate specification where we include a structural break dummy variable which is also interacted with the failed tax changes. In this case, the implied tax multiplier is -2.06 instead of -0.03 from the naive approach.

Table 19 summarizes our result by comparing regression models (24) and (25) under different assumptions about the number of lags between legislation and implementation (baseline: 4 quarters) as well as the number of lags between last congressional action on failed bills and supposed legislation (baseline: 2 quarters). This translates to a 4 quarter lag for legislated tax changes and a 6 quarter lag for failed tax changes. Across all specifications, the proxy variable approach implies a tax multiplier of around -2.06 to -0.54, whereas the naive approach leads to a tax multiplier of around -0.45 to

0.87[35].

2.6 Robustness

We study how the resulting tax multiplier estimate changes with a battery of robustness checks. The results are summarized in table 20.

First, tax increases may be legislated to offset more government spending. If government spending positively affects the future GDP growth, then not controlling for government spending may result in a bias. To address this concern, we add the change in total government expenditures divided by nominal GDP as a control. The results are almost identical to the baseline specification.

How does dropping lagged GDP affect our result? Although we believe it prudent to include lagged GDP as additional potential determinants of future GDP, it is useful to know how the result changes. In this case, the tax multiplier goes from 0.77 to -0.80 when we switch from the naive approach to our proxy variable approach.

We also repeat our analysis using the pre-crisis sample of 1975-2007 instead of the full sample period of 1975-2017. In this case, we obtain a similar conclusion. Not including the proxy variable implies a naive tax multiplier of 0.52, whereas controlling for the proxy implies a multiplier of -1.90.

As mentioned in 2.3, the dominant bill may have multiple JCT revenue estimates on the last congressional action date. In this case, we took a sum over all revenue estimates since for most bills, the different revenue estimates are different components of the bill. Under the alternative approach of taking an average, the tax multiplier estimate becomes smaller and insignificant at -0.69.

Our baseline approach assumes that the tax revenue change happens instantly in the implementation quarter. Alternatively, we could split the tax revenue evenly across the four quarters starting with the implementation quarter and normalize the resulting tax revenue by the GDP in the corresponding quarter. The tax multiplier in this case

[35]Since many failed tax changes are small, the overall lag on the failed tax changes may be smaller than the lag on the legislated tax changes.

goes from a positive 0.66 estimated under the naive approach to a negative estimate of -0.54.

The baseline specification only considers the year 1 revenue estimates for each tax bill. An alternate specification of including year 2 estimates which are to be implemented exactly 4 quarters after the first tax changes were implemented results in negative estimates under both approaches. Upon controlling for the expectations of GDP under the proxy approach, the multiplier becomes significant and more negative at -1.42.

People may follow the permanent income hypothesis and respond to not just the immediate change in tax but also respond to news about the future changes. To address this concern, we add the net present value of tax changes, similar to Romer and Romer (2010). In this case, the tax multiplier estimate becomes more negative at -1.12.

Another concern could be that political parties in power may bias the results as discussed in the introduction. So, we add a dummy variable for the political party in power and test the regression models. Similarly, since there is usually a flurry of new legislation at the beginning of a new Presidency, in another specification, we add a dummy variable for the first quarter of every year post an election. In both cases, the multipliers are identical to the baseline.

2.7 Conclusion

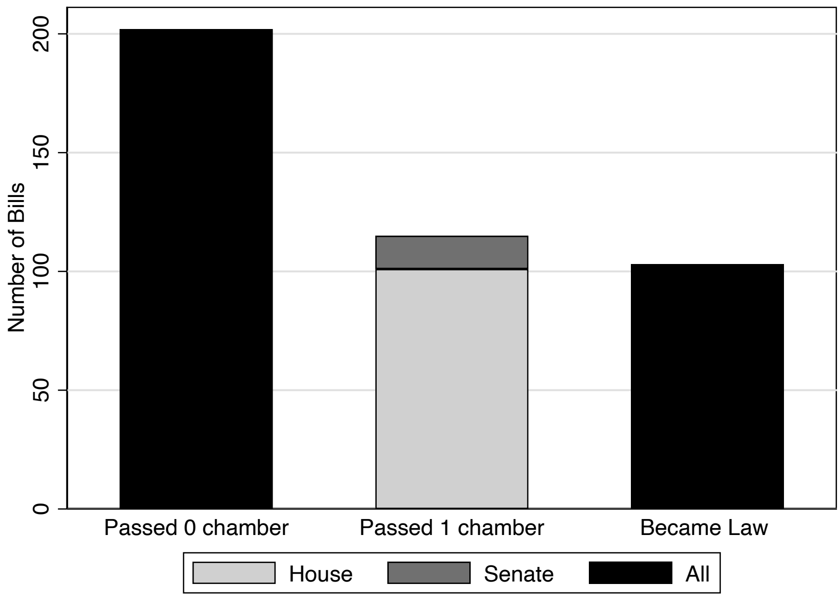
In this paper, we propose correcting for the bias in tax multiplier studies using a failed tax change series as an additional control. Using this approach, we obtain a tax multiplier of around -0.46 to -2.06 in the recent U.S. sample of 1975-2017.

We believe our approach can have fruitful applications. Since it uses readily available information about failed bills, one can apply our method to other fiscal multiplier estimations. It would also be possible to collect state-level legislation information to study local fiscal multipliers. These extensions are left to future studies.

2.8 Appendix

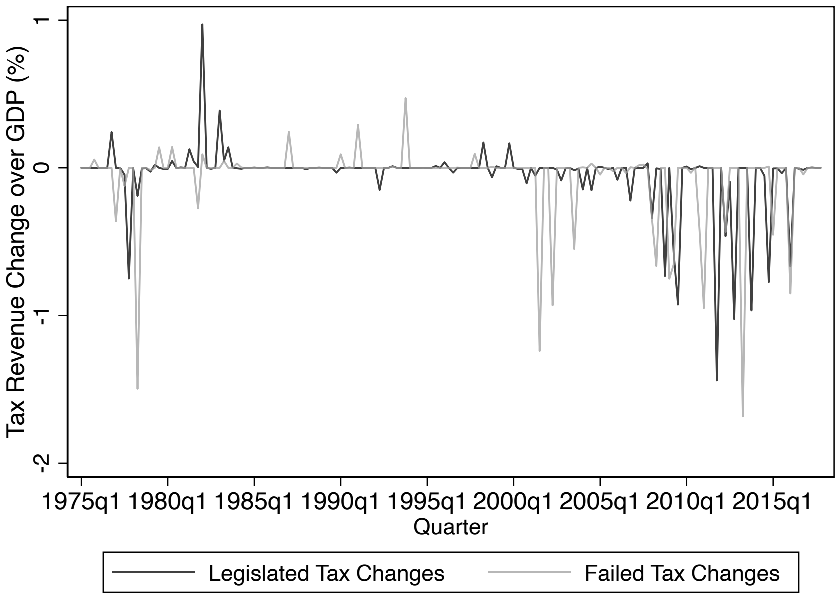
2.8.1 Figures and Tables

Figure 15: Distribution of proposed tax bills by last legislative action



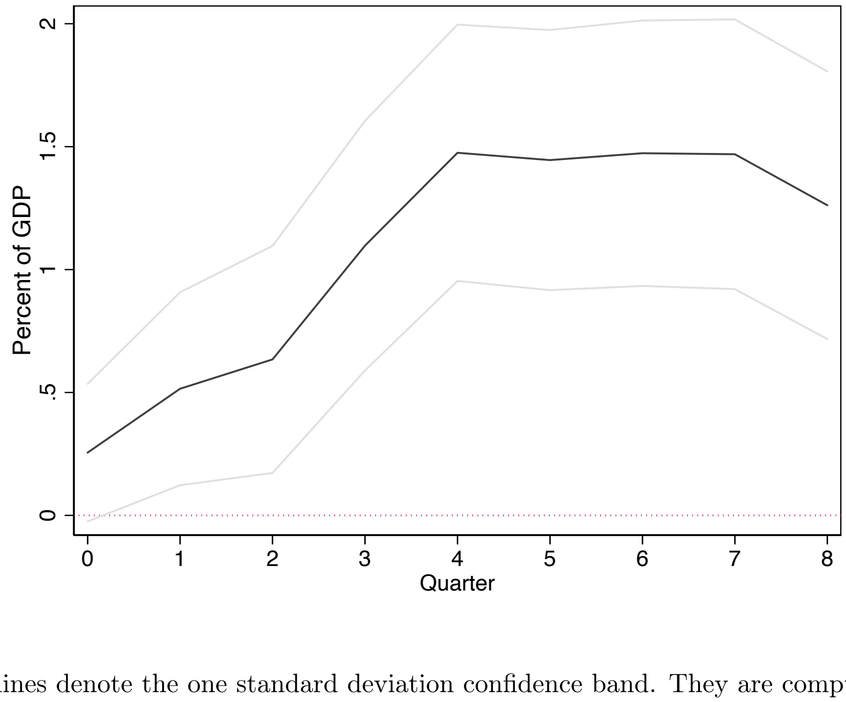
Notes: The figure reports the number of tax bills in our legislated and failed tax revenue change data by three mutually exclusive categories: passed 0 chamber before failing; passed at least 1 chamber before failing; and became law.

Figure 16: Legislated and failed tax changes



Notes: The figure plots the quarterly legislated and failed tax revenue changes over 1975-2017. Each series is normalized by the GDP. The correlation between the two series is 0.11 with a p-value of 0.14.

Figure 17: The failed tax multiplier: Estimated change in GDP associated with a failed tax increase of 1 percent of GDP



Notes: Gray lines denote the one standard deviation confidence band. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients.

Figure 18: The naive tax multiplier on legislated tax changes: Estimated change in GDP associated with an legislated tax increase of 1 percent of GDP

Figure 18a. Baseline specification

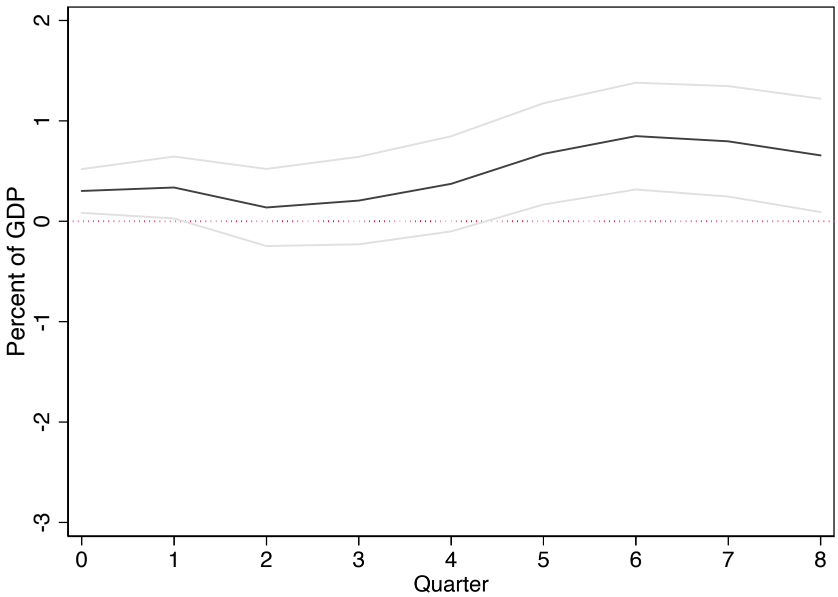
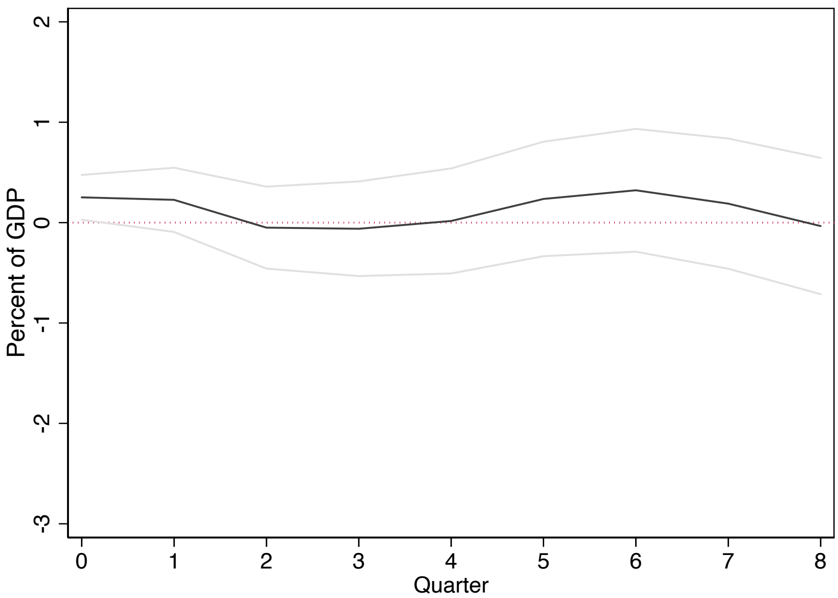


Figure 18b. With a dummy variable for the 1985-2000 sample



Notes: Gray lines denote the one standard deviation confidence band. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients.

Figure 19: Tax multiplier based on the proxy approach: Estimated change in GDP in response to a tax Increase of 1 percent of GDP

Figure 19a. Baseline specification

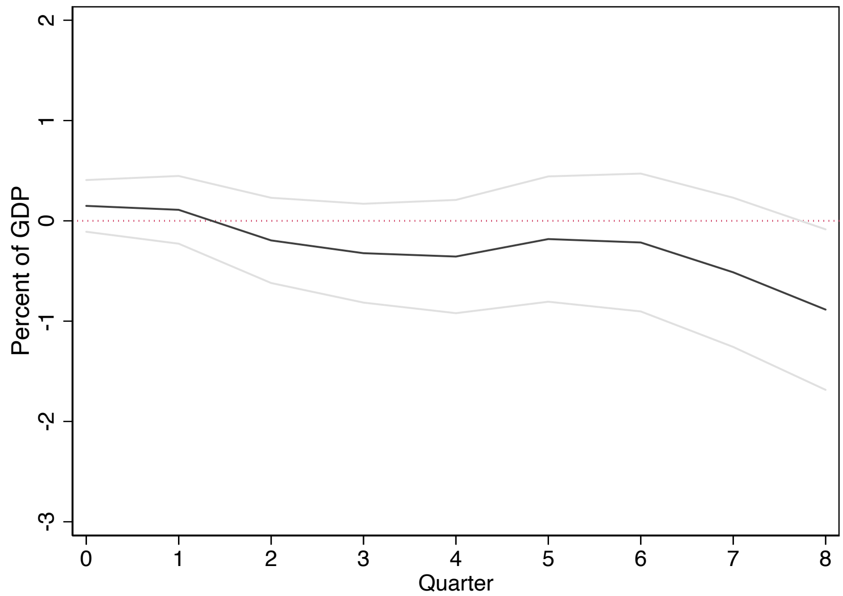
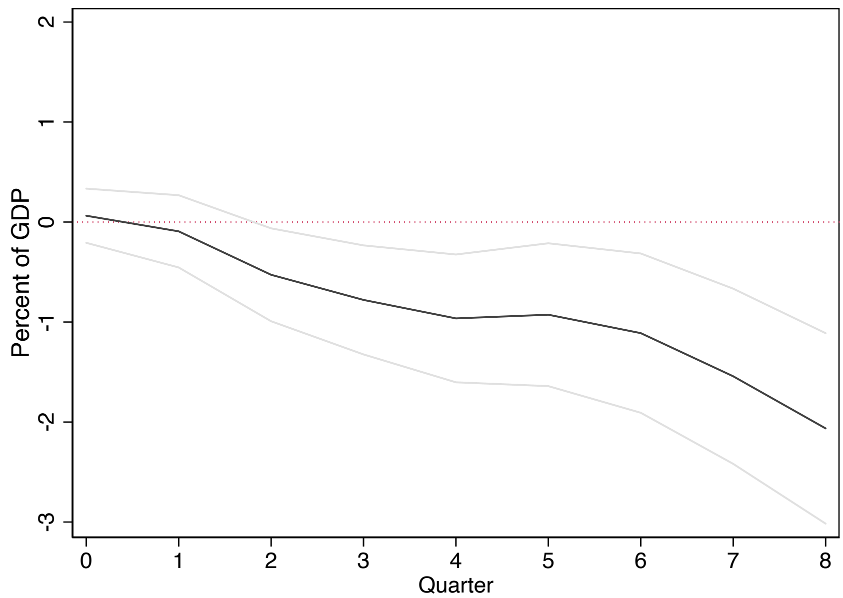


Figure 19b. With a dummy variable for the 1985-2000 sample



Notes: Gray lines denote the one standard deviation confidence band. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients.

Table 18: Predicting GDP growth using failed tax changes

Lag			Controlling for other predictors				
(quarters)	Baseline	Dummy	Lagged GDP	SPF	SC	Greenbooks	Livingstone
2	1.49***	1.07*	1.28**	1.15***	0.42	0.64*	1.27**
	(0.54)	(0.57)	(0.56)	(0.41)	(0.52)	(0.46)	(0.54)
4	1.42***	1.29**	1.50***	1.00**	0.45	0.86*	1.17**
	(0.55)	(0.58)	(0.56)	(0.41)	(0.52)	(0.46)	(0.55)
6	1.26**	1.14*	1.38**	0.94**	0.49	0.88*	1.26**
	(0.54)	(0.58)	(0.56)	(0.41)	(0.52)	(0.49)	(0.53)
8	1.32**	0.92*	1.14**	0.96**	0.59*	0.78*	0.93*
	(0.56)	(0.59)	(0.57)	(0.40)	(0.52)	(0.54)	(0.56)

Notes: The Lag corresponds to the legislation plus implementation lag measured in quarters. The standard errors are reported in parenthesis. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients. The standard errors reported correspond to the cumulative (contemporaneous plus 8 lags) tax multiplier. Greenbooks data is available between the time period 1975-2012 while the Livingstone data is available between the time period 1975-2017 but the data is semi-annual. ICS data is only available for the time period 1978-2017 and is comparable to the baseline which is quarterly data from 1975-2017. *- significant at 32%; ** - significant at 5%; *** - significant at 1%.

Table 19: Tax multiplier on legislated tax changes

Lag on legislated tax changes:	4				6			
Lag on failed tax changes:	2	4	6	8	2	4	6	8
Naive tax multiplier	—— 0.66* ——				—— 0.55 ——			
	(0.56)				(0.56)			
Tax multiplier (corrected using the proxy approach)	-0.94*	-1.06*	-0.88*	-0.46	-0.90*	-0.95*	-0.75	-0.62
	(0.81)	(0.82)	(0.80)	(0.73)	(0.77)	(0.81)	(0.80)	(0.80)

Notes: The lag on legislated and failed tax changes is measured in quarters. The lag on legislated tax changes is the duration of a tax from the time it is legislated to the time it is implemented. The lag on the failed tax change includes the above defined implementation lag as well as the legislation lag which is the duration of an failed tax between its last known congress date and its expected enactment date. The standard errors are reported in parenthesis. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients. The standard errors reported correspond to the cumulative (contemporaneous plus 8 lags) tax multiplier. * - significant at 32%.

Table 20: Robustness checks

	Naive Tax Multiplier	Corrected Tax Multiplier (Proxy Approach)
Baseline specification	0.66	-0.88*
	(0.56)	(0.80)
Structural break dummy	-0.03	-2.06*
	(0.68)	(0.95)
Government spending	0.63*	-0.92*
	(0.58)	(0.81)
Without lagged GDP	0.77*	-0.80*
	(0.57)	(0.82)
Pre-crisis sample	0.52	-1.90*
	(0.81)	(0.86)
Averaging JCT estimates	0.87*	-0.69
	(0.62)	(0.90)
ΔT spread over 1 year	0.66*	-0.54
	(0.61)	(0.92)
Including year 2 estimates	-0.45	-1.42*
	(0.76)	(1.31)
Using net present value	-0.14	-1.12*
	(0.64)	(0.88)

Notes: The standard errors are reported in parenthesis. They are computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients. The standard errors reported correspond to the cumulative (contemporaneous plus 8 lags) tax multiplier. Time period of the regression is 1975-2017. The legislated and failed tax changes are expected to be enacted 4 and 6 quarters after their last congress discussion date. * - significant at 32%.

Chapter 3

3 IT Productivity Paradox: A study across U.S. Manufacturing Industries

3.1 Introduction

Throughout history, technological advances have been known to have had a sharp impact on the growth of an economy. Since the discovery of electricity, one of the largest technological developments has been in the area of Information Technology (IT). The effect of IT on the growth of total factor productivity (TFP)[36] is an important link that has several implications in growth accounting as well as in policy-making, especially considering the large proportion of investments undertaken in it.

In 1987, Nobel laureate Robert Solow observed, "You can see the computer age everywhere but in the productivity statistics." This led to a flurry of research in the 1990s where a wide range of explanations from measurement errors to resource mismanagement was suggested as a response (Brynjolfsson, 1993). However a reversal in the trend of TFP led researchers in the early 21^{st} century to conclude that the IT expansion was having a time-lagged effect on productivity (Fernald 2015; Brynjolfsson, 1993; David, 1991). Several leading researchers since then have considered this 'productivity paradox' to be resolved and no longer an apposite issue.

Bringing this paradox back into the spotlight, Acemoglu et al. (2014) find that there are no significant increases in labour productivity in IT-intensive industries in the U.S. manufacturing sector. Any detectable increases were found to be due to labour contracting faster than output. In fact, when they use TFP as the productivity measure, there is some evidence of a decrease in productivity. However, I find that an increase in the usage of IT in an industry can affect its labour force[37]. More precisely,

[36]Throughout this paper, the term TFP is used to refer to total factor productivity growth.

[37]The chosen measures of IT intensity are negatively correlated with employment shares thus suggesting that a highly IT-intensive sector is more likely to experience a contraction in output and labour.

I show that an industry with higher usage of IT can decrease (increase) the output and induce negative (positive) changes in its number of workers.

Since changes to the employment shares of an industry may directly affect the quality of the workforce and thus their overall efficacy or productivity growth, estimating the effects of technology on productivity may lead to biased estimates of IT induced productivity gains. To resolve this source of endogeneity, I remeasure the TFP growth by taking into account the elasticity of average worker efficacies and labour-income-weighted employment shares. The estimation of this elasticity for the U.S. manufacturing industries is another key contribution of this paper.

There have been relatively few empirical papers that estimate this elasticity which was famously introduced as the slope of the relative supply curve in Roy's selection model. According to Roy (1951), the correlation between average worker efficacy and employment shares, and thus the elasticity is negative. Heckman and Sedlacek (1985) find a negative elasticity of -0.5 and -1 for manufacturing and non-manufacturing industries in the U.S. respectively between 1968 and 1981 while Young (2014) estimates the elasticity of the U.S. economy to be around -0.9 between 1987 and 2010. The elasticity is negative when the average efficacy of a sector's workforce is negatively correlated with its employment share[38]. For example, the elasticity of -0.9 can be explained by the fact that as the service sector expands, it draws in less productive workers leaving the more productive manufacturing workers behind since comparative and absolute advantages are aligned in this scenario.

Within the U.S. manufacturing sector, especially post the IT revolution, the story is very different. The bulk of the workers in the manufacturing sector are production workers and there is sufficient evidence to believe that the worker's productivities in different industries will be positively correlated. Irrespective of the exact industry, the job description across the various industries are very similar- operating assembly lines, measuring, storing material, monitoring etc. Thus, workers shifting between industries

[38]Young (2014) shows this to be the case when workers self-select into sectors based on their relative productivities and when comparative advantage and absolute advantage are aligned.

might require time to learn the industry-specific equipment etc. (learning lag), but will already have the necessary skill sets. Then, as an industry expands and induces an influx of workers by offering them higher relative wages, comparative advantage need not be aligned with absolute advantage anymore.

Thus, in contrast, I find that within the manufacturing sector, the average efficacy of an industry's workforce is positively correlated with its employment share with an estimated elasticity of +1.4. So an industry that is contracting faster than the others will also have a lower average efficacy among its workforce. Not accounting for the change in employment shares can thus underestimate the productivity measures.

This paper finds that revising the TFP measures by accounting for the elasticity of average worker's efficacies with respect to employment shares can explain the lack of observed productivity gains in IT-intensive industries within the manufacturing sector. This is because when TFP is mismeasured, the regression of TFP on IT levels results in biased estimates as the measurement error which contains employment shares is correlated with an industry's IT levels. The specific objectives of this paper are to (a) estimate the elasticity of worker efficacy and employment shares of the IT-intensive industries within the manufacturing sector, (b) use this elasticity to revise the TFP measures and (c) finally, estimate the differential productivity gains in the IT-intensive manufacturing sector using the revised TFP measures.

The next section summarises the relevant literature on the productivity paradox. Section three discusses the model and data, section four lists the results, sections five and six discuss the findings and conclude the paper.

3.2 Literature

Brynjolfsson (1993) was the first to explicitly discuss the productivity paradox. The reasons for there being no considerable increases in TFP due to the advancement of IT since the 1970s were given as mismeasurement of key variables, time lags due to learning, redistribution of profits and mismanagement of IT. Several papers since then have made firm-level and industry-wide analyses citing one of the above reasons or introducing new explanations without reaching any consensus (Zheng and Bloch, 2010; Stiroh, 2002; Macdonald et al., 2000; Murgai, 1999).

In the 1990s, there was a remarkable change in the productivity numbers (Brynjolfsson and Saunder, 2009). This was widely assumed to be proof of the time lag effect of the IT advancements. These theories suggest that to affect productivity, new technologies need to be accompanied by changes in management (Bloom et al., 2014), investment strategies (Brynjolfsson and Hitt, 2000), training and organisational change (Bresnahan, Brynjolfsson, and Hitt, 2002) which take time. Another strand of literature focuses on the mismeasurement argument as an explanation and suggests imbibing knowledge spillovers into the growth accounting framework as positive externalities (Corrado et al., 2014) and compares IT as a technological advancement with steam- dynamo and/or electricity (Crafts, 2002; David and Wright, 1999; David, 1991).

Recently, the productivity slowdown due to the Great Recession, has brought attention to the fact that the productivity numbers seem to have started decreasing well before the global recession (Fernald, 2015). As a possible explanation, Byrne, Fernald, and Reinsdorf (2016) highlight that measurement errors in the deflators for computers and communication equipment are larger after the information and communications technology (ICT) boom period (2004–14) than in the boom years (1995–2004). However, this finding alone cannot account for the slowdown.

Although no consensus has been reached on how productivity due to IT has been evolving, it is apparent that larger investments are being made in IT, that are not complemented by the labour market numbers. Brynjolfsson and McAfee (2011) interpret this to mean that machines are replacing workers and suggest that the emphasis should now be on winning the ‘Race Against the Machine’. They claim that this is due to too much technological progress which unambiguously increases productivity and resolves the productivity paradox.

Acemoglu et al. (2014) analyses the U.S. manufacturing sector and conclude that the fall in labour and output further reinforces the existence of the productivity paradox, since the observed increase in labour productivity is due to larger contractions in labour than in output. However, their analysis does not consider the changing worker efficacy as industries expand and contract within the manufacturing sector.

Within the manufacturing sector, at the advent of the IT revolution, *IT-producing* (different from *IT-intensive*) industries grew, poaching workers from other manufacturing industries. This coincided with the ICT boom period. Similarly, from then until the Great Recession, the changing dynamics of worker reallocations within the manufacturing sector had significant effects on productivity (De Loecker and Konings, 2006). Interestingly, the exact nature of technological change on employment has been elusive due to unobservable components (Sabadash, 2013). In the following sections, I account for the changes in average worker productivity in a sector and labour allocations by studying an individual worker's comparative advantage in choosing to work in a specific sector and how it contrasts with the sector's absolute advantage (Roy, 1951).

3.3 Model Specification and Data

3.3.1 Information Technology

The primary aim of this paper is to evaluate the relationship between IT investment and industry-level TFP in the U.S. Manufacturing sector. Special attention is attributed to the IT-using (*IT-intensive*) industries as most of the productivity gains are concentrated in the *IT-producing* industries. The regression model includes γ, a vector of industry fixed effects and δ, a vector of time dummies. A_{jt} is the growth rate of productivity, TFP_{jt}, IT measures industry IT-intensity[39] which is interacted with year dummies $d_{s,t}$ that equal 1 when year s = year t and 0 otherwise, and e is an error term. The first year of data available, 1980, is used as the base year such that

[39]The chosen IT-intensity measure is transformed such that it has zero mean and unit standard deviation across employment-weighted industries.

$\beta_{1980} = 0$. Thus all the other coefficients on the time interacted IT measure for the subsequent years can be read as the level of β in each subsequent year relative to 1980.

$$A_{jt} = \gamma_j + \delta_t + \sum_{s=1981}^{2009} \beta_s.d_{s,t}.IT_j + e_{jt} \tag{26}$$

The data is taken from the NBER-CES Manufacturing Industry Database[40], which is sourced primarily from the Annual Survey of Manufacturers (Becker, Gray and Marvakov, 2013) for the time period 1980 to 2009.

An alternate regression model where the IT-intensity is interacted with a time trend is also estimated. In this model, the object of interest is the single β which is the coefficient of the chosen IT-intensity measure interacted with a linear time trend T_t. All other variables are defined as before.

$$A_{jt} = \gamma_j + \delta_t + \beta.T_t.IT_j + e_{jt} \tag{27}$$

IT-intensity can be measured in two different ways. The first and commonly used measurement is the ratio of the industry computer (IT) expenditures to total capital expenditures (Acemoglu et al., 2014; Autor, Katz and Krueger, 1998; Berman, Bound and Griliches, 1994). Following earlier preferred terminology, I call this *Computer Investments*. This ratio is available in 1977, 1982, 1987, 1992, 2002 and 2007. The *Computer Investment* IT-intensity measures for the years 1977, 1982 and 1987 are available at the 4-digit sic level for 450 sectors[41]. The 1992 *Computer Investment* measure was transcribed from the manufacturing industry series[42]. These are also available at 4-digit sic levels for 458 sectors. For 2002 and 2007, the data are available

[40] While most of the variables in the NBER-CES are taken from the Annual Surveys of Manufacturing, price deflators and depreciation rates are derived from other data published by the Census Bureau, the Bureau of Economic Analysis, the Bureau of Labor Statistics, and the Federal Reserve Board. NBER-CES data and documentation are available at http://www.nber.org/nberces.

[41] Data is from Berman, Bound and Griliches (1994) although I use the data constructed and made available by Acemoglu et al. (2014)

[42] Found at http: *//www.census.gov/prod/www/economic_census.html*

at U.S. Census Bureau's American FactFinder[43]. These are available at the 6-digit NAICS levels for 467 and 463 sectors respectively. The baseline specification considers the weighted average of *Computer Investments* with a slightly larger weight on the last 2 years to make up for the lack of 1997 data. An alternate specification uses only the 1977 *Computer Investments* ratio as the IT-intensity measure.

Overall, the *Computer Investments* measure only looks at investments in computers and does not capture all the innovations in IT which manifest themselves via new and advanced manufacturing technologies. For that reason, data from the Census Bureau's Survey of Manufacturing Technology (SMT) conducted in 1988 and 1993 is used as the second measure of IT-intensity. This survey covers 17 specific technologies, including computer numerically-controlled machines, computer-aided design, engineering technologies, pick and place robots, automated guided vehicle systems, material working lasers, programmable controllers, and local area networks. IT-intensity is computed as the employment-weighted mean fraction of the seventeen technologies across plants in the 120 4-digit industries that the data is available for, averaged over 1988 and 1993. This is called *Technology Usage* and only considers the SMT-intensive industries that fall under five major high-tech sectors SIC 34-38. An alternate specification only uses the 1988 data.

Similar to Autor, Dorn, and Hanson (2013) and Acemoglu (2014; 2013), the industry classification is done at the 5-digit levels based on the specially constructed "SIC87dd" codes[44]. Both IT measures are converted to this 5-digit level of industry classification.

There are 387 industries under the $SIC87dd$ classification, out of which 28 constitute the computer producing sector which corresponds with NAICS 334. Excluding these 28 industries, I have 359 5-digit industries to work with, when using the *Computer Investment* measure. However, due to the fact that the SMT survey was only administered to those industries that were believed to be SMT-intensive, the data for the *Technology Usage* measure only corresponds to 148 $SIC87dd$ and

[43]Tables EC0231I3 and EC0731I1 respectively

[44]The mapping from SIC codes into SIC87dd codes is based on "sub-file_$sic87dd.do$," available at the webpage ($http://www.ddorn.net/data.htm$).

controlling for those that fall under the NAICS 334 computer producing sector, there are only 120 $SIC87dd$ industries that have a one-to-one correspondence with SIC 34-38.

Figure 20[45] plots the relationship between IT-intensity over time with TFP growth. This is the series of coefficients $\{\beta_{1981}, \beta_{1982}, ..., \beta_{2009}\}$ from equation 26. The figure implies that there is no evidence of relatively faster productivity growth in IT-using industries. With *Technology Usage* as the preferred IT-intensity measurement, there is no significant correlation between the two, while *Computer Investments* suggests a negative relationship.

However, both regression models described in equations 26 and 27 do not account for the changing employment shares which are correlated with both IT-intensity and estimated productivity. Thus, not accounting for this can result in biased coefficients.

3.3.2 Sources of Endogeneity

The current measurement of TFP does not take into account that the average worker efficacy within an industry changes with employment shares. The computation of TFP while accounting for average worker efficacy is described below. After addressing the mismeasurement of TFP, this section discusses how not revising the TFP measures will result in biased estimates in the regression models as long as employment shares and IT-intensity are correlated.

TFP is computed using the NBER-CES "four-factor" method. As shown below, the four factors that output depends on are Capital inputs, Production workers, Non-Production workers and Materials (including Energy).

$$\begin{gathered} Y = AF(K, L_P, L_{NP}, M) \\ \hat{Y} = \hat{A} + \Theta_K.\hat{K} + \Theta_{Lp}.\hat{L}_P + \Theta_{Lnp}.\hat{L}_{NP} + \Theta_M.\hat{M} \end{gathered} \tag{28}$$

The Θ refer to the cost shares of each of the factors averaged over the two years for which the TFP growth is calculated. This is essentially a Tornqvist index (similar

[45]This is my replication of the original graph found in the Acemoglu et al. (2014) paper.

to the BLS calculation of TFP). $\hat{A}$ measures the growth rate of productivity and is calculated by subtracting the cost-share-weighted growth of all the four factors from the growth of real shipments.

As described in appendix section 3.7.2, aggregate labour in any industry can be written as a product of the number of workers in that industry and the average efficacy per worker. Since I have two types of labour input (Production and Non-Production workers), I can extend equation 28 by adding the average efficacies of both types of workers in the production function.

$$\begin{gathered} Y = AF(K, L_P \bar{z}^p, L_{NP} \bar{z}^{np}, M) \\ \hat{Y} = \hat{A} + \Theta_K.\hat{K} + \Theta_{Lp}.(\hat{L}_P + \hat{\bar{z}}^p) + \Theta_{Lnp}.(\hat{L}_{NP} + \hat{\bar{z}}^{np}) + \Theta_M.\hat{M} \end{gathered} \tag{29}$$

Then the measured TFP is very different from the true TFP. Due to the fact that the structural transformation occurred during the IT expansion years, the changing labour numbers might be hiding the true TFP values. Furthermore, there was a large boom in the computer-producing industries, which saw a large increase in labour share compared to the rest of the manufacturing sector that was experiencing a contraction. So it is important to calculate the elasticity and remeasure the true TFP. Using equations 28 and 36, I can rewrite equation 29 as follows:

$$\begin{aligned} \hat{A}(est) &= \hat{Y} - \Theta_K.\hat{K} - \Theta_{Lp}.\hat{L}_P - \Theta_{Lnp}.\hat{L}_{NP} - \Theta_M.\hat{M} \\ &= \hat{A}(true) + \Theta_{Lp}.\hat{\bar{z}}^p + \Theta_{Lnp}.\hat{\bar{z}}^{np} \\ &= \hat{A}(true) + \Theta_{Lp}.\xi.\hat{\pi}^p + \Theta_{Lnp}.\xi.\hat{\pi}^{np} \end{aligned} \tag{30}$$

Here $\hat{\pi}^p$ and $\hat{\pi}^{np}$ refer to the employment share of production and non-production workers in their respective industry[46]. For simplicity, the labour-income-share-weighted sum of the change in employment shares $\Theta_{Lp}.\hat{\pi}^p + \Theta_{Lnp}.\hat{\pi}^{np}$ can be defined as $\hat{X}$.

Returning to the regression models described in equations 26 and 27, not accounting for the change in average worker efficacies will only bias the coefficients of interest

[46] I have refrained from attaching subscript i to above equations 28 and 29 in order to simplify notation, these equations are all indexed at the industry level.

if IT-intensity and employment shares are correlated. The data shows that within the manufacturing sector, the more IT-intensive industries are contracting faster than the rest. This could be partially due to the replacement of labour with technology. Alternately, a decrease in the supply of labour to certain industries might be forcing these industries to adapt and depend on more IT-intensive services. Using either of the IT-measures *Computer Investment* or *Technology Usage*, the correlation between employment shares and IT-intensity is negative at -0.06 (p-value of 0.000). Thus, IT-intensity and employment shares are negatively correlated and not controlling for the effect of employment shares on productivity will result in biased estimates in the regression models.

The direction of bias on the coefficients of IT-intensity still depends on the sign of ξ, the elasticity between employment shares and average efficacy. With a positive elasticity, the bias is downwards, and revising the TFP measures, could possibly result in a less negative or more positive relationship between productivity and IT-intensity.

However, simply adding employment shares to the original regression models will also result in biased estimates of the IT-intensity coefficients since the relationship between IT-intensity and employment shares is inherently endogenous[47]. Although IT-investments indirectly affect employment shares via changes to productivity growth, they can also have direct effects on employment shares. Increased investments in computers and other technology can cause substitutions in factors within industries from labour to capital but can also have a compositional effect wherein economic activity and thus employment shares get reallocated depending on a variety of factors such as demand elasticities and input-output linkages (Acemoglu and Restrepo, 2019).

If the elasticity ξ is known, then the regression models 26 and 27 can be re-estimated with the revised TFP growth measures to get unbiased estimates of β[48]. However, running an OLS (ordinary least squares) regression of TFP growth on the

[47] The coefficient on employment shares, ξ, will also be biased due to endogeneity between TFP growth and employment shares.

[48] The direct effect of employment shares on revised TFP growth has already been taken into consideration and so employment shares do not belong in the regression model once the TFP growth has been revised.

employment shares will result in a biased coefficient ξ. This is because in general, the relationship between productivity and employment shares is endogenous. Higher productivity growth is often accompanied by the creation of more productive jobs and the destruction of less productive ones. So, if the changes in employment shares are driven by responses of relative demand to the changes in relative price levels caused by productivity growth, the ξ will be endogenous. However, there can also be exogenous components to the movement of relative employment shares. For example, demand for a specific industry could be driven by changes in aggregate income which cause an exogenous change in employment shares[49].

The next section discusses conducting a two-stage least squares (2SLS) regression to get unbiased estimates of the elasticity ξ within the manufacturing sectors. Armed with the elasticity estimate, revised TFP growth estimates can be used as the dependent variable in the baseline regression models defined in section 3.3.1 to arrive at unbiased estimates of β.

3.3.3 Estimating Elasticity

The elasticity of average worker efficacy to employment shares has historically been considered to be negative. The simple selection model laid out in Roy (1951) famously showed that the average worker efficacy of a sector was inversely related to its employment shares. However, Young (2014) shows that this prediction is dependent on comparative advantage and absolute advantage being aligned which in turn depends on the correlation between an individual's productivity in different activities. Appendix section 3.7.2 modifies the model described in Young (2014) to fit the manufacturing sector where a worker's productivities in different sectors are highly positively correlated resulting in a prediction of a positive elasticity.

The secondary focus of this paper is to estimate the elasticity of average worker efficacy to employment shares in the US manufacturing sector. The 2SLS specification

[49]This is only true if the preferences of the consumers are non-homothetic.

used to estimate this elasticity is as follows:

$$\begin{aligned}
\hat{A}_{it} &= \alpha_i + \delta_t + \gamma_i \hat{U}_t + \xi \hat{X}_{it} + \epsilon_{it} \\
\hat{X}_{it} &= \alpha_i^X + \delta_t^X + \gamma_i^X \hat{U}_t + \beta_i \hat{Z}_t + \eta_{it} \\
E(\epsilon_{it}\eta_{it}) &\neq 0
\end{aligned} \tag{31}$$

where $\hat{A}_{it}$ is the estimated TFP growth in industry i at time t. α and δ are the industry and time fixed effects. To consider the effect that business cycles might have on productivity growth, the log change in the national unemployment rate $\hat{U}_t$[50] is added and enters the regression separately by industry as γ_i is an industry effect. Thus, any variation in industry TFP growth due to business cycles is captured by this term. Finally, $\hat{X}_{it}$ is the labour-income-share-weighted sum of the change in employment shares and ξ is the elasticity of worker efficacy to employment shares, our object of interest.

To select the best instruments, I start with the three instruments Young (2014) prepares using FRED, Stockholm International Peace Research Institute (SIPRI) and World Bank Data which include (i) the log change in country defense expenditures over GDP; (ii) the average log change in metal prices; and (iii) the average log change in oil prices. I also consider the 18 unique shock instruments identified as per Stock and Watson's (2012) high-dimensional dynamic factor model analysis of the U.S. economy pre and post-recession. Three of the 18 instruments are productivity shocks but I consider the remaining 15 IVs which include oil prices, monetary policy, uncertainty, liquidity/risk and fiscal policy shocks[51]. In the next section, I will identify which instruments robustly satisfy the requirements of both first-stage significance and second-stage exogeneity and use them to estimate the elasticity.

[50]Data on annual unemployment rates are collected from the U.S. Bureau of Labor Statistics
[51]An extensive list of the instruments can be found in appendix section 3.7.1.

3.4 Results

In this section, I identify a good instrument and compute the elasticity ξ of the U.S. Manufacturing industries. I revise the TFP measures using the elasticity computed and estimate the relationship between IT-intensity and the revised TFP as given by the regression models in equations 26 and 27.

3.4.1 Elasticity within manufacturing industries

The first step in remeasuring TFP is to re-estimate the elasticity for the U.S. manufacturing industry. I do this by running the 2SLS model defined in equation 31.

For the 18 instruments chosen in section 3.3.3, I report the first stage significance test results in Table 21. The p-value of the F-test on the instrument after running the first stage regression of equation 31 with one instrument at a time and the total number of observations are reported. Only 5 of the 18 instruments are found to be significant at the 5 percent level. The change in log country defense expenditure per GDP (defense expenditure) and change in log oil prices (Δ oil prices) are highly significant. Only the Hamilton (2003) oil price increase over prior maximum (OP maximum), Romer and Romer (2004) monetary policy shock (RR shock) and interestingly Ramey's NPV Defense spending news per GDP (defense news) are significant among the Stock and Watson instruments.

Panel A of Table 22 lists the results of the regression on equation 31 using OLS and IV with the above mentioned five instruments separately. The elasticity is positive in all of the regressions run. However, only the two oil shock instruments and the defense news instrument satisfy the exclusion restriction. Neither defense expenditure, nor the RR shock confirms their validity as instruments. Moreover, the elasticity while positive varies widely even among the three instruments that satisfy both the first stage significance and the exclusion restriction, thus stressing on the importance of testing the robustness of the baseline specification.

Panels B-G tests the robustness and sensitivity of the baseline specification.

Removing unemployment controls (Panel B) does not change the results significantly and although the p-value of the 2^{nd} stage F test for OP maximum shock has fallen, it still satisfies the exclusion restriction. However substituting out unemployment controls with the Federal Reserve's capacity utilization estimate of aggregate mining, manufacturing and utilities renders defense news to become insignificant (Panel C). Furthermore, apart from the monetary shock, the elasticities in all other IV regressions are revised upwards. For defense expenditure and OP maximum, the elasticity is positive and doubles. Capacity utilization is expected to increase when market demand increases, so controlling for it can give a more accurate estimate of elasticity. However, adding this to the baseline specification instead of substituting for unemployment might be even better as unemployment controls adjust for any relations that productivity and labour allocations may have with the business cycle. This can be seen in Panel D. The elasticities are still positive and greater than 1. Furthermore, the values lie between the panel B and C specifications. The oil shocks remain to be the only instruments that satisfy both 1^{st} and 2^{nd} stage tests with a value for ξ of 1.58. In both the OLS and IV regression (using Δ Oil Prices), the industry coefficients on the unemployment rate and capacity utilization separately remain highly significant (F p-values of 0.000 for both sets of regressors in both regressions) suggesting that there is a business cycle characteristic in the movement of relative productivity and employment that is not restricted to capacity utilization. The results of dropping year dummies from the regression (Panel E) are very similar to the results from when the unemployment controls were dropped.

There is cause for concern that these regressions are capturing only short-term effects which may be very different from long run effects. Short-term effects dictate that if the supply of an industry decreases leading to a decrease in workers, without any change in its productive capacity, there will be a transitory capacity utilization decrease that understates productivity temporarily. This would imply that the short-term elasticity estimate is understated and should actually be more positive. To estimate this effect, I add four lags of the labour-share-weighted change in employment shares as exogenous (predetermined) independent variables to the respective OLS and IV regressions. The sum of the current and lagged values of employment share changes are reported in Panel F and they represent the long run effect on productivity. The long-term estimates are much more positive confirming the concern that the decrease in capacity utilisation is understating productivity[52]. In other words, industries that face contracting employment shares may not show sufficient increases in productivity in the short run.

To test if the IT-producing (computer) industries that were booming had a significantly large effect on ξ, I dropped these industries from the data and re-ran the first stage regressions using the baseline specification. This corresponds to dropping 28 5-digit sic87dd industries from the 387 total manufacturing industries. This has a large impact on estimates as can be seen in Panel G, wherein IV with Δ Oil Prices and the OLS regressions give higher elasticities than in the baseline while the opposite is true for all the other instruments. But while oil shocks continue satisfying both stage tests, the elasticity estimates of both are positive but widely different. However, this may be related to the capacity utilisation problems discussed before as evidenced by panels C and D wherein, the elasticity estimated with Δ Oil Prices as IV increased significantly on adding ln changes to capacity utilisation.

Now suppose, in contrast to equation 30, the elasticities were different for the different types of labour. Then, equation 30 and the key regression to determine the elasticities as in the first line of equation 31 becomes:

$$\hat{A}(est) = \hat{A}(true) + \Theta_{Lp}.\xi_1.\hat{\pi}^p + \Theta_{Lnp}.\xi_2.\hat{\pi}^{np} \tag{32}$$

$$\hat{A}_{it} = \alpha_i + \delta_t + \gamma_i \hat{U}_t + \xi_1 \hat{X}^1_{it} + \xi_2 \hat{X}^2_{it} + \epsilon_{it} \tag{33}$$

$\hat{X}^1_{it}$ is the labour-income-share-weighted sum of the change in employment shares of the

[52]If a sector is expanding, there will also be a learning lag - workers may need time to learn industry-specific skills, so they will be less productive at the beginning - which works in the opposite direction from the capacity utilisation. Young (2014) finds that the capacity utilisation effect which overstates productivity in an expanding industry supersedes the learning lag effect.

production workers and $\hat{X}_{it}^2$ is that of non-production workers. Similarly, ξ_1 and ξ_2 refer to the elasticities of average worker efficacy to the corresponding employment shares. The OLS results of equation 33 are reported in Table 23. The results imply a positive elasticity for the first endogenous term (employment shares of production workers) and a negative elasticity for the non-production employment shares. However, to control for the endogeneity of the employment shares, I redo the first stage regression tests for the two regressors[53]. From the 18 regressions, the only instrument that satisfies the significance tests of both stages is defense expenditure[54]. The results for the IV regression using defense expenditures as instruments, now show a positive elasticity for both regressors although the ξ_1 is now very high at 4.8. Bootstrapping to check how strong the instrument is, is necessary[55]. Thus controlling for endogeneity, I can see that the elasticity for production workers is much more positive than that of non-production workers, whose elasticity is almost zero.

3.4.2 Impact of IT-intensity on revised TFP

Based on the analysis in the previous section, I can conclude that the elasticity is positive. Table 22 highlights the endogeneity issue. Instruments Δ oil prices and the OP maximum which satisfy both the stages of significance tests produce similar estimates around 1.5 when business cycle effects and capacity utilisation changes are considered. As discussed, the long run effects result in much larger, positive estimates than the short run effects implying that industries that were contracting were experiencing a decrease in capacity utilisation. With the IT revolution, high IT-intensive industries might have invested in capital with higher productive

[53]The instruments that satisfy the first stage significance tests for the production workers' employment shares are instruments (i)-(iv), (vii), (ix), (xiii), (xvi) and (xviii) (See Table 21 for the list of instruments in order). Similarly, for non-production workers' employment shares, the instruments are (i) and (x).

[54]Since the instrument is introduced in the IV regression by interacting it with industries, I get 386 (N-1) instruments for the first stage regression.

[55]As I am essentially using a single instrument and interacting it with industry dummies to create 386 instruments, there might be concern that the rank condition isn't satisfied. However, since defense expenditures affect the Explosives sector differently than the Book Publishing sector, the rank condition must be satisfied. Nevertheless, to confirm validity and ensure that the standard errors aren't too big, bootstrapping might be necessary.

capabilities such that even in industries where output was expanding inducing an influx of workers, capacity utilization could actually be falling. This would understate the elasticity estimate which should be more positive, thus providing an explanation for the smaller value of elasticity with OP maximum as an IV. Overall, the elasticity estimate of 1.5 (Panel D) is also close to the long run OLS estimate of 1.4. So, I remeasure TFP using an estimate of 1.4 and plot the coefficients in figures 21b and 22b.

Figure 21a is a replication of the original figure 20 based on the regression model in equation 26 but with the standard errors computed by bootstrapping[56]. It is immediately apparent that the IT-intensity appears to have caused a decrease in the four-factor TFP measure of productivity growth over time. Measuring with *Computer Investments* shows that across the entire manufacturing sector, industries that had a one standard deviation higher rate of IT investment experienced a decline in differential productivity growth of -10 log points over the three decades. However, *Technology Usage* which is a more wholesome measure suggests a smaller decline of -5 log points in 1997 after which the differential productivity losses reduce to zero over the last decade.

Figure 21b accounts for the average worker efficacy and uses the revised TFP estimates. Compared to figure 21a, the correlation of both types of IT-intensity with the corrected TFP measure is less negative. *Technology Usage* saw almost no differential productivity gains between 1980 and 2000 although there were differential productivity gains of 6 log points in the last decade. Pre-1997, the coefficient was slightly negative at around -2 although this is mostly insignificant. On the other hand, *Computer Investments* remains negatively correlated but by less with the differential productivity growth in IT-intensive industries of the magnitude of -5 log points over three decades.

Running the regression model using only the initial values of IT-intensity yields

[56] 10,000 draws are taken of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients.

similar results to the above where weighted averages of IT-intensity were used as the preferred measure. Figures 22a and 22b graph the coefficients on IT-intensity across time from the regression model in equation 26 using initial values of IT-intensity and with the original TFP and revised measure of TFP growth as dependent variables respectively.

Using the initial 1977 values of *Computer Investments* shows a divergence in the last decade. The differential productivity growth for a more IT-intensive industry now becomes -13 log points in 2005 (Figure 22a). However, after revising the TFP measures, the difference in the coefficients between the regression using the initial values and average values for *Computer Investments* disappears. Even in 2005, the difference is less than 1 log point. There isn't much of a difference between the coefficients when using *Technology Usage* as the IT-intensity measure for both specifications.

Under both scenarios of using average and initial values of the two IT-intensity measures, revising the TFP growth by accounting for changes in average worker efficacy results in less negative and more positive differential productivity gains to IT-intensity. To ensure completeness, results from the regression model defined in equation 27 are listed in table 24 where the different IT-intensity measures are interacted with a linear time trend.

Using a weighted average of *Computer Investments* as before implies that an industry with one standard deviation more IT-intensity will have a differential productivity loss of -0.31 log points every year. Using revised TFP measures, the differential productivity growth becomes insignificant at -0.09 log points. With the initial values of *Computer Investments*, the differential productivity loss becomes -0.46 log points per year using the original TFP measures, while the beta coefficient becomes insignificant at -0.09 with the revised TFP measures.

Using the average measure of *Technology Usage*, the beta coefficient goes from an insignificant estimate of -0.08 to a significant 0.2 log points per year with the original and revised TFP as the dependent variables respectively. The initial values of *Technology Usage* change the estimates from an insignificant -0.1 to +0.2 log points.

A battery of IT-intensity measures using all the available values and combinations of IT-intensity are used to check the robustness and sensitivity of the results. There are no significant differences across the different IT measures except for the 2007 *Computer Investments* measure which identifies a significant and negative productivity differential of -0.2 for the revised TFP regression model. However, using the last available IT measure is clearly problematic due to endogeneity concerns.

Overall, irrespective of the IT-intensity measure used, the differential productivity growth due to IT-intensity becomes less negative and more positive when the TFP measures are revised using the elasticity of average worker efficacy and employment shares giving credence to the endogeneity concerns discussed previously.

The theoretical implications of a positive elasticity and other results are discussed in the next section, along with a brief analysis of the relationship between IT-intensity and labour allocations.

3.5 Discussion

I argue that one of the main reasons why productivity is increasing but cannot be seen in the data is a measurement issue as has been discussed in this literature before. By measurement error, in this paper, I refer to the issue of overlooking the difference in the average worker productivities across industries. I have used the framework set by Young (2014) to remeasure TFP growth and re-plot the relationship between IT-intensity and revised TFP measures and find that there are some differences that call for a better understanding of the interaction between IT-intensity and employment shares.

Understanding what the marginal productivity of a worker who reallocates, in terms of his comparative advantage and absolute advantage of a sector, gives us a better idea about the extent to which changing employment shares affect the average productivities of the industries in the manufacturing sector. I find the elasticity of average worker efficacy with respect to the industry's employment share to be positive which implies that within the U.S. manufacturing sector, comparative advantage and absolute advantage are not aligned and that this would be true if workers productivities in different sectors were positively correlated ($\eta > 0$)[57]. However, while this does imply that the relationship between IT-intensity and productivity is more positive than previously thought, it brings our attention to the fact that for the coefficients to have changed, IT-intensity must be related to changing employment shares.

IT-intensity and employment shares. The relationship between IT-intensity and employment shares is an interesting one. As previously explained, the correlation between IT-intensity measures and employment share is negative at -0.06 (p-value = 0.000). Acemoglu et al (2014) observed that within the manufacturing sector, IT-intensive sectors that experience high labour productivity are also experiencing rapidly declining employment. But, due to structural transformation, this is true of most of the manufacturing sector. Thus, it is important to understand whether high IT-intensive sectors which are experiencing larger (smaller) output demands, expand (contract) their employment shares in the manufacturing economy.

I regressed the employment shares on IT-intensity, year dummies, time dummies and unemployment controls and recorded the coefficients. Similarly, I regressed output growth on the same set of independent variables. Figure 23 plots the coefficients together and a positive relationship between the two can be observed[58]. The correlation between the coefficients is 0.783 and without the outliers, becomes 0.739 (p-value =0.000 and 0.000)[59]. This confirms that high IT-intensive sectors

[57] The η references the simple two sector model discussed in Section 3.7.2

[58] Due to the presence of year and industry dummies, I take the first industry of Meat Packing plants (sic87dd = 2011) as the base. Thus all the coefficients in the figure are changes relative to this sector.
Since the data for *Computer Investments* is only available for 6 years, I regress the data for 387 sectors across 6 years. Since the year data points span the period 1977-2007, I believe that this regression while not completely accurate is a reasonable representation of the U.S. manufacturing sector

[59] Output growth coefficients greater than 1 and employment share coefficients greater than 0.2 in absolute terms are dropped.
The average t-statistics computed of the coefficients for employment shares and output growth are 0.650 and 0.743 respectively which implies that industry by industry, the relationship is quite imprecise. However, F-tests from the first stage regressions give a p-value of 0.000 and 0.001 thus confirming

experiencing output growth are also expanding their employment shares. But this also means that there can be high IT-intensive sectors that are experiencing lower output demands and so have lower employment shares. To summarise, I want to draw attention to the fact that the interaction between IT-intensity and employment shares could be leading to severe measurement issues with regards to productivity, therefore, painting a murkier picture regarding the effects of the IT revolution.

Production and non-production labour. Finally, it may be useful to study if both production and non-production workers in the U.S. manufacturing sector behave in the same way. The OLS results in Table 23 serve as a starting point to show that there could be a difference between the two. First stage regressions of employment shares of production workers and non-production workers on IT-intensity give F p-values of 0.000 and 0.030 which implies that IT-intensity does influence both types of employment shares. The correlation between the coefficients of the first stage regression on employment shares of production workers and output growth gives a correlation of 0.734 and a p-value of 0.000 (omitting outliers)[60]. Similarly, I get 0.538 (p-value =0.000) for the employment shares of non-production workers[61].

It can be implied from these results that IT-intensity has a higher effect on production workers than on skilled labour. However, since there is a larger proportion of production workers than non-production workers in the manufacturing sector, this might be more of a comment on the diminishing marginal product of labour. If output demand contracts, firms might be more willing to lay off workers from the ample unskilled labourers in their plants rather than the few skilled workers they have hired. This explains why the variation in the employment shares of the production workers is much larger than that of the non-production workers[62]. The

that overall IT-intensity is significantly correlated with both employment shares and output growth.

[60]Output growth coefficients greater than 1, and employment share coefficients greater than 0.1 in absolute terms are dropped. With outliers, the correlation is 0.761 with a p-value =0.000).

[61]Output growth coefficients greater than 1, and employment share coefficients greater than 0.1 in absolute terms are dropped. With outliers, the correlation is 0.606 with p-value =0.000

[62]Minimum and maximum changes in the employment shares of production and non-production workers are -0.225 and 0.231 & -.0126 and 0.155 respectively with corresponding standard errors being 0.014 and 0.010.

values of the elasticities in turn imply that the changing labour allocations for the production workers have a much larger effect on the sector's average productivity than the movement of skilled workers. Considering that skilled workers from a specific manufacturing industry might be more likely to reallocate outside the U.S. manufacturing sector to the service sector, the near-zero value of the elasticity for non-production workers reallocating within the manufacturing sector is consistent.

Worker's self-selecting outside the manufacturing sector. There may be concern that this paper is not considering workers who leave manufacturing and shift to the service industry. Firstly, as Young (2014) showed, workers who move out of manufacturing and into service sectors tend to have lower efficacies and thus result in increasing the average efficacy of the manufacturing sector. So, the results from this paper are an upper estimate of the elasticity and thus of the effects of IT-intensity on revised productivity. Secondly, this paper only studies the productivity in the IT-intensive manufacturing sectors, so I am concerned only with estimating the elasticity between worker efficacies and employment shares for these industries. Using the elasticity for the entire U.S. economy would provide an incorrect estimate since comparative advantage and absolute advantage may not be aligned between industries within the manufacturing sector but may be aligned between an industry from a manufacturing sector and an industry from the service sector. Future research can look at micro-data to obtain more evidence regarding the change in productivity due to IT-intensity.

3.6 Conclusion

This paper set out to investigate the extent of the productivity gains in the IT-intensive manufacturing sector as a direct consequence of the ICT revolution. The baseline productivity measure was revised since true productivity depends on the average worker efficacy within each sector which in turn changes as workers reallocate across sectors. The results show that these reallocations become crucial to the storyline when considering relative industry movements within the manufacturing sector. Furthermore, the elasticity of average worker efficacy and changing labour allocations turns out to be positive, implying that the comparative advantage and absolute advantage are not aligned within the goods sector as the sectoral productivities of an individual are weakly or strongly positively correlated.

Controlling for these differences in average worker efficacy shows an upwards improvement in the relationship between IT-intensity and the revised productivity measures suggesting that this mismeasurement played a role in the apparent return to the Solow paradox. However, there remains some ambiguity since the effect of IT-intensity, measured by share of investment in computers, on productivity gains remains negative (although smaller than before). However, upon considering a wider range of technology measures, the productivity gains due to *Technology Usage* are found to be significantly positive, although these gains appear with a significant time lag. For future research, extending this analysis by including IT-intensity lags or attempting to control for sector-specific skill learning lags, might better this relationship. Moreover, using micro-data to identify average worker efficacies can also aid the understanding of the effects of IT-intensity on productivity. An unexpected finding from this paper is that IT-intensity has substantial effects on employment shares and a further understanding of this relationship might prove useful in not only understanding the Solow paradox but also determining the effects of automation and technology on labour.

3.7 Appendices

3.7.1 Miscellaneous

List of Stock and Watson Instruments

The list of the Stock and Watson Instruments include (iv) Hamilton's (2003) measure of the increase of the oil price of a quarter relative to the max of the previous 3 years, available for 1962-2010 (constructed from PPI); (v) Kilian's (2008) measure of the OPEC production shortfall from wars and civil strife, available for 1971-2004; (vi) the residuals of Ramey and Vine's (2010) measure of adjusted gasoline prices regressed on various lagged macroeconomic variables, based on their updated spreadsheet (available 1959-2011); (vii) Romer and Romer's (2004) residual of Fed monetary intentions regressed on internal Fed forecasts (1969-1996); (viii) Smets and Wouters' (2007), measure of the shock to the monetary policy reaction function in a DSGE model, updated by King and Watson (2012) (1959-2004); (ix) Sims and Zha's (2006) monetary policy shock estimated in a structural VAR (1960-2002); (x) Gürkaynak, Sack and Swanson's (2005) measure of surprise changes in the target federal funds rate (1990-2004); (xi) innovations in the VIX, computed as the residual from an AR(2) as suggested by Bloom (2009) (1962-2011); (xii) innovations in an AR(2) of the common component of Baker, Bloom and Davis's (2012) policy uncertainty index calculated from media references to economic policy (1985-2011); (xiii) innovations in an AR(2) of the TED spread, as provided by Stock and Watson (1971-2011); (xiv) innovations in an AR(2) of Gilchrist-Zakrajšek's (2012) bond premium (1973-2010); (xv) Bassett et al's (2011) measure of unpredictable changes in bank-level lending standards (1992-2010); (xvi) Ramey's (2011) federal spending news instrument that measures news of changes in the net present value of military spending divided by nominal GDP (1959-2010); (xvii) Fisher and Peters' (2010) measure of excess returns on stocks of military contractors (1959-2008); and (xviii) Romer and Romer's (2010) measure of tax changes relative to GDP (1959-2007). Quarterly or monthly shocks are averaged to annual levels.

3.7.2 Model of Average Efficacy and Employment shares

This section defines and illustrates a simple model of average worker efficacy. For simplicity, I use the same notations as in Young (2014). $z_i(u)$ is the efficacy or productivity of an individual u when they are working in industry i. Suppose each worker is endowed with different industry productivities, then workers will move to the industry that gives them the highest wages or financial gains. The set of individuals that self-select into industry i is given as below.

$$Set_i = \{u | w_i z_i(u) > w_j z_j(u)\}, \quad \forall j \tag{34}$$

The probability that an individual self-selects into industry i is defined as π_i. Then in equilibrium, this is the share of the labour force in an industry i (L_i/L). Moreover, the average efficacy or conditional productivity of a worker in industry i is given by $\bar{z_i}$.

$$\bar{z_i} = E(z_i(u) | u \in Set_i) = \frac{\int_{u \in Set_i} z_i(u) du}{L * \pi_i} \tag{35}$$

Young (2014) proves that regardless of the specific form of the distribution function that generates the productivity draws, the elasticity of average worker efficacy with respect to the industry's employment share is greater than -1.

$$\xi = \frac{d\bar{z_i}}{d\pi_i} \frac{\pi_i}{\bar{z_i}} \tag{36}$$

Although the elasticity ξ can be positive or negative, it has generally been argued that it should be negative (Roy, 1951) i.e. average worker efficacy declines as a sector expands and draws in less productive workers. Young (2014) finds this to be true by considering how worker efficacy changes due to the expansion of the service sector. He finds a value of -0.922 for ξ that implies that the service sector was in fact facing larger productivity gains that were hidden due to lower average efficacy in the expanding service sector. As discussed in the introduction, the situation within the U.S. manufacturing sector is very different as the productivities of the workers across different industries are highly positively correlated. Then, comparative advantage need not be aligned with absolute advantage and the elasticity can be positive.

The required conditions for elasticity ξ to be positive are (i) the sector-specific productivity draws z_i are independent of each other; and (ii) the elasticity of the cumulative distribution function (CDF) for each of the draws, $(dG/dz) * (z/G)$, is increasing in productivity[63]. Using the simple example that Young (2014) uses to explore independence in productivity draws, I discuss the case that is closest to the U.S. manufacturing industry[64]

Regard a two sector model, where the productivity draws are related by $z_i = z_j^{\eta}$ and z_j is a draw from any distribution. Then workers select sector j if $w_j z_j > w_i z_i$ or likewise if $w_j/w_i > z_i^{1-1/\eta}$. Figure 24[65] shows what happens as sector j expands relative to i such that w_j/w_i increases in the case when $\eta > 1$. The top quadrant maps the comparative advantage equation. Workers with draws greater than the marginal draw z_i^* work for sector i while those with smaller draws work in sector j. In the new equilibrium, sector j expands while i contracts. The average productivity of sector i lies to the right of z_i^*, thus as w_j/w_i increases, sector i sheds its workers with less than average productivity. The bottom quadrant though inverted should be read as representing positive values. The average productivity in sector j lies to the north/above z_j^* on the vertical axis. So, as sector j expands, it attracts workers with higher than average productivities. Thus average productivities in both sectors increase and comparative advantage is not aligned with absolute advantage in both sectors. Sector i has a negative elasticity $\xi < 0$ while sector j has a positive elasticity $\xi > 0$.

[63]Proof for the elasticity of the CDF to be decreasing can be found in the appendix of Young (2014). Using the same proof and assuming that $F_a(x) < F_b(X)$ implies $E(a) > E(b)$ thus resulting in an increasing elasticity. Please refer to point (c) of the Appendix of Young (2014).

[64]Young (2015) discusses the cases when productivities are weakly or negatively correlated, I consider the case where productivities are positively correlated.

[65]This figure has been borrowed from Young (2014) and modified by me. Any errors are my own.

Considering a value for $\eta \in (0, 1)$ shows a very similar story where comparative advantage is aligned with absolute advantage in only one of the sectors. However, if productivities in different sectors are negatively correlated i.e. $\eta < 0$, we are in Roy's world and $\xi < 0$. The empirical results find that the elasticity is positive, suggesting that comparative advantage does not always align with absolute advantage within the manufacturing sector.

3.7.3 Choosing a Good Instrument

Of the 18 instruments, only 5 which includes log country defense expenditure per GDP (defense expenditure), change in log oil prices (Δ oil prices), the Hamilton (2003) oil price increase over prior maximum (OP maximum), Romer and Romer (2004) monetary policy shock (RR shock) and Ramey's NPV Defense spending news per GDP (defense news) satisfy the first stage significance.

On entering both Δ oil prices and OP maximum in the first stage significance test, the p-value on the F-test for the former was found to be 0.3100 while that of the latter was 0.0275. Similarly running the first stage regression with the defense expenditure and the defense news instrument jointly gives an F-test p-value of 1.000 for defense news and a value of 0.000 for defense expenditure. The fact that none of the other fiscal policy/ defense shocks were significant in either test, raises the question of whether defense news is a good IV at all. Similarly, the RR shock is also suspect as none of the other monetary shock instruments were significant. However, second stage exclusion restriction also needs to be considered.

Of the 5 IVs that satisfy the first stage significance, only the two oil shock instruments and the defense news instrument satisfy the exclusion restriction. Moreover, the elasticity from an IV that controls for endogeneity is much more positive when looking at the oil shocks, but the elasticity using defense news is much smaller. However, the defense news instrument was not significant at the 1% level in the 1^{st} stage test, implying the oil shocks might be better instruments. This calls for a discussion on which instrument best controls for endogeneity by accounting for changes in the sector's demand and supply but at the same time is not related to the sector's productivity growth.

The U.S. is one of the largest oil producers in the world, contributing to about 12% of the total production. Thus, it is surprising to find that the Δ oil prices survived the exclusion restriction as that implies that changes in productivity growth only affected oil prices by causing changes in employment shares. However as can be seen from the Stock and Watson instruments, the OP maximum instrument is also valid which instils more confidence in the instruments. In fact arguing that oil shocks are primarily caused by changes in the world supply and demand due to a variety of reasons such as war, recessions, weather, politics and primarily due to cartel behaviour, leads us to acknowledge that while productivity growth of U.S. manufacturing industries might affect oil prices, it is not the only or even the primary reason for major oil shocks. In this regard, oil shocks can be considered a reasonable candidate to be a good instrument in our dataset of U.S. manufacturing industries if it will substantially alter relative industry demand and supply and not just macroeconomic demand and supply. So to test this, I check the correlation between the 1^{st} stage coefficient, on employment shares with OP maximum as the dependent variable, and the average energy share of the industries. If it is a good instrument, then I should find a negative correlation i.e. as oil prices rise exogenously, more energy-intensive industries see their relative employment share fall. I find a correlation close to zero[66] for both the oil shock instruments. However, both are insignificant and thus neither confirm nor deny the validity of the instruments.

Although the oil shocks continue satisfying both stage tests across all the robustness tests in table 22, the elasticity estimates of both are positive but widely different when the computer industries are dropped. Although this difference disappears when capacity utilisation changes are added to the regression, it is worthwhile to explore the relation of the IVs a bit more. Focusing on the OP maximum instrument first,

[66] 0.009 for OP maximum and 0.033 for Δ oil prices. Although the sign is wrong, it is close to zero and insignificant.

observe the graph in Figure 25 that maps the correlation between the coefficients of the regression of output change and employment shares on the instrument separately[67]. I find a positive correlation of 0.756 (p-value of 0.000) and removing the outliers a correlation of 0.727 (p-value of 0.000)[68]. Looking at the IT-using and the IT-producing industries separately gives correlations of 0.654 and 0.760 (p-value of 0.000 and 0.000) respectively. Thus, it appears that changes in the instrument do change the output of the industries inducing changes in the employment shares. Moreover, repeating this exercise with the Δ oil price instrument gives an overall correlation is 0.656 (p-value of 0.000) providing us with a similar argument as above.

Although the reported standard errors do not appear very big, the real standard errors might be much larger. As Young (2017) finds, bootstrapping to find the distribution of the coefficients for the IV and non-IV regressions might provide a different solution by helping to pinpoint the stronger instrument and give us a more realistic estimate of the elasticity[69].

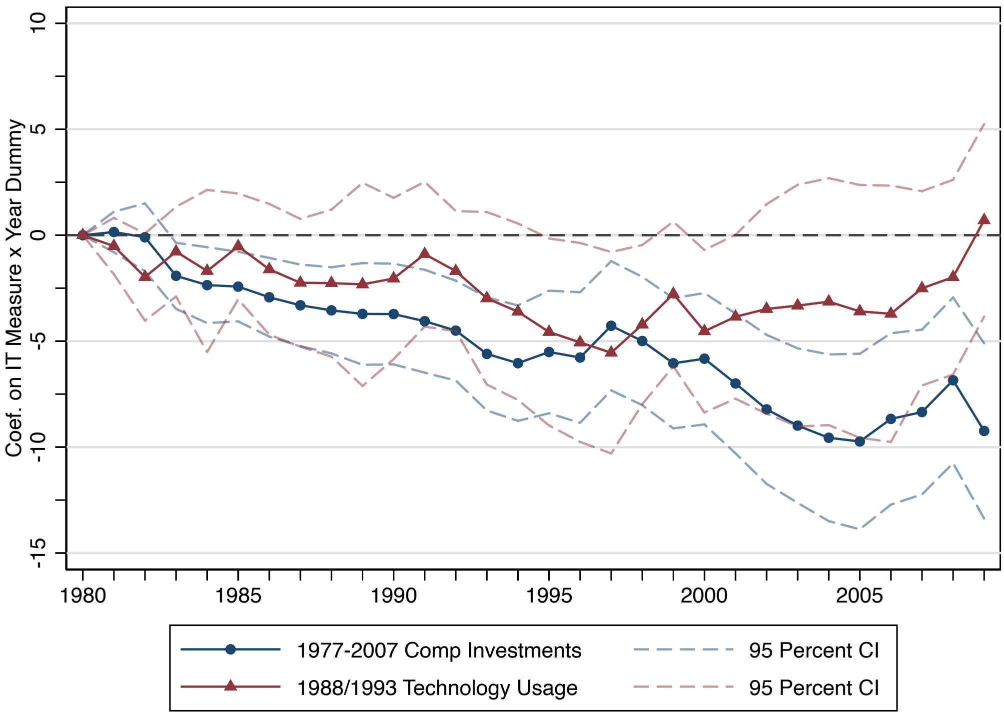
[67]The presence of year and industry dummies indicates that the Meat Packing plants sector (sic87dd = 2011) serves as the base. Thus all the coefficients in the figure are changes relative to this sector.

[68]Outliers are those with employment share coefficients greater than 0.3 or less than -0.3.

[69]To confirm the accuracy of the test statistic of the IV regression, I used Monte Carlo simulations. Using the covariance of the residuals from the first and second stage regressions of the baseline specification with the corresponding instrument, I produce simulated draws of the data. I used 1000 draws and made the assumption that the instruments are valid. The nominal rejection probabilities obtained suggest that the OP maximum instrument is stronger than the Δ oil prices instrument. While 1000 draws is too small for us to conclude accuracy, I hope to extend this to 500,000 draws.

3.7.4 Statistical Tables and Figures

Figure 20: Coefficients from regressions of 100 x log TFP on measures of IT-intensity.



Notes: This graph is a replication of figure A.5 from Acemoglu et al. (2014) based on equation 26. For the series labeled "1977-2007 Comp Investments," the sample consists of 359 non-computer producing manufacturing industries. For the series labeled "1988/1993 Technology Usage," the sample consists of 120 non-computer producing manufacturing industries that fall within SIC codes 34-38. In the technology usage series, an industry's IT-intensity is defined as the employment-weighted share of 17 advanced manufacturing technologies used by plants within that industry. As with the computer investment measure, the technology usage measure is standardized to have zero mean and unit standard deviation across employment-weighted industries. The 95-percent confidence intervals are based on standard errors clustered on industry.

Table 21: 1^{st} Stage p-value in regression of weighted employment share changes on instruments (Instruments evaluated one at a time using specification of equation 31)

	p-value	N
Δ ln Country Defense Expenditures/GDP	0.000	17802
Δ ln Metals Prices	0.102	17802
Δ ln Oil Prices	0.000	17802
Oil Price Increase Over Prior Maximum (Hamilton 2003)	0.000	17802
OPEC Oil Production Shortfall (Kilian 2008)	0.999	13158
Residual of U.S. Gasoline Prices (Ramey & Vine 2010)	0.997	17802
Monetary Policy Shock (Romer & Romer 2004)	0.000	10836
Monetary Policy Reaction Shock (Smets & Wouters 2007)	0.801	15867
Monetary Policy Shock (Sims & Zha 2006)	0.837	15093
Fed. Funds Surprises (Gürkaynak et al 2005)	0.633	5805
VIX Innovation (Bloom 2009)	0.999	17802
Policy Uncertainty Index Innovation (Baker et al 2012)	0.994	9675
TED Spread Innovation (Stock & Watson 2012)	0.109	15093
Bond Premium Innovation (Gilchrist & Kayrajšek 2012)	0.999	14319
Bank Lending Shocks (Basett et al 2011)	1.000	6966
NPV Defense Spending News/GDP (Ramey 2011)	0.035	17802
Excess Returns on Defense Stocks (Fisher & Peters 2010)	0.987	17415
Tax Changes/GDP (Romer & Romer 2010)	0.292	17028

Notes: p-value = F-test p-value on the industry coefficients associated with the instrument. N = observations, sample changes with the availability of the instrument. Instruments (d) – (r) calculated using data from Stock and Watson 2012; instruments (a)-(c) based upon FRED, SIPRI and World Bank data, as described in the text. Each regression follows the first stage specification given in 31, with industry and year fixed effects and the national unemployment rate change and instruments entered separately for each industry. The dependent variable is the labour-share-weighted change in the share of employment by worker type. (Each row represents a separate analysis with the indicated instrument alone.)

Table 22: Annual TFP Growth on changes in employment shares (387 U.S. Manufacturing Sectors: 1963-2009)

	OLS	2SLS by type of instrument				
		Δ Defense Expenditure	Δ Oil Prices	Oil Price Maximum	RR Monetary Shock	Defense News Shock
Panel A. Baseline specification equation 31						
ξ (s.e.)	0.441 (0.088)	1.403 (0.349)	1.461 (0.500)	0.862 (0.478)	1.425 (0.317)	0.143 (0.538)
F & χ^2 p-v		0.000 & 0.000	0.000 & 1.000	0.000 & 0.940	0.000 & 0.000	0.0352 & 1.000
N/K/L	17802	17802/1203/386	17802/1203/386	17802/1203/386	10836/1185/386	17802/1203/386
Panel B. Dropping unemployment controls by industry (BC adjustment)						
ξ (s.e.)	0.452 (0.086)	1.412 (0.354)	1.475 (0.507)	0.738 (0.472)	1.803 (0.330)	0.314 (0.541)
F & χ^2 p-v		0.000 & 0.000	0.000 & 1.000	0.000 & 0.239	0.000 & 0.000	0.070 & 1.000
Panel C. Substituting ln changes in capacity utilization for unemployment controls						
ξ (s.e.)	0.464 (0.090)	2.012 (0.401)	1.611 (0.456)	1.545 (0.442)	1.647 (0.325)	1.614 (0.622)
F & χ^2 p-v		0.000 & 0.000	0.000 & 0.999	0.000 & 1.000	0.000 & 0.000	0.999 & 0.009
Panel D. Adding ln changes in capacity utilization to unemployment controls						
ξ (s.e.)	0.444 (0.091)	1.786 (0.380)	1.574 (0.442)	1.533 (0.433)	1.357 (0.328)	1.547 (0.620)
F & χ^2 p-v		0.000 & 0.000	0.000 & 0.999	0.000 & 1.000	0.014 & 0.014	0.999 & 0.000
Panel E. Dropping year dummies (Common component of TFP)						
ξ (s.e.)	0.373 (0.090)	1.443 (0.354)	1.472 (0.505)	0.921 (0.486)	1.433 (0.326)	1.154 (0.548)
F & χ^2 p-v		0.000 & 0.000	0.000 & 1.000	0.000 & 0.926	0.000 & 0.000	0.042 & 1.000
Panel F. Adding 4 lags of employment share changes						
$\sum \xi$ (s.e.)	1.374 (0.199)	2.128 (0.422)	2.632 (0.523)	2.467 (0.500)	2.781 (0.394)	2.499 (0.686)
F & χ^2 p-v		0.000 & 0.000	0.000 & 0.991	0.000 & 1.000	0.004 & 0.000	0.999 & 0.000
Panel G. Dropping the computer industry sector: Baseline specification						
ξ (s.e.)	0.754 (0.057)	1.027 (0.222)	1.744 (0.319)	0.346 (0.303)	0.094 (0.233)	0.027 (0.348)
F & χ^2 p-v		0.000 & 0.000	0.000 & 0.998	0.000 & 0.518	0.000 & 0.000	0.030 & 0.272

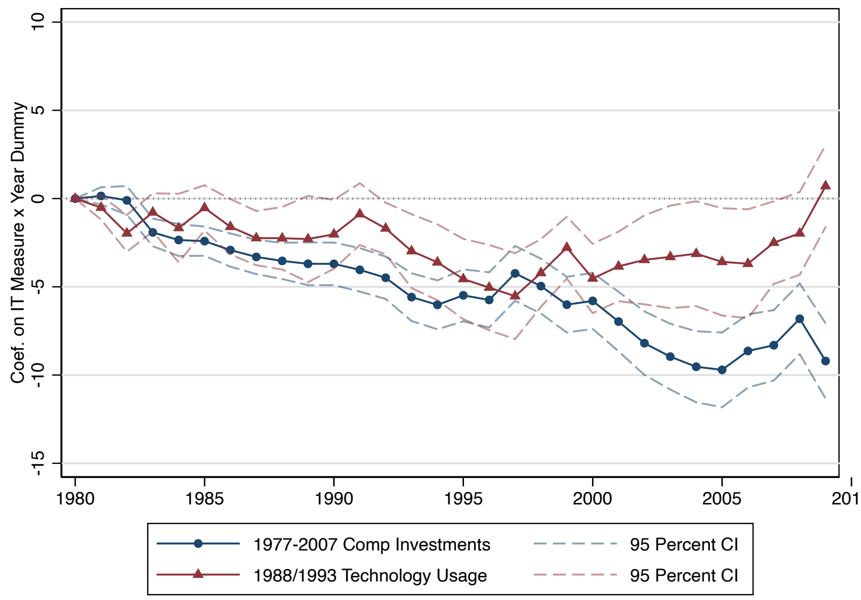
Notes: ξ (s.e) = coefficient (standard error) on labour-share-weighted changes of employment shares by worker type. F & χ^2 p-v= p-value on first stage significance and second stage overidentification tests. N/K/L = number of observations/number of regressors in first stage/excluded instruments in second stage. Because of the joint year and industry dummies, one of the industry coefficients for each of the variables entered by industry (i.e. unemployment changes and instruments) is co-linear with other variables and is dropped in all specifications other than those without year dummies. Thus, there are only 386 excluded instruments in the baseline specification. $\sum \xi$ = sum of the coefficients on current & four lags of weighted employment share changes.

Table 23: Annual TFP growth on changes in production and non-production employment shares

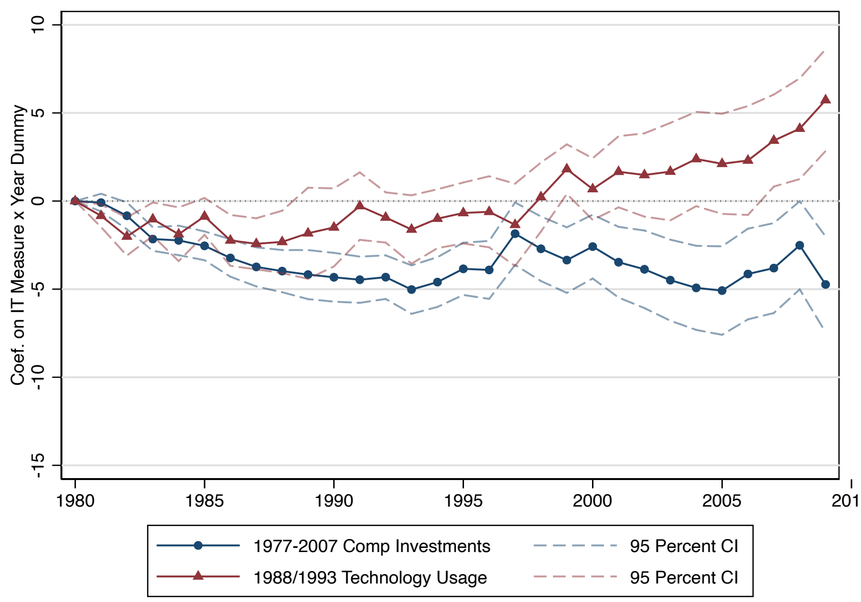
	Production workers	Non-Production Workers
Baseline Specification	1.140 (0.143)	-0.605 (0.190)
Dropping Unemployment Controls	1.103 (0.138)	-0.546 (0.187)
Substituting Capacity Utilization	1.194 (0.146)	-0.597 (0.190)
Adding Cap Utilization	1.182 (0.147)	-0.633 (0.192)
Dropping Time Dummies	1.073 (0.145)	-0.673 (0.193)
Dropping the Computer Sector	0.881 (0.091)	0.549 (0.128)
IV: ln defense expenditures	4.836	0.821

Notes: Each regression follows the 1st stage specification given in equation 33, with industry and year fixed effects and the national unemployment rate change entered separately for each industry. The labour-share-weighted change in the share of employment for production and non-production are considered as separate independent variables providing different estimates of the elasticity. The elasticities are reported with the standard errors in the brackets. The F p-value is 0.000 and 0.000 for both variables in the IV regression.

Figure 21: Coefficients from regressions of 100 x log TFP on average measures of IT-intensity (revised standard errors)



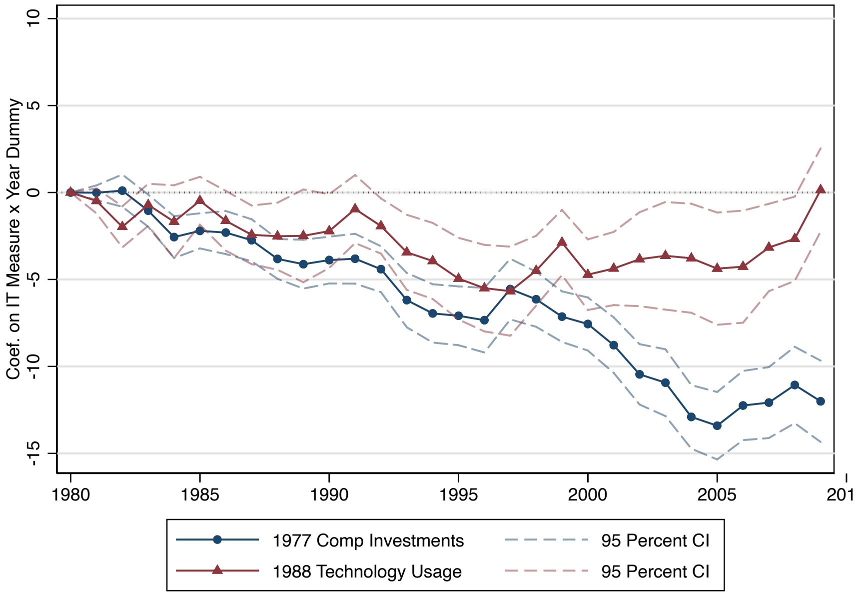
(a) Figure 1 (with revised standard errors)



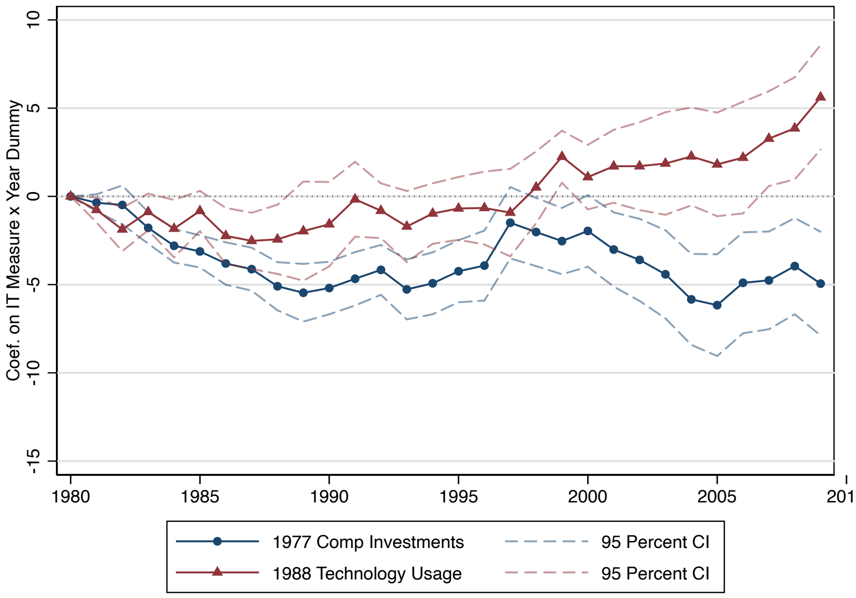
(b) Revised TFP with Elasticity of 1.4

Notes: Details of figure 21a are same as in Figure 20. The Figure 21b refers to TFP growth that has been remeasured as specified in equation 30 with an elasticity value of 1.4. Standard errors have been computed by taking 10,000 draws of the coefficient vector from a multivariate normal distribution with mean and variance-covariance matrix equal to the point estimates and variance-covariance matrix of the regression coefficients.

Figure 22: Coefficients from regressions of 100 x log TFP on initial measures of IT-intensity (revised standard errors)



(a) Original TFP and initial IT-intensity values



(b) Revised TFP and initial IT-intensity values

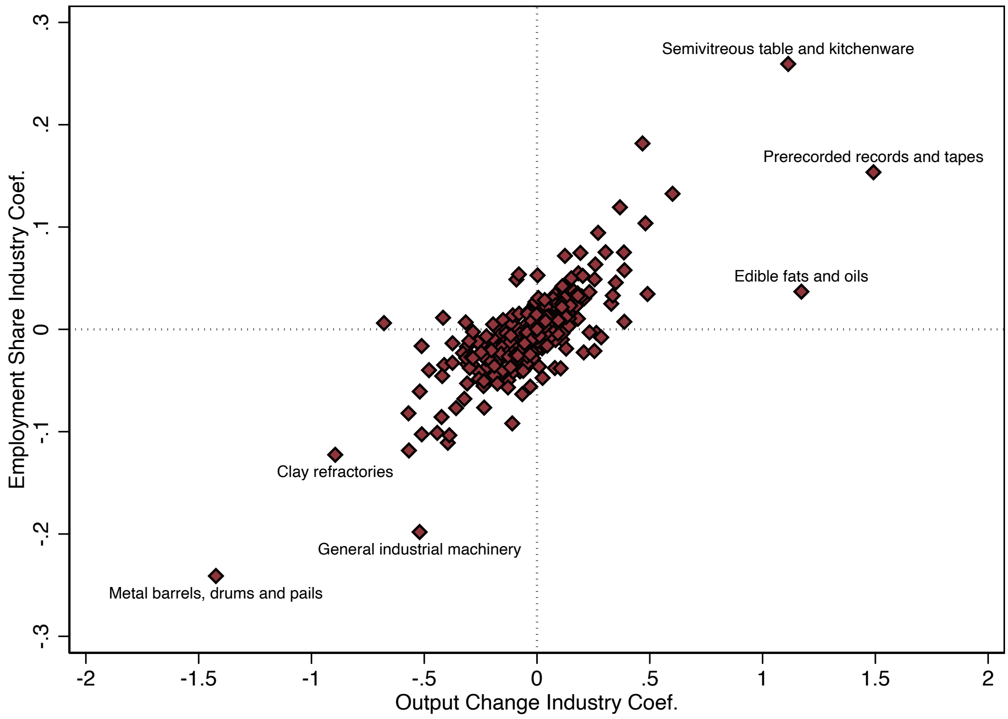
Notes: 22a and 22b graph the series of β_t from equation 26 which vary over time. Both figures use the initial IT-intensity measures i.e. Computer Investments in 1977 and SMT measures in 1988. 22a uses the original TFP growth as the dependent variable while 22b uses the revised TFP growth (with elasticity of 1.4) as the dependent variable. Standard errors are computed as specified in the previous figure.

Table 24: Coefficients from regressions of log TFP (and revised TFP) on different IT-intensity measures interacted with time trend

	Original TFP		Revised TFP	
	Coefficient (β)	s.e.	Coefficient (β)	s.e.
Computer Investments				
1977	-0.459***	(0.073)	-0.094	(0.105)
1982	-0.331***	(0.070)	-0.005	(0.091)
1987	-0.263***	(0.067)	-0.074	(0.069)
1992	-0.177**	(0.083)	0.004	(0.100)
2002	-0.130**	(0.052)	-0.019	(0.078)
2007	-0.228***	(0.065)	-0.203**	(0.083)
1977-1982	-0.461***	(0.073)	-0.052	(0.099)
1987-1992	-0.259**	(0.079)	-0.039	(0.088)
2002-2007	-0.181**	(0.058)	-0.098	(0.084)
Average (1977-2007)	-0.307***	(0.076)	-0.086	(0.098)
Technology Usage				
1988	-0.996	(0.099)	0.197**	(0.091)
1993	-0.043	(0.089)	0.191**	(0.080)
Average (1988-1993)	-0.075	(0.093)	0.200**	(0.088)

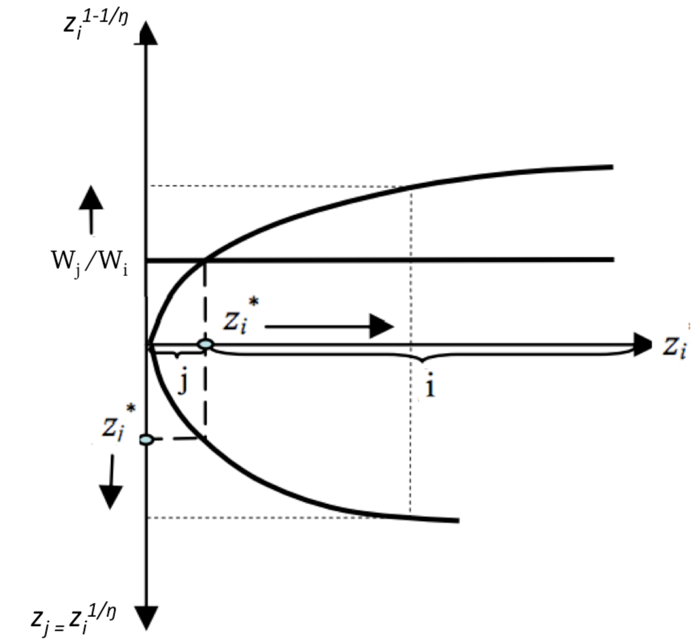
Notes: β is the coefficient on the IT-intensity measure interacted with the time trend from equation 27 and s.e. is the standard error. The dependent variable can be the original TFP growth or revised TFP growth adjusted for changes in employment shares assuming an elasticity of 1.4. *** Denotes significance at 1%, ** Denotes significance at 5%

Figure 23: First Stage Regressions of IT-intensity



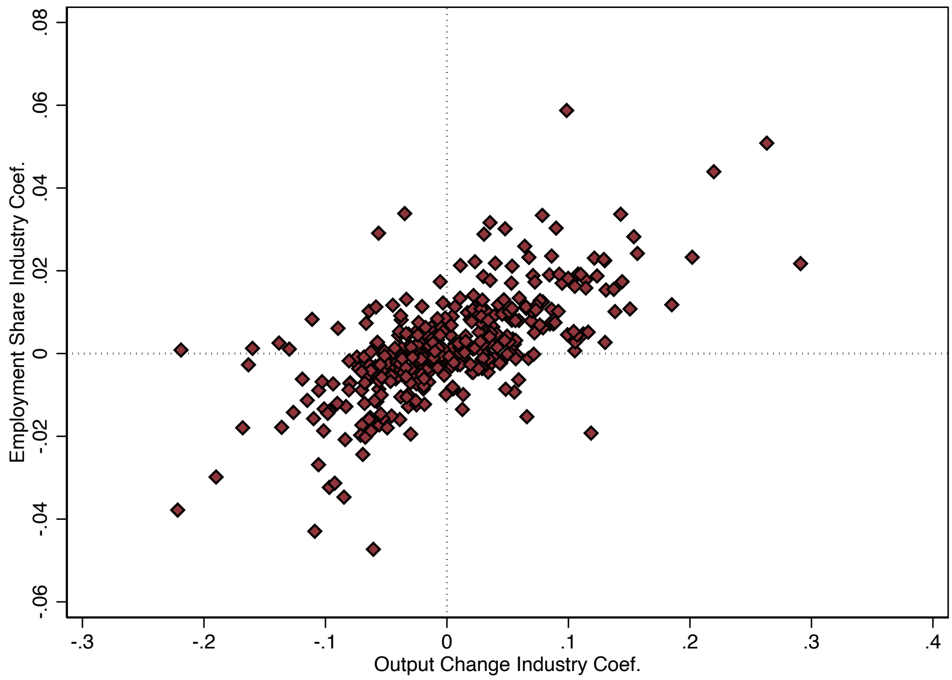
Notes: The output change industry coefficients are taken from the regression of output growth on IT-intensity interacted with industries, time and industry dummies and unemployment controls also interacted with industry dummies. Similarly, the employment share industry coefficients are the coefficients of the instrument interacted with industries on the regression of labour-income-weighted change in employment shares on the same set of independent variables. Since data for IT-intensity only exists for 6 years 1977, 1982, 1987, 1992, 2002 and 2007, NBER-CES data for only these 6 years were used in these regressions.

Figure 24: Example of Positively correlated Productivities

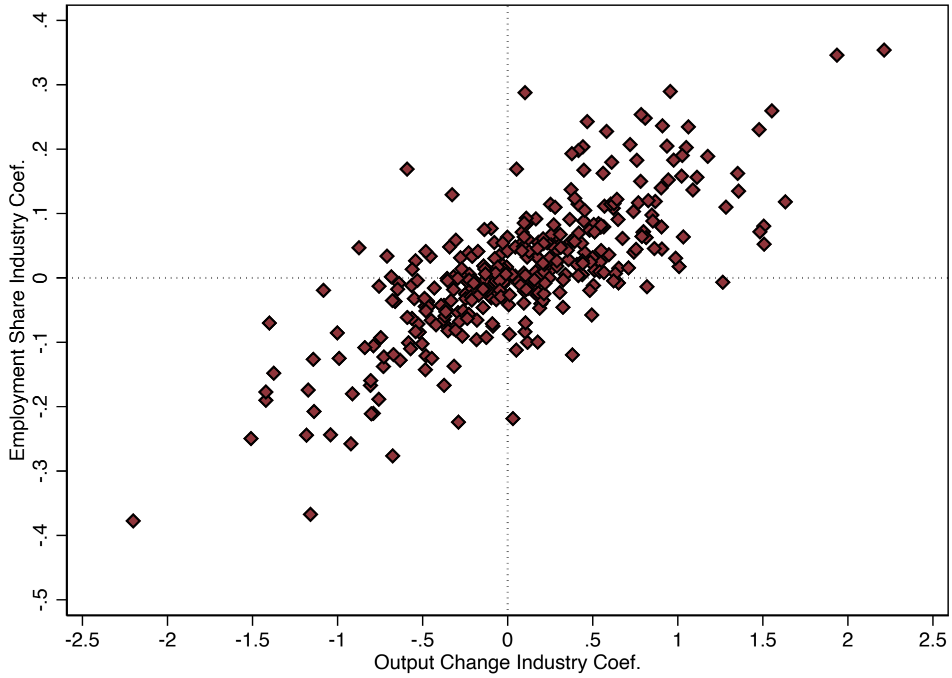


Notes: This graph is borrowed from Young (2014). The axes and labels have been modified to consider the case when $\eta > 0$. The above figure illustrates a situation where w_j/w_i increases and sector j expands while sector i contracts.

Figure 25: First Stage Regressions of instruments



(a) Δ Oil Price



(b) Hamilton Oil Price Maximum

Notes: The output change industry coefficients are taken from the regression of output growth on the instrument interacted with industries, time and industry dummies and unemployment controls also interacted with industry dummies. Similarly, the employment share industry coefficients are the coefficients of the instrument interacted with industries on the regression of labour-income-weighted change in employment shares on the same set of independent variables.

References

[1] Altonji, J.G. and Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives, in (J.M. Abowd and R.B. Freeman, eds.). *Immigration, Trade and Labor, pp. 201–34, Chicago, IL: University of Chicago Press*

[2] Blau, F.D., and Mackie, C. (2017). The Economic and Fiscal Consequences of Immigration. *Washington, DC: National Academies Press*

[3] Borjas, G.J. (1987). Self-Selection and the Earnings of Immigrants *NBER Working Papers 2248, National Bureau of Economic Research, Inc.*

[4] Borjas, G.J. (1991). Immigration and Self-Selection, In Immigration, Trade, and the Labor Market, edited by John M. Abowd and Richard B. Freeman. *Chicago: Univ. Chicago Press (for NBER).*

[5] Borjas, G.J. (2003). The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. *Quarterly Journal of Economics, vol. 118(4), pp. 1335–74*

[6] Borjas, G.J., Kauppinen, I. and Poutvaara, P. (2019) Self-selection of Emigrants: Theory and Evidence on Stochastic Dominance in Observable and Unobservable Characteristics. *The Economic Journal, Volume 129, Issue 617, January 2019, Pages 143–171, https://doi.org/10.1111/ecoj.12585*

[7] Card, D. (1990). The impact of the Mariel Boatlift on the Miami labor market. *Industrial and Labor Relations Review, vol. 43(2), pp. 245–57*

[8] Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics, vol. 19(1), pp. 22–64*

[9] Chiquiar, D., & Hanson, G. (2005). International Migration, Self-Selection, and the Distribution of Wages: Evidence from Mexico and the United States. *Journal of Political Economy, 113(2), 239-281. doi:10.1086/427464*

[10] Chojnicki, X., Docquier, F., and Ragot, L. (2011). Should the U.S. have locked heaven's door? Reassessing the benefits of postwar immigration. *Journal of Population Economics, Vol. 24, pp. 317-359.*

[11] Chojnicki, X., Ragot, L., and Sokhna, N. P. (2018). The fiscal impact of 30 years of immigration in France: an accounting approach. *EconomiX Working Papers 2018-36, University of Paris Nanterre, EconomiX.*

[12] Department of Homeland Security, Office of Immigration Statistics. Lawful Permanent Residents. *Yearbook of Immigration Statistics, multiple years, available online*

[13] Dustmann, C., & Frattini, T. (2014). The Fiscal Effects of Immigration to the UK. *Economic Journal, Royal Economic Society, vol. 124(580), pages 593-643, November.*

[14] Flood, S., King, M., Rodgers, R., Ruggles, S. and Warren, J.R. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. *Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0*

[15] Lee, R. and T. Miller (1997). The Lifetime Fiscal Impacts of immigrants and their Descendants, in Smith, J. and B. Edmonston (eds.). *The New Americans – Economic, Demographic, and Fiscal Effects of Immigration, National Academy, Washington, DC, pp. 297-362.*

[16] Manacorda, M., Manning, A. and Wadsworth, J. (2012). The impact of immigration on the structure of wages: theory and evidence from Britain. *Journal of the European Economic Association, vol. 10(1), pp. 120– 51*

[17] OECD (2013). International Migration Outlook 2013. *OECD Publishing, Paris,* `https://doi.org/10.1787/migr_outlook-2013-en`.

[18] OECD (2021), International Migration Outlook 2021, *OECD Publishing, Paris,* `https://doi.org/10.1787/29f23e9d-en`.

[19] Ottaviano, G.I.P. and Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association, vol. 10(1), pp. 152–97.*

[20] Population Reference Bureau. Elderly Immigrants in the United States. *Today's Research on Aging Program and Policy implications Issue 29, October 2013*

[21] Preston, I. (2014). The effect of immigration on public finances. *Economic Journal, vol. 124(580), pp. F569– 92.*

[22] Rowthorn, R. (2008). The fiscal impact of immigration on the advanced economies. *Oxford Review of Economic Policy, Vol. 24, No. 3, pp. 560-580.*

[23] Rowthorn, R. (2014). A note on Piketty's Capital in the Twenty-First Century *Cambridge Journal of Economics, Oxford University Press, vol. 38(5), pages 1275-1284.*

[24] Roy, A. D. (1951). Some Thoughts On The Distribution Of Earnings *Oxford Economic Papers, Oxford University Press (vol. 3(2))*, 135-146.

[25] Storesletten, K. (2000). Sustaining Fiscal Policy through Immigration. *Journal of Political Economy, Vol. 108, No. 2, pp. 300-323.*

[26] Wilmoth, J. (2012). A Demographic Profile of Older Immigrants. *Public Policy & Aging Report 22, no. 2 (2012): 8-11.*

[27] Alesina, A. and Drazen, A., 1991. Why are stabilizations delayed?. The American Economic Review, 81, pp.1170-1188.

[28] Alesina, A. and Rosenthal, H., 1995. Partisan politics, divided government, and the economy. Cambridge University Press.

[29] Barro, R.J. and Redlick, C.J., 2011. Macroeconomic effects from government purchases and taxes. The Quarterly Journal of Economics, 126(1), pp.51-102.

[30] Blanchard, O. and Perotti, R., 2002. An empirical characterization of the dynamic effects of changes in government spending and taxes on output. the Quarterly Journal of economics, 117(4), pp.1329-1368.

[31] Caldara, D. and Kamps, C., 2012. The analytics of SVARs: a unified framework to measure fiscal multipliers.

[32] Chappell, H.W. and Keech, W.R., 1986. Party differences in macroeconomic policies and outcomes. The American Economic Review, 76(2), pp.71-74.

[33] Chahrour, R., Schmitt-Grohé, S. and Uribe, M., 2012. A model-based evaluation of the debate on the size of the tax multiplier. American Economic Journal: Economic Policy, 4(2), pp.28-45.

[34] Chodorow-Reich, G., 2018. Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?. American Economic Journal: Economic Policy, forthcoming.

[35] Chodorow-Reich, G., Feiveson, L., Liscow, Z. and Woolston, W.G., 2012. Does state fiscal relief during recessions increase employment? Evidence from the American Recovery and Reinvestment Act. American Economic Journal: Economic Policy, 4(3), pp.118-45.

[36] Cloyne, J., 2013. Discretionary tax changes and the macroeconomy: new narrative evidence from the United Kingdom. American Economic Review, 103(4), pp.1507-28.

[37] Fatás, A. and Mihov, I., 2003. The case for restricting fiscal policy discretion. The Quarterly Journal of Economics, 118(4), pp.1419-1447.

[38] Favero, C. and Giavazzi, F., 2012. Measuring tax multipliers: The narrative method in fiscal VARs. American Economic Journal: Economic Policy, 4(2), pp.69-94.

[39] Ilzetzki, E., 2011. Rent-seeking distortions and fiscal procyclicality. Journal of Development Economics, 96(1), pp.30-46.

[40] Ilzetzki, E., Mendoza, E.G. and Végh, C.A., 2013. How big (small?) are fiscal multipliers?. Journal of monetary economics, 60(2), pp.239-254.

[41] Johnson, D.S., Parker, J.A. and Souleles, N.S., 2006. Household expenditure and the income tax rebates of 2001. American Economic Review, 96(5), pp.1589-1610.

[42] Leeper, E.M., Walker, T.B. and Yang, S.C.S., 2008. Fiscal foresight: analytics and econometrics (No. w14028). National Bureau of Economic Research.

[43] Mertens, K. and Ravn, M.O., 2010. Measuring the impact of fiscal policy in the face of anticipation: a structural VAR approach. The Economic Journal, 120(544), pp.393-413.

[44] Mertens, K.R. and Ravn, M.O., 2014. Fiscal policy in an expectations-driven liquidity trap. The Review of Economic Studies, 81(4), pp.1637-1667.

[45] Mountford, A. and Uhlig, H., 2009. What are the effects of fiscal policy shocks?. Journal of applied econometrics, 24(6), pp.960-992.

[46] Parker, J.A., Souleles, N.S., Johnson, D.S. and McClelland, R., 2013. Consumer spending and the economic stimulus payments of 2008. American Economic Review, 103(6), pp.2530-53.

[47] Perotti, R., 1999. Fiscal policy in good times and bad. The Quarterly Journal of Economics, 114(4), pp.1399-1436.

[48] Perotti, R., 2012. The effects of tax shocks on output: not so large, but not small either. American Economic Journal: Economic Policy, 4(2), pp.214-37.

[49] Poterba, J.M., 1994. State responses to fiscal crises: The effects of budgetary institutions and politics. Journal of political Economy, 102(4), pp.799-821.

[50] Ramey, V.A., 2011a. Can government purchases stimulate the economy?. Journal of Economic Literature, 49(3), pp.673-85.

[51] Ramey, V.A., 2011b. Identifying government spending shocks: It's all in the timing. The Quarterly Journal of Economics, 126(1), pp.1-50.

[52] Ramey, V.A. and Shapiro, M.D., 1998, June. Costly capital reallocation and the effects of government spending. In Carnegie-Rochester Conference Series on Public Policy (Vol. 48, pp. 145-194). North-Holland.

[53] Romer, C.D. and Romer, D.H., 2010. The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. American Economic Review, 100(3), pp.763-801.

[54] Valerie A. Ramey, 2011. "Identifying Government Spending Shocks: It's all in the Timing," The Quarterly Journal of Economics, Oxford University Press, vol. 126(1), pages 1-50.

[55] Acemoglu, Daron, David Autor, David Dorn, Gordon H. Hanson, and Brendan Price (2014). Return of the Solow Paradox? IT, Productivity, and Employment in U.S. Manufacturing. *American Economic Review*, 104(5): 394-99.

[56] Acemoglu, Daron and Restrepo, Pascual (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives,* vol 33(2), pages 3-30

[57] Autor, David H., Katz, Lawrence F. and Krueger, Alan B. (1998). Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics, (November 1998, 113 (4))*, 1169–1214.

[58] Autor, David, Dorn, David and Hanson, Gordon (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review, 103(6)*, 2121-2168.

[59] Barro, R. J. (1999). Notes on Growth Accounting. *Journal of Economic Growth, 4*, 119-137.

[60] Berman, Eli, Bound, John and Griliches, Zvi (1994). Changes in the Demand for Skilled Labor Within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing. *Quarterly Journal of Economics, 109(2)*, 367–397.

[61] Bloom, Nicholas and Brynjolfsson, Erik and Foster, Lucia and Jarmin, Ron S. and Patnaik, Megha and Saporta Eksten, Itay and Van Reenen, John (2014). IT and Management in America. *CEPR Discussion Paper No. DP9886.*

[62] Bresnahan, Timothy F. and Brynjolfsson, Erik and Hitt, Lorin M. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *The Quarterly Journal of Economics, Oxford University Press, vol. 117(1)*, 339-376.

[63] Brynjolffson, Erik (1993). The Productivity Paradox of Information Technology: Review and Assessment. *Communications of the ACM, December 1993.*

[64] Brynjolffson, E. and Hitt, L. M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economic Perspectives*, 14(4), 23-48.

[65] Brynjolfsson, Erik, and McAfee, Andrew (2011). Race Against the Machine *Lexington, MA: Digital Frontier Press.*

[66] Brynjolfsson, Erik and Saunders, Adam (2009). Wired for Innovation: How Information Technology is Reshaping the Economy *MIT Press Books,The MIT Press, edition 1, volume 1, number 0262013665.*

[67] Byrne, D., Fernald, J., and Reinsdorf, M. (2016). Does the United States Have a Productivity Slowdown or a Measurement Problem? *Brookings Papers on Economic Activity (Spring 2016)*, 109–157.

[68] Corrado, Carol A. and Haskel, Jonathan and Jona-Lasinio, Cecilia (2014). Knowledge Spillovers, ICT and Productivity Growth. *IZA Discussion Paper No. 8274.*

[69] Crafts, Nicholas (2002). The Solow Productivity Paradox in Historical Perspective. *CEPR Discussion Paper No. 3142.*

[70] David, P. A. (1990). The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox. *American Economic Review, American Economic Association (May 1990)*, vol. 80(2): 355-61.

[71] David, P. A. (1991). Computer and Dynamo: The Modern Productivity Paradox in a Not-Too-Distant Mirror. *OECD, Technology and Productivity: The Challenge for Economic Policy. Paris: OECD*, 315-348.

[72] David, P. A. and Wright, G. (1999). Early Twentieth Century Productivity Growth Dynamics: An Inquiry into the Economic History of 'Our Ignorance' *University of Oxford Discussion Papers in Economic History No. 33.*

[73] De Loecker, Jan and Konings, Jozef (2006). Job reallocation and productivity growth in a post-socialist economy: Evidence from Slovenian manufacturing. *European Journal of Political Economy, Elsevier, (June 2006, vol. 22(2))*, 388-408.

[74] Fernald, J. 2015. Productivity and Potential Output before, during, and after the Great Recession. *NBER Macroeconomics Annual 2014, Volume 29, edited by Jonathan A. Parker and Michael Woodford. Chicago: University of Chicago Press*, 1– 51.

[75] Heckman, James J., and Guilherme Sedlacek (1985). Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-selection in the Labor Market. *Journal of Political Economy* 93 (6): 1077–1125.

[76] Macdonald, Stuart, Anderson, Pat and Kimbel, Dieter (2000). Measurement or Management?: Revisiting the Productivity Paradox of Information Technology

Vierteljahrshefte zur Wirtschaftsforschung / Quarterly Journal of Economic Research, 69, issue 4, 601-617.

[77] Murgai, Rinku (1999). The Green Revolution and the Productivity Paradox: Evidence from the Indian Punjab. *World Bank Policy Research Working Paper No. 2234.*

[78] Roy, A. D. (1951). Some Thoughts On The Distribution Of Earnings *Oxford Economic Papers, Oxford University Press (vol. 3(2))*, 135-146.

[79] Sabadash, Anna (2013). ICT-induced Technological Progress and Employment: a Happy Marriage or a Dangerous Liaison? A Literature Review *JRC Working Papers JRC76143, Joint Research Centre (Seville site).*

[80] Sargent, Timothy C. and Rodriguez, Edgard R. (2000). Labour or Total Factor Productivity: Do We Need to Choose? *International Productivity Monitor, Centre for the Study of Living Standards (Fall 2000, vol 1.)*, 41-44.

[81] Stiroh, Kevin J. (2002). Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? *American Economic Review 92 (5)*, 1559–76.

[82] Solow, Robert M. (1987). We'd Better Watch Out review of Manufacturing Matters: The Myth of the Post-Industrial Economy, by Stephen S. Cohen and John Zysman. *New York Times (July 1987).*

[83] Stock, James H. and Mark W. Watson (2012). Disentangling the Channels of the 2007-09 Recession. *Brookings Papers on Economic Activity (Spring 2012)*, 81-135

[84] Young, Alwyn (2014) Structural Transformation, the Mismeasurement of Productivity Growth, and the Cost Disease of Services. *American Economic Review 104 (November 2014)*, 3635-67.

[85] Young, Alwyn (2017) Consistency without Inference: Instrumental Variables in Practical Application. *Working Paper (February 2017)* http://personal.lse.ac.uk/YoungA/ConsistencyWithoutInference.pdf

[86] Zheng, Simon and Bloch, Harry (2014). Australia's mining productivity decline: implications for MFP measurement. *Journal of Productivity Analysis, Springer, (April 2014, vol. 41(2))*, 201-212.