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The Effects of Undocumented Immigration on the Employment Outcomes of Low-Skill Natives in the United States*

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Abstract: Although international immigrations' impacts on domestic workers are well studied in the United States, data paucity means most researchers have yet to isolate the specific effects of undocumented immigration. Despite limited empirical evidence, many policymakers presuppose undocumented immigrants adversely impact native workers to justify stringent immigration laws. In this paper, we examine the validity of this supposition, offering two contributions. First, we create annual, state-level estimates of the U.S. undocumented population for the period 1994 to 2010 by emulating a methodology adopted by notable demographers. Second, we incorporate these estimates into a fixed-effect, dynamic model to isolate how undocumented immigrants impact low-skill native labor force participation rates and unemployment rates. Overall, we find the total number of international immigrants has a relatively small impact on both. Omitting undocumented immigrants indicates that documented immigrants alone have no significant impact on natives. However, the effects of undocumented immigrants are themselves statistically indistinguishable from the impact of all immigrants. This suggests that neither immigrant group separately has substantive impacts on low-skill natives.

Keywords: undocumented immigration, low-skill workers, labor force participation, unemployment
JEL Codes: J61, J2, J4

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1. INTRODUCTION

Over the past 20 years the United States' undocumented immigrant population has both increased and become more geographically widespread. Although there are no official counts, our own estimates, and those of others (e.g. Passel (2010)) suggest that the number of undocumented immigrants totaled nearly 12 million in 2010, up at least 50 percent from 1990 (Figure 1). In the early 1990s, approximately 85 percent of the undocumented population

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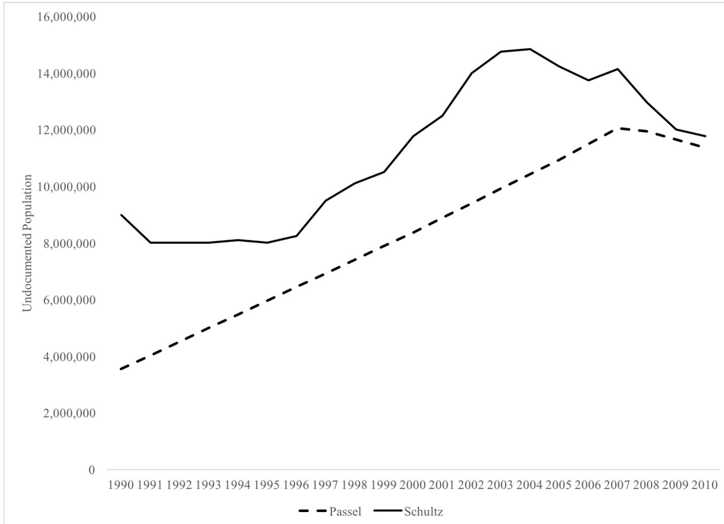
Figure 1: Estimates of Undocumented Population at the National Level



Note: The two line trends presented above have been generated by different sources. The Passel line was produced by data provided by Jeffrey Passel of the PEW Hispanic Center. The Schultz line was produced by data using a methodology presented in Section 3 of this paper.

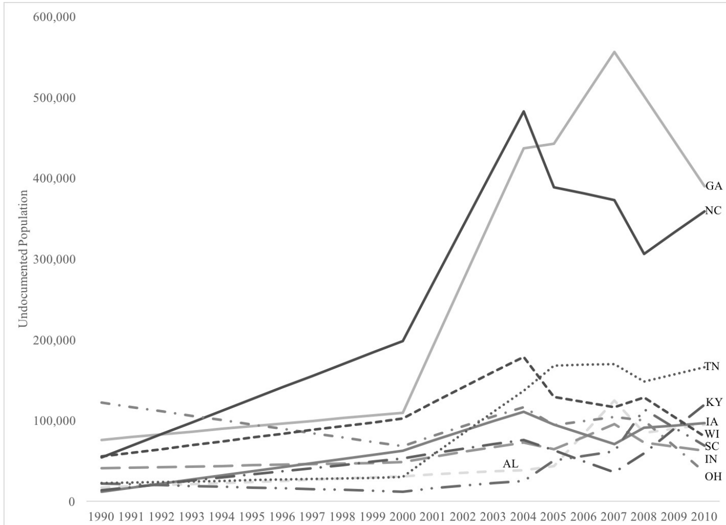
resided in the so-called Big Six states: California, New York, New Jersey, Florida, Illinois, and Texas (Borjas et al., 1996; Martin, 1994). Although the Big Six remain prominent destinations for undocumented immigrants, other states originally harboring low levels of these individuals are now catching upespecially Alabama, North Carolina, Georgia, and Arizona (Figure 2).

These spatial dynamics have expanded controversy over an already polarizing political debate. A prominent concern is that undocumented immigrant workers displace U.S. citizens in the workforce and put adverse pressure on native wages and employment (Krisanow, 2013). Although the Great Recession certainly increased economic hardship for many native workers, states like Arizona have cited such concerns to pass laws in hopes of combating the effects of undocumented immigration (Nowicki, 2010).[1]. Some states are already claiming to have benefited from their new laws. For example, Alabama's 2011 November State Report suggests that their unemployment rate decreased by 0.6 percent because new employment opportunities arose for native-born citizens after a large number of undocumented immigrants left the state (Munro, 2011).

Supporters of immigration reform apply basic labor market theory to justify their stance. In particular, they argue that increases in the labor supply of substitutable workers puts downward pressure on wages and employment rates within labor markets, adversely affecting workers already residing in the area (Card, 2001). Although the theory is straightforward, relatively little empirical evidence supports this prediction. Hotchkiss et al. (2012) use undocumented immigrant data to measure its effects on native wages in Georgia. They conclude that native workers employed by firms hiring undocumented workers earn just 0.15

[1]Other states that have passed controversial immigration reform include Georgia, Indiana, Utah and South Carolina (Bowman, 2010; Dade, 2011; Estes, 2011; Summers, 2011)

Figure 2: Top 10 States with Largest Increases in Undocumented Population Levels



Note: Data for the figure above was generated using estimates from Passel (2009; 2010). These trends appear very linear in nature because linear imputations were used for the years Passel did not explicitly estimate.

percent less than natives employed by firms only hiring documented workers. Given the policy push to stem immigration, such impacts are surprisingly trivial.

Little empirical work has been done nationally on this issue, a shortcoming we attribute largely to the difficulties in quantifying the number of undocumented immigrants, an uncounted population. Jeffrey Passel, a demographer at the Pew Hispanic Center, provides some remedy with sporadic annual state-level estimates (e.g., Passel (2010)). A careful labor market analysis, however, requires a more consistent series. Similar to Warren and Warren (2013), we resolve this problem by leveraging the residual approach to generate annual, state-level undocumented immigrant population estimates between 1994 and 2010 (Figure 1).[2] We then incorporate these estimates into a dynamic, fixed-effect model to examine the relationship between undocumented immigrant concentrations and native, low-skill (ie, without a high school degree) labor force participation rates (LFPR) and unemployment rates.[3]. Because these new data allow us to isolate the impacts of undocumented impacts, we offer an important contribution to the policy debate.

We focus on native LFPR because there is little evidence that total immigration adversely

[2]Passel is one of the leading authorities on estimating the undocumented immigrant population in the U.S. and his work serves as a benchmark for anyone attempting to estimate the undocumented population. Passel has estimated the state-level undocumented population for 1990, 2000, 2005, 2007, 2008, and 2010. As illustrated in Table 1, our estimates are very similar to the available years provided by Passel, which we believe adds credibility to our estimation procedure. This data set is one of the few of which we are aware. Warren and Warren (2013) also created a state-level series using a similar approach, but do not use their data to estimate labor market impacts.

[3]We define low-skill individuals as people who have not graduated high school. This group is the primary target population because they appear to be the only group of natives that are adversely affected by immigration (Borjas, 2004, 2006; Card, 2005; Johannsson and Weiler, 2004)

impacts overall native wages and unemployment rates (Card, 1990, 2001, 2005). Native wages may be unresponsive due to nominal wage "stickiness," while unemployment rates may be unresponsive to immigrant inflows because reductions in local native LFPR's may absorb this shock. Specifically, natives may respond to immigrant inflows by dropping out of the labor force while remaining in the same area, possibly as a prelude to migrating to another area. Such labor force withdrawals decreases the native LFPR, at least partially offsetting the increased labor supply effect from immigrant inflows. Yet such dynamics may still preserve native unemployment rates and wage levels.

Our paper is a state-level analysis, which admittedly is fairly crude (Card, 2005). To some, it is ideal to examine effects at the MSA-level because it more accurately represents local labor markets. Such geographic disaggregation is currently not possible, however, because the data needed to estimate the undocumented population is only available at the state level. To see if this shortcoming is problematic, we benchmark our analysis to Johannsson and Weiler (2004)'s MSA-level research that explores the effect of the total foreign-born (TFB) population, both documented and undocumented, on native low-skill labor force participation rates and unemployment rates.

Our state-level results are consistent with, yet less sensitive than the MSA results from Johannsson and Weiler (2004). In particular, our analysis suggests that a 10 percent increase in the TFB population decreases the native low-skill LFPR by 0.42 percent while Johannsson and Weiler (2004) suggest that the same relationship decreases the low-skill native LFPR by 0.76 percent. These similarities suggest that the state-level model has sufficient credibility to discern the economic impacts of immigration. Moreover, for reasons discussed in Section 2, some researchers actually favor state models over those focusing on MSAs.

Identifying the effects of the TFB population not only adds legitimacy to a state-level model, but also provides a basis for isolating the effects of undocumented immigration. Note that the results from the TFB population demonstrate the combined effect of both documented and undocumented immigrants on low-skill natives. This approach implicitly assumes that both documented and undocumented immigrants participate in a single labor market. If true, both groups compete relatively equally and have similar degrees of substitutability with low-skill natives.

If this assumption is not realistic, however, the isolated impacts of these two labor pools may vary significantly. Specifically, because undocumented immigrants certainly face unique legal restrictions and potentially face greater language barriers, they may be less substitutable for native low-skill workers than are documented immigrants. In this institutional setting, we argue that a single market approach should be accompanied with a dual market approach, which effectively separates labor markets for documented and undocumented immigrants.

As noted above, census-type counts on undocumented immigrant populations are scarce, so we generate our own estimates. To address potential validity concerns, we use two datasets representing the undocumented population to estimate annual levels of each immigrant group. The first was created using methods we describe below. The second corresponds to the estimates created by Passel (2009, 2010).[4] Both datasets produce similar results

[4]Passel does not provide data for all years between 1994 and 2010; we linearly impute estimates for the years

when isolating the effects of documented immigrants.

Our paper's basic conclusion is that undocumented immigration appears to have only minor impacts on both the low-skill native LFPR and unemployment rate. This relationship is highly inelastic and suggests only limited impacts on native low-skill employment opportunities.

When applying the dual market approach, and excluding undocumented immigrants from the TFB population, the relationship between immigrant concentrations and the native low-skill LFPR becomes statistically insignificant. These results suggest that documented immigrants alone do not have a significant impact on low-skill native employment indicators. More importantly, the effects of omitting this group suggest that undocumented immigrants may play a role in the baseline relationship between the TFB population and the native low-skill LFPR. Yet the isolated effects of undocumented immigrants also do not have a statistically distinguishable effect on the low-skill native LFPR, which allows us further to conclude that undocumented immigrants alone do not affect natives either.

In the next section we review the research on immigration's labor market impacts. Section 3 highlights the methods used to estimate the undocumented population at the state-level. We then describe the dynamic fixed effects model used to estimate the effects of immigration on native low-skill labor force participation rates and unemployment rates. In Section 5 we summarize the empirical findings and offer conclusions.

2. SEEKING THE IMMIGRATION EFFECT

Most previous research on this topic uses native wages and unemployment rates as the primary absorption mechanisms in Area Analysis.[5] Because native high school dropouts seem to be most affected by immigration, they tend to be the focal group (Borjas, 2004, 2005, 2006; (Borjas, 2004, 2005, 2006; Card, 2005; Johannsson and Weiler, 2004). These studies usually enlist several assumptions to isolate the effects of immigrant inflows, with many papers using local ratios of low-skill immigrants to low-skill natives as labor supply proxies. These papers also typically apply geographic segmentation, which assumes that certain labor shocks only affect a particular region and do not permeate across space (Hanson et al., 2001). The majority of previous research using Area Analysis invokes similar assumptions, but the specific conclusions do not always coincide. Most of these differences are attributed to the geographic space, the type of model used, and the native born economic indicators used to capture the effects of immigration. These differences are highlighted below.

One important debate is whether MSAs are appropriate geographic spaces to isolate the effects of immigrant concentrations on native low-skill economic welfare. Card (1990, 2001, 2005) is a proponent of MSA-level models, and his research suggests that the foreign born population either has no effect or a minimal effect on native low-skill employment and wages. By favoring state and national models, Borjas (2006) takes a broader geographic scope. His work indicates the foreign-born population has a significantly negative effect on the same native low-skill economic indicators. Cards and Borjas' conclusions often conflict because

he did not address.

[5]For a comprehensive explanation of Area Analysis and the assumptions it adopts, refer to Appendix 1.

they disagree on the effects of native outmigration that take place in response to immigrant inflows. Theoretically, natives may exit a regional labor force if an immigrant displaces them. This leftward shift in the labor supply curve counters the rightward shift resulting from greater immigrant inflows. If native outmigration stabilizes the local labor supply on net, then it makes it difficult to ascertain any relationship between immigration and native economic welfare. Partridge et al. (2008) find evidence, for example, that immigrants may cause existing residents to out-migrate, especially in places with few economic opportunities. However, these effects on the labor supply are essentially offsetting, with little impact on overall real wages or employment rates.

The distortions affecting MSA level models may not have the same effect on models covering larger geographic regions. Borjas (2006) shows that native born labor outmigration and its ensuing effects on labor markets become less apparent as the geographic scope expands. With respect to labor mobility, for every 10 immigrants entering an MSA, approximately 6.1 natives leave the local area. At the state level, the same relationship suggests that only 2.8 natives to leave. If native laborers are more mobile within smaller regions, then their migratory behavior should have a more profound effect on labor markets within those regions. Accordingly, Borjas shows that a 10 percent increase in immigrant concentrations leads to a 4 percent decrease in native low-skill earnings at the national level and a 1.6 percent decrease at the state level.[6]

Card's (2001; 2005) MSA-level models provide contrary evidence, suggesting that native outmigration is not sensitive to immigrant inflows. He uses an OLS regression model to estimate the relationship between low-skill-immigrant concentrations and the overall low-skill concentration. He finds a coefficient near one, implying that immigrants do not displace natives. Card (2005) also reports that changes in immigrant concentrations do not significantly affect native low-skill wages and only affects unemployment rates to a minor degree.[7]

Borjas and Card use different approaches to reach their conclusions. The fact that Borjas provides substantive evidence that state-level models are similarly robust as MSA-level models adds credibility to the state-level model used here.

2.0.1. Evolution of the Models Used to Measure the Effects of Immigration

Most static models, including Altonji and Card (1991); Borjas (1994); Borjas et al. (1996); Card (1990, 2001), use decennial data in cross-section models. Overall, these papers find

[6]Borjas (2006) does not provide an elasticity estimate at the MSA level, but does argue that the coefficient representing wage responsiveness to immigrant inflows is smaller at the MSA-level than at the state or national level. This downward trend of wage responsiveness indicates that the effects of immigration on native economic welfare become more difficult to discern as the geographic scope becomes smaller.

[7]Card (2005) offers two alternative approaches to explain how immigrant inflows are absorbed. The first approach uses a Heckscher-Ohlin framework to illustrate how regional output mixes change in response to immigrant inflows. Firms may flock to regions with greater concentrations of low-skill workers, altering the regional output mix. Firm in-migration will increase labor demand, which counters increases in the labor supply resulting from immigrationthus preserving the low-skill wage and unemployment rate. In addition to output mixes, technology endowments may affect how immigrant inflows are absorbed. Firms may "innovate in a direction that will take advantage of more readily available factors," which suggests that they will not invest in more advanced technology if they anticipate the stock of low-skill workers to increase (p. 314).

immigrant levels have either a moderate effect or no effect on low-skill wages and employment opportunities. Regardless of their conclusions, parameter estimates from such studies are potentially biased due to endogeneity. This can arise from omitted concurrent factors, such as native outmigration, local wage levels, labor demand changes, immigrant concentrations, and the quality of welfare benefits (Altonji and Card, 1991; Ali et al., 2012; Borjas et al., 1996; Carter and Sutch, 1997; Filer, 1992; Friedberg and Hunt, 1995; Kritz and Gurak, 2001; Borjas, 1999; Card, 2001).[8]

To capture endogeneity, one alternative is to substitute static models with dynamic ones. Dynamic models usually produce more robust results because they eliminate the location-specific characteristics that exist with stock variables and focus on immigrants' responsiveness to wage changes rather than wage levels (Friedberg and Hunt, 1995). Many papers adopting dynamic models (e.g. Altonji and Card (1991); Borjas et al. (1996); Johannsson and Weiler (2004)) apply the first-differencing approach to their initial static models to express how changes in immigrant population affect changes in their focal native economic indicator of interest. This paper will adopt a dynamic framework similar to Johannsson and Weiler (2004) to avoid similar endogeneity issues.

In addition to endogeneity concerns, some object to using the immigrant share of total population to express changes in MSA labor supply. Card (2001), for example, argues that this measure is too broad to accurately reflect labor supply changes within certain labor market segments and regions corresponding to specific skills. Put another way, he suggests that immigrants are not always perfect substitutes for native labor because their skills and earnings are heterogeneous. In such cases it may be appropriate to create separate labor markets for each skill level Card (2001).

To account for this heterogeneity, Card (2001) analyzes the effects of immigrant inflows at the *occupation* level, which better acknowledges substitutability between immigrants and natives. He finds that immigrant inflows between 1985 and 1990 "reduced the relative employment rates of natives and earlier immigrants in laborer and low-skilled service occupations by up to 1 percentage point, and by up to 3 percentage points in very high-immigrant cities" (Card (2001), p. 57). The effects in low-immigrant cities and labor markets containing few low-skill workers appear to be less significant.

Although Card's approach is preferable, data paucity means it is currently not possible to estimate the number of undocumented immigrants in specific occupations across labor markets.[9] However, there is enough data covering undocumented immigrants to form specific immigrant/native ratios for separate broad *skill* groups. Overall, we analyze three different ratios of immigrants to natives for low-skill workers. The first includes the entire TFB pop-

[8]Kritz and Gurak (2001) oppose the argument that immigration affects native migratory decisions because they attribute most native labor outmigration to poor economic conditions and not immigrant inflows. Filer (1992), however, reports a significantly negative relationship between native net-migration rates and immigration ratesespecially within a 5-year time frame. These conflicting results, in conjunction with the mixed results of Card and Borjas, imply that future research may need to analyze the effects of immigrant inflows within a 5-year time frame to account for the possibility of native outmigration. However, short-run models may also suffer their own unique shortcomings. We discuss these below.

[9]Passel (2009, 2010) provides some data on which industries undocumented immigrants are most often employed in, but there is not enough information to create sufficient between-year variation in the distribution of undocumented immigrants across different occupations.

ulation while the second and third only include documented and undocumented immigrants, respectively.

In addition to more specific labor supply proxies, some previous research focuses on alternative labor market adjustment mechanisms such as state output mix and the labor force participation rate (LFPR) (Altonji and Card, 1991; Carter and Sutch, 1997; Hanson and Slaughter, 1999; Hanson et al., 2001; Johannsson and Weiler, 2004). In that sense, Johannsson and Weiler (2004)'s paper is especially pertinent because the primary dependent variable is the LFPR. Johannsson and Weiler emphasize the importance of using the native LFPR because it accounts for natives who remain in the same area but exit the labor market, including those who make this a first step in leaving the local area entirely. Hence, the native LFPR may be a more versatile statistic than native wages and employment levels in capturing the effect of immigrant inflows.

In summary, models of immigration's effects on native economic welfare have evolved over time. Early papers used simple cross-section models spanning 10-year periods, offering mixed results. Beyond lacking consensus, such findings should be viewed cautiously because endogeneity may bias parameter estimates. Another shortcoming of earlier models is that their reliance on the decennial census inadequately captures the effects of labor out-migration and firm in-migration between time periods. There are a few subsequent papers addressing these issues via a more dynamic modeling framework. Lastly, some papers claim that labor market mechanisms other than native wage levels and unemployment rates absorb immigrant inflows, while others suggest immigrant heterogeneity is important. We concur, emphasizing low-skill LFPRs to examine the impacts of undocumented immigration in particular.

3. ESTIMATING THE UNDOCUMENTED IMMIGRANT POPULATION

Our empirical analysis relies on undocumented population estimates, data not formally collected. To do so, we parallel a procedure endorsed by Passel (2007), Hill and Johnson (2011), Hoefer et al. (2012), Marcelli and Pastor (2013), and Warren and Warren (2013).[10] These works rely on the "residual method," calculating undocumented population as the difference between the Total Foreign Born (TFB) population stock and the Total Legal Foreign Born (TLFB) population stock. In this section, we summarize an analogous method that provides annual, state-level undocumented population estimates for 1994-2010 (hereafter referred to as Schultz). These stock levels are in turn applied to the dynamic model to estimate how undocumented immigration impacts native workers.

To calculate the stock of the undocumented population we need estimates of the TFB and TLFB stocks. Starting in 1994, annual TFB stock levels are obtainable via the March Current Population Survey (CPS). No data source provides the TLFB stock since 1980 and it must be estimated for subsequent years. The validity of these estimates is central to our

[10] Jeffrey Passel is a senior demographer at the Pew Hispanic Center and a leading authority on estimating the US undocumented immigrant population. Hill and Johnson (2011) and Marcelli and Pastor (2013) use residual data as a benchmark to their novel approaches to estimating the undocumented population. Hoefer et al. (2012) explicitly use a similar residual approach. The increasing popularity of the residual approach adds to the legitimacy of the parallel methodology used in this paper.

research.[11]

We estimate state-level TLFB population between 1980 and 2010 using the most recent year that the TLFB stock was recorded (1980) and applying inflow and outflow data to estimate subsequent years. Documented inflow data is from the Department of Homeland Security (DHS) and its predecessor, the Immigration and Naturalization Service (INS),[12] and comprises three general types: 1) lawful permanent residents, 2) naturalized citizens, and 3) refugees and asylees. Several outflows offset this, including: 1) annual deaths, 2) deportations, and 3) double counting, which we explain in more detail below.

The first step is to identify the 1980 stock level of documented immigrants. To calculate this in subsequent years, we add the number of inflows between 1980 and the year of interest and subtract the number of outflows. For instance, to calculate the national TLFB stock for 1998, we add the number of legal immigrants that entered the US between 1980 and 1998 and subtract the number of legal immigrants that either exited or died during the same time frame. Equation 1 describes how the stock of documented workers in state i is calculated for 1981,[13]

$$\begin{aligned} TLFB_{i,1981} = {} & LegalStock_{1980} + LPRS_{1981} + Naturalizations_{1981} + Refugees_{1981} \\ & + Asylees_{1981} - DeathRate_{i,1981} - DepRate_{i,1981} - DoubleCount_{i,1981} \end{aligned} \tag{1}$$

where $TLFB_{i,1981}$ represents the total stock of the legal foreign born population in 1981 in state i. $LegalStock_{1980}$ is the stock of legal immigrants recorded in 1980. LPR_{1981} is the number of immigrants granted lawful permanent residence in 1981. $Naturalizations_{1981}$ represents the number of immigrants that were naturalized in 1981. $Refugees_{1981}$ and $Asylees_{1981}$ represent the number of foreigners granted refuge and asylum, respectively, in 1981.

$DeathRate_{i,1981}$, $DepRate_{i,1981}$, and $DoubleCount_{i,1981}$ are outflow variables used to deflate the 1981 stock of documented immigrants. $DeathRate_{i,1981}$ is derived from state-level mortality rates from the Center for Disease Control's (CDC) average annual death rate for the overall population between the ages of 35 and 44.[14] Death rates for the documented immigrant population are approximated by multiplying CDC death rates by the TFB population as a fraction of the total population in state i. $DepRate_{i,1981}$ approximates the number of documented immigrants deported from state i in 1981 and is calculated by multiplying the state distribution of the 1981 TFB population by the total number of immigrants deported at the national level. This product is in turn multiplied by the number of legal immigrants in state i as a fraction of the TFB population in state i for 1980.

Finally, $DoubleCount_{i,1981}$ is used to avoid double counting documented immigrants that were included in the 1980 stock of documented immigrants but may have converted their immigration status to another form of documented immigration between 1980 and 1981. For

[11] These estimates may be open to criticism, but our methods subscribe to the highest possible standards with respect to the data sources and methods we use to approximate this population. Our estimates are benchmarked against similar ones created by Passel (2009).

[12] Both the DHS and INS have similar data-gathering methods.

[13] Equation 2 illustrates how TLFB stock-levels are calculated after 1981.

[14] This age group was used because it represents the median age group from an age distribution presented by Passel (2009).

instance, some immigrants convert from refugees and asylees to lawful permanent residents. Additionally, many lawful permanent residents become naturalized. According to several *INS Statistical Yearbooks*, the median length of time needed for lawful permanent residents to naturalize is 8 years. To avoid including the same group of immigrants in both the LPR and Naturalization categories for a certain year, the number of immigrants granted lawful permanent residence in year *t-8* are subtracted from the TLFB stock in year *t*. This method assumes that every person granted lawful permanent residence is naturalized 8 years later. This assumption is strong, but state-level naturalization rates are unavailable.

In addition to naturalization double counts, we must also account for the number of refugees and asylees granted lawful permanent residence. Fortunately, the INS and DHS provide state-level data for most years. Mathematically, the number of refugees and asylees granted legal permanent residence in year t must be subtracted from the total number of immigrants granted legal permanent residence in year t.

To calculate the stock of legal immigrants for future years, a similar process is used; we determine the stock of legal immigrants in year *t-1* and apply the inflow and outflow statistics corresponding to year t.

$$\begin{aligned} TLFB_{i,t} = TFLB_{i,t-1} + LPRS_{i,t} + Naturalizations_{i,t} + Refugees_{i,t} + Asylees_{i,t} \\ -DeathRate_{i,t} - DepRate_{i,t} - DoubleCount_{i,t} \end{aligned} \tag{2}$$

Once the state-level TLFB stock is determined, we can calculate the stock of undocumented immigrants. Intuitively, this is the residual of the TFB and TLFB. Calculating this residual requires two equations. In Equation 3, we first determine the total number of documented and undocumented immigrants ($All_{i,t}$) that remain in the US for relatively longer periods of time.

$$All_{i,t} = TFB_{i,t-1} - TempLegal_{i,t} \tag{3}$$

Here, $TempLegal_{i,t}$ represents the number of non-immigrants admitted to the U.S. for only a short period of time.[15,16]

Recall that TFB includes the three primary documented immigrant inflow groups as well as the number of non-immigrants and undocumented immigrants for each year. After applying Equation 3, we calculate the annual, state-level undocumented stock ($Undocumented_{i,t}$) as a residual (Equation 4).

$$Undocumented_{i,t} = All_{i,t-1} - TLFB_{i,t} \tag{4}$$

[15]It is important to note that the data for the Temporary Legal Citizens include people visiting the U.S. for pleasure or temporary business. These components of the Temporary Legal Citizens data were omitted because these people do not reside in the U.S. long enough to be considered part of the U.S. legal foreign-born population. More importantly, it would not be possible to estimate the illegal immigrant population if these individuals were included because the number of people visiting the U.S. for pleasure or temporary business is so large that it would produce negative estimates for the illegal immigrant population.

[16]This includes foreign students, exchange visitors, and temporary workers, as well as their family members. We assume that these individuals remain in the U.S. for only one year.

In summary, our process to calculate the state-level undocumented population between 1994 and 2010 is very similar to Passel (2007), but digresses for several important reasons. Specifically, Passel applies several undercount rates, derived from the CPS and U.S. Census, to calculate the undocumented population.[17] We did not apply similar undercount rates here because the data for the TLFB is not derived from the CPS. Applying these undercount rates to the DHS and INS data substantially overestimates the undocumented population, which is expected because these undercount rates are not relevant. Moreover, annual undercount rates estimates from DHS, INS, and Census data do not exist to our knowledge. Although our data sources deviate from Passel's, several measures were taken to ensure that our estimates are as consistent as possible (summarized in Appendix 2 with replication sources in Appendix 3). The next section addresses how these undocumented estimates are incorporated into a model that captures the impact of immigration on the native low-skill LFPR and native low-skill unemployment rates.

4. USING UNDOCUMENTED IMMIGRANT DATA TO MEASURE THE EFFECT ON NATIVE WORKERS

Our empirical goal is to measure immigration's impacts on native employment opportunities between 1994 and 2009.[18] We hypothesize that low-skill immigrants are strong substitutes with low-skill natives. Changes in the ratio of low-skill immigrants to low-skill natives are used to proxy changes in the low-skill labor supply. Thus, an increase in immigrant concentrations should increase the low-skill labor supply, putting downward pressure on native-low-skill labor force participation rates and upward pressure on their unemployment rates. We include the latter to test if they are unresponsive to immigration, as suggested by previous research. If unemployment rates are not affected, then our findings support using labor force participation rates as a relevant economic indicator. Our model is similar to Johannsson and Weiler (2004)'s, but is augmented with undocumented immigrant data.

Our first step compares our state-level, single-market approach regarding the relationship between TFB immigrant concentrations and native low-skill LFPR with Johannsson and Weiler (2004)'s MSA-level results. The second step applies a dual-market approach to observe whether documented or undocumented immigration has a greater effect on low-skill natives. Table 1 highlights the empirical objectives.

We use two datasets to incorporate state-level impacts of both the documented and undocumented population. We create the documented estimates by subtracting our undocumented estimates from the TFB population. Thus, unlike previous research, we are able to individually identify the effects of the documented and undocumented populations, test-

[17] An undercount rate is a factor used to scale up the estimates created by the CPS. The CPS has the propensity to understate population estimates due to erroneously omitting certain households and individuals within households while recording the survey (Schmitt and Baker, 2006). To resolve this issue, demographers from the U.S. Census Bureau and the Bureau of Labor Statistics (BLS) use comparable estimates from more rigorously derived decennial Census data to create undercount scalars. Applying these scalars to CPS estimates mitigates any bias that arises while sampling the population.

[18] State level undocumented data is available between 1994 and 2010, but the time frame of study is restricted to 2009 because the model used to measure the effects of immigrant inflows is first-differenced. Immigrants who arrived before the sample period remain categorized as foreign-born.

Table 1: Basic Modeling Objectives

Time Frame	TFB Immigrants (BMS Data)	Documented Immigrants (TFB-Undoc) Schultz Data	Documented Immigrants (TFB-Undoc) Passel Data	Undocumented Immigrants Schultz Data	Undocumented Immigrants Passel Data
1994-2009	Measure the effects of the TFB pop at the state-level using data from the Basic Monthly Survey	Measure the effects of the Documented pop at the state-level using data generated in this paper	Measure the effects of the Documented pop at the state-level using data derived from Passel (2009, 2010)	Measure the effects of the Undocumented pop at the state-level using data generated in this paper	Measure the effects of the Undocumented pop at the state-level using data derived from Passell (2009, 2010)

ing the relevance of the noted dual-market theories. Our dataset is constructed using the methodology presented above. The Passel dataset is constructed using occasional annual estimates provided by Passel (2009, 2010), with missing years imputed linearly. We use this modified Passel dataset as a sensitivity check to the conclusions drawn from our own dataset.

Our basic empirical model is applied to both the single- and dual-market approaches for 1994-2010. Equation 5 is a static version of the fixed-effects regression.

$$Y_{i,t} = \beta_1 IMFR_{i,t} + \beta_2 Race_{i,t} + \beta_3 Sex_{i,t} + \beta_4 Age_{i,t} + \beta_5 GSP_{i,t} + \alpha_i + \mu_{i,t} \tag{5}$$

We examine two separate dependent variables: the native low-skill labor force participation rate and the native low-skill unemployment rate. Only individuals that have not graduated high school are considered low-skill workers.

Before discussing our main variable of interest, we acknowledge other demographic and economic factors may also explain some of the variation of $Y_{i,t}$. Evidence from Card (1990, 2001) and Johannsson and Weiler (2004) suggest that race, sex, and age affect employment opportunities. To account for racial concentration differences across states we include $Race_{i,t}$, which is the state-level labor force share of three different minority groups: African Americans, American Indians or Eskimos, and Asians or Pacific Islanders. Similarly, $Sex_{i,t}$ is the state-level labor force percentage of females. $Age_{i,t}$ is a categorical variable that focuses on natives falling within the 16-64 age bracket. Acknowledging structural differences mean business cycle impacts can vary across states, we include annual gross state product ($GSP_{i,t}$). α_i represents the fixed effects summarizing time-invariant state-specific characteristics. Finally, we assume an independently and identically distributed unobserved term ($\mu_{i,t}$).

We now turn our attention to the focal variable of interest, the state-level ratio of low-skill immigrants to low-skill natives ($IMFR_{i,t}$). We apply this ratio to three different groups: 1) the TFB population, 2) the documented immigrant population, and 3) the undocumented immigrant population. Higher IMFR values represent greater state-level immigrant concentrations. Thus, the IMFR in state i year t is larger when it includes the TFB population for the single-market scenario and smaller when it includes the documented population or the undocumented population for the dual-market scenario. More importantly, the cross-state variation in the IMFR tells us whether immigrant concentrations have a significant impact on native low-skill employment indicators.

As noted earlier, static models are prone to endogeneity because region-specific characteristics may attract higher concentrations of immigrants. Such characteristics can include relatively low native-born employment levels, high immigrant stocks, or advantageous geographical location. To remedy this, we specify a dynamic model (Equation 6).

$$\%\Delta Y_{i,t} = \beta_1 \%\Delta IMFR_{i,t} + \beta_2 \%\Delta Race_{i,t} + \beta_3 \%\Delta Sex_{i,t} + \beta_4 Age_{i,t} + \beta_5 \%\Delta GSP_{i,t} + \mu_{i,t} \quad (6)$$

Equations 5 and 6 are both fixed effects regressions. The only difference is that the latter first-differences continuous variables. First-differencing removes the state effect term and substantially reduces the likelihood of capturing endogenous relationships since any state-specific, time-invariant characteristics are effectively swept from the regression.

We apply a midpoint percentage change in order to normalize the gross change occurring between periods. The β_1 coefficient in Equation 6 captures the relationship between *changes* in immigrant stock levels and changes in the native low-skill labor force participation rate and unemployment rate. We estimate Equation 6 using both Generalized Least Squares (GLS) and Weighted Least Squares (WLS). GLS is a more robust approach than WLS because it accounts for both heteroskedasticity and autocorrelation, which often arises in many panel datasets.

Employing a dual market approach requires us to have undocumented estimates that fall within the 16-64 age group. To achieve this, we use age distributions for low-skill immigrants in the TFB data for each state between 1994 and 2010 to estimate the number of low-skill undocumented immigrants aged between 16 and 64. These estimates were created using data from the Basic Monthly Survey (BMS). Lastly, according to Passel (2009), approximately 47 percent of the total undocumented immigrant population has not graduated high school, which is a good proxy for the number of low-skill undocumented immigrants residing in each state. Thus, 47 percent of each age group will be added to its proper stock of legal immigrants.[19]

The March CPS provides annual estimates of the TFB population between 1994 and 2010. The DHS and its predecessor, the INS, provide the majority of the data needed to estimate annual levels of the TFB. This includes data on the annual inflows of legal permanent residents, naturalized citizens, refugees, and asylees. Both the DHS and INS also provide deportation data as well as the data needed to calculate the double-count rates of documented immigrants. The Department of Health and Human Services provides data on state-level refugee entries between 2000 and 2010. The CDC provides annual death rates at the state-level for all races and sexes for people between ages 35 and 44. This age group was

[19]It is important to note that more than 47 percent of undocumented immigrants are likely to compete with native low-skill workers. According to Passel (2009), approximately 78 percent of undocumented immigrants have at most graduated high school. Some undocumented high school graduates most likely compete with native high school drop outs, but these undocumented individuals were omitted to provide the most conservative effects possible.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor Force Participation Rate	4800	0.562	0.158	0.083	1.000
Unemployment Rate	4800	0.098	0.064	0.000	0.503
IMFR (TFB)	4800	0.337	0.512	0.000	5.360
IMFR Documented (Schultz Data)	4800	0.099	0.204	0.000	2.662
IMFR Documented (Passell Data)	4800	0.143	0.278	0.000	3.072
IMFR Undocumented (Schultz Data)	4800	0.249	0.367	0.000	3.554
IMFR Undocumented (Passell Data)	4800	0.198	0.272	0.000	2.868
GSP	4800	0.048	0.032	-0.120	0.172
Female Labor Force Percentage	4800	0.394	0.086	0.034	0.908
African American Labor Force Percentage	4800	0.116	0.122	0.000	0.731
American Indian Labor Force Percentage	4800	0.030	0.055	0.000	0.625
Asian or Pacific Islander Labor Force Percentage	4800	0.42	0.113	0.000	1.000

used because it represents the median age group from an age distribution presented by Passel (2009). State-level total population data from the U.S. Census was used to convert the death rates from the overall population to the TFB population. Lastly, BMS data was used to estimate annual levels of native low-skill labor force participation rates and unemployment rates for each state between 1994 and 2010, as well as to estimate the concentration of females and different racial groups across states. Table 2 provides descriptive statistics. The means for the native low-skill LFPR and unemployment rate are 56.2 percent and 9.8 percent, respectively.

5. RESULTS

This section summarizes the GLS and WLS estimates of Equation 6. We offer three primary conclusions: 1) changes in TFB immigrant concentrations have small, but statistically significant negative effects on both native LFPR and unemployment rates, with the LFPR results similar in magnitude to, but slightly smaller than, the MSA results from Johannsson and Weiler (2004); 2) documented immigrants alone appear to have no statistically significant effect on either the state native low-skill LFPR or the corresponding unemployment rates; and 3) undocumented immigrants alone appear to have a statistically significant and negative effect on native low-skill LFPR, but these effects are not distinguishable from the effects associated with the TFB population.

Table 3 presents the estimated relationship between immigration and native low-skill labor force participation rates and unemployment rates between 1994 and 2010. To facilitate comparisons, the GLS and WLS coefficients are converted into elasticities. For ease of exposition, Table 3 only highlights the relationships between the various IMFR and the two native low-skill employment indicators (the full results are in Tables 4 and 5). At the state level, a statistically significant and negative relationship exists between low-skill TFB immigrant concentrations and both the native low-skill labor force participation rate and the

Table 3: Econometric Estimation Results: 1994-2009

GLS Model	Elasticity	Coefficient	Std Error	Z-stat	Prob > Chi^2	95% CI	
TBF IMFR	-0.042	0.005	0.000	2.12	0.034	0.000	0.009
Documented IMFR	-0.009	0.001	0.000	1.08	0.280	-0.001	0.004
Passel Documented IMFR	-0.009	0.001	0.000	0.89	0.371	-0.002	0.004
Undocumented IMFR	-0.014	0.002	0.000	1.01	0.313	-0.002	0.005
Passel Undocumented IMFR	-0.095	0.010	0.000	4.02	0.034	0.005	0.015
WLS Model	Elasticity	Coefficient	Std Error	Z-stat	Prob > Chi^2	95% CI	
TBF IMFR	-0.044	0.005	0.002	2.25	0.025	0.001	0.009
Documented IMFR	-0.010	0.001	0.001	1.14	0.253	-0.001	0.004
Passel Documented IMFR	-0.005	0.001	0.001	0.47	0.636	-0.002	0.004
Undocumented IMFR	-0.008	0.001	0.002	0.06	0.564	-0.002	0.005
Passel Undocumented IMFR	-0.096	0.010	0.002	4.10	0.000	0.005	0.015
GLS Model	Elasticity	Coefficient	Std Error	Z-stat	Prob > Chi^2	95% CI	
TBF IMFR	0.052	0.019	0.009	2.23	0.026	0.002	0.036
Documented IMFR	-0.014	-0.007	0.005	-1.39	0.166	-0.016	0.003
Passel Documented IMFR	-0.003	-0.001	0.006	-0.23	0.817	-0.013	0.010
Undocumented IMFR	0.038	0.015	0.007	2.21	0.027	0.002	0.029
Passel Undocumented IMFR	0.014	0.005	0.010	0.50	0.618	-0.015	0.025
WLS Model	Elasticity	Coefficient	Std Error	Z-stat	Prob > Chi^2	95% CI	
TBF IMFR	0.063	0.023	0.009	2.75	0.006	0.007	0.040
Documented IMFR	0.007	-0.003	0.005	-0.70	0.487	-0.012	0.006
Passel Documented IMFR	0.004	0.002	0.006	0.36	0.722	-0.010	0.014
Undocumented IMFR	0.030	0.012	0.007	1.75	0.080	-0.001	0.026
Passel Undocumented IMFR	0.029	0.010	0.010	1.02	0.307	-0.010	0.030

unemployment rate. The single market approach applied to the LFPR is similar in terms of its magnitude, but smaller, when compared to the GLS results from Johannsson and Weiler (2004). In reference to the GLS results, a 10 percent increase in the IMFR decreases native low-skill labor force participation rates by approximately 0.42 percent. The GLS results from Johannsson and Weiler (2004) are that a 10 percent increase in the IMFR decreases native low-skill labor force participation rates by approximately 0.76 percent.

Table 3 also shows the results for the dual market estimation (i.e., separating the impacts of documented and undocumented immigrants). When undocumented immigrants are no longer included as part of the TFB immigrant stock, the relationships between low-skill immigrant concentrations and low-skill native labor force participation rates and the unemployment rate are both statistically insignificant. This suggests that 1) undocumented immigrants have some effect in the single market regressions, and 2) documented immigrants alone do not have a statistically significant effect on the LFPR or unemployment rate of low-skill natives.

Together, these results hint that undocumented immigrants have an isolated impact on the native low-skill LFPR and unemployment rate, but their effects may not differ significantly from the baseline results corresponding to the TFB population. A simple procedure to ascertain whether the undocumented IMFRs have a statistically distinguishable impact is to examine whether their confidence intervals overlap with the TFB baseline results. Table 3 reports the values of these confidence intervals at the 95 percent significance level; Figures

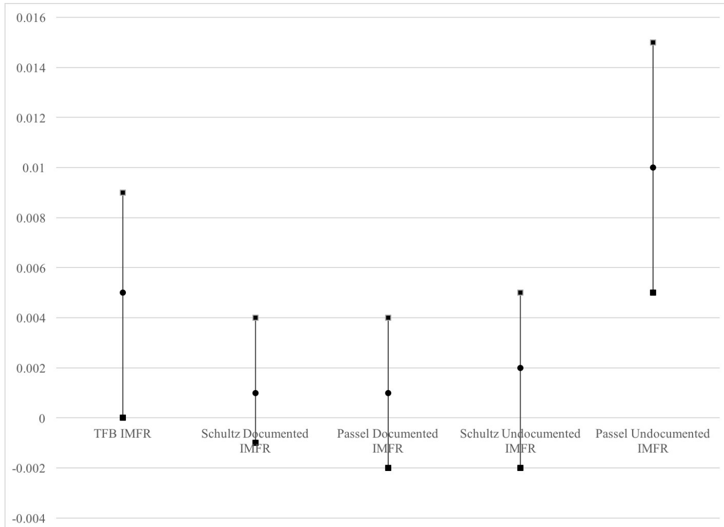
Table 4: GLS Baseline Results (All Variables): 1994-2009

	Constant	$\%\Delta IMFR$	Sex	Afr Am	Nat Am	Aspac	$\%\Delta GSP$
Labor Force Participation Rate (Expressed as $\%\Delta LFPR$)							
TFB	-0.0141	0.0046	0.0267	0.0005	-0.0009	-0.0018	0.1527
Std Error	0.0013	0.0022	0.0076	0.0020	0.0013	0.0013	0.0208
Z-Stat	-11.11	2.12	3.54	0.26	-0.68	-1.37	7.33
Documented	-0.0141	0.0013	0.0265	0.0005	-0.0009	-0.0014	0.1577
Std Error	0.0013	0.0012	0.0076	0.0020	0.0013	0.0013	0.0208
Z-Stat	-11.04	1.08	3.50	0.24	-0.73	-1.12	7.59
Passel Documented	-0.0140	0.0013	0.0265	0.0006	-0.0009	-0.0014	0.1565
Std Error	0.0013	0.0014	0.0076	0.0020	0.0013	0.0013	0.0208
Z-Stat	-11.00	0.89	3.50	0.28	-0.69	-1.13	7.53
Undocumented	-0.0140	0.0017	0.0262	0.0006	-0.0009	-0.0014	0.1552
Std Error	0.0013	0.0017	0.0076	0.0020	0.0013	0.0013	0.0208
Z-Stat	-11.02	1.01	3.47	0.32	-0.69	-1.12	7.47
Passel Undocumented	-0.0146	0.0101	0.0272	0.0006	-0.0007	-0.0021	0.1536
Std Error	0.0013	0.0025	0.0076	0.0020	0.0013	0.0013	0.0207
Z-Stat	-11.45	4.02	3.60	0.28	-0.58	-1.62	7.42
Unemployment Rate (Expressed as $\%\Delta UR$)							
	Constant	$\%\Delta IMFR$	Sex	Afr Am	Nat Am	Aspac	$\%\Delta GSP$
TFB	0.0554	0.0193	-0.0798	0.0209	0.0167	-0.0032	-1.1432
Std Error	0.0047	0.0087	0.0325	0.0083	0.0050	0.0052	0.0795
Z-Stat	11.81	2.23	-2.45	2.51	3.33	-0.61	-14.38
Documented	0.0564	-0.0066	-0.0843	0.0215	0.0169	-0.0001	-1.1305
Std Error	0.0047	0.0048	0.0325	0.0084	0.0050	0.0051	0.0789
Z-Stat	11.98	-1.39	-2.59	2.57	3.37	-0.19	-14.32
Passel Documented	0.0559	-0.0014	-0.0843	0.0213	0.0167	-0.0012	-1.1222
Std Error	0.0047	0.0059	0.0325	0.0084	0.0050	0.0052	0.0788
Z-Stat	11.89	-0.23	-2.59	2.56	3.32	0.22	-14.23
Undocumented	0.0554	0.0151	-0.0828	0.0212	0.0169	-0.0023	-1.1321
Std Error	0.0047	0.0069	0.0325	0.0083	0.0050	0.002	0.0789
Z-Stat	11.89	-0.23	-2.59	2.56	3.32	-0.22	-14.23
Passel Undocumented	0.0554	0.0151	-0.0828	0.0212	0.0169	-0.0023	-1.1321
Std Error	0.0047	0.0069	0.0325	0.0083	0.0050	0.0052	0.0789
Z-Stat	11.81	2.21	-2.55	2.54	3.37	-0.46	-14.36

Table 5: WLS Baseline Results (All Variables): 1994-2009

Labor Force Participation Rate (Expressed as %$\Delta LFPR$)							
	Constant	%$\Delta IMFR$	Sex	Afr Am	Nat Am	Aspac	%ΔGSP
TFB	-0.0131	0.0048	0.0291	0.0000	-0.0010	-0.0019	0.1097
Std Error	0.0016	0.0022	0.0076	0.0019	0.0013	0.0013	0.0232
Z-Stat	-8.37	2.25	3.82	0.05	-0.81	-1.49	4.73
Documented	-0.0130	0.0013	0.0287	0.0000	-0.0011	-0.0015	0.1156
Std Error	0.0016	0.0011	0.0076	0.0019	0.0013	0.0013	0.0231
Z-Stat	-8.33	1.14	3.77	0.04	-0.85	-1.21	4.99
Passel Documented	-0.0129	0.0010	0.0285	0.0002	-0.0011	-0.0015	0.1139
Std Error	0.0016	0.0017	0.0076	0.0019	0.0013	0.0013	0.0231
Z-Stat	-8.28	0.58	3.75	0.10	-0.85	-1.15	4.92
Undocumented	-0.0129	0.0010	0.0285	0.0002	-0.0011	-0.0015	0.1139
Std Error	0.0016	0.0017	0.0076	0.0019	0.0013	0.0013	0.0231
Z-Stat	-8.28	0.58	3.75	0.10	-0.85	-1.15	4.92
Passel Undocumented	-0.0136	0.0102	0.0295	0.0001	-0.0009	-0.0022	0.1127
Std Error	0.0016	0.0025	0.0076	0.0019	0.0013	0.0013	0.0231
Z-Stat	-8.70	4.10	3.88	0.07	-0.70	-1.74	4.89
Unemployment Rate (Expressed as %ΔUR)							
	Constant	%$\Delta IMFR$	Sex	Afr Am	Nat Am	Aspac	%ΔGSP
TFB	0.0459	0.0234	-0.0605	0.0154	0.0168	-0.0002	-0.9296
Std Error	0.0060	0.0085	0.0328	0.0082	0.0050	0.0052	0.0907
Z-Stat	7.60	2.75	-1.84	1.87	3.38	-0.04	-10.24
Documented	0.0423	-0.0032	-0.0648	0.0158	0.0168	0.0021	-0.8952
Std Error	0.0061	0.0046	0.0328	0.0083	0.0050	0.0051	0.0898
Z-Stat	7.64	-0.70	-1.98	1.91	3.37	0.40	-9.96
Passel Documented	0.0459	0.0021	-0.0644	0.0157	0.0168	0.0017	-0.8919
Std Error	0.0061	0.0059	0.0329	0.0083	0.0050	0.0052	0.0898
Z-Stat	7.58	0.36	-1.96	1.90	3.36	0.33	-9.93
Undocumented	0.0456	0.0122	-0.0641	0.0156	0.0167	0.0009	-0.8979
Std Error	0.0060	0.0070	0.0328	0.0083	0.0050	0.0051	0.0898
Z-Stat	7.55	1.75	-1.95	1.89	3.35	0.18	-10.00
Passel Undocumented	0.0453	0.0104	-0.0634	0.0158	0.0168	0.0012	-0.8929
Std Error	0.0061	0.0102	0.0328	0.0083	0.0050	0.0052	0.0898
Z-Stat	7.47	1.02	-1.93	1.91	3.37	0.24	-9.95

Figure 3: LFPR Confidence Intervals for the TFB, Documented, and Undocumented IMFRs



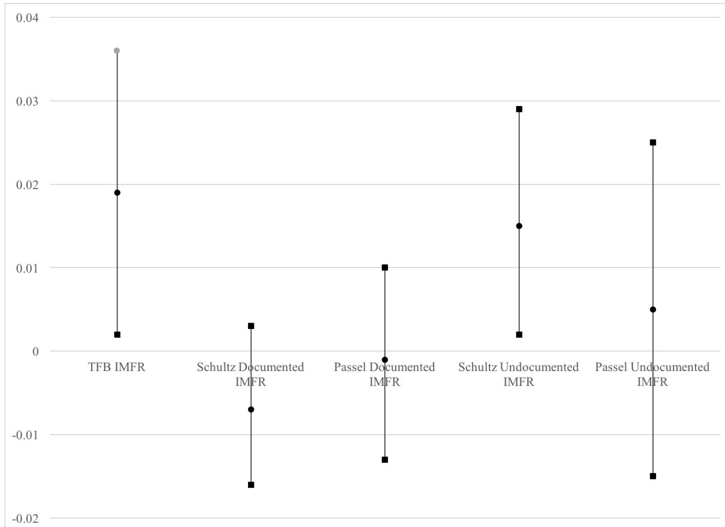
3 and 4 illustrate each confidence interval corresponding to each *IMFR* measure.[20]

Using confidence intervals allows us to more carefully examine the notion that undocumented immigrants embedded in the TFB population significantly affect a specified baseline relationship. In this case, the baseline variable is the TFB population and the baseline relationship is how the TFB population affects the native low-skill worker indicators. If either group has a statistically distinguishable effect on the native low-skill employment, then the confidence intervals they produce should not overlap with the baseline confidence interval. As shown in Figure 3, each IMFR segment overlaps with the baseline IMFR, implying that there is no distinguishable effect attributed to undocumented immigrants. These results also suggest that undocumented immigrants are not more substitutable with low-skill natives than documented immigrants. In summary, undocumented immigrants seem to play some role in the TFB baseline relationship, but there is no evidence that undocumented immigrants affect native low-skill workers more than documented immigrants.

Figures 3 and 4 also provide a good visualization for comparing the relevant coefficient estimates from the Schultz and Passel datasets. For IMFR in the LFPR regressions, the coefficients on the documented population are statistically similar (Figure 3). Likewise, for the dual-market, unemployment rate regressions (Figure 4), both datasets offer statistically similar coefficients for the documented and undocumented IMFR. The datasets provide statistically different coefficient estimates for the undocumented IMFR in the LFPR regression, with the Schultz coefficient statistically insignificant and the Passel estimate statistically significantly positive. It is reasonable to think that the differences in the results between each undocumented IMFR may be because the estimates derived and imputed from Passel (2009, 2010) are more accurate than the annual estimates we produce. Yet our panel data series appears to be relatively similar to the available years estimated by Passel (2009, 2010).

[20] A similar illustration of the confidence intervals produced for the effects of these separate immigrant groups on native low-skill unemployment rates is provided in Appendix 4.

Figure 4: Unemployment Confidence Intervals for the TFB, Documented, and Undocumented IMFRs



These similarities suggest that some other characteristic unique to the dataset derived from Passels estimates is contributing to the statistically significant relationship captured in Table 3.[21]

6. CONCLUSION

Overall, there appears to be a negative, significant, but relatively minor relationship between TFB immigrant concentrations and native low-skill employment indicators. These effects become statistically insignificant when undocumented immigrants are omitted from the model, suggesting that undocumented immigrants play some role in these relationships. Yet the impacts of total foreign born and undocumented immigrant are statistically indistinguishable. Documented immigrants alone appear to have no statistically significant effect on native employment indicators. Given the careful construction of the data and the current lack of alternatives to the approach, the fact that neither immigrant group has a statistically discernible impact on native citizen employment opportunities is already a useful step forward in better understanding this previously-opaque labor market interface.

This paper thus provides substantive insights into the dynamic of undocumented immigration. Due to data paucity, the majority of policymakers leverage often-anecdotal research that is not as rigorously quantitative as the issue requires to support their policies. The present approach contains admitted weaknesses, yet provides objective evidence on a previously understudied immigrant population to begin to answer a complex and polarizing set of

[21] One plausible explanation may be due to the highly linearized nature of the dataset derived from Passel's estimates. Specifically, we used linear imputations over relatively long time frames to create state-level estimates of the undocumented population for the years Passel (2009, 2010) does not address (See Figures 1 and 2). The low level of between-year variation produced from this dataset may either be contributing to a spurious relationship or may be exaggerating the relationship between undocumented immigration and the native low-skill LFPR.

questions. The fact that undocumented immigrants appear to have at best a minor impact on key native-born labor market outcomes is revealing. Further research is needed to solidify these conclusions. However, until data collection methods for undocumented immigrants improve, the indirect approaches proposed by this research are the best benchmarks available to understand the forces in play.

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APPENDIX 1: Area Analysis

It is important to provide a comprehensive description of Area Analysis, one of the most conventional methods used by economists to study immigration. In its simplest form, Area Analysis tries to capture how certain labor market mechanisms used to measure the economic welfare of native citizens absorb changes in the local labor supply that are propelled by immigrant inflows (Friedberg and Hunt, 1995; Borjas et al., 1996). Native wages and unemployment rates have been the primary absorption mechanisms in previous research, decreasing and increasing respectively in response to immigrant inflows. Most previous research using Area Analysis is also reliant on Total Foreign Born (TFB) population data. TFB population estimates help us answer whether immigration in general has an adverse effect on native citizens, but it does not isolate the effects of either documented or undocumented immigration. Area Analysis is reliant on several caveats to isolate the effects of immigrant inflows. These assumptions are addressed below.

A.1.1 Geographic Segmentation: One important assumption is that each labor market is ”distinct and geographically segmented” from other labor markets (Hanson et al., 2001). Geographic segmentation allows us to assume that certain labor shocks only affect a certain region and do not permeate to other regions. The model presented in this paper also adopts this assumption. Although it is considered a caveat, assuming that the labor market effects from immigration are isolated between states is less problematic than assuming a similar framework at the MSA level. Borjas (2006) presents convincing evidence that the omitted variables obfuscating the impact of immigration on natives become less severe as the geographic scope expands. Although this paper assumes that effects within each state are isolated, it does not assume that the effects of documented immigrants are the same as undocumented immigrants. Within the segmented market assumption, this paper will employ both a single and dual labor market approach, as discussed in Section 1, to observe the isolated effects of both documented and undocumented immigrants.

A.1.2 Labor Supply Proxies: Another assumption applied to Area Analysis is that the local ratio of immigrants to natives can be used as a proxy to measure changes in the local labor supply. Using this proxy may be present a severe shortcoming if it is assumed that the entire immigrant stock is a perfect substitute to the entire native stock. Research presented by Card (2001, 2005) suggests that the skills of immigrants are most likely heterogeneous. To resolve this issue, the stocks of natives and immigrants must be separated into different skill groups to form a specific immigrant-to-native ratio for each skill group. Separating these groups is possible because there is enough data on both documented and undocumented immigrants to assign each group to certain skill category. When each individual is assigned to the appropriate skill group, it is safer to assume that the immigrants and natives within each skill group are perfect substitutes. Assuming perfect substitutability is a strong assumption, but research done by Borjas (2006) suggests that there is a high degree of substitutability between immigrant and natives within each skill group. Furthermore, applying a dual market approach addresses the substitutability issue addressed by Card to an even greater degree because documented and undocumented immigrants can be analyzed separately. Overall, there will be three different ratios of immigrants to natives that are analyzed in this paper. The first ratio includes the entire TFB population while the second and third ratios only include documented and undocumented immigrants, respectively.

A.1.3 High School Dropouts: Finally, most previous research using Area Analysis focuses the effects of immigration on native high school drop outs because this group appears to be the most affected by immigration (Borjas, 2004, 2005, 2006; Card, 2005; Johannsson and Weiler, 2004). Low-skill natives in this paper are individuals that have not completed high school and will also be the target population of interest.

APPENDIX 2: Assumptions Needed for Undocumented Estimation Process

Our analysis must be viewed cautiously because the data used to estimate stocks of the TFB and Total Legal Foreign Born (TLFB) is highly limited between 1981 and 1994. State-level estimates for several documented immigrant inflow variables and for the TFB population were estimated either using linear imputations or distributions from the most recent year recorded. These data limitations, in conjunction with the Immigration and Reform Control Act (IRCA) of 1986, affect the accuracy of the undocumented estimates. We use this appendix to summarize the estimation methods and assumptions that were used to account for these issues. It also addresses the issues related to IRCA.

A.2.1 Non-Immigrants: We generated state-level estimates of the TempLegal statistic between 1981 and 1994 by applying a 1995 distribution of TempLegal to national-level estimates between 1981 and 1994. Additionally, non-immigrants are assumed to remain in the U.S. for only one year. We acknowledge some non-immigrants remain in the U.S. for longer than a year, but there is no literature or state-level data specifying how long. Lastly, Maine, Michigan, North Dakota, and Vermont appear to have abnormally high non-immigrant entries for the year 2010. These 2010 levels appear excessively high relative to previous years and have understated the state-level undocumented population estimates compared to Passel (2010). We have found no explanation as to why these states would have had exhibited abnormally high levels of non-immigrant entries for this particular year, which may indicate that this problem originated from a failure to record the data properly. To resolve this problem, 2009 estimates for each state were used in place of these 2010 estimates, which made the results more comparable to Passel (2010).

A.2.2 Total Foreign Born Population (TFB): Two linear imputations were used to approximate the annual TFB population at the state level for the 1981-1989 and 1991-1993 time frames. Linear imputations were required because state-level data was only available from the decennial census until the March CPS began surveying foreign born individuals in 1994.

A.2.3 Refugees and Asylees: The number of asylees and refugees entering the country was not explicitly recorded until 2000. However, according to the 1997 INS Statistical Yearbook, approximately 80 percent of refugees and asylees are granted lawful permanent residence after an average of two years. This means that we can use the number of refugees and asylees granted permanent residence status in year t to approximate the number of asylees and refugees entering the country in year t-2. This process was applied to all states between 1984 and 1999. State-level data for refugees and asylees was not available between 1981 and 1983, so a 1984 distribution was applied to national estimates for these years. Lastly, data for incoming asylees and refugees are only jointly available between 2000 and 2004. State-level asylee data was not available between 2005 and 2010 and only refugees were a part of this group during this time frame. This data limitation does not create any major concern because asylee inflows are relatively small compared to other documented immigrant inflow groups.

A.2.4 Legal Permanent Residents: State-level estimates were not available for 1981 and 1983. Distributions from 1982 and 1984 were applied to national levels recorded in 1981 and 1983, respectively.

A.2.5 Immigration and Reform Control Act (IRCA): In 1986, IRCA granted approximately 2.68 million undocumented aliens legal permanent residence (INS Yearbook 1997). Some of these legalized aliens may be omitted from the recorded lawful permanent resident data when they were granted amnesty, which may understate future estimates of the TLFB stock and overestimate subsequent levels of the undocumented stock.

A.2.6 Double Count Rates: The double count rates applied to the number of people naturalized and granted lawful permanent residence are based off a sample of several years' worth of data. These are not trends that have been calculated over a long time frame. Additionally, assuming that all lawful permanent residents adjust to naturalization status creates a shortcoming and most likely understates annual stock levels of the TLFB. However, there are no state-level naturalization rates available and this method is the only way possible to account for a naturalization double count at the state-level.

A.2.7 Negative Population Estimates: Our method occasionally generated small negative undocumented population estimates for several states. This occurs because of the highly approximated data between 1981 and 1994. Additionally, the data for the TFB is derived from the March CPS, while data for the TLFB is derived primarily from the INS and DHS. The CPS may use different sampling methods from the INS and DHS, which can create negative population estimates if the CPS understates the TFB population or if the INS or DHS overstates the TLFB population. The majority of these problematic estimates are negative at a miniscule level. Additionally, most of the states with negative estimates have very low undocumented population levels according to the results from Passel (2009, 2010). To account for this problem, we replaced the negative estimates with a value of zero before including them into the model measuring the economic effects of undocumented immigrants.

Although this estimation process has several shortcomings, it is one of the only methods available to estimate the undocumented population at the state-level. We compared these estimates to the few years estimated by Passel, finding similar results (Table A.1). The majority of our results fall within the range of the population confidence intervals provided by Passel (2009, 2010). This suggests that our model reasonably measures the undocumented population given the limitations to the data. Moreover, additional data derived from the selected estimates from Passel (2009, 2010) will accompany the dataset created from this paper to fortify the results. Passel's estimates may be more accurate, but they do not contain as much variation over time as the dataset generated from this paper because Passel has only estimated the undocumented population at the state-level for five specific years. The undocumented population from this paper has generated annual estimates for over 30 years and may better capture how immigrant movements over time affect low-skill natives, which will be addressed in the following section.

Table A.1: Comparing Schultz and Passel Results

State	1990 Passel	1990 Schultz	2000 Passel	2000 Schultz	2005 Passel	2005 Schultz	2007 Passel	2007 Schultz	2008 Passel	2008 Schultz	2010 Passel	2010 Schultz
Alabama	5,000	16,845	25,000	30,652	60,000	43,234	110,000	124,333	100,000	84,602	120,000	94,361
Alaska	2,500	8,241	5,000	2,626	5,000	15,786	5,000	2,718	5,000	3,395	5,000	15,190
Arizona	90,000	139,540	300,000	434,708	450,000	577,484	500,000	537,956	500,000	477,748	400,000	427,326
Arkansas	5,000	8,947	30,000	20,763	45,000	29,080	55,000	66,726	60,000	53,418	55,000	50,041
California	1,500,000	2,934,896	2,300,000	3,974,024	2,650,000	4,101,116	2,750,000	3,601,622	2,700,000	3,183,527	2,550,000	3,103,187
Colorado	30,000	51,685	160,000	257,458	240,000	237,818	240,000	199,759	240,000	193,409	180,000	202,732
Connecticut	20,000	136,172	75,000	57,783	85,000	76,935	110,000	129,021	110,000	50,155	120,000	128,685
Delaware	5,000	11,096	15,000	12,780	25,000	33,295	30,000	37,493	30,000	27,018	25,000	23,404
Florida	240,000	810,187	575,000	1,207,492	925,000	1,226,035	1,050,000	1,208,949	1,050,000	987,218	825,000	926,492
Georgia	35,000	75,720	250,000	109,539	425,000	442,597	475,000	555,899	475,000	501,092	425,000	389,850
Hawaii	5,000	41,064	25,000	37,418	25,000	48,698	30,000	47,304	35,000	35,662	40,000	41,038
Idaho	10,000	12,535	25,000	38,346	30,000	46,326	35,000	30,457	35,000	36,228	35,000	23,782
Illinois	200,000	433,411	475,000	378,762	350,000	487,202	500,000	652,128	450,000	471,789	525,000	545,598
Indiana	10,000	40,418	65,000	48,014	85,000	64,184	100,000	95,165	120,000	72,237	110,000	62,126
Iowa	5,000	11,438	25,000	62,161	55,000	94,686	55,000	70,472	55,000	90,890	75,000	96,431
Kansas	15,000	22,777	55,000	83,328	60,000	49,849	70,000	59,872	70,000	61,258	65,000	36,759
Kentucky	5,000	13,405	20,000	52,684	50,000	62,957	45,000	35,429	45,000	59,356	80,000	119,597
Louisiana	15,000	18,513	20,000	26,965	25,000	48,200	35,000	1,112	65,000	6,536	65,000	45,445
Maine	2,500	15,297	5,000	-	5,000	-	5,000	-	5,000	-	5,000	-
Maryland	35,000	148,544	120,000	170,351	250,000	366,272	275,000	311,187	250,000	332,858	275,000	347,220
Massachusetts	55,000	269,265	150,000	267,444	200,000	256,283	190,000	190,378	190,000	128,613	160,000	80,295
Michigan	25,000	181,494	95,000	187,908	120,000	161,626	120,000	23,885	110,000	120,749	150,000	134,292
Minnesota	15,000	33,549	55,000	106,149	85,000	176,556	110,000	136,807	110,000	106,601	85,000	62,032
Mississippi	5,000	7,355	10,000	4,283	40,000	45,444	40,000	33,564	35,000	38,994	45,000	22,624
Missouri	10,000	31,378	30,000	68,915	40,000	17,600	45,000	73,614	45,000	65,593	55,000	33,627
Montana	2,500	6,713	5,000	-	5,000	-	5,000	968	5,000	-	5,000	-
Nebraska	5,000	11,784	30,000	21,141	45,000	41,865	50,000	54,564	45,000	34,053	45,000	48,470
Nevada	25,000	56,107	140,000	197,901	190,000	269,291	240,000	285,245	230,000	285,065	190,000	251,290
New Hampshire	2,500	18,357	5,000	12,235	15,000	8,574	20,000	25,379	20,000	20,303	15,000	19,777
New Jersey	95,000	477,905	325,000	390,230	475,000	636,086	600,000	748,889	550,000	660,199	550,000	702,101
New Mexico	20,000	33,149	55,000	54,904	65,000	121,218	80,000	116,283	80,000	114,334	85,000	101,118
New York	350,000	1,413,568	725,000	1,265,094	675,000	1,204,251	825,000	1,102,894	925,000	1,163,289	625,000	532,602
North Carolina	25,000	54,219	210,000	198,336	375,000	388,566	375,000	372,842	350,000	306,109	325,000	358,807
North Dakota	2,500	2,834	5,000	-	5,000	-	5,000	-	5,000	-	5,000	-
Ohio	10,000	121,610	55,000	67,944	100,000	94,102	100,000	103,967	95,000	99,959	100,000	35,816
Oklahoma	15,000	12,967	50,000	40,749	60,000	75,408	55,000	24,571	55,000	30,802	75,000	58,643
Oregon	25,000	57,357	110,000	138,813	140,000	143,366	140,000	183,058	150,000	166,040	160,000	163,036
Pennsylvania	25,000	156,983	85,000	-	150,000	104,695	140,000	79,197	140,000	72,384	160,000	24,928
Rhode Island	10,000	43,007	20,000	7,036	30,000	46,911	30,000	50,673	30,000	45,903	30,000	31,782
South Carolina	5,000	21,849	45,000	11,727	55,000	50,226	70,000	61,754	70,000	113,444	55,000	68,616
South Dakota	2,500	2,849	5,000	975	5,000	6,887	5,000	6,518	5,000	7,952	5,000	8,572
Tennessee	10,000	21,993	50,000	29,728	130,000	167,588	160,000	169,581	150,000	147,962	140,000	165,669
Texas	450,000	611,847	1,100,000	1,225,954	1,400,000	1,818,686	1,450,000	1,633,593	1,450,000	1,707,264	1,650,000	1,551,354
Utah	15,000	17,455	65,000	53,218	95,000	68,481	120,000	139,103	110,000	111,770	110,000	88,069
Vermont	2,500	5,357	5,000	2,815	5,000	-	5,000	4,148	5,000	-	5,000	-
Virginia	50,000	149,282	150,000	214,404	275,000	296,303	325,000	363,710	300,000	349,413	210,000	184,716
Washington	40,000	154,954	160,000	86,761	200,000	238,426	170,000	265,596	180,000	215,730	230,000	279,807
West Virginia	2,500	5,651	5,000	2,549	5,000	-	5,000	-	5,000	-	5,000	363
Wisconsin	10,000	55,079	50,000	102,168	100,000	128,988	90,000	116,467	85,000	128,046	100,000	80,195
Wyoming	2,500	1,958	5,000	-	5,000	1,120	5,000	2,007	5,000	-	5,000	1,259
Total	3,547,500	8,988,608	8,370,000	11,765,233	10,935,000	14,620,300	12,050,000	14,136,855	11,935,000	12,968,964	11,360,000	11,769,124

APPENDIX 3: Sources Needed to Replicate Key Equations

A.3.1 Estimating Undocumented Immigration Population

The fundamental equation for estimating the undocumented population is:

$$Undocumented_{i,t} = All_{i,t-1} - TLFB_{i,t} \tag{7}$$

where *All* equals *Total Foreign Born (TFB)* stock minus temporary visitors, and *TLFB* equals Total Legal Foreign Born, which represents all documented immigrants. Annual estimates of Total Foreign Born stocks can be found at the Current Population Survey (CPS).[22] Annual estimates of Temporary Visitors can be found at the Department of Homeland Security (DHS) Yearbook of Immigration Statistics from 1996 to 2010.[23] Any similar data points from 1980-1995 come from Immigration and Naturalization Services (INS) Statistical Yearbooks.[24].

The equation for the TLFB is:

$$\begin{aligned} TFLB_{total,i,1981} = {} & LegalStock_{1980} + LPR_{1981} + Naturalizations_{1981} + Refugees_{1981} \\ & + Asylees_{1981} - DeathRate_{i,1981} - DepRate_{i,1981} - DoubleCount_{i,1981} \end{aligned} \tag{8}$$

where *LegalStock* comes from the 1980 INS Statistical Yearbook. Annual estimates of *LPRs*, *Naturalizations*, *Refugees*, and *Asylees* come from the Department of Homeland Security (DHS) Yearbooks of Immigration Statistics from 1996 to 2010. Any similar data points from 1980-1995 come from INS Statistical Yearbooks. Refugee data from 2000 to 2010 was pulled from the Department of Health and Human Services[25] because of a gap in coverage from DHS data. Death Rates come from the Centers for Disease Control.[26] Deportation Rates (*DepRate*) and Double Count (*DoubleCount*) rates are provided by the DHS and INS yearbooks.

A.3.2 Estimating Impact of Undocumented Immigrant Popultion and Labor Market Outcomes

We estimate a model of the form:

$$Y_{i,t} = \beta_0 + \beta_1 IMFR_{i,t} + \beta_2 Race_{i,t} + \beta_3 Sex_{i,t} + \beta_4 Age_{i,t} + \beta_5 GSP_{i,t} + \mu_{i,t} \tag{9}$$

where the dependent variables are low-skill unemployment rates and labor force participation rates come from the Basic Monthly Survey (BMS).[27] Here we conditioned state level unemployment rates and labor force participation rates by low skill citizens, using "Educational Attainment" to extract individuals who did not graduate high school. Total Low Skill

[22] `http://dataferrett.census.gov/`

[23] `https://www.dhs.gov/immigration-statistics/yearbook`

[24] `https://archive.org/search.php?query=Immigration%20and%20Naturalization%20Service%20yearbook`

[25] `https://www.acf.hhs.gov/orr/resource/refugee-arrival-data`

[26] `Phttp://wonder.cdc.gov/ucd-icd10.htmlandhttp://wonder.cdc.gov/cmf-icd9.html`

[27] `http://dataferrett.census.gov/`

Population estimates (via Educational Attainment Classification), Race, Sex, and Age come from the BMS. Gross State Product (*GSP*) estimates come from the Bureau of Economic Analysis.[28]

[28] `https://www.bea.gov/regional/`