THESIS

THE EFFECTS OF UNDOCUMENTED IMMIGRATION ON THE EMPLOYMENT OPPORTUNITIES OF LOW SKILL NATIVES IN THE UNITED STATES

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ABSTRACT

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The economic effects of immigration have been well studied, but the majority of this research has not attempted to isolate the effects of undocumented immigration. Isolating this effect is a difficult task because dearth amounts of data exist for these individuals. This paper provides a substantial contribution to the economic impact of immigration for two reasons. First, it emulates a methodology adopted by notable immigrant demographers to generate annual state level estimates of the undocumented population between 1994 and 2010 in the United States. These estimates alone are very important to this topic because no other entity has attempted to accomplish this task. Secondly, this paper incorporates these estimates into a fixed effect dynamic model to capture the economic impact of undocumented immigrants on low skill native labor force participation rates (LFPR) and unemployment rates across the United States between 1994 and 2009. Overall, undocumented immigrants have a menial impact on the native low skill LFPR and do not affect low skill unemployment rates. Additionally, the methods used in this paper allow us to isolate the effects of documented immigrants on the same native low skill employment indicators. The results suggest that documented immigrants do not have a statistically significant effect to either low skill employment indicator, which is also an important conclusion.

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SECTION 1: INTRODUCTION

The undocumented immigrant population is increasing in the United States (US), which is fostering more controversy over an already polarizing debate between policymakers and US citizens. In reference to Appendices 1, 2, and 3, it is evident that the undocumented population is not only increasing, but is also becoming more widespread in the last 20 years. In the early 1990s, approximately 85% of the undocumented population resided in the Big Six states, which included California, New York, New Jersey, Florida, Illinois, and Texas (Borjas et al 1996; Martin 1994). Although these states remain prominent destinations for undocumented immigrants, many states originally harboring low levels of these individuals are now catching up to the Big Six states—especially Alabama, North Carolina, Georgia, and Arizona. As undocumented immigrants become more widespread, so too does the debate regarding their economic effects. There is a growing concern that undocumented workers displace native citizens in the workforce and put downward pressure on native wages. Although much of the economic hardship associated with native workers may be attributed to the Great Recession, many states have responded to this growing negative sentiment by passing more stringent and controversial immigration laws. These states include Arizona, Alabama, Georgia, Indiana, Utah and South Carolina (Bowman 2010; Dade 2011; Estes 2011; Summers 2011)[1].

Undocumented immigration may have a significantly negative impact on native citizens, but there is little evidence to support either side of the argument. One recent study by Hotchkiss et al (2012) used undocumented immigrant data to measure its effects on native wages in Georgia. They have concluded that native workers employed by firms hiring undocumented workers earn approximately 0.15% less than natives employed by firms only hiring documented

[1] From a thesis submitted to the Academeic Faculty of Colorado State University in partial fulfillment of the requirements for the degree of Masters.

workers. These results are menial at best and do not implicate any significant impact on native workers.

Very little research is dedicated to this topic because it is difficult to accurately estimate the undocumented population. This paper attempts to resolve this problem because it devises a methodology similar to other notable immigrant demographers to estimate the annual undocumented population at the state level between 1994 and 2010 (refer to Appendix 1). No other demographer to date has accomplished this task, which alone is a substantial contribution to this field of research. This estimation process is subject to a great deal of error if done improperly, which is why the undocumented estimates from this paper are compared to similar estimates produced by Jeffrey Passel of the PEW Hispanic Center. Passel is one of the leading authorities on estimating the undocumented immigrant population in the United States and his estimates serve as a benchmark to any party attempting to estimate the undocumented population. Passel has estimated the undocumented population at the state level for the following years: 1990, 2000, 2005, 2007, 2008, and 2010. As illustrated in Appendix 4, the estimates in this paper are very similar to the available years provided by Passel, which adds a great deal of credibility to the estimation process used in this paper.

In addition to its contribution to immigrant demography, this paper incorporates undocumented population estimates into a dynamic fixed effect model to capture the relationship between undocumented immigrant concentrations and native low skill labor force participation rates (LFPR) and unemployment rates[2]. No other paper has attempted to measure these effects. The native LFPR is the primary economic indicator of interest because there is not a great deal of evidence suggesting that immigrants in general have an adverse effect on native wages and

[2] Low skill individuals are 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 (Card 2005, Borjas 2003, 2006, Johannsson and Weiler 2004).

unemployment rates (Card 1990, 2001, 2005). Native wages and unemployment rates may be unresponsive to immigrant inflows because the native LFPR may absorb this shock. Natives may respond to immigrant inflows by either migrating to another area or dropping out of the labor force while remaining in the same area. Either of these effects decreases the native LFPR, but has a countervailing effect on the labor supply from immigrant inflows—thus preserving native unemployment rates and wage levels.

In addition to placing emphasis on the native low skill LFPR, the dynamic model used in this paper will capture the effects of undocumented immigration at the state level, which may be relatively crude (Card 2005). Normally, any comparable labor market research would analyze these effects at the MSA level because it may represent local labor markets more accurately than state level models. However, MSA level analysis is currently impossible for this topic because the data needed to estimate the undocumented population is only available at the state level. To resolve this shortcoming, this paper uses a MSA level model created by Johannsson and Weiler (2004) as a guideline to create a sufficient state level model that captures the effects of undocumented immigration. Johannsson and Weiler's model focuses on the effect the total foreign born (TFB) population has on native low skill labor force participation rates and unemployment rates. The TFB population includes the entire stock of both documented and undocumented immigrants. This statistic is too crude of a measure to isolate the effects of undocumented immigrants, but the TFB results from Johannsson and Weiler (2004) can be used as a benchmark comparison to the TFB results from state level model in this paper. If the TFB estimates from both models are comparable, then the state level model gains credibility because it captures similar effects to immigration as the MSA level model. After emulating a very similar process to Johannsson and Weiler (2004), the state level results between the TFB population and the native LFPR are similar to the MSA results from Johannsson and Weiler (2004). The results from this paper suggest that a 10% increase in the TFB population decreases the native low skill LFPR by 0.44% while the results from Johannsson and Weiler (2004) suggest that the same relationship decreases the low skill native LFPR by 0.76%. Both models also find that the relationship between the TFB population and native low skill unemployment rates is insignificant. These similarities provide evidence that this state level model is both accurate and credible enough to decipher the economic impacts of immigration. Moreover, although many researchers deem state models to be too broad of a geographic space, others are in favor of state level models to analyze this topic. Borjas (2003, 2006) provide convincing evidence that models at both the state and national level capture greater effects to native citizens than at the MSA level[3]. Borjas' conclusions in conjunction with similar estimates purported by Johannsson and Weiler (2004) provide enough evidence to support the use of a state level model in this paper.

Identifying the effects of the TFB population is not only used to add legitimacy to a state level model, but is also used to isolate the effects of undocumented immigration. The results from the TFB population tell us the collective effect both documented and undocumented immigrants have on low skill natives. An assumption underpinning this approach is that a single labor market exists for both documented and undocumented immigrants. If both groups operate in the same labor market, then they each compete relatively equally and have similar degrees of substitutionability with low skill natives. Although the results produced from this approach are useful, they are limited because these assumptions are not realistic. In reality, each group affects low skill natives differently due to the legal restrictions and language barriers undocumented immigrants face when seeking employment. To resolve these issues, a single market approach should be accompanied with a dual market approach because it assumes that documented and

[3] The arguments made by Borjas (2006) will be discusses in more detail in Section 2.

undocumented immigrants operate in separate labor markets and have different degrees of substitutionability with low skill natives. A dual market approach may be more robust because it incorporates each group of immigrants separately into identical models to isolate the effect each group has on low skill natives.

To employ a dual market approach, several steps are needed. The first step involves subtracting the undocumented population estimates from the TFB estimates. The residual values represent the documented immigrant estimates at the state level. These documented immigrant estimates are then incorporated into the same model used to measure the effects of the TFB population. The difference between the effects of the TFB population and the documented immigrant population in both their significance and magnitude provide some information on the economic impact of undocumented immigration. To complete the story, estimates representing only the undocumented population must be incorporated into the same model that analyzes the effects of the documented population. Comparing the isolated effects of both types of immigrants tell us whether documented or undocumented immigration has a greater effect on low skill natives. The group exhibiting the greater effect also suggests that this same group is relatively more substitutable with low skill natives than the other group. It also tells us whether any significant effect captured by the TFB population is primarily attributed to either the documented or undocumented population.

To ensure that the effects of both documented and undocumented immigration are as consistent as possible, two data sets representing the undocumented population are used to estimate annual levels of each immigrant group. The first data set was created using the methodologies from this paper. The second data set corresponds to the estimates generated by Passel (2009, 2010). Passel does not provide annual data between 1994 and 2010, but this paper uses linear imputations to provide estimates for the years he did not address. Both data sets produce similar results when isolating the effects of documented immigrants, which is encouraging.

Overall, undocumented immigration appears to have a minor impact on the low skill native LFPR and does not affect unemployment rates. Again, the estimates from the single market approach suggest that a 10% increase in the TFB population decreases the native low skill LFPR by 0.44%. This relationship alone is highly inelastic and does not favor any significant effect on native low skill employment opportunities. When applying the dual market approach, the relationship between immigrant concentrations and the native low skill LFPR becomes statistically insignificant when undocumented immigrants are omitted from the TFB population. The effects of this omission imply that undocumented immigrants play a critical role in the baseline relationship between the TFB population and the native low skill LFPR. Additionally, these results suggest that documented immigrants alone do not have a significant impact on low skill native employment indicators. To complete the story, the isolated effects of undocumented immigrants do not have a statistically distinguishable effect on the low skill native LFPR. Undocumented immigrants may influence the baseline relationship associated with the TFB population, but not enough evidence exists to argue that undocumented immigrants have a higher degree of substitutionability with low skill natives and affect them more than documented immigrants.

Due to the arduous nature of estimating the economic impacts of undocumented immigration, this paper is broken down into eight additional sections. Section 2 provides a literature review of some of the most prominent research pertaining to immigration. Section 3 highlights the methods used to estimate the undocumented population at the state level. Section 3 will also explain the assumptions that were made to estimate the undocumented population as well as the limitations these assumptions create. Section 4 summarizes the dynamic fixed effects model that is used to estimate the effects of undocumented immigration on native low skill labor force participation rates and unemployment rates. Section 5 explains how the undocumented immigrant estimates addressed in Section 3 are incorporated into the model addressed in Section 4 to isolate the economic impact of undocumented immigration. Section 6 summarizes the data sources needed for the models addressed in Section 3 and Section 4. Section 7 summarizes the results from the model presented in Section 4. Section 8 provides an alternative hypothesis to explain why the results presented in Section 7 are not substantial. Section 9 provides several closing remarks and possible methods that may be used to resolve the shortcomings produced in this paper once the accuracy of undocumented immigrant population levels improves.

SECTION 2: LITERATURE REVIEW

This section summarizes the contributions of previous research as well as how they influence the model created in Section 4 of this paper. This section is broken into three sub-sections. The first subsection provides a comprehensive explanation of the overall approach most previous research has adopted to analyze immigration. This method is referred to as Area Analysis. The second sub-section highlights an ongoing debate between economists on the proper geographic space used to capture the effects of immigration on native employment and income. The third sub-section summarizes how the models and approaches used to capture the economic impact of immigration have evolved over time.

Area Analysis

To begin, it is important to provide a comprehensive description of one of the most conventional methods used by economists to study immigration. This method is referred to as Area Analysis. 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. Native wages and unemployment rates absorb labor supply shocks when they decrease and increase respectively in response to immigrant inflows. Most previous research using Area Analysis is also reliant on TFB population data, which represents the entire immigrant population—both documented and undocumented. 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. One important assumption is that each labor market is "distinct and geographically segmented" from other labor markets (Slaughter and Hanson 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 Section 4 of 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 becomes less severe as the geographic scope expands[4]. Although this

[4] Borjas' evidence will be addressed in greater detail in the next sub-section.

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.

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. The model presented in Section 4 of this paper uses this statistic. 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 (Card 2001, 2005). 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 substitutionability is a caveat, but research done by Borjas (2006) suggests that there is a high degree of substitutionability between immigrant and natives within each skill group. Furthermore, applying a dual market approach addresses the substitutionability issue addressed by Card to an even greater degree because documented and undocumented immigrants will be analyzed separately. Overall, there will be three different ratios of immigrants to natives that will be 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.

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, Johannsson and Weiler 2004, Card 2005). Low skill natives in this paper are individuals that have not completed high school and will also be the target population of interest. The four assumptions of Area Analysis addressed above provide a framework for isolating the effect of immigrant inflows on the local labor supply and its subsequent effects on employment and income levels for low skilled natives (Slaughter and Hanson 2001).

The majority of previous research using Area Analysis applies the assumptions specified above, but the conclusions drawn from each paper do not always coincide. Most of these differences are attributed to the geographic space, the type of model used, and the native economic indicators used to capture the effects of immigration. The remaining portion of this section will summarize the differences in both the theoretical philosophy and the applied methodology that have led to different conclusions about immigration. The first half of this discussion will summarize an ongoing debate between researchers on the appropriate geographic space used to measure the effects of immigration. The second half will elaborate on how the models and approaches used to capture the effects of immigration have evolved over time.

Debate on the Proper Geographic Space Needed to Observe the Effects of Immigration

To begin, there is a contentious debate currently taking place on whether MSAs are appropriate geographic spaces to isolate the effects of immigrant concentrations on native low skill economic welfare. The two economists at the forefront of this debate are David Card of the University of California—Berkeley and George J. Borjas of Harvard University. Both of these economists have contributed substantial research to the economic effects of immigration, but their conclusions are completely opposite. Card 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 (Card 1990, 2001, 2005). Borjas is in favor of using state and national level models and has captured a significantly negative effect with the foreign born population on the same native low skill economic indicators. The methods and conclusions made by Card and Borjas differ because they disagree on the effects of native outmigration that take place in response to immigrant inflows. Theoretically, natives may decide to vacate a region if they are displaced by an immigrant in the workforce. When natives leave an area, they drop out of the local labor market, which decreases the local labor supply. This decrease in the labor supply counters the upward pressure on the labor supply resulting from greater immigrant inflows. If native outmigration is a legitimate phenomenon, then it makes it difficult to ascertain any relationship between immigration and native economic welfare because low skill wages and unemployment levels remain relatively unchanged.

Borjas (2006) provides evidence to suggest that the effects of native outmigration become more apparent the smaller the geographic scope becomes. According to his results, for every 10 immigrants entering an area, approximately 6.1 natives leave the area at the MSA level. At the state level, the same relationship suggests that the entry of 10 immigrants will only cause 2.8 natives to leave the state. These results are consistent with regional economic theory because the transportation costs and opportunity costs of exiting a region become larger the greater the geographic region becomes. The effects of outmigration presented by Borjas (2006) also suggest that the native labor supply becomes more inelastic for larger geographic regions. A more inelastic labor supply will produce greater adverse effects if the labor demands for natives decreases when firms substitute out of hiring natives and instead employ immigrants. The effects of immigration on native wages and unemployment rates suggest that the labor supply is, in fact, more inelastic at the state and national level than at the MSA level. The results from Borjas (2006) show that a 10 percent increase in immigrant concentrations leads to a four percent decrease in native low skill earnings at the national level. At the state level, this same relationship implies that immigration decreases native low skill earnings by only 1.6 percent. Borjas (2006) does not provide an elasticity estimate at the MSA level, but does say 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.

Although Borjas presents a convincing argument in support of models covering large geographic space, Card (2001, 2005) also provides enough evidence to refute Borjas' conclusions. Card is a proponent of MSA level models because his research suggests that native outmigration is not sensitive to immigrant inflows. If natives do not migrate to another area in response to immigration, then MSAs are the most accurate geographic spaces to measure the labor market outcomes of immigration. MSAs are physically better representations of labor markets because they harbor more concentrated economic activity than states and national boundaries and are less prone to omitted variable bias. To support this theoretical approach, Card (2001, 2005) uses a basic regression that captures the relationship between low skill immigrant concentrations and the overall low skill concentration. If immigrants do not displace natives and are merely added to the overall stock of low skill workers, then this regression should produce a coefficient near one. If immigrants displace natives, then this same relationship should produce a zero. The regression results from Card (2001, 2005) show that the coefficient is near one, which implies that immigrants do not displace natives. If immigrants do not affect the migratory patterns of natives, then MSA level models are robust. Given that he provided substantial evidence in favor of no native outmigration, Card (2005) reports that changes in immigrant concentrations do not significantly affect native low skill wages and only affect unemployment rates to a minor degree.

If immigrant laborers do not displace native laborers and also do not affect native employment and income, then some mechanism must be absorbing these inflows. Card (2005) uses a Heckscher-Ohlin (HO) model to suggest that regions are partially absorbing these immigrant inflows by changing their output mix, which is also a topic that is addressed more extensively by Slaughter and Hanson (2001). Card (2005) says that the agriculture and textile industries have flocked to regions with greater concentrations of low skill workers. Firm in-migration into heavily concentrated low skill areas will increase labor demand, which counters increases in the labor supply resulting from immigration—thus preserving the low skill wage and unemployment rate. Another reason why regions may absorb immigration inflows relates to the decisions firms make about technology endowments. Firms may "innovate in a direction that will take advantage of more readily available factors," which suggests that firms will not invest in more advanced technology if they anticipate the stock of low skill workers to increase (314).

Both Borjas and Card use different approaches to justify their conclusions. The fact that both approaches are quite different does not repudiate the others' methodology. The fact that Borjas provides convincing evidence that state level models may be more robust than MSA level models adds credibility to the state level model used in this paper to capture undocumented immigration. The debate on native outmigration may never be resolved, but the fact that this issue has compelled both sides of the argument to devise more advanced methods to support their claims will benefit future research on this topic.

Evolution of the Models Used to Measure the Effects of Immigration

This next section summarizes the different models previous research has used to capture the effects of immigration. These models vary because some are static while others are dynamic. Some models use a conventional approach by measuring the effects of immigration on native low skill wages and unemployment rates while others use take an unorthodox approach to explain how immigration is absorbed through alternative mechanisms—such as regional output mixes and native labor force participation rates. This section will initially discuss the use of static models and they are prone to endogeneity. We will then digress into the use of dynamic models and how they resolve many of the issues related to endogeneity. Finally, this section will summarize some of the key alternative approaches that have influenced the model applied in this paper.

To begin, some of the papers incorporating static models to measure the effects of immigrant inflows include Card (1990), Card (1991), Card (2001), Borjas (1994), and Borjas (1996). Most of these papers capture either a moderate effect or no effect between immigrant inflows and native wages and employment opportunities on a certain target population—usually low skill native citizens. Although the results of some of these models imply that immigrant inflows decrease native wages and employment opportunities, they are criticized for not addressing endogeneity issues that may be distorting their results. These results may be flawed, but static models may be useful if they are accompanied with an instrumental variable (IV) or a dynamic model. The papers summarized below use static models.

Card (1990) analyzed the effects of Mariel Boat Lift, which allowed a massive influx of Cuban immigrants to enter the shores of Miami in 1980. Using cross section summary statistics and regression analysis to describe the differences in wage growth and unemployment rates over time between Miami and other cities with comparable economic growth rates, Card (1990) concluded that the influx of Cuban immigrants had a minimal effect on the Miami labor market. The only group that was affected was the low skill Cuban immigrant population that resided in Miami before the Mariel Boat Lift. Cuban immigrants were the only group in Card's sample that experienced an increase in the wage differential between Cubans residing in Miami and Cubans residing in comparable cities. However, the growth in the wage differential did not persist very long, which suggests that the effects of the immigrant influx did not last long. Card states that the adverse effects from immigrant inflows may have been mitigated by the expansion of several prominent low skill industries, which increased labor demand during the same time frame. Such an event creates an endogeneity issue with the results from Card (1990).

Similar to Card (1990), Borjas et al (1996) use decennial data to develop a cross-sectional model that measures the effect of immigrant inflows on native wages across MSAs between 1980 and 1990. Borjas et al (1996) apply a regression controlling for age, education attainment and gender to measure how changes in immigrant inflows affect the wages of native citizens (247). They apply this cross section regression across a group of MSAs for two different time periods: 1980 and 1990. The results from their model imply that immigrant inflows and native wages are negatively related in 1980 and positively related in 1990. The model created by Borjas et al (1996) is very similar to the model adopted in this paper, but this paper will resolve several shortcomings they did not address.

The results from Card (1990) and Borjas (1996) do not provide convincing evidence that immigrant inflows have a significant effect on the native population. The conclusions drawn from each paper imply that other variables may be affecting the relationship between immigrant inflows and wage levels, which are not captured in the models they developed. For instance, one variable that might affect this relationship is the outmigration rates of native citizens. This topic was discussed heavily in the previous sub-section and will not be addressed in detail here. However, it is important to note that other researchers have delved into this topic and their conclusions also do not share an overall consensus in regards to the relationship between immigration and native outmigration. For instance, the results from Kritz and Gurak (2001) are not in favor of immigration affecting native migratory decisions because they attribute most of native labor outmigration to poor economic conditions and not immigrant inflows. However, research done by Filer (1992) found a significantly negative relationship between native net-migration rates and immigration rates—especially within a 5 year time frame. The mixed results associated with these two researchers in conjunction with the mixed results between Card and Borjas imply that any future research may need to analyze the effects of immigrant inflows within a five year time frame to account for the possibility of native outmigration. However, short run models may also produce their own unique shortcomings, which will be addressed shortly.

In addition to outmigration issues, the cross section models endorsed by Card (1990) and Borjas et al (1996) may be problematic because they treat immigrant inflows as exogenous. In reality, regionally specific characteristics may attract greater inflows of immigrants, which give rise to the possibility of endogeneity. Some regionally specific characteristics may include local wage levels, changes in labor demand, immigrant concentrations, and the quality of welfare benefits (Altonji and Card 1991; Borjas 1996; Borjas 1999; Card 2001; Carter and Such 1999; Friedberg and Hunt 1995).

Two alternative approaches can be applied to account for endogeneity. The first method involves using an instrumental variable that is correlated with immigrant inflows, but not wages. Several papers use instrumental variables to augment their results—such as Card (2001), Borjas (1996), and Altonji and Card (1991). One common instrumental variable is prior immigrant stock levels because immigrants may migrate to areas with high immigrant concentrations. However, we would not expect previous stock levels of immigrants to affect the growth in wages if these stocks are lagged enough (Altonji and Card 1991; Friedberg and Hunt 1995). The other alternative is to develop a dynamic model to measure how changes in immigrant inflows affect wage changes. Dynamic models usually produce more robust results than static models because immigrants' migration decisions are more likely responsive to wage levels than wage changes. Thus, any dynamic model capturing the relationship between immigrant inflows and wage changes should better reflect how immigrant inflows affect wage changes (Friedberg and Hunt 1995). Additionally, dynamic models resolve any issues associated with "location specific effects" that do not vary over time, but give immigrants incentive to migrate there (31). Location specific effects exist with stock variables, but are eliminated when a dynamic approach is used to create flow variables. Many papers adopting dynamic models use the first differencing approach to their initial static models to express how changes in immigrant population affect changes in native wages. First differencing a static model eliminates the fixed effects that distort the relationship between immigration and the desired native economic indicator of interest. Some papers that use first differencing include Altonji and Card (2001), Borjas et al (1996), and

Johannsson and Weiler (2004). This paper will also adopt a dynamic framework similar to Johannsson and Weiler to avoid endogeneity issues.

In addition to applying static models and neglecting native outmigration, some prior research criticizes the use of the immigrant population as a fraction of the total population within an MSA to express changes in immigrant levels (Card 2001). Two papers that use this method are Card (1990) and Borjas et al (1996). Using this statistic as a proxy for increases in the labor supply may be problematic because it is too broad of a measure to capture the effects of labor supply changes within certain labor markets corresponding to specific skills (Card 2001). The skills and earnings of immigrants are relatively heterogeneous, which suggests that all incoming immigrants are not direct substitutes for native labor. If immigration labor is relatively heterogeneous, then it may be more efficient to create separate labor markets for each skill level when measuring the effects of immigrant inflows (Card 2001).

Card (2001) analyzes the effects of immigrant inflows at the occupation level, which accounts for the substitutability issue between immigrants and natives. Card (2001) derives two labor supply and labor demand regressions to show how wages and unemployment rates are functions of a city specific component, an occupation and city specific productivity level, and relative population shares for each occupation. Additionally, Card stratifies each labor market by occupation and includes all observed workers in the labor supply. For people who are unemployed, but are relevant to a certain occupation, Card uses a multinomial logit model to form probability distributions based on an array of observable characteristics to estimate how many people who aren't working pertain to a certain labor supply. In conjunction with incorporating this model into a dynamic framework that uses instrumental variables, the results from Card (2001) imply 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” (57). The effects in low-immigrant cities and labor markets containing few low skill workers appear to be less severe.

The results from Card (2001) provide some of the strongest results to date that are relevant to the effects of immigration because he accounts for endogeneity and isolates the effects of immigrants at the occupation level. However, incorporating a model as detailed as Card (2001) is problematic for this paper because it is currently not possible to use a probability model to estimate the number of undocumented workers in specific occupation markets. There is a limited amount of data provided Passel (2009, 2010) on certain industries undocumented immigrants are often employed in, but there is not enough data to create enough between year variation in the distribution of undocumented immigrants across different occupations. Additionally, the effects of immigrant inflows drawn from the conclusions of this paper remain relatively modest, which may suggest that immigration does not significantly affect native low skill workers. However, models similar to Card (2001) may be either analyzing the effects of immigration over too long of a time frame or are not using the proper statistics to measure native citizens’ welfare. Three papers that use alternative statistics to measure how markets absorb immigrant inflows include Hanson and Slaughter (1999; 2001) and Johannsson and Weiler (2004).

The papers by Slaughter and Hanson use changes in state level output mixes as the primary absorption mechanism for changes in immigrant flows. Slaughter and Hanson (2001) premise their models on the Heckscher–Ohlin (HO) model and the Rybczynski Theorem. The primary theme from the HO model is that any province will produce greater amounts of goods that are derived from its relatively cheapest and most abundant inputs (Acemoglu). As a complement to the HO model, the primary theme drawn from the Rybczynski Theorem is that an increase in the endowment of a certain input will result in an increase in any output that uses that input intensively (Acemoglu). In the case of immigration, the conclusions drawn from Slaughter and Hanson are that states who have become more immigrant-intensive have changed their output mix over time to be more labor intensive because most recent incoming immigrants are low skill laborers (Slaughter and Hanson 2001). Thus, the welfare effects to native low skill laborers are not substantial because output mixes absorb the labor supply shock rather than native wages and employment. Although the model in this paper does not focus on output mixes as an absorption mechanism, the results from Slaughter and Hanson are important because they provide additional evidence to repudiate the use the native wages and unemployment rates to measure the economic impact of immigration.

Hanson and Slaughter (2001) also address the possibility of the native labor force participation rate (LFPR) acting as an alternative absorption mechanism for immigrant inflows, which is a topic that is addressed by several papers—such as Altonji and Card (1991), Carter and Such (1999), and especially Johannsson and Weiler (2004). Johannsson and Weiler emphasize the importance of using the native LFPR because it accounts for natives potentially out-migrating to another area and natives who remain in the same area, but exit the labor market. Using this statistic in an Area Analysis approach is also efficient because it evades many of the issues related to native outmigration. Hence, the native LFPR may be a more versatile statistic than native wages and employment levels in capturing any effects to the native population than.

The work done by Johannsson and Weiler (2004) is unique not only for their use of the native LFPR, but also for their emphasis on utilizing short run models. Many of the papers previously summarized incorporate decennial census data into their models, which may be problematic because data spanning over that long of a time frame may not capture shocks to the labor market that occur during intermediate periods. For instance, natives may migrate out of an area or firms may migrate into an area within a 10 year time frame. Native outmigration decreases the labor supply while firm in-migration increases labor demand. Both of these effects put upward pressure on native wages, which is a countervailing force to immigrant inflows increasing the labor supply. Several papers have addressed this problem—such as Altonji and Card (1991), Card (1990), Filer (1992), Kritz and Gurak (2001), and Johannsson and Weiler (2004). According to Blanchard et al (1992), unemployment rates and wage levels need approximately five to seven years to re-equilibrate from an initial adverse labor market shock. These results encouraged Johannsson and Weiler to develop a model that spans over a five year time frame to measure the effects of immigrant inflows on native employment during periods where the labor market has not fully adjusted to equilibrium. Using a five year time frame may provide greater accuracy because the native workers that are adversely affected will not have migrated out of the area. Moreover, a similar time frame may also mitigate the effects of firm in-migration. Similar to Borjas et al (1996), Johannsson and Weiler (2004) construct both static and dynamic models to capture the effects of immigrant inflows on native low skill employment opportunities. Their dynamic results suggest that a 10% increase in the ratio of low skill immigrants to low skill natives creates a 0.76% decrease in the native low skill LFPR.

In summary, the models used to capture the effects of immigration on native economic welfare have evolved over time. Earlier papers used simple cross-sectional models spanning over 10 year periods. These models are not guaranteed to produce robust results because the relationships they capture may be endogenous. Additionally, these models do not address the effects of labor outmigration and firm in-migration occurring between the recorded time periods if they use decennial data. In response to these issues, subsequent papers adopt a more dynamic framework and use instrumental variables to account for endogeneity. They have also focused on a shorter time frame to capture the adverse welfare effects to native citizens because most of these effects occur before the labor market re-equilibrates. Lastly, some papers claim that native wage levels and unemployment rates are not the primary absorption mechanism for labor supply shocks caused by immigration. Some suggest that other mechanisms absorb this shock more than native wages—such as output mixes and the native labor force participation rate. Although many of these papers offer significant insight regarding how to measure the economic effects of immigration, the model constructed by Johannsson and Weiler (2004) appears to produce some of the most robust results because of their emphasis on the use of the labor force participation rate. Additionally, the model used in Johannsson and Weiler (2004) conforms efficiently to the state level model needed for this paper, which is why this paper will adopt a similar model. Before this model is introduced, it is important to explain how state level undocumented populations are estimated and incorporated in the model presented in Section 4. The next section will highlight these procedures.

SECTION 3: ESTIMATING THE UNDOCUMENTED IMMIGRANT POPULATION

This section summarizes how state level undocumented population estimates are created. The process used to create these estimates is very similar to the one created by Jeffrey Passel. Passel is the senior demographer for the PEW Hispanic Center and is one of the leading authorities on estimating the undocumented population in the United States. Jeffrey Passel (2007) uses the "residual method" to estimate undocumented population levels. This method calculates the difference between the stock of the Total Foreign Born (TFB) population and the stock of the Total Legal Foreign Born (TLFB) population. The residual represents the stock of undocumented workers. This section summarizes a methodology similar to Passel (2007) that is used to estimate the undocumented population between 1994 and 2010. These stock levels will in turn be applied to the dynamic model presented in Section 4 to capture the economic effects of undocumented immigration on native workers.

To begin, estimates of the TFB stock and the TLFB stock must be provided to calculate the stock of the undocumented population. Annual TFB stock levels starting in 1994 are easily obtainable by the March Current Population Survey (CPS). The TLFB stock is not provided by any data source and must be estimated. The process below highlights the procedures needed to estimate the TLFB. Once the TLFB for each year is estimated, it is possible to estimate the population of undocumented immigrants at the state level.

No recent data source provides annual stock estimates of the TLFB, which is also a shortcoming that this paper attempts to resolve because the methods used in this section have estimated the TLFB population between 1980 and 2010. The TLFB must be estimated by using the most recent year that the TLFB stock was recorded and apply flow data to estimate stock levels for subsequent years. The flow data is derived from several sources. Inflow data is provided by the Department of Homeland Security (DHS) and its predecessor the Immigration and Naturalization Service (INS). Both the DHS and INS have similar data gathering methods. The inflow data is used to add groups of incoming documented immigrants to the TLFB stock for each year. The three inflow groups of documented immigrants include the number of lawful permanent residents, naturalized citizens, and refugees and asylees added to the TLFB stock each year. Several outflow statistics accompany these inflow variables to properly deflate the TLFB stock for each year. These outflow statistics include the average annual immigrant death rate, the deportation rate of documented immigrants, and double count rates, which will be explained in more detail shortly.

The first step to estimate the TLFB stock is to identify a base year stock level of documented workers. This base year stock can be added to the following year's inflow of legal immigrants, which provides us with an estimate of the number of documented workers for the following year. The last year the INS recorded the stock of documented workers was 1980, which means that our estimation process must begin in this year. To calculate the stock of documented workers for a subsequent year, we have to add the number of immigrants entering the country between 1980 and the current year of interest and subtract the number of immigrants that have vacated the country. For instance, to calculate the TLFB stock for 1998, we have to add the number of legal immigrants that have entered the US between 1980 and 1998 and subtract the number of legal immigrants that have either exited the country or became deceased during the same time frame. This tells us the net change in the stock of legal immigrants between 1980 and 1998. Equation 1 below represents how the stock of documented workers in state *i* would be calculated for 1981. Another equation will be presented after Equation 1 to illustrate how stock levels of the TLFB are calculated for years following 1981.

$$(1)\ TLFB_{Total,i,1981} = LegalStock_{1980} + LPRs_{1981} + Naturalizations_{1981} + Refugees_{1981} + Asylees_{1981} - DeathRate_{i,1981} - DepRate_{i,1981} - DoubleCount_{i,1981}$$

In reference to Equation 1 above, $TLFB_{Total,i,1981}$ represents the total stock of the legal foreign born population in 1981 in state *i*. $LegalStock_{1980}$ represents the stock of legal immigrants recorded in 1980. The $LPRs_{1981}$ variable represents 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 for the year 1981.

The $DeathRate_{i,1981}$, $DepRate_{i,1981}$, and $DoubleCount_{i,1981}$ figures are outflow variables used to deflate the present year's stock of documented immigrants. The $DeathRate_{i,1981}$ variable is derived from state level mortality rates derived from the Center for Disease Control's (CDC) average annual death rate for the overall population falling between the ages of 35 and 44. Death rates for the legal immigrant population are approximated by multiplying CDC death rates by the Total Foreign Born population as a fraction of the total population in state *i*. The $DepRate_{i,1981}$ variable is an approximation of the number of legal immigrants deported in state *i* in 1981. State level deportation rates in year 1981 are approximated by multiplying the state distribution of the Total Foreign Population in 1981 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 Total Foreign Born population in state *i* for the year 1980. Finally, the $DoubleCount_{i,1981}$ variable is used to avoid double counting documented immigrants that were included in 1980 stock of documented immigrants, but may have converted their immigration status to another form of documented immigration between 1980 and 1981. For 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 presents a severe shortcoming, but there are no state level naturalization rates available. The best option given this limitation is to assume that most legal permanent residents become naturalized. The undocumented immigrant estimation process will significantly improve if state level naturalization rates are created. In addition to a naturalization double count, the number of refugees and asylees granted lawful permanent residence must be accounted for. Fortunately, the INS and DHS provide state level data for this double count for most years in each state. 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*.

In summary, Equation 1 above shows us how the stock of legal immigrants can be calculated from 1980 to 1981. To calculate the stock of legal immigrants for future years, a very similar process is used. To calculate the stock of legal immigrants in year *t*, we must determine the stock of legal immigrants in year *t-1* and apply the proper inflow and outflow statistics corresponding to year *t*. The general process to calculate the legal stock is highlighted by Equation 2 below.

$$(2) \qquad TLFB_{i,t} = TLFB_{i,t-1} + LPRs_{i,t} + Naturalizations_{i,t} + Refugees_{i,t} + Asylees_{i,t} - DeathRate_{i,t} - DepRate_{i,t} - DoubleCount_{i,t}$$

Once the counted TLFB stock at the state level is determined, the stock of undocumented workers can be calculated. Intuitively, the undocumented stock for state *i* in year *t* is represented by the residual of the TFB and TLFB. However, two equations are needed to calculate this residual. The first step requires us to determine the total number of immigrants that remain in the US for relatively longer periods of time. Equation 3 summarizes how this group of immigrants is calculated.

(3) $$All_{i,t} = TFB_{i,t} - TempLegal_{i,t}$$

Where:

1) $All_{i,t}$ = Total number of both documented and undocumented immigrants that stay in the US for relatively long periods of time in state *i*, year *t*

2) $TFB_{i,t}$ = Total Foreign Born population in state *i*, year *t*

3) $TempLegal_{i,t}$ = Temporary Legal non-immigrants staying in the US in state *i* during year *t*.

Equation 3 is needed because the number of temporary legal non-immigrants entering the country each year should not be included the TLFB stock. The $TempLegal_{i,t}$ variable represents the number of non-immigrants admitted to the US in state *i*, year *t*[5]. These people include foreign students, exchange visitors, and temporary workers as well as the family members for each of these three groups. It is assumed that these individuals remain in the US for only one year. Non-immigrants are not included in the TLFB stock because they stay in the United States for relatively short periods of time. In reference to Equation 2 above, the TLFB is calculated by adding inflow and outflow data to the previous year's TLFB. If non-immigrants from year *t*-1 were included in the TLFB for year *t*-1, then all of these non-immigrants would carry into the following year's TLFB stock when the majority of these individuals exit the country after the year *t-1*. In summary, incorporating non-immigrants into the TLFB would overstate the number of legal foreign born people in the US, which is why Equation 3 is needed. The Total Foreign

[5] It is important to note that the data for the Temporary Legal Citizens include people visiting the United States for pleasure or temporary business. These components of the Temporary Legal Citizens data were omitted because these people do not reside in the United States long enough to be considered part of the legal foreign born population of the US. 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 US for pleasure or temporary business is so large that it would produce negative estimates for the illegal immigrant population.

Born (TFB) statistic includes the three primary documented immigrant inflow groups as well as the number of non-immigrants and undocumented immigrants for each year. By subtracting out the number of non-immigrants, Equation 3 provides us with an estimate of $All_{Total,i,t}$, which represents the total number of immigrants—both documented and undocumented—that remain in the US for relatively longer periods of time. Once Equation 3 has been applied to all states across all years, the undocumented stock for state *i* in year *t* is calculated by determining the residual between the appropriate $All_{Total,i,t}$ and $TLFB_{i,t}$. Equation 4 represents this procedure.

(4) $$Undocumented_{i,t} = All_{i,t} - TLFB_{i,t}$$

Where:

1) $Undocumented_{i,t}$ = Total number of undocumented workers in state *i*, time *t*

2) $TFB_{i,t}$ = Total Foreign Born population in state *i*, time *t*

3) $TLFB_{i,t}$ = Total Legal Foreign Born population in state *i*, time *t*

In summary, the process to calculate the state level undocumented population between 1994 and 2010 is very similar to Passel (2007), but digresses from Passel's method for several important reasons. Passel (2007) applies several undercount rates to calculate the undocumented population. These undercount rates were derived from CPS and US Census data. These undercount rates were not applied to the data in this model because the data for the TLFB is derived from DHS and INS data. Applying these undercount rates to the DHS and INS data overestimates the undocumented population to a substantial degree, which is why they were omitted.

Shortcomings of the Undocumented Immigrant Estimation Process

The process highlighted above must be taken with a degree of caution because the data used to estimate stocks of the TFB and TLFB is highly limited between 1981 and 1994. State level estimates for several documented immigrant inflow variables and for the Total Foreign Born population were either estimated 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. The list below summarizes the estimation methods and assumptions that were used to account for these issues. It also addresses the issues related to IRCA.

Non-Immigrants: State level estimates of the *TempLegal* statistic between 1981 and 1994 were generated by applying a 1995 distribution of *TempLegal* to national level estimates between 1981 and 1994. Additionally, non-immigrants are assumed to only remain in the US for one year. There are some non-immigrants that remain in the US for longer than a year, but there is no literature or data that specifies how long these non-immigrants remain in the US at the state level. Lastly, several states appear to have abnormally high non-immigrant entries for the year 2010. These states include Maine, Michigan, North Dakota, and Vermont. These 2010 levels appear excessively high to previous years for these states and have understated the results compare to Passel (2010). No literature as been discovered to explain why these states exhibit normally high levels of non-immigrant entries for this year, which may indicate that this problem originated from data entry errors. To resolve this problem, 2009 estimates for each state were used in place of these 2010 estimates, which substantially improved the results.

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.

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% 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 LPR 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 to other documented immigrant inflow groups.

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

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.

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.

Negative Population Estimates: Negative population estimates have been generated for several states over time. Negative estimates are created 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, these estimates were replaced with a zero before including them into the model measuring the economic effects of undocumented immigrants.

This estimation process possesses several shortcomings, but it is one of the only methods available to estimate the undocumented population at the state level. The results from the method specified in this paper were compared to the years estimated by Passel and the results are similar. These comparisons are provided in Appendix 4. The fact that these results are similar suggests that the model used in this paper adequately measures the undocumented population given the limitations to the data. Moreover, an additional data derived from the selected estimates from Passel (2009; 2010) will accompany the data set created from this paper to fortify the results presented in Section 7. Although Passel's estimates are more accurate, they do not contain as much variation over time as the data set 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.

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

This section highlights the model that will be used to capture the effects of both documented and undocumented immigration using data created from the methods presented in Section 3. This section is broken down into three sub-sections. The first sub-section highlights the overall approach that is applied to measure the effects of immigration on low skill natives. The second sub-section highlights several important arguments to support the use of a long run model to capture the effects of immigration. Some previous research criticizes the use of long run models, but there is also a considerable amount of evidence to support their use. Following this subsection, the third subsection will address the explicit model that will be used to capture the effects of immigration on low skill natives.

Overall Approach

As stated in Section 2, this model will use a form of Area Analysis to measure the effects of immigration on native employment opportunities between 1994 and 2009[6]. This paper hypothesizes that all low skill immigrants have a high degree of substitutionability with low skill natives. Changes in the ratio of low skill immigrants to low skill natives is used as a proxy for changes in the low skill labor supply. Thus, an increase in immigrant concentrations should increase the low skill labor supply and put downward pressure on native-low skill labor force participation rates and upward pressure on unemployment rates. Unemployment rates are included in this model to test whether they are unresponsive to immigration, which is suggested by previous research. If unemployment rates are not affected, then it provides evidence to support the use of labor force participation rates as the primary economic indicator of interest. The model presented in this section is very similar to the one adopted by Johannsson and Weiler (2004), but will be augmented with undocumented immigrant data. There are three primary objectives of this paper. The first is to apply a single market approach, which helps us determine whether the state level model used in this paper produces similar results to the MSA results from Johannsson and Weiler (2004) regarding the relationship between TFB immigrant concentrations and native low skill labor force participation rates. The second goal, as discussed in Section 1, is to apply a dual market approach to observe whether documented or undocumented immigration has a greater effect on low skill natives. There are two steps to this approach. The first step is to omit undocumented immigrants from the total foreign born stock to determine whether this omission affects the significance and magnitude of the results corresponding to the single market approach. The results produced from this process isolate the effects of the documented

[6] 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.

population. To complete the dual market approach, undocumented immigrants must be analyzed by themselves to determine whether they affect low skill natives more significantly than documented immigrants. Table 1 below highlights the objectives of this paper.

As illustrated in Table 1, two data sets will be used to incorporate state level estimates of the both the documented and undocumented population into the model addressed later on in this section. It is important to reiterate that documented immigrant estimates are calculated by subtracting the undocumented estimates from the TFB estimates. Two different data sets were used to not only represent the undocumented population, but also to isolate the effects of the documented population. The Schultz data set has been constructed using the methodology presented in Section 3. The Passel data set was constructed using estimates provided by Passel (2009; 2010). Linear imputations were used to estimate undocumented population levels for years not calculated by Passel. Passel's data was incorporated into this model as a sensitivity check to the conclusions drawn from the Schultz data set. Overall, the conclusions drawn from each data set are similar when applying the dual market approach, which is convincing evidence that the methods used in Section 3 coincide with Passel's methodology fairly well.

TABLE 1

Model Layout					
Time Frame	***TFB Immigrants (BMS Data)***	***Documented Immigrants (TFB - Undocumented) Schultz Data***	***Documented Immigrants (TFB - Undocumented) Passel Data***	***Undocumented Immigrants Schultz Data***	***Undocumented Immigrants Passel Data***
1994-2009	Measure the effects of the TFB population at the state level using data from the Basic Monthly Survey (BMS)	Measure the effects of the Documented population at the state level using data generated from this paper.	Measure the effects of the Documented population at the state level using data derived from Passel (2009, 2010)	Measure the effects of the Undocumented population at the state level using data generated from this paper.	Measure the effects of the Undocumented population at the state level using data derived from Passel (2009, 2010)

Why Applying a Long Run Approach is Legitimate

Before we explicitly address the model that is used to estimate the economic impact of immigration, it is important to discuss differences and shortcomings associated with applying long run analysis versus short run analysis in the context of immigration. Some previous research is in favor of a short run approach while others claim that long run approaches are more robust. This paper analyzes the effects of immigration over the long run, but there is enough evidence to criticize this approach. Although a long run approach may possess several shortcomings, this sub-section provides several arguments to justify why a long run approach is more appropriate than a short run approach to measure the effects of undocumented immigration.

To begin, as stated in Section 2, previous research from Johannsson and Weiler (2004), Blanchard and Katz (1992), and Filer (1992) provide evidence that favors the use of short run models to capture labor market effects from immigration[7]. These papers emphasize the use of short run models to avoid the effects of native outmigration and firm in-migration that occur in response to immigrant inflows. Short run models may be more robust if they analyze the effects of immigrant inflows within a short enough time frame where natives and firms do not change their migratory decisions in response to this shock. Essentially, the evidence from these papers suggests that the effects of immigration can only be captured when the labor market is in disequilibrium from a labor shock propelled by immigrant inflows. Once native outmigration and firm in-migration take place, they decrease the labor supply and increase labor demand respectively, which makes it difficult to measure any welfare effect on native citizens once the labor market re-equilibrates. According to Blanchard and Katz (1992), state level labor markets

[7] However, the success of short run models is contingent on the assumption that state level markets re-equilibrate within a 5-7 year time frame, which may be problematic to assume (Blanchard and Katz 1992). This issue will be addressed later on in this section.

re-equilibrate from an adverse shock after five to seven years. As a result, most proponents of short run analysis ascribe to this time frame to analyze the effects of immigration.

Although these conclusions are important, they are limited because proponents of short run models premise their argument on the idea that labor markets achieve stationary states of equilibrium. In reality, labor markets are constantly changing—especially at the state level. To assume that a labor market experiences a period of time where native low skill labor force participation rates and unemployment rates are in equilibrium and that economic activity is in balance is difficult to prove. In reality, the only relationship we may be able to capture is whether changes in native labor market indicators are responsive to changes immigrant inflows. Analyzing this relationship over a longer time frame may provide more robust results than shorter time frames because there are more observations included in the analysis. Even if markets re-equilibrate, there is no evidence to suggest that these markets approach identical equilibrium levels. There may be a long run effect where immigrant oriented labor shocks put downward pressure on equilibrium levels of native low skill labor force participation rates and unemployment rates, which would be captured using a long run model. Lastly, the conclusions made by Blanchard and Katz (1992) are relatively outdated. No research subsequent to Blanchard and Katz (1992) has attempted to measure the length of time needed for labor markets to re-equilibrate with more updated data. The results from Blanchard and Katz (1992) may apply to more distant time periods, but not to ones in this paper.

In addition to the problems associated with the theoretical underpinnings applied to short run models, the nature in which the undocumented population has grown over time may be more suited to a long run analysis. In reference to Appendix 1, it is evident that periods corresponding to a five to seven year time frame do no experience as big of an increase in the undocumented immigrant population as the entire time frame used in this paper. For instance, let's focus on the following three periods: 1994-1998, 2002-2006, and 1994-2009. In reference to the *Passel* data set from Appendix 1, the undocumented population increased by 112% between 1994 and 2009 while it only increased by 35% and 22% in 1994-1998 and 2002-2006, respectively. These short run models may not capture as great of an effect from the undocumented immigrant population because they do not exhibit as big of a change in the short run. Only a long run model may be appropriate to capture the effects of undocumented immigration.

In addition to undocumented population growth, it is important to note that several prominent researchers rely on long run analysis using decennial data to measure the effects of immigration. These researchers do not place as much emphasis on the short run models as Johannsson and Weiler (2004). Some of these papers include Card (2003, 2005) and Borjas (2003, 2006). These papers present obvious shortcomings because they only have several years worth of data to analyze a long run trend, but this is not the case for this paper. The fact that annual data was used to answer a comparable question adds credibility to using a long run analysis because it captures the effects of immigration during intermediate years that decennial data cannot account for.

In summary, the amount of evidence emphasizing the importance of short run models is not strong enough to repudiate the use of long run models that incorporate annual data. A short run analysis may be more appropriate at the MSA level because the geographic space is small enough to not be impeded by a multitude of omitted variables that distort the effects of immigration. However, since the methods used to estimate the undocumented population limits us to a state level framework, it is important to apply a long run approach.

Model Used to Estimate the Effects of Immigration on Low Skill Natives

Now that the theoretical underpinnings of the model have been explained, it is appropriate to explicitly address the model that will be used to estimate the effects of immigration on low skill native employment indicators. As a reminder, this paper will be observing the relationship between immigrant concentrations and native low skill labor force participation rates and unemployment rates. Based on previous research, the native low skill LFPR appears to be one of the primary absorption mechanisms to immigrant labor supply shocks while unemployment rates appear to be unresponsive.

As stated previously, this paper will adopt both a single market approach and a dual market approach to capture the effects of undocumented immigration. The dynamic equation presented below will be used to apply both approaches. Although it is not relied upon for application purposes, a static cross-sectional model will be presented to explain every variable used in the model. This static model is very similar to the one presented in Johannsson and Weiler (2004). The dynamic model needed to measure the effects of both documented and undocumented immigrants will be presented after the static model. The models presented below will only be applied over a long run time frame and will analyze the effects of immigration on native low skill employment opportunities between 1994 and 2009. Equation 5 below summarizes the static fixed-effect regression that is used to measure the effects of immigrant concentrations on native low skill employment opportunities.

(5) $$Y_{it} = \beta_1 IMFR_{it} + \beta_2 Race_{it} + \beta_3 Sex_{it} + \beta_4 Age_{it} + \beta_5 GSP_{it} + \mu_{it}$$

Where:

1) The *i* subscript represents the different states included in this analysis. All 50 US states are included.

2) The t subscript represents the years analyzed within the 1994-2009 period.

3) Y_{it} = two different dependent variables: Native low skill labor force participation rate and the native low skill unemployment rate.

4) $IMFR_{it}$ = the state level ratio of low skill immigrants to low skill natives. This ratio is applied to three different groups: the TFB population, the documented immigrant population, and the undocumented immigrant population. Only individuals that have not graduated high school are included in this figure.

5) $Race_{it}$ = the state level labor force percentages of three different minority groups: African Americans, American Indians or Eskimos, and Asians or Pacific Islanders. This variable is primarily used to control for differences in racial concentrations across states.

6) Sex_{it} = the state level labor force percentage of females. This variable is primarily used to control for differences in female concentrations across states.

7) Age_{it} = a categorical variable used to separate every dependent, independent, and control variable into the following age groups: 16-19, 20-29, 30-39, 40-49, 50-59, and 60-64.

8) GSP_{it} = gross state product for state i in year t. This variable is used to control for structural shocks originating from the business cycle that apply to each state over time.

10) μ_{it} = error term. The error term is assumed to be independently and identically distributed.

The primary variable of interest in Equation 10 is the *IMFR*. The *IMFR* captures the concentration of immigrants for each state in each year. Higher *IMFR* values represent greater concentrations of immigrants in a state. The value of the *IMFR* will be different depending on whether it includes the total foreign born population, the documented population, or the undocumented population. Johannsson and Weiler (2004) adopt a single market approach and only account for the TFB population in the *IMFR*. They have concluded that a negative relationship exists between *IMFR* levels and native labor force participation rates when only the TFB population is accounted for. The original hypothesis from this paper is that by using a dual market approach that subtracts out undocumented population estimates from the total foreign born *IMFR* will affect the relationship captured by Johannsson and Weiler (2004)—thus providing evidence that undocumented immigrants significantly affect native low skill workers. This process will also reveal the effects of the documented population. To fortify these results, an *IMFR* only including undocumented immigrants will be incorporated into the model to capture the effects the undocumented population alone has on native low skill employment indicators. The results generated from the undocumented population will be compared to the results from the documented population to determine which group has a greater effect on low skill natives.

As stated earlier, only a dynamic model will used to test for the effects of immigration because of endogeneity problems that are associated with the static model. The static model is prone to endogeneity because there may be characteristics of certain regions that attract higher concentrations of immigrants. For instance, areas with relatively lower native employment opportunities may attract more immigrant workers. Additionally, immigrants may flock to regions with relatively higher concentrations of similar immigrants. Immigrants may also migrate to states because of its advantageous geographical location. These endogeneity issues can be resolved with a dynamic model, which is addressed with Equation 6 below.

$$(6) \qquad \frac{Y_{i,t} - Y_{i,t-1}}{Y_{i,t-1}} = \beta_1 \left(\frac{IMFR_{i,t} - IMFR_{i,t-1}}{IMFR_{i,t}}\right) + \beta_2 Race_{it} + \beta_3 Sex_{it} + \beta_4 Age_{it} + \beta_5 \left(\frac{GSP_{i,t} - GSP_{i,t-1}}{GSP_{i,t-1}}\right) + \mu_{it}$$

Equations 5 and 6 are both fixed effects regressions. The only difference between Equation 5 and Equation 6 is that the dependent variables, the *IMFR*, and the GSP control variables are first-differenced in Equation 6. A percentage change approach is applied to these three variables in order to normalize the gross change occurring between each period. The empirical model only focuses on applying percentage changes to these three variables because first differencing the primary dependent variables eliminates all of the time invariant location specific effects that these variables are responsive to. The *IMFR* is first differenced because it helps eliminate the potential issue of reverse causality associated with low skill native employment and immigrant inflows. Finally, the *GSP* variable is first differenced because it is the primary regional control variable. Changes in employment indicators are more likely to be responsive to changes in gross state product than levels of gross state product. In contrast to these three variables, the empirical model uses level analysis for the *Race* and *Sex* variables because changes in the racial and gender composition of each state may be smaller or less volatile over time than the changes in the other variables. If these variables are first differenced, then the amount of across state variation in race and sex that affects native low skill employment may not be accounted for as well as if these variables remain in level form. These assumptions may be considered a caveat and a possible extension to this model would be to first difference every control variable. The B_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. As presented in Equation 5, it is possible for current levels of native low skill participation rates to influence immigrants' migration decisions. However, we would not expect *changes* in the native labor force participation rate to have the same effect. Thus, a significant relationship captured in Equation 6 should provide more robust results. Finally, Equation 6 will be analyzed using both Generalized Least Squares (GLS) and Weighted Least Squares (WLS). GLS is a more robust approach than WLS under these conditions because it accounts for both heteroskedasticity and autocorrelation that exist within the panel data set applied to Equation 6. The GLS results should be observed with greater weight than the WLS results, but applying WLS is still important to check the relative consistency of the GLS approach.

SECTION 5: HOW THE UNDOCUMENTED WORKER DATA IS INCORPORATED INTO THE IMFR

Again, the *IMFR* represents the ratio of low skill immigrants to low skill natives. The *IMFR* in Johannsson and Weiler (2004) represents the ratio of *both documented and undocumented* low skill immigrants to low skill natives. Depending on whether a single labor market or dual labor market approach is applied, the *IMFR* can take on different values. Under a single market approach, the *IMFR* represents the ratio of the TFB population to low skill natives. Once the relationship between these two groups is captured, the first step to the dual market approach is to subtract the state level undocumented immigrant estimates from the TFB estimates. The residual represents state level estimates of the documented population. These documented immigrant estimates will then be incorporated into their own *IMFR* and applied to Equation 6. Running separate regressions on these different *IMFR* values will tell us the isolated effect of documented immigration and shed some light on the effects of undocumented immigrants. To fortify these results, the last step is to run an additional regression where only undocumented immigrants are included into the *IMFR* and applied to Equation 6. Comparing the isolated effects of documented immigration with the isolated effects of undocumented immigration tell us which group has a greater effect on and which group is more substitutable with low skill natives. Depending on the results, it may also tell us that each group has an equal effect or does not have a significant effect on natives unless the other group is included.

Similar to the explanations provided for Equation 5 above, the *IMFR* will be broken down into 6 different age groups to isolate the effects immigration on low skill natives of different ages. The state level undocumented population estimates were not explicitly calculated for these age groups. However, age distributions for low skill immigrants in the total foreign born data for each state between 1994 and 2010 were used to estimate the number of low skill undocumented workers that belonged to each age group. These estimates were generated using data from the Basic Monthly Survey. Lastly, according to Passel (2009), approximately 47% 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% of each age group will be added to its proper stock of legal immigrants[8].

SECTION 6: DATA

This section summarizes the data sources that were used to approximate the undocumented population as well as the sources needed to apply the dynamic model presented in Section 4. The March CPS provides annual estimates of the Total Foreign Born (TFB) population between 1994 and 2010. The Department of Homeland Security (DHS) and its predecessor the Immigration and Naturalization Service (INS) provide the majority of the data needed to estimate annual levels of the TLFB. The DHS and INS provide data on the annual inflows of legal permanent residents, naturalized citizens, refugees, and asylees. Both the DHS

[8] It is important to note that more than 47% of undocumented workers are likely to compete with native low skill workers. According to Passel (2009) approximately 78% of undocumented workers 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.

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 Center of Disease Control (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 used because it represents the median age group from an age distribution presented by Passel (2009). State level total population data from the US Census was used to convert the death rates from the overall population to the TFB population. Lastly, data from the Basic Monthly Survey (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. BMS data was also used to estimate the concentration of females and different racial groups across states.

SECTION 7: RESULTS

This section summarizes the primary results that emerge from the dynamic model specified in Section 4. The fixed effects dynamic model represented by Equation 6 was used to measure the effects of both documented and undocumented immigration on native low skill labor force participation rates and unemployment rates. These regressions were analyzed using both Generalized Least Squares (GLS) and Weighted Least Squares (WLS) between 1994 and 2009. There are five primary conclusions emerging from these results: 1) Changes in total foreign born immigrant concentrations significantly affect native labor force participation rates, but to a small degree 2) These results are similar in magnitude to the MSA results from Johannsson and Weiler (2004), which gives this model more credibility 3) Documented immigrants alone appear to not have an effect on the native low skill LFPR and the corresponding unemployment rates 4) The relationship between immigrant concentrations and native labor force participation rates become insignificant when the undocumented population is taken out of the total foreign born *IMFR* 5) Undocumented immigrants alone do not have a statistically distinguishable effect on the native low skill LFPR. This section is separated into three subsections. The first subsection summarizes the descriptive statistics that correspond to each variable from Equation 6 over the 1994-2009 time frame. The second subsection highlights the results produced by the single market and dual market approaches. The third subsection addresses whether the effects captured by the single and dual market approaches are distributed more heavily in certain states.

Descriptive Statistics

TABLE 2

Descriptive Statistics					
Variable	***Obs***	***Mean***	***Std Deviation***	***Min***	***Max***
Labor Force Participation Rate	4800	0.5621039	0.15783	0.083	1.117
Unemployment Rate	4800	0.0983653	0.0639181	0	0.503
IMFR (TFB)	4800	0.3373636	0.5115608	0	5.36
IMFR Documented (Schultz Data)	4800	0.0985101	0.2035549	0	2.662
IMFR Documented (Passel Data)	4800	0.1433825	0.2783305	0	3.072
IMFR Undocumented (Schultz Data)	4800	0.2486568	0.3674586	0	3.554
IMFR Undocumented (Passel Data)	4800	0.1976298	0.2716994	0	2.868
GSP	4800	0.0481331	0.0321729	-0.12	0.172
Female Labor Force Percentage	4800	0.3942285	0.0863241	0.034	0.908
African American Labor Force Percentage	4800	0.1156084	0.1215382	0	0.731
American Indian Labor Force Percentage	4800	0.030022	0.0547063	0	0.625
Asian or Pacific Islander Labor Force Percentage	4800	0.0420241	0.1129902	0	1

Before delving into the results corresponding to dynamic fixed effects model, it is important to summarize a key feature from the descriptive statistics that emerge from the pooled cross-sectional data between 1994 and 2009. Table 2 above highlights the mean values for the dependent variables, the *IMFR* independent variables, and control variables that apply to the static model represented by Equation 5. The primary statistic of interest in Table 2 is the mean value of the native low skill LFPR, which is approximately 56.2%. This LFPR average is relatively low, which is important because any statistically significant effect captured from

Equation 6 between the native low skill LFPR and immigrant concentrations is more severe for groups of natives with lower LFPR averages than groups with higher averages. In reference to Table 3 below, it is evident that both the TFB population and the undocumented population have a statistically significant, but small impact on the native low skill LFPR. These impacts are small by themselves, but remain significant because the average native low skill LFPR is low.

Primary Results

Table 3 presents the long run effects of immigration on native low skill labor force participation rates and unemployment rates between 1994 and 2009. The *TFB IMFR* in Table 3 represents the ratio of the low skill total foreign born population to low skill natives. The *Passel Documented IMFR* and *Schultz Documented IMFR* figures represent the ratio of low skill immigrants to low skill natives once the low skill undocumented immigrants are taken out of the total foreign born stock. These two figures represent the ratio of documented low skill immigrants to low skill natives. The *Passel Undocumented IMFR* and *Schultz Undocumented IMFR* figures represent the ratio of undocumented low skill immigrants to low skill natives. The coefficients from the GLS and WLS regressions were converted into elasticities for comparability purposes. Table 3 below only highlights the relationships between the various *IMFR*s and native low skill employment indicators. To review the full results corresponding to the GLS and WLS regressions, please refer to Appendix 5 and Appendix 6.

The results below show that a statistically significant relationship exists between low skill TFB immigrant concentrations and native low skill labor force participation rates. The single market approach was captured with both the GLS and WLS estimates and is similar in terms of their magnitude when compared to the GLS results from Johannsson and Weiler (2004). In reference to the GLS results, a 10% increase in the TFB *IMFR* decreases native low skill labor force participation rates by approximately 0.44%. The GLS results from Johannsson and Weiler (2004) are that a 10% increase in the total foreign born *IMFR* decreases native low skill labor force participation rates by approximately 0.76%. Weiler and Johannson's result was analyzed within a shorter time frame, but the fact that the baseline TFB results produced in this paper are similar to Johannsson and Weiler (2004) make a strong argument to support the use of a state level model to measure the isolate effects of both documented and undocumented immigration.

TABLE 3: RESULTS 1994-2009

Labor Force Participation Rate							
GLS Model	***Elasticity***	***Coefficient***	***Std Error***	***Z-Stat***	***Prob>chi2***	***95% Confidence Interval***	
TFB IMFR	-0.04414	0.0048601	0.0021391	2.27	0	0.0006675	0.0090527
Schultz Documented IMFR	-0.00518	0.0007112	0.0011716	0.61	0	-0.001585	0.0030074
Passel Documented IMFR	-0.00766	0.0011559	0.0014425	0.8	0	-0.0016713	0.0039832
Schultz Undocumented IMFR	-0.01522	0.0018069	0.0016745	1.08	0	-0.0014751	0.0050889
Passel Undocumented IMFR	-0.08866	0.0094113	0.0024771	3.8	0	0.0045563	0.0142662
WLS Model	***Elasticity***	***Coefficient***	***Std Error***	***Z-Stat***	***Prob>chi2***	***95% Confidence Interval***	
TFB IMFR	-0.04247	0.0046758	0.0021056	2.22	0	0.0005489	0.0088026
Schultz Documented IMFR	-0.00659	0.0009055	0.0011388	0.8	0	-0.0013265	0.0031374
Passel Documented IMFR	-0.00249	0.0003756	0.0014529	0.26	0	-0.002472	0.0032231
Schultz Undocumented IMFR	-0.00769	0.0009128	0.0016732	0.55	0	-0.0023667	0.0041923
Passel Undocumented IMFR	-0.08778	0.0093177	0.0024656	3.78	0	0.0044853	0.0141501
Unemployment Rate							
GLS Model	***Elasticity***	***Coefficient***	***Std Error***	***Z-Stat***	***Prob>chi2***	***95% Confidence Interval***	
TFB IMFR	0.03616	0.0134171	0.0085063	1.58	0	-0.0032549	0.0300891
Schultz Documented IMFR	-0.00227	-0.00105	0.0047541	-0.22	0	-0.0103679	0.0082678
Passel Documented IMFR	0.00051	0.0002592	0.0057619	0.04	0	-0.011034	0.0115523
Schultz Undocumented IMFR	0.03313	0.0132526	0.0069282	1.91	0	-0.0003263	0.0268316
Passel Undocumented IMFR	0.02859	0.0102257	0.0102635	1	0	-0.0098905	0.0303419
WLS Model	***Elasticity***	***Coefficient***	***Std Error***	***Z-Stat***	***Prob>chi2***	***95% Confidence Interval***	
TFB IMFR	0.05121	0.0189984	0.0083339	2.28	0	0.0026642	0.0353325
Schultz Documented IMFR	0.00003	0.0000149	0.0046127	0	0	-0.0090259	0.0090557
Passel Documented IMFR	0.00648	0.0032918	0.0058222	0.57	0	-0.0081195	0.014703
Schultz Undocumented IMFR	0.02805	0.0112219	0.0070261	1.6	0	-0.002549	0.0249927
Passel Undocumented IMFR	0.04756	0.0170134	0.0101741	1.67	0	-0.0029274	0.0369543

Table 3 also shows the results for the dual market approach used to isolate the effects of both documented and undocumented immigrants. It is evident that that relationship between low skill immigrant concentrations and low skill native labor force participation rates becomes statistically insignificant when undocumented immigrants are no longer included in the TFB immigrant stock. These results confirm that undocumented immigrants play a vital role in the significant relationship captured between the TFB immigrant concentrations and native low skill labor force participation rates. It also suggests that documented immigrants alone do not have a statistically significant effect on low skill natives. When comparing the TFB *IMFR* to the documented *IMFRs*, we cannot say the degree to which undocumented immigrants affect the relationship in terms of its magnitude because the elasticities corresponding to both the *Passel Documented IMFR* and *Schultz Documented IMFR* are statistically insignificant. However, the fact that the entire immigrant population only pushes down the native low skill LFPR by 0.44% suggests that the effects of undocumented immigrants in terms of their magnitude is relatively small.

The inferences made about the undocumented population are confirmed when looking at the results that represent their isolated effect on low skill natives. In reference to the elasticities reported by the *Passel Undocumented IMFR*, a 10% increase in undocumented immigrant concentrations decreases the native low skill LFPR by 0.89%. When compared to the results associated with the *TFB IMFR*, the effects of undocumented immigrants alone appear to have a greater effect in terms of its degree and significance on low skill natives than either documented immigrants or the TFB population in general. To test the validity of these results, one simple procedure we can use to determine whether undocumented immigrants have a statistically distinguishable effect on the native low skill LFPR from the TFB population is to observe whether the confidence intervals from each group overlap. Table 3 above reports the values of these confidence intervals at the 95% significance level. Figure 1 below provides illustrations of each confidence interval corresponding to each type of *IMFR* used to capture the isolated effects of documented and undocumented immigration[9].

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[9] 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.

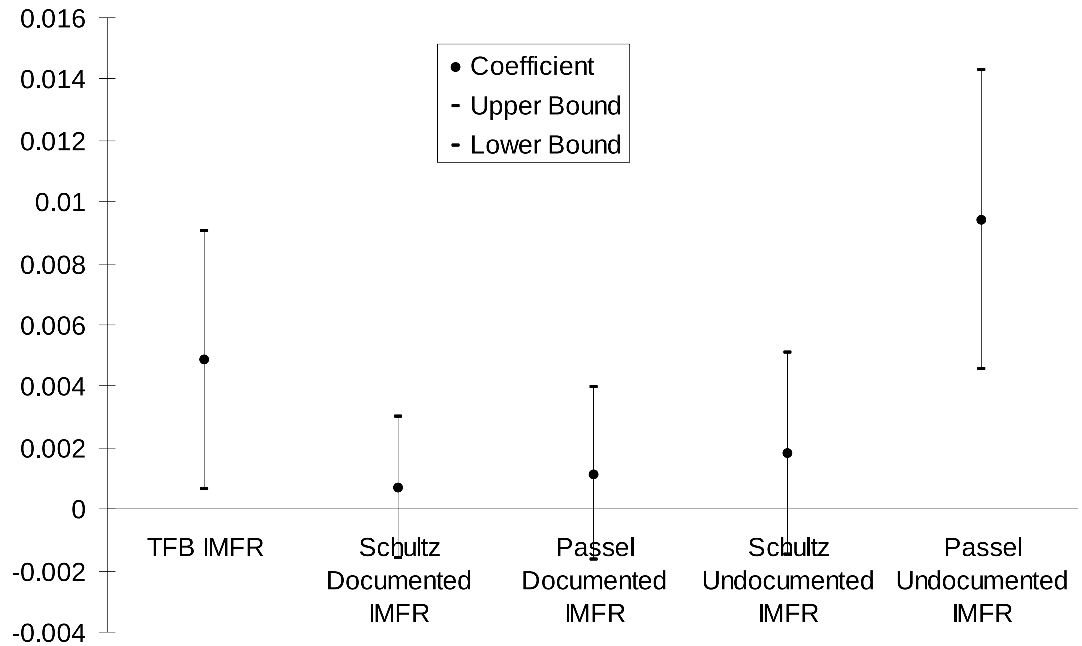

FIGURE 1: LFPR CONFIDENCE INTERVALS FOR THE TFB, DOCUMENTED, AND UNDOCMENTED IMFRS

Using confidence intervals in this context requires us to determine whether certain variables embedded in a baseline variable 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 LFPR. The embedded variables that may affect this baseline relationship are documented and undocumented immigrants. If either group has a statistically distinguishable effect on the native low skill LFPR, then the confidence intervals they produce should not overlap with the baseline confidence interval. To be more specific, we want to determine whether subtracting out the undocumented immigrants from the TFB creates a statistically distinguishable effect on the native low skill LFPR. To do this, we have to observe how much overlap exists between the TFB confidence interval and the (TFB-undocumented) confidence interval. Two separate figures are used to represent the (TFB-undocumented) confidence interval: the *Passel Documented IMFR* and *Schultz Documented IMFR*. To determine whether documented immigrants have a statistically distinguishable effect on the baseline relationship, we have to repeat the same procedures for the *Passel Undocumented IMFR* and *Schultz Undocumented IMFR*. Figure 1 above provides illustrations of the confidence intervals for each *IMFR* figure reported in Table 3.

As illustrated in Figure 1, it is evident that each *IMFR* figure has a considerable amount of overlap with the baseline *TFB IMFR*. These results imply that even though there is some evidence to suggest that undocumented immigrants alone have a statistically significant effect on low skill natives, this effect is not statistically distinguishable from the TFB results. Moreover, the results from *Passel Undocumented IMFR* are not strong enough to claim that undocumented immigrants alone are either greater substitutes to or have a greater effect on low skill natives than documented immigrants. The undocumented population still contributes to the baseline relationship between the TFB population and the native low skill LFPR, but we cannot claim that undocumented immigrants play a more significant role in this relationship than documented immigrants.

In addition to observing the confidence intervals, the results from the *Passel Undocumented IMFR* should not be taken with a high degree of confidence because the results produced by the *Schultz Undocumented IMFR* do not implicate a similar effect. The relationship between undocumented immigrant concentrations and the low skill LFPR implied by the *Schultz Undocumented IMFR* are very insignificant. The differences in the results between each undocumented IMFR may be because the estimates derived from Passel (2009, 2010) are more accurate than the annual estimates produced from Section 3 in this paper. Such a case is highly unlikely because the data produced using the methods in this paper appear to be relatively similar to the available years estimated by Passel (2009, 2010). These similarities suggest that some other characteristic unique to the data set derived from Passel's estimates is contributing to the significant relationship captured in Table 3[10]. One plausible explanation may be due to the highly linearized nature of the data set derived from Passel's estimates. This paper used linear imputations over relatively long time frames to create state level estimates of the undocumented population for the years Passel (2009, 2010) do not address[11]. The low level of within year variation produced from this data set may either be contributing to a spurious relationship or may be exaggerating the relationship between undocumented immigration and the native low skill LFPR. Additional analysis with an alternative data set representing the undocumented immigrant population will be needed to determine whether the results from the *Passel Undocumented IMFR* are more accurate than the results from the *Schultz Undocumented IMFR.* Producing a third undocumented data set is beyond the scope of this paper, but may be addressed in future research.

Distributional Effects of Immigration

In addition to analyzing the effects of immigration on all 50 states, it is possible to observe the distributional effects across states that are associated with the significant relationships presented in Table 3. The two primary relationships discovered from Table 3 are that the TFB and undocumented populations share a negative relationship with the native low skill LFPR. Although these are significant discoveries within themselves, some states' native low skill LFPRs may be more affected by immigrant inflows than other states. One method to determine whether there is a distributional effect is to test whether groups of states experiencing

[10] Please refer to Appendix 1 to observe the similarities between the estimates provided by Passel (2009, 2010) and the estimates provided by the methods specified in Section 3.

[11] Please refer to Appendices 1, 2, and 3 to observe the highly linearized nature of the undocumented estimates produced from the selected years provided by Passel (2009, 2010).

similar increases in the TFB population between 1994 and 2009 are affected more significantly than the baseline relationships captured in Table 3. Grouping states in this manner is relevant because the baseline results corresponding to the TFB population are significant and the effects of undocumented immigrants are not statistically distinguishable from the baseline results. After reviewing the estimates provided by the CPS, it appears that all 50 states can be assigned to one of the four following groups with respect to the gross number of undocumented immigrants that have entered their borders between 1994 and 2009: less than 100,000, between 100,000 and 200,000, between 200,000 and 500,000, and over a 500,000. Table 4 below highlights the states that belong to each group.

TABLE 4: GROSS INCREASE IN THE UNDOCUMENTED POPULATION BY STATE

Changes in Undocumented Population			
Less than 100,000	***100,000-200,000***	***200,000-500,000***	***Greater than 500,000***
Alaska	Alabama	Arizona	California
Delaware	Arkansas	Colorado	Florida
Hawaii	Connecticut	Georgia	Illinois
Idaho	Indiana	Maryland	New Jersey
Iowa	Kentucky	Michigan	New York
Kansas	Massachusetts	Nevada	Texas
Louisiana	Minnesota	North Carolina	
Maine	Missouri	Pennsylvania	
Mississippi	New Mexico	Tennessee	
Montana	Ohio	Virginia	
Nebraska	Oregon	Washington	
New Hampshire	South Carolina		
North Dakota	Utah		
Oklahoma	Wisconsin		
Rhode Island			
South Dakota			
Vermont			
West Virginia			
Wyoming			

Several dummy variables were applied to the *TFB IMFR* to distinguish these four groups of states. To be more specific, a dummy was assigned to each group except the *Less than 100,000* group and incorporated into a regression similar to Equation 6. The baseline relationship in this dummy regression reveals the effect immigrants have on the *Less than 100,000* group while the coefficients produced for each dummy provide the added affects corresponding to each group. These added effects are only significant if the corresponding z-statistic is significant as well. The results illustrated in Table 5 below suggest that the effects from the TFB population are distributed relatively evenly between each group of states because no group exhibits a statistically different effect from the baseline relationship. The baseline relationship is also insignificant by itself. No elasticities are reported because none of the results are significant.

TABLE 5: DISTRIBUTIONAL EFFECTS OF UNDOCUMENTED IMMIGRATION

Labor Force Participation Rate						
TFB Model	***Coef.***	***Std Error***	***Z-Stat***	***Prob>chi2***	***Confidence Interval***	
Baseline Result (<100,000)	0.003828	0.0028097	1.36	0	-0.0016789	0.009335
Greater than 500,000	0.0062982	0.0129899	0.48	0	-0.0191616	0.031758
Between 200,000 & 500,000	0.0022179	0.0064007	0.35	0	-0.0103273	0.014763
Between 100,000 & 200,000	0.0019957	0.004964	0.4	0	-0.0077336	0.0117249
Sex	-0.1018762	0.0139034	-7.33	0	-0.1291265	-0.074626
African American	0.0026899	0.0091943	0.29	0	-0.0153307	0.0207104
Native American	-0.0080444	0.0237486	-0.34	0	-0.0545909	0.038502
Asian/Pacific Islander	0.0319112	0.0186668	1.71	0	-0.0046751	0.0684975
%ΔGSP	0.243428	0.0361443	6.73	0	0.1725864	0.3142696
Constant	0.0179082	0.0060607	2.95	0	0.0060295	0.029787

Overall, there appears to be a very small effect associated with the TFB population and that this effect is distributed relatively evenly across all states. The fact that this effect is small suggests that low skill immigrants in general are not displacing low skill natives in the work force. Some alternative mechanism may be absorbing these inflows or low skill immigrants may be filling in voids in the labor market that are left over from natives upgrading their skills, which is a topic that is addressed in the next section.

SECTION 8: IMMIGRANTS DISPLACING NATIVES

This section briefly addresses whether the long run relationship between the native low skill LFPR and immigrant concentrations validly captures a displacement effect between low immigrants and low skill natives. Immigrants displace natives if they are relatively substitutable and take jobs away from natives. However, if natives upgrade their skills and exit the low skill labor market, this leaves a void for low skill immigrants to fill (Hanson and Slaughter 2001)[12]. In this scenario, immigrants do not displace natives and instead provide a positive economic benefit to their destination regions because they allow low skill industries to remain viable.

The evidence from Section 6 suggests that undocumented immigrants have a very low displacement effect. The results from Section 6 favor the idea that both documented and undocumented immigrants are filling voids in the skill labor markets for most states rather than displacing low skill natives. A simple way to test this hypothesis is to compare the gross changes in the low skill native population to the gross changes in the low skill TFB and undocumented immigrant populations for each of the four groups of states addressed in Table 4. Figure 2 below reports the changes in the low skill native, TFB, and undocumented immigrant populations for these four groups of states between 1994 and 2009. This figure is relatively crude, but reveals a significant effect over time. Excluding the states that have exhibited the greatest increases in the TFB population, the native low skill population decrease is greater than or equal to the immigrant population increase. This suggests that low skill natives may be becoming more educated and upgrading their skills—leaving a void in the low skill labor market for both documented and undocumented immigrants to fill.

[12] Skill upgrading occurs when natives increase their education levels and improve their human capital. When natives upgrade their skills, they usually exit the low skill labor market and enter a labor market that requires higher skills. When low skill natives upgrade their skills, they create a void of jobs that need to be filled by comparable workers. Low skill immigrants can fill this void if they are relatively substitutable to low skill natives.

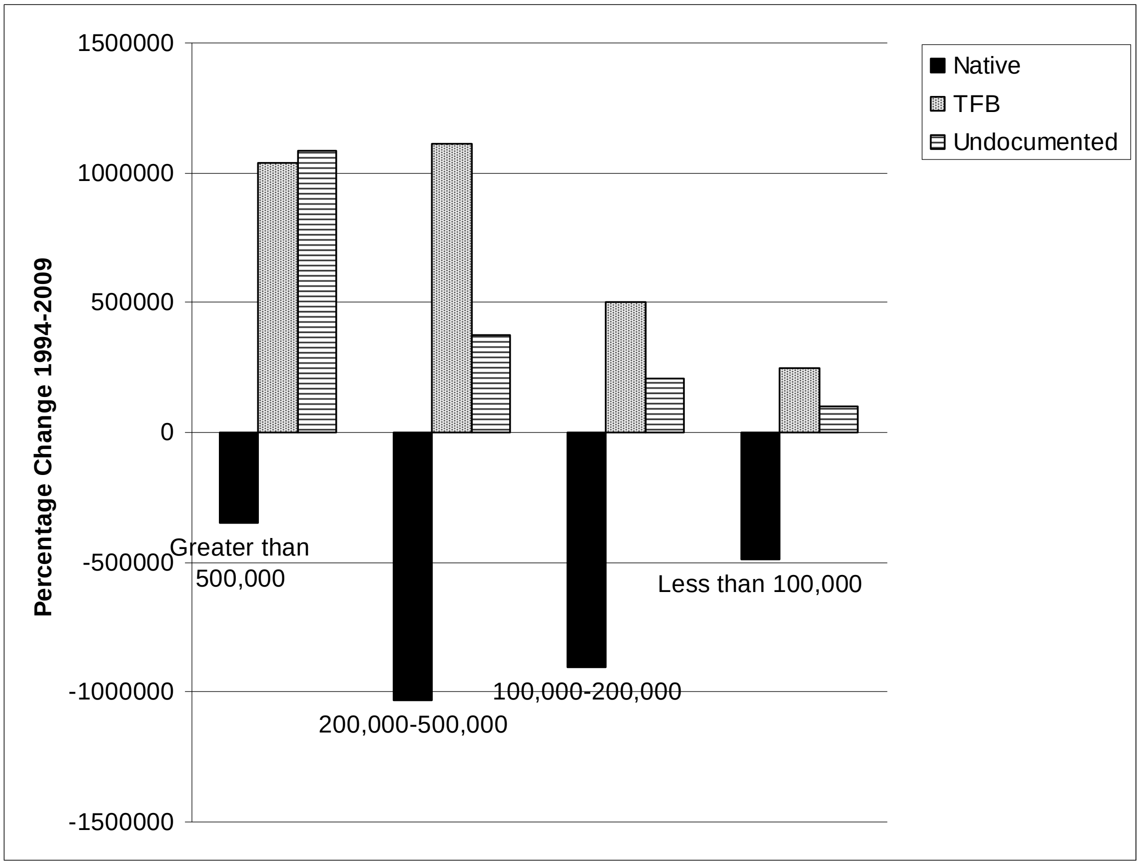

FIGURE 2: CHANGES IN LOW SKILL NATIVE, TOTAL FOREIGN BORN AND UNDOCUMENTED IMMIGRANT POPULATIONS AS A PERCENT OF THE TOTAL POPULATION (1994-2009)

Although Figure 2 may present some evidence against displacement, it is relatively crude and does not present enough evidence to repudiate the negative effect discovered between immigrant concentrations and the native low skill LFPR. Figure 2 alludes to another method emphasized by Slaughter and Hanson (2001) used to measure the effects of immigration and would require a lot more investigating to determine whether skill upgrading has allowed regions to absorb immigrant inflows. This method will not be elaborated on in this paper, but would be an interesting topic to address in the future.

SECTION 9: CONCLUSION

This paper is unique because it is one of the first attempts to estimate the economic impact of undocumented immigration. Overall, there appears to be a significantly negative, but relatively minor, relationship between total foreign born immigrant concentrations and native low skill labor force participation rates. This relationship becomes insignificant when undocumented immigrants are omitted from the model, which is important because it suggests that undocumented immigrants play a vital role in this relationship. However, using confidence intervals show that the effects of undocumented immigration alone are not statistically distinguishable from the effects corresponding to the TFB population. Moreover, the conclusions made from the dual market approach are inconsistent because the undocumented estimates from generated from this paper do not produce similar results. The relationship captured using estimates from Passel (2009, 2010) may be exaggerated due to the linearizations this paper used to create an ample data set. In addition to undocumented immigrants, documented immigrants alone appear to have no statistically significant effect on native employment opportunities, which is also significant. Documented immigration is not as controversial as undocumented immigration, but the fact that this group does not appear to have an economic impact on low skill natives contains policy significance regarding the number of immigrants the US legally allows to enter its borders annually.

To provide a more complete story on the effects of immigration, one possible extension to this model would be to analyze the isolated effects of both documented and undocumented immigration on native low skill wages. The evidence from Borjas (2006) is compelling enough to explore whether undocumented immigrants alone have a significant impact on native low skill income. The fact that the model in this paper can be used to measure the isolated effects of documented and undocumented immigrant inflows may help determine whether either group of immigrants is contributing significantly to the adverse effects on native wages discovered by Borjas (2006).

Although this paper presents several important conclusions on the effects of immigration, they must be taken with a word of caution because the model used to measure these effects has several shortcomings. To begin, this paper analyzes the effect of undocumented immigration at the state level. It is difficult to argue that a state can be classified as a better labor market region than a MSA because the space a state covers is much larger and the level of economic activity in a state is not as concentrated as a MSA. However, evidence from Borjas (2006) and the similarities between this paper and Johannsson and Weiler (2004) add a great deal of credibility to using a state level model. If MSA level data for both the total foreign born population and documented immigrant inflows become available, then it will be possible to test the economic impact on the undocumented population within a geographic space that is more economically concentrated. Additionally, the assumptions needed to estimate undocumented immigrant stock levels for years predating 1994, but carry over into the years that are relevant to this paper, affect the results. Every possible method was exhausted to make these estimates as accurate as possible. The fact that the estimates generated in this paper are similar to the ones created by Passel (2009; 2010) are encouraging and gives the assertions we make in this paper more credibility.

In summary, this paper is one of the first attempts to answer controversial policy questions pertaining to undocumented immigration. This paper does not provide a clear enough answer to determine whether undocumented immigrants adversely affect native citizens. The data sources used to address this question are relatively crude and need to become more accurate to reveal the true effects of undocumented immigration. However, this paper provides some of the best evidence available to answer whether undocumented immigrants affect natives. The fact that undocumented immigrants do not have a statistically significant impact on native citizen employment opportunities could be used to help answer whether undocumented immigration poses a major concern for the US economy. This relationship may not be strong, but hopefully it will be addressed more accurately once the surveying methods covering the undocumented population improve.

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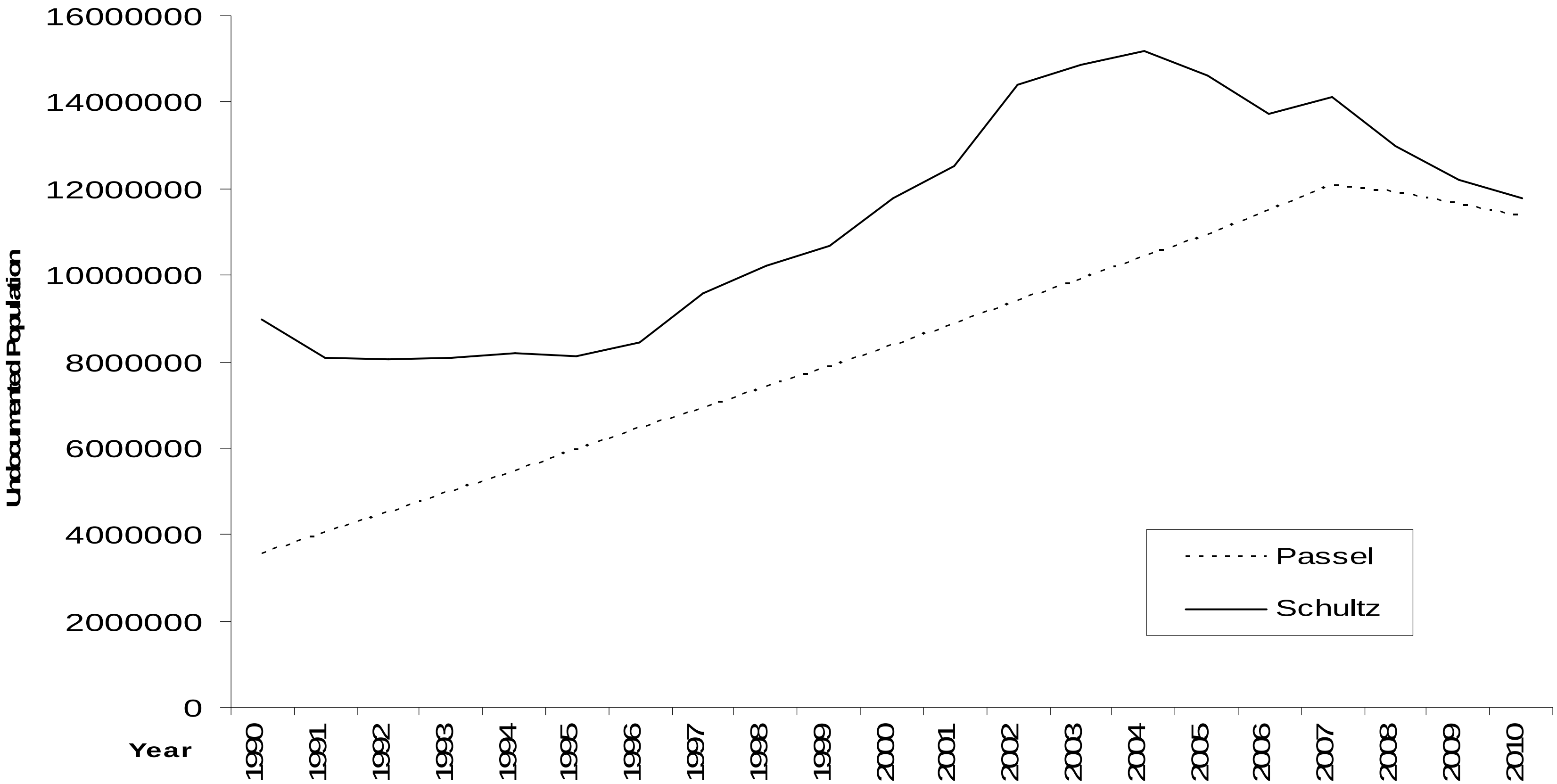
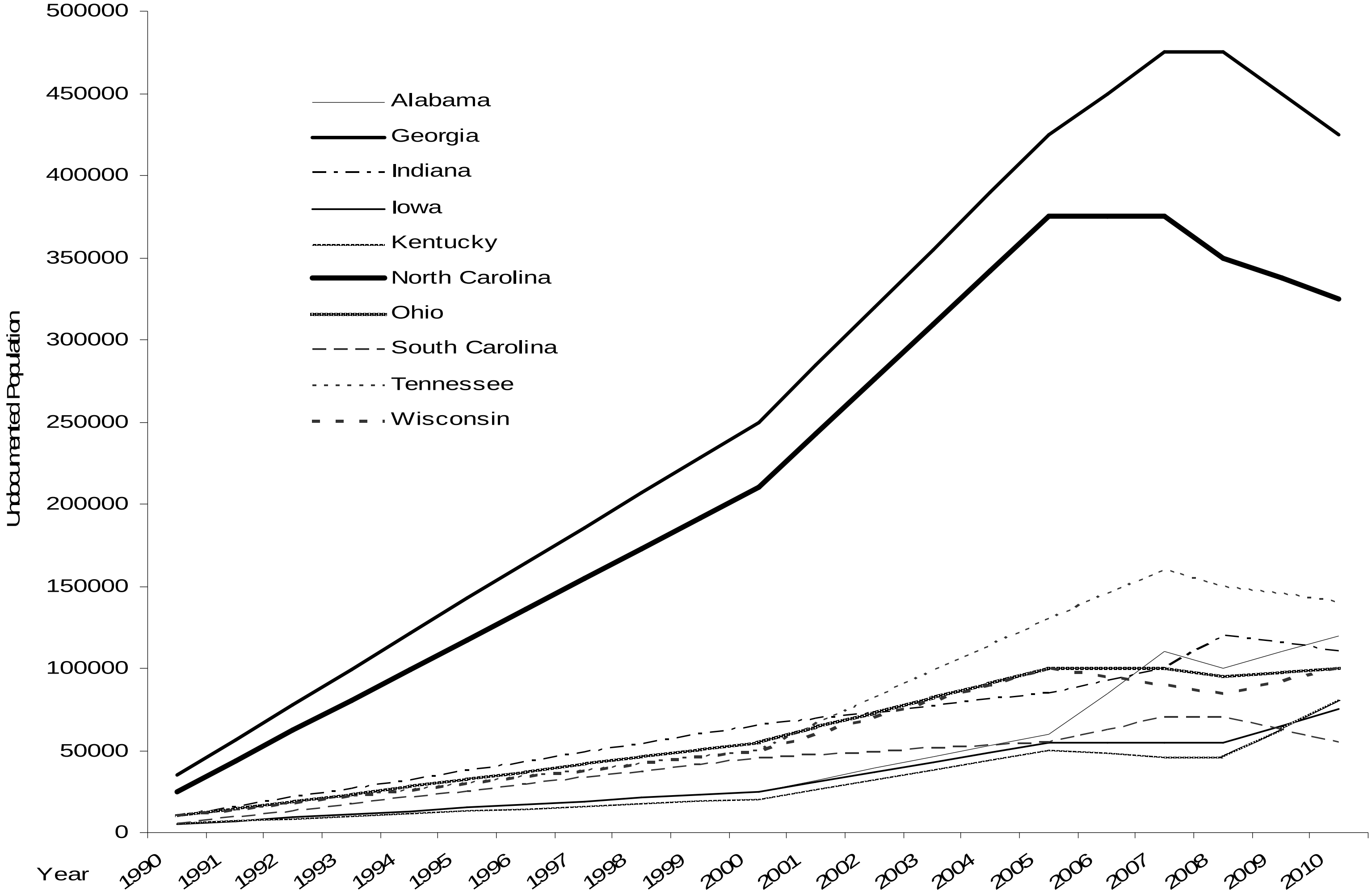
APPENDIX 1: UNDOCUMENTED POPULATION AT THE NATIONAL LEVEL[13]



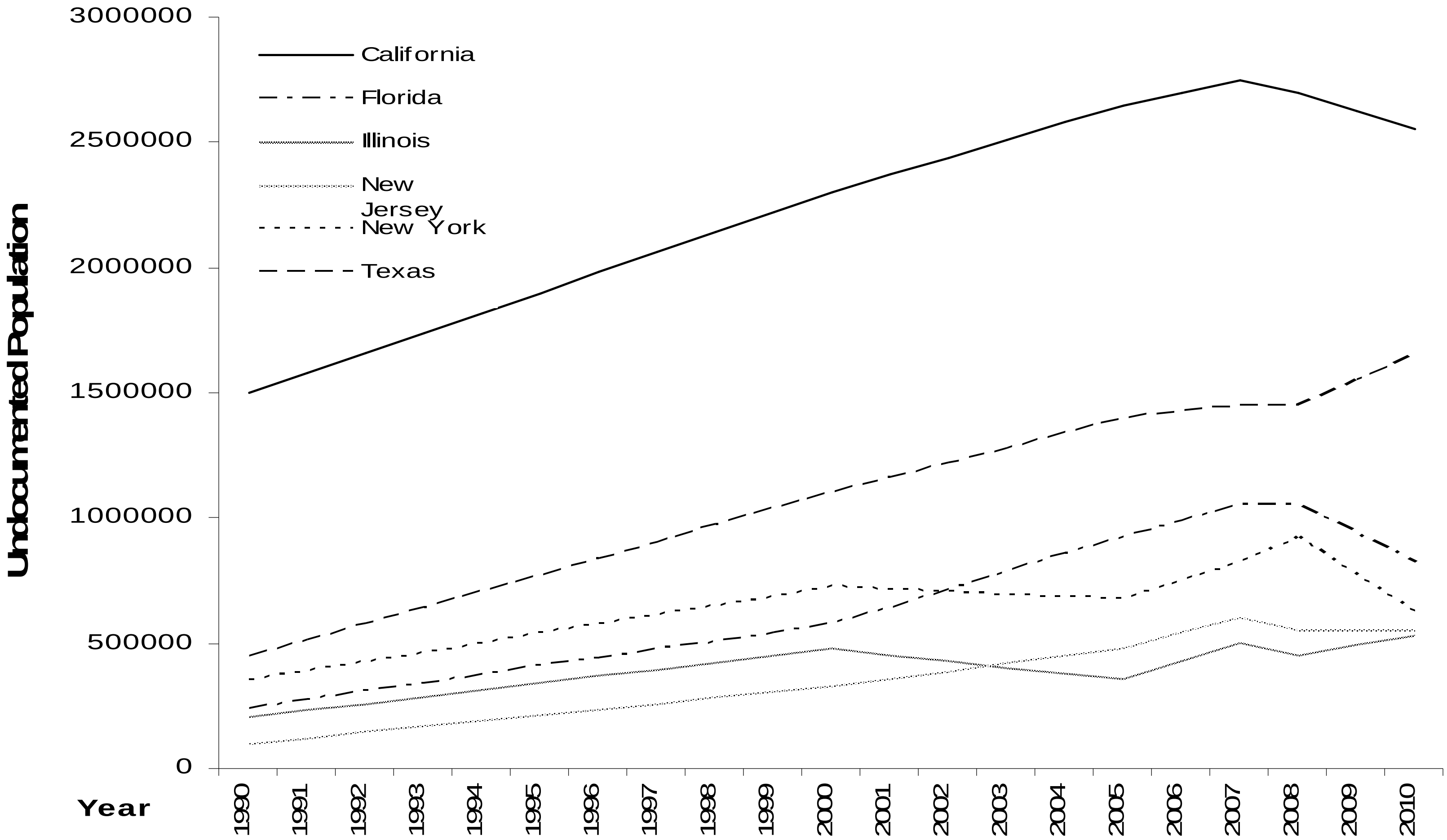
[13] Note: The two line trends presented in above have been generated by different sources. The Passel line was produced by data provided by Jeffrey Passel of the PEW Hispanic Center. The Schultz line was produced by data using a methodology presented in Section 3 of this paper.

APPENDIX 2: TOP 10 STATES WITH LARGEST INCREASES IN UNDOCUMENTED POPULATION LEVELS[14]



[14] 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.

APPENDIX 3: UNDOCUMENTED POPULATION IN BIX SIX STATES[15]



[15] Note: Data for the figure above was generated using estimates from Passel (2009; 2010). Linear imputations were used to illustrate these trends.

APPENDIX 4: COMPARING SCHULTZ AND PASSEL RESULTS[16]

	1990		2000		2005		2007		2008		2010	
State	*Passel*	*Schultz*	*Passel*	*Schultz*	*Passel*	*Schultz*	*Passel*	*Schultz*	*Passel*	*Schultz*	*Passel*	*Schultz*
Alabama	5000	16845	25000	30652	60000	43234	110000	124333	100000	84602	120000	94361
Alaska	2500	8241	5000	2626	5000	15786	5000	2718	5000	3395	5000	15190
Arizona	90000	139540	300000	434708	450000	577484	500000	537956	500000	477748	400000	427326
Arkansas	5000	8947	30000	20763	45000	29080	55000	66726	60000	53418	55000	50041
California	1500000	2934896	2300000	3974024	2650000	4101116	2750000	3601622	2700000	3183527	2550000	3103187
Colorado	30000	51685	160000	257458	240000	237818	240000	199759	240000	193409	180000	202732
Connecticut	20000	136172	75000	57783	85000	76935	110000	129021	110000	50155	120000	128685
Deleware	5000	11096	15000	12780	25000	33295	30000	37493	30000	27018	25000	23404
Florida	240000	810187	575000	1207492	925000	1226035	1050000	1208949	1050000	987218	825000	926492
Georgia	35000	75720	250000	109539	425000	442597	475000	555899	475000	501092	425000	389850
Hawaii	5000	41064	25000	37418	25000	48698	30000	47304	35000	35662	40000	41038
Idaho	10000	12535	25000	38346	30000	46326	35000	30457	35000	36228	35000	23782
Illinois	200000	433411	475000	378762	350000	487202	500000	652128	450000	471789	525000	545598
Indiana	10000	40418	65000	48014	85000	64184	100000	95165	120000	72237	110000	62126
Iowa	5000	11438	25000	62161	55000	94686	55000	70472	55000	90890	75000	96431
Kansas	15000	22777	55000	83328	60000	49849	70000	59872	70000	61258	65000	36759
Kentucky	5000	13405	20000	52684	50000	62957	45000	35429	45000	59356	80000	119597
Louisiana	15000	18513	20000	26965	25000	48200	35000	1112	65000	6536	65000	45445
Maine	2500	15297	5000	0	5000	0	5000	0	5000	0	5000	0
Maryland	35000	148544	120000	170351	250000	366272	275000	311187	250000	332858	275000	347220
Massachusetts	55000	269265	150000	267444	200000	256283	190000	190378	190000	128613	160000	80295
Michigan	25000	181494	95000	187908	120000	161626	120000	23885	110000	120749	150000	134292
Minnesota	15000	33549	55000	106149	85000	176556	110000	136807	110000	106601	85000	62032
Mississippi	5000	7355	10000	4283	40000	45444	40000	33564	35000	38994	45000	22624
Missouri	10000	31378	30000	68915	40000	17600	45000	73614	45000	65593	55000	33627
Montana	2500	6713	5000	0	5000	0	5000	968	5000	0	5000	0
Nebraska	5000	11784	30000	21141	45000	41865	50000	54564	45000	34053	45000	48470
Nevada	25000	56107	140000	197901	190000	269291	240000	285245	230000	285065	190000	251290
New Hampshire	2500	18357	5000	12235	15000	8574	20000	25379	20000	20303	15000	19777
New Jersey	95000	477905	325000	390230	475000	636086	600000	748889	550000	660199	550000	702101
New Mexico	20000	33149	55000	54904	65000	121218	80000	116283	80000	114334	85000	101118
New York	350000	1413568	725000	1265094	675000	1204251	825000	1102894	925000	1163289	625000	532602
North Carolina	25000	54219	210000	198336	375000	388566	375000	372842	350000	306109	325000	358807
North Dakota	2500	2834	5000	0	5000	0	5000	0	5000	0	5000	0
Ohio	10000	121610	55000	67944	100000	94102	100000	103967	95000	99959	100000	35816
Oklahoma	15000	12967	50000	40749	60000	75408	55000	24571	55000	30802	75000	58643
Oregon	25000	57357	110000	138813	140000	143366	140000	183058	150000	166040	160000	163036
Pennsylvania	25000	156983	85000	0	150000	104695	140000	79197	140000	72384	160000	24928
Rhode Island	10000	43007	20000	7036	30000	46911	30000	50673	30000	45903	30000	31782
South Carolina	5000	21849	45000	11727	55000	50226	70000	61754	70000	113444	55000	68616
South Dakota	2500	2849	5000	975	5000	6887	5000	6518	5000	7952	5000	8572
Tennessee	10000	21993	50000	29728	130000	167588	160000	169581	150000	147962	140000	165669
Texas	450000	611847	1100000	1225954	1400000	1818686	1450000	1633593	1450000	1707264	1650000	1551354
Utah	15000	17455	65000	53218	95000	68481	120000	139103	110000	111770	110000	88069
Vermont	2500	5357	5000	2815	5000	0	5000	4148	5000	0	5000	0
Virginia	50000	149282	150000	214404	275000	296303	325000	363710	300000	349413	210000	184716
Washington	40000	154954	160000	86761	200000	238426	170000	265596	180000	215730	230000	279807
West Virginia	2500	5651	5000	2549	5000	0	5000	0	5000	0	5000	363
Wisconsin	10000	55079	50000	102168	100000	128988	90000	116467	85000	128046	100000	80195
Wyoming	2500	1958	5000	0	5000	1120	5000	2007	5000	0	5000	1259
Total	**3547500**	**8988608**	**8370000**	**11765233**	**10935000**	**14620300**	**12050000**	**14136855**	**11935000**	**12968964**	**11360000**	**11769124**

[16] Note: Passel (2009) and (2010) presents most of his estimates using a confidence interval that represents the possible range of values the undocumented population could be for each state. The values presented above are the median values of these confidence intervals. This is important to note because the majority of the results produced using the method in this paper fall within Passel's range. The results from this paper appear to overstate the undocumented population level when compared to Passel's median values, but may not overstate the undocumented population to a substantial degree. The majority of the Schultz estimates fall below the upper bound of Passel's confidence intervals.

APPENDIX 5: GLS BASELINE RESULTS[17]

Model Type	Dependent Variable: Labor Force Participation Rate (Expressed as %Δ LFPR)							Dependent Variable: Unemployment Rate (Expressed as %Δ UR)						
	Cons	%Δ IMFR	Sex	Afr Am	Am Ind	Aspac	%Δ GSP	Cons	%Δ IMFR	Sex	Afr Am	Nat Am	Aspac	%Δ GSP
TFB	0.01792	0.00486	-0.10196	0.00285	-0.00892	0.03195	0.24507	0.21899	0.01342	-0.20200	-0.02695	-0.01726	-0.00702	-2.44423
Std Error	(0.00606)	(0.00214)	(0.01389)	(0.00916)	(0.02370)	(0.01866)	(0.03606)	(0.02286)	(0.00851)	(0.05074)	(0.03655)	(0.09196)	(0.06420)	(0.13374)
Z-Stat	2.96	2.27	-7.34	0.31	-0.38	1.71	6.8	9.58	1.58	-3.98	-0.74	-0.19	-0.11	-18.28
Prob > chi2	0							0						
Schultz Documented	0.01795	0.00071	-0.10197	0.00401	-0.00863	0.03038	0.24849	0.21936	-0.00105	-0.20254	-0.02413	-0.01880	-0.01086	-2.43448
Std Error	(0.00606)	(0.00117)	(0.01390)	(0.00915)	(0.02371)	(0.01865)	(0.03604)	(0.02290)	(0.00475)	(0.05081)	(0.03649)	(0.09219)	(0.06418)	(0.13371)
Z-Stat	2.96	0.61	-7.34	0.44	-0.36	1.63	6.9	9.58	-0.22	-3.99	-0.66	-0.2	-0.17	-18.21
Prob > chi2	0							0						
Passel Documented	0.01793	0.00116	-0.10192	0.00382	-0.00859	0.03067	0.24863	0.21924	0.00026	-0.20255	-0.02390	-0.01863	-0.01089	-2.43341
Std Error	(0.00607)	(0.00144)	(0.01391)	(0.00916)	(0.02371)	(0.01866)	(0.03607)	(0.02288)	(0.00576)	(0.05078)	(0.03648)	(0.09207)	(0.06410)	(0.13367)
Z-Stat	2.96	0.8	-7.33	0.42	-0.36	1.64	6.89	9.58	0.04	-3.99	-0.66	-0.2	-0.17	-18.2
Prob > chi2	0							0						
Schultz Undocumented	0.01787	0.00181	-0.10166	0.00341	-0.00825	0.03067	0.24733	0.21825	0.01325	-0.19967	-0.02825	-0.01278	-0.00759	-2.44595
Std Error	(0.00606)	(0.00167)	(0.01389)	(0.00917)	(0.02371)	(0.01865)	(0.03605)	(0.02285)	(0.00693)	(0.05073)	(0.03658)	(0.09201)	(0.06431)	(0.13364)
Z-Stat	2.95	1.08	-7.32	0.37	-0.35	1.64	6.86	9.55	1.91	-3.94	-0.77	-0.14	-0.12	-18.3
Prob > chi2	0							0						
Passel Undocumented	0.01763	0.00941	-0.10176	0.00223	-0.00788	0.03211	0.24271	0.21848	0.01023	-0.20127	-0.02555	-0.01543	-0.00958	-2.44013
Std Error	(0.00605)	(0.00248)	(0.01386)	(0.00916)	(0.02364)	(0.01864)	(0.03601)	(0.02287)	(0.01026)	(0.05077)	(0.03655)	(0.09203)	(0.06415)	(0.13382)
Z-Stat	2.91	3.8	-7.34	0.24	-0.33	1.72	6.74	9.55	1	-3.96	-0.7	-0.17	-0.15	-18.23
Prob > chi2	0							0						

[17] Note: The symbols "%Δ" represent a percentage change. Additionally, the "Afr American, Nat Am, and Aspac" titles represent state level low skill labor force percentages of African Americans, Native Americans, and Asian or Pacific Islanders, respectively. "Cons" represents the constant for each regression. No elasticities have been calculated in the figure above. Only the coefficients for each independent variable are reported. Additionally, the p-values reported for each model apply to the entire regression itself—not each variable individually.

APPENDIX 6: WLS BASELINE RESULTS[18]

Model Type	Dependent Variable: Labor Force Participation Rate (Expressed as %Δ LFPR)						
	Cons	%Δ IMFR	Sex	Afr Am	Am Ind	Aspac	%Δ GSP
TFB	0.01999	0.00468	-0.10316	-0.00012	-0.00901	0.04025	0.20849
Std Error	(0.00745)	(0.00211)	(0.01704)	(0.01189)	(0.03039)	(0.02348)	(0.04150)
Z-Stat	2.68	2.22	-6.05	-0.01	-0.3	1.71	5.02
Prob > chi2	0						
Schultz Documented	0.01997	0.00091	-0.10317	0.00110	-0.00865	0.03830	0.21226
Std Error	(0.00745)	(0.00114)	(0.01706)	(0.01188)	(0.03041)	(0.02346)	(0.04148)
Z-Stat	2.68	0.8	-6.05	0.09	-0.28	1.63	5.12
Prob > chi2	0						
Passel Documented	0.02002	0.00038	-0.10318	0.00103	-0.00856	0.03814	0.21278
Std Error	(0.00746)	(0.00145)	(0.01707)	(0.01190)	(0.03039)	(0.02347)	(0.04151)
Z-Stat	2.68	0.26	-6.04	0.09	-0.28	1.63	5.13
Prob > chi2	0						
Schultz Undocumented	0.01989	0.00091	-0.10284	0.00076	-0.00846	0.03818	0.21238
Std Error	(0.00745)	(0.00167)	(0.01706)	(0.01189)	(0.03042)	(0.02346)	(0.04149)
Z-Stat	2.67	0.55	-6.03	0.06	-0.28	1.63	5.12
Prob > chi2	0						
Passel Undocumented	0.01978	0.00932	-0.10310	-0.00088	-0.00824	0.04085	0.20570
Std Error	(0.00744)	(0.00247)	(0.01701)	(0.01189)	(0.03031)	(0.02347)	(0.04145)
Z-Stat	2.66	3.78	-6.06	-0.07	-0.27	1.74	4.96
Prob > chi2	0						

Model Type	Dependent Variable: Unemployment Rate (Expressed as %Δ UR)						
	Cons	%Δ IMFR	Sex	Afr Am	Nat Am	Aspac	%Δ GSP
TFB	0.19320	0.01900	-0.18229	-0.02695	-0.05539	-0.00042	-2.10634
Std Error	(0.02927)	(0.00833)	(0.06539)	(0.04996)	(0.12122)	(0.09005)	(0.15823)
Z-Stat	6.6	2.28	-2.79	-0.54	-0.46	0	-13.31
Prob > chi2	0						
Schultz Documented	0.19249	0.00001	-0.18051	-0.02272	-0.05884	-0.00804	-2.08777
Std Error	(0.02931)	(0.00461)	(0.06547)	(0.04993)	(0.12138)	(0.09004)	(0.15821)
Z-Stat	6.57	0	-2.76	-0.45	-0.48	-0.09	-13.2
Prob > chi2	0						
Passel Documented	0.19252	0.00329	-0.18093	-0.02295	-0.05828	-0.00673	-2.08793
Std Error	(0.02930)	(0.00582)	(0.06545)	(0.04991)	(0.12139)	(0.08996)	(0.15822)
Z-Stat	6.57	0.57	-2.76	-0.46	-0.48	-0.07	-13.2
Prob > chi2	0						
Schultz Undocumented	0.19134	0.01122	-0.17814	-0.02562	-0.05341	-0.00389	-2.09294
Std Error	(0.02928)	(0.00703)	(0.06544)	(0.05007)	(0.12120)	(0.09024)	(0.15821)
Z-Stat	6.54	1.6	-2.72	-0.51	-0.44	-0.04	-13.23
Prob > chi2	0						
Passel Undocumented	0.19180	0.01701	-0.17978	-0.02564	-0.05249	-0.00421	-2.10004
Std Error	(0.02926)	(0.01017)	(0.06538)	(0.04998)	(0.12123)	(0.09001)	(0.15825)
Z-Stat	6.55	1.67	-2.75	-0.51	-0.43	-0.05	-13.27
Prob > chi2	0						

[18] Note: The symbols "%Δ" represent a percentage change. Additionally, the "Afr American, Nat Am, and Aspac" titles represent state level low skill labor force percentages of African Americans, Native Americans, and Asian or Pacific Islanders, respectively. "Cons" represents the constant for each regression. No elasticities have been calculated in the figure above. Only the coefficients for each independent variable are reported. Additionally, the p-values reported for each model apply to the entire regression itself—not each variable individually.

APPENDIX 7: CONFIDENCE INTERVALS FOR GLS BASELINE LOW SKILL UNEMPLOYMENT RESULTS