Occupational and Industrial Impacts of the *Plyer* Decision: Past Gains and Future Losses

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Introduction

In 1982, the Supreme Court's landmark decision in *Plyler v. Doe* guaranteed access to public education for undocumented children, reshaping their futures and, in turn, the fabric of the U.S. labor market. By enabling these children to complete high school, the ruling provided essential tools for social and economic integration, equipping them with skills and credentials that opened doors to a broader spectrum of occupations. This access to education not only impacted individual career opportunities but also had ripple effects on the composition of the labor force, influencing occupational trends, skill availability, and industry demands over time.

Existing research underscores the challenges unauthorized immigrants face in the labor market, where they tend to be overrepresented in low-wage, high-risk industries such as agriculture, construction, and hospitality (Hall, Greenman, and Farkas 2010). Lacking legal protections, unauthorized workers are vulnerable to wage suppression, discrimination, and workplace hazards, with limited mobility to transition into better-paying jobs. Various studies highlight that legal barriers confine unauthorized immigrants to low-skill positions, creating cycles of occupational immobility and preventing them from leveraging skills to advance economically (Borjas and Cassidy 2019; Hall and Greenman 2015; Hall, Greenman, and Yi 2019). Yet, by facilitating access to education, *Plyler* is likely to have mitigated some of these constraints, enabling unauthorized youth to break free from paths toward low-wage, high-risk occupations and transition into roles requiring more specialized skills. This educational foundation in turn likely contributed to greater job stability, upward mobility, and overall workforce diversification, benefiting the broader U.S. labor market.

This analysis examines how *Plyler* has shaped the occupational and industrial mix of the U.S. labor market, both by generating gains in workforce diversity and skill availability over recent decades and by considering potential future losses if educational access were restricted. Specifically, the research goals are to: (1) evaluate the extent to which individuals who have previously benefited from *Plyler* are working in skilled occupations and industries; and (2) forecast the potential changes in skilled occupations and industries associated with rescinding *Plyler*.

Analysis Data

To examine these research goals, this analysis uses data from the 2022 American Community Survey (ACS). This analysis uses imputed documentation status data for foreign-born individuals, developed by Philip Connor. Based on these imputations and year of arrival, the data can identify individuals who are likely to have benefited from *Plyler*, in the past (among adults) or at the time of data collection (among children). These data include modified survey weights that integrate the sampling weights provided by Census with estimates of the inflows of immigrants (primarily from Central America) between 2022 and 2023. In total, this population is estimated to be 4.8 million, including 3 million adults who have previously benefited and 1.8 million unauthorized children who currently benefit from *Plyler*. An important caveat is that the number of individuals who *ever* benefited from *Plyler* is likely to be substantially higher given that these data capture the resident population living in the U.S. in 2023, and excludes those individuals who may have benefited from *Plyler* but have deceased or emigrated.

Classifying Occupations and Industries

To describe the occupations and industries potentially most impacted by *Plyler*, they are categorized based on estimated entry-level educational requirements. To do so, the educational distribution of each specific occupation and industry is determined based on the full sample of workers (foreign- and U.S.-born) in the 2022 *ACS*. The entry-level education requirement for each occupation or industry is assumed to be the education level at the 25th percentile of this distribution. This assumes that if 75% of workers in a given occupation or industry have achieved higher levels of education, then that level is likely the entry requirement. The assumed entry-level requirements are then used to classify occupations and industries into three categories: (1) *highly-skilled*, requiring at least some college education; (2) *semi-skilled*, requiring at least a high school diploma; and (3) *less-skilled*, requiring less than a high school diploma. In the full labor force, this grouping equates to 172 highly-skilled occupations (15.2% of labor force), 219 semi-skilled ones (75.9%), and 35 less-skilled occupations (8.8%).[1]

Analytic Approach

The empirical approach to assess both the historical and future occupational impacts of *Plyler* involves a two-part analysis: descriptive analysis of the occupations held by adults in 2022, and predictive modeling to estimate the likely occupational pathways of current children, under the assumption that their current educational levels remain static.

For predictive modeling of future impacts, a random forest algorithm is leveraged to estimate the occupational and industrial skill levels that children might enter into as adults. This model is trained on data from previous beneficiaries of *Plyler* (Plyer adults) who are of prime working age, using a range of predictor variables including years of education, age at arrival, country of birth, sex, race, Hispanic ethnicity, state of residence, and protected legal status. Random forests are particularly effective for classifying categorical variables, such as occupational groupings, due to their ability to capture non-linear relationships and interactions across multiple predictors. By constructing an ensemble of decision trees, each trained on randomly selected subsets of data and predictors, random forests can detect subtle patterns that traditional approaches (like a multinomial) may miss. This design provides more flexible boundaries for classification, allowing random forests to better handle complex, high-dimensional data, as each tree contributes independently to the final classification, enhancing the model's stability and accuracy in predicting categorical outcomes (Athey and Imbens 2019; Mullainathan and Spiess 2017).

Optimization of the random forest model was achieved by maximizing out-of-sample accuracy using a 20% holdout sample of unauthorized adult workers, with systematic testing of parameters including the number of trees, tree depth, and minimum leaf size. The optimized model includes 200 decision trees, each considering a random

[1] Placing more stringent assumptions on the distributional requirement or the educational levels greatly reduces the number of highly-skilled occupations. For instance, there are only 27 occupations where the 10th percentile is a college degree, representing just 5.9% of the labor force. There are 17,459 Plyler adults in these occupations.

subset of 100 predictor variables at each split, with a depth limit of 10 and a minimum of 5 observations required at each leaf node. These parameter choices resulted in a final out-of-sample accuracy of 64% and an in-sample accuracy of 68%. For comparison, a fully specified multinomial model yielded slightly lower accuracies of 61% and 66% for out-of-sample and in-sample predictions, respectively.

References

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