Split Families and the Future of Children:

Immigration Enforcement and Foster Care Placements

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Since 9/11, the United States has witnessed an extraordinary increase in immigration enforcement. Intensified immigration enforcement, particularly at the local and state levels, has been responsible for roughly 1.8 million deportations between 2009 and 2013 alone (Vaughan, 2013). Deportations have broken up households and changed the structure of many families headed by an unauthorized parent –typically through the deportation of fathers (Capps *et al*., 2016). In some instances, the children enter the foster care system when Immigration Customs Enforcement (ICE) detains their parents, or single parent, and the children are left alone. Supporting these concerns, data from the national Adoption and Foster Case Analysis and Reporting System (AFCARS) Foster Care files reveal a distinct trend of Hispanic children entering foster care during the period of intensified enforcement. While the number of Hispanic youth foster care entries rose by 845 percent between 2004 and 2015, it decreased by 66 percent among white non-Hispanic youth over the same period.[3] These are worrisome statistics. In addition to the cost of fostering a child, foster care children are at high risk for severe emotional, behavioural and developmental problems that result in high homelessness and prison rates, as well as in poor labor market outcomes (*e.g.* Doyle, 2007; Doyle, 2008). In light of its negative consequences, we examine how the intensification of immigration enforcement at the local and state levels since the early 2000s might have contributed to the growing share of Hispanic youth entering foster care. Gaining a better understanding of the

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[3] Because the vast majority of Hispanics are white, we will typically use other white, non-Hispanic, youth as a comparison group. Nonetheless, we also look at black youth in our robustness checks.

impact of the piecemeal approach to immigration enforcement on foster care is crucial given the strengthening of enforcement nationwide and the worse long-term outcomes of foster care youth.[4]

1. Data

1.1 Adoption and Foster Care Analysis and Reporting System (AFCARS): We use the Foster Care files from the Adoption and Foster Case Analysis and Reporting System (AFCARS) for the 2001-2015 period.[5] Our dependent variable is the share of Hispanic children per 1,000 Hispanic kids entering foster care in the state. Since approximately 80 percent of undocumented immigrants are Hispanic (Passel and Cohn, 2009), attention to Hispanic children is crucial. Additionally, since AFCARS does not include 'parental deportation' as a motive for foster care placement, we focus on motives more likely marked by Child Protective Services (CPS) following the detention and/or deportation of a parent – namely, parental incarceration, caretaker inability cope, abandonment, relinquishment, or inadequate housing.[6] Finally, while the data set provides a census of all foster care entries, the county is only identified when there are more than 1,000 foster care entries in any given year. Thus, to ensure the representativeness of the data, we exploit its temporal variation at the state level.

1.2 Enforcement: We collect historical data on various immigration enforcement measures. Data on 287(g) agreements at the county and state levels is gathered from the ICEs 287(g) Fact Sheet website,[7] and Kostandini *et al.* (2013). Data on the rolling of the Secure Communities program at the county level is compiled from ICE's releases on activated

[4] The budget for immigration enforcement planned for 2018, it is a 25 percent more than previous year. In comparison, the budget for education or health decrease by 14 and 16 percent respectively.
[5] A complete set of the data for all state is only available after 2001.
[6] We thus exclude foster care entries related to children's behaviors or disabilities, as well as those due to parental physical, sexual, alcohol or drug abuse, death or neglect – all parental behaviors unrelated to noncompliance with immigration laws and that would have, in any case, preceded (as opposed to resulted from) the apprehension and deportation of the parents.
[7] https://www.ice.gov/factsheets/287g

jurisdictions.[8] Data on state level omnibus immigration laws and employment verification mandates is gathered from the National Conference of State Legislatures.[9] Using the aforementioned data sources, we construct an index to capture the *intensity* of immigration enforcement to which families are exposed. It is worth noting that the index is a *proxy* for the intensity of immigration enforcement, since the same measure can be applied more or less strictly in distinct locations depending on the authorities in charge of its implementation. In addition, because the geographic scope of many of the enforcement initiatives is the county, one policy might be activated in one county, but not in others. Therefore, for each enforcement initiative *k*, we calculate the following population-weighted index:

(1) $$IE^{k}{}_{st} = \frac{1}{N_{2000}} \sum_{\boldsymbol{c} \in \boldsymbol{s}}^{\boldsymbol{S}} \frac{1}{12} \sum_{\boldsymbol{m}=\mathbf{1}}^{\mathbf{12}} \mathbf{1}\left(E_{m,c}\right) P_{c,2000}$$

where $\mathbf{1}\left(E_{m,c}\right)$ is an indicator function that informs about the implementation of a particular policy in county *c* during month *m* in year *t*. The index $IE^{k}{}_{st}$ takes into account: (1) the number of months during which policy *k* was in place in year *t*,[10] as well as (2) the size of the state's population affected by its implementation.[11] The overall enforcement to which children living in state *s* and year *t* are exposed to is then computed as the sum of the indices for each enforcement initiative at the (state, year) level:[12]

(2) $$Total\ Enforcement_{s,t} = \ IE_{s,t} = \sum_{k \in K}^{K} IE_{s,t}^{k}$$

2. Methodology

To learn about how tougher immigration enforcement might have contributed to the increase in foster care entries among Hispanic youth, we estimate the following model:

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[8] See: https://www.ice.gov/doclib/secure-communities/pdf/sc-activated.pdf

[9] See: http://www.ncsl.org/documents/statefed/omnibus_laws.pdf

[10] Specifically, the summation over the 12 months in the year captures the share of months during which the measure was in place in any given year.

[11] To weigh it population-wise, we use the term: $P_{c,2000}$ –namely, the population of county *c* according to the 2000 Census (prior to the rolling of any of the enforcement initiatives being considered), and *N* –the total population in state *s*.

[12] Where *k* refers to each policy, *i.e.*: 287(g) local agreements, 287(g) state agreements, Secure Communities, Omnibus Immigration Laws and E-verify mandates.

(3) $$y_{s,t} = \alpha + \beta_1\, IE_{s,t} + \beta_2 High\, LU_{s,t}^{2000} + \beta_3\, IE_{s,t} * High\, LU_{s,t}^{2000} + \gamma_s + \theta_t + \gamma_s t + \varepsilon_{s,t}$$

where $y_{s,t}$ is the share of Hispanic children per 1,000 Hispanic kids entering foster care for the parental motives noted earlier in state *s* and year *t*. $IE_{s,t}$ is the immigration enforcement index capturing the intensity of enforcement to which individuals living in state *s* in year *t* are exposed. $High\, LU_{s,t}^{2000}$ is a dummy variable indicative of whether the state's share of *likely* undocumented immigrants in a given year exceeded the national average in 2000.[13] The shares are constructed using data from the American Community Survey (ACS). Specifically, we rely on ethnicity and citizenship traits (*e.g.* being a Hispanic non-citizen), which have been shown to be good predictors of immigrants' undocumented status (Passel and Cohn, 2009),[14] as well as on information on the educational attainment and length of residency of the foreign-born in each state. We compute the shares of Hispanic non-citizens who have less than a high school education[15] and have resided in the United States for at least 5 years[16] in each state and year, as well as nationwide in the year 2000.[17] Subsequently, using the constructed shares, we create a dummy indicative of whether state *s* in year *t* had a share of likely undocumented immigrants that exceeded the national average in the year 2000.[18] To learn about the differential impact of intensified immigration enforcement in states with a higher (vs. lower) concentration of likely undocumented immigrants, we interact this dummy variable with the immigration enforcement index. In addition, equation (3) incorporates state and year fixed-effects, as well as state-specific time trends to capture unobserved fixed and time-varying traits potentially

[13] To address reverse causality concerns, the reference national share refers to the year 2000 –that is, before any of the immigration enforcement initiatives being examined were enacted. Later on, in the identification checks, we address the potential endogeneity of each state's share of likely undocumented immigrants in any given year.
[14] Examples of works using these predictors include Bohn and Pugatch (2013), Passel and Cohn (2009), Orrenius and Zavodny (2016), to name a few.
[15] This allows us to exclude international students and high-skill migrants with H-1B visas.
[16] This last requirement permits us to exclude low-skill migrants with non-immigrant visas, such as H-2A and H-2B visas, typically of a much shorter duration.
[17] When we use all these traits, along with the ACS weights, we obtain an estimated undocumented immigrant population of 12,791,033 individuals –a figure close to the estimated population of 11 to 12 million undocumented immigrants using the residual method over the period under consideration.
[18] As a robustness check, we also perform the analysis using alternative indicators of which are states with a higher share of likely undocumented immigrants. Results, as we shall discuss, prove robust.

affecting our outcomes and unaccounted for.[19] The equation is estimated by ordinary least squares (OLS). Estimates are weighted by the number of Hispanic children in the 0-17 age range and standard errors are clustered at the state level.

What are our hypotheses? If intensified enforcement impacts Hispanic households through the higher incidence of deportations among such households, we would expect its impact, given by: $(\beta_1 + \beta_3 * \mu_{High\ LU})$,[20] to be positive and different from zero. Additionally, we would expect the impact of intensified enforcement on the share of Hispanic youth entering foster care to be greater in states that likely undocumented immigrants evade, possibly because they feel unsafe, than in states they gravitate to, *i.e.* $\beta_1 > (\beta_1 + \beta_3)$.[21]

3. Results

According to the estimates from estimating equation (3) in column (1) of Table 1, an increase in immigration enforcement equal to its average level over the period under consideration (*i.e.* μ_{IE} = 0.564) raises the share of Hispanic children entering foster care by 14.89 percent.[22] The same increase in immigration enforcement raises the share of Hispanic children entering foster care by 18.98 percent in states with a lower concentration of likely undocumented immigrants.[23] In contrast, in states with a high concentration of likely undocumented immigrants –possibly safer states for likely undocumented immigrants— the same increase in immigration enforcement is associated to a 7.53 percent growth in the share of Hispanic children entering foster care. As a falsification test, we re-estimate equation (3)

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[19] In intermediate model specifications not shown herein, we experiment with including other controls, such as state's unemployment rates, poverty rates and incarceration rates. However, they are collinear with state-specific time trends and drop from our most complete model specification.
[20] Where: $\mu_{High\ LU}$ stands for the mean of $High\ LU_{s,t}^{2000}$.
[21] Note that because likely undocumented immigrants are likely to evade unsafe locations, the estimated impact of intensified immigration enforcement in states that likely undocumented immigrants avoid –those with a low concentration of likely undocumented immigrants– is likely to be downward biased. This could result in a lower-bound estimate of the impact of intensified immigration enforcement, as we shall check on what follows.
[22] This effect is computed as: $[(\beta_1 + \beta_3 * \mu_{High\ LU})$*ΔIE*100]/ μ_y, where: $\mu_{High\ LU} = 0.357$, ΔIE=μ_{IE} = 0.564 and $\mu_y = 1.21$.
[23] The impact in states with: *High LU* = 0 is given by: [(β_1*ΔIE*100)/ μ_y].

using other white non-Hispanic and black children. As shown in columns (2) and (3) of Table 1, the impact of intensified enforcement on foster care entries is unique to Hispanic youth. [24] We also conduct a couple of identification checks. First, we evaluate if the impact attributed to immigration enforcement did not predate its implementation by including a full set of year dummies for up to four years prior to the adoption of any initiative in the state. According to the estimates in Panel A of Table 2, none of the coefficients for the preceding years are statistically different from zero, hinting on no pre-existing impacts.

Secondly, we address the likely non-random residential choices of immigrants. Migrants, especially undocumented ones, may move in response to adopted enforcement measures to evade apprehension. In that case, the OLS estimates might provide a lower bound estimate of the impact of intensified enforcement. To assess if that is the case, we instrument the enforcement to which each child would have been exposed if their parents had settled in the same locations as undocumented immigrants settled *prior* to the rollout of stricter immigration enforcement measures.[25] Panel B of Table 2 displays the results from the two-stage IV estimation.[26] The increase in immigration enforcement raises the share of Hispanic children entering foster care by 20.82 percent,[27] suggesting the OLS estimates provide a lower-bound estimate of the true effect of enforcement.

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[24] Our results are robust to the exclusion of the Recession years (2009-2010) and to alternative definitions of what might be consider a state with a relatively high share of likely undocumented immigrants.

[25] Using ACS data from before the rollout of tougher enforcement, we compute the shares of undocumented immigrants in each state to gauge what their distribution and probable location would have been in the absence of the new enforcement measures. Subsequently, we interact the constructed shares for each state with the immigration enforcement for that state in each year in question and use them as our instrument.

[26] The last rows confirm that the two aforementioned instruments are highly correlated to our key and potentially endogenous regressors. The F-stats from those first stage regressions are significantly different from zero and large (Sanderson and Windmeijer, 2016). Additionally, the estimated coefficients are both positive and statistically different from zero; confirming, in the latter case, the entrenched tendency for immigrants to locate in areas with established networks of alike immigrants (e.g. Card, 2001, among others).

[27] This effect is computed as: $[(\beta_1 + \beta_3 * \mu_{IV\ for\ High\ LU})*\Delta IE*100]/\mu_y$, where: $\mu_{IV\ for\ High\ LU} = 0.0214$, $\Delta IE=\mu_{IE} = 0.564$ and $\mu_y = 1.21$.

4. Summary and Conclusions

We show that the average yearly increase in interior immigration enforcement during the 2001-2015 period has significantly contributed to the share of Hispanic youth entering foster care. To our knowledge, this is the first study examining the impact of interior immigration enforcement on foster care entries. In so doing, it contributes to a literature exploring the reasons behind recent increases in foster caseloads (*e.g.* Swann and Sylvester, 2006; Cunningham and Finlay, 2013). Additionally, the analysis adds to a number of studies exploring the effects of intensified enforcement on undocumented immigrants' residential choices, employment, earnings and on their children's access to health-care (*e.g.* Amuedo-Dorantes and Bansak 2012; Bohn and Lofstrom 2013; Watson 2014). Given the promised increase in deportations by President Donald Trump and the swift implementation of executive orders that revive police-based immigration enforcement, gaining an understanding of how tougher immigration enforcement is likely affecting American children is imperative.

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Table 1: Immigration Enforcement and Foster Care: Main Findings
(Dependent Variable: Share of Children Entering Foster Care)

Column	**(1)**	**(2)**	**(3)**
By Race and Ethnicity:	**Hispanic Children**	**White Non-Hispanic Children**	**Black Children**
Immigration Enforcement (IE)	0.4071***	0.1991	0.2825
	(0.147)	(0.135)	(0.229)
High LU Share	-0.0984	-0.2754	-0.2275
	(0.174)	(0.228)	(0.368)
IE*High LU Share	-0.2455*	0.2165	0.0293
	(0.141)	(0.203)	(0.274)
Observations	733	763	736
R-squared	0.797	0.812	0.781
Mean D.V.	1.21	0.79	2.15

Notes: *Sample*: Share of Children between 0 and 17 years. All Specifications include area FE, year FE and Area-trend. Robust standard errors are in parentheses. Standards errors are clustered at the state level. ***p<0.01, **p<0.05, *p<0.1

Table 2: Identification Tests
(Dependent Variable: Share of Hispanic Children Entering Foster Care)

Panel A: Checking on Parallel Trends		**Panel B: Non-Random Location of Immigrants**	
Event Study Results		**Instrumental Variable Regression Results**	
One Year Before IE>0	0.0147	IE	0.4529***
	(0.083)		(0.155)
Two Years Before IE>0	-0.0508	High LU Share	-0.6418***
	(0.063)		(0.218)
Three Years Before IE>0	-0.0591	IE*High LU Share	-0.2885*
	(0.085)		(0.171)
Four Years Before IE>0	0.0889	Observations	733
	(0.080)	R-squared	0.743
IE	0.4018**		
	(0.158)	*First Stage for "IE"*	
High LU Share	-0.2429*	IV	70.260***
	(0.140)		(8.013)
IE*High LU Share	-0.1186	R-squared	0.83
	(0.168)	Sanderson-Windmeijer Multivariate F-test	58.88
Observations	733	*First Stage for "High LU Share"*	
R-squared	0.798	IV	1.026***
			(0 .040)
		R-squared	0.97
		Sanderson-Windmeijer Multivariate F-test	402.28