The Chilling Effect of ICE: The Effects of a Large Worksite Enforcement Operation on Academic Performance for Young Children in a Targeted Community

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Abstract:

In 2006, the George W. Bush administration introduced new tactics to more aggressively address issues related to document fraud. Specifically, US Immigration and Customs Enforcement (ICE) began focusing its limited resources to target worksites with high concentrations of suspected unauthorized workers (e.g., food processing plants). While large worksite enforcement operations (LWEO) resulted in more arrests than in previous years, they were also criticized for their negative effects on schools and school children. Unfortunately, there is little empirical evidence providing information to policymakers about the harmful effects of LWEOs on academic performance for young children. In this examination, I use Synthetic Control Methods to estimate LWEO effects on reading and math proficiency rates for third graders in a targeted community. Specifically, I focus on a 2006 LWEO in Cactus, TX. Results show the LWEO lowered proficiency rates for third grade children exposed to the LWEO, especially LEP and Hispanic children.

1. INTRODUCTION

One of the most contentious immigration policy debates today concerns the fate of 11.1 million immigrants currently working and living in the US without legal authorization (Passel & Cohn, 2015). Charged with enforcing federal immigration laws, US Immigration and Customs Enforcement (ICE) has a broad set of tools available to identify, arrest, and remove aliens who present a danger to national security, are a risk to public safety, or otherwise undermine the integrity of US immigration laws. Knowing most immigrants come to the US in search of job opportunities, ICE frequently conducts worksite enforcement operations that target employers who knowingly hire immigrants without proper work authorization and undocumented immigrants themselves. In 2006, the George W. Bush administration introduced new worksite enforcement tactics in order to more aggressively address issues related to document fraud (Department of Homeland Security, 2006). Specifically, ICE began focusing its limited resources to target worksites with high concentrations of suspected unauthorized workers (e.g., food processing plants). This means ICE was now planning and implementing larger worksite enforcement operations (LWEO) than in previous years, which in prominent examples resulted in the arrest of hundreds of undocumented immigrants. The results were dramatic: worksite enforcement arrests increased from 1,116 in FY05 to 3,667 in FY06; 4,077 in FY07; and 5,184 in FY08 (Bruno, 2013).

While these numbers indicate substantial improvements on important performance metrics for ICE, LWEOs were heavily criticized due to their "rippling consequences on others in the community" (Forman, 2009, p3). For example, in a 2008 hearing before the Subcommittee on Workforce Protections (ICE Workplace Raids, 2008), critics of LWEOs argued that too many children were being separated from their families because ICE agents were not taking proper precautions to identify humanitarian concerns in targeted communities (e.g., cases involving

nursing mothers or sole caregivers), resulting in immediate and lasting consequences on schools and school children. Perhaps in response to these criticisms, the Obama administration directed ICE to reprioritize its limited resources to target employers using unlawful hiring practices and immigrants charged with serious criminal offenses, not otherwise law-abiding immigrants (Obama, 2014). Furthermore, ICE lowered its cutoff from 150 to 50 targeted persons for arrest to determine when it should take additional steps to identify humanitarian concerns around LWEOs (Forman, 2009). Following these changes, arrests from worksite enforcement operations decreased from 5,184 in FY08 to 1,644 in FY09 (Bruno, 2013). This does not necessarily mean ICE was limited in its ability to fulfill its mission, however, as the number of immigrant removals continued to increase through FY12 (Appendix A).[1]

Despite deporting record numbers of immigrants under the Obama administration, ICE worksite enforcement policy appears to be changing under the Trump administration. For example, ICE was recently instructed to deport anyone in the country without legal authorization, not just those committing serious criminal offenses (Shear & Nixon, 2017). In addition, ICE recently conducted a multi-state worksite enforcement operation resulting in the arrest of hundreds of undocumented immigrants (Rein, Hauslohner, & Somashekhar, 2017), and would have conducted another if not for Hurricane Harvey (Ainsley & Blankstein, 2017). While ICE should not be precluded from planning and implementing worksite enforcement operations entirely, it is crucial that it does so in a manner that limits harms to children. As research shows parental and ethnic capital are important predictors of intergenerational mobility (Borjas, 1992), the significance of this point is clear considering large numbers of children born to undocumented immigrants, an

[1] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

estimated 80 percent of whom are US citizens (Passel & Taylor, 2010), will likely remain in the US and raise families of their own. In other words, exposure to LWEOs could potentially affect educational and labor market outcomes for generations of future US citizens. Unfortunately, prior research describing LWEO effects on schools and school children is somewhat limited. For example, there are two in-depth qualitative studies from the Urban Institute reporting adverse LWEO effects on children in targeted communities (Capps et al., 2007; Chaudry et al., 2010), but they lack methodologically rigorous quantitative analyses that could provide more convincing evidence for policymakers to consider when assessing ICE worksite enforcement strategy.

As political support for more intense immigration enforcement policies renews, the lack of empirical research on LWEO effects on schools and school children is glaring. Therefore, in this examination I use a quasi-experimental research design to estimate LWEO effects on academic performance outcomes for children in a targeted community. Specifically, I focus on a 2006 LWEO in Cactus, TX, which represents one of the six communities targeted by ICE as part of Operation Wagon Train (OWT). OWT is historically significant as the first instance ICE planned and implemented LWEOs. Importantly, although this examination focuses on a LWEO in Cactus, TX, I argue the setting is generalizable given similarities to other potentially vulnerable communities (e.g., relatively small, Hispanic, rural, and the largest employer is a meatpacking plant relying on immigrant labor). To measure academic performance, I use publicly available data from the Texas Education Agency (TEA) reporting district-level proficiency rates for third graders on standardized reading and math subject tests. I estimate LWEO effects on a sample of all children, as well as samples of children identified as limited English proficient (LEP), Hispanic, and non-Hispanic white. I use the sample of all children to estimate overall LWEO effects, and sociodemographic samples to estimate LWEO effects for children most and least likely to be

directly affected by the LWEO (i.e., have a parent apprehended by ICE). Hereafter, I refer to non-Hispanic white children as just white children.[2] Notably, the TEA does not separate LEP samples by ethnicity, meaning there will be overlap between samples of LEP and Hispanic children.

To estimate LWEO effects on reading and math proficiency rates, I use a Synthetic Control Method (SCM) developed in Abadie and Gardaezabal (2003) and Abadie, Diamond, and Hainmueller (2010; 2015). Employing SCM for this examination is appealing because it creates a synthetic control group comprised of districts similar to the district serving Cactus, TX, Dumas Independent School District (ISD), along pre-LWEO trends in proficiency rates and predictors of future academic performance, but importantly not serving communities targeted by the LWEO. As children in Dumas ISD should be affected by the LWEO due to their geographic proximity to the LWEO but not children in the synthetic control group, the estimated LWEO effect is therefore the difference in proficiency rates between the two groups after the LWEO. Importantly, because the synthetic control group resembles Dumas ISD on pre-LWEO observed and unobserved factors, using SCM reduces the likelihood that estimated LWEO effects could be biased by pre-LWEO trends in academic performance or differences between groups. SCM also offers some advantages over traditional difference-in-differences (DD) approaches that could be used to estimate LWEO effects. For example, DD approaches would assume many districts were targeted by the LWEO for proper statistical inference (Conley & Taber, 2011), but here there was only one targeted district because Cactus, TX is served by only Dumas ISD. In addition, DD approaches would commonly use fixed-effect specifications to account for unobserved differences between groups that may be correlated with proficiency rates and therefore bias results, but this assumes these differences are time-invariant. SCM better addresses this potential source of bias by allowing

[2] While Hispanics can racially identify as white, the TEA provides a separate score category for ethnically Hispanic students, which means scores reported for white students are for non-Hispanic white students.

unobserved differences between groups to vary over time (Abadie, Diamond, & Hainmueller, 2010; 2015). Finally, where estimated LWEO effects using DD approaches would be averaged across post-LWEO years, SCM allows for estimated LWEO effects to vary over time.

This examination makes two important contributions to the literature. Primarily, I provide arguably causal evidence about LWEO effects on academic performance outcomes for third graders in a targeted community using publicly available data from the TEA. As mentioned previously, prior research from Urban Institute scholars relies on interviews with parents and teachers to draw conclusions about LWEO effects (Capps et al., 2007; Chaudry et al., 2010), but this means their findings could potentially suffer from various response biases associated with conducting retrospective interviews. Furthermore, these studies only report relatively immediate LWEO effects since interviews were conducted no later than a year or so in targeted communities. Thus, findings from this examination could help schools exposed to LWEOs better anticipate the needs of directly affected children. In addition, as policy decisions can shape political life in our democratic society (Mettler & Soss, 2004), these findings could help discourage future use of the more intrusive elements associated with ICE worksite enforcement policy that narrow conceptions of membership in political communities, negatively influence beliefs and expectations of groups within the polity, and undermine civic capacity.

Findings from this examination also contribute to the broader literature about immigration enforcement intensity and its effect on schooling outcomes for children. For example, research from Amuedo-Dorantes and Lopez (2017) use indices measuring the presence of multiple state and county level immigration enforcement policies to examine the effects of immigration enforcement intensity on educational attainment outcomes for children with at least one noncitizen parent, but this limits the ability to make policy recommendations about specific aspects of

particular immigration enforcement efforts to mitigate negative feedback effects. Thus, by specifically focusing on one of the more intense worksite enforcement operations in ICE history, I can provide more useful evidence for policymakers to consider in regard to future ICE worksite enforcement policy. In addition, I deepen our understanding of the relationship between immigration enforcement intensity and schooling outcomes by estimating effects on academic performance instead of educational attainment. For example, children can be socially promoted to the next grade level even when performing poorly on standardized tests.

The paper proceeds as follows. Section 2 provides background information for this examination, explains the theoretical motivation, summarizes prior research on LWEOs, and reviews related empirical evidence. Section 3 describes the data and Section 4 describes the identification strategy. Section 5 presents the results and Section 6 concludes with a discussion of implications for policy and future research.

2. LITERATURE REVIEW

This section reviews the relevant research on LWEOs. Section 2.1 provides information about OWT and Cactus, TX. Section 2.2 explains the theoretical motivation for this examination and Section 2.3 summarizes the two Urban Institute reports documenting LWEO effects on classroom environments and reviews empirical evidence from research on immigration enforcement policies and community traumatic events.

2.1 Background Information

Operation Wagon Train

One of the largest worksite enforcement operations in ICE history, OWT was implemented on December 12, 2006 and involved more than 1,000 federal agents across six targeted communities. OWT targeted Swift & Co. meatpacking plants (Swift & Co.) and resulted in the arrest of nearly

1,300 employees, 274 of whom were criminally charged (Peterson, 2009). At its conclusion, OWT resulted in 297 arrests in Cactus, TX; 252 arrests in Greeley, CO; 252 arrests in Grand Island, NE; 239 arrests in Worthington, MN; 158 arrests in Hyrum, UT; and 99 arrests in Marshalltown, IA (Kammer, 2009). Importantly, ICE did not collect any data about the number of arrested leaving behind children, but unofficial counts in CO and NE indicate there were at least two directly affected children for every three arrests (Capps et al., 2007).

Urban Institute scholars Capps et al. (2007) summarize the immediate LWEO effects on directly affected children in Colorado and Nebraska after OWT, as well as in Massachusetts after a non-OWT LWEO. In general, their interviews of parents and teachers describe communities in chaos, fragmented families, and economic hardship. For example, many children were left afraid, confused, and in informal caregiving arrangements because arrested parents often had little access to telephones or signed voluntary departure papers without contacting family or legal counsel. In cases where parents were detained for weeks or longer, uncertainty and family fragmentation often resulted in heavy psychological stress for children. The arrest of working parents typically brought economic hardship to families as well, especially if they handled family finances. Exacerbating these difficulties, many immigrant families were afraid to seek assistance from public agencies out of fear that additional exposure would increase the risk of deportation. Fortunately, extended families and other informal networks (e.g., religious groups and community organizations) were often able to provide financial and emotional support for directly affected children. Over time, however, these resources also became stretched thin.

In a follow-up study investigating the longer-run LWEO effects on directly affected children, Urban Institute scholars Chaudry et al. (2010) again interview parents and teachers in

several targeted communities.[3] Most notably, they find that the effects of economic hardship and family segmentation persisted even as chaos in these communities generally subsided. For example, average household incomes for directly affected families after the LWEOs were about half of pre-LWEO income levels because finding new income sources for these families in most cases was extremely difficult, and this often contributed to prolonged housing instability and food-related hardships. In some cases, parents had to make difficult decisions concerning the future of their children in the US; 8 of 20 interviewed families making this decision chose to send their children to their native country.

Cactus, Texas

Cactus, TX is a small city in Moore County located 600 miles north of the US-Mexico border. In the 1970s, Cactus, TX was home primarily to Vietnamese and Laotian refugees, then primarily Mexican and Guatemalan immigrants from the mid-1980s to today (Moreno, 2007). According to the US Census Bureau (2010), about 75 percent of the 3,000 persons living in Cactus, TX identified as Hispanic. To give perspective to the relative size of the LWEO, there were 3,587 paid employees in Cactus, TX in 2012 (US Census Bureau, 2012b), about half of whom lived in the city (US Census Bureau, 2012a). This suggests 8.3 percent of the local labor force was detained in one day.[4] As one could imagine, "The raid at the Cactus plant created a momentary crisis for the community of around 3,000 people. Many children and spouses of deported workers were left behind in distress" (VOA News, 2009). Over a year later, some children still had not seen their parents and nearly 600 people left town for good (McLemore, 2008).

[3] Interviews were conducted again in Nebraska and Massachusetts for the follow-up study. Other locations include Miami, FL; Postville, IA; Van Nuys, CA; and Rogers-Springdale, AR.

[4] This estimate likely overstates the true LWEO effect, as undocumented workers were presumably paid under the table and therefore unreported in government surveys. Estimates for 2012 are shown because this is the earliest year unmasked employment data is published for Cactus, TX in the Survey of Business Owners.

2.2 Theoretical Motivation

This examination of LWEO effects on academic performance outcomes for children in a targeted community is first motivated by the body of literature in political science concerning the theoretical implications of policy feedback effects. Policy feedback, as articulated in Schneider, Ingram, and de Leon (2014), is the notion that "Policy designs have both material and symbolic (reputational or interpretive) effects on target populations that impact their attitudes and political participation. These effects occur through structuring of opportunities that shape life experiences and subtle messages about how government works and how they are likely to be treated" (p 116). In other words, mass opinion and behavior are not just determined by citizen backgrounds and preferences, but also by their interactions with government institutions (Mettler & Soss, 2004). In the context of LWEOs, when ICE apprehends large numbers of undocumented immigrants, most of whom would otherwise be characterized as law-abiding, the government provides a strong, not so subtle message that immigrants are not welcomed to participate in society like others in their community.

According to Campbell (2012), some policy characteristics affecting future mass opinion and behavior include the size of benefits, visibility and traceability of benefits, and concentration of beneficiaries. In the case of LWEOs, however, ICE distributes punishments instead of benefits to undocumented immigrants and their families. Since arrest in these cases ultimately leads to deportation, the punishment is severe. Further, ICE implements LWEOs in a surprise yet overt manner to maximize the number of arrests made, meaning the punishments are visibly and directly traceable to government action. Put together, there is a real incentive to avoid public institutions that could potentially share information with ICE. In support of this implication, recent empirical research focusing on a Midwestern Latino community finds immigrant families are more likely to

seek public assistance before an ICE worksite enforcement operation than afterwards (Lopez et al., 2016). Relatedly, LWEO punishments are likely concentrated in targeted communities. For example, ICE targeted Swift & Co. when it became aware of thousands of Social Security Numbers being misused for securing employment (Department of Homeland Security, 2006). Assuming that family and friends of immigrants in targeted communities live near each other, which is not unreasonable as evidence shows increasing residential separation between Hispanics and non-Hispanic whites in nonmetropolitan counties (Kandel & Cromartie, 2004), the geographic proximity of punishments therefore works to facilitate the spread of information through networks about the risks of public exposure. Related research on LWEOs and discriminatory immigration enforcement policies supports this implication. For example, Novak, Geronimus, and Martinez-Cardoso (2017) find that citizen and immigrant Latinas in Iowa were more likely to give birth to low birthweight infants following a 2008 LWEO in Postville, Iowa due to experiencing racialized stressors. Similarly, research from Vargas, Sanchez, and Valdez (2017) shows discriminatory immigration policies increase the sense of linked fates, or group identity, between Latino citizens and immigrants.

As mentioned before, a criticism of LWEOs believed to result in lasting harms on schools and school children is the perceived lack of concern from ICE to address potential humanitarian cases. This might be expected, however, because citizenship outcomes are often neglected by policymakers when crafting measures to assess program performance (Wichowsky & Moynihan, 2008). Citizenship outcomes, such as social trust in public institutions, are clearly important considerations given the multiple LWEO characteristics theoretically associated with negative policy feedback effects. For example, a primary function of public schools is to assimilate the children of immigrants into the broader community in order to forge common cultural norms and

build human capital, thus it is crucial for the sustainability of our democratic society that immigrant parents send their children to school. This requires immigrant parents to trust public schools and officials with their children. As trust from immigrants vulnerable to deportation towards public schools and officials is likely absent in the aftermath of LWEOs, it would therefore be reasonable to expect rates of absenteeism for their children to increase, which is concerning since prior research shows absences from school lowers academic performance for children (Gottfried, 2010; Morrissey, Hutchison, & Winsler, 2014), and especially for those identified as LEP (Gershenson, Jacknowitz, & Brannegan, 2017).

In addition to theoretical implications of policy feedback effects, this examination is also motivated by a technical report from the American Academy of Pediatrics documenting the dangers of exposure to toxic stress in early childhood (Shonkuff et al., 2012). For example, a child exposed to toxic stress, which occurs when there is strong or prolonged activation of her stress response system without supportive adult relationships and stable environments to provide buffers, can experience permanent changes to brain structure and function that make it more difficult to regulate stress physiology, learn new skills, and develop the capacity to make healthy adaptations to future adversity. In addition, early exposure to toxic stress can increase future risks of adopting unhealthy lifestyles and developing physical and mental illnesses, all of which can hinder future educational success for children. Unfortunately, children directly affected by LWEOs probably lack the supportive adult relationships and stable environments capable of mitigating the harmful effects of exposure to toxic stress. Furthermore, children of undocumented immigrants are likely exposed to multiple risk factors associated with poverty and assimilation difficulties that can compound stressful effects resulting from family fragmentation. It should not surprising then, when Capps et al. (2007) somberly state, “The combination of fear, isolation, and economic

hardship induced mental health problems such as depression, separation anxiety disorder, post-traumatic stress disorder, and suicidal thoughts" (p 4). Though troubling in itself, for the purposes of this examination these implications are concerning as research shows exposure to stress in school, family, or neighborhood settings negatively affects academic performance for low-income children (Morales & Guerra, 2006). Furthermore, research shows that children exposed to troubled peers in classroom settings, whom likely exhibit behavioral problems and psychological distress resulting from exposure to toxic stress, perform worse on reading and math tests compared to children not exposed to troubled peers (Carrell & Hoekstra, 2010). In sum, there is reason to believe LWEOs could still lower academic performance for directly affected children, and possibly other children, even if social trust is quickly restored to prevent increases in absenteeism rates.

2.3 Review of LWEO and Related Research

This examination is primarily informed by the two Urban Institute studies describing LWEO effects on learning environments in several targeted communities (Capps et al., 2007; Chaudry et al., 2010). As expected, both studies report that teachers observed significant increases in absenteeism for directly affected children immediately following the LWEOs, which was believed to cause academic performance to suffer for directly affected children. Capps et al. (2007) also make reference to lesson planning challenges for teachers in the aftermath of LWEOs because they did not know whether to prepare instruction for an entire class or for only a few children, so it is not unreasonable to think other children were at least somewhat affected as well. Along with absenteeism, the two Urban Institute studies emphasize how exposure to stress affected learning environments for children in targeted communities. For example, both reports state that teachers noticed shorter attention spans, psychological distress, and behavioral problems when directly affected children returned to school. In addition, teachers observed a pervasive sense of insecurity

and fear amongst children not directly affected by the LWEO concerning whether their parents would also be arrested. Thus, beyond managing difficulties associated with fluctuating classroom attendance, these reports indicate teachers were also contending with managing behavioral and mental health issues associated with exposure to toxic stress.

Fortunately, both Urban Institute reports mention that attendance rates stabilized after school officials made concerted efforts to inform worried families that ICE was not permitted on school premises, which allowed directly affected children to begin reestablishing normal routines associated with school and access to counseling services. In the follow-up study, Chaudry et al. (2010) note that most parents and teachers thought these efforts helped directly affected children recover academically. In sum, these Urban Institute reports provide ample reason to believe the LWEO in Cactus, TX disrupted learning environments for children and subsequently affected their academic performance, at least initially, with evidence supporting low social trust and exposure to toxic stress as potential mechanisms.

In addition to the Urban Institute reports focusing on LWEOs, this examination is also informed by research on the effects of immigration enforcement intensity and parent legal vulnerability to deportation on child educational outcomes. For example, Amuedo-Dorantes and Lopez (2017) create an interior immigration enforcement index using a combination of Omnibus Immigration Laws (OIL), 287(g) agreements, E-Verify, and Secure Communities (SC) to examine the relationship between immigration enforcement intensity and the likelihood that children with at least one noncitizen parent repeat grades or drop out of school. Using the October Supplement of the Current Population Survey and a DD approach, the authors find that increased police-based immigration enforcement (i.e., 287(g), OIL, and SC) raises the probability that Hispanic children between ages 6 and 13 with at least one noncitizen parent repeat a grade by 14 percent. The authors

find no negative effects from these policies on leaving school, nor do they find significant changes in outcomes associated with employment-based policies (i.e., E-Verify). Another related study from Brabeck and Xu (2010) examines the effect of parent legal vulnerability to deportation on child psychological and academic functioning. Surveying more than 100 parents in immigrant community organizations across the Northeast in 2009, the authors find that higher levels of parent legal vulnerability to deportation, as measured by their citizenship status and experience with deportation, predicts lower levels of perceived child well-being. Importantly, however, this finding does not specifically convey effects on academic performance since child well-being is defined using an index combining psychological and academic functioning.

Finally, research on community traumatic events informs this examination by showing how widespread chaos and stress affects child academic achievement in settings resembling LWEOs. Like terrorist attacks, mass shootings, and natural or man-made disasters, LWEOs can be defined conceptually as community traumatic events because they generally change the daily lives of survivors, regardless of the event location (Praetorius, 2006). These life changes, which may include the onset of depression, anxiety, post-traumatic stress disorder, and even suicide, can result from direct effects of experiencing or observing the event, or they can be indirect for those close to directly affected individuals. LWEOs fit this definition considering they suddenly remove significant numbers of parents from communities, which can lead to an enduring sense of fear in targeted communities. For example, a reporter in Worthington, MN described an important community religious holiday celebration taking place one year after OWT as "forever linked to the immigration raid since they both occurred on the same day, December 12. The gathering last Sunday in Worthington was part religious celebration, part painful memory. Some people cried when they talked about the immigration raid" (Steil, 2007).

Prior research on community traumatic events largely focuses on health outcomes (Green et al., 1991; Shannon et al., 1994; Halpern-Felsher & Millstein, 2002; Neria, Nandi, & Galea, 2008; Schuster et al., 2001), but there are a couple of studies examining effects on academic performance. For example, Gershenson and Tekin (2017) examine the effects of the "beltway" sniper shootings in 2002 using school-level proficiency rates in math and reading for Virginia public schools and find that proficiency scores on both subjects decreased by 2 to 3 percentage points for third graders in schools within five miles of a sniper shooting. In another example, Gershenson and Hayes (2017) examine the effects of exposure to civic unrest following the shooting of Michael Brown in Ferguson, MO using school-level proficiency rates in math and reading for Missouri public schools and find negative effects at both ends of the performance distribution; civic unrest caused a 6 to 7 percentage point decrease in students earning advanced scores in math and reading, and a 10 to 15 percentage point increase in students earning below basic scores.

In sum, the evidence reviewed in this section provides ample reason to believe the LWEO in Cactus, TX disrupted learning environments for children and subsequently affected their academic performance, at least initially. Importantly, while narratives of LWEO effects largely focus on directly affected children, these studies present some evidence suggesting there could be spillover effects on academic performance for other children. Further, in line with the theoretical motivations supplied by policy feedback and medical research, the evidence supports low social trust and exposure to toxic stress as potential explanations of LWEO effects.

This examination makes two contributions to existing research examining educational effects on children resulting from LWEOs and immigration enforcement policy in general. First, I conduct a methodologically rigorous examination of LWEO effects on academic performance

using standardized tests as the outcome of interest. This improves upon existing evidence from Capps et al. (2007) and Chaudry et al. (2010) that generally describe short-term effects on subjective measures of child academic performance (i.e., grades) because, while informative, findings drawn from retrospective interviews could suffer from multiple sources of bias that lead to inaccurate assessments of LWEO consequences. For example, assuming that teachers measure their efficacy in part by how quickly their students recover and adjust to classroom disruptions, LWEO effects could be understated to the extent socially desirable responses were provided to interviewers. The ability to simply recall accurate accounts of child exposure to LWEOs and its effects of subsequent academic performance is also concerning given the widespread chaos and trauma observed in communities following LWEOs. One could imagine that teachers might have unintentionally inflated the number of children affected by the LWEO or conflated its effects on academic performance with other contributing factors, both of which would result in inaccurate assessments of LWEO effects. In other words, I contribute to the literature on LWEO effects by eliminating these threats to internal validity through the use of objective academic performance measures and quasi-experimental methods. Further, using standardized tests that are administered to all children in TX to measure changes in academic performance allows for an examination of potential spillover effects and facilitates the comparison of findings to research on immigration enforcement intensity and community traumatic events. Lastly, I focus on changes in outcomes tied to state accountability assessments of district performance by using standardized tests instead of classroom grades, which can provide more useful information to policymakers about LWEO effects on schooling outcomes for children in targeted communities.

Second, I contribute to the literature documenting the effects of immigration enforcement policies on schooling outcomes by specifically focusing on worksite enforcement operations and

changes in academic performance. For example, Amuedo-Dorantes and Lopez (2017) examine policies with employment or police-based measures for enforcement, but worksite enforcement operations are different in that they combine both elements in an effort to provide a more comprehensive and targeted approach to immigration enforcement. Further, examining LWEOs places explicit emphasis on the most disruptive type of worksite enforcement actions. This is necessary to frame policy discussions in terms of how specific immigration enforcement policies are designed and implemented, which can then help further our understanding of policy feedback effects (Mettler & Soss, 2004). Finally, while these authors find that increasing immigration enforcement intensity results in lower levels of educational attainment for children of noncitizen parents, examining changes in standardized test proficiency rates contributes to our understanding of immigration enforcement effects on academic performance. For instance, third graders failing to meet state standard on subject tests in TX can still be socially promoted to the fourth grade; only in the fifth and eighth grades are children required to meet state standards for promotion to the next grade level.

3. DATA AND METHODOLOGY

This section describes the data and methodology used for this analysis. Section 3.1 describes the data used to measure academic performance and district-level characteristics for the sample, and its limitations. Section 3.2 explains the application of SCM to identify LWEO effects. Finally, Section 3.3 reports the weights and summary statistics produced by SCM for each sample used in this examination.

3.1 Description of the Data

I use publicly available data from the TEA Academic Excellence Indicator System to estimate LWEO effects on third grade proficiency rates for standardized tests in reading and math subjects

in Dumas ISD. This represents an ideal case to begin this line of investigation not only because this LWEO was part of the first major coordinated worksite enforcement operation implemented by ICE, but also because TX provides a wealth of publicly available and readily usable data to examine changes in district-level proficiency rates over time. Other states targeted for OWT either do not provide enough years of data prior to the LWEO to successfully implement SCM, or they do not provide readily usable data for LEP children (i.e., most likely directly affected by LWEOs).

This examination uses pooled cross-sectional data for academic years 2003 to 2010, where years correspond to the spring term (i.e., when standardized tests are administered). The analyses begin in 2003 since it is when the Texas Assessment of Knowledge and Skills (TAKS) was first administered to evaluate student learning instead of the Texas Assessment of Academic Skills. Fortunately, this still provides four years of pre-LWEO data since OWT occurred in the months prior to the 2007 administration of TAKS reading and math subject tests. Data for years 2008 to 2010 are used to estimate longer-run effects on younger children in Dumas ISD in 2007. Finally, I incorporate district-level student, staff, and teacher data from the National Center for Education Statistics (NCES) Elementary/Secondary Information System, which help SCM account for predictors of future academic performance. Details about the LWEO were gathered from The Washington Post (Moreno, 2007).

I measure academic performance using the percentage of children in a district scoring proficient on reading and math TAKS subject tests. The TEA provides these data for samples reflecting a wide variety of sociodemographic characteristics; I focus specifically on samples for all children, LEP children, Hispanic children, and white children. I use the sample of all children to estimate the overall LWEO effect, while the remaining samples estimate LWEO effects on children most and least likely to be directly affected by the LWEO. It is important for this

investigation to consider LEP children are typically Hispanic, but LEP is not a fixed status. This means children in these two samples will overlap to the extent that Hispanic students are LEP. Finally, I focus on outcomes for third graders since most children of undocumented workers are 10 years old or younger (Capps et al, 2007), and third grade is when children are first required to take TAKS reading and math subject tests.

While these data allow for examinations of LWEO effects on proficiency rates measured at the district-level, in an ideal case I would use disaggregated data that tracks individual children over time. However, the TEA does not make this data publicly available for privacy matters. This is a limitation since I do not know which children move over time, either to new districts in TX or out of the state entirely, which could hold different implications for policy recommendations. Importantly, however, if a child moves to a new school within the same district in a given academic year, perhaps due to new caregiving arrangements, her score is still included in the TEA district report. Nonetheless, this means estimated long-run LWEO effects should be interpreted cautiously due to the increased likelihood of selection bias resulting from changing compositions of children in Dumas ISD over time. In other words, I cannot be certain about the extent to which post-LWEO differences in proficiency rates are attributable to children in Dumas ISD in 2007 (i.e., those exposed to the LWEO). While these findings can still be valuable to policymakers since proficiency rates are used in formal assessments of school performance, it does limit the ability to identify the mechanisms driving LWEO effects.

3.2 Synthetic Control Method

To estimate LWEO effects on third grade proficiency rates in Dumas ISD, I need to identify a comparable district that was not exposed to the LWEO in order to establish a counterfactual explanation for what would have happened in Dumas ISD if ICE did not implement the LWEO.

While I could make this choice based on a set of observable characteristics (e.g., student, teacher, or staff characteristics), it is unlikely that any single district will closely resemble Dumas ISD on both observed and unobserved characteristics (e.g. quality of teachers and support staff). This can pose problems for comparative researchers since picking a control group insufficiently similar to Dumas ISD can lead to erroneous conclusions about LWEO effects. Therefore, instead of actively making this choice, I employ the SCM approach developed in Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010; 2015) that systematically creates a synthetic control group best resembling the characteristics of Dumas ISD. More specifically, SCM uses a transparent, data-driven algorithm to create a synthetic control group from multiple comparison districts, where all districts comprising the synthetic control group are assigned positive weighted averages that sum to one and are determined by their similarity to Dumas ISD with respect to proficiency rates observed prior to the LWEO and important predictors of academic performance. This results in a better counterfactual explanation for this examination than could be created using any single district or average of districts for comparison.

There are 1,191 districts reporting proficiency rates on reading and math TAKS subject tests in the sample. To create the synthetic control groups used for this examination, I follow the recommendation from Abadie, Diamond, and Hainmueller (2015) that researchers restrict the set of potential comparison units to a donor pool resembling the treated group to both improve SCM performance and limit biases associated with SCM applications on samples with many potential donors. As Dumas ISD is relatively small, rural, and serves students that are more Hispanic and LEP than the average district in TX, I use district size, student demographics, and urbanicity as restricting parameters. Notably, SCM includes only those districts with complete student performance data for the sample period in the donor pool. Appendix B reports the specific

restricting parameters and donor pool sizes for each synthetic control group approximating Dumas ISD in this examination.[5] These restricting parameters are generally similar to each other, but there is some variation due to cell size reporting requirements that result in uneven numbers of potential donors in the donor pool.

To help SCM create synthetic control groups similar to Dumas ISD I use a rich set of predictor variables associated with district-level sociodemographic characteristics, resources, and pre-LWEO proficiency rates. Selecting these predictors is done with the same logic as if I were selecting control variables for traditional regression analysis. For example, if an important predictor is omitted when applying SCM the consequence is an increased likelihood that the weights applied to potential donors will result in less credible counterfactuals, which could then lead to biased estimates of LWEO effects. To account for sociodemographic characteristics, I use the percent of students in the district that are female, Hispanic, white, eligible for free or reduced-priced lunch (FRPL), and LEP. I also include the total number of students in the district to account for factors associated with district size (e.g., resources available). To control for other important school and classroom inputs responsible for facilitating student success, I use district-level measures for the number of Full-Time Equivalent (FTE) teachers, staff, counselors, and student support staff. I also include the district-level pupil-teacher ratio. Finally, I use TAKS proficiency rates for years 2005 and 2006 to account for unobserved factors associated with pre-LWEO proficiency rates that could predict post-LWEO proficiency rates. This helps SCM produce counterfactuals matching Dumas ISD trends in proficiency rates leading up to the LWEO.

The main identification assumption for SCM to produce unbiased estimates of LWEO effects is no interference between groups (Abadie, Diamond, & Hainmueller, 2010). In other

[5] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

words, children in schools outside of Dumas ISD must not be affected by the LWEO. This may not be the case, however, because LWEOs are designed to spread fear widely (Thronson, 2008). For example, one local resident helping affected families in Cactus, TX stated that the LWEO also affected businesses in communities as far as 60 miles away in Amarillo, TX and Guyman, OK (VOA News, 2009). While schools are not businesses, this provides a reason to believe there could be interference between groups if parents elsewhere similarly kept their children from school to avoid risks associated with public exposure. Yet, even if LWEO effects were completely isolated to Dumas ISD there could still be interference in a different sense considering there were several other worksite enforcement operations in Texas around the same time as the LWEO. More specifically, as reported in Table 1, ICE conducted nine worksite enforcement operations in Texas in FY2006 and FY2007. While these worksite enforcement operations were presumably much smaller in magnitude and therefore not likely to cause the same disruption as the LWEO, the fact that other worksite enforcement operations happened elsewhere in Texas means interference cannot be ruled out completely. However, if there is interference then the consequence should be attenuated estimates of LWEO effects under the assumption that effects from spillovers or other worksite enforcement operations on non-Dumas ISD children in the synthetic control groups would be in the same direction as LWEO effects on children in Dumas ISD.

[Insert Table 1 About Here]

3.3 SCM Weights and Summary Statistics

Appendix C reports the SCM weights applied to each district creating the synthetic control groups used for this investigation.[6] As an example, the synthetic control group approximating math proficiency rates for the sample of all children in Dumas ISD is a weighted average of Channelview

[6] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

ISD (0.771) and Valley View ISD (0.229), with all 31 remaining districts in the donor pool weighted zero. For the synthetic control group approximating reading proficiency rates for the sample of all children in Dumas ISD, SCM applies relatively larger weights to Elgin ISD (0.384), Channelview ISD (0.346), and Winfield ISD (0.146), with four more districts receiving smaller weights and all other remaining donors weighted zero. Other synthetic control groups used for this examination are constructed from about the same numbers of donor districts.

Table 2 compares values for predictors listed in Section 3.2 for the sample of all children in Dumas ISD, the synthetic control groups approximating their reading and math proficiency rates, and all districts in the donor pools. Comparisons for samples of children identified as LEP, Hispanic, and white are reported in Appendix D.[7] With few exceptions, results show synthetic control groups are more similar to Dumas ISD than the average district in the donor pools. For example, a quarter of Dumas ISD children before the LWEO are LEP compared to a third donor districts, and SCM produces counterfactuals with more identical proportions of LEP children (0.25 for reading and 0.29 for math). This pattern holds for other sociodemographic predictors as well. Regarding district resources, however, while SCM still creates a synthetic control group remarkably similar to Dumas ISD when approximating reading proficiency rates, the synthetic control group approximating math proficiency rates is larger with more children, teachers, and staff, but also fewer teachers available per child. Thus, while there are more total resources available in this case to support academic success, this is somewhat negated by there being fewer resources available per child. Finally, examining the RMSPEs of pre-LWEO reading and math proficiency shows the synthetic control groups better track pre-LWEO proficiency rates than donor districts, which is an important reason for favoring SCM over simple comparative analyses. In

[7] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

sum, Table 2 offers descriptive evidence that SCM indeed produces counterfactual trends of Dumas ISD reading and math proficiency rates necessary to provide convincing estimates of LWEO effects on children in a targeted community.

[Insert Table 2 About Here]

4. RESULTS

This section describes the SCM results for LWEO effects in Dumas ISD. Section 4.1 explains the intuition for interpreting SCM output and the primary findings. Section 4.2 describes the process for assessing statistical significance using SCM and its results. Section 4.3 then describes the process for conducting SCM falsification tests and its results to assess the robustness of primary findings. Section 4.4 concludes with an examination of potential mechanisms.

4.1 Main Results

Unlike output from traditional regression analysis that conveys findings through numbers, SCM produces results in the form of graphs. The intuition for identifying LWEO effects on proficiency rates, however, resembles standard DD research designs. To demonstrate, a DD approach would estimate LWEO effects by taking the difference of the differences in proficiency rates between Dumas ISD and synthetic control groups before and after the LWEO, all while controlling for potentially confounding factors associated with the LWEO and proficiency rates that could bias results. Analogously, as SCM creates synthetic control groups with pre-LWEO proficiency rates similar to Dumas ISD, post-LWEO differences in proficiency rates therefore represent the LWEO effect. Further, because the synthetic control group resembles Dumas ISD in both observed and unobserved factors before the LWEO, alternative explanations for the results that could arise from these differences are less likely to be true.

Figure 1 displays district-level reading and math proficiency rates on TAKS subject tests administered from 2003 to 2010 for samples of all children, LEP children, Hispanic children, and white children. In each graph, the solid trend line represents Dumas ISD, and the dotted line represents the counterfactual explanation (i.e., what would have happened in Dumas ISD if the LWEO did not occur). Graphs presented on the left-hand side show reading proficiency rates while those on the right-hand side show math proficiency rates. All graphs feature a vertical line marked on 2006 to indicate when we would expect to see LWEO effects to begin appearing.

[Insert Figure 1 About Here]

Before discussing post-LWEO differences in proficiency rates, a general comment about RMPSE is warranted. If pre-LWEO differences between Dumas ISD and corresponding synthetic control groups are large, then it would be more likely that differences observed post-LWEO reflect poor SCM application instead of the LWEO (Abadie, Diamond, & Hainmueller, 2010; 2015). Referring back to Table 2, however, this should not be an issue since RMSPEs are very small (reading<0.01; math=0.99). This is visually evident in each graph presented in Figure 1; synthetic control group proficiency rates track Dumas ISD proficiency rates closely before the LWEO, especially for TAKS reading subject tests. Therefore, I can be reasonably confident that post-LWEO differences in proficiency rates are the result of the LWEO and not poor SCM applications.

The top set of graphs in Figure 1 present evidence of negative LWEO effects on proficiency rates for the sample of all third-graders in Dumas ISD. More specifically, the average estimated LWEO effect on reading and math proficiency rates is -4.1 and -5.9 percentage points, respectively. It is important to look beyond averages, however, as the results show variation in estimated LWEO effects over time for different cohorts of children exposed to the LWEO. For example, the estimated LWEO effect on reading proficiency rates is -11.7 percentage points in

2007, -0.1 percentage points in 2008, -5.8 percentage points in 2009, and +1.3 percentage points in 2010. Similarly, the estimated LWEO effect on math proficiency rates is -13.4 percentage points in 2007, -2.4 percentage points in 2008, -6.0 percentage points in 2009, and -1.9 percentage points in 2010. Altogether, these results suggest there are immediate effects on third graders exposed to the LWEO, and long-run effects for first graders exposed to the LWEO lasting two years. These estimated LWEO effects are large in size, representing 13.8 and 6.7 percent of synthetic control group reading proficiency rates, respectively, and 15.7 and 7.0 percent of synthetic control group math proficiency rates, respectively.

Remaining graphs in Figure 1 show that not all children are equally affected by the LWEO. For example, estimates for immediate LWEO effects on reading proficiency rates for the samples of LEP, Hispanic, and white children are -23.1 percentage points, -18.0 percentage points, and -0.7 percentage points, respectively. Similarly, for math proficiency rates these estimates are -13.2 percentage points, -11.4 percentage points, and +1.8 percentage points, respectively. Clearly, for both TAKS subject tests the largest estimated immediate LWEO effects are associated with LEP and Hispanic children, which is expected since they are more likely than white children to be directly affected by the LWEO. This finding also holds when examining long-run LWEO effects. For instance, the estimated LWEO effects on reading and math proficiency rates for the sample of LEP children are -2.3 and -12.2 percentage points in 2008, -5.2 and -4.6 percentage points in 2009, and +4.8 and +2.3 percentage points in 2010. Likewise, the estimated LWEO effects for the sample of Hispanic children are -4.5 and -1.6 percentage points in 2008, -8.7 and -6.2 percentage points in 2009, and -2.5 and +6.44 percentage points in 2010. Then, for the sample of white children the estimated LWEO effects are -5.2 and -0.6 percentage points in 2008, -0.3 and +3.4 percentage points in 2009, and +1.9 and +9.5 percentage points in 2010. While the substantively large and

negative estimates of LWEO effects are mostly associated with LEP and Hispanic children, it is worth noting that the estimated LWEO effects on reading proficiency rates in 2008 show white children are most affected. This is an odd finding, however, as this implies spillover effects are greater than direct effects for second graders exposed to the LWEO after one year.

There are two important points to consider when evaluating the validity of these findings. First, results show negative LWEO effects on reading and math proficiency rates in Dumas ISD are largest in 2007, which is expected since this is when the LWEO was presumably most disrupting for children in Dumas ISD. There are relatively large and negative LWEO effects in 2009 as well, suggesting the LWEO affected performance on TAKS subject tests for first graders exposed to the LWEO, but importantly these estimates are always smaller than those in 2007. While it is somewhat puzzling to then see no substantive LWEO effects in 2008, the general point stands that it would be surprising for long-run effects to be larger than immediate effects given accounts from teachers that directly affected children generally recovered academically after reestablishing normal routines associated with school (Chaudry et al., 2010). Due to limitations of the data, however, it must be repeated that I cannot be certain about the extent to which first and second graders exposed to the LWEO contribute to estimated LWEO effects on third grade proficiency rates in later years, especially for LEP children since LEP is not a fixed trait. Second, results for nearly every outcome show the LWEO negatively affected LEP and Hispanic children, but not white children. While it is somewhat surprising to see mostly no LWEO effects for white children given the disruptions to learning environments described in Urban Institute reports (Capps et al., 2007; Chaudry et al., 2010), that the negative LWEO effects of substantive significance are usually associated with LEP and Hispanic children is expected since they are presumably more likely to have a parent legally vulnerable to deportation, which research shows negatively affects

child well-being (Brabeck & Xu, 2010). Furthermore, research shows racialized stressors associated with discriminatory immigration policies and LWEOs produce spillover effects amongst Hispanic adults (Vargas, Sanchez, & Valdez, 2017), but not white adults (Novak, Geronimus, & Martinez-Cardoso, 2017).

Overall, Figure 1 presents strong evidence of negative LWEO effects on reading and math proficiency rates for third graders in Dumas ISD exposed to the LWEO compared to children in a synthetic control group otherwise similar to Dumas ISD on important observable and unobservable characteristics but not exposed to the LWEO. Consistent with prior research on community traumatic events (Gershenson & Tekin, 2017; Gershenson & Hayes, 2017), estimated LWEO effects are larger on average for math proficiency rates compared to reading proficiency rates, perhaps because children are more capable of practicing reading skills than math skills when kept home from school (Currie & Thomas, 2001). These findings are also consistent with Amuedo-Dorantes and Lopez (2017), and importantly reveal that children might not have adjusted to disruptions from the LWEO as quickly as claimed by those interviewed in the Urban Institute reports (Capps et al., 2007; Chaudry et al., 2010).

4.2 Inference Tests

SCM does not allow for inferential techniques associated with traditional regression analysis. Instead, I perform a test recommended by Abadie, Diamond, and Hainmueller (2010) to assess whether SCM results are likely causal. Specifically, I create distributions of placebo effects where each donor district is separately treated as if it experienced the LWEO. If there is a high probability that a placebo effect is larger than the LWEO effect on Dumas ISD, then the main results in Figure 1 are more likely spurious than causal. However, I do not show placebo trends with RMSPEs significantly larger than the Dumas ISD RMSPE since the resultant placebo effects could be

attributed to poor SCM application and therefore lead to inaccurate assessments for inference (Abadie, Diamond, & Hainmueller, 2010).[8] Notably, I set the cutoff for placebo RMSPEs at 1.0 when evaluating estimated LWEO effects on reading proficiency rates for the sample of all children and LEP children, while all other cutoffs are set at three times the Dumas ISD RMSPE.[9]

Evidence presented in Figure 2 generally supports causal interpretations for the estimated immediate LWEO effects shown in Figure 1. For example, there are no placebo effects in 2007 on math proficiency rates larger than the estimated LWEO effects for the samples of all children and children identified as LEP and Hispanic. This is also true for placebo effects on reading proficiency rates for the samples of all children and Hispanic children. Thus, only for LEP reading proficiency rates is there a placebo effect observed in 2007 larger than the estimated LWEO effect. In this instance, the probability is one in seven, or 14.3 percent, which falls just beyond the traditional bounds to be considered statistically significant. In contrast, little evidence presented in Figure 2 supports causal interpretations of estimated long-run LWEO effects. More specifically, the respective probabilities that a placebo effect is as large as the estimated LWEO effect on reading and math proficiency rates in 2009 is 20 and 23.5 percent for the sample of all children, 42.9 and 41.7 percent for the sample of LEP children, and 22.2 and 44.4 percent for the sample of Hispanic children. Clearly, none of these probabilities come close to the threshold required for statistical significance, which might not be too surprising given the limitations of the data with respect to tracking individual children over time in the first-grade cohort. It is worth noting, however, that only one of the eight placebo effects on reading proficiency rates for the sample of white children

[8] Graphs showing the full distribution of placebo effects can be found in Appendix E. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

[9] RMSPE values are very small for synthetic control groups approximating reading proficiency rates for all children and LEP children. Therefore, I use larger values for these RMSPE cutoffs, which are still reasonably small, to better support these inference tests.

in 2008 is larger than the estimated LWEO effect. This translates to a probability of 12.5 percent, which falls just beyond the threshold of statistical significance.

[Insert Figure 2 About Here]

4.3 Leave-one-out Robustness Checks

A primary concern for using SCM in this examination is that a single donor district used to create the synthetic control group is responsible for the estimated LWEO effect. In other words, I might be worried that the large weight assigned to Elgin ISD (0.384) produces the estimated -11.7 percentage point LWEO effect on reading proficiency rates in 2007 for the sample of all children instead of the LWEO. To determine whether this is the case, I re-estimate the SCM models creating the graphs shown in Figure 1 where donor districts receiving weights greater than 0.1 are dropped iteratively from the donor pool. If the leave-one-out counterfactual trends still show the LWEO negatively affected proficiency rates for children in Dumas ISD, then I can be more confident that the main results are due to the LWEO instead of the SCM algorithm. Focusing on the estimated LWEO effects determined to be statistically significant or near marginal significance in Figure 2, Figure 3 graphs show the differences in proficiency rates between Dumas ISD and leave-one-out synthetic control groups in some cases shrink, but never close completely. As such, I can be more confident that immediate LWEO effects on proficiency rates estimated for the samples of all children and children identified as LEP and Hispanic in the third grade exposed to the LWEO, as well as the long-run LWEO effect on reading proficiency rates estimated for the sample of white children in the second grade exposed to the LWEO, are more likely due to the LWEO and not the particular combination of districts used to create the synthetic control groups.

[Insert Figure 3 About Here]

4.4 Potential Mechanisms

As evidence shows the LWEO negatively affected reading and math proficiency rates for third graders in Dumas ISD in 2007, I now test for potential causes of these effects. While the motivations for this examination point to low social trust and exposure to toxic stress as explanations for why LWEOs would affect proficiency rates for young children in targeted communities, without psychometric data I can only examine mechanisms associated with social trust. For example, low social trust could explain the main results to the extent children are kept home from school and, as mentioned before, research shows absenteeism harms academic performance for children (Gottfried, 2010; Morrissey, Hutchison, & Winsler, 2014; Gershenson, Jacknowitz, & Brannegan, 2017). Or, as newspaper accounts mention numerous families leaving Cactus, TX after the LWEO (The Dallas Morning News, 2008), lower proficiency rates might instead occur if high performing children left Dumas ISD in higher rates after the LWEO than low performing children. However, it must be repeated that I cannot directly assess the extent to which attrition occurs according to academic ability because the data do not identify individual children. Nonetheless, if obvious changes in measures of social trust in the aggregate do occur, then there would be some justification for it to be identified as a potential mechanism. To assess the extent to which declining social trust explains the results, I examine changes in LEP attendance rates, TAKS participation rates, and enrollments for Dumas ISD. I focus on LEP children in particular because the main results show they are most affected by the LWEO. Importantly, NCES does not separate LEP enrollments by grade level, so these values reflect LEP enrollments for grades K through 12. Table 3 displays these results.

[Insert Table 3 About Here]

Descriptive evidence presented in Table 3 provides little support for declining social trust as a cause of the estimated LWEO effects in 2007 shown in Figure 1. Regarding absenteeism, for

example, results show attendance rates for LEP children in Dumas ISD decrease by 0.5 percent between 2006 and 2007, meaning LEP children did not miss significantly more school days in the LWEO year compared to the previous year. Attendance rates span the entire academic year, though, so it is possible that increased absenteeism amongst directly affected children in the aftermath of the LWEO would not be observed if their attendance rates later increased. This seems plausible since TAKS participation rates for LEP children in Dumas ISD are highest in 2007. In other words, despite being administered in the months after the LWEO, there were higher proportions of LEP children enrolled in Dumas ISD attending school and taking TAKS subject tests in 2007 compared to the same period in previous years. While unexpected, this could be due to the concerted efforts made by school officials to get directly affected children back into classrooms after the LWEO (Chaudry et al., 2010).

Examining changes LEP enrollments, results show 217 fewer children in 2007 compared to 2006 in Dumas ISD. While this points to the composition of children as cause for the estimated immediate LWEO effects shown in Figure 1, this result is misleading because enrollments are counted in October. Put differently, the decline in LEP enrollments for Dumas ISD in 2007 occurred two months before the LWEO. Looking at changes in third and fourth grade enrollments for Dumas ISD suggests this decline in LEP enrollments would likely be irrelevant anyhow. For example, there are no corresponding drops in third grade enrollments from 2007 to 2008, nor between third grade enrollments in 2007 and fourth grade enrollments in 2008. Even with the limitations of the data, if the LWEO caused young LEP children to leave Dumas ISD, I would have expected for there to be larger enrollment declines for young children in Dumas ISD in 2008 compared to 2007, but this did not happen. Instead, it could be that older LEP children in Dumas

ISD left school to find employment. For example, labor force and employment levels for Moore County, TX are relatively stable from 2003 to 2005, then increase through 2009 (Appendix F).[10]

5. DISCUSSION AND IMPLICATIONS FOR POLICY AND FUTURE RESEARCH

Estimating LWEO effects on child academic performance is important because unlike mass shootings, terrorist attacks, or natural disasters, worksite enforcement operations are the result of government action. From this examination, I provide evidence that a LWEO in Cactus, TX lowered proficiency rates in 2007 (i.e., the year of the LWEO) for third graders in Dumas ISD by 11.7 percentage points on the TAKS reading subject test and 13.4 percentage points on the TAKS math subject test. These LWEO effects are estimated using SCM, which compares proficiency rates for children in Dumas ISD exposed to the LWEO against children in a synthetic control group created from a weighted average of districts in Texas not exposed to the LWEO that is similar to Dumas ISD on important pre-LWEO observable and unobservable factors. Importantly, this means the results are unlikely to be confounded by pre-LWEO differences between groups. When compared to previous research, these estimated LWEO effects on proficiency rates are larger than those associated with other community traumatic events like random shootings or civic unrest (Gershenson & Tekin, 2017; Gershenson & Hayes, 2017), and the results are consistent with evidence showing increasing immigration enforcement intensity lowers educational attainment for children with at least one noncitizen parent (Amuedo-Dorantes & Lopez, 2017).

Additional analyses reveal that not all children are equally harmed by the LWEO. Specifically, a comparison of estimated LWEO effects in 2007 shows the LWEO adversely affected reading and math proficiency rates for LEP children and Hispanic children, whom are more likely to have parents vulnerable to deportation, but not white children. I find little evidence

[10] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi- bin/jhome/34787.

to support absenteeism or changing compositions of children in Dumas ISD as potential causes of these effects. As this suggests declining social trust in targeted communities is not a likely cause of these LWEO effects, a mechanism identified from implications associated with policy feedback (Mettler & Soss, 2004; Campbell, 2012), it might therefore be more likely the cause is due to exposure to toxic stress, of which the effects are well-established in the medical field (Shonkuff et al., 2012). Interestingly, despite there being no support for causal interpretations of estimated long-run LWEO effects for children identified as LEP and Hispanic, there is suggestive evidence the LWEO adversely affected reading proficiency rates for second grade white children exposed to the LWEO lasting one year. This is an unexpected finding, but should be interpreted cautiously considering the aggregate nature of the data limits the ability to attribute differences in proficiency rates in 2008 to children exposed to the LWEO in 2007. For example, it could be that more low-performing white children moved to Dumas ISD in 2008, perhaps due to new employment opportunities, compared to other districts in the synthetic control group.

In conclusion, as advocated by Wichowsky and Moynihan (2008), these findings suggest it would be prudent for policymakers to more carefully consider citizenship outcomes when assessing the rationale for changing ICE worksite enforcement strategy, not just potential efficiency gains and increases in the number of arrests and fines resulting from worksite enforcement operations. Thus, even as comprehensive policy solutions to prevent document fraud and unauthorized employment of immigrants in the US are necessary for the federal government to maintain the integrity of its border control efforts, keep the public safe, and ensure jobs and public resources are available for citizens in need, I provide compelling and empirically verifiable evidence that reemphasizing the use of LWEOs would be unwise if policymakers care about minimizing harms to schools and school children. Instead, given that prior research shows

immigration enforcement policies specifically targeting the hiring practices of employers (i.e., E-Verify) do not harm young children of likely undocumented immigrants (Amuedo-Dorantes & Lopez, 2017), most of whom are likely US citizens (Passel & Taylor, 2010), it would be better for ICE to maintain the priorities set by the Obama administration. However, because it is unreasonable to preclude ICE from ever planning and implementing worksite enforcement operations, further research should investigate the relationship between effects from worksite enforcement operations on young children and the extent to which ICE follows its guidelines for identifying humanitarian concerns in targeted communities. ICE may now consider these guidelines when planning and implementing smaller worksite enforcement operations, but this likely matters only to the extent recommended actions are followed.

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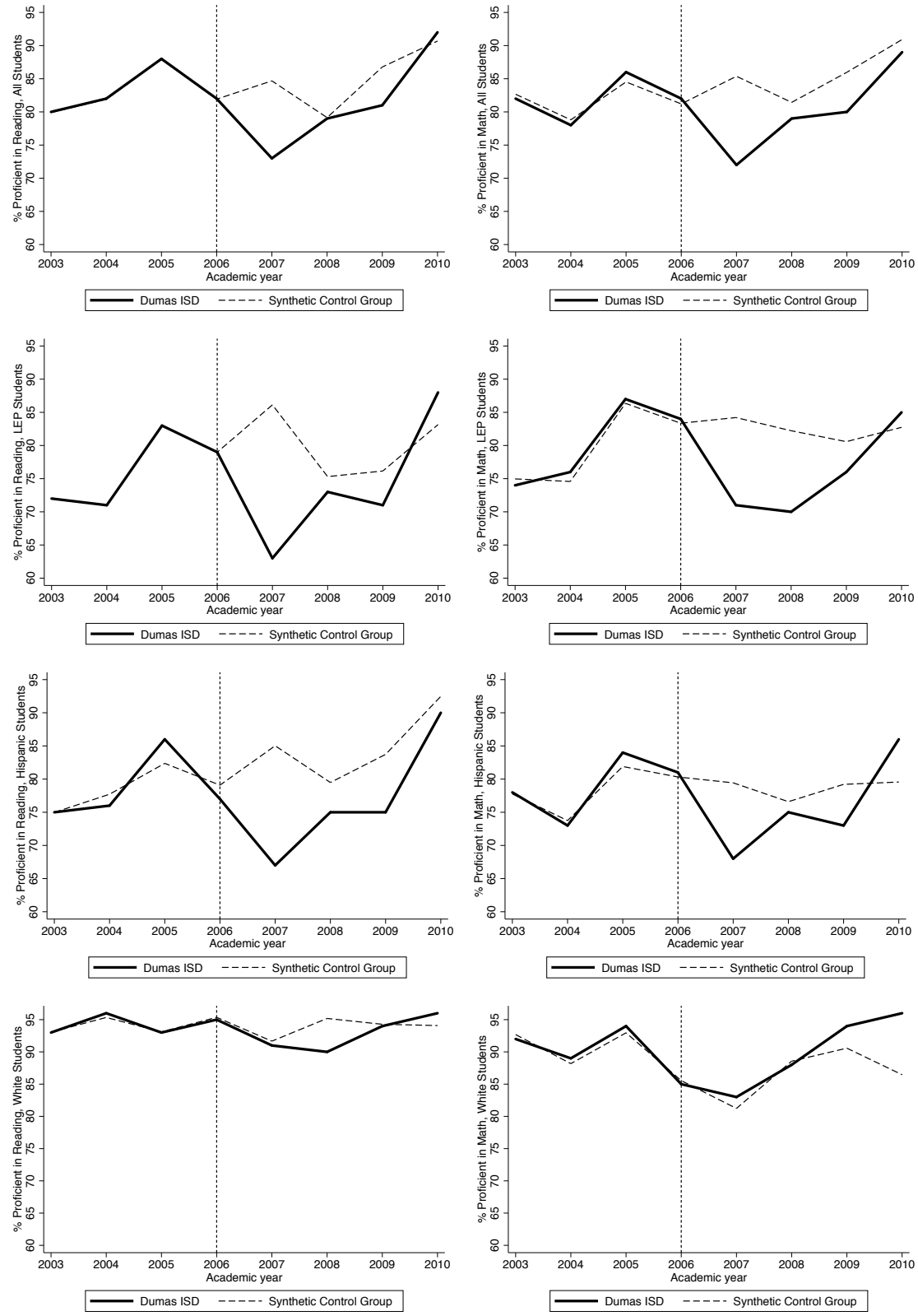


Figure 1. LWEO effect on third grade proficiency rates for all children, LEP children, Hispanic children, and white children in Dumas ISD, years 2003-2010.

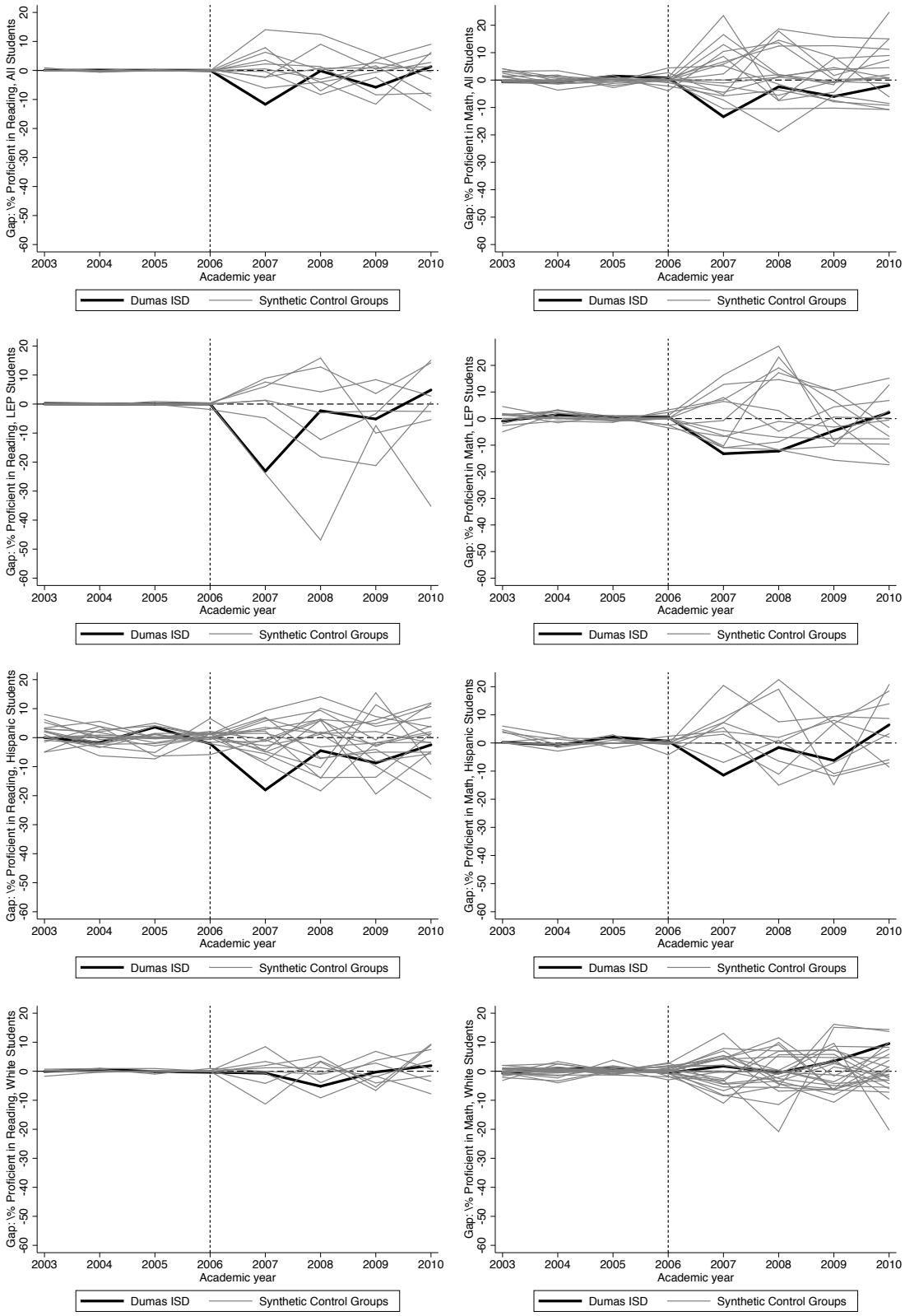


Figure 2. Placebo tests for statistical inference.

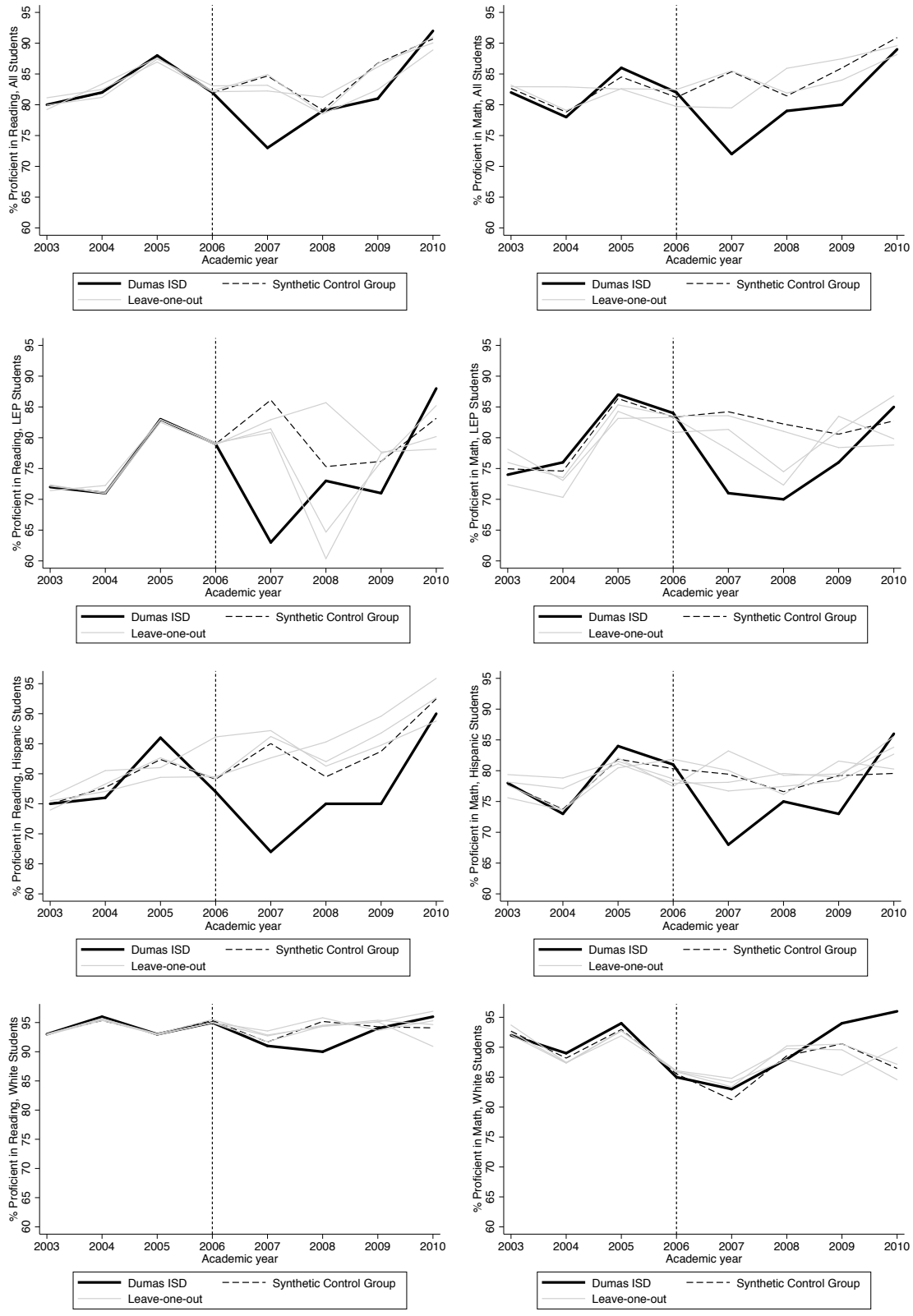


Figure 3. Leave-one-out robustness checks.

Table 1. Location and number of search warrants issued for worksite enforcement operations in Texas for ICE fiscal years 2004-2010

Field Office	ICE Fiscal Year	Business Search Warrants Issued
Alpine, TX	2004	1
Dallas, TX	2004	1
Galveston, TX	2004	5
Harlingen, TX	2004	1
Harlingen, TX	2005	4
El Paso, TX	2005	8
Amarillo, TX	2006	1
Austin, TX	2006	1
Houston, TX	2006	1
San Angelo, TX	2006	2
Amarillo, TX	2007	1
Houston, TX	2007	1
Lubbock, TX	2007	4
Dallas, TX	2008	3
El Paso, TX	2008	4
Houston, TX	2008	1
Houston, TX	2009	1
Midland, TX	2009	1
San Antonio, TX	2009	1
Dallas, TX	2010	2
Houston, TX	2010	1

Notes. Information obtained from a Freedom of Information Act Request.

Table 2. Pre-LWEO summary statistics for the sample of all children for Dumas ISD, synthetic control groups, and all potential donor districts.

	Reading			Math	
	Dumas ISD	Synthetic Control Group	Donor Pool	Synthetic Control Group	Donor Pool
Percent Female	0.48	0.48	0.48	0.48	0.49
Percent Hispanic	0.67	0.58	0.83	0.66	0.88
Percent White	0.30	0.30	0.11	0.20	0.07
Percent Eligible for FRPL	0.57	0.57	0.49	0.50	0.48
Percent LEP	0.25	0.25	0.33	0.29	0.34
Total Number of Students	4,118.50	4,507.84	2,638.32	6,608.46	2,678.73
Number of FTE Teachers	297.83	283.87	176.54	395.49	177.89
Pupil-Teacher Ratio	13.80	14.87	14.09	16.60	14.32
Total Number of Staff	581.80	606.40	407.74	855.26	415.17
Total Number of Counselors	8.10	9.53	6.59	14.53	6.76
Total Student Support Staff	6.25	5.93	3.40	7.74	3.45
Percent Proficient (2005) Reading	88.00	87.91	82.85		
Percent Proficient (2006) Reading	82.00	81.92	84.73		
Percent Proficient (2005) Math	86.00			84.52	70.54
Percent Proficient (2006) Math	82.00			81.21	75.25
RMSPE		<0.01		0.99	

Notes. Corresponding summary statistics for LEP children, Hispanic children and white children are reported in Appendix C.

Table 3. Dumas ISD values for potential mechanisms of LWEO effects.

	2003	2004	2005	2006	2007	2008	2009	2010
LEP Attendance Rate	97.10	96.90	96.90	96.50	96.00	95.70	96.40	96.10
LEP TAKS Participation Rate	79.80	85.70	90.90	88.20	92.90	80.60	65.40	57.70
LEP Student Enrollment	1,062	1,052	987	992	775	987	1,143	1,278
Third Grade Enrollment	305	302	313	315	314	324	336	325
Fourth Grade Enrollment	311	290	299	307	294	303	336	325

Notes. Student enrollments are measured in October of the Fall term. Attendance rates are measured across the school year where the denominator is the total number of days of membership in the district. LEP student enrollments span grades K through 12.

Appendix A. Total number of removals (000s) by Area of Responsibility

Area of Responsibility	FY 03	FY 04	FY 05	FY 06	FY 07	FY 08	FY 09	FY 10	FY 11	FY 12
Total	157.1	175.1	180.2	207.8	291.1	369.2	389.8	392.9	396.9	409.8
Atlanta	3.1	3.6	4.1	5.2	11.3	18.6	18.8	20.3	23.0	19.2
Baltimore	0.8	0.9	0.9	1.0	1.1	0.8	0.7	0.9	1.8	1.7
Boston	2.3	2.7	2.6	2.9	3.6	4.1	3.2	3.0	3.3	3.7
Buffalo	1.4	1.6	1.9	2.4	2.9	3.5	2.9	2.9	3.5	3.2
Chicago	5.2	6.6	6.8	7.4	9.1	11.6	9.8	10.3	11.8	10.3
Dallas	5.3	6.6	6.8	7.4	13.7	18.0	19.2	16.1	15.9	14.8
Denver	3.3	3.2	3.1	3.9	5.7	6.3	7.4	6.6	5.6	4.5
Detroit	1.8	2.2	2.4	3.2	5.1	8.0	8.4	8.1	7.3	5.9
El Paso	9.4	10.4	11.6	17.4	19.2	17.9	19.3	21.3	36.2	48.8
Houston	11.3	9.0	6.8	8.5	13.9	17.3	21.2	21.6	20.5	18.5
Los Angeles	12.7	12.9	10.5	13.3	21.0	24.2	25.5	23.9	24.8	21.0
Miami	8.0	7.5	7.7	7.2	9.3	13.6	16.5	15.3	16.6	12.4
New Orleans	4.5	4.5	3.5	4.5	9.9	14.8	15.5	15.1	15.4	14.2
New York City	1.7	2.7	3.1	3.4	2.7	2.2	2.4	2.0	3.5	3.4
Newark	3.3	3.0	3.1	3.1	3.4	4.5	5.1	5.5	5.3	5.7
Philadelphia	4.1	3.7	3.4	3.7	5.6	5.5	6.4	6.6	6.7	7.0
Phoenix	27.2	35.6	42.5	39.9	44.7	76.5	81.5	92.6	56.2	39.6
Salt Lake City	3.4	3.4	3.7	3.6	6.0	6.9	8.4	7.7	6.6	6.0
San Antonio	10.8	14.5	22.8	35.3	53.4	55.2	58.1	55.1	63.1	93.7
San Diego	21.6	23.6	17.1	16.9	23.9	24.5	23.2	18.1	33.0	46.4
San Francisco	6.6	7.4	6.1	7.3	12.1	17.2	17.2	21.4	19.1	14.5
Seattle	4.6	4.3	4.4	5.3	7.8	10.9	10.8	9.8	7.6	6.7
St. Paul	3.5	3.4	3.2	3.2	4.2	5.3	6.4	5.9	5.7	4.8
Washington	1.2	1.6	1.8	1.9	1.5	2.0	1.9	1.8	2.8	3.6
NCATC	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	1.5	0.5

Notes. Information obtained online from ICE FOIA library. NCATC stands for National Criminal Analysis and Targeting Center

Appendix B. Details for restricting parameters and donor pool size.

Sample	Parameter Values	Donor Pool Size
All children	Total students in district < 10,000; Percent LEP > 10; Percent Hispanic > 30; Percent White < 50; Not located in a large city.	Reading=33; Math=34
LEP children	Total students in district < 10,000; Percent LEP > 5; Percent Hispanic > 50; Not located in a large city.	Reading=33; Math=35
Hispanic children	Total students in district < 10,000; Percent LEP > 5; Percent Hispanic > 50; Percent Hispanic < 80; Not located in a large city.	Reading=20; Math=22
White children	Total students in district < 10,000; Percent LEP > 5; Percent Hispanic > 20; Percent White < 50; Not located in a large city.	Reading=23; Math=35

Notes. Donor districts receiving positive weights in SCM analyses are listed in Appendix C.

Appendix C. List of donor districts receiving positive SCM weights.

Sample	TAKS Subject	
	Reading	Math
All children	Elgin ISD=.384 Channelview ISD=.346 Winfield ISD=.146 Los Fresnos CISD=.045 Roma ISD=.038 Anthony ISD=.029 Presidio ISD=.011	Channelview ISD=.771 Valley View ISD=.229
LEP children	Muleshoe ISD=.393 San Marcos CISD=.200 Channelview ISD=.149 Los Fresnos CISD=.079 Spearman ISD=.074 Floyada ISD=.044 La Villa ISD=.019	Channelview ISD=.492 Denver City ISD=.224 Valley View ISD=.183 Muleshoe ISD=.066 Hereford ISD=.025 Kermit ISD=.009
Hispanic children	Channelview ISD=.473 Floyada ISD=.325 Friona ISD=.202	Channelview ISD=.377 Reagan County ISD=.233 Muleshoe ISD=.197 Schleicher ISD=.149 San Marcos CISD=.043
White children	San Marcos CISD=.325 Diboll ISD=.310 Palestine ISD=.143 Everman ISD=.111 Elgin ISD=.074 Terrell ISD=.037	Everman ISD=.479 Center ISD=.229 Terrell ISD=.199 Lufkin ISD=.092

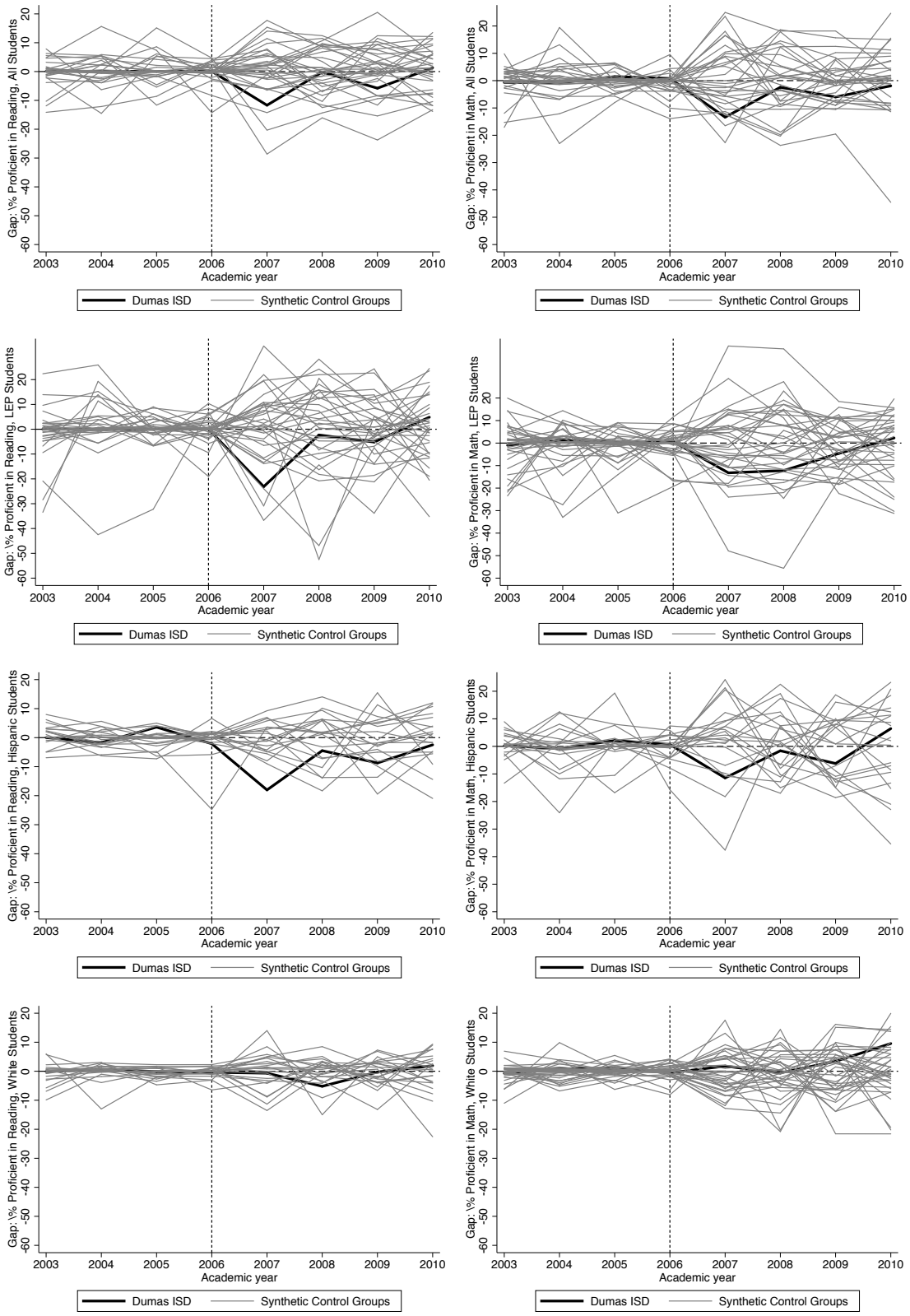
Notes. Weights shown may not sum to 1 due to rounding.

Appendix D. Summary statistics for samples of children identified as LEP, Hispanic, and white for Dumas ISD, synthetic control groups, and donor pools.

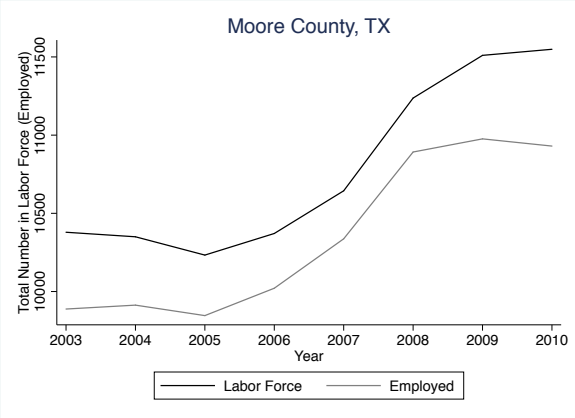
	Reading			Math	
	Dumas ISD	Synthetic Control Group	Donor Pool	Synthetic Control Group	Donor Pool
Panel A: LEP Children					
Percent Female	0.48	0.49	0.49	0.49	0.49
Percent Hispanic	0.67	0.69	0.86	0.67	0.86
Percent White	0.30	0.26	0.12	0.24	0.12
Percent Eligible for FRPL	0.57	0.59	0.50	0.52	0.51
Percent LEP	0.25	0.16	0.27	0.25	0.28
Total Number of Children	4,118.50	3,902.42	2,911.62	4,842.19	2,775.00
Number of FTE Teachers	297.83	261.58	195.94	297.71	188.65
Pupil-Teacher Ratio	13.80	13.79	14.20	15.50	14.08
Total Number of Staff	581.80	562.87	446.64	641.01	435.81
Total Number of Counselors	8.10	8.65	7.49	10.79	7.19
Total Student Support Staff	6.25	5.84	3.58	5.87	3.49
Percent Proficient (2006) Reading	79.00	78.99	76.97		
Percent Proficient (2005) Reading	83.00	82.99	73.67		
Percent Proficient (2006) Math	84.00			83.36	68.54
Percent Proficient (2005) Math	87.00			86.36	64.69
RMSPE		<0.01		0.94	
Panel B: Hispanic Children					
Percent Female	0.48	0.48	0.49	0.48	0.49
Percent Hispanic	0.67	0.64	0.65	0.62	0.65
Percent White	0.30	0.26	0.29	0.30	0.30
Percent Eligible for FRPL	0.57	0.65	0.64	0.57	0.62
Percent LEP	0.25	0.18	0.15	0.16	0.15
Total Number of Children	4,118.50	4,193.77	1,899.65	3,745.26	1,698.55
Number of FTE Teachers	297.83	266.25	138.98	240.75	126.58
Pupil-Teacher Ratio	13.80	13.94	12.66	13.48	12.10
Total Number of Staff	581.80	568.47	298.34	505.52	273.43
Total Number of Counselors	8.10	9.39	4.26	8.09	3.95
Total Student Support Staff	6.25	5.31	2.56	4.68	2.50
Percent Proficient (2006) Reading	77.00	79.09	80.65		
Percent Proficient (2005) Reading	86.00	82.38	87.35		
Percent Proficient (2006) Math	81.00			80.32	66.04
Percent Proficient (2005) Math	84.00			81.90	73.68
RMSPE		2.26		1.13	

Appendix D (Cont.). Summary statistics for samples of children identified as LEP, Hispanic, and white for Dumas ISD, synthetic control groups, and donor pools.

	Reading			Math	
	Dumas ISD	Synthetic Control Group	Donor Pool	Synthetic Control Group	Donor Pool
Panel C: White Children					
Percent Female	0.48	0.48	0.48	0.49	0.49
Percent Hispanic	0.67	0.48	0.44	0.30	0.47
Percent White	0.30	0.33	0.35	0.29	0.33
Percent Eligible for FRPL	0.57	0.61	0.61	0.55	0.60
Percent LEP	0.25	0.12	0.14	0.15	0.14
Total Number of Children	4,118.50	4,220.75	4,502.80	4,093.33	3,824.69
Number of FTE Teachers	297.83	292.32	304.11	277.25	262.17
Pupil-Teacher Ratio	13.80	14.15	14.60	14.81	14.28
Total Number of Staff	581.80	619.79	663.75	570.02	574.36
Total Number of Counselors	8.10	9.09	9.72	8.89	8.66
Total Student Support Staff	6.25	6.41	5.78	5.28	4.92
Percent Proficient (2006) Reading	95.00	95.36	93.26		
Percent Proficient (2005) Reading	93.00	93.11	91.13		
Percent Proficient (2006) Math	85.00			85.54	85.00
Percent Proficient (2005) Math	94.00			92.96	86.85
RMSPE		0.38		0.78	



Appendix E. Placebo tests for statistical inference, none omitted.



Appendix F. Labor force and employment levels for Moore County, TX.