The Effects of Border Enforcement on Migrants’ Border Crossing Choices: Diversion or Deterrence?\textsuperscript{1}

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Abstract

Illegal migration from Mexico into the United States has long led to discussions of the proper form of enforcement along the border. Past border enforcement expansion has targeted specific sectors rather than across the board budget increases. We assess the implications of this pattern by examining how Mexican immigrants have responded to sector-specific expansions in border enforcement. We estimate how many immigrants are deterred from migrating and remain in Mexico, and how many migrants are diverted to crossing at other sectors of the border. While the popular press and anecdotal evidence point towards the existence of a strong diversion effect, the magnitude of this effect has yet to be estimated. Using micro level data on the decisions of Mexican migrants, we employ a discrete choice model to estimate the causal effects of increased enforcement on migration patterns. The causal effect of enforcement on crossing decisions is identified using a new set of instruments for border enforcement that vary both cross-sectionally and across time. The implied substitution patterns of our model allow us to decompose an overall effect of enforcement on migration into a diversion and deterrence portion. We find there to be a significant diversion effect, and we explore the policy implications of this finding.
I. INTRODUCTION

Illegal immigration and immigration reform have recently risen to the forefront of public policy debate. Current estimates put the stock of unauthorized immigrants in the United States at 10.3 million, 5.9 million from Mexico alone. Proponents of a tougher policy towards illegal immigration favor stronger enforcement of the U.S.-Mexican border to deter further illegal entry into the United States. A recently signed bill authorizes 700 more miles of fencing along the 2000 mile wide U.S.-Mexico border. The President also plans to add 6,000 agents to the U.S. Border Patrol (AZ Star Sep 2006). Current and proposed measures involve spending substantial amounts of taxpayer resources. While the US government currently spends $2.2 billion annually on border enforcement, the construction of the proposed physical barriers is estimated to cost $2 billion to $5 billion (Hanson, 2005a).

Accordingly, any change in policy should be accompanied by a better understanding of how migrants react to increases in border enforcement. In this paper we add to a small but growing literature on border enforcement by addressing a crucial policy question: does increasing enforcement along one part of the border deter unauthorized crossers from coming at all, as intended, or merely divert these crossers to other parts of the border?

There are two major consequences of ignoring the diversion effect. From a policy point of view the existence of a strong diversion effect would suggest that border enforcement is not as effective as it may appear at first blush. To achieve desired levels of deterrence at a national level, enforcement would need to be strengthened across the board and not just in the places that currently experience high rates of illegal crossings. During the 1990’s the U.S. Border Patrol significantly increased the intensity of enforcement in urban crossing zones, starting with El Paso and San Diego. While these operations were deemed successful at the local level, it is estimated that
a ten-fold increase in the number of border patrol agents would be needed in order
to apply the same intensity of enforcement across the entire border (Arizona Daily
Star Sep 2006). Clearly, when policy makers conduct cost-benefit analysis of border
security measures, the magnitude of the diversion effect will have a significant impact
on the costs that will need to be incurred to achieve given border security goals.

The El Paso and San Diego operations (“Operation Hold the Line” and “Operation
Gatekeeper”, respectively) were followed by a large spike in the number of migrant
deaths in the isolated desert stretches of the border. In his best selling book The
Devil’s Highway, Luis Alberto Urrea documents the attempted crossing of 26 migrants
from southern Mexico, 14 of whom died in the summer heat of the Arizona desert.
While such large groups of deaths remain relatively rare, it is well established that
migrant crossing deaths have increased significantly in the years following Gatekeeper
and Hold the Line. A report by the General Accounting Office documents that deaths
along the border doubled between 1995 and 2005 (GAO, 2006). In the presence of a
strong diversion effect, these deaths can be viewed as an unintended consequence of
increased enforcement.

Popular media and anecdotal evidence frequently suggest that there is indeed a
strong diversion effect, of that this passage from an AP article is typical:

"It’s known as the water-balloon effect: Squeeze one spot and ille-
gal immigration will bulge elsewhere along the 1952 mile frontier......A
crackdown launched in 1994 [in San Diego, CA] and modeled on a similar
effort in El Paso, Texas, pushed many migrants away from the border’s
two largest cities and into Arizona’s mountains and deserts." (Arizona
Daily Star Aug 2006)

A few previous studies have used time-series variation to identify an overall migra-
tion response to tighter border enforcement. Aside from Angelucci(2005), we are the
first to use panel data to evaluate how migrants respond to enforcement. This will allow us to provide the first econometric estimates of the magnitude of the diversion effect. The panel nature of our data will also allow us to control for the effects of time invariant characteristics of border crossings on migrations decisions, as well as the effects of border wide changes in government policy over time.

Identification of our model requires us to use instrumental variables for border enforcement that contain both cross-sectional and time series variation. Using these instruments and Mexican Migration Project (MMP) micro level data on the crossing choice of illegal immigrants, we estimate a discrete choice model. Our estimates from this model then allow us to decompose the effect of a marginal increase in enforcement into a deterrence effect and a diversion effect. We then run counterfactual estimations to evaluate the effects of past border patrol operations. While we find that more border enforcement in a given sector does indeed deter migrants, it also diverts a significant number of migrants to other sectors. These findings suggest that estimates of the effect of border enforcement on migration in a particular geographic area that ignores the diversion effect may overstate the impact of enforcement on migrations into the United States.

II. LITERATURE REVIEW

A number of recent papers have sought to estimate effects of border enforcement rates on border crossings. Gordon Hanson (2005a) provides a comprehensive review of the literature on illegal migration from Mexico to the United States. Hanson and Spilimbergo (1999) was one of the first papers to look at the estimates of the effects of border enforcement on apprehensions. Since enforcement is endogenous to apprehensions, they use instrumental variables for enforcement using U.S. government expenditures on national defense and the timing of U.S. presidential, gubernatorial and Senate elections. OLS estimates will be biased upwards, but IV estimation shows
a strong positive causal relationship between apprehensions and enforcement after controlling for endogeneity.

Hanson and Spilimbergo (2001) model the importance of political lobbying on border enforcement. They found that price shocks to sectors employing large numbers of undocumented workers are negatively correlated with the level of border enforcement. These results are evidence that employers lobby behind the scenes to weaken enforcement when prices and wages rise. Hanson, Robertson and Spilimbergo (2002), meanwhile, find that increased border enforcement has little impact on labor markets on either the United States or Mexican side of the border. This is consistent with two hypotheses: either enforcement has little impact on migration levels, or immigration has little impact on wages.

Using data on migrant deaths, Cornelius (2001) found that border enforcement has rechanneled flows of unauthorized migrants towards more hazardous areas and discouraged unauthorized migrants already in the United States from returning to their places of origin. However, Cornelius did not find evidence that the strategy is deterring or preventing significant numbers of new entries, particularly given the absence of a serious effort to curtail employment of unauthorized migrants through worksite enforcement.

Orrenius and Zavodny (2003) examined whether mass legalization programs reduce future undocumented immigration. They found that directly after the 1986 Immigration Reform and Control Act, the apprehensions of persons attempting to cross the U.S.-Mexico border illegally declined, but the amnesty program did not change long-term patterns of undocumented immigration from Mexico.

Bean et al (1994) studied the effect of “Operation Hold the Line” in the Border Patrol’s El Paso sector. This operation marked a sharp change in the enforcement strategy, shifting the focus of enforcement from internal checkpoints to line watch. They considered this change to be an exogenous shock to the level of border enforce-
ment. In contrast to other findings, the increase in enforcement intensity reduced the number of apprehensions. However, they also found evidence that half of the decrease in the flow of migrants, as measured by the level of apprehensions, was offset by an increase in flows to other border sectors.

Carrión-Flores (2005) found that increased border enforcement may increase the trip duration of migrants engaging in repeat migrations. Angelucci (2004) develops a model of return migration, and estimated the impacts of increased border enforcement on both the probability of a migrant undertaking a trip from Mexico to the United States, and of migrants already living in the United States returning to Mexico. She found that while increased border enforcement discourages migrants from crossing into the United States, it may discourage the return to Mexico of migrants already in the United States.

III. MODEL

Consistent with Sjaastad (1962), our model of migration represents that of a utility maximizing individual. A potential migrant living in Mexico chooses between migrating illegally to the United States or remaining in Mexico. Should he choose to migrate illegally, he will also have to decide through which of the nine US Border Patrol sectors to cross. The utility of the $i^{th}$ individual remaining at home (choice $o$) in origin $l$ during time period $t$ is defined as

$$U_{iotl} = W_{it} \gamma + \xi_{otl} + \varepsilon_{iotl}$$

(1)

where $W_{it}$ is a set of characteristics of the home location, and $\gamma$ is a vector of marginal utilities of these characteristics on the utility of the decision. The term $\xi_{otl}$ represents the common component of the unobserved utility of staying at the origin, which is observed by the individual, but unobserved by the econometrician, and $\varepsilon_{iotl}$ is a random utility term that varies across individuals.
The utility to the individual of crossing into the United States through Border Patrol sector \( j \) is

\[
U_{ijtl}^* = \alpha \cdot Enf_{jt} + X_{jtl} + \xi_{jtl}^* + \sigma \cdot \zeta_{ilt} + (1 - \sigma) \cdot \epsilon_{ijlt}^* \quad \text{for } j = 1, \ldots, 9
\]

The \( Enf_{jt} \) variable is a measure of the intensity of border enforcement at crossing \( j \) during year \( t \), and \( \alpha \) is the marginal disutility of this enforcement resulting from the increased probability of apprehension. The expression \( X_{jtl} \beta \) represents the portion of the utility of the choice resulting from other observables, and \( \xi_{jtl}^* \) is the unobserved aspect of the utility of the choice. In order to allow for a correlation among random utility terms for all choices that involve immigrating into the US, we express random utility as the sum of two terms, following Cardell’s (1997) modification of McFadden’s (1973) choice model. The \( \zeta_{ilt}^* \) is constant across \( j \neq o \), while \( \epsilon_{ijlt}^* \) is \( i.i.d \) over \( j \).

This correlation between the utility of the choices in \( j \) is captured by the correlation coefficient, \( \sigma \). An estimate of \( \sigma = 0 \) implies that there is no correlation between random utility terms for different crossing locations, while an estimate of \( \sigma \) close to 1 implies nearly perfect correlation.

To simplify the model, we normalize the utility of remaining at home to 0 by subtracting it from the utility of each of the choices that involve migrating:

\[
U_{iol} = 0 \quad \text{(3)}
\]

\[
U_{ijtl} = \alpha \cdot Enf_{jt} + X_{jtl} + \xi_{jtl} + \sigma \cdot \zeta_{ilt} + (1 - \sigma) \cdot \epsilon_{ijlt} \quad \text{for } j = 1, \ldots, 9 \quad \text{(4)}
\]

Define \( Y_{ijlt} \) as a binary variable taking on the value of 1 if individual \( i \) from origin \( l \) chooses choice \( j \) in time period \( t \), and 0 otherwise. \( Y_{ijlt} \) will then take the value of 1 if \( U_{ijtl} > U_{ikt} \) \( \forall j \neq k \). If we assume that \( \sigma \cdot \zeta_{ilt} + (1 - \sigma) \cdot \epsilon_{ijlt} \) takes the Type I Extreme Value distribution, the probability that \( j \) will be the utility-maximizing
choice is

\[
\Pr(Y_{ijt} = 1) = p_{jit} = \frac{\exp(\delta_{jit})}{\sum_{j=1}^{9}\exp(\delta_{jlt})} \times \frac{\prod_{j=1}^{9}\exp(\delta_{jlt})^{1-\sigma}}{1 + \prod_{j=1}^{9}\exp(\delta_{jlt})^{1-\sigma}} \quad \text{for } j = 1, \ldots, 9
\]

(5)

\[
\Pr(Y_{iotl} = 1) = p_{otl} = \frac{1}{\sum_{j=1}^{9}\exp(\delta_{jlt})^{1-\sigma} + 1}
\]

(6)

where \( \delta_{jit} = \alpha \cdot En_{jlt} + X_{jlt}^t/\beta - W_{it}^l\gamma + \xi_{jit} \). Note that these probabilities are equal to those of a standard conditional logit when \( \sigma \) takes the value of 0.

Once we have obtained consistent estimates of the parameters of this model, we can return to our original question: how does an increase in border enforcement affect the border crossing choices of migrants? A negative and significant value of \( \alpha \) tells us that border enforcement does indeed push migrants away from sector \( j \); however it is not immediately obvious whether the migrant will be pushed to another border sector \( k \neq j \), or deterred from crossing altogether and choosing to remain at home \( o \).

To answer this question we turn to the implied substitution patterns of the model. Below, we consider the marginal effects of enforcement on the probability of choosing a given option. As \( \varepsilon_{ijt} \) is distributed i.d.d. across the population, these changes in probabilities for a single individual can also be interpreted as changes in the shares of the population making the choice.

The substitution effect away from a choice with respect to a change in the characteristic of that choice is derived in Berry (1994) and Cardell (1997):

\[
\frac{\partial p_{jit}}{\partial En_{jlt}} = \partial p_{jit} \cdot \frac{\partial \delta_{jit}}{\partial En_{jlt}} = a \cdot p_{jit} \cdot \frac{1}{1 - \sigma} \left[ 1 - \sigma \frac{p_{jit}}{1 - p_{otl}} - (1 - \sigma)p_{jit} \right]
\]

(7)

This total effect encompasses both divergence and deterrence. The diversion effect is the cross effect between an increase in enforcement at \( j \) and the increase in the probability of substituting to all other crossings. The deterrence effect is the change in the probability of deciding not to migrate, and to stay in Mexico, as a result of the increase in enforcement at \( j \). Consider the deterrence effect. The term \( DIV_{jit} \)
represents the change in the probability of a migrant from origin \( l \) in year \( t \) choosing to cross at all alternative crossings when enforcement increases in \( j \). \( DET_{jtl} \) is the change in the probability of this migrant remaining in the origin as a result of increased enforcement at \( j \).

\[
DIV_{jtl} = \sum_{j \neq k} \frac{\partial p_{kl}}{\partial En_{jt}} \\
DET_{jtl} = \frac{\partial p_{otl}}{\partial En_{jt}} = -\alpha \cdot p_{otl} \cdot p_{jtl}
\] (8) (9)

Having calculated both the total effect and the deterrence effect, we can decompose the total effect into the deterrence proportion and the diversion proportion\(^3\). Because the migrants’ choice set represents mutually exclusive options, the decrease in the probability of migrating to \( j \) (the total effect) must equal the increases in the probabilities of all other choices.

\[
-\frac{\partial p_{jtl}}{\partial En_{jt}} = \frac{\partial p_{otl}}{\partial En_{jt}} + \sum_{j \neq k} \frac{\partial p_{kl}}{\partial En_{jt}} \\
= DET_{jtl} + DIV_{jtl}
\] (10) (11)

The deterrence effect, as a share of the total effect, can then be expressed as

\[
PCTDET_{jtl} = \frac{\frac{\partial p_{otl}}{\partial En_{jt}}}{\frac{\partial p_{otl}}{\partial En_{jt}} + \sum_{j \neq k} \frac{\partial p_{kl}}{\partial En_{jt}}} = \frac{\frac{\partial p_{otl}}{\partial En_{jt}}}{\frac{\partial p_{jtl}}{\partial En_{jt}}}
\] (12)

\(^3\)This relationship is similar to the "market-stealing" vs. "market-expansion" analysis found in Berry and Waldfogel (2001). This analysis is of the effect of changes in radio broadcasting variety. An important question in that market is whether this increased product choice resulted in creating more listeners, or simply diverting (stealing) listeners from a pre-existing station to a new station.
Substituting from equations 7 for \( \frac{\partial p_{jlt}}{\partial Enf_{jt}} \) and 8 for \( \frac{\partial p_{otl}}{\partial Enf_{jt}} \)

\[
PCTDET_{jlt} = \frac{-\alpha \cdot p_{otl} \cdot p_{jlt}}{(1 - \sigma) \cdot p_{otl} \cdot \left[1 - \sigma \cdot \frac{p_{jlt}}{1 - p_{otl}} - (1 - \sigma) \cdot p_{jlt}\right]} (13)
\]

\[
PCTDET_{jlt} = \frac{-\alpha \cdot p_{otl} \cdot p_{jlt}}{(1 - \sigma) \cdot p_{otl} \cdot \left[1 - \sigma \cdot \frac{p_{jlt}}{1 - p_{otl}} - (1 - \sigma) \cdot p_{jlt}\right]} (14)
\]

This term will be both decreasing and concave in the correlation coefficient \( \sigma \); for a \( \sigma = 1 \) there will be no deterrence. The intuition of this comes out of the model. We have grouped all of the migration-related choices together. The \( \sigma \) term measures the degree of correlation among the \( \varepsilon \) terms in the group. If there is perfect correlation between these terms, when a characteristic of the utility maximizing choice changes, individuals will substitute only to another choice that is in the same group.

Using some reasonable values of \( p_{otl} \) and \( p_{jlt} \), in Figure I we plot the percentage the deterrence share is of the total effect against \( \sigma \).

The structural nature of our model allows us to conduct policy experiments to evaluate the effects of Border Patrol policies such as Hold the Line and Gatekeeper. By predicting crossing probabilities under counterfactual enforcement levels (\( \hat{p}_{jlt}^*(Enf_{jt}^*) \)) and then comparing them to the predicted probabilities under historical values of enforcement (\( \hat{p}_{jlt}(Enf_{jt}) \)) we can identify a total impact of the change in policy on migration rates. Computing the same figure for changes in the share of migrants choosing to remain in the origin under counterfactual values (\( \hat{p}_{otl}^*(Enf_{jt}^*) \)) and historical values (\( \hat{p}_{otl}(Enf_{jt}) \)) allows us to decompose the effect into diversion and deterrence.

\[
PCTDET_{jlt}^* = \frac{\hat{p}_{otl}^*(Enf_{jt}^*) - \hat{p}_{otl}(Enf_{jt})}{\hat{p}_{jlt}^*(Enf_{jt}^*) - \hat{p}_{jlt}(Enf_{jt})} (15)
\]

**IV. IDENTIFICATION**

In this section we describe the strategies that we employ to estimate the parameters of the model. First we describe the instrumental variables we develop for the
endogenous enforcement variable. After motivating the use of these instruments, we present two estimation strategies that we use to estimate causal effects of enforcement on migration.

**A. Instrumental Variables**

A major issue in identifying this model is the endogeneity of border enforcement. Recall the term $j_{jt}$:

$$j_{jt} = \alpha \cdot Enf_{jt} + X_{jt}\beta - W_{jt}\gamma + \xi_{jt}$$

The $\xi_{jt}$ term represents the unobserved utility of the choice. Observations with high values of $\xi_{jt}$ will attract more migrants. The Border Patrol would be expected to increase the allocation of resources to sectors during times in when they are experiencing a large number of illegal crossings. Accordingly, we would expect a positive correlation between $\xi_{jt}$ and $Enf_{jt}$; standard methods of estimating $\alpha$ will lead to biased and inconsistent estimates. The estimates will most likely be biased in a positive direction.

Relevant and valid instruments will be correlated with the level of enforcement in a given Border Patrol sector, but uncorrelated with the unobservables affecting the share of migrants from a given origin who cross through that sector in year $t$. For a set of potential instruments, we turn to the political process determining the level of funding in each sector. Hanson and Spilimbergo (2001) provide evidence of the importance of local politicians on the level of enforcement in the sector. Their principal finding is that border enforcement is reduced when output prices increase for goods whose production process involves the labor of undocumented immigrants as an input. This suggests that pressure groups are able to exert influence over the process determining how strictly the border is patrolled.

We exploit variation in enforcement caused by political lobbying to serve as an
instrument for the observed level of enforcement. For example, variables such as the party of the Congressional representatives of border sector constituents may be correlated with the level of funding for the sector. While relevant, these instruments may also be invalid. The election of these representatives is likely a function of unobservable characteristics of the district, as a constituency that votes for a representative who is "tough on illegal migration" is likely composed of individuals who have a distaste for migration that may directly affect the utility of migration.

Suppose that all elected officials have some demand for increased funding in their home sector, if not to crack down on illegal immigration, simply to increase the amount of federal funds and jobs provided to constituents in their district. Then variables that do not measure a politicians' desire to increase enforcement resources, but rather their ability to increase local level enforcement should be valid.

We create two such "political supply" instruments to identify our model. Our first instrument for border enforcement is the size of the Congressional delegation representing the Border Patrol sector. Specifically, we count how many Congressional districts share the sector's border with Mexico. As shown in Table I and Figure II, in Arizona the Yuma county Border Patrol sector includes only Yuma county (the most western border county), which is represented by the 7th Congressional District. The Tucson sector includes the three border counties to the east of Yuma County and is represented by both the 7th and 8th Congressional districts. Thus the Tucson sector has two representatives who have an interest in securing funding for the sector, while the Yuma sector has only one. As the size of the sector's lobby in Congress grows, so should its budget and accordingly the level of enforcement. We refer to this variable as NUMREPS. Values of this instrument will vary not only across sectors, but also over time as redistricting occurs every ten years.

Our second instrument for enforcement is the strength of the state Congressional delegation representing a Border Patrol sector. We count how many members from
the state’s delegation are on the House Appropriations committee and then match these state delegations to Border Patrol sectors. Note that the El Paso sector includes counties in both Texas and New Mexico, while the Marfa sector includes only counties in Texas. This variable is named STATEAPP. Thus, the delegation that has an interest to procure funds for the El Paso sector is larger than the delegation representing Marfa.\footnote{Constructed using data from Congressional Quarterly Almanac.}

B. Aggregate Discrete Choice Model Approach

One method to identify the parameters of the nested logit model we describe in Section III is by using Berry’s (1994) inversion of this model. The probability that an individual from origin \( l \) will migrate through crossing \( j \) in year \( t \) is estimated using the share of individuals from \( l \) making this choice in year \( t \), we have

\[
s_{jtl} = \Pr(Y_{ijtl} = 1) = \frac{\exp(\delta_{jlt})}{\sum_{j=1}^{9} \exp(\frac{\delta_{jlt}}{1-\sigma})} \times \frac{[\sum_{j=1}^{9} \exp(\frac{\delta_{jlt}}{1-\sigma})]^{1-\sigma}}{1 + [\sum_{j=1}^{9} \exp(\frac{\delta_{jlt}}{1-\sigma})]^{1-\sigma}} \quad \text{for } j = 1, \ldots, 9 \tag{17}
\]

\[
s_{olt} = \Pr(Y_{iotl} = 1) = \frac{1}{1 + [\sum_{j=1}^{9} \exp(\frac{\delta_{jlt}}{1-\sigma})]^{1-\sigma}} \tag{18}
\]

Taking the log of the ratio of these two expressions

\[
\ln\left(\frac{s_{jtl}}{s_{olt}}\right) = \delta_{jtl} + \sigma \ln\left(\frac{s_{jtl}}{1-s_{olt}}\right) \tag{19}
\]

\[
= \alpha \cdot Enf_{jlt} + X_{jlt}\beta - W_{lt}\gamma + \sigma \ln\left(\frac{s_{jlt}}{1-s_{olt}}\right) + \xi_{jlt} \tag{20}
\]

The key advantage of this approach is that it allows \( \alpha \) to be estimated using Two Stage Least Squares (2SLS). One complication with Berry’s model is the inclusion of an additional endogenous variable, \( \ln\left(\frac{s_{jlt}}{1-s_{olt}}\right) \). This variable, whose variation identifies \( \sigma \), can be interpreted as the share of individuals from origin \( l \) who choose to migrate.
to the United States in year $t$ through crossing $j$, conditional on choosing one of the 9 crossings; this is the "within group share". Recall that $\xi_{jtl} = \xi_{j*tl} - \xi_{otl}$; the right hand side contains both unobserved characteristics of the choice $j$ and the outside alternative $o$. Thus we should expect $\ln\left(\frac{s_{jtl}}{1-s_{otl}}\right)$ to be correlated with $\xi_{jtl}$.

Berry (1994) suggested the following instruments: 1) the number of choices in the group, and 2) characteristics of other choices in the group. In motivating the first instrumental variable, we can imagine that subdividing a choice set into smaller and smaller choices should decrease the probability of an individual choosing any one of the given choices. However, each migrant in our data set faces a choice of nine Border Patrol sectors through which to cross; thus we have no variation in this potential instrument.

The second set of instruments captures the effect of competing locations on crossings shares. These variables will be relevant, as by changing the utility of alternative choices, they will directly affect the share of individuals choosing a given choice. Recall that for an instrument to be valid in this model, it must be uncorrelated with the unobservable characteristics of the choice. If we believe that these characteristics are jointly determined, these potential instruments would likely be invalid. For example, as the level of border enforcement in all sectors is greatly influenced by policy at a national level, enforcement in El Paso is likely to be an invalid instrument for enforcement in San Diego. However, it is reasonable to believe that distance is a predetermined variable, as the location of origin communities are fixed and the Border Patrol sectors do not change their geographic boundaries throughout the period of our study. We try a number of instrumental variables for $\ln\left(\frac{s_{jtl}}{1-s_{otl}}\right)$; however strong instruments remain elusive; our current estimates of $\sigma$ are most likely biased upwards. This will be the case if unobserved characteristics of the choice affect the probability of migrating through $j$ in the same direction they affect the probability through $j$, conditional upon migrating at all.
As the values of enforcement will not vary across observations that are from the same crossing sector and year, we expect serial correlation to be a problem in obtaining consistent estimates of standard errors. Accordingly, we cluster our standard errors at the year and crossing sector level.

One additional issue with the aggregate discrete choice model is how to handle "0 shares". For a large portion of our data set, we observe no individuals from the origin choosing a particular choice in a given year. As our left hand side variable is the logarithm of these shares, we add a number arbitrarily close to zero number to each of these observations.

C. Individual level data

An alternative to the aggregate discrete choice model would be to estimate our model using individual level data. Recall the following choice probabilities:

\[
\begin{align*}
\Pr(Y_{ijt} = 1) &= p_{jlt} = \frac{\exp(\delta_{jlt})}{\sum_{j=1}^{9} \exp(\delta_{jlt})} * \frac{[\sum_{j=1}^{9} \exp(\delta_{jlt})]^{1-\sigma}}{1 + [\sum_{j=1}^{9} \exp(\delta_{jlt})]^{1-\sigma}} \quad \text{for } j = 1, \ldots, 9 \quad (21) \\
\Pr(Y_{iotl} = 1) &= p_{otl} = \frac{1}{[\sum_{j=1}^{9} \exp(\delta_{jlt})]^{1-\sigma} + 1} \quad (22) \\
\delta_{jlt} &= \alpha \cdot Enf_{jt} + X_{jlt}^\beta - W_{it}^\gamma + \xi_{jlt} \quad (23)
\end{align*}
\]

The major complication in estimating this model is the correlation between enforcement and unobserved characteristics of the choice. Following a similar approach to binary models taken by Blundell and Smith (1989), Petrin and Train (2004) develop a strategy for obtaining consistent estimates under this condition. Their control function approach involves estimating a first stage linear model of the endogenous variable:

\[
Enf_{jt} = g(z_{jt}) + \mu_{jt} \quad (24)
\]
Assuming our instruments $z$ are uncorrelated with $\xi$, the residual term $\mu$ will capture all the variation in the endogenous $Enf$ variable that is correlated with the second stage error term $\xi$. Thus, by controlling for this variation in the second stage, the remaining correlation between $Enf$ and the dependent variable can be interpreted causally. This becomes easier to see after we decompose the second stage error term into two parts:

$$\xi_{jit} = \lambda_j\hat{\mu}_{jit} + \tilde{\xi}_{jit}$$  \hspace{1cm} (25)

The $\delta$ term becomes

$$\delta_{jit} = \alpha \cdot Enf_{jit} + X_{jit}\beta - W_{it}\gamma + \lambda_j\hat{\mu}_{jit} + \tilde{\xi}_{jit}$$ \hspace{1cm} (26)

where $E[\tilde{\xi}_{jit}|Enf_{jit}] = 0$.

Petrin and Train compare estimates obtained using this estimator to estimates obtained using a computationally intensive approach implemented on disaggregated data by Berry Levinson and Pakes [BLP] (2001), based upon the estimator in BLP (1995). While the assumptions behind the control function approach have been questioned as stronger than those of the BLP estimator, Petrin and Train show that in the general case, the assumptions for each estimator are different, with neither set of assumptions necessarily being a subset of another. In their application of the estimators, the two methods provide nearly identical estimates. A future draft will implement this strategy for our model$^5$.

$^5$Currently, we have applied this estimator to a conditional logit model. The findings are consistent with what we would expect: the fitted residuals are positive and significant, and their inclusion leads to significantly more negative estimates of the effect of enforcement. We are in the process of programming a maximum likelihood estimator of the nested logit model presented above, which will allow us to use this approach to identify sigma without needing instruments other than our instruments for enforcement.
V. DATA

The data on the choices of migrants comes from the Mexican Migration Project (MMP), a survey constructed jointly by researchers in Mexico and the United States. Separate waves of the survey have taken place annually, starting in 1982. In order to construct our dependent variable, we must determine how many individuals migrated from each origin in each year, and where they crossed. One of the data sets created by the MMP includes a comprehensive migration history. From this, we are able to compute the share of household heads from each origin who migrated through each of the Border Patrol sectors in each year prior to the survey, as well as the share who remain in the origin in each year.

Our unemployment variable is constructed from BLS data from both the city and state level. For each of the nine border crossing sectors, we tabulate the most popular destinations inside the United States for migrants crossing through the sector over a number of years. We then create a weighted average of the unemployment rate for each of the three most popular destinations, where the weights are the proportion of migrants choosing the location over the entire period of our study. When city unemployment rates are unavailable, we use state unemployment rates as a proxy. Other right hand side variables include the distance between the origin and the principal crossing in each sector, the unemployment rate in principle labor markets located near each of the sectors, the size of the origin community, and the average level of education in the origin community.

Due to confidentiality concerns, the MMP does not disclose the home community of survey respondents, but the state of each community is given. Distance from the home community to the border crossing is proxied by distance from the capital of the home state to the border. The MMP gives data on the Municipio\(^6\) of the migrants

\(^6\)A mutually exclusive sub-state geographic division in Mexico, similar to counties in the United
crossing. As our choice set for migrants is one of nine border crossing sectors, rather than a continuum of crossings, we compute the distance from the state capital to the primary crossing location in each sector. Educational achievement rates and population figures are provided by the MMP at the origin and year or decennial level.

The border enforcement data were originally used in Hanson and Spilimbergo (1999). They provide rich information on both the number of apprehensions and line watch hours (the number of labor hours spent patrolling the border) in the nine Border Patrol sectors. Monthly data by sector are provided from 1977 to 2000. Table II provides enforcement hours per mile of border for 1980, 1990 and 2000.

Instruments are constructed using data from the Congressional Quarterly Almanac and Congressional District Almanac. For each Congress, we count the number of members of each state delegation who sit on the House of Representatives Appropriations Committee and assign these values to the appropriate Border Patrol sector. The variable measuring the number of Representatives responsible for each sector (as described in Section IV A) was constructed by overlaying maps of Congressional District boundaries with those of the Border Patrol Sector. As redistricting takes place with each decennial census in the US, these variables vary across both time and space. Table III presents summary statistics of our data. The NUMREPS variable varies between 1 and 3 with a mean of 1.61 representatives per sector, while the STATEAPP variable has a mean of 3.35, a minimum of 0 and a maximum of 7. The there is substantial variation across both time and space for each of these instruments. The panel nature of our data allows us to control for both time and location fixed effects in our estimation, eliminating a number of sources of potential endogeneity.

7 The total for the California delegation to San Diego and El Centro, the total for the Arizona delegation to the Yuma and Tucson delegation, the total for the New Mexico and Texas delegation to the El Paso sector, and the total from only the Texas delegation to the Marfa, Del Rio, Laredo and McAllen sectors.
VI. RESULTS

Table IV presents results from our estimations. The first three models we estimate force $\sigma = 0$ (Conditional Logit Models), while the second three models identify $\sigma$ (Nested Logit Models). Initial estimates of the effect of enforcement on the log share ratio described in Section IV B are positive and statistically significant for both the Conditional and Nested Logit Models. If one were to interpret these estimates as causal, it would imply that migrants are attracted to locations with higher levels of enforcement. Clearly this is evidence of endogeneity. Our panel data allows us to control for time invariant unobservable characteristics of each crossing as well as border wide unobserved aspects of enforcement in each year. After the inclusion of these fixed effects, the estimate of the effect of enforcement on crossings becomes statistically insignificant for both models.

We present first stage results of our IV estimation in the column to the right of our final stage results. Both instruments perform as expected, indicating that as a sector is represented by a more powerful or bigger congressional delegations, the level of enforcement increases. An F-statistics of 28.15 and partial $R^2$ of .15 are sufficiently high to reject weak instrument tests. After instrumenting, the estimates of the effect of enforcement become negative and significant, as theory would predict. The $\sigma$ parameter is estimated to be between .34 and .38 in each of the nested logit models, suggesting a strong correlation in the random utility terms that involve migrating.

Other characteristics of the choices yield the expected results; individuals are more likely to emigrate if they come from smaller communities, less likely to migrate through a given crossing as distance to that crossing increases, and less likely to move to a crossing where nearby cities have high levels of unemployment. Raising the average level of human capital in an origin will increase the probability of out-migration up to a point, at which migration becomes less likely as the rate of educational attain-
ment increases further. As education will likely be correlated with the wealth of the origin, these results are consistent with theory and the results presented in Angelucci (2004).

Marginal effects are computed using the estimates from the IV specifications of the nested logit model, to the right of the conditional logit estimations that restrict the value of the $\sigma$ parameter to 0. Note that when $\sigma$ is restricted to 0, the diversion effect is negligible. This is a result of the familiar Independence of Irrelevance Alternatives (IIA) property of logit models: substitution patterns are a function solely of the proportions of people choosing the two alternatives. As the outside option, remaining in Mexico, is by far the most common choice made in our data set, the bulk of people will substitute to the outside option rather than to one of the other crossing choices.

As the nested logit allows for correlation between the random utility draws that influence the nine border crossing choice, the data are allowed more of a hand in identifying the substitution patterns, rather than the structure of the model. Once the nested model provides an estimate of $\sigma$, this story changes significantly. For eight of the nine sectors, a third of the effect of a marginal increase in enforcement is to divert migrants into other sectors. The diversion effect for San Diego is notably lower. This is most likely because the substitution patterns are still a function of the observed shares. A majority of migrants cross the border through the San Diego sector. This large share of migrants implies only the outside good possesses a high enough predicted share value to a significant number of migrants, creating a lower diversion effect for San Diego.

In addition to estimating the marginal effects, we also run three counterfactuals, reported in Table VI and Table VII. The first eliminates border enforcement altogether, and compares the predicted crossing rates for the nine sectors with observed levels of enforcement, and the predicted crossing rates with no enforcement. The key observation from this exercise is that the predicted crossing rates into San Diego
more than double from 41% to 90%, while all other crossing rates decline. In the absence of enforcement effects, it makes sense that the majority of migrants who tend to want to move to California would choose the most direct route through the San Diego sector. This expansion of enforcement does not slow immigration to California as much as it does lead people to California through more indirect routes.

Finally, we estimate the effects of both Operation Gatekeeper and Operation Hold the Line. Operation Gatekeeper resulted in an 85% increase in enforcement in the San Diego sector of the border between 1994 and 1996. To evaluate the effects of this policy, we set the 1996 level of enforcement in San Diego equal to the 1994 level; thus eliminating the increase in enforcement.

From Table VII, we see that the predicted probability that a representative migrant will cross through the San Diego sector, rises from .2% (\( \hat{p} \)) to .26% (\( \hat{p}^* \)) when the increase in enforcement is eliminated. Thus, the migration rate declined by .06 percentage points, or 23% of the original rate of .26 percentage points in response to Gatekeeper. This reaction to an 85% increase in the rate of enforcement implies an elasticity of migration rates to enforcement levels of -.27, given in the final column of the table. At the same time, the rate of crossings through all other sectors increased by 8.4%, implying a cross elasticity of .10%.

Under some assumptions, we can use these results to find the effect of the policy on the total number of unauthorized crossings. A strong assumption to make would be that our sample of household heads in communities sampled from the MMP is fully representative of the entire Mexican population. A weaker assumption to make would be that the migration rates we observe are not representative of the entire population, but the mean responses are. Current estimates put 10% of the Mexican population in the United States. As we are interested in the effects of border enforcement, we are only concerned with the subset of migrants living in the United States without documents, 6% of the Mexican population. Carrion-Flores (2005) finds average mi-
migration spells in the U.S. are 24 month. From this we can estimate that roughly one half of the stock of migrants enters the United States in this two year period. In our sample, 40% of unauthorized crossings take place through the San Diego sector.

Using the above numbers, the effect of Gatekeeper would be to decrease migration through San Diego from roughly 1.52 million migrants to 1.23 million migrants. At the same time migrations elsewhere would have increased from approximately from 1.63 million to 1.77 million; we estimate that Gatekeeper decreased migration to San Diego by 286,000 while at the same time increase migration elsewhere by 137,000, for a net decrease of 149,000. For Hold the Line, similar analysis shows that the effect of the increase in enforcement was a decrease of 79,000 migrants while at the same time diverting 16,000 migrants to other crossings for a net effect of 63,000 migrants diverted. Both of these policy evaluations suggest a significant diversion effect.

VII. CONCLUSION

As the debate about immigration reform and increased border security continues, it is increasingly important for policy makers to have a better understanding of the effectiveness of border enforcement, particularly when changes in enforcement usually target specific parts of the border. A popular perception is that the U.S.-Mexican border suffers from a "water-balloon" effect: when one part of the border is tightened immigrants flow through the next easiest place to cross. The effect thus nullifies a good portion of the attempt to stem the flow of illegal immigrants into the United States.

In this paper we estimate the magnitude of this diversion effect. We face several challenges in identifying this effect. First, we use instrumental variables with cross-sectional and time series variation to instrument for the variation in border enforcement across space. We are able to do so with the use of "political supply" variables, that measure the ability of a local political lobby to procure funds to in-
crease the intensity of border patrol in the locale. Our use of panel data also allows us to control for time invariant characteristics of each border crossing, as well as border wide changes in policy in each year. Prior studies, using only time series variation in enforcement, have been unable to hold these factors constant.

Second, to properly identify the diversion and deterrence effects, we must use a random utility model that produces reasonable substitution patterns. To do this, we model the utility of each choice in a more realistic way, taking into account the fact that migrants who have a strong preference to migrate into the United States through one border crossing likely also have a strong preference to migrating through another sector. The correlation among these preferences, identified as $\sigma$ in our model, allows us to estimate more realistic patterns of substitution between crossing choices when enforcement changes. The decomposition of the effect of border enforcement into diversion and deterrence is straightforward.

In future research we will estimate $\sigma$ using micro level data that does not require the same assumptions for identification. Our preliminary estimates suggest that there is indeed a strong diversion effect present: while border enforcement may appear very effective at the local level, a good part of this effect will be offset by an increase in migration through other sectors.
Tables and Figures

Figure 1: Deterrence and $\sigma$

![Graph showing the relationship between PCT deterrence and $\sigma$.]

Figure 2: AZ Congressional Districts

![Map of Arizona congressional districts.]
<table>
<thead>
<tr>
<th>Sector</th>
<th>Counties</th>
<th>Principal Crossing</th>
<th>Miles of Border</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego</td>
<td>San Diego (CA)</td>
<td>Tijuana-San Diego</td>
<td>66</td>
</tr>
<tr>
<td>El Centro</td>
<td>Imperial (CA)</td>
<td>Mexicali-Calixico</td>
<td>75</td>
</tr>
<tr>
<td>Yuma</td>
<td>Yuma (AZ)</td>
<td>SL Rio Colorado-Yuma</td>
<td>118</td>
</tr>
<tr>
<td>Tucson</td>
<td>Pima, Santa Cruz, Cochise (AZ)</td>
<td>Nogales-Nogales</td>
<td>261</td>
</tr>
<tr>
<td>El Paso</td>
<td>Hidalgo, Luna, Dona Ana (NM), El Paso, Hudspeth (TX)</td>
<td>Ciudad Juarez-El Paso</td>
<td>289</td>
</tr>
<tr>
<td>Marfa</td>
<td>Presidio, Brewster (TX)</td>
<td>Ojinaga-Presidio</td>
<td>420</td>
</tr>
<tr>
<td>Del Rio</td>
<td>Terrell, Val Verde (TX)</td>
<td>Del Rio-Piedras Negras</td>
<td>205</td>
</tr>
<tr>
<td>Laredo</td>
<td>Kinney, Maverick, Webb, Zapata (TX)</td>
<td>Nuevo Laredo-Laredo</td>
<td>171</td>
</tr>
<tr>
<td>McAllen</td>
<td>Starr, Hidalgo, Cameron (TX)</td>
<td>McAllen-Reynosa</td>
<td>284</td>
</tr>
</tbody>
</table>
Table II: Border Enforcement in Annual Labor Hours Per Mile

<table>
<thead>
<tr>
<th>Sector</th>
<th>1980s</th>
<th>1990s</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego</td>
<td>7236</td>
<td>7769</td>
<td>30764</td>
</tr>
<tr>
<td>El Centro</td>
<td>1422</td>
<td>2849</td>
<td>9210</td>
</tr>
<tr>
<td>Yuma</td>
<td>1955</td>
<td>1880</td>
<td>2680</td>
</tr>
<tr>
<td>Tucson</td>
<td>550</td>
<td>994</td>
<td>7950</td>
</tr>
<tr>
<td>El Paso</td>
<td>928</td>
<td>1456</td>
<td>2849</td>
</tr>
<tr>
<td>Marfa</td>
<td>195</td>
<td>137</td>
<td>248</td>
</tr>
<tr>
<td>Del Rio</td>
<td>1134</td>
<td>1372</td>
<td>3217</td>
</tr>
<tr>
<td>Laredo</td>
<td>573</td>
<td>1566</td>
<td>4848</td>
</tr>
<tr>
<td>McAllen</td>
<td>574</td>
<td>954</td>
<td>5183</td>
</tr>
</tbody>
</table>

Hanson and Spilemergo (1999)
Table III: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable Description</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s$</td>
<td>Share</td>
<td>.002</td>
<td>.001</td>
<td>.0</td>
<td>.220</td>
</tr>
<tr>
<td>$\ln\left(\frac{s}{s_o}\right)$</td>
<td>Log Observed Migration Share Ratio</td>
<td>-14.518</td>
<td>4.023</td>
<td>-16.118</td>
<td>-1.258</td>
</tr>
<tr>
<td>$\frac{s}{s_o}$</td>
<td>Share Conditional Upon Migrating</td>
<td>.111</td>
<td>.225</td>
<td>.0000004</td>
<td>1</td>
</tr>
<tr>
<td>$\ln\left(\frac{s}{s_o}\right)$</td>
<td>Log Share Within</td>
<td>-7.593</td>
<td>5.242</td>
<td>-14.650</td>
<td>0</td>
</tr>
<tr>
<td>STATEAPP</td>
<td>State Congressional Delegation on Appropriations Committee</td>
<td>3.028</td>
<td>1.714</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>NUMREPS</td>
<td>Number of Reps Representing Sector</td>
<td>1.525</td>
<td>.608</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>lnDist</td>
<td>Log of Distance from Origin to Border Crossing</td>
<td>6.808</td>
<td>.715</td>
<td>0</td>
<td>7.648</td>
</tr>
<tr>
<td>UR</td>
<td>Unemployment Rate</td>
<td>6.973</td>
<td>1.671</td>
<td>3.464</td>
<td>12.460</td>
</tr>
<tr>
<td>HomePop</td>
<td>Origin Community Population (1000s)</td>
<td>122.578</td>
<td>261.527</td>
<td>0</td>
<td>1650</td>
</tr>
<tr>
<td>EDUCATION</td>
<td>Percent Origin 6+ Years Education</td>
<td>.441</td>
<td>.197</td>
<td>0</td>
<td>.865</td>
</tr>
<tr>
<td>EDUCATION^2</td>
<td></td>
<td>.233</td>
<td>.179</td>
<td>0</td>
<td>.749</td>
</tr>
</tbody>
</table>
Table IV: Results of Estimation on Log-Share Ratio

<table>
<thead>
<tr>
<th>Variable</th>
<th>Conditional Logit</th>
<th>Nested Logit</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS IV</td>
</tr>
<tr>
<td>lnEnf</td>
<td>1.136***</td>
<td>.767***</td>
</tr>
<tr>
<td>ShareWithin</td>
<td>-</td>
<td>.376***</td>
</tr>
<tr>
<td>lnDist</td>
<td>-.375*** -.427*** -.44*** .002</td>
<td>-.311** -.375*** -.372*** .002</td>
</tr>
<tr>
<td>UR</td>
<td>-.028 -.127***</td>
<td>.084*** .028*** -.084*** -.140*** -.084***</td>
</tr>
<tr>
<td>HomePop</td>
<td>-.001*** -.001*** .000</td>
<td>-.001*** -.001*** -.001*** -.001*** .000</td>
</tr>
<tr>
<td>EDUCATION</td>
<td>1.283 -.114 .001</td>
<td>3.213*** .305 .306 .002</td>
</tr>
<tr>
<td>EDUCATION^2</td>
<td>-3.856** -2.493*** .000</td>
<td>-6.096*** -4.12*** -4.12*** -.004</td>
</tr>
<tr>
<td>NUMREPS</td>
<td></td>
<td>.255***</td>
</tr>
<tr>
<td>STATEAPPS</td>
<td></td>
<td>.061**</td>
</tr>
<tr>
<td>Sector Dummies</td>
<td>X X X X</td>
<td>X X X X X</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>X X X</td>
<td>X X X X</td>
</tr>
<tr>
<td>R2</td>
<td>.10 .19</td>
<td>.3261 .37</td>
</tr>
<tr>
<td>F Test on IV’s</td>
<td>28.08***</td>
<td>28.15***</td>
</tr>
<tr>
<td>Partial R2 of IV’s</td>
<td>.15</td>
<td>.15</td>
</tr>
<tr>
<td>Hanson P-Val</td>
<td>.27</td>
<td>.29</td>
</tr>
<tr>
<td>N</td>
<td>18180 18180 18180</td>
<td>18180 18180 18180 18180</td>
</tr>
</tbody>
</table>

* significance at 10% level, ** significance at 5% level, *** significance at 1% level

(standard errors clustered at Crossing/Year level)
<table>
<thead>
<tr>
<th>City</th>
<th>Total (For $\sigma = 0$)</th>
<th>Diversion (For $\sigma = 0$)</th>
<th>PCT Diversion (For $\sigma = 0$)</th>
<th>Total (For $\hat{\sigma}$)</th>
<th>Diversion (For $\hat{\sigma}$)</th>
<th>PCT Diversion (For $\hat{\sigma}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego</td>
<td>-0.001489</td>
<td>0.000002</td>
<td>0.1%</td>
<td>-0.0017042</td>
<td>0.0002174</td>
<td>13.1%</td>
</tr>
<tr>
<td>El Centro</td>
<td>-0.0000565</td>
<td>0.000002</td>
<td>0.4%</td>
<td>-0.0000849</td>
<td>0.0000287</td>
<td>34.1%</td>
</tr>
<tr>
<td>Yuma</td>
<td>-0.0000366</td>
<td>0.000002</td>
<td>0.4%</td>
<td>-0.0000555</td>
<td>0.0000191</td>
<td>34.3%</td>
</tr>
<tr>
<td>Tucson</td>
<td>-0.0000895</td>
<td>0.000003</td>
<td>0.4%</td>
<td>-0.0001346</td>
<td>0.0000454</td>
<td>33.7%</td>
</tr>
<tr>
<td>El Paso</td>
<td>-0.000075</td>
<td>0.000003</td>
<td>0.4%</td>
<td>-0.0001129</td>
<td>0.0000383</td>
<td>33.9%</td>
</tr>
<tr>
<td>Marfa</td>
<td>-0.0000349</td>
<td>0.000001</td>
<td>0.4%</td>
<td>-0.000053</td>
<td>0.0000182</td>
<td>34.5%</td>
</tr>
<tr>
<td>Del Rio</td>
<td>-0.0000429</td>
<td>0.000001</td>
<td>0.4%</td>
<td>-0.0000651</td>
<td>0.0000223</td>
<td>34.3%</td>
</tr>
<tr>
<td>Laredo</td>
<td>-0.000152</td>
<td>0.000006</td>
<td>0.3%</td>
<td>-0.0002257</td>
<td>0.0000743</td>
<td>33.0%</td>
</tr>
<tr>
<td>McAllen</td>
<td>-0.0000831</td>
<td>0.000003</td>
<td>0.4%</td>
<td>-0.000125</td>
<td>0.0000423</td>
<td>33.8%</td>
</tr>
</tbody>
</table>
### Table VI: Counterfactual: No Enforcement

<table>
<thead>
<tr>
<th>Location</th>
<th>Predictions with Actual Enforcement</th>
<th>Predictions with No Enforcement</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego</td>
<td>.41</td>
<td>.90</td>
<td>.49</td>
</tr>
<tr>
<td>El Centro</td>
<td>.06</td>
<td>.02</td>
<td>-.04</td>
</tr>
<tr>
<td>Yuma</td>
<td>.04</td>
<td>.01</td>
<td>-.03</td>
</tr>
<tr>
<td>Tucson</td>
<td>.10</td>
<td>.01</td>
<td>-.09</td>
</tr>
<tr>
<td>El Paso</td>
<td>.09</td>
<td>.01</td>
<td>-.08</td>
</tr>
<tr>
<td>Marfa</td>
<td>.04</td>
<td>.00</td>
<td>-.04</td>
</tr>
<tr>
<td>Del Rio</td>
<td>.05</td>
<td>.01</td>
<td>-.04</td>
</tr>
<tr>
<td>Laredo</td>
<td>.12</td>
<td>.03</td>
<td>-.09</td>
</tr>
<tr>
<td>McAllen</td>
<td>.09</td>
<td>.01</td>
<td>-.08</td>
</tr>
</tbody>
</table>

### Table VII: Evaluating Gatekeeper and Hold the Line

<table>
<thead>
<tr>
<th>Gatekeeper</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \hat{p} )</td>
<td>( \hat{p}^* )</td>
<td>( \Delta \hat{p} )</td>
<td>( \frac{\hat{p}}{\hat{p}^*} )</td>
<td>( \eta )</td>
</tr>
<tr>
<td>San Diego: 1996</td>
<td>0.0020034</td>
<td>0.0026096</td>
<td>-0.0006062</td>
<td>-23.2%</td>
<td>-.27</td>
</tr>
<tr>
<td>All Others: 1996</td>
<td>0.0001399</td>
<td>0.0001290</td>
<td>0.0000109</td>
<td>8.4%</td>
<td>.10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hold the Line (( \Delta Enf = 82.6% ))</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>El Paso: 1995</td>
<td>0.001311</td>
<td>0.001828</td>
<td>-0.000517</td>
<td>-28.3%</td>
<td>-.34</td>
</tr>
<tr>
<td>All Other: 1995</td>
<td>0.003412</td>
<td>0.003391</td>
<td>0.000021</td>
<td>.006%</td>
<td>.008</td>
</tr>
</tbody>
</table>
REFERENCES


