Seeing is Believing: The Effect of Television on the Identity and Lives of Hispanic People*

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February 2020

Abstract

Here's an abstract

*We would like to thank XYZ and Trip from SatelliteGuys for technical advice.
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1 Introduction

[Television] has altered every phase of the American vision and identity.

- Marshall McLuhan, *War and Peace in the Global Village*

We spend our waking hours inundated in mass media. The internet, newspapers, radio, and television stations broadcast to us a constant stream of facts, beliefs, entertainment, and ideas—ideas that percolate in our heads, and, we argue, ideas that shape our own identities and the way we live our lives. In this paper, we examine the impact of Spanish Language Television (SLTV) on Hispanics, focusing our analysis on three domains—the professional, the educational, and the political. In each case, we find that SLTV induces changes in behavior that we can attribute (at least in part) to a stronger sense of identity; causality is established via a spatial regression discontinuity introduced by a regulation on television network protection.

There's good reason to believe that identity, as reinforced through mass media, has a large effect on the lives people lead. @CITE Olken finds that that radio and television decrease 'social capital' in Indonesia, in line with @CITE Putnam's argument. @CITE Yanigazawa-Drott (QJE 2014) shows that radio broadcasts in Rwanda contributed to the violence and genocide that took place in the 90s. **??** find Fox News.[1]

When explicitly looking at the effect of television on Hispanics, Oberholzer-Gee and Waldfogel (2009) demonstrate that the presence of Spanish language local news increases Hispanic voter turnout Velez and Newman (2019), who first developed the instrument used in this paper, show that SLTV leads to lower voter turnout rates. **?** run an experiment testing trust in the government and the census based on a soap opera scene. We extend on this literature by expanding the scope to a national-level analysis, while simultaneously exploring outcomes beyond the political realm.

We focus on Hispanic consumption of television for several reasons.

- Media plays a large role in shaping our lives

- Latino consumption of broadcast TV remains relevant

- Relevant subquestion: how identity is affected

Three domains

- Firms **?** negative ; **?** better control – but both explicit target shows with programming Difficult to get entrepreneurrship/mixed: **?** **?** (vs. us!)

- Education **?** **?** **?** vs. **??** Gentzkow and Shapiro 2008 Preschool

? - school segregation

- Politics Gentzkow and Shapiro 2008 (Competition and Truth in News Market), Gentzkow 2006 on turnout ; Stromberg 2004 on policy outcomes ; **??**

The high level research question is to look at the effect of reinforcing identity within Hispanic populations on their schooling outcomes. Specifically, I'll be using the influence of Spanish language

[1]Other examples of media affecting identity and personal beliefs include **??**, **??**, , **??**, **?**. For an overview, see **?**

television as the channel by which identity is reinforced, and look at how it affects everything from graduation rates to disciplinary action taken to math abilities and English proficiency for Hispanic students in public schools. In short, if I have access to more programming from my home country, does this make me less engaged in school (perhaps because there are more distractions or because it socially ostracizes me etc.), or does this make me perform better (perhaps because l have more role models or because I have something to talk with peers about in school, and hence motivation to attend/perform)?

Compared to other viewers of television, Hispanics are uniquely likely to watch television in a social context rather than watching alone—this is partially driven by the fact that non-Hispanic households have 40% more TV sets per person than Hispanic ones (Coghill and McGinnis, 2018). This social aspect, wherein SLTV is watched with family/friends (or people that speak Spanish), may be one way in which identity is reinforced through television.

More directly, SLTV programming is simply more likely to contain content that is directly salient to a Hispanic person's identity. This occurs not only because of the language of the broadcast, but also its content: roughly 20% of programming on SLTVs are telenovelas produced in foreign (Latin American) countries, with a similar proportion of programming dedicated to non-locally produced news and paid programming, which may come from abroad as well.[2]

The rest of the paper is structured as follows: Section 2 presents the data used across later sections, Section 3 addresses the empirical strategy. The following three sections, Section 4, Section 5, and Section 6, present data, results, and discussion on the results for our analysis on firms, schools, and campaign contributions respectively. Finally, Section 7 concludes.

2 Data

2.1 Broadcast TV and Geography

The central instrument in this paper is the discontinuity in coverage contours introduced via FCC regulation.

Coverage Contours Digital and satellite TV stations operate by broadcasting signals from a central antenna, and the field strength at a given point resulting from this antenna is a mechanical product of several factors: The antenna's ERP (Effective Radiated Power, which is the amount of input power given to the antenna adjusted for idiosyncrasies in the antenna that may boost or attenuate the effective power), the antenna's HAAT (High Above Average Terrain), and the distance from the point to the antenna.

[2] The statistics come from **?**, but unfortunately, the dataset they use do not allow them to precisely determine from whence the programming originated.

This signal declines in strength as one grows more distant from the station, making it subject to interference. The FCC regulation OET Bulletin No. 69 @CITE protects signals for commercial TV stations from interference in a contour area for which service holds at 50% of locations 90% of the time.[3] An example of this coverage contour can be seen in Figure 4; note that they tend to be sizable enough to fully cover major metropolitan areas, with contours boundaries ending substantially beyond them.

To build the coverage contours of SLTV stations in the US, we collected a list of the callsigns for all SLTV stations via the TMS (a large provider of data on TV, movies, and other media) API.[4] There are 100 of these stations located across the United States. These callsigns were then matched against data from the FCC's OET Bulletin 69 and the FCC's CDBS Database to directly obtain the relevant coverage contour boundaries as prescribed and regulated by the FCC. [5] A map of all these contours can be seen in Figure 5.

Geocoding Location data for outcomes was all collected in the form of text addresses. To transform this into proper spatial data/coordinates, two geocoding tools were used: (1) ArcGIS, which has its own proprietary database of locations. Over 99% of addresses were successfully matched to one location and geocoded. This was used to geocode the schooling data, as well as portions of the campaign contribution data. (2) The US Census Geocoder, which contains the census database of locations. Over 80% of addresses were successfully matched to one location and geocoded.[6] This was used to geocode the business data, as well as portions of the campaign contribution data. It is unlikely for non-geocoded addresses to be correlated with the instrument, given the relatively narrow band around the contour retained for the spatial regression discontinuity.

For data that take the form of spatial points (such as the location of a school), determining its distance to the boundary and whether the datapoint falls within the coverage boundary is a straightforward process. For data that cover a wider area (such as a county), in the standard specification, the area is said to fall within the coverage boundary if at least some portion of it does, and the distance from the area to the boundary is taken as the minimum distance from the boundary to the area. In locations covered by multiple SLTV stations, the distance to the boundary is taken as the distance to the closest boundary.

[3] There is a small adjustment made for different channel numbers, which have varying noise-limited coverage.

[4] A TV station is defined to be SLTV if at least one of the primary broadcasts languages are Spanish.

[5] 2015 coverage contour data is used due to the 'FCC Spectrum Repack' that began in 2018, which relocates a number of signals, affecting the reception and coverage for a substantial number of stations (Fletcher, Heald and Hildreth, 2018).

[6] The US Census geocoder, unlike the ArcGIS geocoder, is free. However, due to the higher precision of the ArcGIS geocoder, data constructed from it is used wherever possible.

2.2 Controls and Other Non-Outcome Data

Controls at the county level are sourced from IPUMS and consist of basic relevant demographic information: population, income, percent of county that is Hispanic etc. County level data is mapped to its relevant location using census data as well.

Data on migration comes from the 2011-2015 ACS, which reports the number of people moving from each origin county to destination county (aggregated over the years).[7] This sample also contains migration flows by Hispanic origin, allowing us to determine whether they move based on geographic boundaries.

Finally, data for specific outcomes are discussed under their relevant section.

3 Empirical Strategy

To isolate the causal effect of Spanish language television, I adopt the technique used in Velez and Newman (2019) and generalize it from two counties to the entirety of the US.[8] Newman and Velez exploit a FCC (Federal Communications Commission) regulation which determines the distance from a TV station in which the station's broadcast signal is protected from interference.

This creates a natural spatial regression discontinuity, where the decaying strength of a signal over distance is combined with this cutoff in broadcast protection to create a split among people just inside and outside these coverage contours that are presumably comparable save for their access to broadcast TV. This minimizes the potential concern of omitted variable bias, as the groups we are comparing across this border should share many overarching characteristics.

In the case of Spanish language TV in particular, this should allow us to examine its causal effect on Hispanic populations for spatially located outcomes. As mentioned, these contours are purely determined by an algorithm and is only dependent on physical variables like local elevation and antennae strength. Thus, the precise regulatory boundaries are located in more or less random locations, and coverage is large enough that these contours tend to cut across towns and suburbs, rather than large cities — television networks are not constructing their antennas to be just large enough to only cover the most dense and populous areas. This implies that network executives, if they are aiming to maximize profit, ratings, or audiences, would not consider these boundaries at the forefront of their calculus.

In order for the causal effect of SLTV to be identified, the actual coverage of the contours must be uncorrelated with any of the other determinants for the outcome variables with which we are interested. One reassurance is that the interference protection regulation, OET Bulletin 69, was only codified in 1977 — in contrast, Univision, the largest owner of SLTV stations, was founded

[7] Historically, approximately 15% of the ACS migration data has been allocated, or imputed based on salient characteristics (United States Census Bureau (2020*a*)).

[8] The paper was retracted in 2019, but this was due to usage of unauthorized data, and unrelated to the efficacy of the underlying identification strategy.

in 1955, and had built a substantial number of their television stations and antennas by 1977.[9] Nonetheless, one may be concerned that SLTV stations target areas with more Hispanic people, or wealthier communities, or more populous areas, all of which are factors that could affect the areas of interest. Hence, we include explicit controls for these variables in the regression.

The instrument therefore consists of two variables interacted: First, a dummy for whether the outcome data falls within a SLTV station's coverage contour boundaries, and second, the distance from the outcome of interest to the closest coverage boundary. To guarantee similarity between the people inside and outside the boundaries, only data points located within a distance of 100 KM of the boundary are kept.[10]

Several concerns that potentially remain:

- *Can we guarantee that it is Hispanic people who watch SLTV?* If it were the case that non-Hispanic people were frequent viewers of SLTV, the interpretation of the main effects would potentially be different: we would be looking at the effect of SLTV on all people. Thus, though outcomes restrict the analysis to how the lives of Hispanic people change, this could be driven by, for instance, white people treating Hispanic people differently due to having viewed SLTV. This does not empirically bear out—only 4% of total SLTV station programming watched can be attributed to non-Hispanic people, a number that is only as high as it is because some SLTV stations also broadcast in English. (**?**) Similarly, < 1% of all programming watched by non-Hispanics is in the Spanish language.

- *How do we account for the possibility of selection?* It is theoretically possible that Hispanic people move in response to these television coverage contour boundaries, and that the effects seen are therefore a result of Hispanic people self-sorting. If this were true, it would be a fairly remarkable result—people moving in significant quantities for access to better television in a way that influences life outcomes ranging from education to business to politics. As the subsection on Migration beneath demonstrates, the selection story does not appear to be borne out by the data.

3.1 Main Specification

A standard regression thus looks like restricting the universe of observations to only those within a small radius of the contour boundary, where the key independent variable of interest is an indicator for the observation being inside or outside the boundary, interacted with the distance to the

[9] Though Telemundo, the second largest owner of SLTV, was technically founded in 1984, the stations it initially acquired were built in 1954. It also primarily expanded through the acquisition of existing stations, rather than building out its own new ones.

[10] Using a round number in kilometers rather than miles makes the cutoff less likely to be correlated with some real-world phenomena.

boundary:

$$Y_i = \beta_0 + \beta \mathbb{I}[InsideContour_i] \times Distance_i + \gamma X_i + \epsilon_i \quad \epsilon \overset{iid}{\sim} N(0, \sigma_i^2)$$

where Y_i is an outcome for observation i and X is a vector of controls for the observation. The main coefficient of interest is β, and due to the nature of our instrument, we place the majority of interpretive weight on the indicator for being inside the television coverage contour.

In this case, the unit of observation is deliberately left vague—this varies depending on the set of outcomes we are looking at. For firm data, we aggregate our data into a set of grid points (typically roughly 2 × 2 KM in size) so that we can compare the number of firms across areas.[11] For school data, the unit of observation is a single school, as we have school-level controls. For our campaign contribution data, our unit of observation is similarly also aggregated into grid points. We typically aggregate into grids by taking the sum of observations within grids (i.e., the number of Hispanic-owned businesses within a grid point, or the number of contributors to Trump within a grid point), except where otherwise noted.

We prefer to leave standard errors robust, and separately check for robustness with respect to spatial autocorrelation for each main result. Other fixed effects/clusters options are treated similarly.

3.2 Spatial Autocorrelation

Spatial autocorrelation, or spatial dependence, occurs when our outcomes of interest are correlated with itself in space (Cliff and Ord, 1973). In general, this only means that we allow for $Cov(Y_i, Y_j) \neq 0$ when $i \neq j$ for locations i, j. For tractability, when given a dataset with n locations, we place more structure on the problem, constructing a $n \times n$ spatial weights matrix W with entries $w_{ij} = 1$ if locations i, j are considered neighbors, and $w_{ij} = 0$ otherwise (Anselin and Bera, 1998). For data that takes the form of grids in space, we construct weights based on the rook criterion (grid points have unit weight if they share an edge), while for points in space, we assign unit weight to the four nearest neighbors for comparability.

There are two primary models of spatial autocorrelation that we conduct robustness tests for:

The Spatial Autoregressive Model In this model, the spatial autocorrelation enters directly into the model:

$$Y = \beta_0 + \rho WY + \beta \mathbb{I}[InsideContour] \times Distance + \gamma X + \epsilon$$

This model is identical to the prior main specification, except for the addition of the ρWY term,

[11] In addition to providing cleaner interpretability, grouping data into 'raster' form is also less computationally intensive.

where W is the aforementioned spatial weights matrix, and ρ the autoregressive coefficient. In this model, spatial dependence affects the outcome variable only (e.g. person X donating to Trump induces their neighbor to donate to Trump as well if $\rho > 0$).

The Spatial Error Model In this model, the autocorrelation occurs in the error term:

$$Y = \beta_0 + \beta \mathbb{I}[InsideContour] \times Distance + \gamma X + \epsilon$$

$$\epsilon = \lambda W \epsilon + \nu$$

This model is identical to the main specification, except the error terms are now additionally correlated due to the addition of the $\lambda W \epsilon$ term. In this model, spatial dependence enters through the presence of missing spatial covariates which may affect the outcome.[12]

3.3 Migration

While it is theoretically conceivable that Hispanics would move based on access to SLTV, causing results to be driven by selection and confounding the direct effect of television itself, we demonstrate that movement across these coverage contours is fairly minimal.

As mentioned in Section 2, the migration data from the ACS is provided at the county-county level. Given the relative size of a county, to define whether a county is inside a coverage contour or not, we further impose that at least 95% of the area that the county encompasses must be inside of the coverage contour.[13] We present summary statistics for this sample in Table 1.

Tables 3 and 4 present the results on migration. These tables present results at the origin county - destination county level, tracking the Inverse Hyperbolic Sine (IHS) transformed values of the number of Hispanic migrants between the two counties.[14] Table 3 restricts to only origin counties that are within 100 KM of a coverage contour (the standard cut-off distance used for later outcomes).[15] In panel A, this is further restricted to origin counties inside the television contour, and so the main variable of interest is the dummy for the destination county being outside the TV contour. We observe a clear negative and significant relationship for migrations that cross the coverage contour. We interact the distance to the origin/destination with the TV dummy to ensure that are controlling for all distance related effects, and control for county level characteristics including Log Population, Log Income, and percent of the county that is Hispanic for both origin and destination. All specifications also include origin fixed effects.

[12] In particular, this allows us to further adjust for unique features of Hispanic communities, such as the geographic clustering of immigrants as **?** and **?** find.

[13] Results are robust to different area cut-offs for a county to be considered inside the coverage contour.

[14] The IHS transform can be interpreted similarly to the Log transform, but has the added advantage of being able to handle cases when 0 is the observed value.

[15] There are 636 such counties. The average origin county has 20 destination counties for which there is significant enough cross-county Hispanic migration that the ACS reports data for it.

In panel B, we restrict to origin counties outside the television contour, and the main variable of interest is the dummy for the destination county being *inside* the TV contour. In this case, the point estimate is negative, although results are overall insignificant—this is sufficient for us to make our argument, given that so long as there are not positive coefficients, there is no evidence of migration across borders.

Table 4 repeats the analysis, this time restricting to only destination counties within 100 KM of a coverage contour. Results closely echo those seen in the prior table, with negative coefficients associated with migration across coverage contours, significant when the destination is inside the contour and not when they are outside.

These results combined indicate that movement across coverage contours is not a major threat to identification. Even in cases where insignificant results are observed, the base rate of migration is not very high to begin with—in our origin county sample, an average of 84 Hispanic people are observed to move between each county-county pair (median: 25) over the five year period which the dataset spans. This also speaks to the magnitude of the coefficients observed, where the drop in 10 to 40% of migrants observed still falls within a plausible range. Though we do not have theories as to why people may be *averse* to moving across coverage contour boundaries, it is in and of itself an interesting result perhaps worth further investigation.

4 Firms

In this section, we examine Hispanic firm ownership and firms adopting Hispanic names, showing that both increase under the influence of SLTV.

4.1 Data

From Florida's Division of Corporations, we obtain complete records of business filing data from the years 2010 to 2019.[16] Unfortunately, there is no readily available (and free) national firm database that also contains addresses and owner names, so analysis had to be restricted to the state level instead. We pick Florida as our state to analyse for several reasons: (1) Florida hosts a significant Hispanic population (23.2% of Florida's population, 8% of the US total), and contains 11 SLTV stations (11% of the US total), (2) Florida makes its voting registration data public, which we use to predict ethnicity from names, and (3) Florida makes its business filing data public.

From the business filings, we keep all firms that we are able to successfully geocode, leaving us with a universe of 146,032 firms; though this unfortunately is not a sizable fraction of the total filings available, the sample restriction is unlikely to introduce any bias into the sample.[17]

[16] Businesses in Florida are generally required to refile their data every 3 years.

[17] The total number of firms for which we have filing data is on the order of 3 million. However, the amount of locations that could be geocoded was unfortunately rate-limited by the classification method used, and so we are left with the first 146,032 firms geocoded. Given that they were geocoded in chronological order corresponding to date

We aggregate data into a grid with each square having size .02 degrees latitude by .02 degrees longitude, approximately 2×2 KM^2. Our two outcomes of interest are whether the firms are owned by Hispanics, and whether the firm names play into Hispanic identities—for each of these outcomes, we take the sum of the number of businesses that fit this criteria within the grid as our outcome. Summary statistics for the outcomes and controls are presented in Panel A of Table 2. To construct these outcomes, we use two separate methods of classification:

Principal Name Classification To determine whether a business is owned and run by a Hispanic person or not, we run the Python machine learning classifier 'ethnicolr' to predict ethnicity based on the first and last names of a business' principal.[18] The classifier contains three models trained on separate data sources: (1) Data from the US census in 2000 and 2010, (2) data from the Florida voter registration database in 2017, and (3) Wikipedia data collected by Skiena et al. We use the Florida voter registration data because it closely matches the sample that we are working with.

The model uses TensorFlow (an open source software library developed by Google for training Machine Learning applications) to train a Long Short-Term Memory (LSTM) model based on the bigrams (two character chunks) present in the names. An out of sample validation exercise using the voter registration data yields an 85% overall accuracy.[19]

Overall, 23.5% of principals are classified as Hispanic (.3% higher than the proportion of the population that Hispanics make up). As a final check, we randomly selected one hundred names to verify, and the model appears to be at least 85% correct on inspection (no name was obviously incorrectly classified). For instance, 'Manuel Lorenzo' and 'Mildred Sosa' are classified as Hispanic, 'Peter Yu' and 'Haresh Karamchandani' are classified as Asian, 'Tony Walker' and 'Dwayne Demarie' are classified as Black, and 'Robert Bronson' and 'Nathan Smith' are classified as White.

Firm Name Classification Unlike the names of firm principals, there is no readily available or standardized method to determine whether a firm's name is characteristic of a Hispanic identity or not. Although a machine learning approach is still theoretically possible under these circumstances, a quick visual inspection of the data revealed that a relatively low percentage of firms had names

filed (beginning with 2010 firms, and ending around mid-2010), there is no reason to believe that there would be any bias introduced by this limitation; there would need to be some omitted variable determining both the location of the firm and the firm filing its data in the first 6 months of 2010. It is unclear what that any such variable exists.

[18] Corporations are required to file personal data for their Registered Agent as well up to six Principals, the latter of which must be a President, Treasurer, Chairman, Vice President, Secretary, or Director of the firm. In some small number of cases, the Principal is a corporation — these observations are dropped. When there are multiple principals for which we have data, we use the classification for the highest ranked principal.

[19] The neural net is much less (30% less) accurate at identifying blacks and Asians compared to Hispanics. In addition to a best guess at ethnicity, the model also provides the percentage probability that a name is associated with a specific ethnicity. Using this percentage instead of a dummy for whether a name is Hispanic or not does not change the results.

that were explicit tied to a Hispanic identity—hence, many approaches would likely identify a significant number of false positives.

In order to be conservative and ensure that firms identified as bearing Hispanic names actually are such, we construct a measure that classifies a firm name as Hispanic if it contains certain keywords that are explicitly associated with a Hispanic identity. These keywords are split into three major categories: (1) References to countries in Latin America or Latin America itself. Firms that include the base forms of country names in Latin America are considered to be explicitly referencing a Hispanic identity (examples include: 'Cuban Guys 102, LLC' , 'Bravo Latino Brands, LLC.') (2) Names containing common one of the top 50 most Spanish words (that are not also in English) (examples include: 'La Joya Estates, Ltd.', 'Conselho Nacional De Saude Mental E Medicina Psicossomatica Inc.'), and (3) Names containing common Hispanic foods. (examples include: 'Charlie Cactus Tacos, LLC', 'Taqueria Casas 2 Inc.') Due to the lack of a systemic means to classify this category, we conduct robustness checks dropping this category; results do not substantially change when omitting this third category.

Out of our sample, 1.1% of firms meet this criteria (1% if omitting the food based names). A manual check of firms that are classified as Hispanic also confirms that the firm name classification process succeeds.

4.2 Results

Table 5 presents results on the effect of SLTV on Hispanic business ownership. The main coefficient of interest, the IHS transformed number of Hispanic-owned firms located inside a television coverage contour, is positive and significant at the $\alpha = .01$ level in all specifications. Columns (2), (3), and (4) add in county level controls for log population, the percent of the county that is Hispanic, and log income respectively. Once controls are added at the county level, the coefficient appears to stabilize at approximately .1.

Table 6 presents results on the effect of SLTV on whether firm names present as Hispanic or not. Given the low frequency of firms exhibiting such names, we construct a binary variable for whether any firm within the grid point contains a Hispanic name and run a logit (logistic) regression on the outcome. The first four columns mirror the prior table in terms of controls added, and show a positive coefficient significant at the 1% level. Column (5) restricts the analysis to only Hispanic business owners, whilst column (6) restricts the analysis to only non-Hispanic owners. The results look similar in both these cases.

Robustness To test the robustness of these results, we present Table 7. Column (1) presents the baseline results (it is identical to column (5) of Table 6), while column (2) includes the interaction of the TV dummy with the distance to the boundary squared. This is plausibly relevant to the main effect, given that television signals decay in strength in proportion to the square of the distance.

Column (3) additionally controls for the total number of businesses in the grid point. Column (4) uses an alternate definition of Hispanic named businesses that does not consider food as part of the criteria for classifying a firm name as Hispanic. Columns (5) and (6) reduce the cutoff distance from the boundary to one half and one third of the original 100 KM limit. Columns (7) and (8) vary the grid size to 9 KM^2 and 1 KM^2 respectively. The robustness checks hold up across the board with all columns maintaining significance and positive sign. Robustness checks on the other outcome variables of interest hold up to a similar analysis.

One remaining concern is that there may be some degree of spatial autocorrelation in the data which is driving the results. A Moran's I test using 4 nearest neighbours between the grid points (rook style) indicate that there is spatial autocorrelation in the data (p-value less than 10^{-16}). Hence, Table 8 presents two alternate models that control for the effects of spatial autocorrelation. Column (1) presents the baseline results in column (2) of Table 5.[20] Column (2) uses a spatially autoregressive lag model, wherein the outcome variable may be correlated with its neighbours. Column (3) uses a spatially autoregressive error model, wherein the presence of missing spatial covariates (causing correlated errors) is adjusted for. In both cases, the alternate models yield results that closely resemble the standard specification in column (1).

4.3 Discussion

The magnitude of the increase in the number of firms owned by Hispanics under the presence of SLTV is fairly remarkable—once controls are added, this amounts to 11-13% more firms.[21] The increase in number of firms that exhibit Hispanic names is also remarkable: an increase of between 1.8 to 2.2 in the log odds ratio at a baseline rate of 1% constitutes roughly a doubling in the number of such names. Both of these findings are rather substantial effects in size, and the robustness across specification lends credibility to their external validity.

The increase in Hispanic firm names would be difficult to explain without touching on identity in some manner—either these firms are operationally similar to others, in which case the names act a prominent identity-based signal to consumers (McDevitt, 2014), or there are material changes in a firm's operation. But in these cases, changes in name are still linked to the type of operational change made by the firm (Horsky and Swyngedouw, 1987), still pointing to an identity-based mechanism.

[20] Due to computational limitations, standard errors cannot be effectively computed when more controls are added. The point estimates, however, remain similar. Additionally, results for firm names are also robust to spatial autocorrelation specifications, though they are more difficult to interpret.

[21] Because we do not have access to data on the relative size of these firms (revenue, profits, number of employees etc.), we are unable to say whether this actually leads to more economic activity overall—it is possible that there are more firms, but that firms on the whole are smaller. **?** find this substitution effect to be the case with regards to consumption in response to television advertising in former East Germany. Nonetheless, given the recent slump in US rates of entrepreneurship (Decker et al., 2014), and the fact that minority owners are disproportionately entrepreneurs (Feldman, Koberg and Dean, 1991), we are optimistic towards on the implications of this finding towards overall economic growth.

The issue is less clear cut in the case of firm ownership. The additional number of firms could be tied to stronger advertising networks, noting that paid programming makes up 30.9% of Hispanic owned SLTV networks programming time, compared to 10.8% in the general population (**?**). Nonetheless, there is reason to believe that this effect may also be driven by identity: Piperopoulos (2012) notes that ethnic minorities often start businesses on the basis of stronger cultural knowledge and ties to the community.

Given this, two interesting questions arise: (1) Accounting for the fact that there are now more businesses overall, does the proportion of Hispanic named firms increase? (2) Are the increases in Hispanic firm names driven by demand or supply side effects? To tackle (1), we note that in Table 7 that, even controlling for the total number of firms in area, the number of Hispanic named firms still increases; hence, in addition to there being more Hispanic owned firms, the proportion of Hispanic named firms also increases.[22]

We examine the second question by first noting that non-Hispanic people only minimally engage with SLTV. Hence, if SLTV operated exclusively through a supply-side channel (changing the information or preferences of the owner, for instance), we would expect to see Hispanic owners but not non-Hispanic owners to more frequently adopt Hispanic names for their businesses. Instead, in Table 6, we see that there are positive, significant increases in Hispanic business names for businesses owned both by Hispanics and non-Hispanics. We are unable to reject the hypothesis that the coefficients are equal, and this suggests that it is instead the demand-side (Hispanic consumers who watch SLTV) that dominates—consistent with other findings in the meat and cigarette industry which show that content shown on television influences what consumers choose to purchase (Baltagi and Levin (1986) Verbeke, Ward and Viaene (2000)) and making the novel extension to firm ownership and naming schemes.

5 Public Schools

In this section, we examine the performance of Hispanics in public schools and find that while academic achievement generally increases and disciplinary issues generally decrease in response to SLTV, the opposite holds true when the measures are more directly to identity.

5.1 Data

The data on public schools comes from the US Department of Education's CRDC (Civil Rights Data Collection) dataset in 2015. In order to prevent discrimination and for transparency purposes, all public schools in the United States are required to report a substantial amount of information

[22] This holds when alternatively controlling for the total number of Hispanic owned firms.

for the CRDC on an annualized basis.[23]

The dataset contains information on a total of 96,350 schools across 17,280 school districts. Figure 6 contains a map of these schools, while summary statistics for the outcomes and controls are presented in Panel B of Table 2.

The outcome data from the CRDC can be split into two categories:

- **Academic Achievements:** We focus on two outcomes that track the effect of television on the top end of the academic distribution of students: the number of Advanced Placement (AP) classes students enrol in and pass, as well as the number of students placed into gifted programs, and one outcome on the bottom: the number of students with Limited English Proficiency (LEP).

  The AP program is administered by the College Board, and defines a standardized college-level curriculum that is taught to high school students in AP Classes. In conjunction with AP Classes, AP Exams are national examinations which are designed to test mastery of material taught in AP classes. These exams are given scores ranging from 1 to 5, with scores below a 3 marked as a failed exam. Even among the selective students who opt into these classes (22% in 2015[24]), a substantial number of students who take these exams fail them - approximately 35% (College Board (2020*b*)).

  Gifted and talented programs are "programs during regular school hours that provide special educational opportunities including accelerated promotion through grades and classes and an enriched curriculum for students who are endowed with a high degree of mental ability or who demonstrate unusual physical coordination, creativity, interest, or talent." (**?**) These programs, while not mandatory, are common across school districts, and vary in their implementation.

  LEP students (also called English Learner students) are students that, as a result of their limited command over the English language, have difficulty participating in regular school activities.[25] 9% of all public school students are considered LEP, and while students are placed into the program is at the discretion of individual school districts, all districts must provide

[23] In practice, this data is not released to the public every year. Furthermore, not all schools report all data (or correct data) required of them, which is why the number of observations for different variables in this dataset fluctuates. Some data, such as that on AP examinations, are not mandatory, but the bulk of outcome variables are, with non-compliance on the mandatory data typically representing < 1% of total data.

[24] Data computed from number of high school graduates in 2015 (National Student Clearinghouse Research Center (2015*a*)), and number of seniors who sat an AP exam in 2015. This is how the College Board currently tracks national AP participation (no comparable summary statistic was released in 2015) (College Board (2015*b*))

[25] The specific definition of a LEP student depends on individual state regulation, but must also satisfy the criteria outlined under Title IX of the Elementary and Secondary Education Act (US Department of Education (2004)). The most salient features of Title IX are that students must either not speak English as a native language or come from an environment where non-English languages are dominant, and also face substantial difficulty in engaging with others on the basis of their English ability.

language assistance services and have staff qualified to implement the LEP programs.[26]

- **Disciplinary Issues:** Three forms of academic discipline are considered as outcome variables: the number of out of school suspensions, the number of absences, and the amount of harassment and bullying on the basis of race/ethnicity experienced by students.

  Out of school suspensions are instances "in which a child is temporarily removed from his/her regular school for at least half a day (but less than the remainder of the school year) for disciplinary purposes to another setting (e.g., home, behavior center)." (**?**) We consider only students without disabilities, and note that depending on school policy, educational services may still be provided during this time.[27]

  A chronically absent student is one "who is absent 15 or more school days during the school year. A student is absent if he or she is not physically on school grounds and is not participating in instruction or instruction-related activities at an approved off-grounds location for at least half the school day." (**?**) Each day for which a student is absent for 50 percent or more of the school day is counted. Absences are counted regardless of whether they are excused or not, and so include absences due to illness, needing to care for a family member, or simple truancy.

  Harassment or bullying on the basis of race, color, or national origin "refers to intimidation or abusive behavior toward a student based on actual or perceived race, color, or national origin. Harassing conduct may take many forms, including verbal acts and name-calling, as well as non-verbal behavior, such as graphic and written statements, or conduct that is physically threatening, harmful or humiliating. The conduct can be carried out by school employees, other students, and non-employee third parties. Bullying on the basis of race, color, or national origin constitutes racial harassment." (**?**) Though there are other categories of bullying and harassment reported (and other types of infractions and disciplinary measures taken), these are less directly relevant to the question at hand.

Notably, all the outcome information described above is also provided for Hispanic subpopulations — hence, the outcome of interest is generally the number of Hispanic students passing AP tests, or being bullied on the basis of their ethnicity, etc. These variables are all reported at the school level.

School level controls include the number of teachers, the number of total students, the number of Hispanic students, as well as dummies for whether the school contains a primary school, middle school, and high school. Demographic control variables are sourced at the county level (income,

[26] Department of Justice and Department of Education (2015*c*) contains a full enumeration of the responsibilities school districts have. It further includes requirements such as ensuring equal access to various school programs etc.

[27] Students with disabilities served under IDEA face substantially different suspension policy.

percent Hispanic, population) from IPUMs as described in the Data section. These schools are geolocated using ArcGIS.

5.2 Results

Table 9 presents the standard specification for the education dataset, looking at the effect of television on schools within 100 KM of a coverage contour. For each of these measures of academic achievement, column (1) includes only county level controls, column (2) adds controls for school size (number of students and teachers), and column (3) adds controls for whether the school contains primary/middle/high school divisions. Panel A examines the effect of television on the IHS of the number Hispanic students considered gifted,[28] while panel B and C look at the effect on the number of Hispanic students enrolled in an AP course or passing at least one AP course respectively. The coefficient of interest, the dummy for whether the school is located within a coverage contour or not, is significant at the 5% level for all columns and panels. The effect sizes are modest, but non-trivial: an approximately 1.5% increase in the number of gifted students, and increases on the order of roughly 5% for the number of students involved in Advanced Placement curricula.

Table 10 examines the effect of SLTV on disciplinary incidents: Panel A presents the effect on the number of Hispanic students ever given an out of school suspension over the prior school year, while Panel B presents this on the number of Hispanic students considered chronically absent. These results are all significant at the 1% level for all columns and panels. The effect sizes are comparable to that regarding academic achievement, displaying a 1.5% decrease in the number of students suspended, and a 7% decrease in the number of students who are chronically absent.

Table 11 examines the effect of SLTV on outcomes more directly tied to identity: Panel A presents the effect on the number of students categorized as having Limited English Proficiency. These effects are significant at the 1% level, and represent a 3-4% increase in the number of students designated under this category. Panel B, on the other hand, presents the effect on the number of Hispanic students who are ever victims of harassment on the basis of their ethnicity. These results are significant at the 10% and 5% levels, and account for a small .2% bump in the number of such cases.

Robustness To test the robustness of these results, we present Table 12, which uses as its outcome variable the number of Hispanic students passing the AP. We choose to present robustness on this outcome in particular due to its lower sample size — it is a priori the most likely to be underpowered. Column (1) presents the baseline results (it is identical to column (3) of Table 9), while column (2) includes the interaction of the TV dummy with the distance to the boundary squared. This is plausibly relevant to the main effect, given that television signals decay in strength in proportion to the square of the distance. Columns (3) and (6) reduce the cutoff distance from the boundary

[28] IHS, or inverse hyperbolic sine, is comparable to the log transformation, but allows for 0s to be considered

to one half and one third of the original 100 KM limit. Column (4) includes county level fixed effects. Column (5) additionally controls for the total number of APs passed by all students. The robustness checks hold up across the board with all columns maintaining significance, although the 33 KM boundary limit is close to underpowered. Robustness checks on the other outcome variables of interest hold up to a similar analysis.

Finally, we may be concerned about the potential effects of spatial autocorrelation in the data. A Moran's I test using 4 nearest neighbours between the schools indicate that there is spatial autocorrelation at any reasonable level α. Hence, Table **??** presents two alternate models that control for the effects of spatial autocorrelation. Column (2) uses a spatially autoregressive lag model, wherein the outcome variable may be correlated with its neighbours. Column (3) uses a spatially autoregressive error model, wherein the presence of missing spatial covariates (causing correlated errors) is adjusted for. In both cases, the alternate models yield results that closely resemble the standard specification in column (1).

5.3 Discussion

Evidence of Identity as a Mechanism The results in Table 11 provide some concrete evidence that identity changes as a result of the effect of television. We believe that access to SLTV reinforces Hispanic identities, making them more salient to the Hispanic individuals consuming the broadcast programs. The most direct evidence for this stems from the results on harassment and bullying based on ethnicity. Given that very few non-Hispanic people view SLTV programming, the fact that more Hispanic students are bullied on the basis of their ethnicity suggests that some change must be occurring within the students along this dimension.[29]

A substantial literature has shown that increased visibility of (non-majority) ethnicities is associated with greater amounts of bullying,[30], consistent with the results that we see. Though it is impossible to rule out all other stories (perhaps children who watch more TV overall are more likely to be victims of bullying—but this is not supported by the literature. If anything, there is support for television causing children to become bullies Kuntsche et al. (2006), but this is not borne out in our data), the most parsimonious explanation is one in which television increases identity salience and hence ethnicity-based bullying.

We make a similar argument in the interpretation of the greater number of Hispanic students classified as having Limited English Proficiency. This increase demonstrates that these students possess a lower degree of command over the English language, suggesting two possibilities: either (1) that academic/linguistic abilities are lowered across the board, or that (2) there is some sub-

[29] This increase in bullying does not appear to be the result of 'retaliation' to Hispanic students bullying others: the coefficient only attenuates slightly when further controlling for the total number of students bullied, and running the main specification with the number of Hispanic students as perpetrators of race/ethnicity based bullying yields an insignificant negative coefficient.

[30] See Scherr and Larson (2009) for a review of this literature.

stitution in ability towards the Spanish language instead. Given that academic abilities appear to be *enhanced* by the presence of SLTV, the substitution story appears more plausible to us.[31] Unfortunately, we do not have direct evidence on the Spanish-speaking abilities of students, and so recognize that this is not a settled matter. Thus, while the evidence presented is fairly suggestive, more research could be done on this matter.

Effects on Academic Achievement and Discipline We next turn our attention to the results presented in Tables 9 and 10. The results on academic achievement unambiguously show that, for the top end of Hispanic students, performance is bolstered by the presence of SLTV. This effect appears to hold across students of all ages — while gifted programs are typically aimed at students in primary and middle schools, AP courses and exams are almost exclusive taken by high schoolers.

The number of observations recorded for these regressions is worth addressing: compared to the 40,000 schools seen in other regressions, there are only 26,000 seen for gifted students, and fewer than 10,000 for the AP results. In the case of gifted programs, this drop is due to the fact that schools which do not have gifted student programs were omitted from the sample. We find it unlikely that the presence of a gifted program in a school is correlated with the the school being placed just inside or outside a television coverage contour, and so do not believe that this omission introduces any bias. Similarly, in the case of the AP results, only 9,765 of the schools in the sample are high schools with 12th graders enrolled in them—hence, the observed 6,089 schools opting to self-report AP course results is still sizable. Though the number of schools reporting AP exam results is substantially lower and may be concerning for this result, this can at least partially be attributed to the fact that students directly receive their AP scores, and the schools at which they are enrolled may not always have access to their AP scores. Furthermore, given that overall AP scores do not meaningfully change, it is unlikely that there is substantial selection into score reporting over the concerns of Hispanic students passing AP scores—especially because there are no real-world incentives or benefits attached to doing so.

Noting that increases in AP enrolment are predictive of higher rates of college enrolment and degree attainment (Speroni, 2011), it is likely that SLTV can have downstream effects beyond simply greater academic attainment in the short term. Running counter to the mainstream narrative, these increases in academic performance match the results found by **?**, who find that television increases test scores for preschoolers (and in particular, preschoolers from households where English is not the dominant language).

Similarly, these increases in disciplinary outcomes can ameliorate the serious downstream effects that exist beyond the disciplinary event itself: the literature suggests that not only are suspended students at immediate risk of academic harm and further disciplinary issues (Arcia, 2006), but

[31] Granted, the measures of academic ability measure only the performance of students at the top end. But given the existence of these results, a countervailing narrative in which SLTV decreases the academic performance for other Hispanic students would need require a mechanism that could produce such differential effects.

that these students are also more likely to be incarcerated as adults (Wolf and Kupchik, 2017). Non-disciplined students appear to suffer from spillover effects in their academic performance as well (Perry and Morris, 2014).

On the whole, this suggests that the lives of Hispanic students living may materially improve along academic and social dimensions as a result of SLTV.

The Difference Between 'Identity' and Other Outcomes It appears that while Hispanic discipline issues are generally improved by SLTV, this does not extend to the measure directly tied to identity: bullying and harassment based on ethnicity. Similarly, while academic achievement is generally improved by SLTV, this finding does not also generalize to LEP rates. This puzzle—explaining how identity driven results move in opposite directions from the others—is not easily resolved.

Though we do not have a rigorous argument that can resolve this puzzle, one potential explanation would be a substitution effect based on SLTV affecting identity. That is, SLTV might in the immediate affect the identity based mechanisms that we see (more social issues, worse academic performance on metrics tied to identity), but that student performance in other non-identity tied outcomes might in turn shift to make up for the difference. If this were the case, we would expect to see results in line with what we see.

6 Campaign Contributions

In this section, we examine how Hispanic campaign contributions respond to the presence of SLTV.

6.1 Data

The data on campaign contributions comes from the US Federal Election Commission (FEC) campaign contribution receipts for the campaigns 'Donald J. Trump For President, Inc.' and 'Hillary Clinton For President' from the inception of the campaigns to the date of the 2016 US presidential election. These receipts are only legally required to be filed for individual contributions exceeding \$50 or aggregating over \$200 over the course of a year, and contain both the contributor's name and address. We aggregate data into a grid with each square having size .02 degrees latitude by .02 degrees longitude, approximately 2×2 KM^2. Summary statistics for the outcomes and controls are presented in Panel C of Table 2.

Following the approach taken to firms, donor names are also classified using 'ethnicolr'. Since the dataset is now national in nature, instead of using the model trained on the Florida voter registry, we use the model trained on the US census data. This model also utilizes LSTM based on the bigrams present in names, and an out of sample validation exercise yields an 85% overall accuracy as well.

We geocode addresses using a combination of ArcGIS and the US Census Bureau geocoder, which yields 651,404 addresses that ever contributed to Trump, and 41,080 addresses that ever contributed to Clinton.[32]

6.2 Results and Discussion

Table 13 presents the main table for this result, which follows the specification in Table 5—only grid points within 100 KM of the border are kept, and we add successive county controls for log population, percent county Hispanic, and log income in Columns (2), (3) and (4). Results across the board are highly significant, but point in opposite directions: Hispanic contributions to Trump increase under the presence of SLTV, while contributions to Clinton decrease under the presence of SLTV.

We are constrained in this analysis for a number of reasons. First, we do not observe smaller donations that do not have to be reported to the FEC—these made up a substantial part of both Clinton and Trump's campaign contributions,[33] and so we are missing data on a large number of donors. Second, while results are robust (to other specifications/spatial autocorrelation as in prior sections) in that sign and significance are maintained, the coefficient moves substantially enough that interpretation is quite difficult—it appears to be that power comes from the sheer number of observations. Finally, we are unable to explicitly provide evidence towards an identity mechanism occurring in this setting. Though politics is often identity driven, and we do advance some ideas below relating to this, we cannot guarantee that these results are produced as a result of Hispanic identities being influenced or tapped on in some way. Thus, we present these results mainly for suggestive purposes and to indicate an area of research that we believe may prove fruitful for others to pursue.

Nevertheless, the magnitude of these coefficients in quite substantial: the average number of campaign contributions for Trump in a grid point is .08, meaning the presence of SLTV marks an increase of between 7 to 24% in contributions among Hispanics. The average number of campaign contributions for Clinton in a grid point is .049, meaning the presence of SLTV marks a decrease of between 16 to 40% in contributions among Hispanics. These are large quantities that certainly warrant further exploration.

The direction of the results is also somewhat of a puzzle: Hispanics traditionally lean Democrat, so why would SLTV, aimed at Hispanics, induce more campaign contributions to the Republican and not Democrat presidential candidate? We posit two potential reasons for this:

(1) SLTV broadcasts in and of themselves do not have to lean liberal (Vega, 2012). In fact, if they broadcast content produced by or geared towards Latin American audiences, SLTV programming

[32] This corresponds to 892,102 and 119,338 total contributions to Trump and to Clinton respectively.

[33] 25.94% of total funding in the case of Trump and 18.58% in the case of Clinton (OpenSecrets (2017)), but noting that the total number of contributors is likely to constitute a far greater proportion, given the fact that many smaller donations need to be solicited in order for them to equal the dollar value of a larger one.

may reflect the social conservativeness in these nations as tends to be associated with the Evangelical Christian movement (Lissardy, 2018), or more recently, the wave of populist governments bearing resemblance to Trump's campaign and presidency (**?**).

(2) A sizable number of Hispanics still do support Trump and the broader Republican platform—there is a substantial number of naturalized citizens who view themselves as distinct from (and even critical towards) immigrants (Ramos (2020), Navarette (2019)), and hence if SLTV makes the identity of immigrants more salient, this can trigger a 'backlash' effect where more Hispanics may donate to Trump to signal their beliefs or uphold what they believe to be sounder policy.[34] This argument is more plausible when one considers that due to the contribution censoring, we are likely observing how the wealthy respond to SLTV—it is possible that there is substantial heterogeneity being masked.

This finding also helps to explain part of the conflicting narrative in the literature: while **?** finds that local news in Spanish boosts voter turnout, Velez and Newman (2019) comes to the opposite conclusion. Notably, however, the two districts covered under Velez and Newman's analysis, North Carolina's 1st Congressional District and Florida's 22nd both voted majority Democrat over the time-period surveyed, whereas Oberholzer-Gee and Waldfogel take voter turnout data from the 2000 Presidential Election over a large section of the United States—an election that was eventually decided in favor of Republicans. If the campaign contribution findings are a proxy for political engagement, then our results would explain the heterogeneity in the data: areas that lean Democrat are likely to see depressed turnout under SLTV, while the opposite would be true in Republican areas.

7 Conclusion

Summary

Future work: Political angle, examining mechs, complement or substitute with other news

[34] Fortin (2015) is a similar example involving women and in-group backlash.

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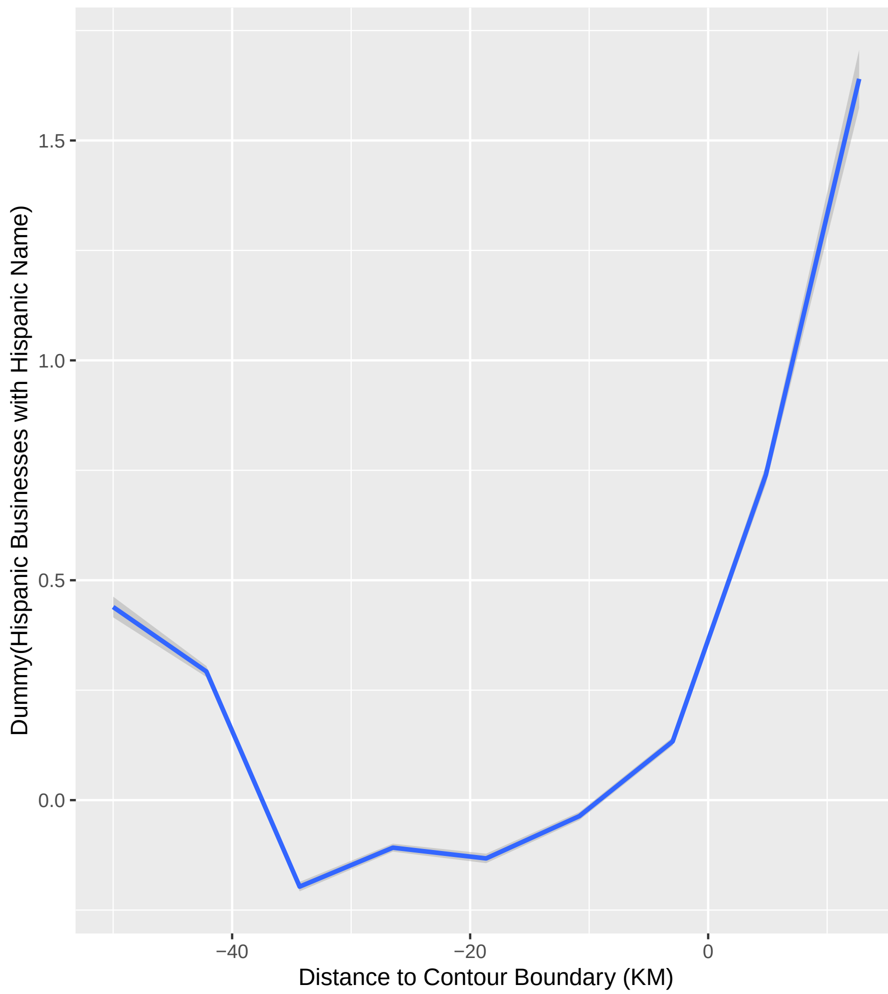
Figures and Tables

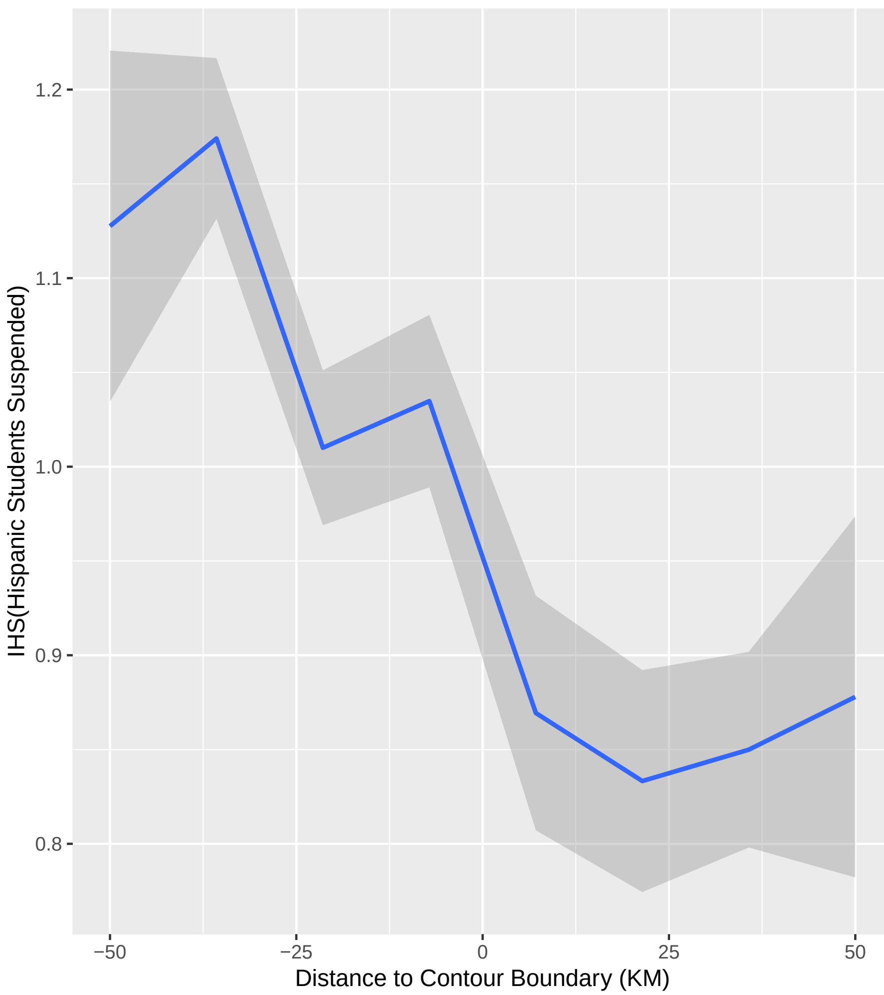
7.1 Figures

Figure 1: Dummy for Hispanic Owned Business with Hispanic Name by Distance to Contour Boundary



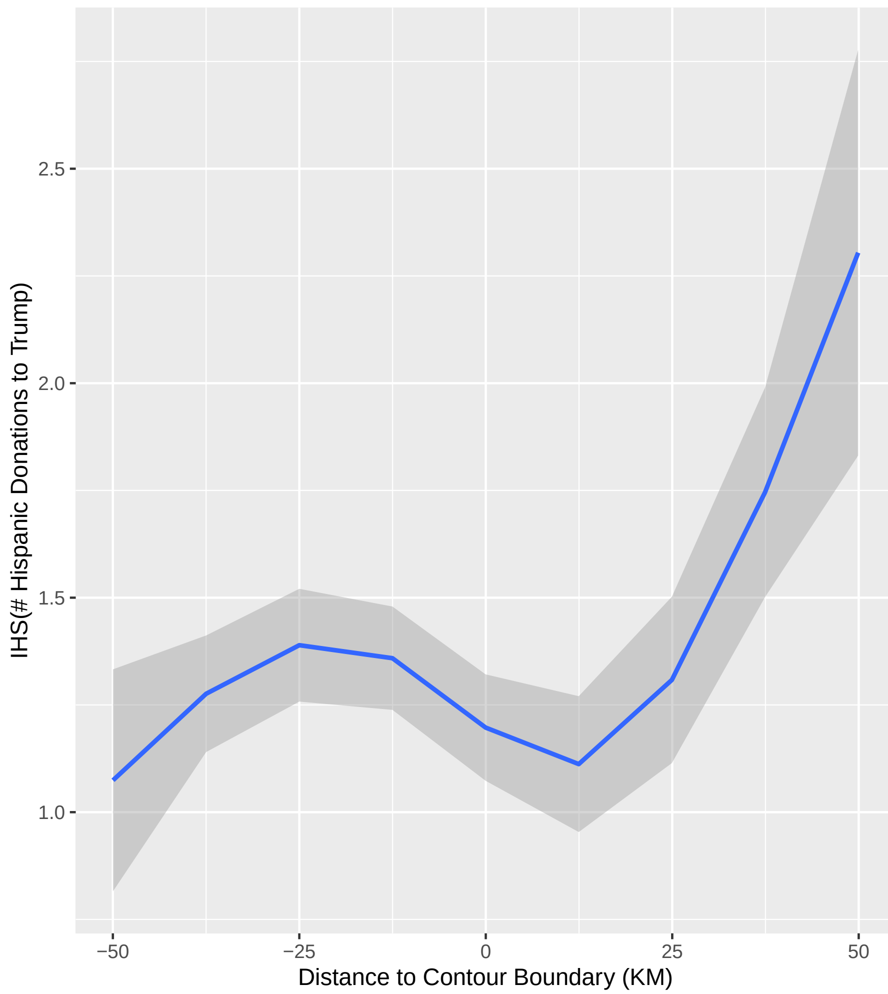
Notes: The figure presents data at the firm level, where a smoothed average of a residualized dummy for Hispanic businesses with Hispanic-indicating names is plotted against the distance of the school to the closest Spanish Language Television station contour boundary. Positive distances denote schools that are located within the boundary, while negative distances denote schools outside of them. Controls at the county level include log population, income, and percentage population Hispanic.

Figure 2: IHS(# Hispanic Students Suspended) by Distance to Contour Boundary



Notes: The figure presents data at a school level, where a smoothed average of the inverse hyperbolic sine transformed counts of Hispanic students suspended is plotted against the distance of the school to the closest Spanish Language Television station contour boundary. Positive distances denote schools that are located within the boundary, while negative distances denote schools outside of them.

Figure 3: IHS(# Hispanic Donations to Trump) by Distance to Contour Boundary



Notes: The figure presents data aggregated into squares of size approximately 4 KM^2, where a smoothed average of the inverse hyperbolic sine transformed counts of Hispanic campaign contributions to Trump for the 2016 election is plotted against the distance of the school to the closest Spanish Language Television station contour boundary. Positive distances denote schools that are located within the boundary, while negative distances denote schools outside of them.

Figure 4: Coverage Map for TV Station WUVC-DT

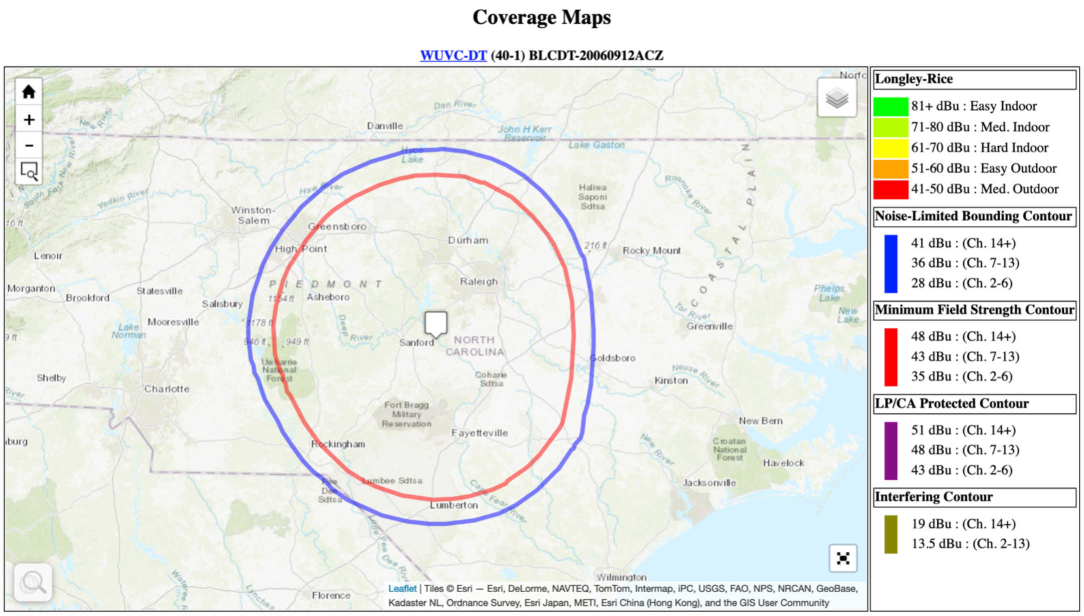


Figure 5: The Coverage Contours of Spanish Language TV stations

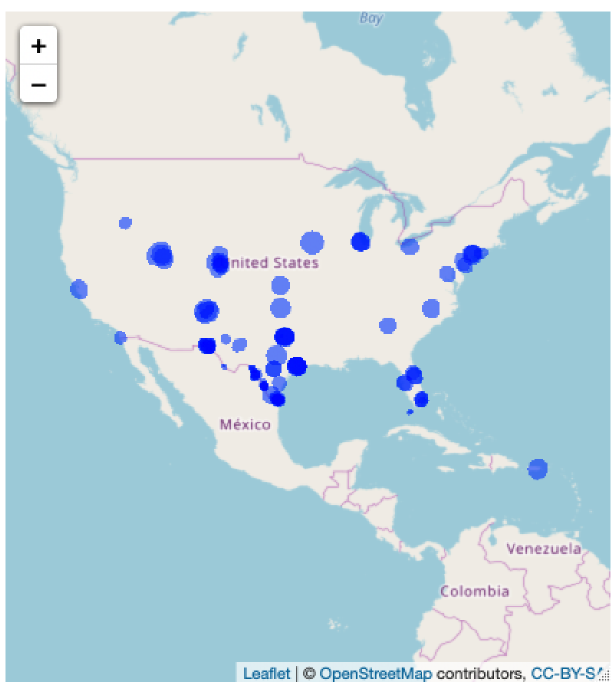
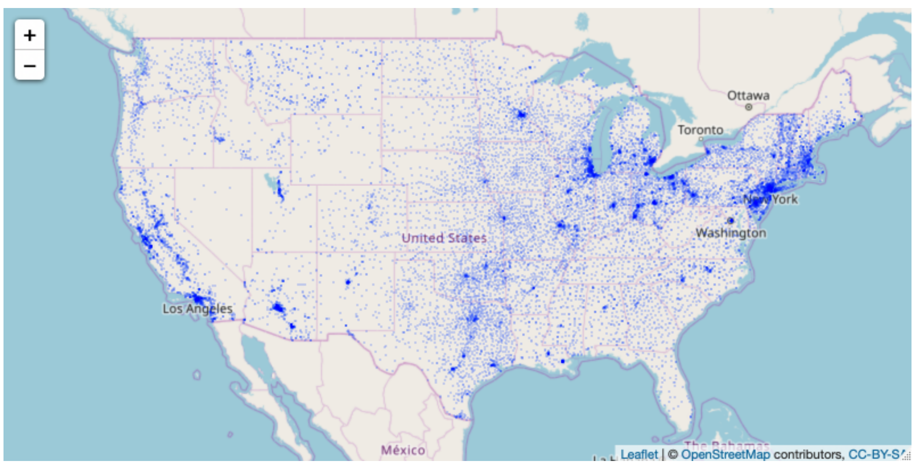


Figure 6: Map of School Districts in the US



7.2 Tables

Table 1: Summary Statistics

	All	*No TV*	*TV*
	(1)	(2)	(3)
Panel A: Migrations			
IHS(Hispanic Migrants)	4.331	4.035	4.462
	1.297	1.204	1.316
Log Income	9.513	9.449	9.541
	(0.281)	(0.201)	(0.305)
Log Population	12.358	11.942	12.542
	(1.516)	(1.640)	(1.419)
Fraction County Hispanic	0.124	0.085	0.141
	(0.155)	(0.122)	(0.164)

Notes: The table presents means (and standard deviations). Variables in Panel A are data from counties within 100 KM of a coverage contour. Columns 2 and 3 show data for the subsample without and with SLTV coverage, respectively. No control is significantly different across the coverage contour at the $\alpha = .1$ level.

Table 2: Summary Statistics

	All	*No TV*	*TV*
	(1)	(2)	(3)
Panel A: Firms			
IHS(Hispanic Owned Firms)	0.992	0.671	1.225
	(1.694)	(1.308)	(1.892)
Hispanic Named Firms	0.027	0.006	0.042
	(0.161)	(0.080)	(0.200)
Log Income	9.498	9.463	9.523
	(0.241)	(0.284)	(0.201)
Log Population	11.954	11.206	12.497
	(1.398)	(1.253)	(1.239)
Fraction County Hispanic	0.086	0.063	0.103
	(0.105)	(0.061)	(0.125)
Panel B: Schools			
IHS(Hispanic Gifted Students)	1.988	1.262	2.380
	(1.552)	(1.238)	(1.563)
IHS(Hispanic AP Enrolment)	3.192	2.091	3.778
	(1.937)	(0.646)	(0.918)
IHS(Hispanic AP Passes)	4.087	3.497	4.181
	(0.917)	(0.646)	(0.918)
IHS(Hispanic Suspensions)	0.957	0.676	1.102
	(1.273)	(1.044)	(1.353)
IHS(Hispanic Absentees)	2.655	1.881	3.054
	(1.765)	(1.536)	(1.742)
IHS(Hispanic Limited English Proficiency)	2.915	2.113	3.331
	(2.040)	(1.820)	(2.024)
IHS(Hispanic Harassment)	0.045	0.027	0.055
	(0.273)	(0.211)	(0.299)
Log Income	9.547	9.430	9.608
	(0.303)	(0.200)	(0.328)
Log Population	12.484	11.559	12.964
	(1.576)	(1.471)	(1.405)
Fraction County Hispanic	0.107	0.037	0.143
	(0.160)	(0.079)	(0.179)
# School Teachers	39.591	32.684	43.169
	(30.764)	(24.090)	(33.146)
# Hispanic Students	164.343	68.500	214.011
	(259.096)	(117.433)	(295.883)
# Total Students	581.524	478.166	635.086
	(482.595)	(383.924)	(518.467)
Panel C: Campaign Contributions			
Hispanic Trump Donations	0.080	0.032	0.175
	(1.165)	(0.047)	(1.900)
Hispanic Clinton Donations	0.049	1.407	1.187
	(3.014)	(1.476)	(4.773)
Log Income	9.279	9.253	9.329
	(0.270)	(0.232)	(0.327)
Log Population	10.830	10.084	10.969
	(1.514)	(1.372)	(1.607)
Fraction County Hispanic	0.148	0.134	0.176
	(0.214)	(0.200)	(0.236)

Notes: The table presents means (and standard deviations). Variables in Panel A and C aggregate data from firms and campaign contributions into 2 KM^2 grid points in Florida and the USA respectively. Variables in Panel B refer to our schools sample. Column 1 shows data for all observations. Columns 2 and 3 show data for the subsample without and with SLTV coverage, respectively. All panels only keep observations within 100 KM of the coverage contour. No control is significantly different across the coverage contour at the $\alpha = .1$ level.

Table 3: Influence of Spanish Language Television on Migration Between Counties - Origin Sample

	IHS(# Hispanic Migrants)		
Panel A: Origin Inside Contour	(1)	(2)	(3)
Dummy: Destination Outside TV Contour	-0.387^{***}	-0.286^{***}	-0.280^{***}
	(0.048)	(0.044)	(0.044)
TV Dummy × Distance to Origin	-0.003^{**}	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)
TV Dummy × Distance to Destination	0.001	-0.002^{*}	-0.002
	(0.001)	(0.001)	(0.001)
Distance from Contour to Origin (KM)	0.001	0.003^{*}	0.003
	(0.002)	(0.002)	(0.002)
Distance from Contour to Destination (KM)	-0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)
Origin Log(Population)	0.146^{***}	0.161^{***}	0.150^{***}
	(0.020)	(0.017)	(0.021)
Destination Log(Population)	0.150^{***}	0.136^{***}	0.125^{***}
	(0.014)	(0.013)	(0.016)
Origin % Hispanic		0.792^{***}	0.881^{***}
		(0.103)	(0.141)
Destination % Hispanic		1.485^{***}	1.573^{***}
		(0.122)	(0.141)
Origin Log(Income)			0.093
			(0.094)
Destination Log(Income)			0.090
			(0.078)
Observations	8,479	8,479	8,479
Panel B: Origin Outside Contour			
Dummy: Destination Inside TV Contour	-0.078	-0.123	-0.120
	(0.108)	(0.096)	(0.096)
TV Dummy × Distance to Origin	-0.003^{*}	-0.004^{***}	-0.004^{***}
	(0.002)	(0.001)	(0.001)
TV Dummy × Distance to Destination	-0.004^{***}	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Distance from Contour to Origin (KM)	-0.0003	0.001	0.001
	(0.001)	(0.001)	(0.001)
Distance from Contour to Destination (KM)	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0003)	(0.0003)
Origin Log(Population)	0.164^{***}	0.131^{***}	0.094^{***}
	(0.017)	(0.021)	(0.026)
Destination Log(Population)	0.150^{***}	0.128^{***}	0.125^{***}
	(0.023)	(0.020)	(0.021)
Origin % Hispanic		1.328^{***}	1.611^{***}
		(0.295)	(0.329)
Destination % Hispanic		1.485^{***}	1.481^{***}
		(0.293)	(0.318)
Origin Log(Income)			0.407^{**}
			(0.193)
Destination Log(Income)			0.003
			(0.087)
Observations	4,062	4,062	4,062
Origin F.E.	Yes	Yes	Yes

Notes: The table presents coefficient estimates from regressions at the county-county level, only keeping origin counties within 100 KM of a contour boundary. The dependent variables are inverse hyperbolic sine transformed counts of Hispanic migrants from the origin county to the destination county. The key dependent variable of interest is the TV Dummy, which tracks whether the destination county is inside or outside the TV contour. This is interacted with the distance to the boundary for both the origin and destination county. County controls include log income, log population, and percentage county Hispanic for both origin and destination county. All regressions also contain origin county fixed effects. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Influence of Spanish Language Television on Migration Between Counties - Destination Sample

	IHS(# Hispanic Migrants)		
Panel A: Destination Inside Contour	(1)	(2)	(3)
Dummy: Origin Outside TV Contour	-0.410^{***}	-0.356^{***}	-0.349^{***}
	(0.088)	(0.082)	(0.081)
TV Dummy × Distance to Destination	-0.007^{***}	-0.008^{***}	-0.008^{***}
	(0.003)	(0.003)	(0.003)
TV Dummy × Distance to Origin	-0.002	-0.004^{**}	-0.004^{*}
	(0.002)	(0.002)	(0.002)
Distance from Contor to Destination (KM)	0.002	0.004^{**}	0.004^{**}
	(0.002)	(0.002)	(0.002)
Distance from Contour to Origin (KM)	0.001	0.004	0.003
	(0.002)	(0.002)	(0.002)
Destination Log(Population)	0.179^{***}	0.181^{***}	0.175^{***}
	(0.019)	(0.016)	(0.019)
Origin Log(Population)	0.115^{***}	0.117^{***}	0.102^{***}
	(0.018)	(0.017)	(0.020)
Destination % Hispanic		1.384^{***}	1.428^{***}
		(0.183)	(0.205)
Origin % Hispanic		0.813^{***}	0.949^{***}
		(0.182)	(0.203)
Destination Log(Income)			0.041
			(0.099)
Origin Log(Income)			0.138
			(0.109)
Observations	4,338	4,338	4,338
Panel B: Origin Outside Contour			
Dummy: Origin Inside TV Contour	-0.140	-0.194	-0.193
	(0.152)	(0.144)	(0.144)
TV Dummy × Distance to Destination	-0.004^{*}	-0.007^{***}	-0.007^{***}
	(0.002)	(0.002)	(0.002)
TV Dummy × Distance to Origin	-0.007^{**}	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
Distance from Contor to Destination (KM)	-0.0003	0.002	0.002
	(0.002)	(0.001)	(0.001)
Distance from Contour to Origin (KM)	-0.001^{***}	-0.002^{***}	-0.002^{***}
	(0.0004)	(0.0004)	(0.0004)
Destination Log(Population)	0.253^{***}	0.169^{***}	0.153^{***}
	(0.041)	(0.023)	(0.030)
Origin Log(Population)	0.182^{***}	0.181^{***}	0.181^{***}
	(0.035)	(0.030)	(0.034)
Destination % Hispanic		2.324^{***}	2.471^{***}
		(0.389)	(0.411)
Origin % Hispanic		1.276^{**}	1.253^{**}
		(0.602)	(0.584)
Destination Log(Income)			0.181
			(0.196)
Origin Log(Income)			-0.015
			(0.192)
Observations	1,659	1,659	1,659
Destination F.E.	Yes	Yes	Yes

Notes: The table presents coefficient estimates from regressions at the county-county level, only keeping destination counties within 100 KM of a contour boundary. The dependent variables are inverse hyperbolic sine transformed counts of Hispanic migrants from the origin county to the destination county. The key dependent variable of interest is the TV Dummy, which tracks whether the destination county is inside or outside the TV contour. This is interacted with the distance to the boundary for both the origin and destination county. County controls include log income, log population, and percentage county Hispanic for both origin and destination county. All regressions also contain destination county fixed effects. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Influence of Spanish Language Television on Hispanic Business Ownership

	IHS(# Hispanic Owned Businesses)			
	(1)	(2)	(3)	(4)
TV Dummy	0.261***	0.122***	0.112***	0.132***
	(0.014)	(0.014)	(0.014)	(0.015)
TV Dummy × Distance to Boundary	0.010***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Distance to Boundary (meters)	0.006***	0.009***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Log(Population)		0.412***	0.388***	0.342***
		(0.011)	(0.012)	(0.014)
County % Hispanic			1.261***	1.414***
			(0.133)	(0.136)
Log(Income)				0.391***
				(0.070)
Observations	23,853	23,853	23,853	23,853

Notes: The table presents coefficient estimates from regressions at aggregated into grids of size approximately 4 KM^2, only keeping grid points within 100 KM of a contour boundary. The dependent variable is the inverse hyperbolic sine transformed counts of Hispanic owned firms within the grid. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. Controls are at the county level. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Influence of Spanish Language Television on Businesses with Hispanic Names

	Hispanic Named Business Dummy					
	(1)	(2)	(3)	(4)	(5)	(6)
TV Dummy	0.839***	0.638***	0.637***	0.769***	0.849***	0.775***
	(0.052)	(0.066)	(0.066)	(0.071)	(0.077)	(0.071)
TV Dummy × Distance to Boundary	0.008***	0.002	0.002	0.0002	−0.0002	0.0002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Distance to Boundary (meters)	0.010**	0.021***	0.021***	0.031***	0.035***	0.031***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Log(Population)		0.957***	0.979***	0.702***	0.761***	0.701***
		(0.052)	(0.070)	(0.074)	(0.081)	(0.074)
County % Hispanic			−0.151	1.428***	1.514***	1.434***
			(0.312)	(0.367)	(0.388)	(0.368)
Log(Income)				2.350***	2.534***	2.356***
				(0.319)	(0.344)	(0.320)
Observations	23,853	23,853	23,853	23,853	23,853	23,853
Only Hispanic Owners	No	No	No	No	Yes	No
Only Non-Hispanic Owners	No	No	No	No	No	Yes

Notes: The table presents coefficient estimates from logit regressions at aggregated into grids of size approximately 4 KM^2, only keeping grid points within 100 KM of a contour boundary. The dependent variable is a dummy for whether there is a firm with a Hispanic name within the grid. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. Controls are at the county level. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Robustness of Influence of Spanish Language Television on Hispanic Owned Businesses with Hispanic Names

	Hispanic Owned and Named Business Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TV Dummy	0.849***	1.071***	0.305***	.8677***	0.927***	0.596***	0.624***	1.144***
	(0.077)	(0.115)	(0.078)	(0.079)	(0.098)	(0.118)	(0.078)	(0.076)
TV Dummy × Distance to Boundary	−0.0002	−0.008	−0.003	−0.001	−0.002	0.042***	0.001	−0.001
	(0.002)	(0.007)	(0.002)	(0.002)	(0.004)	(0.010)	(0.002)	(0.002)
Distance to Boundary (meters)	0.035***	0.123***	0.013***	0.036***	0.049***	−0.097***	0.026***	0.042***
	(0.005)	(0.021)	(0.005)	(0.005)	(0.012)	(0.035)	(0.005)	(0.006)
Total Businesses			0.023***					
			(0.001)					
Observations	23,853	23,853	23,853	23,853	20,404	14,386	10,598	95,373
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance Cutoff	100	100	100	100	50	25	100	100
Grid Size (KM^2)	4	4	4	4	4	4	9	1
$Distance^2$	No	Yes	No	No	No	No	No	No
No Food Names	No	No	No	Yes	No	No	No	No

Notes: The table presents coefficient estimates from logit regressions at aggregated into grids, only keeping grid points within a certain cutoff of a contour boundary. The dependent variable is a dummy for whether there is a firm with a Hispanic name owned by a Hispanic person within the grid. Column (1) is the same specification as Table 6 Column (5). The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. Controls are at the county level, and include log population, log income, and percentage of county that is Hispanic. Total Businesses is the total number of businesses in the grid, while No Food Names removes references to various Hispanic foods as part of the criterion for selection of Hispanic business names. Various distance cut-offs, grid sizes, as well as the interaction with distance squared are presented. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Spatial Robustness of Influence of Spanish Language Television on Hispanic Firm Ownership

	IHS(# Hispanic Owned Firms)		
	(1)	(2)	(3)
TV Dummy	0.122***	0.022***	0.126***
	(0.014)	(0.006)	(0.036)
Observations	23,853	23,853	23,853
Log Likelihood		−38,404	−38,440
σ^2		1.168	1.170
Akaike Inf. Crit.		76,821	76,894
Wald Test (df = 1)		65,139***	63,913***
LR Test (df = 1)		24,759***	24,687***
County Controls	Yes	Yes	Yes
Model	OLS	SAR Lag	SAR Error

Notes: The table presents coefficient estimates from regressions at aggregated into grids of size approximately 4 KM^2, only keeping grid points within 100 KM of a contour boundary. The dependent variable is the inverse hyperbolic sine transformed counts of Hispanic owned firms in the grid. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. County controls include log population. Additionally controlling for log income and percentage county Hispanic for the county which the grid is in yields similar coefficients, although standard errors cannot be estimated due to computational limitations. The SAR Lag model is a spatial autoregressive lag model and the SAR Error model is a spatial autoregressive error model, both with weight matrices based on 4 nearest neighbours. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Influence of Spanish Language Television on Hispanic Academic Achievement

Panel A: IHS(# Hispanic Gifted Students)	(1)	(2)	(3)
TV Dummy	0.016***	0.015**	0.013**
	(0.006)	(0.006)	(0.006)
TV Dummy × Distance to Boundary	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (meters)	0.0002	−0.0002	−0.0002
	(0.0003)	(0.0003)	(0.0003)
# Hispanic Students	0.003***	0.002***	0.002***
	(0.00003)	(0.00004)	(0.00004)
Observations	26,065	26,065	26,065
Panel B: IHS(# Hispanic Students Taking AP)			
TV Dummy	0.072***	0.051***	0.047***
	(0.016)	(0.015)	(0.015)
TV Dummy × Distance to Boundary	0.002***	0.002***	0.003***
	(0.0003)	(0.0003)	(0.0003)
Distance to Boundary (meters)	−0.003***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)
# Hispanic Students	0.002***	0.001***	0.001***
	(0.00004)	(0.0001)	(0.0001)
Observations	6,089	6,089	6,089
Panel C: IHS(# Hispanic Students Passing AP)			
TV Dummy	0.034**	0.042***	0.039***
	(0.014)	(0.013)	(0.013)
TV Dummy × Distance to Boundary	0.0003	0.0003	0.0003
	(0.0003)	(0.0002)	(0.0002)
Distance to Boundary (meters)	0.002**	0.002*	0.001
	(0.001)	(0.001)	(0.001)
# Hispanic Students	0.001***	0.001***	0.001***
	(0.00003)	(0.00004)	(0.00004)
Observations	2,205	2,205	2,205
County Controls	Yes	Yes	Yes
School Size Controls	No	Yes	Yes
School Type Controls	No	No	Yes

Notes: The table presents coefficient estimates from regressions at the school level, only keeping schools within 100 KM of a contour boundary. The dependent variables are inverse hyperbolic sine transformed counts of Hispanic students in gifted programs in Panel A, Hispanic students enrolled in AP courses in Panel B, and Hispanic students passing AP courses in Panel C. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. County controls include log income, log population, and percentage county Hispanic for the county which the school is located in. School size controls account for the number of teachers and total number of students at the school, while school type controls include dummies for whether the school contains a primary, middle, and high school division. All regressions also control for the number of Hispanic students enrolled at the school. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Influence of Spanish Language Television on Hispanic Disciplinary Outcomes

Panel A: IHS(# Hispanic Out of School Suspensions)	(1)	(2)	(3)
TV Dummy	-0.011^{**}	-0.018^{***}	-0.016^{***}
	(0.005)	(0.005)	(0.005)
TV Dummy × Distance to Boundary	0.0004^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (meters)	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0002)	(0.0002)	(0.0002)
# Hispanic Students	0.003^{***}	0.002^{***}	0.002^{***}
	(0.00002)	(0.00003)	(0.00003)
Observations	40,864	40,864	40,864
Panel B: IHS(# Hispanic Students Chronically Absent)			
TV Dummy	-0.067^{***}	-0.073^{***}	-0.074^{***}
	(0.006)	(0.006)	(0.006)
TV Dummy × Distance to Boundary	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (meters)	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.0003)	(0.0003)	(0.0003)
# Hispanic Students	0.004^{***}	0.003^{***}	0.003^{***}
	(0.00003)	(0.00004)	(0.00004)
Observations	40,869	40,869	40,869
County Controls	Yes	Yes	Yes
School Size Controls	No	Yes	Yes
School Type Controls	No	No	Yes

Notes: The table presents coefficient estimates from regressions at the school level, only keeping schools within 100 KM of a contour boundary. The dependent variables are inverse hyperbolic sine transformed counts of Hispanic students who have received an out of school suspension in the prior year in Panel A, and Hispanic students chronically absent (over 15 days a year) in Panel B. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. County controls include log income, log population, and percentage county Hispanic for the county which the school is located in. School size controls account for the number of teachers and total number of students at the school, while school type controls include dummies for whether the school contains a primary, middle, and high school division. All regressions also control for the number of Hispanic students enrolled at the school. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Influence of Spanish Language Television on Hispanic Identity

Panel A: IHS(# Hispanic Students Limited English Proficiency)	(1)	(2)	(3)
TV Dummy	0.040***	0.039***	0.031***
	(0.007)	(0.007)	(0.007)
TV Dummy × Distance to Boundary	0.003***	0.003***	0.003***
	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (meters)	−0.002***	−0.002***	−0.002***
	(0.0004)	(0.0004)	(0.0003)
# Hispanic Students	0.004***	0.004***	0.004***
	(0.00003)	(0.00004)	(0.00004)
Observations	40,864	40,864	40,864
Panel B: IHS(# Hispanic Victims of Ethnicity-Based Harassment)			
TV Dummy	0.003**	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
TV Dummy × Distance to Boundary	−0.0001**	−0.00005*	−0.00005*
	(0.00002)	(0.00002)	(0.00002)
Distance to Boundary (meters)	−0.0004***	−0.0004***	−0.0004***
	(0.0001)	(0.0001)	(0.0001)
# Hispanic Students	0.0001***	0.00003***	0.00004***
	(0.00001)	(0.00001)	(0.00001)
Observations	40,811	40,811	40,811
County Controls	Yes	Yes	Yes
School Size Controls	No	Yes	Yes
School Type Controls	No	No	Yes

Notes: The table presents coefficient estimates from regressions at the school level, only keeping schools within 100 KM of a contour boundary. The dependent variables are inverse hyperbolic sine transformed counts of Hispanic students who have Limited English Proficiency Panel A, and Hispanic students bullied or harassed on the basis of their identity in Panel B. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. County controls include log income, log population, and percentage county Hispanic for the county which the school is located in. School size controls account for the number of teachers and total number of students at the school, while school type controls include dummies for whether the school contains a primary, middle, and high school division. All regressions also control for the number of Hispanic students enrolled at the school. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Robustness of Influence of Spanish Language Television on Hispanic Students Passing the AP

	IHS(# Hispanic Students Passing AP)					
	(1)	(2)	(3)	(4)	(5)	(6)
TV Dummy	0.039***	0.049***	0.044***	0.044***	0.036***	0.032*
	(0.013)	(0.017)	(0.016)	(0.017)	(0.013)	(0.018)
TV Dummy × Distance to Boundary	0.0003	0.0001	0.001	0.001*	0.0001	0.001
	(0.0002)	(0.001)	(0.001)	(0.0004)	(0.0004)	(0.001)
Distance to Boundary (meters)	0.001	0.012***	0.006***	0.006***	0.003**	0.001
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)
# Hispanic Students	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00004)	(0.00004)	(0.00005)	(0.0002)	(0.00004)	(0.0001)
Total APs Passed					0.003***	
					(0.0001)	
Observations	2,205	2,205	1,525	1,525	1,525	1,095
County/School Controls	Yes	Yes	Yes	Yes	Yes	Yes
Distance Cutoff (KM)	100	100	50	50	50	$33\ \frac{1}{3}$
Distance^2 Interaction	No	Yes	No	No	No	No
County F.E.	No	No	No	Yes	No	No

Notes: The table presents coefficient estimates from regressions at the school level. The dependent variable is the inverse hyperbolic sine transformed counts of Hispanic students who have passed an AP exam. The key dependent variable of interest is the TV Dummy, which tracks whether the school is within a coverage contour boundary for a Spanish language television station. This is interacted with the distance to the boundary. County and school controls include log income, log population, percentage county Hispanic for the county which the school is located in, and the number of teachers, total number of students at the school, and dummies for whether the school contains a primary, middle, and high school division. Various distance cut-offs to the boundary are presented, as well as the TV dummy interacted with the square of the distance. All regressions also control for the number of Hispanic students enrolled at the school. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Influence of Spanish Language Television on Campaign Contributions

	# Hispanic Campaign Contributions			
Panel A: Contributions to Trump	(1)	(2)	(3)	(4)
TV Dummy	0.019***	0.010***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
TV Dummy × Distance to Boundary	0.002***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (KM)	0.0001	0.0003***	0.0003***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Population)		0.081***	0.084***	0.058***
		(0.001)	(0.001)	(0.001)
County % Hispanic			0.084***	0.265***
			(0.007)	(0.008)
Log(Income)				0.00003***
				(0.00000)
Observations	619,011	619,011	619,011	619,011
Panel B: Contributions to Clinton				
TV Dummy	−0.008**	−0.014***	−0.019***	−0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
TV Dummy × Distance to Boundary	0.003***	0.002***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance to Boundary (KM)	0.0002	0.0004**	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Population)		0.053***	0.056***	0.038***
		(0.003)	(0.003)	(0.003)
County % Hispanic			0.106***	0.229***
			(0.019)	(0.022)
Log(Income)				0.00002***
				(0.00000)
Observations	619,011	619,011	619,011	619,011

Notes: The table presents coefficient estimates from regressions that divide the US up into grid points of size 4 KM^2. The dependent variables are the summed counts of Hispanic contributions to political campaigns in the 2016 presidential election. The key dependent variable of interest is the TV Dummy, which tracks whether the destination county is inside or outside the TV contour. This is interacted with the distance to the boundary. County controls include log income, log population, and percentage county Hispanic. Standard errors are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.