Local Economic Benefits Increase Positivity toward Foreigners

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Can exposure to discernible economic benefits associated with the presence of a high-socioeconomic status (SES) immigrant group reduce xenophobic and anti-foreigner attitudes? We explore this question using the case of Chinese internationals in the United States and an exogenous influx of foreign capital associated with their presence. Using a difference-in-differences design with panel data, along with analyses of pooled cross-sectional data, we find that immigration attitudes, as well as views toward China, became more positive over-time among Americans residing in locales whose economies were stimulated by Chinese foreign investments. Our findings have implications for research on public attitudes toward immigration in an era of growing flows of high-SES immigrants to the United States and other immigrant-receiving nations.

Can exposure to discernible economic benefits associated with the presence of a high-socioeconomic status (SES) immigrant group reduce xenophobic and anti-foreigner attitudes? Scholarship on immigration politics over the past decade has produced a robust body of evidence that citizens in the United States and other immigrant-receiving nations strongly prefer high- to low-SES migrants.[1–3] The primary explanation offered for this finding is that citizens' preference for high-SES immigrants is due to economic sociotropic considerations: high-SES immigrants are believed to generate more economic benefits (e.g., strengthening the economy and increasing tax revenues) and impose fewer costs (e.g., driving down wages and consuming public resources) than low-SES immigrants.

One critical and testable implication of this research is that the xenophobic and anti-foreigner sentiment present among the populace in many immigrant-receiving nations may be abated by exposure to economic benefits brought about by the presence of high-SES immigrants. What is distinctly missing from the literature, however, is a study that offers an empirically rigorous test of whether or not citizens react positively to a discernible economic benefit generated by the presence of high-SES immigrants. In this study we provide such a test, focusing on an important economic benefit associated with the presence of high-SES Chinese immigrants—foreign capital—and assessing whether Americans residing in locales whose economies were stimulated by an exogenous influx of Chinese foreign capital became less hostile to immigrants generally, and to China specifically, as a result.

We utilize new administrative data on the annual number and location of Chinese international students[4]—an empirical proxy for recent exposure to the investments—and combine these data with national panel survey data spanning from 2010 to 2014. The linchpin of our research design is the start of a nationwide anti-corruption campaign in China in November of 2012 that stimulated an exogenous shock in the influx of capital from China to the United States in the form of foreign real estate investment (FREI). This influx of FREI was distributed mainly to locales housing affluent Chinese international students and led to substantial increases in housing values, which has been shown to provide local benefits such as increased consumer spending,[5–7] firm investments,[8] employment,[9] and economic growth.[10] These local benefits were especially critical in many U.S. regions that were still recovering from the housing market crash of the late-2000s.[11] For example, media reports illustrate how local governments and companies in Texas were not only aware of the tax-revenue and consumer-spending benefits that followed Chinese FREI, but that they even approved development projects and introduced direct flights to court Chinese buyers.[12] Reports also depict how local real estate agents have associated the growth in home purchases with Chinese buyers "whose children attend, or plan to attend, nearby colleges" and recommended buying "where the Chinese are buying because they perpetuate the price increase."[13] Furthermore, even university administrators have assisted parents of Chinese international students who were seeking to purchase U.S. homes.[12] Indeed, while the academic and political discourse on the benefits of high-SES immigration often centers on their provision of occupational skills, talent, and entrepreneurship,[14] an increasingly important economic benefit associated with high-SES immigrants is foreign capital—particularly given the growth of financial globalization. The economic benefits stemming from such capital investment are the focus of this study.

Leveraging the shock, we employ a difference-in-differences (DiD) analysis with panel data to assess whether Americans exposed to Chinese foreign investment became more positive toward foreigners following the sudden inflow of capital. We then complement this analysis with an investigation of pooled cross-sectional data. Overall, we find that xenophobic sentiment—specifically, immigration attitudes, as well as views toward China—became more positive over time among Americans residing in locales whose economies were stimulated by Chinese FREI. Importantly, a range of placebo tests rules out the possibility that our findings are driven by pre-treatment trends, unobserved local features, or un-theorized temporal shocks. Finally, consistent with previous research,[15] the effects seem to be driven by sociotropic concerns as opposed to naked self-interest: there is limited evidence of a difference in how homeowners and non-homeowners responded to Chinese FREI, even though homeowners experienced the most capital appreciation. Indeed, we uncover suggestive evidence that the effect of Chinese FREI exposure on attitudes toward foreigners may be driven by the communotropic benefits it engenders. Specifically, we demonstrate through a series of DiD analyses that Americans residing in locales exposed to Chinese FREI witnessed greater increases in median income, employment, new business establishments, and consumer spending than those residing in locales not exposed to Chinese FREI.

These findings contribute to a growing literature that uses a design-based, case-driven approach to assess the impact of immigration on natives' attitudes and political behavior.[16] Importantly, while these previous studies explore the causal effect of an influx of people (i.e., immigrants), we analyze the causal effect of a discernible economic benefit (i.e., foreign capital) associated with the presence of people (i.e., high-SES immigrants). While our study focuses on the U.S. case, global trends in Chinese FREI suggest that our findings may be generalizable beyond the United States. Many developed economies such as the United Kingdom, Canada, and Australia experienced a similar surge in Chinese FREI and an associated boost in their local economies during the same period.[17] Given that (a) the United States is one of the most preferred destinations in the world for Chinese homebuyers,[18] (b) Chinese immigrants are strongly associated with the model minority stereotype, and (c) Chinese economic investments in the United States expanded at a crucial time in the wake of the Global Financial Crisis, our findings should provide insights on the upper bound of a positive communotropic effect of higher-SES immigrants (i.e., a "most likely case"). As such, this study is well-designed for identifying mechanisms that heretofore have been difficult to observe. If we fail to find evidence for economic benefits as a key explanatory variable even in this most-likely case, then it suggests that the literature's focus on this mechanism may be misguided.

To be sure, prior research documents how exposure to Asian immigration reduces xenophobic attitudes.[19–22] This work, however, relies on model-based approaches using cross-sectional data that are susceptible to concerns over omitted variable bias linked to residential self-selection. Other research has examined the effect of local contextual features such as fiscal pressure[23] and local economic forces.[24] However, the independent variables in these studies are endogenously selected domestic policies. The uniqueness of our study is that we examine the effect of an exogenous shock in capital investments generated from external (push) factors rather than internal (pull) factors generated by domestic politics. Finally, our findings are relevant given demographic patterns in the United States. Over the past ten years, immigration from Asia has surpassed Latino immigration, and Asian-Americans are forecasted to be the largest ethnic minority group by mid-century.[25] Relevant to the study of the politics of immigration, the rise in Asian immigration has meant growth in the population of high-SES immigrants—and the potential influx of foreign capital and associated economic benefits.

Below, we present results based on two independent studies we conducted. Demonstrating similar findings across two independent datasets yielding distinct analytic approaches increases our confidence in the findings and reduces the possibility that we have found a result due to chance alone. In the discussion, we note various limitations of the study, including our use of proxy measures for xenophobic attitudes.

Results

Study 1

We first present the results of Study 1, the analysis of panel data from the Cooperative Congressional Election Study (CCES). As shown on the left-hand side of the left panel in Figure 1, the DiD estimate of Chinese FREI exposure [β_3 from equation (3)] is -0.50 ($p = .04$, two-tailed,

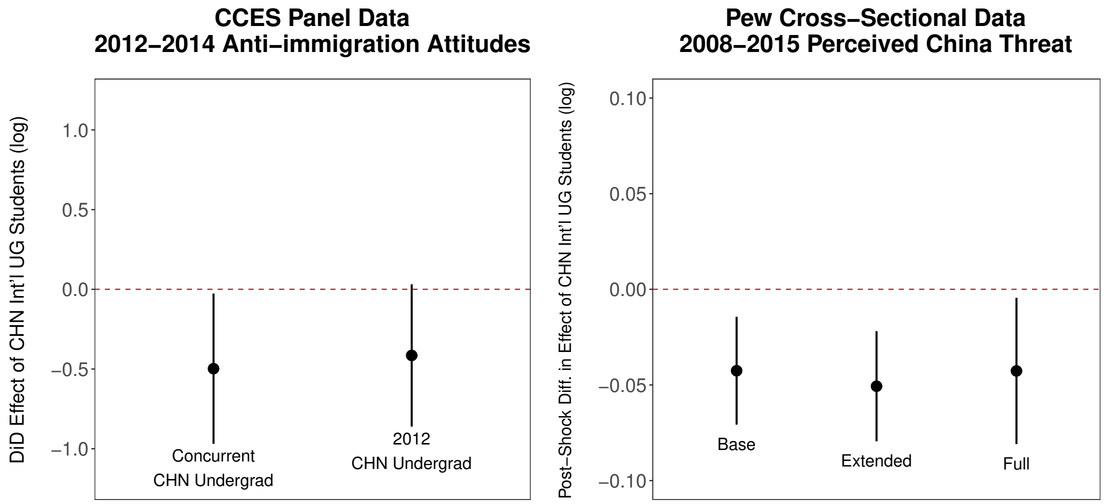

Figure 1. The Effect of Chinese FREI Exposure on Individual Attitudes. This figure presents point estimates and 95% confidence intervals. The left panel presents CCES estimates using concurrent (n = 17,264) and 2012 (n = 17,264) measures of Chinese FREI exposure. The right panel presents Pew estimates from baseline (n = 7,526), extended (n = 6,743), and full (n = 6,730) model specifications, respectively. See Supplementary Tables 4 and 12 for details on model specifications and estimates.

95% C.I. = -0.97 to -0.03, see Supplementary Table 4 for details). This suggests that a one-unit increase in Chinese FREI exposure makes people more pro-immigration by 0.50 percentage points. Given that the range of the Chinese FREI exposure variable is 7.4 units, this suggests an overall effect of 3.7 percentage points. How big is this in substantive terms? The effect of moving from the bottom to the top category of education—arguably the strongest predictor of immigration attitudes[15]—is 28.5 percentage points. Hence, the effect of Chinese FREI exposure is approximately 13% of the effect of education. As shown on the right-hand side of the left panel in Figure 1, the DiD estimate from equation (4) based on an alternative operationalization of our exposure variable is similar in size, but more imprecisely estimated and not statistically significant at the $p = .05$ level (.41 percentage points, $p = .07$, 95% C.I. = -0.86 to 0.03).

To assess the robustness of these results, we conduct a variety of placebo checks. First, we perform temporal placebo checks. For a placebo version of equation (3), we see if changes in Chinese FREI exposure between 2012 and 2014 predict attitude change between 2010 and 2012—before the anti-corruption campaign was implemented. As shown in column (1) of Supplementary Table 5, this DiD estimate is statistically insignificant and the opposite sign of what we present in Figure 1. Similarly, when we fit a version of equation (4) in which we predict the change in attitudes from 2010 to 2012 with the 2012-level of Chinese FREI exposure, we again find that the estimate is oppositely signed and statistically insignificant (see column 2). Finally, we also conduct similar analyses as in equations (3) and (4) except only examine changes between 2010 and 2012—when there was no anti-corruption campaign—as opposed to changes between 2012 and 2014. Again, we observe insignificant and oppositely signed point estimates [see columns (3) and (4)]. The results point to an effect of the anti-corruption campaign *per se* as opposed to general secular trends in both Chinese undergraduate mobility and immigration attitudes.

Next, we conduct placebo tests using international student populations demonstrated in the Methods section to be unrelated to the geographic distribution of Chinese FREI in the United States—namely, Indian undergraduates and Chinese graduate students. First, we re-estimate equations (3) and (4) but use the log of the number of Indian undergraduates. Note that there was no exogenous policy change by the Indian government in 2013 related to FREI. Further, if our estimates are simply picking up an unobserved feature of localities, then the number of Indian undergraduates should produce a similar effect since Indian and Chinese undergraduates tend to target similar universities. For example, among the top one hundred universities Chinese international undergraduates have enrolled in since 2000, 52% overlap with the top one hundred universities for Indian international undergraduates. In contrast, there is only a 25% overlap in top universities between Chinese and Canadian international undergraduates.[4] As shown in columns (1) and (3) in Supplementary Table 6, the point estimates associated with the interaction terms are smaller and statistically insignificant when focusing on Indian undergraduates instead of Chinese undergraduates. We also estimate models using Chinese graduate students instead of Chinese undergraduate students. Chinese graduate students, who are mainly covered by fellowships/grants and whose families are less capable of investing,[26] represent a different population who were generally unaffected by the anti-corruption campaign. As shown in columns (2) and (4) of Supplementary Table 6, the point estimates associated with the interaction terms are small and statistically insignificant. The null effects for Chinese graduate students show that the effects of Chinese undergraduate students are due to Chinese FREI *per se* and not some un-theorized temporal shock that caused attitudes to become more positive in places housing Chinese internationals in general—as such an unobserved shock would affect attitudes in contexts housing Chinese graduate students as well. Instead, the effects are confined to affluent Chinese international undergraduate students, who are uniquely linked to FREI and increasing home values.

Lastly, we explore the potential mechanisms underlying the main result. As an important caveat, firmly establishing mechanisms is extremely difficult in social science research.[27] Hence, these findings should be viewed as more tentative. We test two competing mechanisms: (1) the FREI shock increased positive views toward foreigners because it improved personal financial positions (pocketbook considerations), and (2) the investment shock increased positive views because it improved the local economy in which people resided (communotropic considerations).

We find little evidence for the first mechanism—that residents affected by Chinese FREI exposure became more pro-immigrant simply due to their material interests as property values increased. The housing market crash of the late-2000s sent many households into negative equity on their homes (i.e., the principal value of the mortgage is greater than the value of the property). Thus, it is possible that "underwater" homeowners became more pro-immigrant as the surge in Chinese FREI helped them climb out of negative equity. In column (2) of Sup-

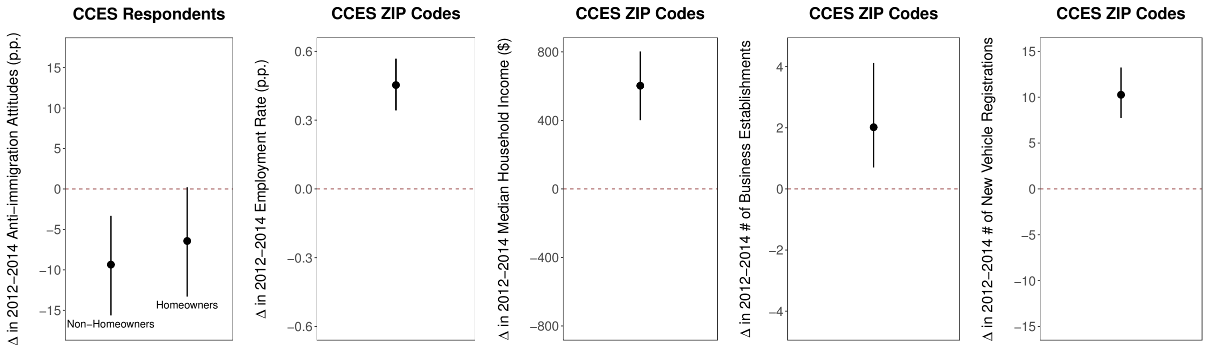

Figure 2. Potential Mechanisms: Substantive Effects of Chinese FREI Exposure. This figure presents point estimates and 95% confidence intervals. Effects are based on 1,000 Monte Carlo simulations when increasing Chinese FREI exposure from one standard deviation below the mean to above. The simulations use the empirical distribution of the data (from left to right, n = 15,118, n = 11,961, n = 11,956, n = 11,959, and n = 11,961) and full model specifications. See Supplementary Tables 7–11 for details on model specifications and estimates.

plementary Table 7, we fit a model analyzing whether the Chinese-FREI effect differs between homeowners who owned a property throughout the panel and other respondents. We also control for demographic characteristics that may be correlated with homeowner status. We find that the effect of Chinese FREI exposure on anti-immigration attitudes is not significantly different between homeowners and non-homeowners. The interaction term between homeowner status and FREI exposure is not statistically significant at the $p = .05$ level ($\beta = 1.17$, $p = 0.08$, 95% C.I = -0.16 to 2.51), and the opposite sign of what would be expected if self-interest was driving the result. The first panel from the left in Figure 2 presents the size of the substantive effects for each group when increasing Chinese FREI exposure from one standard deviation below the mean to above. Overall, the finding is consistent with research that has shown that homeowners and renters often share similar political preferences when it comes to issues involving housing.[28]

However, we do find evidence consistent with the second mechanism described above—increased exposure to Chinese FREI strengthened CCES respondents' local economy between 2012 and 2014. We employ four different ZIP-code level measures of the strength of CCES respondents' local economy: employment rate, median household income, the number of business establishments, and the number of new vehicle registrations. We rely on the U.S. Census Bureau for data on the first three measures and acquired data for the fourth measure from Hedges & Company. The fourth measure follows a well-established literature in economics that uses new vehicle registrations to proxy for levels of local consumer spending.[6] In Supplementary Tables 8–11, we fit DiD models similar to our previous analyses but substituting in these four measures as the outcome variable to analyze whether Chinese FREI exposure strengthened CCES respondents' local economy. We also control for ZIP-code characteristics that may be correlated with both Chinese FREI exposure and the strength of the local economy. The four panels from the right in Figure 2 present the main results. Substantively, we find that increasing exposure to Chinese FREI from one standard deviation below the mean to above (i.e., increasing the ZIP-code population of Chinese international undergraduate students from around one to thirteen) increases a CCES ZIP-code's (1) employment rate by 0.45 percentage points (95% C.I. = 0.34 to 0.57, 0.05 s.d. of the outcome), (2) median household income by $603 (95% C.I. = 401 to 803, 0.03 s.d. of the outcome), (3) number of business establishments by 2.02 (95% C.I. = 0.70 to 4.12, 0.004 s.d. of the outcome), and (4) number of new vehicle registrations by 10.3 (95% C.I. = 7.74 to 13.24, 0.01 s.d. of the outcome). Overall, our finding that the positive effect of capital infusion produces communotropic rather than pocketbook effects is consistent with many previous studies that have found that sociotropic concerns, as opposed to self-interest, influence immigration attitudes.[15] It is important to note, however, that our findings regarding mechanisms are not dispositive, and the evidence could be read in multiple ways. For example, the positive effect of FREI on local economic characteristics could have also provided pocketbook benefits to individuals, which may then explain people's attitudes.

In summary, the findings from Study 1 show that exposure to Chinese FREI arising from China's 2013 anti-corruption campaign reduced anti-immigration attitudes among Americans. The results also suggest that exposure to discernable regional economic benefits associated with the presence of high-SES immigrants can make people more positive toward foreigners. By demonstrating a case where attitudes toward immigrants improve in response to the materialization of local economic benefits tied to a high-SES immigrant group, the findings support the claim that citizens prefer high-SES immigrants for economic sociotropic reasons. More broadly, the findings lie in sharp contrast to the bulk of research showing that exposure to primarily low-SES immigrants induces threat and makes people more anti-immigrant.[15,20,29]

Study 2

We now turn to Study 2, which analyzes pooled cross-sectional survey data collected from 2008 through 2015 by the Pew Research Center. Overall, we find that, across various model specifications and estimators, increased exposure to Chinese FREI reduces respondents' perceptions of threat from China. The right panel of Figure 1 summarizes the main results (see Supplementary Table 12 for details). For example, estimates from the full OLS model specification [equation (5)] show that a one-unit increase in exposure to Chinese FREI reduces respondents' perceived level of threat from China by around 0.04 units (on a linear scale, $p = 0.03$, two-tailed, 95% C.I. = -0.08 to -0.004) during the post-campaign period compared to the pre-campaign period.

To help gauge the size of the substantive effect, Figure 3 plots changes in the predicted level of a perceived threat from China as ZIP codes increase their exposure to Chinese FREI. The left panel shows that before the anti-corruption campaign ZIP codes with minimum exposure (zero, which is still greater than one s.d. below the mean) see China as a threat at the level of 2.44 (95% C.I. = 2.36 to 2.51). Furthermore, increasing a ZIP code's exposure from zero to one standard deviation above the mean [2.33, or $\exp(2.33) \approx 10$ Chinese international undergraduate students] has no statistically significant effect on changes in threat perceptions (0.03, 95% C.I. = -0.04 to 0.10). Since the anti-corruption campaign, however, the right panel shows that a similar increase in exposure reduces the perceived China threat by around 0.075 (95% C.I. =

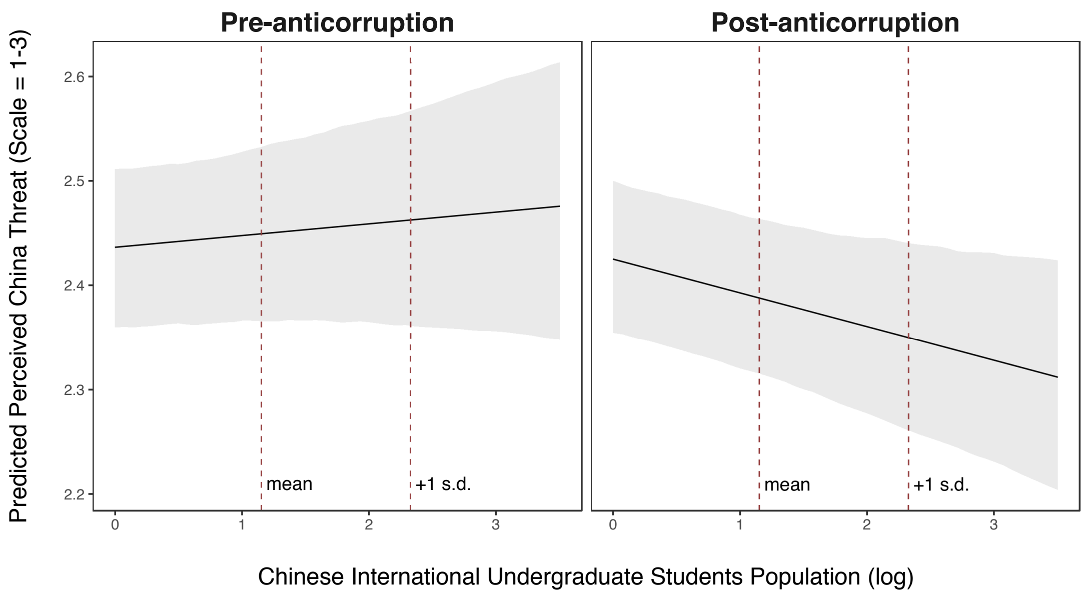

Figure 3. Predicted Perception of China Threat. This figure shows the predicted level and 95% confidence intervals of perceived China threat in a ZIP code as its exposure to Chinese FREI increases. Predictions are based on 1,000 Monte Carlo simulations using the full model specification and the empirical distribution of the data (n = 6,730). We truncate the x-axis to two standard deviations above and below the mean. The vertical dash line represents the mean (1.15) and one standard deviation above the mean (2.33). See Supplementary Table 12 for details on model specifications and estimates.

-0.13 to -0.02), which represents approximately 4% of the variation in the outcome variable or a 0.11 standard deviation change. In comparison, increasing a respondent's education level from one standard deviation below the mean to above reduces the level of perceived China threat by around 0.09. In other words, the effect of Chinese FREI exposure is approximately 83% of the effect of education.

We conduct two sets of placebo tests to assess the robustness of these results. First, the surge in Chinese FREI stemming from the anti-corruption campaign should only affect respondents' perceived threat from China and not from other countries. To test this, we examine the impact of Chinese FREI exposure on the level of the perceived threat from placebo countries such as North Korea, Russia, and Iran. In particular, we re-estimate equation (5) using Pew survey questions about the level of a perceived threat from each placebo country as the outcome variable. Second, we again examine the two categories of placebo international students—Indian undergraduates and Chinese graduate students. Our expectations suggest that increases in the population size of either of these placebo students should not change respondents' perceived threat from China as they do not imply higher Chinese FREI exposure. Here, we re-estimate equation (5) but substitute Chinese undergraduates with the log number of each type of placebo student.

We find that the post-shock effects of Chinese FREI exposure on the three placebo countries were statistically insignificant and smaller compared to the main results (see Supplementary Table 13 for details). Furthermore, the direction of the effects was mixed—point estimates were negatively signed for Russia and Iran but positively signed for North Korea. Next, we find that the post-shock effects of the placebo students on the perception of a China threat were also statistically insignificant and smaller in magnitude (see Supplementary Table 14 for details). Lastly, ordered logistic regressions yield null findings similar to the results of OLS regressions (see Supplementary Tables 13 and 14).

Together, the findings from our second study show that exposure to Chinese FREI is associated with lower levels of a perceived threat from China. These findings suggest that the influx of foreign capital tied to the presence of an immigrant group can generate positive impressions of that group's origin country. These findings complement the general pro-immigration effects of Chinese FREI exposure found in our first study. Moreover, these findings provide a validity check on our research design by demonstrating a unique and systematic connection between exposure to Chinese FREI and attitudes toward China. Lastly, a distinct possibility at the outset of Study 2 was that exposure to Chinese investments might trigger a backlash by augmenting the perceived threat of China via the nation's growing economic power. For example, recent research finds that Chinese firm-led Foreign Direct Investment (FDI) in sensitive industries can trigger threat perceptions among citizens in recipient nations.[30] This possibility, however, was not borne out in the data, as we uncover suggestive evidence that exposure to Chinese FREI reduced perceptions of threat from China. Thus, our findings suggest that attitudes toward the influx of foreign capital can be more nuanced, especially when they generate wide-ranging and substantial communotropic benefits.

Discussion

This study has demonstrated that exposure to economic benefits via an exogenous increase in foreign capital investment associated with the presence of a high-SES immigrant group resulted in more pro-immigrant and less xenophobic attitudes. While there are clear strengths of our research design, and we replicate our findings across different data sets and outcome variables, there are important limitations of our analyses that should be acknowledged.

First, one assumption we make is that residents were aware that rising home values (and consequent improving economic conditions) were linked to Chinese FREI. Unfortunately, we were unable to locate any survey data with questions directly asking about Chinese foreign investment or its link to economic conditions in respondents' residential context. In the absence of such data, we are unable to provide any direct tests of the assumption of resident awareness of the connection between rising home values and Chinese FREI. At best, we are able to offer evidence that Americans were aware of the presence of Chinese international students in their local context, that the inflow of Chinese FREI had demonstrable and wide-reaching positive economic impacts, and that key stakeholders in recipient communities (e.g., local media, real estate professionals, university administrators) were keenly aware of the connections between Chinese FREI and local economic conditions. In the Methods section, we report findings from the 2008 and 2012 Collaborative Multiracial Post-Election Surveys indicating that the local presence of Chinese international students increased American residents' perception of the presence of Asians in their neighborhood. In the end, if people were completely unaware of the link between Chinese FREI and local economic conditions, it would be unlikely for us to have found a positive attitudinal effect, and any lack of awareness of such a link should push our estimates toward zero.

A second limitation of our analysis concerns the outcome variables we use in each study. Ideally, our analyses would have estimated the effect of exposure to Chinese FREI on attitudes toward Chinese immigrants. However, we were unable to locate any survey data containing questions soliciting attitudes specifically about Chinese immigrants during the relevant period under analysis. As such, our use of immigration policy preferences as the outcome measure in Study 1 provides only an indirect view on the effect of exposure to Chinese FREI on attitudes toward immigrants themselves or even Chinese immigrants specifically. That said, preferences over immigration policies are a very common indicator of xenophobic sentiment in the social science literature,[16,29,31–33] and there is abundant evidence that views toward immigrants and immigration policies are highly correlated.[32,34,35] Finally, while the policies we analyze in Study 1 concern "irregular" or illegal migrants, existing research finds that Americans' preferences over policies concerning legal immigration are highly correlated with their preferences over policies concerning illegal immigration,[35] and that prejudice toward immigrant ethnic groups serves as a significant predictor of preferences over policies affecting legal and illegal migrants alike.[35,36] In sum, with respect to Study 1, our focus on immigration policy preferences captures an important dimension of xenophobic and anti-foreigner sentiment, and one that likely reflects—albeit indirectly—attitudes toward immigrants themselves.

Turning to Study 2, one limitation worth noting is that perception of threat from a foreign nation is a less commonly used indicator of xenophobic and anti-foreigner sentiment, and similar to the outcome in Study 1, it does not directly capture attitudes toward Chinese immigrants. That said, research exploring public opinion in international relations finds that ethnocentrism and hostility toward ethnic outgroups are highly predictive of opposition to free trade and foreign investment.[37] Furthermore, research focusing specifically on U.S.-China relations identifies Americans' views on globalization, international trade, and immigration as interrelated attitudes linked to xenophobic and protectionist stands toward China.[38] Indeed, accounts of the 2016 U.S. Presidential Election suggest that support for Donald Trump was rooted in a set of interrelated political attitudes, including anti-immigrant sentiment[39] and opposition to free trade agreements like the Trans-Pacific Partnership.[40] In short, while not directly measuring attitudes toward immigrants or immigration policy, existing research demonstrates that perceptions of threat from foreign nations are linked to ethnocentrism, opposition to immigration, and trade protectionism.

Beyond serving as a feasible indicator of anti-foreigner sentiment, a key benefit of the usage of a perceived threat from China as the outcome measure in Study 2 is that it serves as a validity check. In theory, there should be a correspondence between the sender-nation of our FREI treatment and threat perceptions. This is precisely what we find: exposure to the Chinese FREI shock was associated with reduced threat perception from China but had no statistically discernible effects on threat perceptions from other nations (e.g., Russia, Iran, North Korea).

One direction for future research is to examine the scope conditions of our findings. The results presented here may be specific to the unique situation studied—wealthy Chinese homebuyers infusing capital into U.S. housing markets in the wake of the Global Financial Crisis. We thus encourage scholars to explore further how economic benefits stemming from immigration influence policy attitudes and policymaking. At the same time, our findings demonstrate the critical influence that economic benefits associated with immigration can have on politics. According to surveys conducted by the Pew Research Center, there is widespread perception that China represents a competitive threat to the United States,[41] with roughly a third of Americans thinking that limiting China's power and influence should be a major foreign policy goal[42] and a majority believing that China will overtake the United States as the global superpower.[43] The fact that economic benefits can increase positivity toward foreigners, and China specifically, given this opinion environment is telling of the importance of observing the economic benefits of immigration in countering the type of nativist sentiments typically observed among citizens in the United States and other immigrant-receiving nations.

Methods

Research Design

Our research design takes advantage of an exogenous shock in Chinese FREI following the inauguration of an anti-corruption campaign in China in late 2012. According to data from the National Association of Realtors (NAR), Chinese acquisitions of U.S. residential property has grown significantly in recent years, increasing more than seven-fold from $4 billion in 2009 to around $29 billion in 2015.[44] However, closer scrutiny of the data shows that Chinese acquisitions were mostly stagnant between 2010 and 2012. Furthermore, much of the growth occurred between 2013 to 2015, with increases of around $8 billion per year. In fact, China surpassed Canada and became the largest foreign buyer of U.S. homes in 2013 (see Supplementary Figure 1). The significant acceleration of Chinese FREI since 2013 matches the start of Chinese President Xi Jinping's anti-corruption campaign and increasing political risks. This ongoing campaign began following the end of the 18th National Congress of the Communist Party of China in November 2012. In 2014 alone, the Chinese Communist Party disciplined more than 71,000 party members.[45] As of July 2018, more than 2,400 officials have been arrested or sentenced in criminal corruption cases.[46] The mass crackdown led to the fear of political targeting and asset expropriation, which helped accelerate Chinese capital flight.[47]

The massive spike in Chinese FREI beginning in 2013 represents a shock to local recipient economies throughout the United States that is exogenous to local residents' political attitudes or U.S. domestic policies. As such, our causal variable of interest is American citizens' exposure to Chinese FREI. The most direct measure of this variable would capture home purchases in the United States by individuals residing in China. However, systematic data on specific U.S. home purchases by Chinese nationals are not readily available due to privacy and proprietary concerns. Further, many Chinese nationals form shell companies to purchase real estate assets in the United States.[48]

Given these challenges, we argue that the best available option is to use the local presence of Chinese internationals as a proxy to capture variation throughout the United States in exposure to Chinese FREI. Specifically, we focus on a ZIP code's population of Chinese international undergraduate students using new administrative data acquired through a Freedom of Information Act request to U.S. Immigration and Customs Enforcement,[4] which draws on individual-level administrative records of every international student in the United States since 2000 to compute annual estimates for all ZIP Code Tabulation Areas (ZCTAs)]. The idea is that these undergraduate students tend to come from more affluent families, and FREI follows affluent international students because it serves the dual purpose of supporting child education and portfolio diversification. This idea is supported by many existing surveys of Chinese FREI motivations.[18,44] As a result, we expect ZIP codes with a larger population of Chinese international undergraduate students to attract more Chinese FREI after the start of the campaign.

Although spatial variation in Chinese international undergraduate students in the United States is nonrandom and Americans' exposure to them is subject to selection bias, the change in Chinese FREI associated with this population before and after November 2012 is exogenous to American citizens' attitudes toward foreigners. That is, Americans' attitudes did not play a role in Chinese domestic policy decisions about combating corruption. Thus, the research design accounts for such selection bias through between-ZIP code differences in pre-treatment attitudes. Furthermore, the nature of our DiD models allows us to carefully distinguish between the effects of people versus capital. In particular, the models estimate (1) the effect of exposure to Chinese international undergraduate students in the pre-treatment period, (2) the effect of exposure to these students in the post-treatment period, and (3) the difference in the effects of these students, which is attributed to the drastic influx of FREI after the anti-corruption campaign in locales housing Chinese international undergraduate students. Lastly, since the distribution of Chinese international undergraduate students among ZIP codes is highly skewed to the right, we take the natural log of the measure to reduce the influence of extreme values in our analyses.

Using a series of DiD models that examine the effect of Chinese FREI exposure on local home prices (median value per square feet, Zillow, see http://www.zillow.com/research/data/), we demonstrate the suitability of the ZIP-code presence of Chinese international undergraduate students as a proxy for exposure to Chinese FREI. If the research design is valid, ZIP codes with a larger population of affluent Chinese international undergraduate students right before the anti-corruption campaign (groups exposed to a high dosage of the treatment) should receive more investments after the shock than ZIP codes that have a smaller population (groups exposed to lower dosages of the treatment). A surge in Chinese FREI, in turn, should lead to greater local demand for housing and thus larger increases in home prices in treated ZIP codes, *ceteris paribus*. In contrast, we should not observe greater increases in home prices in ZIP codes with either a larger population of placebo Chinese international graduate students or Indian international undergraduate students. The former group represents students who are from the same national origin but mainly rely on institutional funding and whose families are less capable of investing.[26] The latter represents students who are at the same academic level but from an origin-country not tied to China's investors and the anti-corruption campaign. Lastly, the positive effect of a ZIP code's population of Chinese international undergraduate students on home prices should be significantly smaller before the anti-corruption campaign and the acceleration of Chinese FREI.

Formally, we fit the DiD model below following existing research:[4]

$$M_{zt} \;=\; \lambda_z + P_t + \beta_1(P_t C_{z,2012}) + \boldsymbol{\beta_2}(P_t \boldsymbol{S}_{z,2012}) + \beta_3 \boldsymbol{U}_{zt} + \beta_4 P_t \boldsymbol{U}_{zt} + \epsilon_{zt}, \tag{1}$$

where the outcome variable M_{zt} measures the log-transformed median home value per square feet ($) in ZIP code z in year t using data from Zillow. The treatment-condition variable $C_{z,2012}$ indicates the natural log of the population of Chinese international undergraduate students in 2012 (right before the anti-corruption campaign). The treatment-period dummy variable P_t equals 1 for years starting from 2013 and 0 otherwise. The variable λ_z represents ZIP-code fixed effects, which accounts for any time-invariant features of ZIP codes that are likely to be correlated with the presence of Chinese international undergraduate students. For example, college towns may be more diverse or hold more human capital and thus recover faster after the housing market crash. Note that ZIP-code fixed effects subsume the constitutive terms for international students as they do not vary over t. The variables $\boldsymbol{S}_{z,2012}$ measure the population of placebo international students discussed above. The variables $\boldsymbol{U}_{zt}$ indicate time-varying covariates that capture minor imbalances across ZIP codes that may undermine assumptions about parallel trends. These include several ZIP-code factors that can affect the demand and supply of local homes but also influence home prices, such as employment share, the share of adult population, population density (log), the share of white population, median household income, the share of population enrolled in college or above, the total population enrolled in college or above, effective real estate tax rates (%), and the share of vacant houses. The Census Bureau provides data for these covariates since 2011. To account for any trending effects from these controls, we also include $P_t\boldsymbol{U}_{zt}$ in the model specification. We cluster standard errors by ZIP codes to allow for within-unit correlation of errors. The coefficient of interest is β_1, which is the DiD estimate for the price effect of exposure to Chinese FREI. We fit the model to four different periods: 2011–2012, 2012–2013, 2012–2014, and 2012–2015.

Figure 4 summarizes the main results (see Supplementary Table 1 for formal estimates of the regression models). The left panel shows a steady growth in the positive effect of Chinese FREI exposure on home prices since the 2013 anti-corruption campaign. Substantively, simulation results based on the 2012–2013 model suggest that increasing Chinese international undergraduates from one standard deviation below the mean (0) to above the mean (38) raises a ZIP code's median home value per square feet by $6.2, which corresponds roughly to a $15,200 spike in home prices for a median-sized (2,457 square feet) single-family house completed in 2013. In contrast, the effect was barely existent during the pre-treatment period (2011–2012). Furthermore, the middle panel shows null or even negative effects between 2012–2013 by the placebo international students. Lastly, the right panel illustrates relatively similar growth in Chinese international undergraduate and graduate students between 2011–2013 based on the administrative data. This pattern suggests that the price effect is not simply due to the presence of Chinese international students, but rather confined to the presence of Chinese international students who attract FREI. Together, the results provide extensive evidence supporting the validity of our research design.

As an additional validity check, we also examine the extent to which Americans were aware of the presence of Chinese international undergraduate students in their local area of residence. Observing a treatment effect for exposure to Chinese FREI entails that citizens were aware of the presence of the foreign students drawing these capital investments, as the awareness of these students underscores citizens' ability to make connections between improving local economic conditions, FREI, and immigration. To test for Americans' awareness of these students, we draw on the 2008 and 2012 Collaborative Multiracial Post-Election Surveys (CMPS, https://cmpsurvey.org/). The survey is unique because, to the best of our knowledge, no other surveys ask Americans about the presence of Asian persons (native or foreign-born) in their local residential context. In particular, both the 2008 and 2012 CMPS ask the following questions:

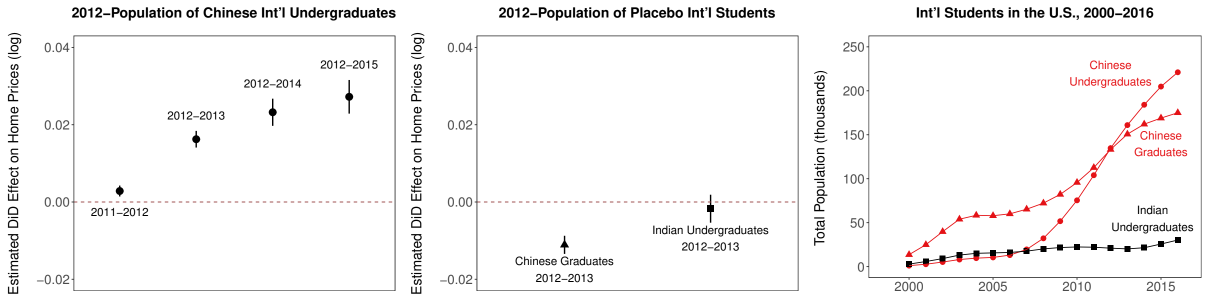

Figure 4. The Effect of Chinese FREI Exposure on Home Prices in U.S. ZIP Codes. The left and middle panel present DiD point estimates and 95% confidence intervals. The sample sizes underlying estimates in the left panel are (from left to right): n = 24,831, n = 24,851, n = 24,821, n = 24,723. The sample size for estimates in the middle panel is n = 24,851. Home prices rely on Zillow's measure of median value per square feet (log). See Supplementary Table 1 for details on model specifications and estimates. The right panel shows the population of international students in the United States by year, country of origin, and academic level using administrative data.

(1) "Would you describe the neighborhood where you currently live as mostly Black, mostly White, mostly Hispanic, mostly Asian, or mixed?" (2) "Is it almost entirely [ANSWER TO FIRST QUESTION] or is it mostly [ANSWER TO FIRST QUESTION]?" Following existing research,[49] we use respondents' answers to the two questions to create an ordinal measure of the perceived prevalence of Asians in respondents' neighborhood: 0 = "partially", 1 = "mostly", and 2 = "entirely." We then fit the OLS regression model below to data from each survey to see if the local population of Chinese international undergraduates is systematically and positively linked to residents' perception of the prevalence of Asians in their neighborhoods in that year:

$$N_{iz} = \alpha + \beta_1 C_z + \beta_2 \boldsymbol{I}_{iz} + \beta_3 \boldsymbol{U}_z \epsilon_{iz}, \tag{2}$$

where i indexes respondents, z indexes ZIP codes, N_{iz} represents individual's perceived neighborhood prevalence of Asians, C_z represents the log of Chinese international undergraduate students in a ZIP code in the same year, and ϵ_{izt} is the stochastic error. The variables $\boldsymbol{I}_{it}$ stand in for respondent-level controls (age, education, white, and income) while the variables $\boldsymbol{U}_z$ indicate ZIP-code level controls (median household income, population density, and the share of the population with a bachelor's degree or higher). The coefficient of interest is β_1, of which a positive sign represents a positive correlation between the population size of Chinese international undergraduates and respondents' perceived prevalence of Asians. As robustness checks, we fit models with or without control covariates. Additionally, we fit an ordered logistic regression model to account for the categorical nature of the dependent variable.

Overall, we find that the coefficient for the population of Chinese international undergraduates is positive and statistically significant at $\alpha = 0.05$ across all model specifications, years, and estimators (see Supplementary Tables 2 and 3 for details). Together, these findings show supportive evidence that Americans were aware of the presence of Chinese international undergraduate students residing in their ZIP code of residence.

Study 1: CCES Longitudinal Data

Our first study takes advantage of a three-wave longitudinal panel collected as part of the Cooperative Congressional Election Study (CCES, https://cces.gov.harvard.edu/). The CCES seeks to obtain a representative sample of Americans by matching respondents who take surveys as part of an opt-in Internet panel to administrative datasets such as the U.S. Census Bureau and voter files. This sample matching procedure has been shown to produce nationally representative data.[50] Respondents completed both pre- and post-election surveys in 2010, 2012, and 2014. Given that the Chinese anti-corruption campaign was rolled out in 2013, the timing of the surveys provides us with an ideal opportunity to investigate how immigration attitudes changed between 2012 and 2014. As discussed below, the 2010 wave allows us to conduct placebo tests.

The dependent variable is anti-immigration attitudes. The CCES asked three questions related to immigration enforcement to the full sample of respondents in all three waves. The questions were asked in a binary (yes/no) fashion where respondents offered their opinions of various policy proposals about what “the U.S. government should do about immigration”: (1) “Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years and not been convicted of any felony crime”; (2) “Increase the number of border patrols on the U.S.-Mexican border”; (3) “Allow police to question anyone they think may be in the country illegally.” While these items do not refer to China specifically, the three items generally tap an underlying latent construct (Cronbach’s alpha = .76) and reflect an anti-immigrant disposition. We average the three items and rescale so that the index lies between 0 (pro-immigration) and 100 (anti-immigration). The independent variable is Chinese FREI exposure as operationalized by the natural log of the number of Chinese international undergraduate students living in a ZIP code.

We fit the following OLS regression model using the 2012 and 2014 waves:

$$A_{izt} = \alpha + \beta_1 C_{zt} + \beta_2 P_t + \beta_3 (C_{zt} \times P_t) + \lambda_z + \epsilon_{izt} \tag{3}$$

where i indexes respondents, z indexes ZIP codes, t indexes year, A_{izt} represents individual immigration attitudes, C_{zt} represents the log of Chinese international undergraduate students in a ZIP code in a given year, P_t is a dummy variable taking on the value of 1 if the survey data is from 2014 (after the anti-corruption campaign started), λ_z represents ZIP-code fixed effects, and ϵ_{izt} is stochastic error. Standard errors are clustered by ZIP code. The inclusion of ZIP-code fixed effects accounts for any time-invariant demographic features of ZIP codes that are likely to be correlated with the presence of Chinese international undergraduate students. For instance, these ZIP codes are primarily located in university towns which tend to be more liberal, diverse, and better educated. The coefficient of interest is β_3, which is the DiD estimate. Given that the dependent variable is scaled such that higher values indicate anti-immigration attitudes, a positive coefficient on β_3 indicates that the increase in Chinese FREI exposure led people to become more anti-immigrant whereas a negative coefficient on β_3 would mean that people became more pro-immigrant. Given that we are primarily relying on within-ZIP code variation in FREI to identify the effect of foreign investments (and ZIP-code fixed effects account for time-invariant features of ZIP codes), our design does not require the inclusion of individual-level demographic covariates. However, we also fitted models that included individual-level controls and obtained similar results [see column (1) of Supplementary Table 7]. Additionally, we estimated models with individual-level fixed effects and obtained virtually identical results to those using ZIP-code fixed effects (see columns (3) and (4) of Supplementary Table 4].

As a robustness check, we estimate a second version of equation (3) where we operationalize Chinese FREI exposure only as a pre-treatment characteristic of ZIP codes in 2012 (as opposed to measuring the change from 2012 to 2014):

$$A_{izt} = \alpha + \beta_1 P_t + \beta_2 (C_z \times P_t) + \lambda_z + \epsilon_{izt} \tag{4}$$

Note that in equation (4) the constituent term for the natural log of the number of Chinese immigrants drops out because the value does not change across the panel. β_2 is the coefficient of interest and is interpreted in a similar fashion as in equation (3).

Study 2: Pew Research Pooled Cross-Sectional Data

Our second analysis takes advantage of seven cross-sectional surveys conducted by the Pew Research Center (https://www.pewresearch.org/) between 2008 to 2015 that each include a China-specific survey item: the 2008 September Political/Foreign Policy Survey, 2009 June Political Survey, 2009 November "America's Place in the World" Survey, 2012 U.S.-China Security Perceptions Project Survey, 2013 November "America's Place in the World" Survey, 2014 August Political Survey, and the 2015 December Political Survey. Each survey contains a question soliciting the perception of threat from China and is a representative sample of adult Americans conducted by telephone using random digit dialing. Thus, this analysis builds on Study 1 by enabling us to assess whether exposure to Chinese FREI influences attitudes concerning China specifically.

The dependent variable is the perception of a China threat. In these seven surveys, Pew asked respondents whether they think "China's emergence as a world power" is a "major threat, a minor threat, or not a threat to the well-being of the United States." While the question does not directly ask respondents about their attitudes toward Chinese FREI *per se*, we believe that it reflects a general attitude toward growing Chinese influence via trade, investment, and immigration. To code the response to this question, Pew assigned the value of 1, 2, and 3 for "major threat," "minor threat," and "not a threat," respectively. We reverse Pew's coding so that 3 represents a "major threat" and 1 represents "not a threat," to be consistent with Study 1. Our independent variable is, again, Chinese FREI exposure.

We pool the cross-sectional surveys and fit the following OLS regression model:

$$\begin{aligned} A'_{izt} = \alpha + \beta_1 C_{zt} + \beta_2 P_t + \beta_3 (C_{zt} \times P_t) + \\ \beta_4 \boldsymbol{I}_{it} + \beta_5 \boldsymbol{U}_{zt} + \beta_6 (\boldsymbol{U}_{zt} \times P_t) + \epsilon_{izt}, \end{aligned} \tag{5}$$

where i indexes respondents, z indexes ZIP codes, and t indexes year. The outcome variable A'_{izt} represents individual perceptions about a China threat. The treatment-condition variable C_{zt} represents the log of Chinese international undergraduate students in a ZIP code in a given year. The treatment-period dummy variable P_t takes on the value of 1 for surveys conducted in 2013 and after (the post-treatment period) and 0 otherwise. The variables $\boldsymbol{I}_{it}$ stand in for respondent-level controls while the variables $\boldsymbol{U}_{zt}$ indicate ZIP-code level controls. Standard errors are clustered by ZIP code. For individual-level controls, we include a respondent's age, education level, ethnicity, income, party identification, and ideology. For ZIP-code level controls, we account for the median household income, population density, and the share of the population enrolled in college or above. The coefficient of interest is β_3, which is the post-shock estimate of Chinese FREI exposure.

We fit three different model specifications. The baseline model only includes the treatment-condition variable C_{zt}, the treatment-period dummy variable P_t, and their interaction term. An extended model adds individual-level controls $\boldsymbol{I}_{it}$. The full model augments above models with ZIP-code level controls $\boldsymbol{U}_{zt}$ and their interaction with the treatment-period dummy variable P_t. As robustness checks, we fit a linear mixed-effects model with varying intercepts for ZIP codes. These intercepts account for time-invariant characteristics of ZIP codes related to both Chinese international undergraduate students and perceptions of a China threat. We also fit an ordered logistic regression model that accounts for the categorical nature of the dependent variable.

Reporting of Methodology

We used an alpha level of .05 (two-tailed) for all statistical tests in this study. All estimated models assume that the errors are normally distributed (not the variables themselves). Error distributions were assumed to be normal, but this was not formally tested as it is impossible to observe properties of the error term directly. As discussed, in some cases where there was skewness in a key independent variable (e.g., the population of undergraduate students), the variable was logged.

In this observational study, we did not independently collect survey data, perform any randomization, or directly involve human participants. Further, given that the data are observational and not experimental, data collection and analysis were not performed blind to the conditions of the experiments. The sample sizes were determined based on the availability of relevant survey data (i.e., number of years $\times$ number of respondents) and the number of ZIP codes in the United States. No data were excluded from the main analysis.

Data Availability Statement

Replication data is available on the Harvard Dataverse at: https://doi.org/10.7910/DVN/GY8PXP.

Code Availability Statement

Replication code is available on the Harvard Dataverse at: https://doi.org/10.7910/DVN/GY8PXP.

References

1. K. Bansak, J. Hainmueller, D. Hangartner, How Economic, Humanitarian, and Religious Concerns Shape European Attitudes toward Asylum Seekers. *Science* p. aag2147 (2016).

2. J. Hainmueller, D. J. Hopkins, The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants. *American Journal of Political Science* **59**, 529–548 (2015).

3. B. J. Newman, N. Malhotra, Economic Reasoning with a Racial Hue: Is the Immigration Consensus Purely Race Neutral? *The Journal of Politics* **81**, 153-166 (2019).

4. S. Liao, Chinese Foreign Real Estate Investment and Voting in U.S. Presidential Elections (2019). *Working Paper*. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3504861.

5. J. Y. Campbell, J. F. Cocco, How do House Prices Affect Consumption? Evidence from Micro Data. *Journal of Monetary Economics* **54**, 591–621 (2007).

6. A. Mian, K. Rao, A. Sufi, Household Balance Sheets, Consumption, and the Economic Slump. *The Quarterly Journal of Economics* **128**, 1687–1726 (2013).

7. D. Berger, V. Guerrieri, G. Lorenzoni, J. Vavra, House Prices and Consumer Spending. *The Review of Economic Studies* **85**, 1502-1542 (2018).

8. T. Chaney, D. Sraer, D. Thesmar, The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. *American Economic Review* **102**, 2381-2409 (2012).

9. K. K. Charles, E. Hurst, M. J. Notowidigdo, The Masking of the Decline in Manufacturing Employment by the Housing Bubble. *Journal of Economic Perspectives* **30**, 179-200 (2016).

10. N. Miller, L. Peng, M. Sklarz, House Prices and Economic Growth. *The Journal of Real Estate Finance and Economics* **42**, 522–541 (2011).

11. M. Zonta, S. Edelman, The Uneven Housing Recovery (2015). Available at https://cdn.americanprogress.org/wp-content/uploads/2015/10/30051742/UnevenHousingRecovery-reportB.pdf.

12. D. Searcey, K. Bradsher, Chinese Cash Floods U.S. Real Estate Market (2015). *The New York Times*. Available at https://www.nytimes.com/2015/11/29/business/international/chinese-cash-floods-us-real-estate-market.html.

13. The Economist, College Towns: A Roaring Trade (2016). Available at http://www.economist.com/news/united-states/21700660-chinese-tiger-mums-start-college-town-housing-boom-roaring-trade.

14. N. Kaushal, M. Fix, The Contributions of High-Skilled Immigrants (2016). *Migration Policy Institute*. Available at https://www.migrationpolicy.org/research/contributions-high-skilled-immigrants.

15. J. Hainmueller, D. J. Hopkins, Public Attitudes Toward Immigration. *Annual Review of Political Science* **17**, 225–249 (2014).

16. D. Hangartner, E. Dinas, M. Marbach, K. Matakos, X. Dimitrios, Does Exposure to the Refugee Crisis Make Natives More Hostile? *American Political Science Review* **113**, 442–455 (2019).

17. T. Phillips, 'This is Just the Start': China's Passion for Foreign Property (2016). *The Guardian*. Available at https://www.theguardian.com/cities/2016/sep/29/inside-china-passion-foreign-property-investment-uk.

18. K. Rosen, A. Margon, R. Sakamoto, J. Taylor, Breaking Ground: Chinese Investment in U.S. Real Estate (2016). Available at https://asiasociety.org/files/uploads/66files/Asia%20Society%20Breaking%20Ground%20Complete%20Final.pdf.

19. J. Citrin, B. Reingold, D. P. Green, American Identity and the Politics of Ethnic Change. *The Journal of Politics* **52**, 1124–1154 (1990).

20. S. E. Ha, The Consequences of Multiracial Contexts on Public Attitudes toward Immigration. *Political Research Quarterly* **63**, 29–42 (2010).

21. M. Hood III, I. L. Morris, Brother, Can You Spare a Dime? Racial/Ethnic context and the Anglo Vote on Proposition 187. *Social Science Quarterly* **81**, 194–206 (2000).

22. M. Hood III, I. L. Morris, ¿Amigo o enemigo?: Context, Attitudes, and Anglo Public Opinion toward Immigration. *Social Science Quarterly* **78**, 309–323 (1997).

23. G. H. Hanson, K. Scheve, M. J. Slaughter, Public Finance and Individual Preferences over Globalization Strategies. *Economics & Politics* **19**, 1–33 (2007).

24. R. M. Dancygier, *Immigration and Conflict in Europe* (Cambridge University Press, Cambridge, 2010).

25. M. H. Lopez, J. Passel, M. Rohal, Modern Immigration Wave Brings 59 Million to US, Driving Population Growth and Change Through 2065 (2015). *Pew Research Center*. Available at http://www.pewhispanic.org/2015/09/28/modern-immigration-wave-brings-59-million-to-u-s-driving-population-growth-and-change-through-2065/.

26. Y.-L. Liu, China's Nouveau Riche Have Landed on America's Campuses. *Foreign Policy* (2015). Available at https://foreignpolicy.com/2015/09/01/chinas-nouveau-riche-have-landed-on-americas-campuses/.

27. D. P. Green, S. E. Ha, J. G. Bullock, Enough Already about Black Box Experiments: Studying Mediation Is More Difficult than Most Scholars Suppose. *The ANNALS of the American Academy of Political and Social Science* **628**, 200-208 (2010).

28. M. Hankinson, When Do Renters Behave Like Homeowners? High Rent, Price Anxiety, and NIMBYism. *American Political Science Review* **112**, 473–493 (2018).

29. B. J. Newman, Acculturating Contexts and Anglo Opposition to Immigration in the United States. *American Journal of Political Science* **57**, 374–390 (2013).

30. D. Tingley, C. Xu, A. Chilton, H. V. Milner, The Political Economy of Inward FDI: Opposition to Chinese Mergers and Acquisitions. *The Chinese Journal of International Politics* **8**, 27–57 (2015).

31. R. D. Enos, Causal Effect of Intergroup Contact on Exclusionary Attitudes. *Proceedings of the National Academy of Sciences* **111**, 3699–3704 (2014).

32. N. Malhotra, Y. Margalit, C. H. Mo, Economic Explanations for Opposition to Immigration: Distinguishing between Prevalence and Conditional Impact. *American Journal of Political Science* **57**, 391–410 (2013).

33. S. Pardos-Prado, C. Xena, Skill Specificity and Attitudes toward Immigration. *American Journal of Political Science* **63**, 286–304 (2019).

34. J. Citrin, D. P. Green, C. Muste, C. Wong, Public Opinion Toward Immigration Reform: The Role of Economic Motivations. *The Journal of Politics* **59**, 858–881 (1997).

35. E. O. Pérez, Explicit Evidence on the Import of Implicit Attitudes: The IAT and Immigration Policy Judgments. *Political Behavior* **32**, 517–545 (2010).

36. M. Wright, M. Levy, J. Citrin, Public Attitudes toward Immigration Policy across the Legal/Illegal divide: The Role of Categorical and Attribute-Based Decision-Making. *Political Behavior* **38**, 229–253 (2016).

37. E. D. Mansfield, D. C. Mutz, Support for Free Trade: Self-Interest, Sociotropic Politics, and Out-Group Anxiety. *International Organization* **63**, 425–457 (2009).

38. B. I. Page, T. Xie, *Living with the Dragon: How the American Public Views the Rise of China* (Columbia University Press, New York, NY, 2010).

39. B. J. Newman, S. Shah, L. Collingwood, Race, Place, and Building a Base: Latino Population Growth and the Nascent Trump Campaign for President. *Public Opinion Quarterly* **82**, 122–134 (2018).

40. Stokes, Bruce, Republicans, Especially Trump Supporters, See Free Trade Deals as Bad for U.S. (2016). Available at https://www.pewresearch.org/fact-tank/2016/03/31/republicans-especially-trump-supporters-see-free-trade-deals-as-bad-for-u-s/.

41. Pew Research Center, Partisans Have Starkly Different Opinions About How the World Views the U.S. (2017). Available at https://www.people-press.org/2017/11/09/partisans-have-starkly-different-opinions-about-how-the-world-views-the-u-s/.

42. Pew Research Center, Conflicting Partisan Priorities for U.S. Foreign Policy (2018). Available at https://www.people-press.org/2018/11/29/conflicting-partisan-priorities-for-u-s-foreign-policy/.

43. Pew Research Center, The Pew Research Center for the People & the Press Poll Database (2018). Available at https://www.people-press.org/question-search/?qid=1926220&pid=51&ccid=50#top.

44. National Association of Realtors, 2016 Profile of International Activity in U.S. Residential Real Estate (2016). Available at https://www.nar.realtor/sites/default/files/reports/2016/2016-profile-of-international-home-buying-activity-06-06-2016.pdf.

45. S. Leng, D. Wertime, China's Anti-Corruption Campaign Ensnares Tens of Thousands More (2015). *Foreign Policy*. Available at http://foreignpolicy.com/2015/01/09/chinas-anti-corruption-campaign-ensnares-tens-of-thousands-more/.

46. ChinaFile, Visualizing China's Anti-Corruption Campaign (2017). Available at http://www.chinafile.com/infographics/visualizing-chinas-anti-corruption-campaign.

47. E. S. Prasad, *Gaining Currency: The Rise of the Renminbi* (Oxford University Press, Oxford, 2016).

48. Reuters, U.S. Targets Money Laundering in All-Cash Home Sales in Miami, Manhattan (2016). Available at http://reut.rs/1UPpGty.

49. B. Wilcox-Archuleta, The Treatment Works: Revisiting a Key Link in Contextual Theories of Political Behavior. *Research & Politics* **5** (2018).

50. S. Ansolabehere, B. F. Schaffner, Does Survey Mode Still Matter? Findings from a 2010 Multi-Mode Comparison. *Political Analysis* **22**, 285–303 (2014).

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Author Contributions

S.L., N.M., and B.J.N. conceived the research, designed the analyses, conducted the analyses, and wrote the manuscript.

Competing Interests

The authors declare no competing interests.

Supplementary Information for

Local Economic Benefits Increase Positivity toward Foreigners

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This PDF file includes:

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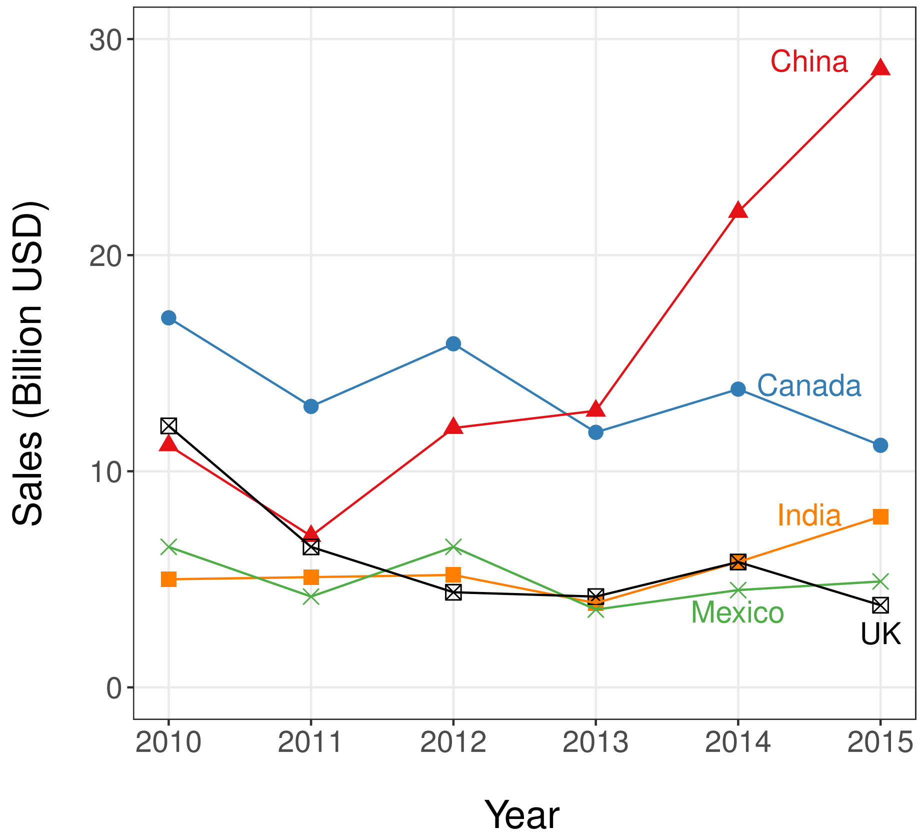

Supplementary Figure 1. Top 5 Foreign Buyers of U.S. Residential Real Estate, 2010–2015. This figure shows the significant growth of Chinese FREI by total dollar volume. Data source: NAR.

Formal Estimates: Home Price Analysis

Supplementary Table 1. DiD Regression Results: Home Prices

	Dependent Variable: Median Home Value ($) per Square Feet (log)					
	(1) Base: ’12–’13	(2) Extended: ’12–’13	(3) Full: ’12–’13	(4) Full: ’11–’12	(5) Full: ’12–’14	(6) Full: ’12–’15
2013 Anti-corruption Campaign (Dummy)	0.028 (0.026, 0.030) p < 0.001	0.030 (0.027, 0.032) p < 0.001	−0.027 (−0.041, −0.012) p < 0.001		−0.017 (−0.041, 0.008) p = 0.189	0.037 (0.005, 0.069) p = 0.024
Placebo Anti-corruption (2012)				−0.081 (−0.093, −0.068) p < 0.001		
2013 Anti-corruption × Log Chinese Undergrads in ZIP Code (2012)	0.016 (0.014, 0.017) p < 0.001	0.022 (0.019, 0.025) p < 0.001	0.016 (0.014, 0.019) p < 0.001		0.023 (0.019, 0.027) p < 0.001	0.027 (0.022, 0.032) p < 0.001
2013 Anti-corruption × Log Chinese Grads in ZIP Code (2012)		−0.008 (−0.011, −0.006) p < 0.001	−0.011 (−0.014, −0.008) p < 0.001		−0.016 (−0.021, −0.012) p < 0.001	−0.015 (−0.021, −0.009) p < 0.001
2013 Anti-corruption × Log Indian Undergrads in ZIP Code (2012)		0.002 (−0.002, 0.007) p = 0.338	−0.002 (−0.006, 0.003) p = 0.430		0.0005 (−0.007, 0.008) p = 0.902	0.001 (−0.008, 0.010) p = 0.791
Placebo Anti-corruption (2012) × Log CHN Undergrads in 2012				0.003 (0.001, 0.005) p = 0.001		
Placebo Anti-corruption (2012) × Log CHN Grads in 2012				−0.002 (−0.003, 0.0003) p = 0.104		
Placebo Anti-corruption (2012) × Log IND Undergrads in 2012				−0.0003 (−0.003, 0.003) p = 0.842		
Share of Employment			0.028 (−0.043, 0.099) p = 0.442	0.009 (−0.053, 0.071) p = 0.781	0.092 (0.007, 0.178) p = 0.035	0.171 (0.078, 0.264) p < 0.001
Share of Adult Pop.			−0.086 (−0.177, 0.006) p = 0.068	−0.083 (−0.162, −0.004) p = 0.039	−0.175 (−0.289, −0.061) p = 0.003	−0.174 (−0.290, −0.057) p = 0.003
Log Population Density			0.060 (0.028, 0.092) p < 0.001	0.023 (−0.006, 0.051) p = 0.119	0.102 (0.065, 0.138) p < 0.001	0.122 (0.083, 0.161) p < 0.001
Share of White Pop.			0.031 (−0.049, 0.110) p = 0.447	0.043 (−0.012, 0.099) p = 0.128	0.069 (−0.026, 0.164) p = 0.155	0.077 (−0.018, 0.171) p = 0.111
Median Household Income ($10,000)			−0.008 (−0.011, −0.004) p < 0.001	−0.001 (−0.004, 0.002) p = 0.549	−0.010 (−0.015, −0.006) p < 0.001	−0.008 (−0.013, −0.003) p = 0.002
Share Enrolled in College or Above			0.108 (−0.109, 0.324) p = 0.330	0.020 (−0.186, 0.226) p = 0.848	0.273 (−0.008, 0.553) p = 0.057	0.409 (0.108, 0.710) p = 0.008
Log Pop. Enrolled in College or Above			−0.005 (−0.012, 0.003) p = 0.250	−0.002 (−0.010, 0.007) p = 0.675	−0.010 (−0.021, 0.002) p = 0.093	−0.014 (−0.026, −0.001) p = 0.031
Effective Tax Rate (%)			0.035 (0.016, 0.055) p < 0.001	−0.054 (−0.070, −0.038) p < 0.001	−0.039 (−0.060, −0.018) p < 0.001	−0.141 (−0.163, −0.119) p < 0.001
Share of Vacant Houses			0.020 (0.009, 0.031) p < 0.001	0.004 (−0.004, 0.012) p = 0.354	0.025 (0.011, 0.039) p = 0.001	0.035 (0.020, 0.049) p < 0.001
2013 Anti-corruption × Share of Employment			−0.101 (−0.124, −0.078) p < 0.001		−0.188 (−0.228, −0.148) p < 0.001	−0.216 (−0.267, −0.164) p < 0.001
2013 Anti-corruption × Share of Adult Pop.			0.150 (0.117, 0.182) p < 0.001		0.233 (0.178, 0.287) p < 0.001	0.279 (0.208, 0.349) p < 0.001
2013 Anti-corruption × Log Population Density			0.007 (0.006, 0.008) p < 0.001		0.013 (0.011, 0.015) p < 0.001	0.017 (0.015, 0.020) p < 0.001
2013 Anti-corruption × Share of White Pop.			0.016 (0.006, 0.025) p = 0.002		0.019 (0.002, 0.035) p = 0.029	0.014 (−0.007, 0.036) p = 0.188
2013 Anti-corruption × Median Household Income ($10,000)			0.005 (0.004, 0.006) p < 0.001		0.008 (0.006, 0.009) p < 0.001	0.006 (0.005, 0.008) p < 0.001
2013 Anti-corruption × Share Enrolled in College or Above			−0.088 (−0.121, −0.054) p < 0.001		−0.207 (−0.265, −0.148) p < 0.001	−0.318 (−0.391, −0.246) p < 0.001
2013 Anti-corruption × Log Pop. Enrolled in College or Above			0.007 (0.005, 0.008) p < 0.001		0.013 (0.010, 0.015) p < 0.001	0.014 (0.011, 0.017) p < 0.001
2013 Anti-corruption × Effective Tax Rate (%)			−0.020 (−0.022, −0.018) p < 0.001		−0.028 (−0.032, −0.024) p < 0.001	−0.032 (−0.037, −0.027) p < 0.001
2013 Anti-corruption × Share of Vacant Houses			−0.032 (−0.038, −0.026) p < 0.001		−0.063 (−0.073, −0.053) p < 0.001	−0.089 (−0.103, −0.076) p < 0.001

Placebo Anti-corruption (2012) × Share of Employment				−0.031		
				(−0.050, −0.012)		
				p = 0.001		
Placebo Anti-corruption (2012) × Share of Adult Pop.				0.104		
				(0.078, 0.130)		
				p < 0.001		
Placebo Anti-corruption (2012) × Log Population Density				0.001		
				(−0.0001, 0.002)		
				p = 0.070		
Placebo Anti-corruption (2012) × Share of White Pop.				0.048		
				(0.041, 0.056)		
				p < 0.001		
Placebo Anti-corruption (2012) × Median Household Income ($10,000)				0.002		
				(0.001, 0.003)		
				p < 0.001		
Placebo Anti-corruption (2012) × Share Enrolled in College or Above				0.007		
				(−0.018, 0.032)		
				p = 0.594		
Placebo Anti-corruption (2012) × Lop pop. Enrolled in College or Above				0.002		
				(0.001, 0.004)		
				p < 0.001		
Placebo Anti-corruption (2012) × Effective Tax Rate (%)				−0.007		
				(−0.009, −0.005)		
				p < 0.001		
Placebo Anti-corruption (2012) × Share of Vacant Houses				−0.003		
				(−0.008, 0.002)		
				p = 0.257		
Fixed Effects: Zip Code Tabulation Area (ZCTA)	✓	✓	✓	✓	✓	✓
Number of ZIP Codes	12,700	12,700	12,461	12,456	12,458	12,497
Observations	25,374	25,374	24,851	24,831	24,821	24,723
R^2	0.997	0.997	0.998	0.999	0.994	0.991
Adjusted R^2	0.995	0.995	0.995	0.997	0.987	0.981
Residual Std. Error	0.042	0.042	0.038	0.028	0.063	0.078

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code. ZIP-code fixed effects subsume ZIP-code level measures of international students in 2012.

Formal Estimates: Perceived Neighborhood Prevalence of Asians

Supplementary Table 2. The Presence of Chinese International Students and the Perceived Neighborhood Prevalence of Asians, 2008

	Dependent Variable: 2008 CMPS Respondent's Perception of an Asian Neighborhood			
	Ordinal (2 = Entirely, 1 = Mostly, 0 = Partially)			
	OLS	OLS	OLS	Ordered Logit
	(1)	(2)	(3)	(4)
Log Chinese Undergraduate Population	0.029 (0.020, 0.038) $p < 0.001$	0.029 (0.018, 0.041) $p < 0.001$	0.023 (0.009, 0.036) $p = 0.001$	0.493 (0.203, 0.784) $p = 0.001$
Homeowner		−0.003 (−0.027, 0.021) $p = 0.816$	−0.002 (−0.027, 0.022) $p = 0.842$	0.217 (−0.457, 0.891) $p = 0.529$
Age		0.001 (0.0001, 0.001) $p = 0.025$	0.001 (0.0001, 0.001) $p = 0.023$	0.016 (−0.001, 0.032) $p = 0.065$
Education		0.009 (0.002, 0.017) $p = 0.017$	0.008 (0.000, 0.015) $p = 0.050$	0.233 (0.013, 0.453) $p = 0.038$
White		−0.034 (−0.055, −0.013) $p = 0.002$	−0.033 (−0.055, −0.011) $p = 0.003$	−1.559 (−2.508, −0.610) $p = 0.001$
Income		0.001 (−0.005, 0.006) $p = 0.807$	−0.003 (−0.009, 0.003) $p = 0.398$	−0.029 (−0.190, 0.132) $p = 0.723$
ZIP-Code Median Household Income			0.009 (0.003, 0.014) $p = 0.003$	0.196 (0.071, 0.320) $p = 0.002$
ZIP-Code Population Density			0.005 (−0.001, 0.011) $p = 0.086$	0.340 (0.122, 0.557) $p = 0.002$
ZIP-Code Share of Pop. with a BA Degree or Higher			−0.018 (−0.105, 0.069) $p = 0.689$	−0.268 (−2.361, 1.824) $p = 0.801$
y>=1				−9.846 (−12.285, −7.406) $p < 0.001$
y>=2				−10.525 (−12.976, −8.074) $p < 0.001$
Constant	0.013 (0.003, 0.023) $p = 0.015$	−0.053 (−0.100, −0.006) $p = 0.026$	−0.113 (−0.178, −0.048) $p = 0.001$	
Observations	4,307	2,949	2,949	2,949
R^2	0.009	0.016	0.022	0.120
Adjusted R^2	0.009	0.014	0.019	
χ^2				82.510 (df = 9)

Note: 95% confidence intervals and p-values are presented.

Supplementary Table 3. The Presence of Chinese International Students and the Perceived Neighborhood Prevalence of Asians, 2012

	Dependent Variable: 2012 CMPS Respondent's Perception of an Asian Neighborhood			
	Ordinal (2 = Entirely, 1 = Mostly, 0 = Partially)			
	OLS	OLS	OLS	Ordered Logit
	(1)	(2)	(3)	(4)
Log Chinese Undergraduate Population	0.008 (0.005, 0.012) $p < 0.001$	0.008 (0.004, 0.012) $p < 0.001$	0.008 (0.003, 0.013) $p = 0.001$	0.676 (0.303, 1.049) $p < 0.001$
Homeowner		0.0004 (−0.011, 0.012) $p = 0.941$	−0.0003 (−0.012, 0.011) $p = 0.956$	0.027 (−1.125, 1.179) $p = 0.963$
Age		−0.0002 (−0.0005, 0.0001) $p = 0.300$	−0.0002 (−0.0004, 0.0001) $p = 0.308$	−0.013 (−0.043, 0.016) $p = 0.378$
Education		−0.002 (−0.006, 0.001) $p = 0.173$	−0.003 (−0.006, 0.001) $p = 0.167$	−0.247 (−0.616, 0.121) $p = 0.188$
White		−0.004 (−0.014, 0.005) $p = 0.391$	−0.004 (−0.014, 0.006) $p = 0.414$	−0.473 (−1.669, 0.724) $p = 0.439$
Income		0.003 (−0.0002, 0.006) $p = 0.070$	0.002 (−0.001, 0.005) $p = 0.309$	0.164 (−0.146, 0.473) $p = 0.301$
ZIP-Code Median Household Income			0.004 (0.001, 0.007) $p = 0.010$	0.387 (0.115, 0.658) $p = 0.005$
ZIP-Code Population Density			0.001 (−0.002, 0.004) $p = 0.418$	0.378 (−0.021, 0.776) $p = 0.064$
ZIP-Code Share of Pop. with a BA Degree or Higher			−0.030 (−0.075, 0.016) $p = 0.206$	−3.293 (−7.435, 0.848) $p = 0.119$
y>=1				−9.586 (−13.763, −5.409) $p < 0.001$
y>=2				−10.996 (−15.239, −6.752) $p < 0.001$
Constant	−0.002 (−0.009, 0.005) $p = 0.509$	0.006 (−0.014, 0.027) $p = 0.544$	−0.012 (−0.042, 0.017) $p = 0.414$	
Observations	2,593	2,593	2,593	2,593
R^2	0.007	0.009	0.012	0.141
Adjusted R^2	0.007	0.007	0.009	
χ^2				34.635 (df = 9)

Note: 95% confidence intervals and p-values are presented.

Formal Estimates: CCES Analysis

Supplementary Table 4. DiD Regression Main Results: Anti-immigration Attitudes

	Dependent Variable: 2012–2014 Anti-immigration Attitudes			
	(1) Scale	(2) Scale	(3) Scale	(4) Scale
Log Chinese Undergrads in Zip Code	1.71 (−0.88, 4.30) p = 0.20		1.71 (−0.85, 4.28) p = 0.19	
Post-anti-corruption Campaign (2014)	−0.18 (−1.07, 0.71) p = 0.69	−0.05 (−0.90, 0.79) p = 0.90	−0.18 (−1.07, 0.71) p = 0.69	−0.05 (−0.90, 0.79) p = 0.90
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	−0.50 (−0.97, −0.03) p = 0.04		−0.50 (−0.97, −0.03) p = 0.04	
Log Chinese Undergrads in Zip Code (2012) × Post-anti-corruption Campaign (2014)		−0.41 (−0.86, 0.03) p = 0.07		−0.41 (−0.86, 0.03) p = 0.07
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓		
Fixed Effects: Individual			✓	✓
Group Size	5,982	5,982	8,632	8,632
Observations	17,264	17,264	17,264	17,264
R^2 (within)	0.0003	0.0003	0.001	0.001

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code. Models in columns (3)/(4) produce virtually identical estimates to those in (1)/(2).

Supplementary Table 5. DiD Regression Results: Time Placebo Tests

	Dependent Variable: 2010–2012 Anti-immigration Attitudes			
	(1) Scale	(2) Scale	(3) Scale	(4) Scale
Log Chinese Undergrads in ZIP Code (Lead)	−0.63 (−3.40, 2.13) p = 0.65			
Pre-anti-corruption Campaign (2012)	−4.10 (−5.05, −3.14) p < 0.001	−4.13 (−5.03, −3.23) p < 0.001	−4.06 (−5.02, −3.11) p < 0.001	−4.10 (−4.94, −3.26) p < 0.001
Log Chinese Undergrads in ZIP Code (Lead) × Pre-anti-corruption Campaign (2012)	0.32 (−0.18, 0.82) p = 0.20			
Log Chinese Undergrads in ZIP Code (2012) × Pre-anti-corruption Campaign (2012)		0.30 (−0.18, 0.78) p = 0.22		
Log Chinese Undergrads in Zip Code			−0.62 (−3.35, 2.11) p = 0.66	
Log Chinese Undergrads in ZIP Code × Pre-anti-corruption Campaign (2012)			0.40 (−0.22, 1.01) p = 0.20	
Log Chinese Undergrads in ZIP Code (2010) × Pre-anti-corruption Campaign (2012)				0.37 (−0.18, 0.92) p = 0.19
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓	✓
Number of ZIP Codes	5,956	5,956	5,956	5,956
Observations	17,146	17,146	17,146	17,146
R^2 (within)	0.006	0.006	0.006	0.006

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 6. DiD Regression Results: Origin Placebo Tests

	Dependent Variable: 2012–2014 Anti-immigration Attitudes			
	(1) Scale	(2) Scale	(3) Scale	(4) Scale
Log Indian Undergrads in ZIP Code	0.22 (−2.22, 2.66) p = 0.86			
Post-anti-corruption Campaign (2014)	−0.41 (−1.15, 0.32) p = 0.27	−0.25 (−1.11, 0.61) p = 0.57	−0.42 (−1.15, 0.32) p = 0.27	−0.21 (−1.06, 0.64) p = 0.63
Log Indian Undergrads in ZIP Code × Post-anti-corruption Campaign (2014)	−0.35 (−1.18, 0.47) p = 0.40			
Log Chinese Grad Students in ZIP Code		1.16 (−2.14, 4.46) p = 0.49		
Log Chinese Grad Students in ZIP Code × Post-anti-corruption Campaign (2014)		−0.34 (−0.83, 0.15) p = 0.17		
Log Indian Undergrads in ZIP Code (2012) × Post-anti-corruption Campaign (2014)			−0.35 (−1.17, 0.47) p = 0.40	
Log Chinese Grad Students in ZIP Code (2012) × Post-anti-corruption Campaign (2014)				−0.30 (−0.77, 0.16) p = 0.20
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓	✓
Number of ZIP Codes	5,982	5,982	5,982	5,982
Observations	17,264	17,264	17,264	17,264
R^2 (within)	0.0002	0.0002	0.0002	0.0002

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 7. Heterogeneous Treatment Effects by Homeownership

	Dependent Variable: 2012–2014 Anti-immigration Attitudes	
	(1) Scale	(2) Scale
Log Chinese Undergrads in Zip Code	2.17 (−0.84, 5.18) p = 0.16	13.13 (6.13, 20.14) p < 0.001
Post-anti-corruption Campaign (2014)	−0.36 (−1.35, 0.63) p = 0.48	7.01 (1.60, 12.42) p = 0.01
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	−0.55 (−1.09, −0.02) p = 0.04	−3.80 (−6.42, −1.19) p = 0.004
Stable Homeowner		4.45 (−2.59, 11.49) p = 0.22
Log Chinese Undergrads in ZIP Code × Stable Homeowner		−1.69 (−5.18, 1.79) p = 0.34
Post-anti-corruption Campaign (2014) × Stable Homeowner		−1.74 (−4.57, 1.10) p = 0.23
Log Chinese Undergrads in ZIP Code × Post-anti-corruption Campaign (2014) × Stable Homeowner		1.17 (−0.16, 2.51) p = 0.08
Age	18.99 (9.15, 28.83) p < 0.001	36.34 (20.01, 52.67) p < 0.001
Log Chinese Undergrads in ZIP Code × Age		−10.43 (−18.31, −2.56) p = 0.01
Post-anti-corruption Campaign (2014) × Age		−6.50 (−12.83, −0.16) p = 0.04
Log Chinese Undergrads in ZIP Code × Post-anti-corruption Campaign (2014) × Age		2.64 (−0.58, 5.85) p = 0.11
Education	−3.91 (−5.02, −2.80) p < 0.001	−3.97 (−5.74, −2.21) p < 0.001
Log Chinese Undergrads in ZIP Code × Education		0.16 (−0.78, 1.10) p = 0.74
Post-anti-corruption Campaign (2014) × Education		−0.18 (−0.91, 0.55) p = 0.63
Log Chinese Undergrads in ZIP Code × Post-anti-corruption Campaign (2014) × Education		−0.10 (−0.47, 0.27) p = 0.60
White	4.70 (0.78, 8.61) p = 0.02	12.20 (5.96, 18.44) p < 0.001
Log Chinese Undergrads in ZIP Code × White		−4.47 (−7.64, −1.29) p = 0.01
Post-anti-corruption Campaign (2014) × White		−1.29 (−4.67, 2.08) p = 0.45
Log Chinese Undergrads in ZIP Code × Post-anti-corruption Campaign (2014) × White		1.17 (−0.42, 2.76) p = 0.15
Income	0.32 (−0.16, 0.81) p = 0.19	0.51 (−0.31, 1.33) p = 0.22
Log Chinese Undergrads in ZIP Code × Income		−0.14 (−0.56, 0.27) p = 0.50
Post-anti-corruption Campaign (2014) × Income		−0.12 (−0.47, 0.24) p = 0.52
Log Chinese Undergrads in ZIP Code × Post-anti-corruption Campaign (2014) × Income		0.06 (−0.12, 0.24) p = 0.52
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓
Number of ZIP Codes	5,596	5,596
Observations	15,118	15,118
R^2 (within)	0.02	0.03

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 8. DiD Regression Results: Employment Rates in CCES Respondents' ZIP Codes

	Dependent Variable: 2012–2014 ZIP-Code Employment Rates (Percentage Points)		
	(1)	(2)	(3)
Log Chinese Undergrads in Zip Code	−0.206 (−0.461, 0.049) $p = 0.113$		−0.200 (−0.456, 0.056) $p = 0.125$
Post-anti-corruption Campaign (2014)	−0.956 (−1.074, −0.839) $p < 0.001$	−0.958 (−1.069, −0.846) $p < 0.001$	−0.966 (−1.086, −0.846) $p < 0.001$
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	0.191 (0.140, 0.242) $p < 0.001$		0.187 (0.137, 0.237) $p < 0.001$
Log Chinese Undergrads in Zip Code (2012) × Post-anti-corruption Campaign (2014)		0.190 (0.139, 0.241) $p < 0.001$	
Log Population Density			−3.172 (−12.852, 6.507) $p = 0.521$
Total Population (1,000)			0.116 (−0.156, 0.388) $p = 0.403$
Share of Population Enrolled in College or Above			−1.077 (−25.406, 23.252) $p = 0.931$
Log Population Enrolled in College or Above			0.530 (−0.928, 1.988) $p = 0.476$
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓
Number of ZIP Codes	5,981	5,981	5,981
Observations	11,961	11,961	11,961
R^2 (within)	0.078	0.078	0.082

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 9. DiD Regression Results: Median Household Income in CCES Respondents' ZIP Codes

	Dependent Variable: 2012–2014 ZIP-Code Median Household Income ($10,000)		
	(1)	(2)	(3)
Log Chinese Undergrads in Zip Code	−0.027 (−0.072, 0.018) $p = 0.237$		−0.027 (−0.071, 0.017) $p = 0.233$
Post-anti-corruption Campaign (2014)	0.018 (0.002, 0.034) $p = 0.032$	0.018 (0.002, 0.034) $p = 0.025$	0.009 (−0.008, 0.025) $p = 0.312$
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	0.028 (0.019, 0.037) $p < 0.001$		0.025 (0.016, 0.034) $p < 0.001$
Log Chinese Undergrads in Zip Code (2012) × Post-anti-corruption Campaign (2014)		0.028 (0.019, 0.037) $p < 0.001$	
Log Population Density			0.600 (0.039, 1.161) $p = 0.036$
Total Population (1,000)			0.014 (−0.003, 0.031) $p = 0.096$
Share of Population Enrolled in College or Above			−1.681 (−4.026, 0.663) $p = 0.160$
Log Population Enrolled in College or Above			0.015 (−0.121, 0.151) $p = 0.828$
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓
Number of ZIP Codes	5,978	5,978	5,978
Observations	11,956	11,956	11,956
R^2 (within)	0.024	0.024	0.037

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 10. DiD Regression Results: Business Establishments in CCES Respondents' ZIP Codes

	Dependent Variable: 2012-2014 ZIP-Code Log Number of Business Establishments		
	(1)	(2)	(3)
Log Chinese Undergrads in Zip Code	0.007 (0.0001, 0.014) $p = 0.045$		0.007 (0.0005, 0.014) $p = 0.036$
Post-anti-corruption Campaign (2014)	0.008 (0.005, 0.011) $p < 0.001$	0.009 (0.006, 0.012) $p < 0.001$	0.004 (0.001, 0.007) $p = 0.004$
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	0.003 (0.002, 0.005) $p < 0.001$		0.002 (0.001, 0.003) $p = 0.001$
Log Chinese Undergrads in Zip Code (2012) × Post-anti-corruption Campaign (2014)		0.004 (0.003, 0.006) $p < 0.001$	
Log Population Density			0.003 (−0.113, 0.119) $p = 0.959$
Total Population (1,000)			0.013 (0.009, 0.016) $p < 0.001$
Share of Population Enrolled in College or Above			−0.409 (−0.885, 0.067) $p = 0.092$
Log Population Enrolled in College or Above			0.024 (−0.007, 0.056) $p = 0.125$
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓
Number of ZIP Codes	5,981	5,981	5,980
Observations	11,962	11,962	11,959
R^2 (within)	0.053	0.052	0.098

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 11. DiD Regression Results: New Vehicle Registrations in CCES Respondents' ZIP-Codes

	Dependent Variable: 2012-2014 ZIP-Code Log Number of New Vehicle Registrations		
	(1)	(2)	(3)
Log Chinese Undergrads in Zip Code	0.017 (0.010, 0.025) p < 0.001		0.018 (0.010, 0.025) p < 0.001
Post-anti-corruption Campaign (2014)	0.134 (0.131, 0.136) p < 0.001	0.136 (0.134, 0.138) p < 0.001	0.132 (0.130, 0.134) p < 0.001
Log Chinese Undergrads in Zip Code × Post-anti-corruption Campaign (2014)	0.004 (0.003, 0.006) p < 0.001		0.004 (0.002, 0.005) p < 0.001
Log Chinese Undergrads in Zip Code (2012) × Post-anti-corruption Campaign (2014)		0.006 (0.005, 0.007) p < 0.001	
Log Population Density			−0.046 (−0.080, −0.012) p = 0.009
Total Population (1,000)			0.008 (0.006, 0.009) p < 0.001
Share of Population Enrolled in College or Above			−0.136 (−0.372, 0.099) p = 0.257
Log Population Enrolled in College or Above			0.007 (−0.005, 0.020) p = 0.247
Fixed Effects: ZIP Code Tabulation Area (ZCTA)	✓	✓	✓
Number of ZIP Codes	5,981	5,981	5,981
Observations	11,962	11,962	11,961
R^2 (within)	0.868	0.867	0.870

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Formal Estimates: Pew Analysis

Supplementary Table 12. DiD Regression Results: Perceived China Threat

	Dependent Variable: Perceived China Threat				
	(1) OLS Baseline	(2) OLS Extended	(3) OLS Full	(4) Linear Mixed Effects	(5) Ordered Logit
Anti-corruption Campaign (dummy)	0.012 (−0.032, 0.056) p = 0.602	0.009 (−0.037, 0.055) p = 0.702	−0.010 (−0.145, 0.126) p = 0.887	−0.010 (−0.147, 0.128) p = 0.890	−0.059 (−0.468, 0.350) p = 0.776
Log Chinese Undergrads in ZIP Code	−0.030 (−0.052, −0.008) p = 0.007	0.001 (−0.022, 0.024) p = 0.935	0.011 (−0.018, 0.040) p = 0.457	0.011 (−0.019, 0.041) p = 0.463	0.028 (−0.057, 0.113) p = 0.517
Log Chinese Undergrads in ZIP Code × Anti-corruption Campaign (dummy)	−0.043 (−0.071, −0.014) p = 0.003	−0.051 (−0.079, −0.022) p = 0.001	−0.043 (−0.081, −0.004) p = 0.029	−0.042 (−0.080, −0.004) p = 0.032	−0.105 (−0.214, 0.004) p = 0.059
Respondent's Age		0.004 (0.003, 0.005) p < 0.001	0.004 (0.003, 0.005) p < 0.001	0.004 (0.003, 0.004) p < 0.001	0.011 (0.008, 0.014) p < 0.001
Respondent's Highest Level of Education		−0.029 (−0.038, −0.020) p < 0.001	−0.026 (−0.035, −0.016) p < 0.001	−0.026 (−0.035, −0.016) p < 0.001	−0.080 (−0.108, −0.051) p < 0.001
Respondent's Race: White (dummy)		−0.045 (−0.088, −0.003) p = 0.038	−0.048 (−0.091, −0.005) p = 0.029	−0.047 (−0.089, −0.006) p = 0.025	−0.174 (−0.299, −0.049) p = 0.006
Respondent's Family Income Level		0.001 (−0.001, 0.002) p = 0.326	0.001 (−0.001, 0.002) p = 0.232	0.001 (−0.001, 0.002) p = 0.297	0.003 (−0.001, 0.007) p = 0.203
Respondent's Party Identification		0.019 (0.008, 0.031) p = 0.001	0.019 (0.007, 0.031) p = 0.001	0.019 (0.007, 0.031) p = 0.001	0.051 (0.016, 0.085) p = 0.004
Respondent's Political Ideology		0.096 (0.076, 0.115) p < 0.001	0.094 (0.075, 0.114) p < 0.001	0.094 (0.075, 0.113) p < 0.001	0.276 (0.219, 0.333) p < 0.001
Median Household Income ($10,000)			−0.009 (−0.020, 0.001) p = 0.087	−0.009 (−0.020, 0.001) p = 0.080	−0.028 (−0.059, 0.003) p = 0.076
Median Household Income ($10,000) × Anti-corruption Campaign (dummy)			0.003 (−0.012, 0.017) p = 0.710	0.003 (−0.011, 0.017) p = 0.708	0.012 (−0.030, 0.053) p = 0.581
Log Population Density			−0.012 (−0.026, 0.002) p = 0.098	−0.012 (−0.026, 0.002) p = 0.106	−0.035 (−0.077, 0.007) p = 0.105
Log Population Density × Anti-corruption Campaign (dummy)			0.003 (−0.017, 0.023) p = 0.768	0.003 (−0.017, 0.023) p = 0.766	0.005 (−0.055, 0.065) p = 0.864
Share Enrolled in College or Above			0.067 (−0.390, 0.523) p = 0.775	0.065 (−0.392, 0.521) p = 0.782	0.128 (−1.205, 1.461) p = 0.850
Share Enrolled in College or Above × Anti-corruption Campaign (dummy)			−0.487 (−1.113, 0.138) p = 0.127	−0.489 (−1.111, 0.133) p = 0.123	−1.188 (−2.961, 0.585) p = 0.189
y>=2					1.480 (1.097, 1.863) p < 0.001
y>=3					−0.492 (−0.871, −0.112) p = 0.011
Constant	2.480 (2.452, 2.508) p < 0.001	2.073 (1.983, 2.164) p < 0.001	2.188 (2.060, 2.315) p < 0.001	2.189 (2.062, 2.317) p < 0.001	
Varying Intercepts: ZIP Code				✓	
Number of ZIP Codes	5,673	5,224	5,211	5,211	5,211
Observations	7,526	6,743	6,730	6,730	6,730
R^2	0.013	0.058	0.059		0.071
Adjusted R^2	0.013	0.056	0.057		
Log Likelihood				−6,935.905	
Akaike Inf. Crit.				13,907.810	
Bayesian Inf. Crit.				14,030.470	
Residual Std. Error	0.687	0.674	0.673		
χ^2					417.982

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.

Supplementary Table 13. DiD Regression Results: Placebo Outcomes

	Dependent Variable: Perceived Threat from Placebo Countries					
	North Korea		*Russia*		*Iran*	
	(1) OLS	(2) Ordered Logit	(3) OLS	(4) Ordered Logit	(5) OLS	(6) Ordered Logit
Anti-corruption Campaign (dummy)	0.003 (−0.118, 0.124) p = 0.958	−0.090 (−0.528, 0.348) p = 0.686	−0.105 (−0.268, 0.057) p = 0.205	−0.280 (−0.787, 0.227) p = 0.279	−0.102 (−0.217, 0.012) p = 0.080	−0.521 (−0.983, −0.060) p = 0.027
Log Chinese Undergrads in ZIP Code	−0.012 (−0.039, 0.016) p = 0.409	−0.031 (−0.127, 0.064) p = 0.520	0.036 (−0.010, 0.082) p = 0.123	0.121 (−0.020, 0.261) p = 0.094	0.005 (−0.021, 0.031) p = 0.728	0.020 (−0.081, 0.121) p = 0.696
Log Chinese Undergrads in ZIP Code × Anti-corruption Campaign (dummy)	0.002 (−0.033, 0.037) p = 0.895	0.009 (−0.109, 0.128) p = 0.880	−0.036 (−0.089, 0.017) p = 0.184	−0.120 (−0.283, 0.042) p = 0.147	−0.024 (−0.059, 0.010) p = 0.167	−0.090 (−0.216, 0.037) p = 0.164
Respondent's Age	0.003 (0.002, 0.003) p < 0.001	0.009 (0.006, 0.012) p < 0.001	0.003 (0.002, 0.004) p < 0.001	0.010 (0.007, 0.014) p < 0.001	0.003 (0.002, 0.004) p < 0.001	0.011 (0.008, 0.014) p < 0.001
Respondent's Highest Level of Education	−0.026 (−0.035, −0.017) p < 0.001	−0.111 (−0.141, −0.081) p < 0.001	−0.004 (−0.016, 0.009) p = 0.587	−0.017 (−0.056, 0.023) p = 0.409	−0.014 (−0.022, −0.006) p = 0.001	−0.068 (−0.099, −0.036) p < 0.001
Respondent's Race: White (dummy)	−0.018 (−0.057, 0.021) p = 0.371	−0.118 (−0.251, 0.016) p = 0.084	−0.010 (−0.062, 0.043) p = 0.723	−0.094 (−0.256, 0.068) p = 0.254	−0.006 (−0.045, 0.032) p = 0.746	−0.073 (−0.211, 0.065) p = 0.299
Respondent's Family Income Level	0.001 (−0.0005, 0.002) p = 0.233	0.003 (−0.002, 0.007) p = 0.280	−0.007 (−0.016, 0.003) p = 0.182	−0.024 (−0.054, 0.005) p = 0.102	0.001 (−0.0004, 0.002) p = 0.236	0.003 (−0.002, 0.007) p = 0.287
Respondent's Party Identification	0.008 (−0.002, 0.019) p = 0.104	0.029 (−0.007, 0.066) p = 0.110	0.003 (−0.011, 0.017) p = 0.652	0.009 (−0.034, 0.052) p = 0.681	0.034 (0.024, 0.044) p < 0.001	0.144 (0.105, 0.183) p < 0.001
Respondent's Political Ideology	0.073 (0.056, 0.090) p < 0.001	0.249 (0.190, 0.309) p < 0.001	0.097 (0.075, 0.120) p < 0.001	0.297 (0.228, 0.367) p < 0.001	0.104 (0.087, 0.121) p < 0.001	0.381 (0.317, 0.444) p < 0.001
Median Household Income ($10,000)	−0.008 (−0.017, 0.002) p = 0.123	−0.033 (−0.066, 0.001) p = 0.055	−0.012 (−0.025, 0.001) p = 0.066	−0.043 (−0.082, −0.004) p = 0.030	−0.009 (−0.018, −0.0001) p = 0.047	−0.044 (−0.078, −0.010) p = 0.012
Median Household Income ($10,000) × Anti-corruption Campaign (dummy)	−0.006 (−0.020, 0.008) p = 0.391	−0.014 (−0.058, 0.031) p = 0.544	0.005 (−0.012, 0.021) p = 0.584	0.013 (−0.037, 0.062) p = 0.615	0.0003 (−0.012, 0.013) p = 0.968	0.011 (−0.033, 0.056) p = 0.618
Log Population Density	0.0004 (−0.012, 0.013) p = 0.948	−0.002 (−0.049, 0.045) p = 0.924	−0.014 (−0.032, 0.004) p = 0.123	−0.037 (−0.092, 0.019) p = 0.196	−0.007 (−0.019, 0.005) p = 0.249	−0.029 (−0.078, 0.021) p = 0.259
Log Population Density × Anti-corruption Campaign (dummy)	−0.003 (−0.021, 0.015) p = 0.756	−0.001 (−0.065, 0.063) p = 0.970	0.020 (−0.004, 0.044) p = 0.104	0.060 (−0.014, 0.135) p = 0.113	0.008 (−0.010, 0.025) p = 0.381	0.038 (−0.030, 0.106) p = 0.278
Share Enrolled in College or Above	−0.277 (−0.734, 0.180) p = 0.234	−0.972 (−2.493, 0.548) p = 0.210	−0.587 (−1.187, 0.013) p = 0.055	−1.843 (−3.663, −0.023) p = 0.047	−0.221 (−0.647, 0.205) p = 0.309	−0.914 (−2.472, 0.645) p = 0.251
Share Enrolled in College or Above × Anti-corruption Campaign (dummy)	−0.276 (−0.879, 0.327) p = 0.370	−0.674 (−2.611, 1.262) p = 0.495	0.512 (−0.227, 1.252) p = 0.175	1.539 (−0.692, 3.770) p = 0.176	0.031 (−0.539, 0.600) p = 0.916	0.483 (−1.466, 2.432) p = 0.627
y>=2		2.472 (2.046, 2.898) p < 0.001		1.605 (1.110, 2.099) p < 0.001		1.798 (1.360, 2.235) p < 0.001
y>=3		0.304 (−0.107, 0.715) p = 0.147		−0.836 (−1.323, −0.349) p = 0.001		−0.384 (−0.809, 0.040) p = 0.076
Constant	2.435 (2.322, 2.549) p < 0.001		2.136 (1.978, 2.294) p < 0.001		2.266 (2.161, 2.371) p < 0.001	
Number of ZIP Codes	5,202	5,202	3,613	3,613	5,207	5,207
Observations	6,754	6,754	4,308	4,308	6,756	6,756
R^2	0.048	0.061	0.040	0.052	0.085	0.112
Adjusted R^2	0.046		0.037		0.083	
Residual Std. Error	0.597		0.636		0.570	
χ^2		342.004		191.686		627.168

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code. The drop in observations for Russia is due to the Pew survey not asking questions regarding perceived Russian threat in October 2013.

Supplementary Table 14. DiD Regression Results: Placebo Student Treatments

	Dependent Variable: Perceived China Threat			
	China		*India*	
	(1) OLS	(2) Ordered Logit	(3) OLS	(4) Ordered Logit
Anti-corruption Campaign (dummy)	0.017 (−0.125, 0.160) p = 0.811	0.012 (−0.417, 0.442) p = 0.955	0.026 (−0.112, 0.164) p = 0.716	0.016 (−0.400, 0.433) p = 0.940
Log Chinese Grads in ZIP Code	−0.009 (−0.039, 0.021) p = 0.561	−0.020 (−0.109, 0.069) p = 0.664		
Log Chinese Grads in ZIP Code × Anti-corruption Campaign (dummy)	−0.014 (−0.054, 0.025) p = 0.484	−0.033 (−0.146, 0.080) p = 0.570		
Log Indian Undergrads in ZIP code			−0.006 (−0.052, 0.039) p = 0.789	0.003 (−0.131, 0.137) p = 0.969
Log Indian Undergrads in ZIP code × Anti-corruption Campaign (dummy)			−0.025 (−0.088, 0.038) p = 0.432	−0.077 (−0.254, 0.100) p = 0.393
Respondent's Age	0.004 (0.003, 0.005) p < 0.001	0.011 (0.008, 0.014) p < 0.001	0.004 (0.003, 0.005) p < 0.001	0.011 (0.008, 0.014) p < 0.001
Respondent's Highest Level of Education	−0.026 (−0.035, −0.016) p < 0.001	−0.080 (−0.108, −0.052) p < 0.001	−0.026 (−0.035, −0.016) p < 0.001	−0.080 (−0.109, −0.052) p < 0.001
Respondent's Race: White (dummy)	−0.052 (−0.095, −0.009) p = 0.018	−0.183 (−0.309, −0.058) p = 0.004	−0.051 (−0.094, −0.008) p = 0.021	−0.180 (−0.305, −0.055) p = 0.005
Respondent's Family Income Level	0.001 (−0.0005, 0.002) p = 0.212	0.003 (−0.001, 0.007) p = 0.190	0.001 (−0.0005, 0.002) p = 0.214	0.003 (−0.001, 0.007) p = 0.192
Respondent's Party Identification	0.019 (0.007, 0.030) p = 0.002	0.050 (0.016, 0.085) p = 0.004	0.019 (0.007, 0.031) p = 0.002	0.051 (0.016, 0.085) p = 0.004
Respondent's Political Ideology	0.094 (0.074, 0.113) p < 0.001	0.275 (0.218, 0.332) p < 0.001	0.094 (0.075, 0.114) p < 0.001	0.276 (0.219, 0.333) p < 0.001
Median Household Income ($10,000)	−0.009 (−0.019, 0.002) p = 0.119	−0.026 (−0.057, 0.005) p = 0.098	−0.009 (−0.020, 0.002) p = 0.107	−0.027 (−0.058, 0.004) p = 0.086
Median Household Income ($10,000) × Anti-corruption Campaign (dummy)	0.002 (−0.013, 0.016) p = 0.811	0.009 (−0.032, 0.051) p = 0.658	0.001 (−0.014, 0.016) p = 0.893	0.008 (−0.033, 0.049) p = 0.705
Log Population Density	−0.008 (−0.022, 0.007) p = 0.317	−0.025 (−0.070, 0.020) p = 0.284	−0.009 (−0.023, 0.005) p = 0.210	−0.030 (−0.073, 0.012) p = 0.165
Log Population Density × Anti-corruption Campaign (dummy)	−0.003 (−0.024, 0.018) p = 0.790	−0.011 (−0.074, 0.053) p = 0.746	−0.005 (−0.025, 0.015) p = 0.633	−0.012 (−0.072, 0.047) p = 0.679
Share Enrolled in College or Above	0.204 (−0.263, 0.671) p = 0.393	0.461 (−0.910, 1.831) p = 0.510	0.168 (−0.289, 0.625) p = 0.472	0.311 (−1.035, 1.657) p = 0.651
Share Enrolled in College or Above × Anti-corruption Campaign (dummy)	−0.711 (−1.338, −0.084) p = 0.026	−1.754 (−3.533, 0.026) p = 0.053	−0.701 (−1.328, −0.074) p = 0.029	−1.643 (−3.425, 0.139) p = 0.071
y>=2		1.431 (1.035, 1.828) p < 0.001		1.456 (1.066, 1.846) p < 0.001
y>=3		−0.540 (−0.932, −0.147) p = 0.007		−0.515 (−0.900, −0.130) p = 0.009
Constant	2.168 (2.036, 2.300) p < 0.001		2.173 (2.043, 2.303) p < 0.001	
Number of ZIP Codes	5,211	5,211	5,211	5,211
Observations	6,730	6,730	6,730	6,730
R^2	0.059	0.070	0.058	0.070
Adjusted R^2	0.057		0.056	
Residual Std. Error	0.673		0.673	
χ^2		414.947		414.253

Note: 95% confidence intervals and p-values are presented. Calculations are based on robust standard errors clustered by ZIP code.