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11195
2024

June 2024

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 11195*

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Abstract

We address the question of the impact of a possible Trump reelection on the location choices of potential Mexican migrants. We use migration aspiration data from the Gallup World Poll Surveys which provide the preferred location choices of Mexican respondents before, during and after the Trump Presidency. We show that Trump presidency led to an increase in disapproval rates about the US leadership among Mexican respondents, which in turn led to a reduced level of attractiveness of the US location. Using a Cross-Nested Logit model that allows to account for the heterogeneity in the substitution patterns between alternative locations to the US, we simulate the impact of a possible reelection of Donald Trump based on different scenarios about these disapproval rates. We find that such a reelection would lead to an increase in the number of stayers in Mexico but would also create heterogeneous immigration pressures from Mexico across potential foreign locations. In particular, countries such as Canada, the UK, Germany, Spain, and France would face significantly higher increases in Mexican immigration pressures. We also show that the reelection of Donald Trump would lower the skill content of Mexican potential immigrants in the US and would induce an opposite effect in destinations that are perceived as close substitutes.

JEL-Codes: C250, F220, J610.

Keywords: location choice models, migration aspirations, Mexican immigrants, substitution effects.

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We thank for comments and suggestions by seminar participants in Oxford, Lausanne, Luxembourg, Caglio, Liège, the SEA, and the Annual Conference on Immigration in OECD Countries in Paris. We are indebted for useful comments to M. Brulhart, F. Docquier, G. Markarian, A. Mesnard, H. Rapoport, J. Shamsi, M. Thoenig and many others. This research was funded in whole or in part, by the Luxembourg National Research Fund (FNR), grant reference MIGDCM, and the Swiss National Science Foundation. Of course the usual disclaimer applies.

1 Introduction

In November 2016, Donald Trump was elected as US President. Both the statements before his election and the policy conducted during his presidency were characterized by a strong aversion for immigration and a strong willingness to curb the inflow of migrants to the US. During his campaign in 2016, candidate Trump made harsh statements about Mexican and Latino immigrants. As illustrated by the promise of building a wall on the Mexican-US border, one of the cornerstone policies of President Trump was to decrease drastically the number of documented and undocumented Mexican immigrants as well as to prevent their possible integration in the US society. While Mexico was not included in the list of targeted countries, the January 27 2017 Executive Order 13739 attempting to block migrants entries from 7 origin countries illustrates that the pre-election statements about immigration were not cheap talk and were matched by actual policies after the election. On November 15 2022, Donald Trump officially declared that he would run for a second mandate in 2024. The first phase of the 2024 electoral campaign suggests that the anti-immigration rhetoric is very similar to the one adopted in 2016.[1] Unsurprisingly, like during his previous campaign, this declaration raised many concerns abroad and in particular in neighbouring countries such as Mexico.

In this paper, we address the question of the possible consequences for Mexican potential immigrants of a reelection of Donald Trump in 2024. In particular, we look at the impact of such an event on the change in the location choices of these immigrants. This question is of overwhelming importance for Mexican people. Mexico is a traditional emigration country, with long-run emigration rates higher than 6% and a proportion of people considering to leave their country of about 20%.[2] In spite of the size of the country and its internal mobility, it is the highest emigration rate among OECD countries. The US represent by far the most popular destination for Mexican migrants. In 2022, about 40% of Mexican people willing to leave their country state the US as their preferred destination. In 2024, 99% of actual Mexican emigrants were US residents. Given the offensive statements and policies of President Trump with respect to Mexican immigrants, a possible reelection is expected to exert important consequences on their preferences in terms of emigration. In this paper, we consider three major aspects related to this question. First, what could be the importance of such a reelection as a determinant of attractiveness of the US destination for Mexican

[1] See for instance the anti-immigration statements of Donald Trump after winning the 2024 Iowa Republican caucuses.

[2] The stock of Mexican emigrants was estimated at 8.35 millions in 2024, of which 8.25 millions lived in the US. The intended rate of emigration is computed as the average rate over 2016-2023 from the Gallup World Poll Survey.

immigrants? Second, to what extent a reelection would lead to strong increase of the number of Mexican people willing to stay in their country ? Third and even importantly, to the extent that the inception of Donald Trump as president would lead to a lower level of attractiveness of the US location, would all other foreign countries face a similar increase of immigration pressures of Mexican immigrants? Using discrete choice models and intention data about location from Mexico, we address these questions and quantify the possible changes in the number of Mexican people willing to locate in each major country of the world induced by this new election.

In order to address these questions, we rely on data capturing individual aspirations of location of Mexican residents collected by the Gallup World Poll Surveys (GWPS). The GWPS provide comprehensive and harmonized surveys on an annual basis in almost all countries of the world. We make use of questions raised to Mexican respondents about their preferred future location. The time span (2008-2023) of these annual surveys allow us to collect data before, during and after Donald Trump's presidency. Using these aspiration data, we model the location choices of Mexican respondents using an advanced discrete choice model able to capture complex substitution patterns across alternative locations. Our model includes the usual determinants of location choices identified in the literature such as income, networks, distance but also individual characteristics such as age, gender and education. In order to capture the impact of Trump's presidency, we rely on the individual perceptions about US leadership collected by Gallup among Mexican respondents.

One crucial aspect of our modelling approach is the implications of our estimation results in terms of substitution patterns across alternative locations. Our approach takes into account that some particular countries are closer substitutes to the US compared to other destinations and more likely to be affected by such a major political shock. Our Cross-Nested Logit model (CNL) yields interesting simulations in the number of new potential migrants induced by the reelection of Donald Trump in each potential destination. In order to simulate the consequences of Trump's reelection, we consider scenarios based on the dynamics of disapproval of Mexican respondents about the US leadership. An interesting aspect is that before 2017, the average disapproval rate of Mexican respondents about the US leadership oscillated around 35%. This rate skyrocketed during the first presidential office of Donald Trump, reaching levels above 75%.[3] Our various scenarios assume a similar change in the case of Trump's reelection. In the base scenario, we assume that the average individual probability of disapproval would raise from 35 to 75% for all types of respondents. We also capture heterogeneity in the reaction among respondents in alternative scenarios. We expect that educated respon-

[3]Interestingly, the average rate after Biden's election got back to the levels observed before the Trump's presidency.

dents as well as women would disapprove another Trump presidency more. This expectation is supported by our data. We therefore also simulate effects assuming a higher increase in the disapprovals among educated Mexican respondents (skill scenario) and for women (gender scenario). Following Beine et al. (2024), we also consider a (more unrealistic) scenario of total US border closure in the aftermath of Trump's reelection to better illustrate the heterogeneity in terms of immigration pressures across different foreign countries.

Our main findings are the following ones. First, we find that approval of US leadership is a factor of attractiveness of the country. Our estimation results show that Mexican respondents disapproving the US leadership are, everything equal elsewhere, less keen to choose the US as their preferred location. From the estimations of the CNL and a scenario replicating the same consequences of his presidency, Trump's reelection would lead to an average decrease in the probability of choosing the US of about 19%, which is equivalent to a reduction in the number of potential Mexican immigrants of about 1.1 mio. Second, estimations and simulations based on the CNL suggest that such a reelection would induce a relatively modest increase in the number of intended stayers in Mexico. The reason is that, in contrast to a simple model like the multinomial logit, the CNL accounts for the fact that Mexico is not a close substitute to the US for potential Mexican emigrants. In the base scenario, the typical increase induced by the CNL of people willing to stay in Mexico amounts to about 67000. This contrasts with a much stronger figure predicted by the multinomial logit (405000). Third, our CNL identifies which countries would face the strongest immigration pressures from Mexico due to this substitution process. Countries such as Canada, the UK, Germany, France and Spain would be the most affected. To illustrate, in the base scenario, Canada would face 172000 additional immigration requests of Mexican potential immigrants. This is to be compared to a much more modest number implied by the multinomial logit for the same scenario (55000). An important implication of this results is that ministers of immigration in countries that are perceived as close substitutes to the US by Mexican residents would be better off being equipped with modelling tools capturing the heterogeneity in the substitution patterns across countries. Finally and importantly, we find that the reelection of Donald Trump would induce selection effects in terms of the skill levels of intentional Mexican immigrants, not only in the US but also in alternative foreign countries. In particular, we find that the reelection would significantly decrease the proportion of skilled Mexican immigrants in the US, while generating an opposite variation in foreign countries that are perceived as close substitutes.

Our work is related to several literatures in political science and in economics. We identify links with 4 particular branches of the migration literature.

We connect to a first strand of the literature addressing the impact of governance quality, populism and attitudes towards migration as a factor of attractiveness for migration decisions. A set of papers have looked at the impact of governance at destination on its attractiveness: Poprawe (2015); Baudassé et al. (2018); Hiskey et al. (2014); Ariu et al. (2016). Related to that, some papers have also looked at the role of integration policies (Beine et al., 2020). More recently, a specific literature has looked at the impact of the rise of populism on the mobility of individuals. Bellodi et al. (2023) look at the emergence of populist leaders on the internal mobility of natives and immigrants across Italian municipalities. More broadly speaking, a new strand of the literature looks at the role of anti-immigration attitudes of natives of the willingness to migrate: Tonini et al. (2023); Battiston et al. (2023); Beine et al. (2023); Gorinas and Pytliková (2017); Slotwinski et al. (2017). Our work contributes to that large literature by analyzing the global impact of major political shock with a clear component of populism and anti-immigration policy stance in the main traditional destination of potential migrants.

A second literature has looked at substitution effects of factors of attractiveness on location decisions of individuals.[4] In models using individual data, the identification of substitution effects across potential destination is related to the validity of the hypothesis of independence from irrelevant alternatives (Train, 2009). Deviations from this hypothesis imply that a particular shock will have unequal consequences in terms of immigration between alternative locations. A couple of papers have attempted to provide solutions to account for these deviations (Monras, 2020; Buggle et al., 2023; Beine et al., 2024). In gravity models that rely on aggregate bilateral data, heterogeneity in the substitution effects are related to the concept of Multilateral Resistance to Migration (Anderson, 2011; Bertoli and Fernández-Huertas Moraga, 2013). A limited number of papers have provided an explicit analysis of heterogenous substitution effects in terms of international migration. Guichard and Machado (2024) provide evidence of direct and indirect effects across destinations of bilateral asylum policies in the form of setting up lists of safe countries in OECD countries. Görlach and Motz (2020) investigate the same effects of variation in recognition rates across European destinations for Syrian refugees. Bratu et al. (2020) provide evidence of substitution effects of stricter immigration policies for family reunification in Denmark and show that it spurred emigration to Sweden. Beverelli and Orefice (2019) document how provisions embedded in preferential trade agreements between two countries might induce migration deflections from a third origin country. Our work contributes to that literature by emphasizing the

[4]What we call substitution effects has been also coined in the literature diversion effects, deflection effects, spill-over effects, indirect effects or externalities. This refers to the fact that the magnitude of migration flows between an origin and a destination might be affected by variations in factors that primarily affect another corridor of mobility.

heterogeneity of substitution effects across potential locations of a major political shock in an important destination for potential migrants.

Our paper relies on data capturing location intentions. In particular, we use aspiration data of mobility. In that sense, our work also connects with a recent literature making use of intention data for migration. This type of data has been increasingly used to identify self-selection factors of migration (see for a review of works in social sciences Aslany et al., 2021). In economics, such data have been used to address various questions (Docquier et al., 2014; Manchin and Orazbayev, 2018; Ruyssen and Salomone, 2018; Dustmann and Okatenko, 2014; Clemens and Mendola, 2020). Migration intentions have been subject to specific modelling approaches (Bertoli and Ruyssen, 2018; Beine et al., 2024). They have also been used as a way to predict global future migration flows (World Bank, 2018). Needless to say, there are discussions about the implications of these data for understanding real movements of individuals, with evaluation of the various concepts regarding intentions (Migali and Scipioni, 2019; Huber et al., 2022).

Finally, our paper considers the case of the Mexican-US migration corridor. This corridor is the most important one worldwide and it is no surprise that the migration between Mexico and the US has been extensively used as a lab to address key questions in the economic literature of human mobility. Self-selection in migration has been addressed using the Mexican-US case (Borjas, 1987; Chiquiar and Hanson, 2005). The income maximisation approach that underlies the modelling of migration decision have been also evaluated using this context (Grogger and Hanson, 2011). The impact of networks on negative selection of Mexican migrants has been proposed by McKenzie and Rapoport (2010) while labour market implications of migration restrictions associated to the Bracero program has been addressed by Clemens et al. (2018). Related to this part of the literature, we rely on the Mexican-US case to analyse the implication of a major political shock in a destination that represent the optimal location for about 99% of actual migrants.

The paper is organized as follows. Section 2 presents the modelling approach of the location choices of Mexican respondents and of the impact of a new election of Donald Trump. Section 3 gives details about the data that we use in the econometric setting. Section 4 gives the main estimation findings while section 5 presents the simulation results of a possible reelection of Donald Trump. Section 5 provides some additional discussions and concludes.

2 Modelling impact of Trump on location preferences

In order to estimate the possible impact of a reelection of Donald Trump, we model the location decisions of Mexican residents using a discrete choice approach based on a Random Utility Model of location preferences.

In this approach, Mexicans maximize their utility over all alternative potential locations j including the domestic one ($j = 0$). Utility of individual n associated to location j is given by U_{jn}. The RUM approach breaks down U_{jn} into a deterministic part V_{jn} and a stochastic one, ϵ_{jn}:

$$U_{jn} = V_{jn} + \epsilon_{jn}. \tag{1}$$

It is useful to see how both components contribute specifically to the estimation. The specification of V_{jn} pertains to the choice of the factors of location that we include to explain location preferences. An important element is how we model the possible effect of reelection through the disapproval of Mexican residents about the US leadership. This effect will serve as the basis for the simulations of a reelection of Donald Trump in 2024. The choice of the underlying distribution for the stochastic part ϵ_{jn} is directly related to the choice of the specific discrete choice model (DCM) that we bring to the data. In this paper, we use a CNL model that is able to capture complex and realistic patterns of substitution. This model has been introduced in the migration literature by Beine et al. (2024) who document its superiority in terms of fit, out-of-sample predictions and generated substitution patterns compared to the usual alternative models (Multinomial Logit and Nested Logit).

The specification for the V_{jn}, the deterministic part of the utility of destination j includes the usual main determinants of migration identified in the literature. Our strategy here is not to identify the full set of potential determinants as the list is close to infinite but to account for the main factors that have been shown as very robust throughout the literature.[5]

For the sake of exposition, we distinguish between the specification of the domestic utility, i.e. the utility of staying in Mexico, and the one of the utility associated to each foreign location. Both specifications are jointly estimated within the same estimation.

[5]It should also be emphasized that we model location preferences that are clearly influenced by less objective factors, i.e. perceptions by respondents. Therefore, it can be anticipated that even with a very long stretch of factors included in the specification, a substantial part of the variation will be driven by ϵ_{jn}.

The utility associated with the domestic location, i.e. to staying in Mexico is denoted by V_{0n} given by :

$$V_{0n} = D'_n\beta. \tag{2}$$

where $j = 0$ stands for Mexico and where D'_n is a vector of individual characteristics such as age, gender, marital status. We include the level of education of individual n using dummy variables for low, medium, and high skilled. Following the literature on networks, (Beine, 2020; Beine et al., 2011; Munshi, 2003) we include a variable capturing whether the individual has a network abroad. Since the existing literature suggests that the sensitivity to network differs across education levels, the network effect is estimated separately for each education level through an interaction with the level of education. We also include personal income at origin. We provide details about each variable below in the data section as well and in Appendix A. Estimates of β provide an assessment of the impact of each determinant on the probability of emigration.

The utility associated to any foreign destination ^{j} other than the US one is specified as:

$$V_{jn} = Z'_{jn}\gamma + \delta_{m(j)}, \quad j = 1, ..., J-1 \tag{3}$$

We first account for the determinants of attractiveness of foreign locations. We account for distance, income at destination and networks. These factors are interacted with each education level since, once again, their influence is likely to depend on the skill level. The $\delta_{m(j)}$ are dummies specific to the category that underlies the composition of nest m in the distribution of ϵ_{jn} (see below). The $\delta_{m(j)}$ play a similar role as the one played by fixed effects in linear panel data models. They capture the attractiveness of a category of destinations, which allows to account for the unobserved factors specific to that category.[6]

The utility associated with moving or relocating to the US is given by

$$V_{jn} = Z'_{jn}\gamma + \delta_{m(j)} + \theta z_{US,n}, \quad j = \text{US} \tag{4}$$

[6]It should be emphasized that the role of $\delta_{m(j)}$ is quite different from the one played by the nests. Indeed, the nests allow to capture the similarity between a subset of destinations and therefore allows to capture higher substitution rates among those destinations. In contrast, $\delta_{m(j)}$ capture the specific attractiveness of this subset of destinations.

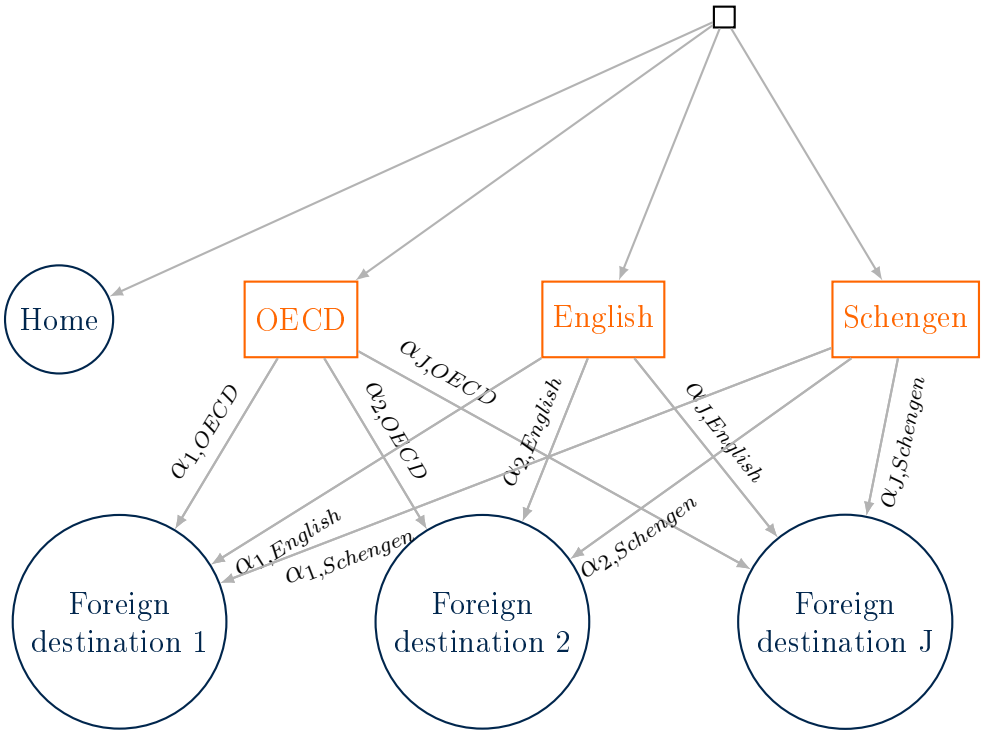
In the utility of the US destination, we include a variable $z_{US,n}$ capturing whether individual n disapproves US leadership. This variable will be the main channel through which we assess the effect of a possible reelection of Donald Trump on the perceived attractiveness of the US for Mexican respondents. It should be clear that given the specification, the estimate of θ will deliver a direct and an indirect effect of the reelection. The direct effect comes from the perceived decrease in the attractiveness of the US as a destination. It can be visualized as the estimated elasticity of a change in disapproving the US leadership on the likelihood to choose the US. The indirect effect relates to the attractiveness of the alternative locations. It is visualized by the cross-elasticity of each alternative location to the disapproval associated to the estimate of θ. It is important to note that the elasticities and the cross-elasticities depend on the choice of the distribution for the stochastic component of 1, ϵ_{jn}.

The specification of the stochastic component of utility ϵ_{jn} plays not only an important role for the estimation of equations (2-4) but also for the estimations of the substitutions generated by the election of Donald Trump. In this paper, we adopt the Multivariate Extreme Value (MEV) that is associated to the CNL Model. We present only the intuition behind this choice and do not present the technical details here. These technical details are presented in the Appendix and can also be found in Beine et al. (2024) who introduce this type of model to capture the substitution patterns in the location choices of Indian respondents.

The adoption of the MEV distribution and the CNL requires the choice of nests of potential destinations. The CNL partitions the choice set of foreign destination into several nests, each of these nests relying on a specific criterion. Each criterion defines a subset of foreign destinations that share some similarity and that are subject to higher substitutability between them, compared to the other destinations not complying with this criterion. In our CNL model, we define three nests based on (i) OECD membership, (ii) Schengen membership and (iii) English-speaking. For instance, the model will allow for English speaking countries to be more substitutable among them as they share unobserved factors of higher similarity related to the English language. Unlike some models like the Nested Logit model that relies on a single criterion, the CNL combines the various criteria to define overlapping nests. Figure 1 presents the way the CNL partitions the choice set of alternative locations.

After estimating the model, one can compute the elasticities and cross-elasticities with respect to our key variable, i.e. the disapproval of US leadership, in order to document the substitutions generated by Trump reelection. More specifically, for each location and each respondent, we can compute the cross-elasticity of disapproving US leadership under a specific scenario. These cross-elasticities capture the sensitiveness of the attractiveness of each location for each individual (in case of a Trump reelection). It is based on the comparison of

Figure 1: Structure of the CNL model for migration.



the probabilities of choosing each location with and without Donald Trump as the next US president. Once again, we skip the technical details here. Appendix B provides the technical exposition of the estimations of the cross-elasticities.

3 Data

In order to estimate model (2-4), we collect data from various sources. The key data concerning location preferences and individual characteristics of the respondents come from the Gallup World Poll (GWPS) conducted in Mexico. From the GWPS, we also draw the disapproval of Mexican respondents with respect to US leadership. We also supplement the GWPS with other data to capture measures of destination-specific covariates.

3.1 Location preferences

The GWPS is probably the most comprehensive source of data on migration aspirations worldwide. The GWPS is conducted in more than 160 countries (representing 95 percent of the world's population aged 15 and over) and is repeated almost every year. Our case study focuses on migration aspirations from Mexico, which is the most important source of emigrants in the US. GWPS data provide information on migration aspirations from about 1,000 individuals per wave. Data are collected by telephone or through face-to-face interviews. We use data collected between 2007 and 2021.[7]

In our analysis, we exploit two specific questions on migration aspirations. The first one is: *"Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country?"* For respondents who answered affirmatively, a follow-up question asked about the preferred location: *"To which country would you like to move?"*.[8] Combined with data on individual characteristics, the GWPS is a rich data source to identify the self-selection factors of international migration and the substitution patterns within the choice set.

How closely do migration aspirations in the GWPS reflect actual movements and existing diasporas? Table 1 lists the most popular destinations for Mexicans in the Gallup World Poll and emphasizes the outstanding role of the US. In Panel (a), more than 40 percent of those who aspire to move abroad name the US as their first option. Canada, Spain, and Germany follow at a large distance from the US (Jann, 2007).

Panel (b) supplements mentioned aspiration with the stock of the Mexican diaspora in a destination. The US accounts for 97.4 percent of the total Mexican diaspora (and no other one for even one percent). Apart from missing data in the GWPS in the case of Guatemala as a potential destination, the main destinations are similar for aspiration and realized migration.

To motivate our estimations and simulations in this paper, Table 2 provides a description of the main location preference of Mexican respondents for three separate periods of time, given availability: before (2007–2016), during (2017–2019), and after the Trump presidency (2021–22). The upper panel provides location preferences for all respondents, including those who state they would prefer to stay. The lower panel focuses on aspirational movers only, i.e.

[7] We exclude the years 2006 and 2020 from our sample because Gallup did not collect data on relevant variables in these years. We use 2022 as the baseline for our simulations of immigration pressures.

[8] In our sample, we can only consider respondents who state a preference to move *and* for a distinct country, i.e. we exclude those with missing or unspecific information in either question. For example, Gallup recorded answers such as African Country, Arab Country, or Island Nations, which represent more general responses without a specific country in mind. Furthermore, we drop observations with a preference for non-sovereign countries (Nagorno-Karabakh, Northern Cyprus, Somaliland).

Table 1: Most Popular Destinations for Mexicans in Gallup World Poll (2007–2019) and United Nations – International Migrant Stock in 2019.

(a) Stated Aspiration in Gallup World Poll

WP3120 — Country Would Move To	Freq.	Percent	Cum.
United States	1,002	42.40	42.40
Canada	321	13.58	55.99
Spain	187	7.91	63.90
Germany	155	6.56	70.46
France	111	4.70	75.16
Italy	52	2.20	77.36
Brazil	48	2.03	79.39
Japan	46	1.95	81.34
United Kingdom	39	1.65	82.99
China	35	1.48	84.47
Switzerland	31	1.31	85.78
Cuba	30	1.27	87.05
Australia	28	1.18	88.24
Albania	24	1.02	89.25
Argentina	24	1.02	90.27
Netherlands	22	0.93	91.20
Russia	20	0.85	92.04
Colombia	13	0.55	92.59
Norway	12	0.51	93.10
Venezuela	10	0.42	93.53
Afghanistan	10	0.42	93.95
⋮	⋮	⋮	⋮
Total	2,363		100.00

(b) Mexican Diaspora in *United Nations – International Migrant Stock in 2019.*

Diaspora	Freq.	Percent
United States	11,489,684	97.36
Canada	85,825	0.73
Spain	53,158	0.45
Guatemala	18,003	0.15
Germany	16,892	0.14
France	13,851	0.12
United Kingdom	10,457	0.09
Bolivia	10,396	0.09
Italy	9,441	0.08
Switzerland	7,789	0.07
Chile	6,887	0.06
Australia	6,760	0.06
Panama	5,141	0.04
Netherlands	4,932	0.04
Caribbean	4,169	0.04
Peru	3,926	0.03
Belize	3,866	0.03
Venezuela	3,752	0.03
Brazil	3,601	0.03
Sweden	3,153	0.03
Costa Rica	3,145	0.03
Colombia	3,050	0.03
⋮	⋮	⋮
Total	11,800,660	100.00

those who responded positively to the first question. A couple of comments are in order. The aspirational emigration rate oscillates between 17% and 30%. Over the period, the proportion of those willing to leave Mexico tends to increase over time, probably due to deteriorating conditions at the origin. Focusing on the preferences for foreign locations, the data confirm that overall the US is the most popular destination. Nevertheless, from the lower panel of Table 2, the proportion of intended movers to the US experienced a drop during the Trump period, to rebound after the election of Joe Biden. Focusing on a specific alternative location, one can see a big increase of intended movers to Canada during the Trump presidency. This very raw evidence is suggestive of substitution effects, but will be assessed more specifically in the rest of the paper.

Table 2: Most Popular Destinations for Mexicans in Gallup World Poll (2007–2022) by Pre- and Post-Period.

(a) Non-missing respondents

WP3120 — Country Would Move To

	2007-2016			2017-2019			2021-2022		
	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.
Stay	8,639	83.27	83.27	2,251	78.21	78.21	1,358	70.66	70.66
United States	**790**	**7.61**	**90.88**	**212**	**7.37**	**85.58**	**212**	**11.03**	**81.69**
Canada	184	1.77	92.66	137	4.76	90.34	135	7.02	88.71
Spain	137	1.32	93.98	50	1.74	92.08	46	2.39	91.10
Germany	108	1.04	95.02	47	1.63	93.71	42	2.19	93.29
France	79	0.76	95.78	32	1.11	94.82	23	1.20	94.49
Italy	38	0.37	96.14	14	0.49	95.31	10	0.52	95.01
Brazil	36	0.35	96.49	12	0.42	95.73	4	0.21	95.22
Japan	35	0.34	96.83	11	0.38	96.11	13	0.68	95.9
United Kingdom	29	0.28	97.11	10	0.35	96.46	5	0.26	96.16
China	25	0.24	97.35	10	0.35	96.81	4	0.21	96.37
Albania	24	0.23	97.58	-	-	96.81	-	-	96.37
Cuba	23	0.22	97.80	7	0.24	97.05	-	-	96.37
Switzerland	22	0.21	98.01	9	0.31	97.36	14	0.73	97.1
Australia	20	0.19	98.21	8	0.28	97.64	4	0.21	97.31
Argentina	20	0.19	98.40	-	-	97.64	-	-	97.31
Netherlands	14	0.13	98.53	8	0.28	97.92	9	0.47	97.78
Afghanistan	10	0.10	98.63	-	-	97.92	-	-	97.78
Venezuela	9	0.09	98.72	-	-	-	97.92	-	97.78
Colombia	9	0.09	98.80	4	0.14	98.06	3	0.16	97.94
Algeria	8	0.08	98.80	-	-	98.06	-	-	97.94
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Total	10,375	100.00	100.00	2,878	100.00	100.00	1,922	100.00	100.00

(b) Potential movers

WP3120 — Country Would Move To

	2007-2016			2017-2019			2021-2022		
Country	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.
United States	**790**	**45.51**	**45.51**	**212**	**33.81**	**33.81**	**212**	**37.59**	**37.59**
Canada	184	10.60	56.11	137	21.85	55.66	135	23.94	61.52
Spain	137	7.89	64.00	50	7.97	63.64	46	8.16	69.68
Germany	108	6.22	70.22	47	7.50	71.13	42	7.45	77.13
France	79	4.55	74.77	32	5.10	76.24	23	4.08	81.21
Italy	38	2.19	76.96	14	2.23	78.47	10	1.77	82.98
Brazil	36	2.07	79.03	12	1.91	80.38	4	0.71	83.69
Japan	35	2.02	81.05	11	1.75	82.13	13	2.30	85.99
United Kingdom	29	1.67	82.72	10	1.59	83.72	5	0.89	86.88
China	25	1.44	84.16	10	1.59	85.31	4	0.71	87.59
Albania	24	1.38	85.54	-	-	85.31	-	-	87.59
Cuba	23	1.32	86.87	7	1.12	86.43	-	-	87.59
Switzerland	22	1.27	88.13	9	1.44	87.87	14	2.48	90.07
Australia	20	1.15	89.29	8	1.28	89.15	4	0.71	90.78
Argentina	20	1.15	90.44	-	-	89.15	-	-	90.78
Netherlands	14	0.81	91.24	8	1.28	90.43	9	1.60	92.38
Afghanistan	10	0.58	91.82	-	-	90.43	-	-	92.38
Venezuela	9	0.52	92.34	-	-	90.43	-	-	92.38
Colombia	9	0.52	92.86	4	0.64	91.07	3	0.53	92.91
Algeria	8	0.46	93.32	-	-	91.07	-	-	92.91
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Total	1,736	100.00	100.00	627	100.00	100.00	564	100.00	

The table considers all non-missing values, while excluding ambiguous locations and inconclusive answers. There are no data for 2020.

3.2 Disapproval of US leadership

We will capture the impact of a possible reelection of Donald Trump on location preferences of Mexican respondents by their varying disapproval of US leadership. To that aim, we rely on a question asked in the GWPS to all respondents whether they approve of the current US leadership or not. With the exception of 2020, this question is asked throughout the whole period of availability in the GWPS (2009–2022). Observations with unspecific and missing answers of disapproving US leadership are dropped from our sample below. Panels (a) and (b) in Fig. 2 plot the rates of approval among Mexican respondents for US leadership during the terms of Presidents Obama (2009–2016), Trump (2017-2020), and Biden (2021-2023). Panel (a) plots the evolution of approval and disapproval for all respondents, while Panel (c) considers only the subsample of respondents willing to go to the US. Both panels show the exceptional unpopularity of the Trump administration.[9]

Panel (d) provides the evolution of approval and disapproval rates for Mexican respondents aspiring to migrate to Canada. The evolution of disapproval of these respondents is even more pronounced during the Trump presidency, which is suggestive that this political shock could have played a significant role in terms of generated substitution effects to alternative destinations.

Panel (b) suggests that the variation of disapproving US leadership is connected with a more direct question about the US president. Unfortunately, this question is unavailable across most waves. It is also worth noticing that the rates of approval after the Trump presidency got back to pre-Trump levels, although there exist differences in the way Presidents Obama and Biden are perceived. All in all, the global picture suggests that the evolution of disapproving US leadership is closely connected to the inauguration of President Trump and offers a way to capture the role of a possible reelection on the individual preferences of location.

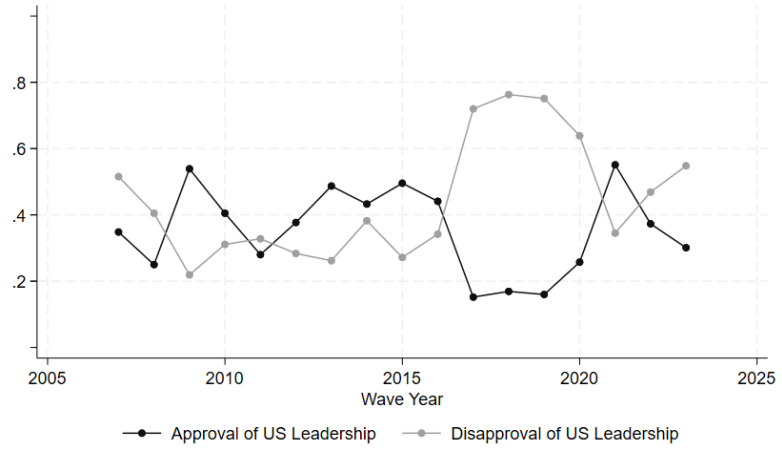
3.3 Individual characteristics of respondents

An appealing feature of the GWPS is that it documents a large set of respondents' personal characteristics, including age, gender, education level, income, family structure, and having a friend or family member abroad (i.e., a personal network link). These characteristics can be used in the modeling of emigration aspirations in Eq. (2). In our empirical analysis, we

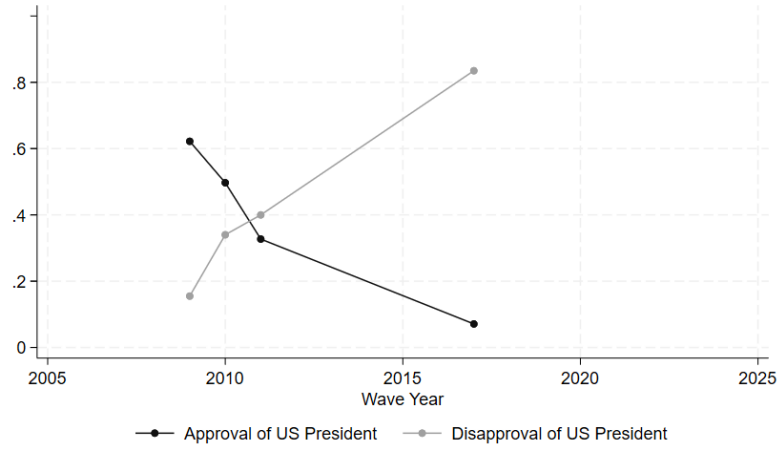
[9]PEW's Global Indicators Database aligns with these trends and emphasize Mexicans' *relative* disfavor in a global context. See `https://www.pewresearch.org/global/database/indicator/6/country/mx/`. The survey provides information on confidence in the US president (Mexico is at the bottom in 2017–2019 with 5–8 percent stating confident; not included in 2016, 2020, and 2021) and the general opinion on the US.

Figure 2: Approval and Disapproval for US Political Institutions in Mexico.

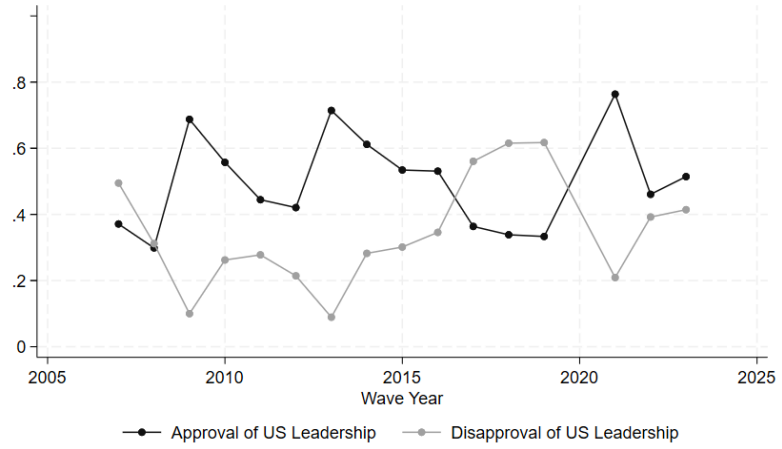
(a) US Leadership



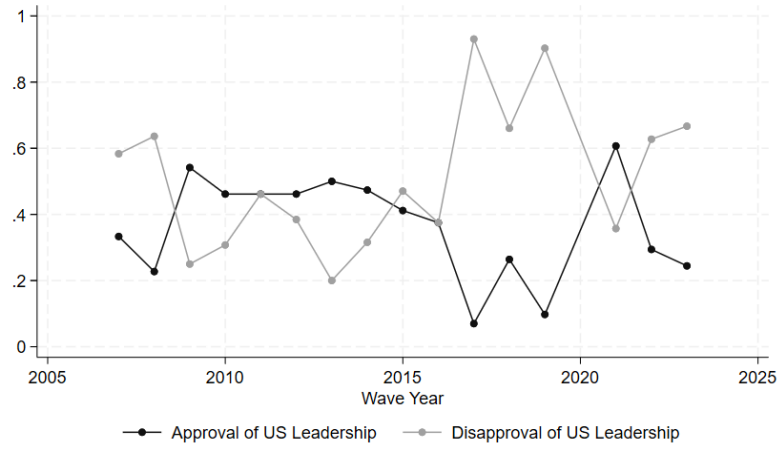
(b) US President



(c) Moving to US: approval of US Leadership



(d) Moving to CA: approval of US Leadership



Note there are no observations for aspired migration destinations for 2020. Missing or refused answers are not included.

thus control for individual characteristics that have been described in existing literature as influencing the propensity to emigrate.[10] We include the log of income per household member in the place of origin (Dao et al., 2018), the existence of a network link abroad (Beine et al., 2011; Munshi, 2003), marital status, the age of the respondent (Beine, 2020), gender, and education level (primary, secondary, or tertiary education). Individual income is derived from household income and is adjusted using an equivalence scale. See Appendix A.3 for details and explanations about the way individual income is measured.

3.4 Destination-specific covariates

We supplement and combine the individual characteristics D'_n with destination-specific variables X'_{jn}. These variables capture the deterministic part of the attractiveness of potential foreign destinations in the choice set. These include the main time-varying determinants already identified in existing literature: GDP per capita (Grogger and Hanson, 2011), the size of the Mexican diaspora (Beine et al., 2011) and population at destination. In contrast to studies on actual migration flows (in which population is used as a proxy for the absorption capacity of the destination country), the effect of population on migration aspirations is more likely to be governed by other factors such as the media coverage and "visibility" of the destination, or an effect of the market size on the variety of goods available to consumers. We also include distance between the location of the respondent and each potential destination. Note that we make use to that aim of the information about the regional location since GWPS gives information about the state of residence of each respondent.

The destination-specific variables can be retrieved from macroeconomic data sources and are observed on an annual basis. We match the year of observation for these data with the year of the GWPS wave. For variables that have less frequent observations, such as the Mexican diaspora, we match each GWPS wave with observations for the closest year. A description of the variables' sources and their definition is reported in Table A.3 in Appendix A.

3.5 Preliminary evidence of substitution effects

At this stage, it is useful to document some preliminary evidence about substitution effects associated to the inauguration of Donald Trump in 2017. This preliminary evidence should of course be taken with caution as it overlooks many aspects that will be taken into account in

[10] Table A.2 in Appendix A provides the exact sources of the various individual specific data in the GWPS survey data.

the estimation of our DCM model. To recall, Table 2 demonstrates the changes in destination popularity from the pre- to the post-period, defined by Trump's inauguration in 2017. While the US remains the primary destination for Mexican potential emigrants, the US experiences a drop by almost twelve percentage points in the years since 2017. In contrast, Canada has received more interest (an increase of about 11 percentage points) by potential migrants from Mexico.

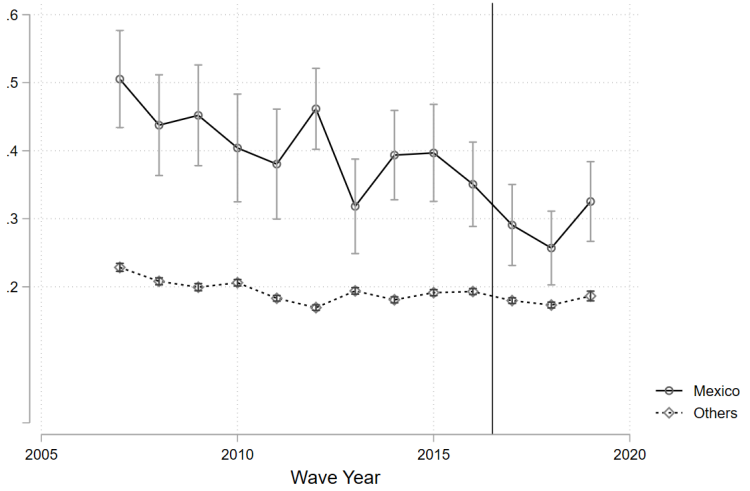
As a preliminary analysis, we conduct some diff-in-diff estimations in order to grab potential substitution effects. In these analyses, the treated group include respondents from Mexico while the control group are respondents from other origin countries covered in the GWPS.[11] The details of the analysis are provided in Appendix D. It should be noted that while the diff-in-diff analysis belongs to the usual toolbox of applied econometricians interested in policy evaluation, it nevertheless rests on some assumptions whose validity might be questioned. For instance, one key assumption is the absence of any shock affecting location preferences in alternative destinations in the post estimation period. For some destinations, this assumption might be quite strong. For instance, the analysis involving the UK assumes that in the post period (2017–2020), the prospects of the Brexit did not affect the attractiveness of the UK for Mexican respondents. If this assumption is violated, such a shock might offset and hide the substitution effect at stake for the UK. In contract with the diff-in-diff, our substitution effects identified in the DCM models rest on the estimation of the cross-elasticities associated to the disapproval about US leadership and are therefore not subject to above-mentioned concern. A second assumption of the diff-in-diff is that the respondents in the control group were not affected by the inauguration of President Trump. This assumption tends to be quite strong as well. Our DCM estimates are not subject to this concern.

With this word of caution in mind, we provide some estimates of the diff-in-diff analyses for a set of popular destinations using alternative setups. We first use an underlying linear model for the diff-in-diff estimations. We then use a multinomial logit model to account for the discretionary nature of the dependent variable. The full results are provided in Appendix D in order to save space here. We provide only a few figures here. In a nutshell, the diff-in-diff estimates suggest a significant decrease in the attractiveness of the US destination for Mexicans. In terms of the substitution effects, the estimates clearly suggest a positive spillover effect for Canada. For the other destinations, the picture is much less clear.

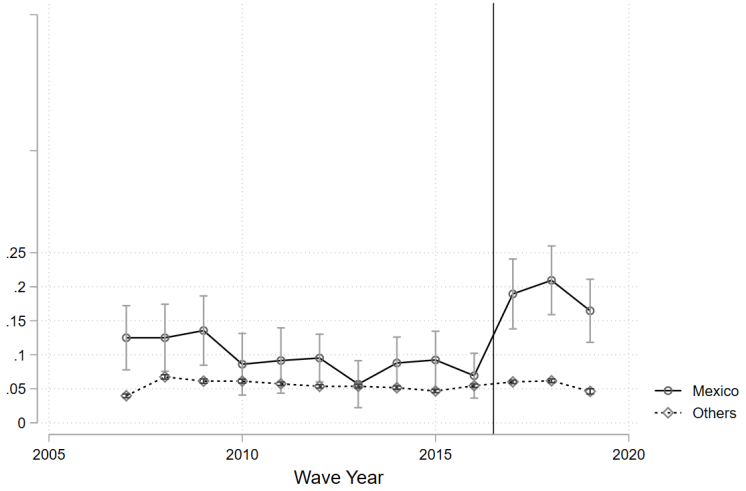
[11] In the diff-in-diff analysis, we excluded all other Central American countries because they may rather mirror Mexico than other origin countries.

Figure 3: Trends of Migration Aspiration Toward Main Destinations over Time for Different Immigrant Groups.

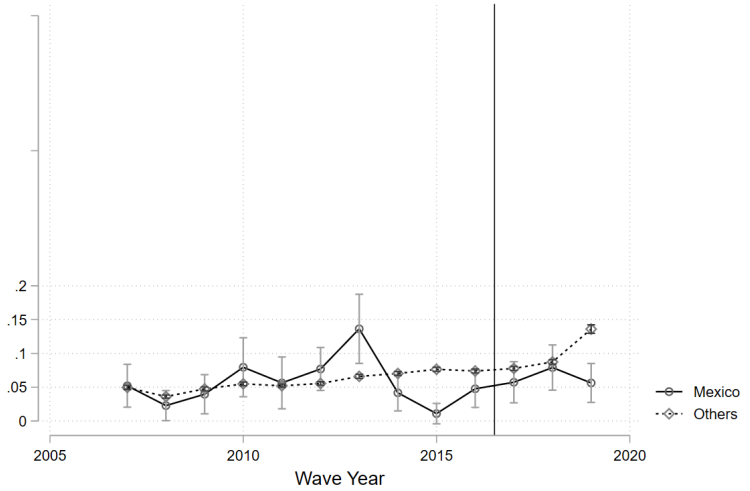
(a) USA



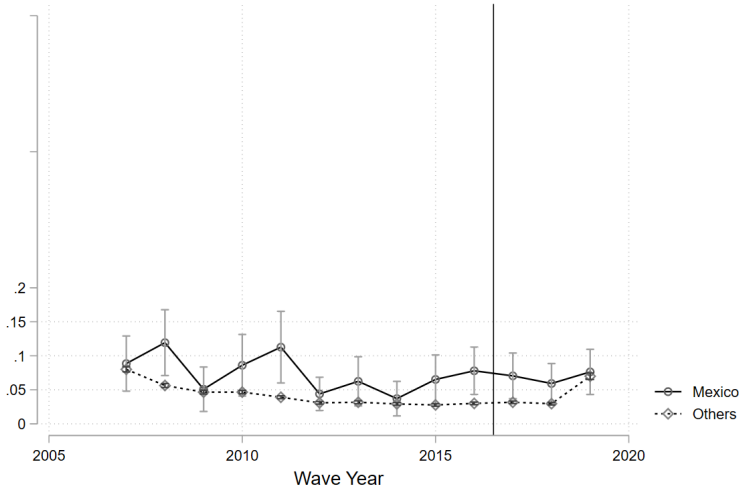
(b) Canada

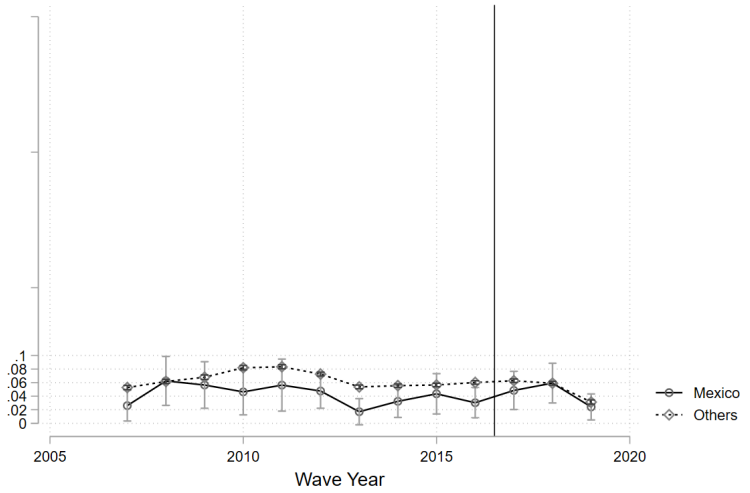


(c) Germany

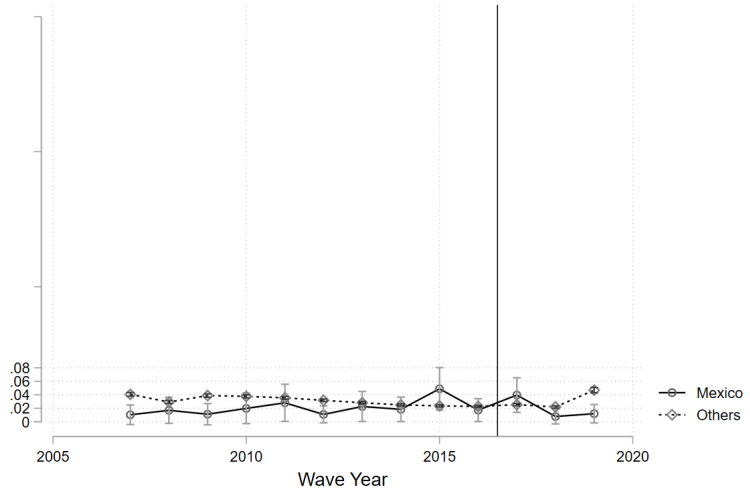


(d) Spain

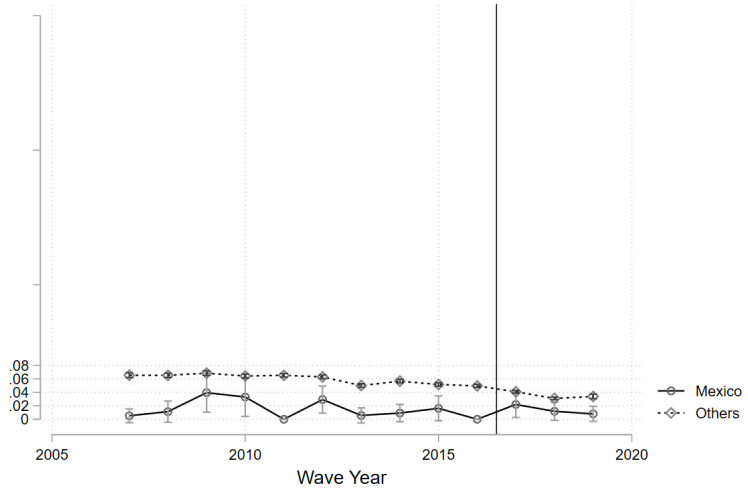




(e) France



(f) Italy



(g) UK

The graph pictures the means and the 95 percent confidence intervals derived from the sample of aspiring migrants. The vertical lines represent Donald J. Trump's election to US president in November 2016.

4 Estimation results

Table 3 reports the estimation results. We provide results for different models (different choices of ϵ_{jn}), different samples and different specifications of V_{jn}. In columns (1-4), we provide estimation results with an impact of disapproval that is homogenous across individuals. In columns (5-7), the models allow for an effect that differs across the three education levels. In column (4), we provide for comparison purposes estimations only for intended movers, i.e., respondents willing to emigrate to a foreign country. Our preferred model is the CNL model allowing for heterogeneous substitution patterns. The estimation results are provided in columns (3) and (7).[12] We also provide for comparison purposes estimates with simpler models, i.e. multinomial logit (columns 1,4 and 5) and NL (columns 2 and 6). All simulation results will be based on the CNL model.

As mentioned above, we include destination-specific constants for English-speaking, OECD and Schengen memberships, which capture the attractiveness of each category of destinations. These dummies are chosen in accordance with the nesting structure of the CNL. The CNL models include a nest for each category, allowing to capture higher potential substitutions between destinations belonging to each nest. The nests capture the similarities of countries within each underlying category m. The associated parameter of similarity is μ_m and a test with $H_0 : \mu_m = 1$ against $H_A : \mu_m > 1$ allows to validate each nest empirically.

The estimation results of the models are in line with the main findings of the literature. With respect to the determinants of the propensity to emigrate that can be inferred from the specification of the domestic utility (V_{0n}), we find a role for education level, network, gender, marital status and age. Intended emigration rates are increasing in the emigration rates, confirming positive selection of aspirational migrants. Personal networks abroad increase the propensity to emigrate. Men, young and single individuals are more prone to go abroad. We do not find a significant role for income at origin, confirming its ambiguous role on intended mobility (Beine et al., 2024; Clemens and Mendola, 2020).

The determinants of the location choices across foreign destinations can be inferred from the specification of the foreign utilities (V_{jn}). In line with the literature, we find a positive role of

[12]Findings reported in Table 3 support the use of the CNL as the preferred model. Estimates of the μ_m support the relevance of the three nests partitioning the choice set of foreign destinations. Destinations included within the same nest are perceived as more substitutable by respondents, compared to destinations not included in the nest. Likelihood ratio tests confirm the dominance of the CNL compared to the ML (column 1) and the NL (column 2). This is in line with the results of Beine et al. (2024) who show the superiority of this model on Indian preference data. Therefore, we will draw on these estimates to compute the cross-elasticities contingent on each scenario and to document the substitution patterns generated by a possible reelection.

Table 3: Impact of Trump reelection on location choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Homogeneous model				Heterogeneous model		
	ML	NL	CNL	ML, movers only	ML	NL	CNL
	Utility of staying in the domestic location (V_{0n})						
Low-skilled (LS)	15***	1.93***	11.2***		14.9***	2.05***	11.2***
	(0.584)	(0.185)	(0.585)		(0.586)	(0.186)	(0.588)
Medium-skilled (MS)	15.1***	1.69***	10.9***		15.1***	1.82***	10.9***
	(0.392)	(0.159)	(0.539)		(0.392)	(0.159)	(0.537)
High-skilled (HS)	15***	1.27***	10.1***		15.1***	1.41***	10.2***
	(0.578)	(0.191)	(0.636)		(0.584)	(0.193)	(0.635)
Male	-0.179***	-0.181***	-0.178***		-0.18***	-0.181***	-0.179***
	(0.0537)	(0.0535)	(0.0538)		(0.0538)	(0.0535)	(0.0538)
Single	-0.236**	-0.233**	-0.238**		-0.236***	-0.234***	-0.238***
	(0.0652)	(0.0648)	(0.0652)		(0.0652)	(0.0648)	(0.0652)
Network × LS	-0.596***	-0.603***	-0.594***		-0.604***	-0.603***	-0.598***
	(0.134)	(0.133)	(0.134)		(0.133)	(0.133)	(0.133)
Network × MS	-0.489***	-0.502***	-0.485***		-0.49***	-0.501***	-0.486***
	(0.0684)	(0.068)	(0.0684)		(0.0684)	(0.068)	(0.0683)
Network × HS	-0.327**	-0.331**	-0.319**		-0.302**	-0.329**	-0.304**
	(0.147)	(0.147)	(0.147)		(0.15)	(0.147)	(0.149)
Age under 65	0.0225***	0.0227***	0.0224***		0.0224***	0.0227***	0.0223***
	(0.00249)	(0.00248)	(0.00249)		(0.00248)	(0.00248)	(0.00249)
Age over 65	0.0567***	0.0555***	0.0567***		0.0564***	0.0556***	0.0565***
	(0.0182)	(0.018)	(0.0182)		(0.0181)	(0.018)	(0.0181)
Log of income at origin	-0.0451	-0.0531	-0.0444		-0.0457	-0.0524	-0.0448
	(0.0335)	(0.0333)	(0.0335)		(0.0335)	(0.0333)	(0.0335)
	Utility of moving to a foreign location (V_{jn})						
Log of distance	-0.134***	-0.0278***	-0.16***	-0.608***	-0.136***	-0.0332***	-0.161***
	(0.0413)	(0.00487)	(0.0342)	(0.08)	(0.0413)	(0.00513)	(0.0342)
Log GDP × LS	0.423***	0.0253***	0.332***	0.544***	0.431***	0.0313***	0.336***
	(0.162)	(0.00843)	(0.119)	(0.161)	(0.161)	(0.00967)	(0.119)
Log GDP × MS	0.689***	0.0368***	0.439***	0.789***	0.694***	0.0445***	0.443***
	(0.0901)	(0.00749)	(0.0807)	(0.0953)	(0.0898)	(0.00794)	(0.0813)
Log GDP × HS	0.95***	0.049***	0.465***	1.05***	0.952***	0.0581***	0.466***
	(0.132)	(0.0104)	(0.11)	(0.129)	(0.136)	(0.0111)	(0.111)
Log of diaspora × LS	0.271***	0.0106***	0.183***	0.226***	0.259***	0.0116***	0.175***
	(0.0209)	(0.00237)	(0.0178)	(0.0247)	(0.0217)	(0.00248)	(0.0182)
Log of diaspora × MS	0.224***	0.00837***	0.147***	0.178***	0.222***	0.0098***	0.146***
	(0.0132)	(0.00185)	(0.0129)	(0.017)	(0.0133)	(0.00194)	(0.0129)
Log of diaspora × HS	0.164***	0.00555***	0.107***	0.118***	0.182***	0.00844***	0.123***
	(0.016)	(0.00146)	(0.0143)	(0.019)	(0.0166)	(0.00184)	(0.0152)
Log of population	0.534***	0.0292***	0.262***	0.627***	0.535***	0.0349***	0.264***
	(0.0448)	(0.00457)	(0.0415)	(0.0298)	(0.0448)	(0.00482)	(0.0416)
Disapproval of US leadership	-0.586***	-0.0555***	-0.497***	-1.2***			
	(0.0782)	(0.00968)	(0.0585)	(0.102)			
Disapproval of US leadership × LS					-0.247	-0.0425***	-0.302**
					(0.178)	(0.0149)	(0.136)
Disapproval of US leadership × MS					-0.554***	-0.0619***	-0.459***
					(0.0929)	(0.01)	(0.0686)
Disapproval of US leadership × HS					-1.37***	-0.12***	-1.01***
					(0.258)	(0.0219)	(0.178)
δ_{OECD}	0.0485	0.00556	1.93***	0.121	0.0434	0.00626	1.91***
	(0.107)	(0.00515)	(0.194)	(0.109)	(0.107)	(0.00613)	(0.194)
$\delta_{Schengen}$	0.304***	0.0235***	0.577***	0.508***	0.301***	0.0277***	0.583***
	(0.0902)	(0.00565)	(0.0836)	(0.0956)	(0.0902)	(0.00624)	(0.0838)
$\delta_{English}$	0.406***	0.0237***	0.177	0.512***	0.407***	0.0283***	0.192
	(0.0786)	(0.00538)	(0.147)	(0.0816)	(0.0784)	(0.00586)	(0.144)
	Parameters of the nest structure (μ_m)						
μ_{Foreign}		21.4***				17.9***	
		(3.83)				(2.68)	
μ_{OECD}			2.31***				2.28***
			(0.176)				(0.168)
μ_{Schengen}			3.41***				3.4***
			(0.663)				(0.66)
μ_{English}			1.29***				1.29***
			(0.0886)				(0.0867)
Log-likelihood	-9,380.25	-9,331.42	-9,260.97	-4,811.71	-9,373.01	-9,323.25	-9,254.59
Observations	10,081	10,081	10,081	1,821	10,081	10,081	10,081
Parameters	23	24	26	12	25	26	28

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

diasporas, income at destination, size of the country (as a measure of hosting capacity) and a negative effect of distance. Also, importantly, sensitivities depend on the skill level, with variation across education levels in line with the previous evidence. Estimation of dummies show that OECD membership, Schengen countries and English-speaking destinations are relatively more attractive.

The key estimate of this specification refers to the impact of the disapproval with respect to US leadership. In column (3), the estimated coefficient of this variable shows that Mexican respondents disapproving US leadership are less keen to choose the US as their optimal location. In the base scenario (that assumes a disapproval rate similar to the one observed during the first mandate of Trump- see below for more details), we find an elasticity of about -0.22. This means that compared to other respondents, on average, individuals disapproving US leadership have, everything equal elsewhere, a 22% lower probability of choosing the US as their optimal location. Of course, this elasticity depends on the exact scenario about the impact of a Trump reelection on the propensity of disapproving and might differ across individuals. Nevertheless, this provides an idea of the role of such a political factor in the way individuals elicit their location preferences. It should be stressed that the negative impact on the attractiveness of the US is not a result specific to the CNL model. Results in columns 1, 2, 5 and 6 obtained with alternative models also support the negative impact of the disapproval of US leadership. We should also expect this impact to be stronger when estimated on the sub-sample of intended movers. Such an expectation is confirmed by results in column (4). In other terms, Mexican respondents willing to leave Mexico are significantly more affected by a possible reelection of Donald Trump.

The estimates from column (5-7) support an heterogenous impact of the disapproval variable across education levels. We find that the disapproval of US leadership is associated with a stronger decrease in the attractiveness of the US for highly-educated respondents. The estimates are increasing in absolute terms in the education level of respondents. The null hypothesis of equal coefficients is strongly rejected between high-skilled and low-skilled respondents on the one hand, and between high- and middle-skilled on the other hand. This heterogeneity might be driven by several mechanisms that are hard to identify empirically. Nevertheless, we can expect that more educated respondents are better informed about Trump's policy proposals and more able to understand its consequences for future Mexican immigrants. This heterogeneity could be also related to different sensitivities across education levels to higher levels of discrimination with respect to immigrants. Whatever the underlying mechanisms driving these results, we will use the estimates from column (7) to simulate the impact of a Trump reelection on the skill selection of intended Mexican migrants in the different locations.

5 Simulating the impact of a reelection of Donald Trump

We build on the estimation results of our CNL model to simulate the impact of a reelection of Donald Trump on the magnitude of immigration pressures coming from Mexico to all potential locations. The simulations involve the computation of elasticities and cross-elasticities based on the estimate of θ (equation 4). They also involve the choice of particular scenarios regarding the impact of such a reelection on the probability of disapproving US leadership for each respondent. Finally, they also involve the application of our sample estimates to the adult population of Mexico.

5.1 Scenarios

The key mechanism through which we simulate the impact of a Trump reelection goes through its impact of the disapproval by Mexican respondents. Therefore, the various scenarios consider different patterns in terms of disapproving US leadership. We consider three different scenarios related to the disapproval of US leadership. On top of that, in a fourth one, we also simulate the impact of a total closure of US borders to Mexican immigrants in order to replicate the simulations considered in Beine et al. (2024). While this last exercise considers a more unrealistic development, it generates more extreme immigration pressures in alternative locations.

We first use the estimates from column (3) in Table 3 that are based on a model with an homogeneous impact of disapproval across education levels of the respondents In the base scenario, we assume that for each individual, the probability of disapproving would raise to 75%. This corresponds to what is observed on average during the Trump presidency between 2017 and 2020: on average, this probability jumped from 35% to 75%. This scenario nevertheless neglects the fact that the election of Donald Trump had heterogeneous effects in terms of disapproval across types of individuals. Table 4 makes clear that, after 2017, the propensity to disapprove was (i) higher for highly-skilled respondents and (ii) higher for women. In order to match this piece of evidence, we consider a second scenario in which women tend to disapprove more (90% probability instead of 77%). We coin this the gender scenario. In a third scenario, called the skill scenario, we consider an increase of disapproval of 85% for skilled respondents (as opposed to 75%). We define this scenario the skill scenario. Finally, in order to replicate the analysis of Beine et al. (2024), we consider a more radical (and less realistic) scenario in which President Trump would close the US borders to new Mexican immigrants. We call this counterfactual event the border scenario.

Table 4: Binary Logit Model Results on Disapproval

	Pre-Trump		**Trump presidency**	
	Value	Rob. t-test	Value	Rob. t-test
Constant	-0.983	-16.2	0.812	9.65
β_{MS}	0.273	4.3	0.405	4.17
β_{HS}	0.36	3.63	0.341	2.02
β_{income}	-0.0915	-2.79	0.148	2.8
β_{male}	0.0421	0.817	-0.289	-3.2

5.2 Simulation procedure

It is important to understand how these simulations are conducted. First, for each scenario and each individual, we draw a value of $z_{US,n}^{scenario}$, i.e. whether individual n disapproves or not after a Trump reelection. The probability generating this value depends in the second and third scenario of the characteristics of n, in particular the gender and the education level. Based on the draw for $z_{US,n}^{scenario}$, we can compute $\Delta\check{z}_{US,n}$, the change in the disapproval between the baseline period and the period after the reelection. We use 2022 for the baseline period and use the observed value of $z_{US,n}$.

Using the estimates for θ in specification 3, we compute ARC elasticities for each location.[13] This allows to compute $\Delta prob_{j,n}$, i.e. the change in the probability of choosing location j for individual n. Then, by summing up these probabilities, we can compute the number of intended migrants under the scenario and the change in intended migrants for each location. Finally, using data for the adult population in Mexico (using extrapolations from the 2020 Mexican census data), we extrapolate our findings relative to our sample to the Mexican population observed in 2024 to obtain simulated immigration pressures for each destination.

5.3 Results

Cross elasticities

Figure 2 reports the various aggregate (ARC) elasticities of US disapproval computed for each location in the four scenarios using the CNL model of Table 3 (column 3). The estimated ARC elasticities are quite different across locations, suggesting heterogeneous substitution patterns across foreign destinations. The elasticity for the US amounts to -0.22, showing

[13] Note that, at the aggregate level, ARC elasticity for location j takes the following form : $E_{z_{US}}^{P_j} = \frac{P_j^{z_{US}^{scenario}} - P_j^{z_{US}}}{P_j^{z_{US}}}$

that a reelection of Donald Trump would be a factor of decrease in the attractiveness of the US. The cross-elasticity estimated for Mexico with the CNL amounts to 0.013 (see Figure 2). This low value reflects that Mexico appears as a poor substitute to the US location for Mexicans. Therefore, the estimates suggest that a reelection would lead some intended emigrants of Mexico to reshuffle their preferred location to another foreign destination rather than staying at home.

The cross elasticities reported in the 4 panels show that some destinations would be much more affected than others in case of a Trump reelection. The heterogeneity in the estimated cross-elasticities depends on various factors. One key factor is the way the model partitions the choice set in terms of nests. Figure C.2 In Appendix C provides a comparison of the relationship of the cross-elasticity for a given destination along with the number of common nests this destination shares with the US. We provide this for the base scenario.[14] The value of the cross-elasticity for a given location is increasing in the number of nests shared with the US.

Simulated immigration pressures

Table 5 reports the simulated variations in immigration pressures coming from Mexico across all alternative locations. By immigration pressures, we mean exactly the variation due to the Trump reelection of people willing to settle in a specific location. These figures are based on an extrapolation of our findings obtained from our sample of respondents to the Mexican population, using sample weights of the GWPS. These are expressed in thousands of individuals. We provide the simulated pressures for the four scenarios. For instance, the first number of Table 5 indicates that a Trump reelection would induce about 1.1 millions more Mexicans to stay in Mexico (rather than intending to migrate to the US).[15]

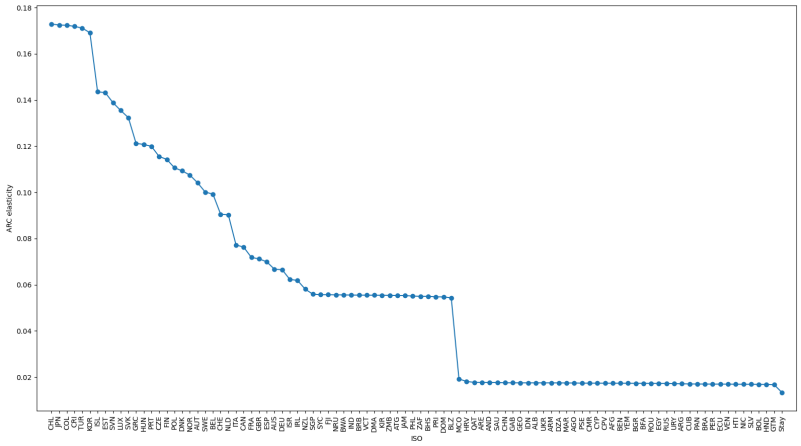
What emerges from Table 5 is that countries would be affected very differently by a Trump reelection. Of course, in absolute terms, larger countries would be more affected than smaller destination countries. Nevertheless, size is far from being the driving feature of the heterogeneity. Some smaller destination countries such as the Netherlands, Switzerland or Ireland would be much more affected in absolute terms compared to large countries such as Brazil or Russia. This means that the countries that are seen as close substitutes would face much higher immigration pressures in relative terms, i.e., as a proportion of their population. The exact magnitude of the simulated immigration pressures depends on the scenarios. The pat-

[14] We provide this comparison only for the base scenario here for the sake of brevity. We obtain similar patterns for the gender, the skill and the closing border scenario. These are available upon request.

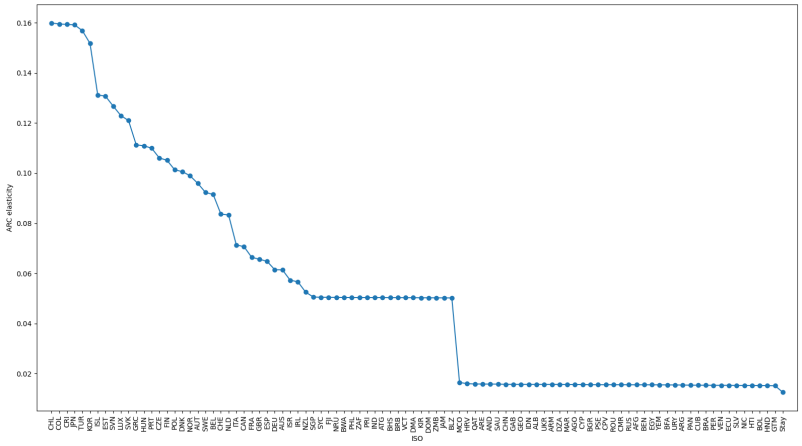
[15] As another example, in the row Canada, the number in column (3) would mean that such a reelection would induce about 93000 more Mexicans to intend to migrate to Canada if we allow more educated Mexican respondents to be more affected by the reelection of Trump.

Figure 2: ARC elasticities for the 4 scenarios.

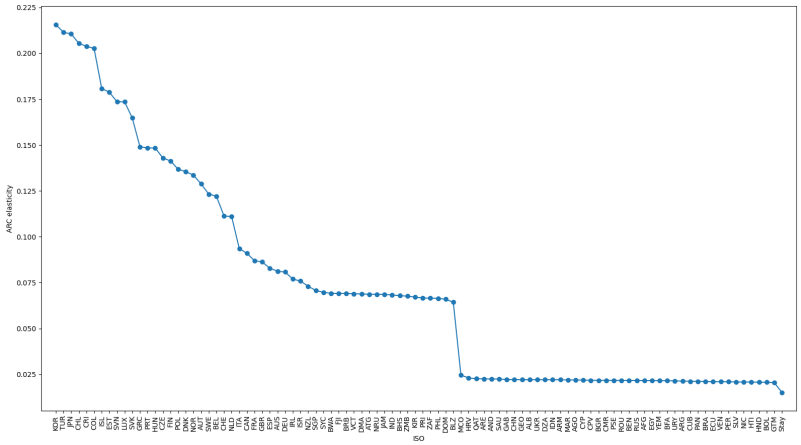
(a) Base scenario



(b) Gender scenario



(c) Skill scenario



(d) Border closure

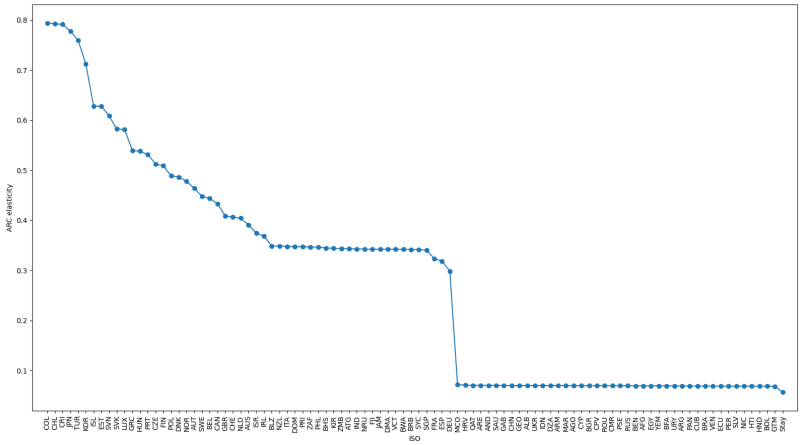
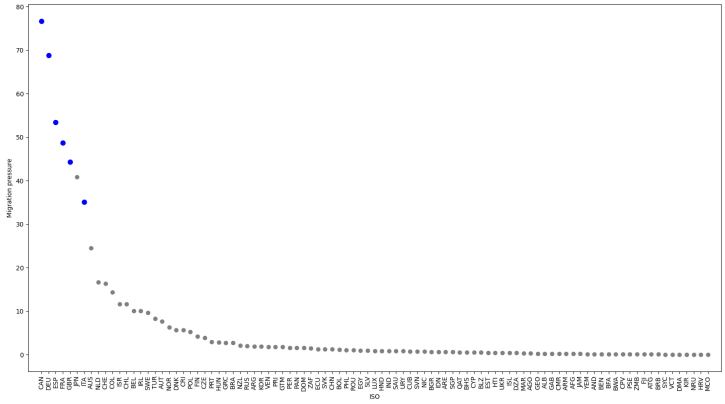


Table 5: Simulated immigration pressures due to Trump reelection

Country	(Scenario) Base.	Gender	Skill:	Border
Stay	1083.951	1016.613	1228.885	4790.077
Canada	76.689	70.686	92.708	579.501
Germany	68.869	63.353	84.750	376.659
Spain	53.410	49.257	64.057	300.017
France	48.700	44.790	59.771	270.913
United Kingdom	44.330	40.680	54.464	335.213
Japan	40.879	37.285	51.534	279.494
Italy	35.110	32.256	43.172	197.825
Australia	24.573	22.500	30.317	187.773
Netherlands	16.644	15.258	20.846	96.002
Switzerland	16.415	15.073	20.579	95.029
Colombia	14.425	13.202	17.410	101.701
Israel	11.712	10.717	14.444	91.064
Chile	11.687	10.688	14.284	81.856
Belgium	10.087	9.234	12.674	59.291
Ireland	10.054	9.163	12.679	77.245
Sweden	9.627	8.812	12.103	56.676
Turkey	8.358	7.566	10.685	55.762
Austria	7.649	6.990	9.674	45.222
Norway	6.319	5.771	8.042	37.491
Denmark	5.697	5.202	7.228	33.998
Costa Rica	5.691	5.219	6.932	40.052
Poland	5.233	4.753	6.626	31.001
Finland	4.269	3.895	5.408	25.746
Czech Republic	3.930	3.577	4.983	23.650
Portugal	2.975	2.703	3.776	18.031
Hungary	2.872	2.614	3.616	17.561
Greece	2.784	2.533	3.508	17.017
Brazil	2.725	2.463	3.390	11.665
New Zealand	2.168	1.952	2.765	16.595
Russia	1.990	1.794	2.504	8.457
Argentina	1.931	1.744	2.417	8.244
South Korea	1.925	1.702	2.553	11.869
Venezuela	1.846	1.669	2.294	7.911
Puerto Rico	1.805	1.653	2.220	14.620
Guatemala	1.787	1.620	2.194	7.709
Peru	1.646	1.487	2.043	7.048
Panama	1.642	1.485	2.054	7.033
Dominican Republic	1.612	1.475	1.964	13.081
South Africa	1.496	1.365	1.830	12.055
Ecuador	1.338	1.209	1.662	5.731
Slovakia	1.275	1.154	1.633	7.839
China	1.261	1.130	1.597	5.310
Bolivia	1.172	1.060	1.443	5.030
Philippines	1.097	0.999	1.337	8.812
Romania	1.074	0.968	1.354	4.563
Egypt	1.016	0.914	1.275	4.313
El Salvador	1.010	0.913	1.251	4.335
Luxembourg	0.919	0.825	1.216	5.495
Honduras	0.896	0.811	1.106	3.852
India	0.884	0.798	1.101	6.951
Saudi Arabia	0.851	0.762	1.087	3.577
Uruguay	0.849	0.766	1.065	3.617
Cuba	0.771	0.695	0.963	3.296
Slovenia	0.756	0.683	0.975	4.683
Nicaragua	0.748	0.676	0.925	3.207
Bulgaria	0.701	0.631	0.884	2.976
Indonesia	0.701	0.628	0.886	2.952
United Arab Emirates	0.684	0.613	0.875	2.872
...	...	...	...	...
Dominica	0.063	0.057	0.079	0.496
Kiribati	0.022	0.020	0.027	0.176
Nauru	0.022	0.020	0.027	0.172
Croatia	0.000	0.000	0.000	0.001
Monaco	0.000	0.000	0.000	0.000
United States	-1257.486	-1195.964	-1390.746	-8591.92

Figure 3: Immigration pressures from Mexico (in thousands), base scenario.



tern of heterogeneity emphasized above is the same across the scenarios. The takeaway of the quantified immigration pressures is that the election of Trump would be more important for some countries than others. Our findings allow to identify these countries and quantify the consequences for them. In a nutshell, the most affected countries are the UK and its former dominions (Canada, Australia and New Zealand), most of the Western European countries and a couple of developed Latin American destinations such as Costa Rica, Chile or Columbia. Figure 3 provides a graphical visualization of Table 5 for the base scenario for all destinations except the US and Mexico.

The importance of heterogeneous substitution patterns

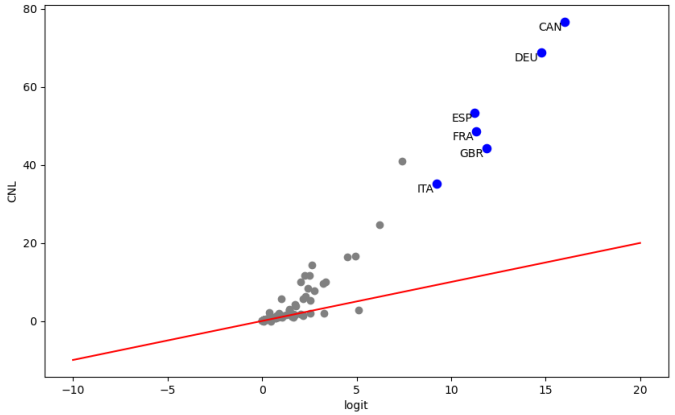
How important is the heterogeneity between countries in generating the substitution patterns (as opposed for instance to size of the population at destination)? This is related to the heterogeneity in the cross-elasticities and the way our model is able to capture the complexity of the adjustment. To get a sense of that, we provide two additional sets of results. First, for each scenario and each location, we provide Figures comparing the cross-elasticities estimated from our model and a simple one (the logit) that ignores the complexity of the substitution (see in the Appendix (section C). Second, in Figure C4, we provide the comparison of the simulated immigration pressures based on our model and the logit model for the set of foreign destinations.[16].

What emerges from this comparison is that the way heterogenous substitution patterns are accounted in the models for plays a crucial role for some countries. For many countries that are seen as poor substitutes to the US location, differences in simulated pressures are

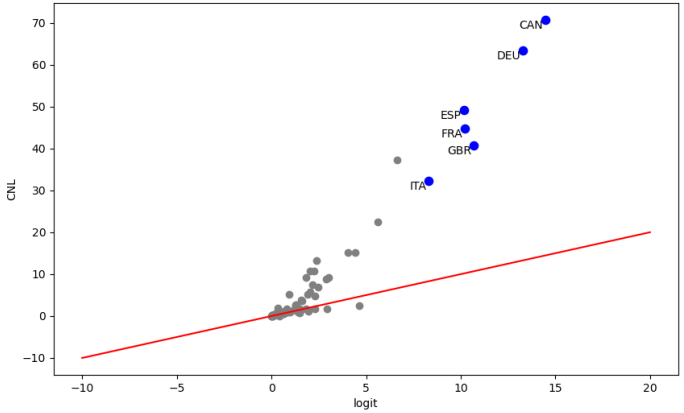
[16]Because the scale of the simulated flows is very different for the US and Mexico, the figures do not report the comparison for these two locations. The figures including the US and Mexico are provided in the Appendix (section section C)

Figure 4: Predicted immigrations in alternative foreign destinations, Logit and CNL.

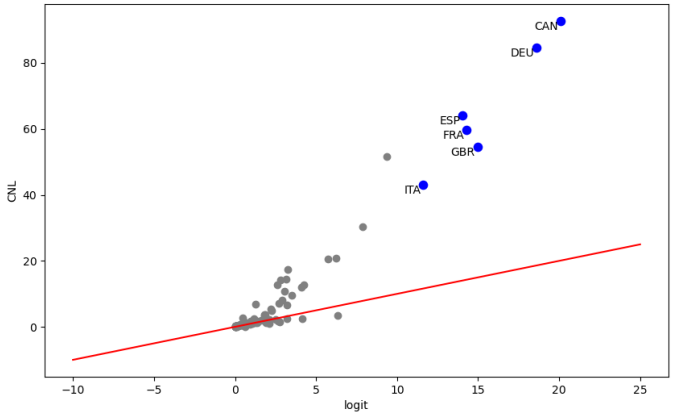
(a) Base scenario



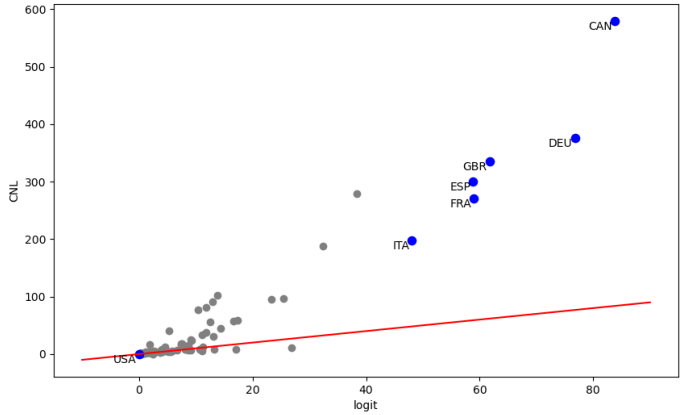
(b) Gender scenario



(c) Skill scenario



(d) Border closure



negligible. For these countries, the type of estimation tools do not matter at the end of the day. Nevertheless, for the countries mentioned above, the type of model matters. The use of a "wrong" model would lead ministers of immigration of these countries to significantly underestimate the number of additional Mexican immigrants willing to come in their countries. The magnitude of this underestimation can be substantial. To illustrate, the Canadian minister of immigration would underestimate the flows of intended Mexican immigrants by a factor of about five.

The case for a vicious circle and selection effect

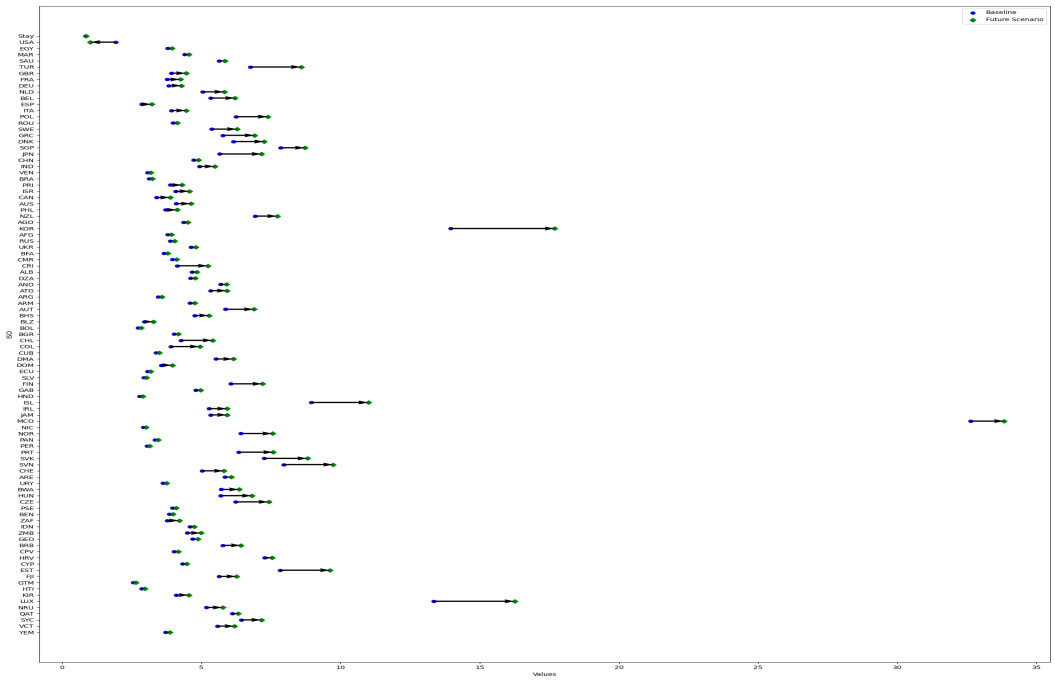
The reelection of Donald Trump can exert an impact not only in terms of the size of immigration flows, but also on their composition. Estimations in column (7) of Table 3 suggest that highly-skilled Mexican respondents are more sensitive to the type of US leadership than low-skilled respondents. These results are in line with previous work. For instance, Bratsberg et al. (2019) analyze political participation in Norway and find that highly-skilled immigrants are more likely to seek office in local elections compared to low skilled. Other mechanisms such as fear of discrimination or desire to integrate in the host society might explain the higher sensitivity to political factors. Bellodi et al. (2023) analyze the impact of populist parties on the internal mobility of individuals and find that highly-skilled native residents are likely to relocate across Italian municipalities. Such an evidence opens the case for a vicious circle of populism in general, and of a Trump reelection in particular.

How does such a vicious circle affect the composition of intended flows to the various locations? To address this question, we simulate the model with heteregeneous impact of disapproval for the skill scenario. It is important to see that education plays a double role in this context. First, in the skill scenario, higher-educated immigrants are more likely to disapprove US leadership after the election, for instance due to a better learning process. Second, educated potential immigrants are more sensitive to this political shock. This double effect of education contributes to the variation of selection in average education levels of immigrants. To capture this, we provide variation in the ratio of highly-skilled immigrants to low-skilled ones ($\frac{HS}{LS}$). We also consider alternative indicators of selection, such as share of highly-skilled immigrants or ratio of highly-skilled immigrants to low- and middle-skilled ones. [17]

Figure 5 provides the variation of the selection ratio for all potential locations. The Figure shows that, in line with the previous evidence, there is a lot of heterogeneity across locations in the selection indicator. Three points are in order here. First, there is a significant drop in the selection for the US $\frac{HS}{LS}$ which shifts from 1.92 to 1.01. In other words, while highly-

[17] These are not reported here but provide a very similar pattern. They are available upon request.

Figure 5: Variation in selection ratios of immigration, all locations

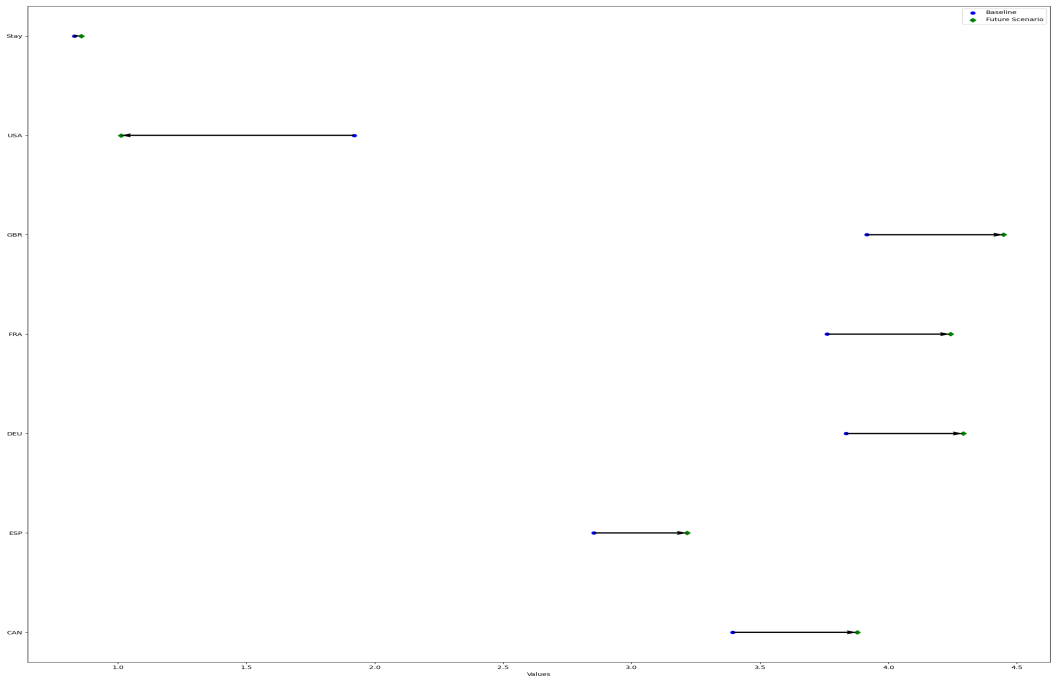


skilled aspirational migrants were about twice more likely to come to the US compared to low-skilled, the reelection of Donald Trump would make selection neutral. In turn, this might create a vicious circle between "quality" of immigration and anti-immigration attitudes. Anti-immigration attitudes are more likely to raise if the share of low-skilled immigrants increases, which in turn deter more higher-educated immigrants to come.

Second, we do not find significant variations in terms of selection of the intended stayers for Mexico. Selection is hardly affected, as shown by the very small change in the upper left part of both panels. Third and more importantly, Trump's reelection would generally improve the skill selection of aspirational migrants in alternative locations, but in a very heterogeneous way. For most locations, selection is hardly affected. Nevertheless, for some destinations, selection becomes more positive. Figure 6 provides a zoom for a set of selected destinations. Once again, these destinations are the ones perceived as close substitutes to the US (Canada, UK, France, Germany, Spain). They face an increase in the immigration pressures but also benefit from an improvement of the selection ratio. In other terms, a reelection of Donald Trump generates significant spill-overs in terms of the "quantity" and "quality" of potential immigrants for alternative destinations.

Of course, the skill scenario associated with the heterogeneous impact of disapproval also generates different magnitudes of immigration pressures. While the magnitudes might differ

Figure 6: Variation in selection ratios of immigration, selected locations, CNL

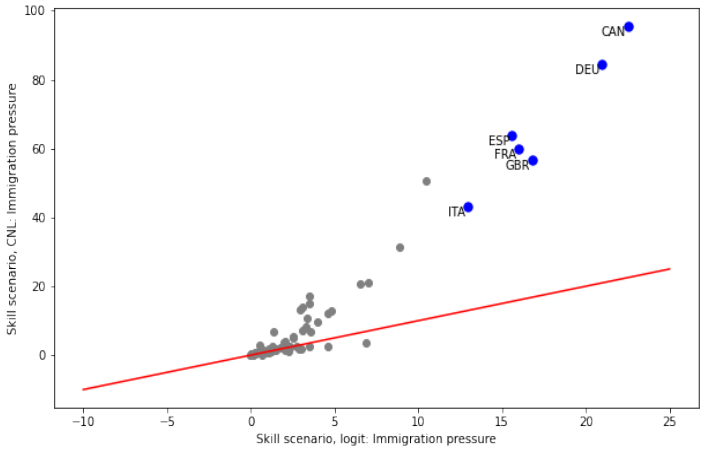


with respect to the previous simulations, the global pattern remains the same, i.e. country that are substitutes to the US would face higher immigration pressures after Trump's reelection. Figure 7 provides, for the foreign destinations, the change in the immigration pressures.

6 Additional discussions and conclusion

A reelection of Donald Trump is likely to affect the perceived attractiveness of the US for potential migrants from many origin countries. Given the anti-immigration rhetoric of Donald Trump and the stigmatization against Mexicans, potential immigrants from Mexico are expected to account for such a political development in their future location choices. In this paper, using survey data including location preferences of Mexican respondents and a discrete choice modelling approach, we find that a reelection of Donald Trump would clearly lead to a decrease of the attractiveness of the US location for Mexican respondents. We predict that the number of Mexican potential emigrants to the US would decrease by a number comprised between 1.2 and 1.4 millions, depending on the considered scenarios. Building on this, we look at how such a decrease would lead to a substitution towards alternative locations. Using a cross-nested logit model that allows to capture the complex patterns of substitution

Figure 7: Immigration pressures in selected foreign destinations: Logit vs CNL



across alternative locations, we find that Mexican respondents would reshuffle their location choices mainly to a subset of alternative destinations. The model and our simulations allow to identify these alternative locations and to quantify the variation in immigration pressures faced by these countries under different scenarios.

Our simulation of immigration pressures depends on several alternative scenarios, relying on how a reelection of Donald Trump would affect the evaluation of Mexican respondents regarding the US leadership. Our base scenario simply considers that average disapproval rates would increase to levels observed during the Trump presidency, amounting to about 75% of the respondents. Alternative scenarios consider heterogeneous responses in terms of disapproval , either higher increases for women or for highly-skilled respondents. Nevertheless, regardless of the considered scenario, a couple of interesting findings emerge. First, while a reelection would clearly increase the number of Mexicans willing to stay in their country, compared to the usual logit model, our model would predict a lower increase. In contrast to other modeling approaches, our model captures the heterogeneity in the substitution patterns and the fact that Mexico is a relatively poor substitute to the US for Mexicans willing to leave their country. Second, we identify the set of foreign destinations that would face the highest increase in immigration pressures associated to the substitution of location choices induced by the reelection. These countries involve Canada and Western European countries such as Germany, Spain, France and the UK. Importantly, compared to the multinomial logit model, our model predicts a much higher increase in immigration pressures. To illustrate this, while the logit would predict an increase of 16000 aspirational migrants to Canada in

the base scenario, the predicted number by our CNL model is 5 times larger. An important implication of our work is that any minister of immigration in one of these countries should be equipped with the right predicting tool in order to quantify the consequences of a Trump reelection on their immigration pressures.

We also find that the reelection of Donald Trump would create a vicious circle for the US in terms of education levels of intentional immigrants. A reelection would deter more high-skilled Mexican immigrants than low-skilled ones to choose the US as their preferred destination. As a result, this would substantially decrease the proportion of skilled immigrants for the US. The ratio kigh-skilled/low-skilled immigrants would be divided by 2, changing the skill composition of immigrants from positive to neutral. Conversely, for destinations that are perceived as close substitutes to the US and which would face a significant rise in immigration pressures, this ratio would increase substantially, leading to an improvement in the education levels of the potential immigrants.

One important caveat about our analysis is that our estimations and simulations are based on migration aspirations to capture immigration pressures. The share of aspirational migrants in Mexico over the last 10 years is about 20%, close to the world average (22.1%). Another measure provided in surveys (albeit on a much shorter period of time) like the GWPS pertains to intentions. Intentional migrants are aspirational migrants having carried out some mobility plans over the last 12 months. In Mexico, the share of intentional migrants in aspirational ones is about 11% over the period of investigation. One could think about using this number to deflate our simulated immigration pressures. Nevertheless, one should emphasize two important aspects before doing that. First, the 12 month horizon on mobility plans is highly restrictive and allows to capture only the short-run effect of a political shock on location choices.[18] Second, both measures of intentions capture only primary migrants and do not allow to capture the dynamic impact of a change in location decisions (for instance due to the family reunification schemes). Therefore, it is unclear whether our results underestimate or overestimate immigration pressures, both in the US and in alternative destinations. Finally, one should emphasize that our main results pertain to the pattern of relocation choices across countries due to the reelection of Donald Trump. In that respect, this does not depend on the exact type of migration intentions used in the analysis and we do not see any reason why the substitution patterns would be different with intentions rather than with aspirations.

While the focus of this analysis is on the consequences of a reelection of Donald Trump, our paper confirms the importance of political shocks on immigration pressures. In particular,

[18] Think for instance to some students wishing to complete their education first and to emigrate afterwards. Note that the GWPS includes this type of respondents.

our analysis shows that big political shocks can have direct and indirect consequences in terms of intended immigration. While estimating the direct consequences is something natural, our work shows that it is important to measure the indirect consequences, i.e. the spill-overs on some other countries. Our results show furthermore that these indirect consequences are highly heterogeneous across alternative countries. While some countries remain almost unaffected, other countries should clearly anticipate these spill-overs. To that aim, the use of an appropriate tool such as the CNL is key. Failure to use the appropriate tool leads to significant mistakes in predicting additional immigration pressures created by the initial shock.

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Appendix

A Data

A.1 Choice set

Table A.1: Choice Set and Participation Parameters for Nests.

(a) Chosen countries

	$\alpha_{j,English}$	$\alpha_{j,OECD}$	$\alpha_{j,Schengen}$
Afghanistan	0	0	0
Albania	0	0	0
Algeria	0	0	0
Andorra	0	0	0
Angola	0	0	0
Antigua and Barbuda	1	0	0
Argentina	0	0	0
Armenia	0	0	0
Australia	0.5	0.5	0
Austria	0	0.5	0.5
Bahamas	1	0	0
Belgium	0	0.5	0.5
Belize	1	0	0
Brazil	0	0	0
Bulgaria	0	0	0
Burkina Faso	0	0	0
Cameroon	0	0	0
Canada	0.5	0.5	0
Chile	0	1	0
China	0	0	0
Colombia	0	1	0
Costa Rica	0	0	0
Cuba	0	0	0
Denmark	0	0.5	0.5
Dominica	1	0	0
Dominican Republic	1	0	0
Egypt	0	0	0
El Salvador	0	0	0
Finland	0	0.5	0.5
France	0	0.5	0.5
Germany	0	0.5	0.5
Greece	0	0.5	0.5
India	1	0	0
Iceland	0	0.5	0.5
Ireland	0.5	0.5	0
Israel	0.5	0.5	0
Italy	0	0.5	0.5
Jamaica	1	0	0
Japan	0	1	0
Morocco	0	0	0
Netherlands	0	0.5	0.5
New Zealand	0.5	0.5	0
Nicaragua	0	0	0
Norway	0	0.5	0.5
Panama	0	0	0
Peru	0	0	0
Philippines	1	0	0
Poland	0	0.5	0.5
Portugal	0	0.5	0.5
Puerto Rico	1	0	0
Romania	0	0	0
Russia	0	0	0
Saudi Arabia	0	0	0
Singapore	1	0	0
Slovakia	0	0.5	0.5
Slovenia	0	0.5	0.5
South Korea	0	0	0
Spain	0	0.5	0.5
Sweden	0	0.5	0.5
Switzerland	0	0.5	0.5
Turkiye	0	1	0
United Arab Emirates	0	0	0
United Kingdom	0.5	0.5	0
United States	0.5	0.5	0
Uruguay	0	0	0
Venezuela	0	0	0

(b) Unchosen countries

	$\alpha_{j,English}$	$\alpha_{j,OECD}$	$\alpha_{j,Schengen}$
Barbados	1	0	0
Benin	0	0	0
Botswana	1	0	0
Cabo Verde	0	0	0
Croatia	0	0	1
Cyprus	0	0	0
Czechia	0	0.5	0.5
Estonia	0	0.5	0.5
Fiji	1	0	0
Georgia	0	0	0
Guatemala	0	0	0
Haiti	0	0	0
Hungary	0	0.5	0.5
Indonesia	0	0	0
Kiribati	1	0	0
Luxembourg	0	0.5	0.5
Nauru	1	0	0
Palestine	0	0	0
Qatar	0	0	0
Saint Vincent and the Grenadines	1	0	0
Seychelles	1	0	0
South Africa	1	0	0
Yemen	0	0	0
Zambia	1	0	0

This list includes the 96 countries in the choice set and the nests they belong to with the respective values for $\alpha_{j,m}$. Computational limitation restricts the use of more countries.

A.2 Individual-specific Variables

Table A.2: Sources and Descriptions of Individual-specific Variables in the Gallup World Poll (2007–2019).

Variable	Description	Gallup question code	Time Horizon
Age	Age of the respondent	WP1220	2008–2019
Approval of US leadership	Perception of respondent	WP151	2007–2019
Education level	Education level of the respondent	WP3117	2007–2019
Income	Computed income of individual	Authors' calculation based on equivalence scale[a]	2009, 2011–2019
Income per capita	Average income in the household	INCOME_4	2009–2019
Male	Dummy= 1 if respondent is male	WP1219	2007–2019
Network abroad	Dummy= 1 if respondent has a network abroad	WP3333	2007–2019
Region	Greater region of location of individual	REGION2_MEX	2008–2009
Single	Dummy= 1 if respondent is single	WP1223	2007–2019
State	Mexican state of location of individual	REGION_MEX	2010–2019

[a] See Appendix A.3 for further details.

A.3 Individual Income

We use an equivalence scale, following Beine et al. (2024), to derive individual income from household income per capita (variable INCOME_4). First, we compute total household income (h_n) by multiplying household income per capita by the household size (variable HHSIZE). We then consider the number of adults (WP12) and children (WP1230) in the household, where an age of 15 is the threshold for adults. Lastly, we obtain individual income I_n from the following formula:

$$I_n = \frac{h_n}{1 + 0.5\ (adults_n - 1) + 0.3\ children_n}.$$

A.4 Destination-specific Variables

Table A.3: Sources and Descriptions of Destination-specific Variables.

Variable	Description	Source	Time Horizon	Time Frequency
Approval of US leadership	Perception of leadership abroad (only considered for the US)	Gallup World Poll	2007–2019	Annual
Diaspora	Total stock of Mexico-born	United Nations: International Migrant Stock in 2019	2005–2019	5 years (2005–2015), 2019
Distance	Distance between Mexico and destination	CEPII: Mayer and Zignago (2011)[a]	time-invariant	
Income	GDP per capita	World Bank: GDP per capita (current US$)	2007–2019	Annual
Population	Total population at destination	United Nations: Population prospects in 2019		5 years

[a]We recode *Belgium and Luxembourg* to both respective capitals and recode those for Burundi, Myanmar, Sri Lanka, and Tanzania to reflect their moves. Corrections were necessary for the capitals in Hong Kong, Israel, Palestine, Tuvalu, and West Sahara. We also insert the coordinates for the Democratic Republic of the Congo, Kosovo, Liechtenstein, Monaco, Montenegro, Serbia, Timor-Leste, and Vatican City. Lastly, we choose the coordinates for countries with multiple capitals to represent Pretoria (South Africa), Mbabane (Eswatini), Amsterdam (Netherlands), Sucre (Bolivia), and Kuala Lumpur (Malaysia). Appendix A.5 provides more details on the computation.

A.5 Individual Geodesic Distances

A person's location determines the individual geodesic distance between origin and destination. We use information on the Mexican state or greater region (Norte, Sur, Centro) in the GWPS (see Table A.2 for more information). Note that the state is only available in years since 2010, whereas the region is covered since 2008 and does not coincide with administrative units in Mexico.

We use the geodesic coordinates for each state's capital and destination country's capital to compute the great circle distance by Stata command *geodist*. For the region, we ascribe an approximate centroid to each region, namely Estación Camacho in the North, Minatitlán in the South, and Mexico City in the center.

B The Cross-nested logit model

Many migration studies assume that ε_{jn} is independent and identically distributed across destinations and individuals, and follows an Extreme Value Distribution (EVD) of type 1. This is the underlying assumption of the traditional logit model (McFadden, 1974). While mathematically convenient, this assumption is violated in most contexts where discrete choice models are applied (Train, 2009). We claim that the location choice is no exception in this regard. As stated above, correlation across some subsets of destinations is a natural ingredient of location decisions for several reasons. First, intended stayers and intended movers are very different, and foreign destinations are therefore likely to be more correlated with each other than with the domestic destination. This has motivated the use of separate nests for the domestic location and the foreign potential locations in recent studies (Buggle et al., 2023; Monras, 2020). Second, some foreign destinations will be more correlated among themselves compared with others. While careful specification of the deterministic component V_{jn} might capture some part of these correlation patterns, unobserved shared characteristics will result in correlation in the stochastic terms. Hence, it is unlikely that the ϵ_{jn}s comply with the independence assumption.

Following Beine et al. (2024), we adopt a more general approach allowing us to capture more complex patterns among the error terms. We adopt a Multivariate Extreme Value (MEV) model that is derived from the RUM approach. Suppose that the choice set C is divided into M overlapping subsets of destinations ($m = 1, .., M$). The CNL model generates the following probability function:

$$P_n(j|C) = \sum_{m=1}^{M} \frac{\left(\sum_{k\in\mathcal{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{kn}}\right)^{\frac{\mu}{\mu_m}}}{\sum_{p=1}^{M}\left(\sum_{k\in\mathcal{C}_n} \alpha_{kp}^{\mu_p/\mu} e^{\mu_p V_{kn}}\right)^{\frac{\mu}{\mu_p}}} \frac{\alpha_{im}^{\mu_m/\mu} e^{\mu_m V_{in}}}{\sum_{j\in\mathcal{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{jn}}}, \tag{5}$$

which can nicely be interpreted as

$$P_n(j) = \sum_{m=1}^{M} P_n(m|\mathcal{C}_n) P_n(j|m), \tag{6}$$

where

$$P_n(j|m) = \frac{\alpha_{jm}^{\mu_m/\mu} e^{\mu_m V_{jn}}}{\sum_{k\in\mathcal{C}_n} \alpha_{km}^{\mu_m/\mu} e^{\mu_m V_{kn}}}, \tag{7}$$

In this model, the parameters μ_ms capture the similarity between the ϵ_{jn}s within nest m. The α_{jm} parameters are participation parameters, capturing the extent to which destination j belongs to nest m. In the CNL, μ_m and α_{jm} jointly capture the correlation between the destinations.[19] This specification generalizes the NL approach, in which each destination is assigned to a single nest (i.e., $\alpha_{jm} = 1$ for one m, and 0 for the others). In the CNL specification, this restriction is relaxed. We impose that $\sum_{m=1}^{M} \alpha_{jm} = 1 \ \forall j$. Therefore, the NL model might be seen as a linear restriction of the CNL model. In turn, the logit model can be obtained as a particular case of the NL with $\frac{\mu}{\mu_m} = 1$ for each m. The probability function (5) makes clear that the probability for each individual to choose a specific location depends on the parameters related to the nesting structure (μ_m and α_{jm}).

In our study, we will partition the choice set using three separate nests ($M = 3$) of foreign destinations ($J = 1, .., J$) as well as a domestic nest embedding Mexico ($j = 0$). The three criteria for the foreign nests ($m = 1, 2, 3$) will be OECD membership, English as an official language and Shengen membership in Europe. We will discuss the choice of the nests below. Importantly, the nests can be statistically validated using hypothesis tests regarding each μ_m. In particular, a validation of nest m requires $H_0 : \mu_m = 1$ to be rejected in favour of $H_A : \mu_m > 1$. For the sake of understanding, Figure 1 provides a graphical representation of the partitionning of the choice set done by the CNL. Note that while the μ_m are estimated, the participation parameters are chosen using a conservative approach. [20]. Table A.1 gives the values of the α_{jm} for all foreign destinations included in the sample.

The choice of the distribution of ϵ_{jn} is important for capturing the patterns of substitution across locations generated by the initial shock, i.e. the reelection of Donald Trump. The logit model that relies on the extreme value distribution of type 1 implies very restrictive substitution patterns. This can be directly seen by computing, the cross-elasticity, i.e. the change in the probability of choosing a particular location linked to a change in the value of

[19] See Bierlaire (2006) for a discussion of the conditions to define a GEV function and its properties. In particular the generating density function has properties of non negativity and homogeneity, and complies with some limit properties and the sign of its derivatives. The CDF of the MEV distribution and the expected maximum utility can be directly derived from G.

[20] For each foreign destination, we compute first the number of nests to which destination j belongs, say K. Then we set $\alpha_{jm} = 0$ if destination j does not belong to nest m, and $\alpha_{jm} = \frac{1}{K}$ if it does. For the purpose of the estimation and in order to comply with the constraint $\sum_{m=1}^{M} \alpha_{jm} = 1$, we create a fourth nest $M + 1$ with a fixed parameter $\mu_m = 1$ in which we include all destinations that do not belong to any of the three nests. For these destinations, we set $\alpha_{j,M+1} = 1$. As an example, France is a member of the OECD and the Schengen area without English as an official language. This implies $\alpha_{France,Schengen} = \alpha_{France,Schengen} = 0.5$ and $alpha_{France,English} = 0$. In contrast, for non-English-speaking countries, which do not participate in either OECD or Schengen, such as Afghanistan, $\alpha_{Afgh,Schengen} = \alpha_{Afgh,English} = \alpha_{Afgh,OECD} = 0$ and $\alpha_{Afgh,M+1} = 1$

an attribute z_{jn} specific to another location (Train, 2009):

$$\frac{\partial P_n(j|C)}{\partial z_{kn}} = -\gamma_z P_n(j|C) P_n(k|C). \tag{8}$$

The corresponding elasticity is given by:

$$E_{j,z_{kn}} = -\gamma_z z_{kn} P_n(k|C), \tag{9}$$

where γ_z is the estimated effect of covariate z.

The cross-elasticity for destination j implied by the logit model is the same across all other destinations (i.e., it does not depend on the specificity of location j). A given increase in the probability of disapproval of US leadership for individual n that leads to a decrease in the utility of the US will induce the same proportional increase in the probability of choosing all the other destinations. This pattern of substitution is called *proportionate shifting* and implies that the ratio of the probabilities of two locations stays constant when an attribute specific to a third one changes (for more details, see Train (2009)). It is a manifestation of the IIA property of the logit model at the disaggregated (individual) level. Drawing on Bierlaire (2006), who studies the theoretical properties of the CNL model, one obtains a corresponding cross-elasticity such as:

$$E_{j,z_{kn}} = z_{kn} \left[-\gamma_z + \frac{1}{G_j} \frac{\partial G_j}{\partial z_{kn}} - \frac{\partial ln(\sum_{p \in C} e^{V_p G_p})}{\partial z_{kn}} \right], \tag{10}$$

where $G_j = \frac{\partial G}{\partial z_{jn}}$ (for more details, see Bierlaire (2006)). Eq. (10) makes it clear that the substitution between destination j and k depends on the characteristics of destination j. For instance, through the G_j terms, it depends on the way the choice set is partitioned, the similarity parameters μ_m and the participation parameters α_{jm}. In other terms, the CNL models allows us to compute substitution rates that are destination specific and that depends on the structure of overlapping nests.

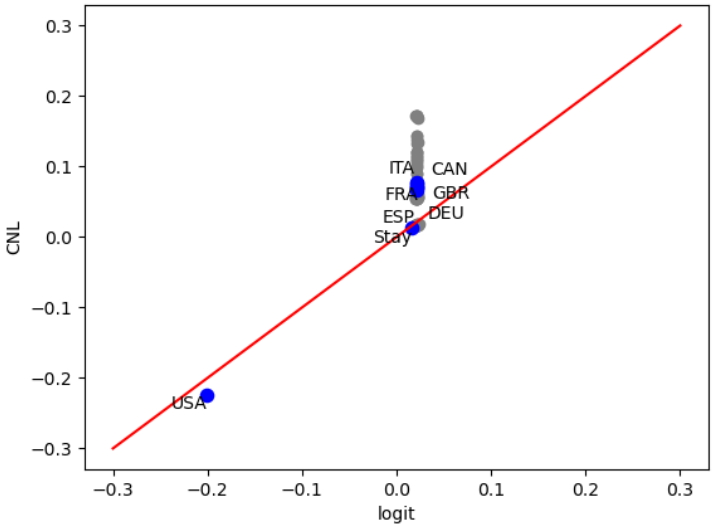
For the estimation of these cross-elasticities, three points are in order here. First, given the analytical complexity of Eq. (10), one needs to compute the cross-elasticities and substitutions at the individual level numerically after estimation. Second, since the disapproval about US leadership is a dummy variable, one has to compute ARC elasticities. Third, for a given location, the value of the cross-elasticity will depend on the type of scenario regarding the impact of a reelection on the probability of disapproving.

C Comparison of results with the Logit model

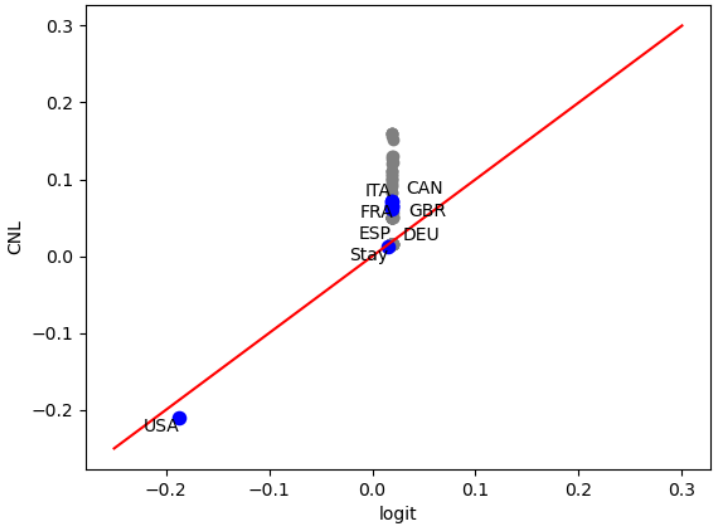
To what extent do the predictions between the ML and the CNL differ? Given the higher complexity of the CNL in terms of specification and estimation, it is important to check whether the predicted pressures are significantly different, at least for a set of destinations. To that aim, Figure C.4 provides the difference in these predicted magnitudes between the CNL and the ML for all destinations, for the 4 scenarios. The Figure shows that for some locations, the difference is substantial. This is the case for Mexico: for instance, in the base scenario, the ML model would predict about 200000 more stayers compared to the CNL. For the destinations that are perceived as close substitutes to the US, the relative difference can also be substantial. For instance, while the CNL would predict 77000 more aspirational immigrants, the ML would predict about 16000 additional ones, i.e. a figure about 5 times lower. In contrast, for many destinations, the difference is negligible, since these foreign destinations are poor substitutes to the US and therefore hardly affected by a Trump reelection. All in all, this illustrates the importance of using the right distribution for the stochastic component of utilities in the underlying RUM model. Table E.1 in Appendix provides a comprehensive account of the predicted immigration pressures, for all scenarios and for a set of selected destinations.

Figure C.1: Comparison of ARC elasticities between logit and CNL.

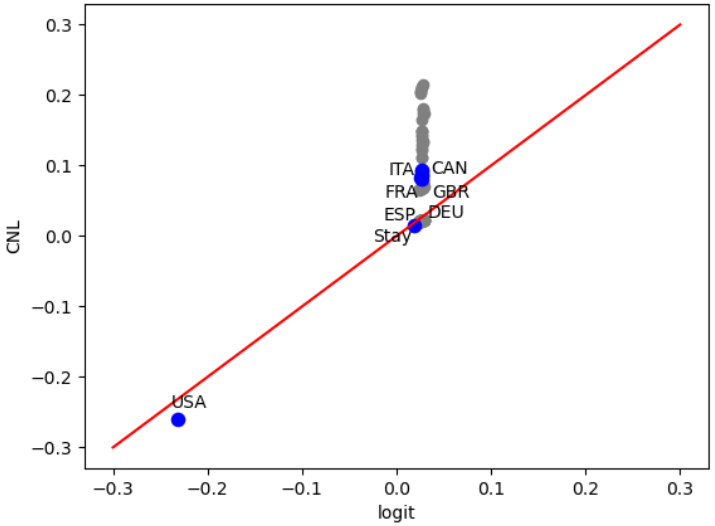
(a) Base scenario



(b) Gender scenario



(c) Skill scenario



(d) Border closure

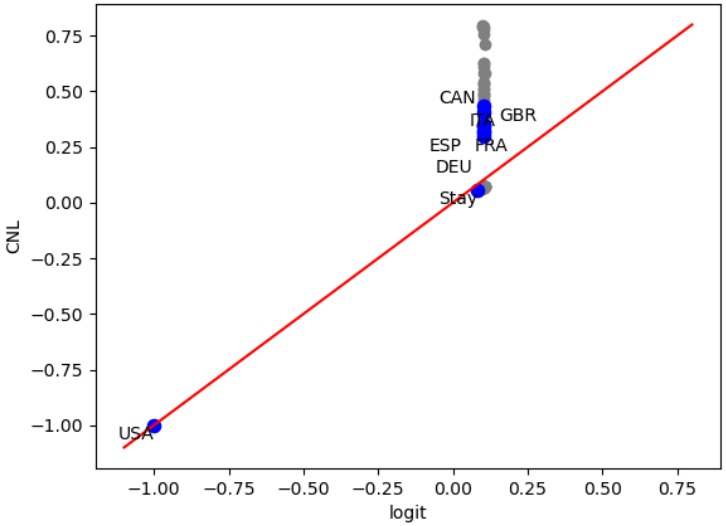
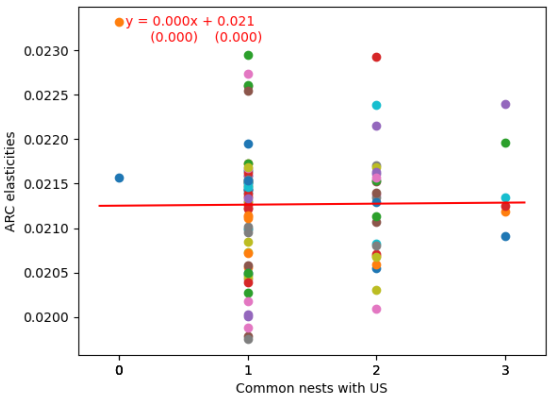


Figure C.2: ARC elasticities and Number of Common Nests with US Destination.

(a) Base scenario: logit



(b) Base scenario: CNL

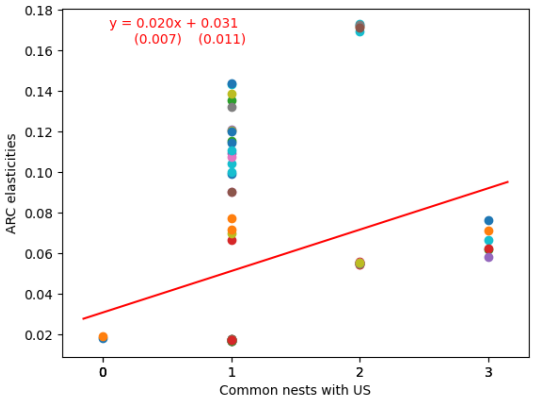
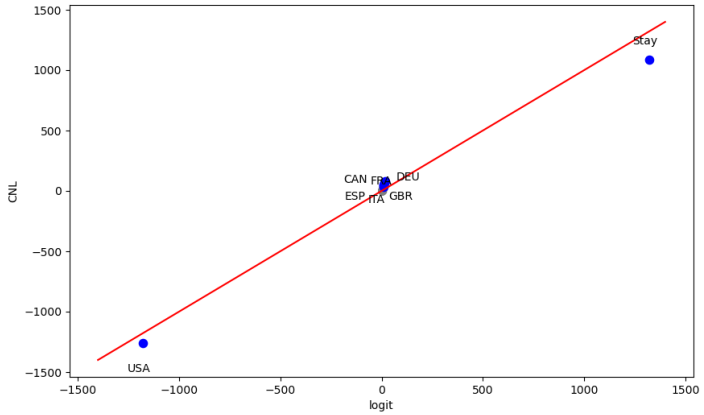
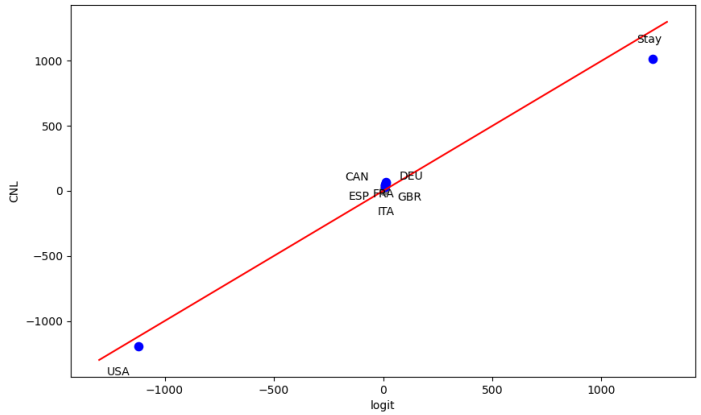


Figure C.3: Predicted immigration pressures by location, Logit and CNL.

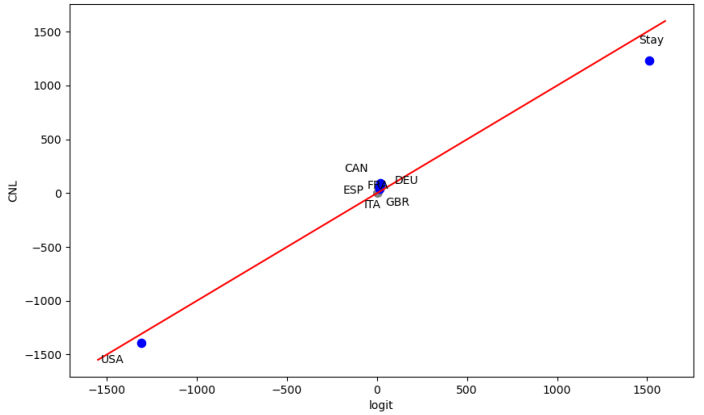
(a) Base scenario



(b) Gender scenario



(c) Skill scenario



(d) Border closure

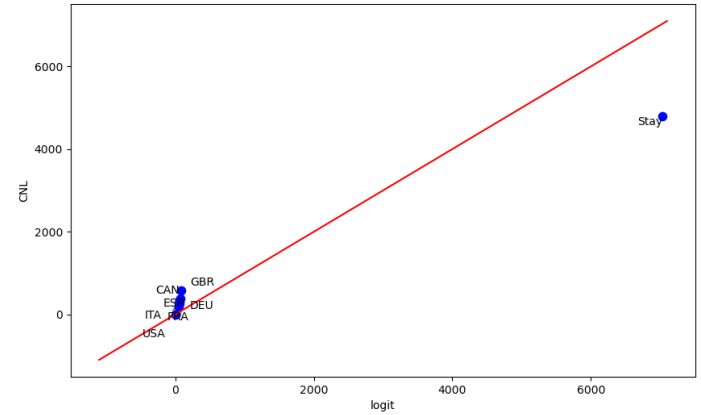
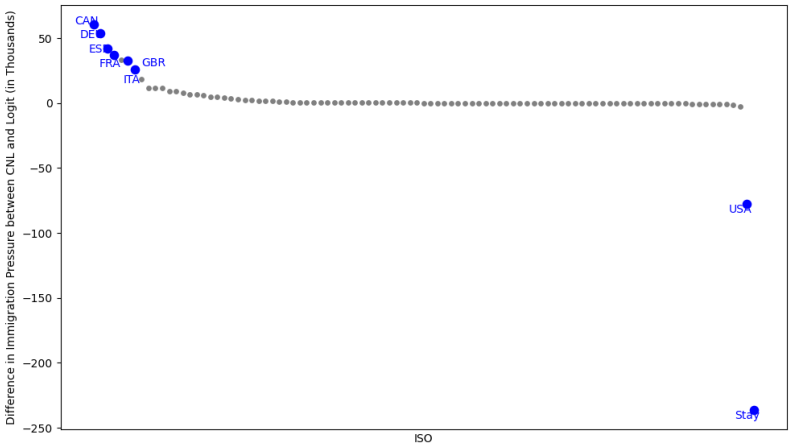
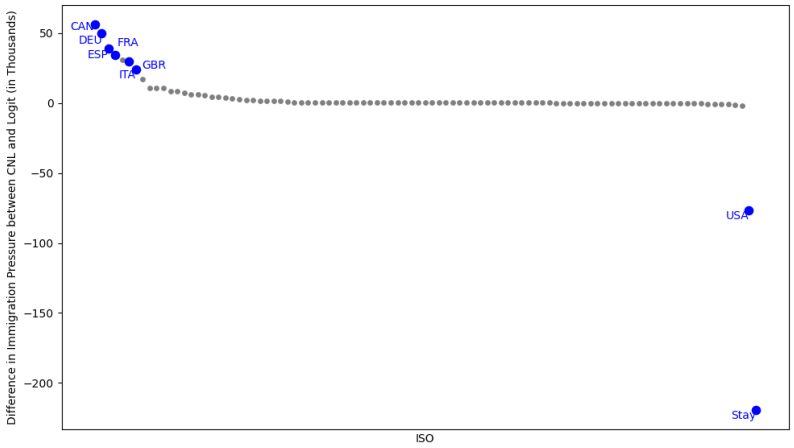


Figure C.4: Differences in predicted immigration pressures between Logit and CNL.

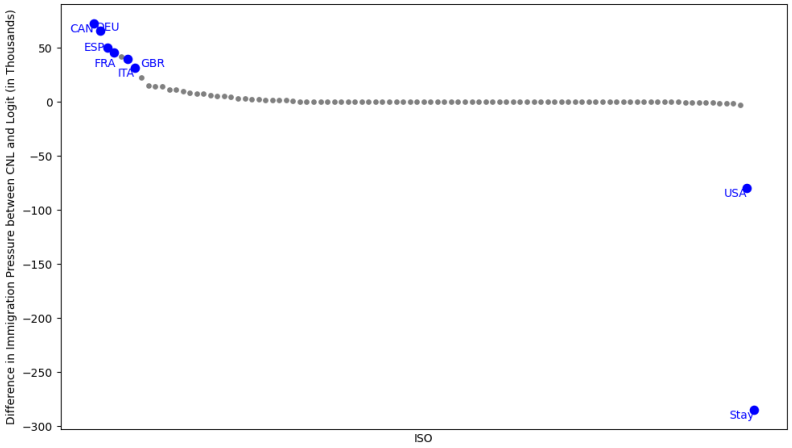
(a) Base scenario



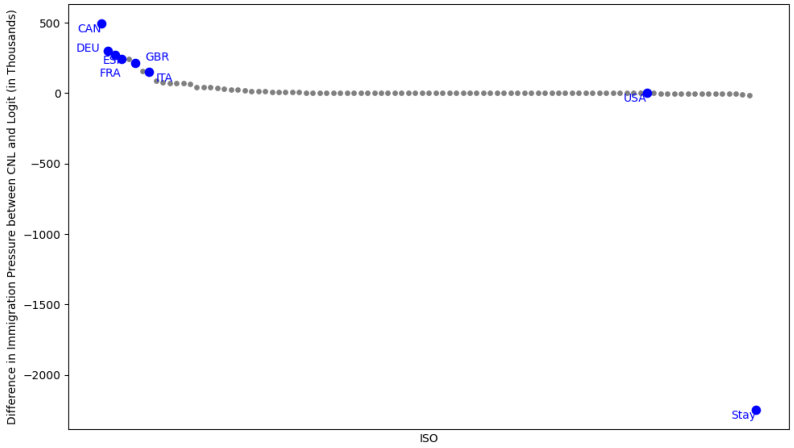
(b) Gender scenario



(c) Skill scenario



(d) Border closure



D Difference-in-differences Estimations

Our goal is to provide evidence of shifts in Mexicans' location choices following Trump's victory in the 2016 US presidential election. We restrict our analysis to the years 2007–2019. To assess the likelihood of moving to the US, we employ the following model for person i in country c at time t:

$$\begin{aligned} moveto US_{ict} = \alpha + \beta_1 Post_t + \beta_2 Mexico_{ic} + \beta_3 Post \times Mexico_{ict} \\ + \rho_c country_c + \tau_t year_t + \gamma \mathbf{X}_{it} + u_{ict}. \end{aligned} \tag{11}$$

Here, β_1 captures the average effect since 2017, β_2 represents Mexico's average effect, and β_3 their interaction. Fixed effects over countries and years enter in ρ_c and τ_t, while $\mathbf{X}_{it}$ controls for individual characteristics such as age, gender, marital status, and education level.

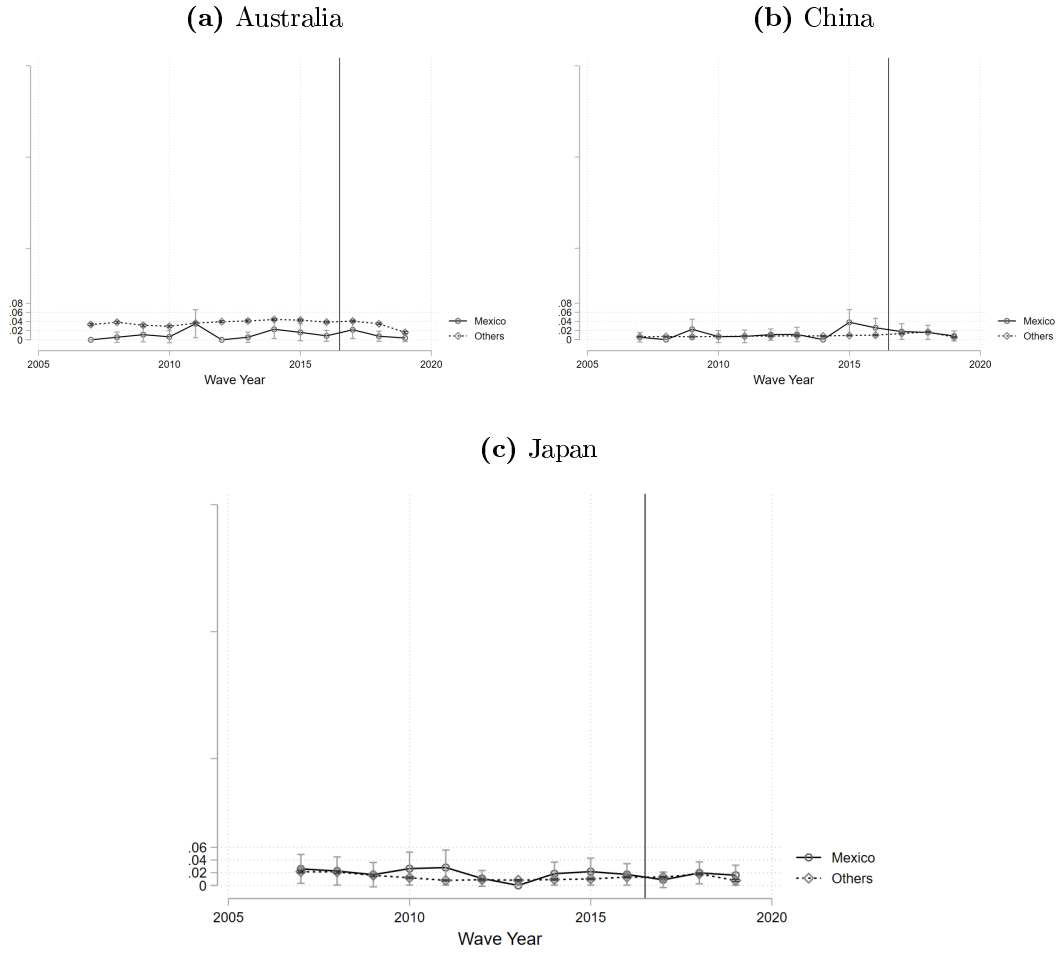
Our analysis focuses on Mexicans' migration choices regarding major destination choices, excluding Central American countries from the control group due to similarities in migration aspirations.[21]

We examine major destinations such as the US, Canada, Spain, and Germany (cf. Table 1). To reiterate, Table 2 reveals a significant decline in Mexicans aspiring to migrate to the US during the Trump presidency, while Canada's attractiveness increases in the same period. Panels (a) and (b) in Fig. 3 visualize these impacts on the likelihood of going to the US and Canada for Eq. (11). While the decline in the US preference continues under the Trump administration, it is statistically negligible. In contrast, Canada experiences a clear and statistically significant uptick. We explore other destinations for Mexicans in Fig. 3 and Appendix D.5, finding no evident changes elsewhere. These results affirm our earlier findings, suggesting these countries are largely irrelevant to Mexicans' location choices and may be perceived as a inferior substitutes to the US compared to Canada.

The key takeaway is the heterogeneous nature of the shift away from the US. While Mexicans are less inclined to choose the US as their top destination during the Trump presidency, countries like Canada, France, and the UK become more attractive. All of this suggests that destinations are not equally substitutable and models of migration decisions should capture this heterogeneity.

[21] We follow the *United Nations geoscheme for the Americas* to exclude Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama from our sample. Alternative specifications on our model for all Central American countries lead to similar outcomes and are available on request.

Figure D.5: Trends of Migration Aspiration Toward Destinations over Time for Different Immigrant Groups.



The graph pictures the means and the 95 percent confidence intervals derived from the sample of aspiring migrants. The vertical lines represent Donald J. Trump's election to US president in November 2016.
Data source: Gallup World Poll (2022).

E Predicted number of aspirational immigrants

Table E.1: Immigration pressure under four scenarios (thousands immigrants).

	Base scenario			Gender scenario			Skill scenario			Border closure		
	logit	CNL	Diff	logit	CNL	Diff	logit	CNL	Diff	logit	CNL	Diff
Canada	16.013	76.689	60.676	14.477	70.686	56.210	20.080	92.708	72.628	83.773	579.501	495.728
Germany	14.754	68.869	54.115	13.292	63.353	50.062	18.620	84.750	66.130	76.769	376.659	299.890
Spain	11.236	53.410	42.174	10.160	49.257	39.097	14.044	64.057	50.012	58.798	300.017	241.219
France	11.325	48.700	37.375	10.210	44.790	34.580	14.265	59.771	45.505	58.996	270.913	211.917
United Kingdom	11.857	44.330	32.473	10.683	40.680	29.996	14.952	54.464	39.512	61.719	335.213	273.494
Italy	9.225	35.110	25.885	8.316	32.256	23.940	11.615	43.172	31.557	48.053	197.825	149.772
Australia	6.233	24.573	18.339	5.605	22.500	16.895	7.879	30.317	22.438	32.348	187.773	155.425
Switzerland	4.515	16.415	11.899	4.054	15.073	11.019	5.735	20.579	14.844	23.388	95.029	71.641
Colombia	2.631	14.425	11.795	2.382	13.202	10.820	3.251	17.410	14.159	13.826	101.701	87.875
Netherlands	4.919	16.644	11.725	4.419	15.258	10.839	6.235	20.846	14.610	25.502	96.002	70.500
Chile	2.249	11.687	9.438	2.032	10.688	8.657	2.804	14.284	11.480	11.765	81.856	70.092
Israel	2.495	11.712	9.217	2.245	10.717	8.472	3.148	14.444	11.297	12.968	91.064	78.096
Ireland	2.027	10.054	8.027	1.808	9.163	7.356	2.592	12.679	10.088	10.412	77.245	66.833
Belgium	3.362	10.087	6.725	3.020	9.234	6.214	4.262	12.674	8.412	17.427	59.291	41.865
Sweden	3.224	9.627	6.403	2.896	8.812	5.917	4.089	12.103	8.014	16.707	56.676	39.969
Türkiye	2.406	8.358	5.952	2.161	7.566	5.405	3.042	10.685	7.643	12.473	55.762	43.289
Austria	2.766	7.649	4.882	2.481	6.990	4.509	3.514	9.674	6.160	14.312	45.222	30.910
Costa Rica	1.015	5.691	4.676	0.918	5.219	4.301	1.262	6.932	5.670	5.324	40.052	34.727
Norway	2.287	6.319	4.033	2.048	5.771	3.723	2.912	8.042	5.130	11.806	37.491	25.685
Denmark	2.148	5.697	3.549	1.926	5.202	3.277	2.730	7.228	4.498	11.105	33.998	22.894
India	1.671	0.884	-0.787	1.504	0.798	-0.705	2.087	1.101	-0.986	8.696	6.951	-1.745
China	2.170	1.261	-0.908	1.940	1.130	-0.810	2.748	1.597	-1.150	11.186	5.310	-5.876
United States	-1179.787	-1257.486	-77.699	-1119.140	-1195.964	-76.823	-1311.038	-1390.746	-79.708	-0.000	-0.000	0.000
Stay	1320.164	1083.951	-236.212	1235.810	1016.613	-219.197	1513.611	1228.885	-284.726	7037.649	4790.077	-2247.573