"Descended from Immigrants and Revolutionists:" How Family History Shapes Immigration Policymaking*

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Abstract

Does family history matter for policymaking in democracies? Linking members of Congress to the census, we observe countries of birth for members, their parents, and their grandparents, allowing us to measure ancestry for the politicians in office when U.S. immigration policy changed dramatically, from closing the border in the 1920s to reshaping admittance criteria in the 1960s. We find that legislators descended from immigrant parents or grandparents support more permissive immigration legislation. They are also less likely to speak negatively about immigration in speeches before Congress. A regression discontinuity design analyzing close elections, which addresses district-level selection and holds district composition constant, confirms our results on roll call voting and speech. Efforts to account for selection into immigration—such as comparing international immigrants to domestic migrants and exploiting variation in restrictive legislation targeting specific regions of origin—further confirm the relationship between family immigration experience and more permissive stances on immigration policy. We then explore mechanisms, finding support for in-group identity in connecting family history with policymaking. MCs name their children in ways that express immigrant identity, and immigrant-descended MCs discuss immigration using more personal frames, emphasizing family over economic considerations. Our findings illustrate the important role of personal background in legislative behavior in democratic societies, even on major and controversial topics like immigration, and suggest how experiences transmitted from previous generations can inform lawmakers' views.

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> The whole debate we are now undertaking over immigration and the Dreamers has become somewhat personal for me because it has reminded me, in a very strong way, that I and my brother are first-generation Americans. We are the sons of an immigrant who came to this country at the age of 17 without a nickel in his pocket…
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> – Senator Bernie Sanders, Speech on Floor of Senate, February 14, 2018

1 Introduction

Since the Naturalization Act of 1790 passed during the First Congress, immigration and citizenship questions have been among the most fraught domains of political contestation in the United States. Public support for restrictive immigration legislation has been commonplace (Hainmueller and Hopkins 2014), with the arrival of immigrants often triggering intense political backlash and demands for immigration restrictions (Alesina and Tabellini 2024; Alsan, Eriksson and Niemesh 2020; Tabellini 2020).[1] Though U.S. immigration policy has oscillated between expansive and restrictive regimes (Tichenor 2002), at least rhetorically the U.S is a "nation of immigrants." One reason the long- and short-run reactions to immigration could diverge (Giuliano and Tabellini 2020) is that many U.S. citizens, including members of Congress (MCs), have their own personal or family stories of immigration; even several generations back, an immigrant family history might anchor permissive attitudes towards immigration. Though only a small share of MCs are or were immigrants themselves (historically or today, see Figure I), a significant number have foreign-born parents or grandparents. For example, in the 115th Congress (serving 2017-2019), while only 11 representatives (2.5%) and a single senator were immigrants, 11.8% of representatives and 14.6% of senators had at least one foreign-born parent. In the first half of the 20th century, the share of representatives with at least one foreign-born parent reached as high as 30 percent of the chamber and even more had at least one foreign-born grandparent.

[Figure 1 about here.]

In this paper, we ask if electing legislators with family histories of immigration matters for setting national policy. Though MCs often cite their personal or family history when discussing immigration (Swarns 2006; Burden 2007, p.18), does having a Congress composed of lawmakers with an immigrant background ever meaningfully alter policy decisions in areas of fierce political conflict? MCs might support permissive immigration policy for many reasons, but two central explanations are: (1) because it aligns with their electoral incentives, or (2) because of their own preferences. Senator Edward Kennedy's

[1] The political effects of immigration are not always homogeneous; for example, Mayda, Peri and Steingress (2022) show that low-skilled immigration decreased Republican vote share, while high-skilled immigration had the opposite effect.

role in formulating and passing the U.S. Diversity Visa lottery serves as a distillation of these concepts and the challenges in distinguishing between them empirically. Kennedy pushed for the policy change both because of his own family connection to immigration *and* because his constituents included a large share of people with family histories of immigration (Law 2002).[2] Our empirical approach allows us to estimate the relationship between family history and legislative behavior holding electoral districts and other important background characteristics constant and to distinguish between explanations based upon personal preference and electoral incentives in a variety of ways.

To understand the behavior of legislators with immigrant family backgrounds, we turn to the most consequential period of immigration law-making in U.S. history and study lawmakers in the U.S. House and Senate from the 51st to 91st Congresses (1889–1971). Our sample period includes the exclusion of Chinese immigrants in the late 19th century, the closing of the border in the 1920s, and the reshaping of immigration in 1965 by the Immigration and Nationality Act, policy choices that affected millions of lives over multiple generations. Our period also allows us to work with direct measures of legislator family backgrounds. We link lawmakers to the historical complete count census data from 1880–1940 to observe their family histories (Ruggles et al. 2020). This census match allows us to examine the countries of origin of the lawmakers themselves, their parents, and, in most cases, their grandparents. We then estimate the differences between MCs with and without a family history of immigration on two canonical forms of legislative behavior for MCs: legislative voting and speeches on the floor of Congress.

We find that having a recent family history of immigration is associated with legislators supporting more permissive immigration policy. MCs with family histories of immigration cast pro-immigration votes—against restrictive bills or in favor of expanding immigration—at higher rates during this period. Our results hold for both landmark immigration bills and for all immigration bills with final passage votes. Moreover, the relationship holds whether we measure the immigration history of MCs' parents or grandparents or a weighted combination.

These results could reflect the ideological effects of family background, district-level electoral incentives, district-level selection, or selection into immigration. Districts that prefer more expansive immigration policy might be more likely to elect MCs with a family history of immigration, or individuals who decide to immigrate, and their descendants, might differ from non-immigrants in their personal charac-

[2]While most Americans (with the exception of Native Americans and descendants of enslaved Africans) are descended from immigrants (as Franklin Delano Roosevelt stated in the full quotation we use in the title, "Remember always that all of us, and you and I especially, are descended from immigrants and revolutionists") we focus on more recent family history of immigration for two reasons. First, we are constrained to the family history we can observe in the U.S. Census, where we are limited to the parents and grandparents of MCs. Second, this more recent history is more likely to be tied to immigrant identity than immigration experiences many generations in the past and out of living memory.

teristics. We distinguish between the possible explanations in four ways. First, all of our results on the relationship between immigration history and roll call voting hold with a rich set of controls for the composition of, and views on, immigrants in an MC's district (and crucially, constituent immigrant ancestry). Second, MC personal background has a stronger association with immigration voting patterns than does district composition, suggesting that district-level electoral incentives may not be the primary factor when MCs take immigration votes. Third, we use a regression discontinuity in congressional elections to compare districts just barely or barely not represented by immigrant-background MCs. This approach holds constant the district-level electorate and its level of demand for immigrant-descended candidates, helping to eliminate some concerns over why districts elect representatives with (or without) immigrant family histories (e.g., district-level selection), and it confirms our main finding: congressional seats quasi-randomly assigned to MCs with family histories of immigration favored expansive immigration policies at higher rates. Finally, to account for selection into migration of individuals and ancestors, we hold characteristics associated with an immigrant background constant while allowing key experiences to vary. Immigrant ancestors were self-selected and might vary on dimensions including entrepreneurship, grit or determination, risk-taking, or openness to new settings. Domestic migrants and their descendants might also be self-selected on similar characteristics, so we isolate the role of international immigration specifically by comparing to a history of domestic migration. MCs with family histories of *international* immigration, not those with family histories of *domestic* migration, appear to drive the support for more open immigration policies. Furthermore, holding immigration history fixed, MCs with immigrant heritage targeted specifically by restrictive immigration bills were increasingly likely to oppose such bills. Our story, we argue, is particularly about immigration and the response to policies targeting it, rather than other traits that could be common to all migrants (e.g., domestic and foreign).

Do MCs with immigrant family backgrounds also give more voice to the issue of immigration? Here, we distinguish between the quantity and quality of speeches on immigration. Drawing on newly-scored speech data from Card et al. (2022), we show that MCs with immigrant ancestry are more likely to have a positive tone about immigration and immigrants when speaking in Congress. These correlations with MC ancestry are also relatively large compared to correlations of tone with district composition or party. These results for tone of immigration speech also hold in a parallel RDD analysis: in districts with close elections between candidates with different immigration histories, immigrant-descended MCs speak with a more positive tone about immigration. However, this change in tone appears driven by a reduction in the number of negative speeches about immigration among MCs with immigrant family histories, rather than an increase in positive speeches. Overall, the RDD suggests that MCs with immigrant family histories give slightly less voice to the question of immigration, but the speeches that they avoid making are the negative ones. This strategic approach to immigration policy could allow MCs to support an immigration agenda through votes without drawing attention from constituents or fellow MCs to their position, or appearing to advocate for narrow interests (Cormack 2016).

Why do elected officials with immigrant backgrounds take more permissive stances on immigration policy? We explore three possible mechanisms: in-group identity, information about immigration, and correlated preferences. While we cannot distinguish between these possibilities fully, we find the most support for a theory about in-group identity. MCs with immigrant family histories exhibit a heightened sense of a connection to group identity based on source country even before entering Congress, as demonstrated by choices of culturally-specific first names for their children. Once in Congress, when immigrant-descended MCs do speak about the topic of immigration, they do so in more personal terms, referring to family more frequently and making economic arguments less often as compared to MCs without immigrant family history. Levels of support for permissive immigration policy can break down along narrower lines of source country, ethnic or racial identity. Meaningful group boundaries may form at the level of a specific nation of origin (e.g, Italian immigrants, Irish immigrants), pan-ethnic group, or for an American national identity in which immigration is valued (Masuoka 2006; Schildkraut 2014). And, indeed, when faced with legislation restricting immigration based on national origin, we find that MCs with family histories rooted in nations unaffected by the restriction opposed it at lower rates than colleagues with family origins in targeted countries. Thus, while MCs with family histories of immigration share a common tendency towards permissive immigration policy, narrower group identity based on nation of origin subsumes it under some conditions.

A second possible mechanism could be information about immigration. Information particular to an MC with a family history of immigration might include an understanding of the plight of new immigrants, the efficiency gains from immigration, the perils of zero-sum thinking, or the potential upward mobility of immigrant populations. This knowledge could lead an MC to support more immigration. While difficult to reject this explanation fully, we show that MCs who could more easily observe the relatively higher upward mobility among immigrants (based on district-level variation in intergenerational mobility (Abramitzky et al. 2021a)) do exhibit increased support for immigration, but this tendency does *not* differ between descendants of immigrants and other MCs.

Third, MCs could support more immigration for ideologically strategic reasons. Potential immigrants—who might shape a future electorate—may have political leanings aligned with MCs with immigrant family histories. Support for an expanded welfare state among immigrants, as in Giuliano and Tabellini (2020), could be one possibility. For this correlated preferences mechanism to be at work, immigrant family history would need to matter for many policy domains beyond immigration and at a magnitude similar to what we observe for immigration. However, placebo tests show roll call voting in other areas generally does not change with MC immigration history. In areas where we do observe some changes, the magnitudes are not as large as for immigration. And, when assessing the sensitivity of district-level roll call voting to changes in immigrant family history induced by members dying in office, no topic area other than immigration approaches statistical significance. These findings make it unlikely that MCs support immigration primarily to shape the demographics of future constituents because of correlated ideological preferences.

Based on our findings, this article makes four distinct contributions. Our first contribution is to the political economy of immigration literature. Past work on the determinants of immigration policy has emphasized the initial backlash effects of immigration on the views of the US-born (Alesina and Tabellini 2024), misperceptions about immigrants (Alesina, Miano and Stantcheva 2023), institutional conditions in Congress (Tichenor 2002), political, economic, and social conditions in the US (Goldin 1994; Timmer and Williamson 1996), or international events (Zolberg 2009). Looking at migration policy internationally, Facchini and Mayda (2009) note that, given such high levels of opposition to immigrants, "it is a puzzle that migration is allowed to take place at all" and turn to an interest group model as explanation. We posit that the fact that legislatures are composed of lawmakers with family histories of immigration plays an important and underappreciated role in immigration policy. Although legislator background is hardly the only force relevant to this policy area, little attention has been paid to its role in debates over immigration policy in Congress and in other legislatures.

This perspective speaks directly to some long-standing themes in the political economy literature. There is considerable evidence of direct competition between new and prior immigrants (Abramitzky et al. 2023). However, we show that districts with greater foreign-born population shares and, independently, a lawmaker's personal connection to immigration, *both* are associated with increased support for permissive immigration policies. These results imply that, on average, people in immigrant-heavy districts may have placed more weight on new immigrants seeking opportunity than on any potential labor-market harms from these populations.

Second, we contribute to the understanding of what factors influence how legislators vote, along the lines of Mian, Sufi and Trebbi (2010), including views shaped by individual experience and background. When considering legislative decisions, MCs weigh some combination of their personal views along with the preferences of the national party (Lee, Moretti and Butler 2004) and their "economic interest" in getting reelected (Stigler 1971; Kalt and Zupan 1984).[3] Our main finding—MCs with immigrant family backgrounds support more open immigration policy—holds when controlling for party and constituency, and when applying a regression discontinuity that generates quasi-random assignment of MCs to districts. When we standardize our measures of background and constituency to compare magnitudes, background is more important than both district and party. Approaches designed to account for self-selection into migration point to similar conclusions. Thus, we find that legislators' own views matter *and* that those views are explained by their backgrounds and experiences. Past work has shown that lawmaker race (Canon 1999), gender (Fridkin and Kenney 2014), economic class (Carnes 2012), prior political experience (Keena and Knight-Finley 2017) and the gender of their children (Washington 2009) also play a significant role in legislative behavior.[4] Background can matter specifically for controversial and hotly-debated policies: McGuirk, Hilger and Miller (2023) show that having draft-age sons pushes lawmaker-parents to vote against conscription. However, we are the first to rigorously study lawmaker immigrant background, a central feature of U.S. identity in popular discourse, through this lens.

Third, we contribute to the study of immigration during the 20th century. A growing literature exploits changes in policy to estimate the effects of immigration on labor markets (Tabellini 2020; Abramitzky et al. 2023; Jaeger et al. 2018; Clemens et al. 2018), growth (Ager and Brueckner 2013), innovation (Moser and San 2020), investment (Burchardi, Chaney and Hassan 2019), and health (Ager et al. 2024). In addition to deepening our understanding of the political economy forces that shaped legislation during this era, our study also points to a potential longer-term effect of immigration that plays out over multiple generations. Where Giuliano and Tabellini (2020) highlight contact theory and cultural transmission from immigrants to the US-born in shaping long-run preferences for the welfare state (horizontal transmission), our results point to the potential influence of individuals' family histories on public opinion and political preferences (vertical transmission, over generations); the personal histories of the descendants of immigrants predict how legislators wield political power, and could similarly matter for everyone in daily economic and social interactions. Through this channel, immigration policy is multigenerational and potentially persistent.

Finally, we also contribute to the "identity on the job" literature in a new context. Ethnic divisions induce some workers to discriminate against colleagues (Hjort 2014), biased managers to harm the per-

[3] A legislator's own views sometimes appear to outweigh these other considerations, with some estimates suggesting that a Senator's personal ideology holds more weight than any other factor in a legislator's decision function (Levitt 1996).

[4] The role of personal background in decision making extends beyond just legislators (Glynn and Sen 2015). Immigrant history matters for non-politicians as well. In survey experiments, priming on family history (Williamson et al. 2021) or a history of forced displacement (Dinas, Fouka and Schläpfer 2021) increased sympathy for immigrant outgroups and refugees, respectively.

formance of their supervisees (Glover, Pallais and Pariente 2017), and job seekers to decline offers of employment (Oh 2023). However, in-group bias could also reflect better information (Fisman, Paravisini and Vig 2017), and it may fade over time (Ghosh 2022). New in our context is that the job in question is as a politician, and policymaking and congressional speech represent salient outcomes about immigration policy, a topic closely related to the identity we study.

2 Data

We focus on immigration legislation from 1889 to 1971, corresponding to the congresses where we can match the most members to the 1880 through 1940 censuses to collect family immigration histories. In this section, we describe the history of immigration legislation during this period, the specific bills we will analyze, and our congressional speech data. We conclude by documenting our process for matching lawmakers to the complete count historical censuses.

The size and scope of immigration to the U.S. has been determined by three main factors historically: the costs of migration, the benefits to the migrants, and U.S. policy (Abramitzky and Boustan 2017). As these three factors have changed over time, total flows and the selection of immigrants has changed. The Age of Mass Migration—dating from the late nineteenth century to the immigration restriction acts of 1917, 1921, and 1924—was made possible by falling costs of trans-Atlantic transportation, relatively open border policies, and the industrializing and urbanizing U.S. economy (Abramitzky and Boustan 2017). This historical moment did not just coincide with an increase in the number of immigrants but also a significant shift in their source countries. In 1850, more than 90% of the foreign born in the U.S. came from Northern and Western Europe, mostly Great Britain, Ireland, and Germany. Seventy years later, the foreign-born population in the U.S. was split between old and new Europe, as 45% came from "old" sending countries and 41% from "new" sending countries in eastern and southern Europe.

2.1 Legislative Outcome: Roll Call Votes on Landmark Immigration Bills

To assess legislative behavior related to immigration policy, we identified key immigration bills in the 1889–1971 period (the 51st through 91st Congresses) using Stathis' (2014) compilation of landmark legislation and key bills identified by Tichenor (2002). We selected this time period for two reasons: (1) this period spans many major immigration bills of the 19th and 20th century; and, (2) members serving in this period were likely to be identifiable in the 1880–1940 censuses.[5] We begin by focusing on landmark

[5]Goldin (1994) also studies the political economy of immigration restriction, focusing in particular on the anti immigrant literacy test bills passed by Congress from 1897 to 1917 but ultimately vetoed by presidents of both parties. She finds that districts

immigration legislation because these bills had high stakes and directly determined the key parameters of immigration policy during our time period; importantly, any member casting a vote understood it directly affected the fate of immigrants. Table I lists the twelve bills in our analysis, and Appendix B.1 describes the legislation in detail. These bills represented major changes to U.S. immigration policy. Nine of the bills restricted immigration, and three increased immigration or reduced restrictions. We identified the final roll call vote in each chamber for each landmark bill—either the vote on final passage or on the conference vote—using the VoteView database (Lewis et al. 2017). Several potential landmark bills were dropped because final votes on the bill were not recorded.

[Table 1 about here.]

2.2 Legislative Outcome: Roll Call Votes on All Immigration Bills

While landmark bills represent the most salient and historically notable immigration votes from the 51st–91st Congresses, we also collected data tracking the full set of final passage votes on immigration legislation considered during our period. This wider set of votes supplements the landmark legislation in three important ways. First, these votes are included in the sample regardless of their outcome; this contrasts with landmark bills, some of which gained historical importance precisely because they had important legislative effects ex post. Second, a wider set of votes helps illustrate whether the relationships we observe still hold for votes less visible than landmark legislation. Third, this full set of bills allows us to use methods, such as regression discontinuity, that require a large amount of data to estimate the relationship between electing immigrant-descended MCs and vote choice.

To construct this sample of immigration votes, we relied upon categorizations from Lewis et al. (2017). Specifically, we started with all bills categorized as "Immigration/Naturalization," and we again identified whether a vote occurred for the final passage of an immigration bill.[6] We filtered out any roll call votes that, based on reading contemporaneous descriptions, were not related to immigration or were simply amendments to landmark immigration bills in the same session as the bill's passage.

with slower wage growth or fewer immigrants were more likely to vote against immigration. Goldin's analysis, however, does not extend to the characteristics of the MCs.

[6] To determine whether a roll call vote was for final passage, we check for Final Passage labels in Crespin and Rohde (2018); Roberts, Rohde and Crespin (2018) or in the description field in the VoteView data. If no final passage votes were recorded, we then checked for a vote for a Final Amendment to the legislation, and if not, a final recorded roll call vote.

2.3 Legislative Outcome: Congressional Speech

Our other primary outcome is congressional speech for the 51st–91st Congresses. We focus on the count, tone, and content of members' speeches about immigration. We draw upon speeches recorded in the *Congressional Record*, which are processed and assembled in Gentzkow, Shapiro and Taddy (2019) and Card et al. (2022). Both sources allow us to count speeches about immigration by MC and congress: Gentzkow, Shapiro and Taddy (2019) constructed keywords to identify speeches on 22 substantive topics including immigration, while Card et al. (2022) trained a machine learning classifier to identify speeches on the subject of immigration in Congress. Of course, speech can be positive or negative; to study this dimension of speech, we use a measure of tone from Card et al. (2022) where a different machine learning classifier identifies the sentiment of speeches, allowing for member-level measures of speech tone as well as tallies of positive and negative speeches.[7] Finally, to help us understand mechanisms—why exactly MCs with an immigrant family history might be more likely to support pro-immigration legislation—we use a set of "frames" capturing different qualitative elements of speech (Card et al. 2022), measures of the emotionality of speech (Gennaro and Ash 2022), and the unstructured text of speeches on immigration, which allows us to analyze member speeches without relying on pre-established frames. See Section C.5 for more details on the Card et al. (2022) data.

2.4 Identifying Immigration Background

To estimate the relationship between family immigration background and MC vote choice, we use individual-level data from historical U.S. Censuses. We begin by constructing a linked sample, locating MCs in the 1880, 1900, 1910, 1920, 1930, and 1940 Federal censuses, based on the Integrated Public Use Microdata Series (IPUMS) complete counts (Ruggles et al. 2020). In this subsection, we detail the complete count census data and the congressional data, we document the machine learning approach to census linking, and we summarize what the census data says about MCs.

To start, we identify all MCs serving between 1889 and 1971. We extract their full names, dates of birth, and states of birth from the *Biographical Directory of the United States Congress*.[8] We then link all members to their census records in 1880, 1900, 1910, 1920, 1930, or 1940 with the linking method described in Feigenbaum (2018).[9] Linking historical records is complicated by the lack of a unique identifier. Instead,

[7]For both the relevance (is this speech about immigration?) and tone (is this speech positive, neutral, or negative?) classifiers, Card et al. (2022) start with a RoBERTa neural language model and fine-tune it with several thousand annotations.

[8]For members born abroad, we search for their family backgrounds manually and record their ancestry directly. Members born abroad to at least one U.S. citizen parent are not considered immigrants, as they are citizens from birth.

[9]See Appendix C.1 for a full description of this approach to census-linking.

we rely on variables like name, place of birth, and date of birth, which should not change over time.[10] We apply a machine learning approach, training an algorithm to learn to make matches based on a smaller sample of carefully hand-linked data. A priori, the costs of discrepancies in record features are unknown, so the approach makes the implicit rules used by a human linker explicit.

Overall, we link 88.5% of the MCs in our study sample to at least one of the six decennial censuses. Our match rates into each of the six censuses—limited to MCs alive in a given census year—are all above 63%, peaking at 68.6% matching into the 1930 census. The true positive rate is 91% in cross-validation: this suggests that the linking algorithm is very efficient, able to identify nearly all of the matches that a human trainer would have made, but doing so at scale and with defined linking rules. In addition, our cross-validation implies that the linking algorithm makes the same choice as a careful and well-trained hand linker 85.4% of the time based on our precision or positive predictive value.[11]

Census questions vary slightly year to year, but they nonetheless provide a wealth of information for each person we can link. For studying family immigration history, we focus on questions asked about birthplace. All people enumerated in 1880, 1900, 1910, 1920, and 1930 were asked their place of birth and their mother's and father's places of birth.[12] Because members of the same households are linked in the enumeration, when we observe MCs as children, we also observe all their grandparents' birthplaces, using their mothers' and fathers' answers to their own parents' places of birth questions.

We present three examples of MCs from the linked data in Table C.1. Former Speaker of the House Carl Albert was born in Oklahoma in 1908, to a mother from Texas and a father from Missouri. All four of his grandparents were born in the United States as well. Clinton Anderson, a former MC, Senator, and Secretary of Agriculture, was born in 1895 in South Dakota, to a mother from South Dakota and a father who immigrated from Sweden. His maternal grandmother was born in Illinois, his maternal grandfather in Wisconsin. His father's census records report that Anderson's paternal grandparents were both born in Sweden as well. Finally, former Boston Mayor, Massachusetts Governor, FCI Danbury inmate, and MC, James Michael Curley was born in Massachusetts in 1874 to Irish immigrant parents. In 1900, his mother reports that her parents were both born in Ireland; though his Irish immigrant father died in 1884, we

[10]Our use of last names in the linking complicates matching women who might be expected—particularly in the early 20th century—to change names upon marriage. However, during this time period, very few women served in Congress.

[11]Consistent with the machine learning procedure, our match rates also replicate the match rates of our human trainer in each census. Our match rates are generally higher than common census to census linking attempts for three reasons. First, we start with Congressional biographical data with accurate names, including middle names, and exact dates of birth. Abramitzky et al. (2021b) documents the gains from middle initials and names in linking. Second, MCs are a selected population—majority male, white, and high-status—in ways that have historically increased match rates. Finally, we search for fixed characteristics (place of birth and parents' place of birth) in multiple censuses, allowing us to include MCs even if we cannot match them in every census.

[12]In 1940, parents' birthplace was a sample line question, asked only of 2 people on each 40 person census page.

assume Curley's paternal grandparents were born in Ireland as well. These examples highlight the diversity of MC family histories. While all three are white men who served in Congress in the 1940s, their immigration backgrounds vary substantially.

Our primary measures of immigration history are counts of foreign-born parents and foreign-born grandparents. As Table C.2 reports, the average MC in our sample had 0.4 foreign-born parents and 1.6 foreign-born grandparents; 16 percent had both parents foreign born and 32 percent had all grandparents foreign born.[13] We observe little difference in immigration histories across party in our sample.

Overall, we observe the number of foreign-born parents for 89.6% of voting members and the number of foreign-born grandparents for 60.0% of voting members. Successfully measuring grandparent nativity is more difficult because we only record it when we observe an MC's parents; this missingness occurs most frequently in the early years of our sample, particularly among older MCs who were not living with their parents during the 1880 or 1900 censuses.[14] For those MCs without missing data, we also construct an "Immigration Index" summarizing immigration history with a weighted average over places of own birth, parents' birth and grandparents' birth:

$$\text{Immigration Index} = 1 \cdot (\text{Foreign-Born MC}) + \frac{\begin{array}{c}\text{\# Foreign-Born}\\ \text{Parents}\end{array}}{2} + \frac{\begin{array}{c}\text{\# Foreign-Born}\\ \text{Grandparents}\end{array}}{4} \tag{1}$$

ranging from 0 (all grandparents, parents, and MC U.S.-born) to 3 (MC and all ancestors foreign born).

We also construct name-based proxies for family immigration history. We focus on two methods, a relatively simple surname score and the f-index based on Abramitzky, Boustan and Eriksson (2020); both are constructed from the 90 to 140 million people enumerated in each decennial census. For the surname scores, we calculate the share foreign born, mean number of foreign-born parents, mean number of foreign-born grandparents and average Immigration Index among each enumerated person with that surname. The

[13]We focus on the foreign-born status of MCs' parents and grandparents rather than the MCs themselves for two reasons. First, only 4% of the MCs in our sample are foreign-born. Second, most immigrants to the United States do not become naturalized citizens and are therefore ineligible to serve in Congress. Table A.1 displays summary statistics for MCs who cast landmark immigration votes and who cast any immigration votes, respectively. We exclude MCs who were foreign born as citizens (such as those born to ambassadors or military personnel abroad). We code foreign-born non-citizen MCs as having foreign-born parents and grandparents.

[14]Grandparent nativity is recovered from questions about mother and father's place of birth asked of the MC's mother and father. Thus, we can only record an MC's grandparents' birthplace if we observe an MC in a household with the MC's parents who then answer the census question on where their parents were born. If the nativity of one grandparent was missing, we made the assumption that the missing grandparent had the same odds as the non-missing grandparents of being foreign born.

f-index, meanwhile, is a likelihood ratio. We construct a different index for each generation as:

$$\text{ForeignnessIndex}_{\text{name}} = 100 \cdot \frac{\frac{\text{\# foreign born}_{\text{name}}}{\text{total \# foreign born}}}{\frac{\text{\# foreign born}_{\text{name}}}{\text{total \# foreign born}} + \frac{\text{\# non-foreign born}_{\text{name}}}{\text{total \# non-foreign born}}} \tag{2}$$

where *# foreign born*$_{name}$ counts the number of foreign-born people with a given surname or the number of foreign-born parents with children with a given surname or the number of foreign-born grandparents with children with a given surname; and *total # foreign born* counts the total number of foreign-born people or the total number of foreign-born parents or the total number of foreign-born grandparents. We then built an analogous Immigration Index by summing the self, parent, and grandparent based f-indices.

We performed each surname calculation both nationally and by census region. We prefer the regional measures because the same surname can denote meaningfully different immigration histories depending on region of the country, but (as we will show) our results are robust to both measures.[15] We matched an individual's surname to the Surname Scores calculated for the census preceding their election to Congress and the relevant region (See Appendix C.2). We also built name scores and f-indices based on first names and full names, which we use for robustness checks.

3 Roll Call Vote Analysis

Family immigration background could be related to legislative behavior. To test this, we evaluate the relationship between an MC's immigration history and vote choice on (1) landmark 19th and 20th Century immigration votes and (2) all immigration bills from the 51st–91st Congresses. We employ a model of the form

$$y_{ib} = \alpha + \delta \cdot \text{Immigration History}_i + X \cdot \beta + \gamma_b + \epsilon_{ib} \tag{3}$$

where i indexes individual MCs and b indexes bills. X is a matrix of covariates including a key control for the log foreign-born population in a district because, of course, districts with a large number of foreign-born residents could both prefer representatives with immigrant backgrounds and offer in-office MCs strong electoral incentives to support permissive immigration policies.[16] We also include indicators

[15]We prefer surname scores within census region because names might have different levels of "immigrant ancestry" signal in different regions of the country. For example, in 1910, 41% of nearly 1300 people with the surname of Champagne were foreign-born in the Northeast while only 1% of the 840 Champagnes in the South were foreign-born, reflecting the regions' different immigration histories. The Champagnes in the South likely descended from 18th century French colonists in Louisiana; Champagnes in the Northeast were more likely to be recent immigrants from French Canada.

[16]We use census data to calculate the foreign-born population in a district or state. County-level data is mapped to congressional districts using the shapefiles from Lewis et al. (2013) and crosswalks from Ferrara, Testa and Zhou (2024). The foreign-born population in a district correlates very highly with measures of the number of residents who have foreign-born parents or foreign-born grandparents and with the average immigration index of a district (the correlations across counties between

for chamber, party, and census region, as well as controls for age and tenure, district (log) total population, and district (log) black population. Our main specification pools across bills and therefore also includes γ_b, a bill fixed effect.

For each of the bills listed in Table I and for the broader set of immigration bills, we determined whether a “yea” or “nay” vote best aligned with a political position generally favoring a less restrictive immigration policy.[17] We coded MCs who cast pro immigrant votes in this direction with a 1 and those who did not with a 0. We excluded MCs who abstained from the sample.[18]

We find a strong relationship between immigration history—measured either by number of foreign-born parents, number of foreign-born grandparents, or our summary immigration index—and pro-immigration votes, as we report in Table II. We see this relationship both for landmark bills (Panel A) and all immigration bills (Panel B). We focus first on landmark bills. We start with a parsimonious specification where the only controls we include are bill and chamber fixed effects and controls for the foreign-born population and total population of a district in columns 1, 4, and 7. We find that having one foreign-born parent is associated with a nearly 8 percentage point increase in casting a pro vote and having one foreign-born grandparent is associated with a 3.7 percentage point increase. In each case, the coefficients are substantively and statistically significant.

[Table 2 about here.]

As we show in the second and third specifications of Table II, we continue to find a strong relationship between immigration history and pro-immigration votes when we include a host of additional control variables at both the CD and MC level. In columns 2, 5, and 8, we add census region fixed effects and a control for the black population in the CD. The coefficients are quite stable, suggesting that foreign-born ancestry and total population, which we always include, are the key district-level correlates of MC voting on immigration roll calls. In columns 3, 6, and 9, we add controls at the MC level including party fixed effects and quadratics in age and tenure. Since party strongly predicts vote across many domains, we particularly want to know if immigration history explains variation in vote choice conditional on party.

foreign-born share and ancestry based shares are are all greater than 0.935). Thus, we consider foreign-born population to be a more general proxy for constituencies where the residents have their own family histories of immigration. For robustness, we show in Tables A.3, A.4, and A.5 that our results hold when we construct district-level controls for foreign-born population with a census-linking based procedure like we used to measure MC ancestry.

[17] Yeas and Nays in the regression analyses include announced votes and paired votes. To determine whether members cast votes in favor of or against permissive immigration policies, two researchers manually coded each vote as either pro immigration or anti immigration based on the text of the bill along with the contemporaneous newspaper coverage of the legislation and discussion of the legislation on the floor of congress. In the few cases where coders disagreed, we conducted additional research until we had enough information to resolve how to code the vote. A list of all bills included in the sample and their pro- or anti-immigration coding is included in the replication data.

[18] In this era, missed votes occurred frequently and were due more to travel and scheduling limitations than strategic absences.

However, an MC's immigration history may influence choice of party, so conditioning on this choice may also induce bias. Though the coefficients of interest drop slightly when we move to our third specification, adding the controls for party drives this change.[19]

When we turn to all immigration bills in Panel B of Table II, we find similar results. Though the magnitudes of the associations between family immigration history and voting shrink, we continue to find that MCs with more recent immigrant background are more supportive of pro-immigration legislation. Again, the inclusion of controls for party and other CD or MC level covariates do not eliminate the associations.

Across all models in Table II, we find a positive and statistically significant relationship between immigration experience and voting in favor of immigration in Congress.[20] The coefficients decline by roughly half with each preceding generation's immigration history, but recall that our measures of MC immigrant ancestry are counts: MCs could have 0, 1, or 2 foreign-born parents and 0 to 4 foreign-born grandparents. Thus, the association of immigration background with voting is similar for a US-born MC with two immigrant parents and a US-born MC with four immigrant grandparents, while the association is smaller for an MC with one immigrant grandparent as compared to one immigrant parent.

The most obvious confounding factors vary at the level of an electoral constituency. Moving beyond the controls in Table II, we further examine the sensitivity of the relationship between family history and immigration votes to a variety of additional controls accounting for various forms of district heterogeneity. Figure II documents that the main coefficients on MC immigrant ancestry remain robust to a rich and wide-ranging set of controls. Specifically, our story remains intact when we (1) include three controls for the log of the foreign-born population from New Europe, Old Europe, and Non-Europe in each district to more precisely control for immigrant composition; (2) include controls for the log of the urban population in each district; (3) include a control for the size of the foreign-born voting age population; (4) include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout); and, (5) include controls in the first and second dimensions of DW-Nominate scores for MCs. Our results are also robust to a variety of fixed effects including state fixed effects (see also Table A.12); local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends; and congressional district fixed effects both on their own and interacted with year trends. The state by party fixed effects, along with a version interacted with year trends, both help account for

[19]Though our results are stronger for Democrats than Republicans, the patterns generally hold when we analyze within party, as we show in Tables A.10 and A.11.

[20]When we exclude foreign-born MCs from the sample, we find nearly identical results in Table A.2 to those in Table II.

varying base constituencies in particular.

We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, as the relationship between these local conditions and support (or opposition) to immigration is well established (Goldin 1994).[21] We also see that our results are robust to controlling for local ethnic fractionalization and controls for the ancestry of constituents.[22] Finally, we show in the last row of Figure II that our results remain robust when controlling for all substantive covariates considered in the figures simultaneously. The bottom row excludes the more than one thousand different fixed effects and year trends since, when including so many right-hand side variables in one regression in conjunction with the relatively limited number of votes on landmark bills, we lack the statistical power to make conclusions about *any* explanatory variables.

[Figure 2 about here.]

Since an MC's role as a representative of the electorate may explain immigration-related legislative behavior, it is particularly important that we consider additional ways to measure the electorate's preferences regarding immigration. To this end, we show that our estimated coefficients on MC immigrant ancestry are robust to two different methods of measuring local attitudes about immigration. First, we extend a strategy from Fouka, Mazumder and Tabellini (2022) to use newspaper content as a method to uncover local sentiment.[23] To do this, we collected data from Newspapers.com for our entire sample period and measure at the district-by-year level the usage of various terms. To identify key terms that might signal local interest or preferences over immigration, we follow Fouka, Mazumder and Tabellini (2022). We have: general interest in immigration topics (words like immigration, immigrant, etc); terms about immigration restriction; terms about various prominent ethnicities and religions of immigrants; and finally, ethnic slurs (ethnophaulisms) based on Allen (1983), which proxy for the most severe anti-immigrant sentiment, and KKK-related terms also measuring nativist sentiment. Because the Newspapers.com database changes over time (Beach and Hanlon 2023), we normalize by counts of the word January, following the historical newspaper literature

[21]Specifically we draw on data from Fulford, Petkov and Schiantarelli (2020), which measured the economic performance of US counties from 1850 to 2010. The authors construct measures of county-level employment rates, income per capita, and income per worker, as well as a Gini coefficient based on occupation scores to measure local inequality. We crosswalk this to our CD-level data to control for local economic conditions.

[22]To study this, we draw on ancestry data constructed by Fulford, Petkov and Schiantarelli (2020) reporting county-level share of ancestry from various sending countries. Because different groups might be differentially politically engaged or have different views on future immigration, this control should capture some dimensions of constituent preferences. Figure A.1 controls for each source country on its own and all together, illustrating that the correlation between MC ancestry and roll call voting remains robust to these ancestry controls.

[23]Fouka, Mazumder and Tabellini (2022) show that after inflows of African American migrants during the Great Migration, newspaper mentions related to immigrants and immigration decline.

(Gentzkow, Glaeser and Goldin 2006). As we see in Figure A.2, the primary coefficients of interest on MC ancestry remain extremely stable when accounting for local attitudes using newspaper content.

Second, we document the robustness of our main results to historical constituency preferences. Because we lack rich contemporaneous polling data and samples of the polls that do exist are small, we use multilevel regression with post stratification (MRP) to estimate the opinions of constituencies from the polling data that does exist. MRP combines constituency-level characteristics and individual-level characteristics to estimate the outcome variable (responses to a specific poll question) even when only a handful of observations for each constituency are available in the original data. We draw data from the Roper iPoll Gallup archive for 8 polls conducted between 1951 and 1965 with questions about immigration.[24] With complete count census data, our measurement of the demographics of each constituency are precise and we include several individual traits in our predictions (sex, race, education, occupation, and age). As we see in Figure A.3, our main finding is robust to controlling for these MRP-based estimates of local attitudes.

Our main results are also generally robust to the double or debiased machine learning procedure (Chernozhukov et al. 2018), as Table A.8 illustrates. In short, we "learn" very flexible mappings from our set of control variables to our variable of interest (MC immigrant ancestry) and to our roll call outcomes with a random forest model. We do this for a feature set including just the baseline controls in Table II and for an extended set of controls. We find positive point estimates for all measures in both the landmark and all bills samples and only three of our 28 specifications include zero in their confidence intervals.

Our core findings withstand inclusion of an extensive set of controls, but we can also test how much additional explanatory power any other unobserved confounders would need to have to push our coefficients of interest on family immigration history to zero, following Cinelli and Hazlett (2020). We report these results in Table A.9. Rather than imagine how strong a hypothetical confounder would have to be, the method proposed by Cinelli and Hazlett (2020) suggests comparing unobserved confounders to important covariates we do observe (and that we control for). We focus on our key measure of local demographics—the log of the foreign-born population in the district—as our initial point of comparison. Because of demands for descriptive representation, foreign-born population correlates very strongly with MC Ancestry; because it may also proxy for district preferences about immigration, it should also correlate strongly with our outcome, roll call voting on immigration legislation. Considering our specifications with CD and MC

[24] For full details of our MRP analysis, see Appendix C.4. We follow best practices from Hanretty (2020) in constructing our MRP estimates of immigration attitudes. Though the specific poll questions vary (see the full text in Table C.3), we are able to code each from least to most supportive of future immigration. Because the polling only starts in 1951, our MRP measures are an imperfect control, especially when we look farther back in time. However, we expect these estimates to be a reasonable proxy for local attitudes.

controls, we find in Table A.9 that an unobserved confounder would have to be at least 1.9 times and often 3 or more times as strong as foreign-born population (that is, as highly correlated with both our covariates of interest and our outcome variable) to attenuate the estimates fully. We can also benchmark unobserved confounders against party fixed effects: for that case, an unobserved confounder would have to be at least 2 times as strong as party fixed effects. Given the wide set of observables we have tested for, are other confounders with explanatory power double the size of party plausible? We think such scenarios appear unlikely, especially given the extensive robustness checks presented in Figure II.

Also consistent with our findings thus far, in Appendix A.2 we show that family history of immigration helps explain ideologically-surprising or "miscast" votes on immigration issues. Foreign-born parents or grandparents predict a reduced rate of diverging from pre-existing ideology when an MC is predicted to vote in favor of immigration and an increased rate of diverging when an MC's pre-existing ideology predicts a vote against permissive immigration policy.

The results in Table II, supported by this extensive battery of robustness checks, suggest that our estimates for family background do not just reflect MC electoral incentives for roll call voting on immigration policy. That is, despite the fact that electorates with large shares of immigrants (and their descendants) might prefer more lenient immigration policy and representatives are incentivized to be responsive to these preferences, the relationship between MC ancestry and policy survives a wide set of district-level controls. In the next subsection, we continue to probe this relationship in analyses examining the importance of family background relative to constituency as well as other key factors.

3.1 Relative Importance of Family Immigration History

What is the relative explanatory power of MC personal background versus district composition? By standardizing our independent and dependent variables in Table A.6, we can provide a quantitative answer. In Panel A, the outcome is roll call voting on landmark bills. We see that family history is three to five times as important as district composition (measured by foreign-born population; columns 1, 3 and 5) and also two to three times as important as party identification (columns 2, 4 and 6). These results generally hold for all bills as well (Panel B).

The results in Table A.6 imply that the relative explanatory power of immigrant family background is substantially larger than district composition or party. But our measures of MC ancestry and district ancestry are not exactly the same; for MCs we measure ancestry back to grandparents while for districts we have simply used foreign-born population as a proxy. However, as we show in Table A.7, when we use district composition measures that correspond exactly to our MC measures—foreign-born parents, foreign-born grandparents, and immigration index based on census linking—the results remain unchanged.[25]

To offer an additional angle on the relative importance of family history as compared to other key variables, we also build ridge regression prediction models and benchmark family history's importance for prediction against other variables. Appendix E describes our methodology, the details of the predictive models, their performance in and out of sample, as well as the details of the results summarized here below.

First, we directly evaluate variable importance with a standard machine-learning approach (Fisher, Rudin and Dominici 2019), permuting each predictor so as to be random and then calculating the loss in predictive power when assessing model predictions. Applying this variable importance approach to an extensive set of covariates, we find that family history ranks in the top five variables of more than thirty assessed and has predictive power comparable to canonical variables in legislative studies such as political party.

Second, we study how much changes in the composition of Congress could have mattered for whether legislation passed. For example, consider the set of restrictive immigration bills that passed in our time period: for such legislation, a one standard deviation increase in immigrant family history would predict that the majority support would flip in 5% of Landmark bills and 6% of all immigration bills. In comparison, a counterfactual shift of all MCs to the Republican party produces a similar magnitude change in bill outcomes. Overall, placing bounds on possible shifts in bill passage rates, we estimate that changes in the composition of Congress in terms of MCs descended from immigrants could plausibly have predicted shifts in roughly 15% of immigration legislation.[26]

More broadly, with these prediction exercises we do not seek to claim that family immigration history always amounts to the most important explanatory factor. Such a claim would be implausible, as well-known factors such as political ideology and party clearly structure a large part of activity in Congress, including immigration policymaking. Instead, these analyses show that for legislative behavior related to immigration, family immigration background rises to a point of importance approaching other well-studied characteristics thought to explain member behavior.

[25]The standardized regressions we report in Tables A.6 and A.7 might be complicated by the expected high correlation between MC ancestry and CD ancestry, but we found there is considerable variation in the correlation between district and MC-level variables depending on "generation," as we plot in Figure C.1 (0.41 for parents, 0.495 for grandparents, and 0.515 for immigration index). While some of these correlations are high, the comparisons we present in Tables A.6 and A.7 are meaningful and do not include two perfectly correlated variables.

[26]One important caveat to this exercise, discussed further in Appendix E, is that changes in the composition of Congress along any dimension might also shift the legislative agenda, including what legislation reaches the floor for a vote in the first place; thus, while helpful for exploring counterfactual scenarios, we urge some caution in moving beyond marginal interpretations for the role of legislator characteristics in explaining legislative outcomes.

3.2 Regression Discontinuity Analysis

The previous analyses demonstrate the strong correlation between an MC's immigration background and vote choices on immigration policy, even when accounting for the electoral incentives facing lawmakers in office through district-level controls. But district-level selection, where districts with a preference for inclusive immigration policies elect candidates with immigrant backgrounds, and not legislator's personal background and preferences, could also explain our results. While the sensitivity analysis performed in Section 3 suggests such a scenario is unlikely, we can nonetheless do more to separate the effect of electing immigrant-descended MCs from the effect of district preferences.

Figure C.1 plots the relationship between a district's foreign-born population share and the ancestry of the lawmaker it elects. We can compare MC and CD ancestry at the first-, second-, or third-generation or compare our summary immigration index measure. In all cases, the relationship is positive and close to linear. A district's composition correlates with both the immigrant background of lawmakers and with the votes cast by lawmakers representing those districts, presenting a potential challenge to estimating the effect of electing an immigrant-descended lawmaker.

To address this issue, we implement a regression discontinuity design (RDD) in which we compare the voting records for MCs from districts who *narrowly* elected a candidate with an immigrant background to districts who narrowly did not elect a candidate with an immigrant background. See Appendix D for more technical details on the RDD.

We want to be clear about what our RDD can (and cannot) estimate. Family immigration history is an immutable characteristic and could influence a person's entire life. The experiment generated by narrow elections between candidates with and without immigrant background allows us to unpack several key factors related to how MCs vote on legislation, but it does not necessarily allow us to compare the legislative behavior of two otherwise identical MCs. An immigrant background correlates with other characteristics too, and randomization of who wins through close elections may not entirely separate the effect of immigrant background from other *personal* characteristics. However, because the same district could be represented by an MC with or without an immigrant background, the RDD does allow us to better hold fixed district composition and thus the demand for an MC who is or is not descended from immigrants. Thus, this empirical exercise is particularly useful for accounting for district-level factors related to selection of congressional lawmakers.

To implement our RDD, we identify the electoral contests immediately preceding the term of each vote on immigration-related legislation. We focus on the full set of immigration final passage votes from the

51st–91st Congresses. Our design requires that we restrict our sample to a subset of elections in which a candidate with an immigrant background faces a candidate with no immigrant background and the outcome is close. We draw upon election data that includes the names and vote shares for candidates.[27]

We are unable to match losing candidates to the census—to determine their family immigration history—because we lack even the most basic information on their ages and places of birth. Instead, for the RDD analysis, we impute all candidates' immigration histories based on two name-based proxies for immigration history: our surname scores and f-indices (Abramitzky, Boustan and Eriksson 2020). Recall, the surname scores impute, based on surname and region for each candidate, immigration history based on the average number of foreign-born individuals, parents and grandparents for everyone recorded in the Census with that surname. The f-index is based on similar data but uses a normalized index and is less sensitive to outliers (rare names). For the sake of consistency, we use these surname-based approaches for election winners as well.[28]

How do we identify close elections where one candidate has a name that denotes an immigrant background and where one candidate does not? We coarsen the key measure of immigration history into a binary variable that denotes whether or not a candidate is considered to have a family history of immigration based on their surname. We chose a simple rule of thumb and set the binary indicator for a family immigration history equal to one for MCs with a Surname Score in the top half of the distribution for their region (or nationally when we use the national measure). We set the indicator to zero for MCs with a Surname Score in the bottom half of the distribution for their region (or nationally). Finally, so that someone with a surname in the 50.1 percentile would not be considered treated and compared to someone in the 49.9th percentile as a control, we applied a donut and excluded surnames that fell in the interval $(0.45, 0.55]$.[29] This approach restricts the sample to elections with one candidate with an immigrant background and one without such a background based on these thresholds for the Surname Score. We apply the same procedure when we use f-indices rather than Surname Scores to proxy for family history.

To make our procedure concrete, in the 1910 Census someone with the surname "FEIGENBAUM" residing in the northeast averaged 3.98 foreign-born grandparents. This ranked in the 82nd percentile in

[27] We focus on the top two vote getters. We exclude at-large House districts; often these districts attracted many candidates from the same party or had multiple winners.

[28] Appendix C.2 provides details and illustrates the close relationship between Surname Score, f-index, and actual immigration history. In Table D.8, we show robustness to using *actual* immigration histories for winning candidates (for whom we know the true ancestry from census linking) against *imputed* ancestry for the losers. We see that for most specifications our main finding holds: MCs with more immigrant ancestry are more likely to vote in favor of permissive immigration policies. These results are robust to all measures of immigrant ancestry among the losing challengers.

[29] $1(\text{Immigration History}_i)$ equals one when $F_{SS}(\text{Surname Score}_i) > 0.5 + x$, where $x = 0.05$; and, $1(\text{Immigration History}_i)$ equals zero when $F_{SS}(\text{Surname Score}_i) \leq 0.5 - x$, where again $x = 0.05$. All observations in $(0.5 - x, 0.5 + x]$ are excluded from the sample.

terms of foreign-born grandparents. Conversely, someone with the surname "PALMER," which averaged 1.20 foreign-born grandparents in 1910, ranked in the 17th percentile of surnames in terms of foreign-born grandparents. Thus, a close election between candidates named Feigenbaum and Palmer would generate as good as random variation in immigrant background as the winner would represent the same district in Congress, but possess different (imputed) immigration histories.

We estimate an equation of the form

$$y_{ib} = \alpha + \theta \cdot 1(\text{Immigration History Winner}_{ib}) + f(V_{ib}) + \gamma_b + \epsilon_{ib} \tag{4}$$

where $1(\text{Immigration History Winner}_i)$ denotes that the *winner* of the election has a Surname Score in the top of the distribution for the relevant measure of immigration history. θ, the parameter of primary interest, provides an estimate of the effect on vote choice of the as-if random assignment of an MC classified as having an Immigration History as compared to the vote choice by an MC classified as not having an Immigration History. The outcome variable y_{ib} denotes whether or not an MC cast a "pro" immigration vote. To estimate the RDD, we calculate optimal bandwidths (following Calonico, Cattaneo and Titiunik (2014)) and also use rule-of-thumb bandwidths of ± 5 and ± 10 for each regression. The term $f(V_{ib})$ is a function of the winning candidate's vote margin, which determines who wins the election and therefore treatment status, and we use a local linear specification estimated separately on each side of the threshold. We include bill fixed effects, γ_b.

[Table 3 about here.]

Estimating the effects separately using our three different measures of immigration history—parents, grandparents and Immigration Index—and our four different methods to convert surnames into ancestry—share or f-index, regional or national—we find a positive effect of having an immigration history on the probability of casting pro-immigration votes across all measures in Table III. The sizes of the point estimates vary only slightly depending on bandwidth. We start with Panel A where candidate ancestry is predicted using regional surname shares. When estimating the effect of electing an MC with foreign-born parents on pro-immigration votes, our results suggest a statistically and substantively significant increase of about 10 percentage points in the rate of casting a pro-immigration vote when we predict MC ancestry using the regional surname share (columns 1-3). Use of optimal, ± 5 or ± 10 bandwidths appears to make no appreciable difference for the magnitude or significance of this result. For grandparents and our immigration index, shown in columns 4 to 9, the estimates retain similar levels of statistical significance.

Ranging between 9 and 18 points, these coefficient estimates show that across the board electing MCs with immigrant family histories causes an increase in pro-immigration votes in Congress. The results from our other methods of predicting ancestry from surnames in Panels B, C, and D are similar. Overall, the effects are positive, of a notable magnitude, and statistically significant for all 36 specifications in Table III.

Figure III illustrates the main findings graphically using a linear functional form. The figures model the discontinuity between a narrow loss and a narrow win for a candidate with an immigration history (based on Surname Scores for each of our four measures) as compared to a candidate without such a history. As is evident, there is a visible discontinuity in the voting record at the threshold between a narrow loss and a narrow win for a candidate with an immigrant background.

[Figure 3 about here.]

Defining when candidates with "high" versus "low" probability of family immigration history actually face each other represents a key choice in our RDD. However, as we see in Figure IV where we plot the RDD results for different threshold choices, our results are robust no matter the precise threshold used. As we move to the right in Figure IV, we increasingly restrict the size of the sample by increasing the difference required to classify candidates as having more- or less-immigrant backgrounds.

[Figure 4 about here.]

Across all measures and all Surname Score thresholds, the results remain positive. In general, as we grow more restrictive in defining who has a surname denoting a family immigration history the effect sizes increase. This makes intuitive sense: setting $x = 0$ classifies some people as having an immigration history equal to one and others with an immigration history equal to zero when their Surname Scores are very similar. Such a coarse division likely adds considerable noise to our estimates. As the threshold grows more stringent, the distinction between a surname indicating an MC with a family history of immigration with an MC who does not have such a history grows sharper; but this comes with a loss of power and eventually we no longer have enough observations to estimate the effects.

We also confirm our RDD findings with a battery of additional robustness checks in Appendix D. Figures D.1 and D.2 show that our results are robust to changes in the RD bandwidth or using different local polynomial degrees. Table D.6 shows the discontinuity occurs at the 50-50 cutoff between winning and losing rather than at alternative placebo thresholds. Table D.7 shows that the effects also remain robust when dropping elections around the 50-50 threshold, suggesting that our results are not sensitive to strategic sorting or that immigrant candidates who narrowly win are more likely to moderate or (alternatively) emphasize their pro-immigrant views precisely when winning a narrow election. Tables D.9 and D.10 show that our findings are generally robust to using full names or first names to impute candidate immigrant ancestry, though the results using first name are noisier, likely because first names carry a weaker signal of ancestry. Tables D.11 and D.12 show that our findings are robust to using a triangular or uniform kernel rather than a Epanechnikov kernel when weighting observations around the cutoff in the RDD.[30]

Finally, Table D.1 shows that all district-level covariates are uncorrelated with an immigrant winning a narrow election.[31] Similarly, when we look at the characteristics of MCs in the districts with narrow elections in the Congress *before* the close election, we see balance across all MC-level covariates (see Table D.2).[32] Consistent with the fact that a close election between immigrant and non-immigrant candidates may not hold all other personal characteristics constant (since other personal characteristics correlate with immigrant status), we do observe that immigrant candidates who narrowly win elections are slightly more likely to be Democrats and to have less seniority than when a non-immigrant candidate wins. Thus, our RDD bundles the treatment of electing a candidate with an immigrant background with a treatment of electing a Democrat and a member with less seniority.[33] Importantly, however, our treatment does not appear to bundle ideology as we see balance on both dimensions of DW-Nominate.

3.3 Summary of Roll Call Vote Analysis

To summarize our findings on roll call voting, immigration family history correlates strongly with pro-immigration vote choices; this pattern holds even when accounting for party and underlying political ideology. These findings hinge neither on the varying compositions of the districts electing MCs nor varying electoral incentives faced by MCs in office.[34] The relative coefficient on family history is larger than that for district composition or party in standardized regressions, and family history ranks in the top handful of variables when benchmarked in variable importance against a wider set of variables in an alternative ridge

[30]In Table D.5, we present RDD results for our sample of landmark bills. We see positive effects in all but one case, echoing our results from Table III. However, only one of the 12 estimates is statistically significant at conventional levels (column 4). This is not surprising as we are under-powered compared to the all-bills case because the effective sample was several times larger in Table III than in the landmark sample.

[31]District-level characteristics include census region indicators; political outcomes (Presidential vote share and Presidential turnout); demographics (logs and shares of the foreign-born population, black population, female and male populations, urban population, and total population); ancestry shares by origin from Fulford, Petkov and Schiantarelli (2020); and economic measures from Fulford, Petkov and Schiantarelli (2020). In Table D.3, we report balance on our measures of local sentiment based on newspaper terms.

[32]MC-level characteristics include age, party, and tenure in Congress. We also see balance in lagged values of DW-Nominate first and second dimensions and lagged values of speech tone and counts from Card et al. (2022).

[33]However, as we show in Table D.4, our RDD results are robust to controlling for these bundled covariates of party and tenure.

[34]Differential patterns of missing data from census linking also do not appear to explain the results. Table A.31 replicates Table II using Surname Scores, which exist for all MCs.

regression predictive model (Appendix E.2). Based on counterfactual shifts, the composition of family histories in Congress could have proven pivotal in a meaningful share of immigration votes, comparable to canonical variables such as party, region and seniority (Appendix E.3). Finally, accounting for district-level selection through an RDD approach reveals that districts electing immigrant-descended MCs increase the odds of support for permissive immigration policies.

4 Congressional Speech and Immigrant Background

We next evaluate how an immigrant family history relates to an MC's presentation of self through floor speech. Floor speeches "increase members' visibility and voice in the legislative process" and provide chances for MCs to emphasize a policy area to their colleagues, constituents and the press (Pearson and Dancey 2011). At the same time, speech serves as a potentially less costly signal than a vote on a key policy issue. Speech is not binding; listeners interpret a speech's meaning, which can be revised and reinterpreted in ways that a roll call vote cannot. However, congressional speech is not entirely cheap talk; by taking a position on the record, MCs signal their views and priorities, and they may face consequences later for taking votes contrary to their speeches. Furthermore, giving a speech may involve a degree of agenda-setting power absent from roll call votes. Whereas a roll call vote involves casting a "yea" or "nay" vote on a question generally determined by congressional leadership, giving a speech involves making a less constrained choice about the subject matter to cover during a member's floor time. In this manner, choices made about the subject of a speech offer insight into a member's priorities and agenda.

Ultimately, our findings on speech echo our results in the previous section on roll call voting. We find that MC ancestry correlates with more positive speech sentiment about immigration and immigrants from MCs. We also see much larger correlations with ancestry than with district demographics or party in our standardized results. The close election RDD reveals that electing MCs with more immigrant ancestry leads on net to more positive tone about immigration and immigrants, holding district characteristics constant. We conclude by unpacking our tone results by speech frequency. We find that MCs with immigrant ancestry speak relatively *less* frequently about immigration and do not speak in positive terms more often than other MCs; instead, MCs with immigrant ancestry speak slightly less frequently about immigration in general and use negative language around immigration less often.

We start by estimating Equation 3 but replace the outcome with a measure of the tone of immigration speeches. Specifically, we use a measure of tone that ranges from -1 to 1 (with positive values indicating more positive tone) constructed in Card et al. (2022). We also include Congress and chamber fixed effects.

Table IV presents our first set of speech tone results. Across all three specifications and for all three of our measures of MC ancestry, we observe a positive and statistically significant association between family immigration history and the tone of immigration speeches; for instance, an additional foreign-born parent is associated with a roughly 0.018 to 0.023 point shift towards a more positive tone (roughly 7%-9% of a standard deviation). These results are also generally robust to the same additional controls that we used in the previous section on roll call votes as we document in Figures A.4, A.5, A.6, and A.7. The controls include additional extended district demographics, additional fixed effects, measures of local attitudes about immigration from newspapers constructed via MRP, local economic conditions, and local source-country immigrant ancestry shares.[35]

[Table 4 about here.]

When standardizing coefficients and comparing estimates for family history, district foreign-born population, and party, we find that family history appears to have the largest magnitude coefficients of these three explanatory variables for all specifications (Table A.20). A one standard deviation increase in Foreign-Born Parents is associated with a roughly ten percent of a standard deviation increase in the share of positive immigration speeches given by an MC, an estimate nearly three times larger than the magnitude of the estimate for district foreign-born population. In this manner, the results for tone align closely with our standardized regression results on roll call voting.[36]

Yet, just as with our roll call results, it could be the case that districts that demand MCs who talk more positively about immigration are also the districts most likely to elect MCs with immigrant family history. To hold demand for such MCs constant, we again turn to an RDD design and isolate the effect of electing MCs with a family immigration history on the tone of immigration speeches. Table V and Figure D.3 present the RDD results for speech. We see that the change from electing an MC with a family history of immigration to one without such a background leads to a positive shift in tone. The exact point estimate fluctuates between 0.03 and 0.20 points (where standard deviation in tone of speech is 0.21) depending on

[35]Of all the robustness results presented in Figures A.4, A.5, A.6, and A.7, only a handful of specifications, such as those with CD fixed effects and CD fixed effects by year trends, are not statistically significant. In Table A.14 our speech tone results are as robust as our roll call results to concerns about unobserved confounders, as any unobserved confounder would have to be as strong if not stronger than important controls like party fixed effects or district foreign-born population. In Table A.13, we also show that our speech tone results remain generally robust to the double or debiased machine learning procedure proposed by Chernozhukov et al. (2018). We find positive point estimates for all measures and only one of our 14 specifications includes zero in the confidence intervals.

[36]In parallel to our results for roll call voting, we also assess variable importance for tone of speech via a ridge regression model. Figure E.2 Panel B illustrates that, as with roll call voting, family history ranks among the most important variables in terms of predictors for tone on speech. When benchmarked against our other key variables, counterfactual scenarios with different compositions of Congress (e.g., more or fewer MCs with family histories of immigration) predict changes in tones of speech of a magnitude on the order of what would occur for similar changes in the composition of Congress along the dimension of political party. Appendix E provides the full details.

the exact specification and bandwidth and remains statistically significant in only 28 of 36 specifications, but the balance of the evidence suggests a positive effect.[37]

[Table 5 about here.]

As the tone of a speech involves a strategic expression of a members' ideological position, it follows that the results here echo our findings on roll call voting. But speech could be measured in quantity as well as quality. Counting speeches may capture different aspects of congressional behavior. Specifically, frequency of speech could help capture willingness to spend a member's valuable floor time on the topic of immigration. So, do MCs with immigrant ancestries allocate their floor time differently? We find that they do but in a surprising way.

We decompose the speech tone measure from Card et al. (2022) and count directly the numbers of positive and negative speeches about immigration MCs give. We turn to our RDD specification that generates variation in the ancestry of the winning candidate for a given district with a close election. Our outcome variables are $log(1+FloorSpeech_{it})$, where we count the total number of speeches about immigration or the number of positive or negative speeches as scored by the model in Card et al. (2022).[38]

In Table D.21 Panel A, we see a consistently negative estimate of the effect of electing an immigrant-descended MC on the frequency of congressional floor speeches about immigration, though the results are less statistically precise than our roll call or tone results (only two estimates are significant at better than the 5% level). As we see in Panels B and C, the reduction in immigration speech overall appears to be explained by declines in anti-immigration speeches rather than increases in pro-immigration speeches. We estimate null effects for changes in pro-immigration speeches (Panel B), but for anti-immigration speeches we observe effects ranging from -5 to -16 percent depending on specification (Panel C). Such a result appears consistent with MCs with family histories of immigration refraining from speaking during moments of anti-immigration sentiment in Congress, rather than making additional pro-immigration speeches.

Floor speech and roll call votes are two canonical forms of legislative behavior. However, MCs have historically used their voting and strategic communication tools differently, and we find that is the case in our context as well. While floor speeches allow MCs to engage in position taking—local press often reported directly on speeches given by a district's representatives—they retain discretion over whether to speak and what to say. Local press rarely reports on what MCs do *not* say. MCs with immigrant family

[37]Figures D.4-D.6 and Tables D.13-D.19 report a full battery of robustness checks. Table D.20 illustrates that the speech RDD results are again robust to including controls for party and tenure.

[38]We present the specification where treatment is defined using surname scores based on regional shares but our results are robust to the constructions of treatment. Our results are also robust to using inverse hyperbolic sine (Table D.22).

backgrounds appear to avoid outsize shows of pro-immigration rhetoric compared to MCs with no such family history; this could allow them to advance their agenda through votes without fomenting backlash from certain constituents or fellow members of Congress—especially during moments of fierce political conflict over immigration and assimilation, such as when landmark immigration legislation was on the agenda. Adopting a more cautious approach to floor speeches avoids drawing attention to their own heritage, signals their own assimilation, and avoids appearing to advocate for narrow, particularistic interests. These strategic choices by immigrant-descended MCs could allow them to to build coalitions and advance other policy priorities even while voting in favor of pro-immigration policies.

5 Selection into Immigration

Based on RDDs accounting for district-level selection, electing MCs with immigrant family histories directly increases both the number of lawmaker votes cast on permissive immigration policies and leads to speeches with on net more positive tones. While the RDD approach helps account for district-level selection, it does not address the possibility that the choice to immigrate (and thus who is descended from immigrants) is closely related to many other individual-level or family-level characteristics that might also contribute to support for permissive immigration policies. We therefore now seek to hold immigration-related background characteristics constant while allowing specific experiences related to international immigration to vary. This approach helps confirm that being descended from immigrants, and not other related characteristics, best explains the patterns we observe.

5.1 Family Traits

The decision to immigrate might be driven by a broader set of traits or values passed intergenerationally and also affecting MC ideology. Immigration, especially in the era we study, was a difficult journey that required severing ties with those left behind. It was also an expensive and risky undertaking, with potential immigrants moving to a new country they had likely never seen before. For these reasons, and more, self-selection might cause immigrant ancestors to vary on some dimensions, ranging from entrepreneurship, grit, and risk-taking to openness to new settings. MCs with immigrant family histories might support looser immigration restrictions because of these traits rather than international immigration itself.

But immigrants are not the only MC ancestors who might be self-selected. Migration *within* the US in the 19th and early 20th centuries shared many of the same challenges as international immigration, including long journeys, uncertain prospects, and breaking social bonds with familiar people and places, though of course, immigrants faced additional barriers, including language, culture, and navigating the immigration and legal systems. In an effort to account for these factors and to separate the role of international immigration from other elements common to both immigrants and migrants, we ask: Is there a difference between a family history of *immigration* and a family history of *migration* for immigration policymaking?

To answer this question, we examine the birthplaces, by state, of MCs, their parents, and their grandparents. We define migration history to be comparable to our definition of immigration family history but where migration identifies people who move across states within the U.S. An MC's parent is defined as a migrant if the MC was born in a different state from the MC and an MC's grandparent is defined as a migrant if the MC's parent was born in a different state from the MC's grandparent. As with immigration, we count the number of migrant parents and grandparents an MC has.

[Table 6 about here.]

Table VI replicates the paper's main results but includes controls for family migration history. We find that MC support for more open immigration policies is driven by MCs with family histories of international immigration not those with family histories of domestic migration. Across all specifications, the coefficient on immigrant family history is roughly three to eight times larger in magnitude than the coefficient on domestic migrant family history. Formal hypothesis tests where the null is equality between the coefficients estimated for immigrant ancestry and migrant ancestry allow us to reject the null in all specifications for both landmark and all bills, as reported in the bottom row of each panel. Furthermore, the coefficient on MC Migrant Ancestry is statistically distinguishable from zero in only a handful of cases, whereas the coefficients for MC Immigrant Ancestry are statistically significant across all specifications. In addition, under the theory that internal migrants who traveled longer distances may be most comparable to international immigrants, specifications accounting explicitly for distance traveled reveal that domestic migrants traveling longer distances appear no more likely to support permissive immigration policies (see Table A.28).

Finally, as one additional piece of evidence against selection based on family traits, in Table A.29, we also show that our main results are robust to controlling for an MC's own father's socio-economic status. Once we control for family immigration history, there is little to no correlation between father's economic status and how his future-MC child votes on immigration legislation, suggesting that although MCs with a family history of immigration were more likely to come from more humble backgrounds (lower father economic status), this does not explain our findings. Based on these results, we argue that our story is particularly about immigration, rather than some trait(s) common to all migrants.

5.2 Targets of Restrictive Immigration Policy

While "immigrant" or "descendant of immigrants" is one salient dimension of MC background, it elides variation in immigrant experience by country or continent of origin. Immigration bills can be coded as pro- or anti-immigration, but the legislation is often more complex: as an example, while the Johnson-Reed Act in 1924 severely curtailed immigration from Italy, the quotas were non-binding on Irish immigrants.

These targeted restrictions allow us to hold MCs' immigration experiences constant while varying whether MC family background is differentially targeted. We start by pooling landmark immigration votes where the countries of origin for some MCs in our sample were differentially targeted. Landmark bills voted on after the onset of WWI provide ideal test cases for the effects of differential targeting.[39]

To analyze the effects of differential targeting, we implement the estimation approach in Equation 3 but add an additional term interacting family immigration history with a variable indicating if the legislation targeted the nation of origin for an MC's immigrant ancestors. Specifically, we coded the target of legislation indicator to take the value of one if a member's parent (columns 1-4) or grandparent (columns 5-8) had a nation of origin targeted by the legislation, and the indicator takes a value of zero otherwise. For legislation that was permissive and had a mixed target, we coded all MCs' target indicator variable as zero.

Table VII, which reports the results, illustrates that not only does immigrant ancestry retain a positive association with permissive voting (e.g., voting against restrictive legislation and for permissive legislation), but also this relationship grows larger when MCs voted on legislation explicitly targeting their nation of origin. The coefficient estimate for immigrant ancestors targeted by the legislation is comparable to or larger than the estimate for immigrant ancestry on its own in every specification. While columns 1-3 and 5-7 replicate our previous approaches, columns 4 and 8 include MC fixed effects that leverage within-member variation in targeting. Since immigrant ancestry remains constant for each member, the individual fixed effect absorbs that coefficient; however, the interaction of the target term with immigrant ancestry yields a within-member estimate for targeting. In each case, we estimate a strong positive relationship between a member's ancestry being a target of legislation and permissive voting. Since this approach holds immigrant ancestries fixed while allowing specific experiences to vary, including within members, it again suggests that selection into immigration is unlikely to drive our results.[40] Furthermore, it points to the importance of group boundaries based upon nation of origin within the broader category of "immigrant" or "descendent of immigrant," which we explore further in the next section.

[39]The landmark bills before World War I either did not differentially target different foreign origins or, when they did, primarily targeted Chinese-origin immigrants, of whom there were none in Congress.

[40]We thank an anonymous reviewer for suggesting this approach.

[Table 7 about here.]

6 Mechanisms

We have established several results about the relationship between MCs with family histories of immigration and their stances on immigration policy. First, more recent familial immigration history correlates with MCs both casting roll call votes in support of more permissive immigration policies and speaking with more positive tone about immigration. Second, neither district composition nor party explain support for permissive immigration policies as well as family history does among MCs in office. Third, the core relationship between family history of immigration and legislative behavior persists when we take measures to account for district-level candidate selection and selection into immigration.

We now turn to the possible mechanisms that may help explain the relationship between immigration background and legislative behavior for members. We focus on three possible mechanisms: in-group identity, information, and correlated preferences.

6.1 In-Group Identity

Aspects of identity can be important components in economic decision making (Akerlof and Kranton 2000; Kranton 2016) and identity's effects extend to political choices—even of professional political actors. As the children or grandchildren of immigrants, MCs are members of an identity group. In-group identity in this context refers to the sense of belonging and shared experience that legislators feel due to their family's immigrant background and connection to a source country. MCs who are part of an immigrant-descended group may possess unique information about immigrants or share broader political preferences aligned with immigrant interests, but here we conceive of legislative behavior arising from group identity as driven by these MCs favoring others because they belong to the same group.

A long research tradition suggests that in-group identity can motivate favorable treatment towards other members of the same group (Tajfel 1982; Ben-Ner et al. 2009; Everett et al. 2015).[41] In the congressional context, group boundaries could reflect specific source countries of origin or encompass a broader immigrant identity, or multiple boundaries could prove salient. For instance, both an identity as "descended from Italian immigrants" and an identity based on the broader class "descended from immigrants" may matter to an MC whose grandparents immigrated from Italy. Our approach is to treat the extent to which different boundaries have mattered as an empirical question. To assess the evidence for a group

[41] Appendix Section B.3 provides detail on related concepts in the study of group identity that may motivate such behaviors.

identity mechanism as an explanation for permissive stances on immigration among MCs with a family history of immigration, we ask: (1) Do MCs with family histories of immigration exhibit behavior consistent with a group identity mechanism in general (e.g., pre-congressional career)? (2) Do they exhibit behavior consistent with a group identity mechanism while in Congress?

This paper documents three sets of results that all clarify how group identity may play a role. First, we will show that a family history of immigration correlates positively with a key indicator of identity expression, the first names MCs give to their own children born before their congressional careers. This action is consistent with attachment to a cultural identity related to the source country in MCs' immigrant family histories. Second, we will document that once in Congress MCs descended from immigrants speak about immigration using frames that are more personal, particularly appearing more likely to reference family and less likely to reference economic arguments when discussing immigration policy. Third, we have already documented that identity boundaries *within* the immigrant group grow more salient when particular bills restricted immigration differentially by nation of origin. This illustrates that group identities may emerge for specific sub-groups within the broader category of those descended from immigrants and that ethnic identity and immigrant history may interact. We will further explore the boundaries of these relationships by examining how MCs voted based on region of origin in a bill-by-bill analysis of landmark legislation. All together, these empirical patterns underscore the role of in-group identity, characterized by personal connection to an immigrant experience and cultural heritage, for immigrant-descended MCs.

6.1.1 MC Ancestry and Their Children's Names

Scholars view names as "signals of cultural identity" (Abramitzky, Boustan and Eriksson 2020, p. 126), and the choice of name for a child proxies for efforts at assimilating versus retaining connection to a source country identity. Studying naming has the advantage of offering insight into a choice made fully by the immigrant parents (Fouka 2019, p. 408), and for our purposes has the added advantage that we can focus on child names given before an MC ever served in Congress.[42] In this manner, studying MCs' choices about naming their children illuminates their attachments to group cultural identity in a manner plausibly distinct from concerns about catering to a political base constituency.

We begin by assessing simply whether MCs with histories of immigration tended to be more likely to give their children first names suggesting an immigrant identity. To measure the foreignness of a first name, we follow Abramitzky, Boustan and Eriksson (2020) and construct an f-index. The national distribu-

[42]Since 91% of MC children were born before the MCs entered Congress, this restriction barely shrinks our sample.

tion of first names in the population, recorded in each decennial census, determines a child's f-index score. Names held only by US-born individuals receive a score of 0; names held only by foreign-born individuals garner a score of 100. Our main dependent variable is simply the percentile of these f-index scores.[43]

[Table 8 about here.]

In Table VIII, we regress the foreignness of a child's first name on their MC parent's immigrant ancestry. In all specifications we include fixed effects and child-level characteristics including age, sex, and their interaction, as well as census year and MC chamber. We cluster our standard errors at the MC level to account for MCs with more than one child and multiple observations of the same child across censuses.

MCs with immigrant ancestry retain a connection to a group identity connected to immigrant status: As we see in Table VIII, MC Immigrant Ancestry predicts the granting of more foreign-sounding first names to MC children. Across all methods of measuring MC ancestry, we estimate a positive relationship. For example, an additional foreign-born parent predicts an increase in f-index of roughly 2 percentage points off an average base of 44, or a five percent increase. When we replicate this exercise for the full population from 1880-1940 in Table A.21, we also find a positive and statistically significant relationship between immigrant ancestry and f-index for child's first name for both MCs and non-MCs. Though the magnitude is larger for non-MCs, MCs still make naming choices based on their ancestry, just like others in the population descended from immigrants. Clearly, non-MCs do not make their naming choices based on electoral concerns and so these results suggest that non-electoral factors explain at least some part of MC naming choices as well. MCs with immigrant ancestry appear to have cultural attachments to an immigrant identity based on country of origin and not purely for political or strategic reasons.

6.1.2 Personal Frames in Immigration Policy Speech

In this subsection, we examine how family background correlates with specific *frames* and phrases MCs used in speech on immigration.[44] The logic behind this empirical test stems from past research showing that group membership based on a shared characteristic may lead people to "project relational (e.g., personal) ties onto relatively large collectives composed of many individuals with whom they have no personal relationships" (Swann et al. 2012, p. 441). Evidence of language evoking personal or family ties

[43] To assemble the data, we collected census observations of each MCs' children. We observe an MC's child in any census in which the MC and their children are co-habitating and we limit our sample to MC children who are born before their parent enters Congress. We construct these first name indices by sex to account for names that are used by both boys and girls during this period but are robust to using first name indices that do not vary by sex.

[44] Card et al. (2022) examine how MCs from different parties employ a variety of frames in their speech, which cover issues including "crime", "threat", "migration", "family" and several more.

in congressional debates would suggest that immigrant-descended MCs see immigration policy as a political issue intertwined with their own group identity. Specifically, language used on the floor of Congress that projects personal and family connections onto immigrant populations, and the polices affecting them, aligns with the theoretical prediction that group membership can foster a sense of personal connection even without a direct relationship with individuals comprising an immigrant group.

To convert immigration frames into an outcome variable, we calculate the share of all immigration speeches made by each MC in each Congress in each frame. Regressing this share on family immigration history using otherwise the same specifications as previously, we find that frames revolving around notions of "contribution", "culture", and "family" are all correlated positively (and statistically significantly) with a family history of immigration. On the other hand, frames related to "economic", "labor", and "legality" all register negative and statistically significant associations. Frames related to "crime" have negative coefficients but are not statistically distinguishable from zero in any of our specifications. Figure V reports the results for our specifications with and without controls for these key frames of immigration speech.[45]

[Figure 5 about here.]

This exercise requires parceling the immigration speech data into many subcategories, but the observed empirical patterns are still highly suggestive. MCs with immigrant family histories are more likely to emphasize family (both their own and families of immigrants generally). This more personal framing suggests group identity may play a meaningful role in motivating support for more permissive immigration policies (Scabini and Manzi 2011). Similarly, emphasizing cultural contributions of immigrants (the culture and contribution frames) aligns with valuing these group identities. In contrast, those with family histories of immigration also appear less likely to use economic or labor-related frames.

To assess further whether immigrant-descended MCs address immigration in a way that reflects a personal connection to the topic, we also examine the emotional affect displayed in their speeches on immigration. Past research has found that a salient group identity can lead to more intense emotional reactions to issues perceived as having relevance to the group (Kuppens and Yzerbyt 2012). Regressing a measure of emotional affect from Gennaro and Ash (2022) on our set of covariates, we find a positive association of family immigration history with the emotionality measured in MC immigration speeches in Table A.27. We view heightened emotionality for immigrant-descended MCs discussing immigration policy as also consistent with the increased personal connection to the topic of immigration evident in our study of speech frames.

[45]For the remaining frames, see Figure A.8. Figures A.9-A.14 report robustness checks to additional district-level covariates.

Finally, an unstructured approach to evaluating the content of immigration-related speech again broadly aligns with our findings using pre-determined frames and measures of emotional affect. When we evaluate the most distinctive phrases used by members with family histories of immigration versus those with no such family history using term frequency–inverse document frequency (tf-idf) for trigrams and bigrams, we find that the most distinctive phrases for members descended from immigrants are populated by terms related to family and humanitarian issues such as "mother american citizen", "wives children aliens", and "admission orphan children". In contrast, the most distinctive common phrases for members without family history of immigration include concerns about negative economic and cultural effects of immigration, characterized by terms such as "oversupply unskilled labor", "average farm wage", and references to "alien influences". Appendix I provides full details and additional discussion on our findings based on the exercise of comparing the most distinctive terms used by MCs across family histories of immigration.

Measuring the character of immigration speech through pre-established frames, emotional affect, and unstructured text, MCs descended from immigrants exhibit an increased tendency to discuss immigration in terms related to family and to immigrant well-being, and their language is more emotional. This constellation of findings suggests MCs descended from immigrants behaved in a manner consistent with belonging to an in-group based on immigrant identity while in Congress.

6.1.3 Nation of Origin

When examining landmark bills differentially targeting immigrants in Congress based upon source country, we observed that MCs descended from targeted countries were even more likely than their peers to oppose the restrictive legislation. A family history of immigration correlated with more permissive immigration policy stances on these landmark bills, but specific source country identities mattered as well. To explore the boundaries of group identity further, we examine bill-by-bill results decomposed by region of origin for landmark immigration bills. On a bill-by-bill basis, region of origin again tends to correlate with immigration vote choices when those votes targeted members' narrower (region-based) identity groups.

In the period between the world wars, MCs with family trees rooted in southern and eastern Europe (the "New European" source countries during the Age of Mass Migration), are more likely to vote against immigration restriction bills than MCs of "Old European" stock, and subtleties about the exact restrictions mattered as well.[46] On the other hand, for broadly permissive bills that did not target based on nation of origin and helped reshape U.S. immigration policy—e.g., post-WWII bills such as the Immigration and Na-

[46]We base these codings on Goldin (1994). Section C.6 in the Appendix lists the countries and regions that comprise Old Europe and New Europe, drawing on IPUMS birthplace codes.

tionality Act of 1965—the estimates are similar across MC immigrant backgrounds, regardless of whether the MCs' parents or grandparents came from New or Old Europe or the rest of the world. Similarly, during the pre-WWI era—when landmark legislation targeted groups not present in Congress such as Chinese immigrants—support did not differ meaningfully across regions of origin. To provoke heterogeneous responses from MCs appears to have required legislation targeting nations from which some immigrant MCs came and others did not. In this manner, the empirical evidence points to group boundaries mattering at both an immigrant-group level as well as a national- or regional-group level, with the salience of these demarcations depending upon specific legislative contexts.

The immigration restriction bills of the interwar era present the most direct test of whether nation of origin mattered (Pre-WWII Panel of Figure VI). The latter two of these bills symbolically and practically targeted immigrant populations other than those from Old Europe. The Immigration Quota Act (1921) sought to alter the distribution of immigrants such that Old Europe source countries would comprise 55% of immigrants and New Europe countries would comprise 45%; the Johnson-Reed Act aimed to further tip the balance to 84% Old Europe and 16% New Europe (Tichenor 2002, p. 145). The Immigration Act (1917) did not target New Europe immigration explicitly, but it implemented a literacy test and restricted Asian immigration (and also included exemptions for close family members of current immigrants). We regress a dummy for pro-immigration votes on MC immigrant family history, dividing origins by region: New Europe, Old Europe, and Non Europe.[47] We count the number of parents and number of grandparents born in each region, with US-born parents and grandparents as the reference group. Though MCs with any (recent) European family immigration history are more likely to vote against the three immigration restriction bills, the estimates are much larger for MCs with more parents or grandparents from New Europe when New Europe immigrants were targeted. Hypothesis tests comparing coefficient estimates for New Europe ancestry to coefficient estimates for Old Europe ancestry can be rejected at $p < 0.01$ for both the Immigration Quota Act and the Immigration Act of 1924. The Immigration Act of 1917, which differentially targeted Asian immigrants, does not allow us to reject the null of no difference in estimates for Non Europe ancestry versus New or Old Europe ancestry in three of four cases—an unsurprising result given that the non-Europe ancestry MCs in our sample at this time did not have Asian ancestry.[48]

[47] We report the regression results in Table A.16 Panel A and a series of explicit hypothesis tests in Table A.18. As some of these bills only saw recorded roll call votes in the Senate and we are running bill-by-bill regressions, we are not able to include our full set of controls.

[48] In Figure VI, we distinguish between Old and New Europe. However, this divide does not perfectly correlate with restrictive immigration policy, in particular the 1921 and 1924 quotas. In Table A.25, we partition countries into quota exposure based on the predicted missing immigrants measure from Ager et al. (2024), cutting at the median. The implications are essentially unchanged.

In the Post WWII Panel of Figure VI, we ask if the patterns changed after the war.[49] The McCarran Internal Security Act, enacted over Truman's veto, targeted Communists early in the Cold War. One provision relevant for our study: immigrants could have citizenship revoked if found in violation of the law within five years of naturalization. Old European heritage correlated with voting pro immigrant (against the act); New European heritage did as well. A hypothesis test does not allow us to reject the null of equality between these coefficient estimates. The McCarran-Walter Immigration and Nationality Act, enacted two years later and retaining a quota system, resembled in some ways the pre-WWII immigration restriction bills, and it targeted New Europe and Non Europe ancestry differentially. Consistent with this, we find that MCs with New Europe immigration history were much more likely to oppose it than those from Old Europe; hypothesis tests allow us to reject equality between the Old and New Europe coefficients at $p < 0.01$.

But while the McCarran-Walter bill activated identity based on national origins just as pre-WWII restriction bills had, the Refugee Relief Act of 1953 and the Immigration and Nationality Act of 1965, which both loosened immigration laws, appear different. MC immigrant background had a similar (positive) relationship with casting a permissive vote, regardless of where those MCs' families came from originally. None of the estimates (presented in the Figure and columns 5-8 of Table A.16 Panel B) allow us to reject the null of no difference between Old Europe and New Europe coefficients.[50]

More broadly, our results on group identity due to nation of origin highlight that national and ethnic identity likely help demarcate sub-group boundaries within the broader category of "immigrant". MC voting behavior for bills presenting stark demarcations based on ethnic identity, such as legislation related to Chinese exclusion, also align with this idea. We estimate the relationship between MC family immigration history and permissive immigration votes while including an interaction term between family history and an indicator for bills on the subject of Chinese Exclusion in Table A.17. While the main ancestry coefficient is positive and statistically significant, the interaction term attenuates the relationship completely: MCs descended from immigrants did not vote more permissively than their non-immigrant-descended

[49] Table A.16 Panel B reports the underlying regression results and Table A.18 again reports results of explicit hypothesis tests.

[50] For completeness, we also examine the landmark immigration legislation of the pre-WWI era in the top panel of Figure VI and Table A.15. The Geary Act (1892) extended the Chinese exclusion passed ten years before and added additional restrictions (e.g., identification requirements). Given that we observe no presence of Chinese-origin MCs during the period of voting on this bill, a theory of in-group identity depending on region of origin does not suggest differences in support for the legislation based on nation or region of origin here. As illustrated in the Pre-WWI panel of Figure VI and confirmed explicitly with hypothesis tests in Table A.18, we observe no meaningful difference in coefficient estimates broken out by region of origin for this vote. An important caveat for these estimates is that they reflect a small sample size since the early time period means we cannot successfully match as many MCs to their parents and grandparents. Furthermore, we did not have sufficient presence of MCs with New Europe ancestry for two of the Pre-WWI votes to make an estimate for this group. The next landmark bills during the pre-WWI period—the Immigration Act of 1903 and the Immigration Act of 1907—did not restrict immigrant groups specifically by region, rather targeting anarchists (the former bill) as well as people suffering from disabilities (both the former and, with some expansions, latter bill). We again do not observe any statistically significant differences by origin for MCs voting on this legislation.

counterparts when the subject of the vote was Chinese exclusion. This holds both overall and during the 51st through 64th Congresses when this subject was most salient to debates about immigration. Any sense of pan-ethnic immigrant identity appears to have run up against its limits when voting on Chinese Exclusion.[51]

[Figure 6 about here.]

Overall, these results suggest that when MCs faced a vote on legislation restricting immigration of people with family backgrounds similar to themselves, they were more likely to oppose the bill. While immigrants of all backgrounds had higher probabilities of opposing immigration restrictions on most votes, legislation targeting people of different backgrounds produced different levels of opposition. This points to the possibility of a role for immigrant "group identity" in legislative behavior, but also the conditions under which support for permissive immigration legislation based on background may break down.[52]

6.2 Information

The second possible mechanism we explore is information. In contrast to MCs with no (recent) foreign-born ancestry, MCs with a family history of immigration might possess more accurate information about immigration (and thus about the effects of restricting or liberalizing immigration policy). These MCs have first-hand experience with immigrants and immigration that could make them more empathetic to the plight of new immigrants. They might better understand the efficiency gains from immigration. Or, as a particularly successful descendant of immigrants, they might recognize, through introspection, the (high) potential upward mobility of immigrants to the US (Abramitzky et al. 2021a). Their own experience of mobility might also make them less likely to engage in zero-sum thinking (Chinoy et al. 2023). Though the information mechanism is a challenging one to assess, in this subsection, we present evidence that suggests that information about immigrant potential for upward mobility may increase support for immigration. However, this estimate is the same across MC immigrant backgrounds, consistent with an effect

[51] A final test approaches group identity from a different angle. How do MCs whose families descended from English-speaking source countries vote in Congress? While descended from immigrants, assimilation could have been easier due to shared language (and perhaps ethnic identity). Table A.26, where we include an interaction between MC family history and an indicator for recent UK, Irish, or Canadian ancestry, illustrates that *overarching* immigrant identity matters: even these MCs are still more likely to support pro-immigration legislation.

[52] A related question involves whether behavior related to group identity arises from intrinsic versus extrinsic motivations. Appendix F assesses this question in detail by examining MC behaviors across differing levels of district composition, differing levels of visibility of MC actions, and accounting for differing levels of visibility of immigrant background. Across these scenarios, actual family immigration history retains a stable and significant relationship with downstream outcomes. While a sense of group identity can matter whether arising from intrinsic (e.g., internal) or extrinsic motives (e.g., strategic motives related to base constituency), our analyses suggest that intrinsic factors play some role.

that is *not* differential between the descendants of immigrants and other MCs; thus, information about upward mobility appears unlikely to be driving our results.

To assess the information mechanism, we construct measures of intergenerational mobility. We summarize our approach—which follows Abramitzky et al. (2021a) but extends the sample to many more census-to-census links—here and provide full details in Appendix C.7. We use linked samples of fathers and sons to estimate rates of economic intergenerational mobility for the sons of immigrants and the US-born from 1850 to 1940 for each state and decade. We focus on the expected ranked outcome of a son with a father at the 25th percentile and rank states by mobility within each census.

We turn to the relationship between MC support for immigration and intergenerational mobility in Table A.19, with landmark bills in Panel A and all immigration bills in Panel B. We see that MCs from states with higher intergenerational mobility (a higher rank) are more likely to vote in favor of immigration, both on landmark bills and all immigration bills. This positive pattern holds whether we measure local mobility using overall rates (columns 1-2) or just mobility among the foreign-born (columns 3-4). This could signal that information about the prospects of immigrants matters; MCs from districts with more mobility might welcome more immigration because they have local evidence of immigrants moving up the intergenerational status ladder. However, it does not appear that MCs with more or less immigrant ancestry are differentially affected by this information. Interactions of intergenerational mobility with MC ancestry are economically small and not statistically significant in any of our four specifications.[53]

6.3 Correlated Preferences

Our third possible mechanism asks whether MCs might support immigration for ideologically strategic reasons. Efforts to shape the electorate—usually gerrymandering but also selective enfranchisement or disenfranchisement—date to at least the founding era. Immigration also changes the electorate. Potential immigrants, or their children, could eventually naturalize and become citizens and subsequently vote. If these future voters have political leanings aligned with MCs with immigrant family histories, then ideologically-motivated MCs might view increased immigration as a tool for bending policy in their preferred direction. One possibility is suggested by Giuliano and Tabellini (2020), who found stronger support for an expanded welfare state among immigrants than the US-born. In this case, lawmakers might sup-

[53]Three caveats to our mobility analysis: First, we cannot say whether mobility overall or among the sons of immigrants is driving our results because the rates are highly correlated. Related, we have no evidence that these higher rates of mobility were observable contemporaneously; other local conditions that might correlate with mobility could push MCs. Finally, other information about immigration and immigrants (and their effects) could be important and differential across MCs with and without (recent) immigrant ancestry.

port permissive immigration policies because inflows of immigrants to their districts would help build a constituency more likely to support their preferred policies.

To begin with, we view this mechanism as unlikely based on timing. Immigrants could only naturalize after five years and naturalization was far from universal (Shertzer 2016). While non-citizen immigrants were able to vote in 24 states and territories in the mid-19th century, during our period only a handful of states still allowed non-citizens to vote and none did after 1926 (Henderson 2017). Combined with high levels of geographic mobility among immigrants (Biavaschi and Facchini 2020), it appears unlikely that MCs expected immigration to alter the ideological make-up of their electorate.

Beyond timing, as we show in this subsection, there are empirical reasons to doubt the correlated preferences mechanism as well. We identify a distinction between support for permissive immigration and other liberal policies: controlling for other factors, lawmakers with an immigrant background do *not* generically favor liberal policies at a level that would suggest their strong support for increased immigration is merely a strategic attempt to change their future constituents. Instead, we find that immigrant family history is uniquely important for immigration policy.

[Figure 7 about here.]

Our analysis is straightforward: we compute the share of bills in different topic areas where immigration family history was a statistically significant predictor of liberal roll call voting. We do this in two samples: across all bills and across specific landmark legislation. First, we consider all bills in the 51st–91st Congresses. To implement this analysis, we classified bills with topic codes from Peltzman (1984), supplemented by our set of all immigration bills. These relatively broad topics include issues such as the Budget, Defense, and Domestic Social Policy. Following Washington (2009), we identified votes where the majority of one party favored legislation and the majority of the opposing party did not (that is, there was conflict over the vote) and coded these votes based on whether an MC supported the ideologically left position when voting (again, based on which party supported the legislation).[54] For each topic, we then ran regressions, bill-by-bill, of liberal votes on MC's Immigration Index. In Figure VII (other than the bottom 4 rows), we report the share of votes for each topic where we found a statistically significant result of Immigration Index on MC vote choice, controlling for other factors. By chance, we should expect 5 percent of individual votes to have a statistically significant relationship at $p < 0.05$ (the dotted vertical line). As the figure makes apparent, the Immigration category registers by far the greatest share of roll call votes where an MC's immigration history mattered, and it is also statistically different from the estimate

[54]We make this restriction to identify bills with substantively meaningful conflict, rather than all members voting the same way.

observed by chance. Immigrant background could of course matter for some other policy topics as well. We do observe that family immigration history predicts a liberal vote for topics related to Budget (General Interest) and Regulation (General Interest). But the results are not remotely as strong as in the immigration policy topic. For votes spanning the 51st–91st Congresses, an immigrant family history mattered most for bills related to immigration policy.

Second, we also directly compare landmark legislation on Immigration to other topic areas with major legislation (see the bottom four rows of Figure VII). We focus on landmark legislation passed in the areas of social welfare, transportation and the environment, selecting landmark votes using the same source and procedure as for the landmark immigration votes (Stathis 2014). Compared to major legislation, immigration legislation again registers the greatest share of roll call votes where an MC's immigration history mattered. In fact, neither the transportation nor the environment topics included a single bill where immigrant family background was correlated with vote choice at a statistically significant level. For social welfare, immigrant background helps explain some share of votes, though the estimated magnitude is still not as large as for immigration.

Overall, the share of bill-by-bill regressions where family immigration history is a significant explanatory factor is higher for immigration legislation than for other legislation. Averaging across bill topics, family immigration history is statistically significant in roughly 5% of regressions for other legislation; for immigration legislation, family immigration history is statistically significant at $p < 0.05$ about 24% of the time (Table G.1). Furthermore, these core results hold up under alternative approaches including a version where we place no restrictions on the direction of the vote (e.g., allowing for more liberal/permissive or conservative/restrictive changes in policy for immigration and other topic areas) as well as when we expand the pool of votes beyond those involving a high level of partisan conflict to all votes. Appendix G reports the full results of these exercises.

Finally, an alternative method for identifying the effects of leaders due to Jones and Olken (2005) yields the same, or possibly even stronger, conclusions about the unique importance of family history for immigration votes. When a turnover in MC due to death occurs that involves a within-district change in immigration background, immigration legislation is the *only* topic area where we can identify a change in the roll call voting behavior related to this change in office-holding. Appendix H reports the full results.

7 Conclusion

This paper has analyzed the relationship between lawmakers' immigrant backgrounds and their legislative behavior. We studied both landmark immigration legislation and general roll call votes related to immigration policy, as well as congressional speeches about immigration. Our results demonstrate a strong relationship between personal immigration history and MC vote choice on immigration policy from the late 19th century to the mid-20th century. MCs with parents or grandparents born abroad voted in favor of pro-immigration policies more than those whose families immigrated to the United States in earlier generations. Recent immigration experiences strongly predict votes for permissive policies, based on ideology measured through past roll call votes. Furthermore, this voting behavior is not just the result of pro-immigrant electorates selecting MCs with recent family immigration background, but occurs when implementing approaches designed to account for district-level characteristics, district-level selection and individual selection into immigration. The tone MCs use in their speech follows a similar pattern: electing MCs with more recent family history of immigration yields a more positive tone on average when talking about immigration, though this occurs because they make relatively fewer negatively-coded speeches about immigration.

Ultimately, an MC's group identity—belonging to a group based on family background, and making choices favorable to that group—appears to be the most crucial factor in explaining our findings. MCs, like the rest of the population with more recent immigrant family history, are more likely to give their children more foreign first names. In their speeches, MCs with immigrant family histories tend to emphasize personal and cultural aspects of immigration rather than economic or labor-related frames. Furthermore, the importance of in-group identity extends to one's specific nation or region of origin: we find that immigrants from Old Europe source countries reacted differently than immigrants originating from New Europe source countries when legislation differentially targeted New Europe immigrants with restrictions. Immigrant group identity also had some racial limits: when 19th century legislation limited Chinese immigration, MCs with immigrant ancestry did not vote differentially, as no MCs had Chinese immigrants in their family trees.

We find little support for other accounts that would explain the link between immigrant family history and permissive attitudes on immigration. The possibility that other characteristics common to migrants (domestic or international) explain our findings—consistent with explanations related to selection into immigration—do not appear consistent with the evidence we examine. A family history of domestic migration does not have the same explanatory power as a history of international immigration. Nor can we explain our findings with a correlated preferences account, in which MCs with immigrant backgrounds seek (through immigration) to reshape the electorate and further a broad set of policy goals. An immigrant family history appears to possess unique explanatory power for decisions related to future immigration policy, but not for roll call votes on many other policies.

Our findings highlight the critical role of identity in politics—for politicians themselves and for citizens in general. Much of the literature on political identities focuses on descriptive characteristics such as race and gender, but other characteristics, somewhat less easily observable, also play a critical role in explaining MCs' legislative behavior. While immigration is closely tied to race and ethnicity, being an immigrant is also a distinct identity that varies within racial and ethnic groups. Immigration background has a crucial temporal component—people with the same ethnic backgrounds may be immigrants themselves or descendants of immigrants with widely varying generational proximity to the immigration experience.

Our paper also helps unpack what group boundaries are most relevant in a policymaking context by treating the extent to which group boundaries have mattered as an empirical question to test. We have let group boundaries vary in our assessment of immigrant history—considering not only temporal aspects (proximity/generational distance), but also visibility (surname), subregional identities (and when these are/are not salient), and the extent to which a group is targeted by restrictive policies. By unbundling immigrant background into component parts, we have sought to add breadth and depth to accounts of the role of immigrant identity.

Finally, personal characteristics and identity cannot be overlooked when seeking to understand legislative behavior. Fenno (1978) famously asked what elected representatives see when they look at their constituency. Our paper has sought to turn a lens inward. What do legislators see when they look at themselves? This paper provides evidence that when setting immigration policy personal and family history matter, even several generations into the past; and, our findings raise the possibility that other dimensions of family history should be taken into account when studying the behavior of elected representatives in other policymaking domains.

Supplementary Material

An Online Appendix for this article can be found at The Quarterly Journal of Economics online.

Data Availability

Data and code replicating the tables and figures in this article can be found in Feigenbaum et al. (2025) in the Harvard Dataverse, https://doi.org/10.7910/DVN/R1PCY6.

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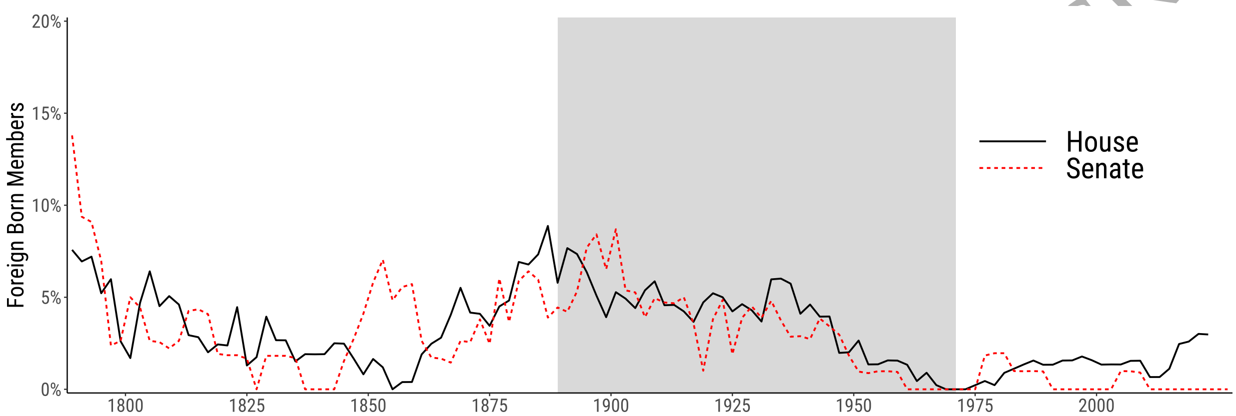
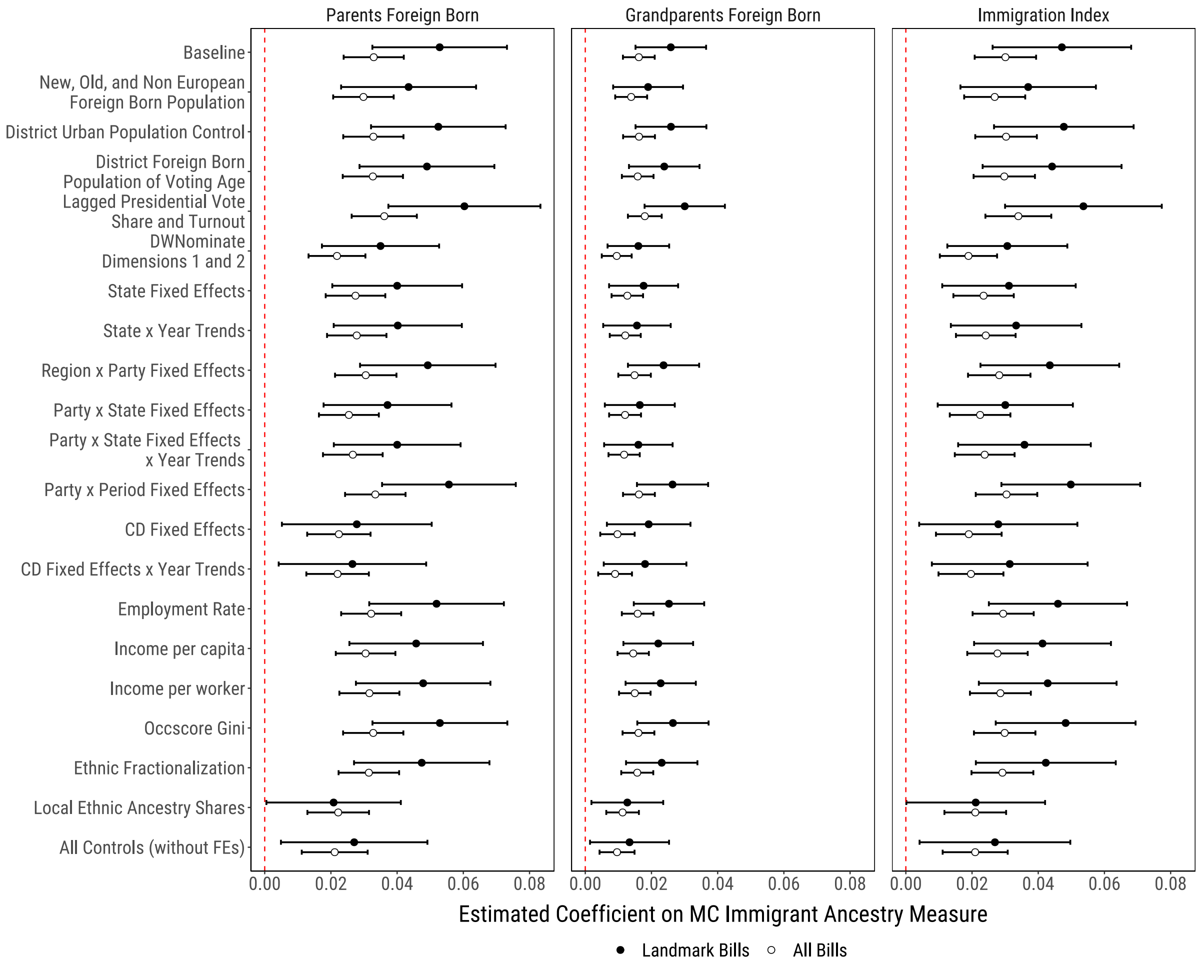
Figure I: Foreign-Born Members of Congress, 1789-2018



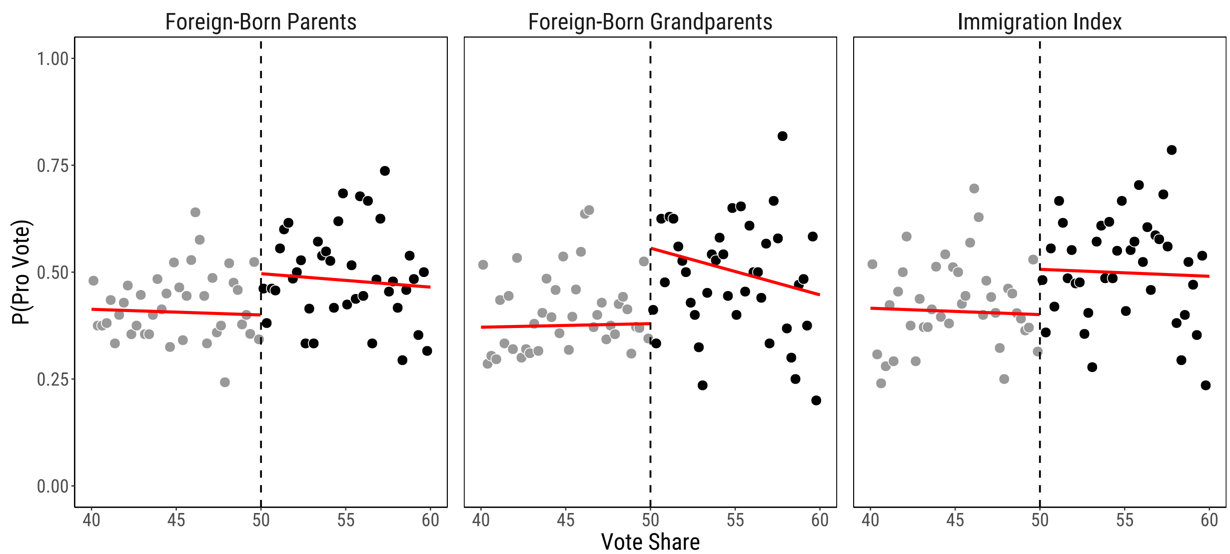
Note: This figure illustrates the percentage of foreign-born members in the US House of Representatives (solid red line) and in the US Senate (dashed blue line). MC birthplace is drawn from the Biographical Directory of the United States Congress. The period studied in this paper is denoted with a a gray box. While MC birthplace is relatively simple to collect for this period, tracing foreign-born family history requires additional sources like linking to the complete count censuses. With some notable exceptions (in the 1850s for example) the House has tended to have a larger share of foreign-born members than the Senate. From the 1870s to the 1930s, both chambers of Congress reached or surpassed five percent of all members as foreign born. Since then, both chambers have seen sustained declines.

Figure II: Robustness of Immigration History and MC Vote Choice



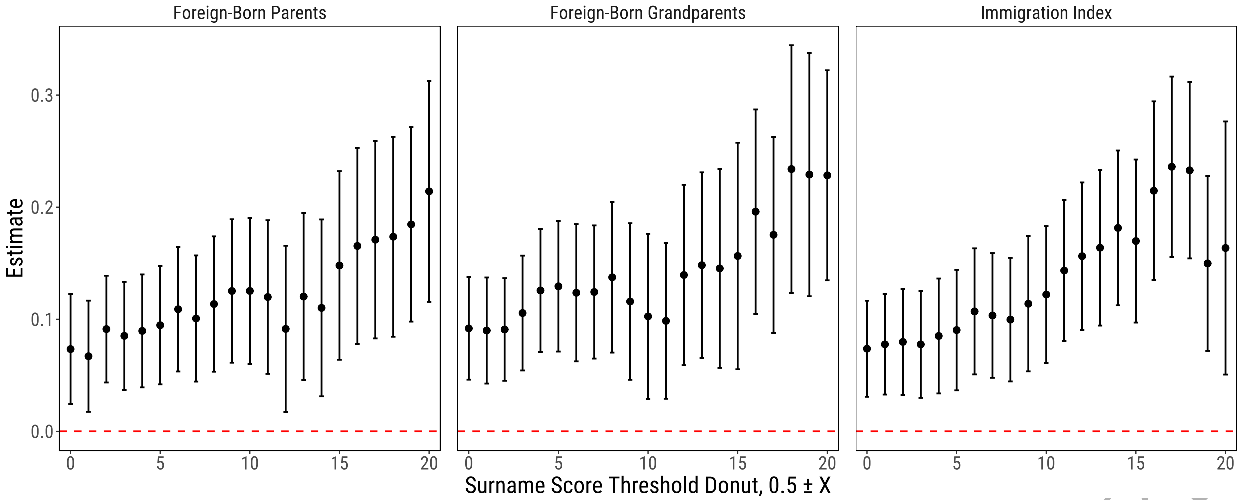
Note: This figure reports results from regressing an indicator for pro immigration roll call votes on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. The black points indicate models using the landmark immigration legislation listed in Table I and white points indicate models using all immigration bills. In the first row (baseline), the estimates include bill fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, black population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the foreign-born population from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford, Petkov and Schiantarelli (2020). Next, we show that our results are robust to controlling for local ethnic fractionalization and then local ethnic population shares. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level. See the Table II notes for more on MC immigrant ancestry definitions.

Figure III: RDD: Effect of MC Immigration History (Surname Score) on probability of casting Pro Immigration Vote, 51st–91st Congresses



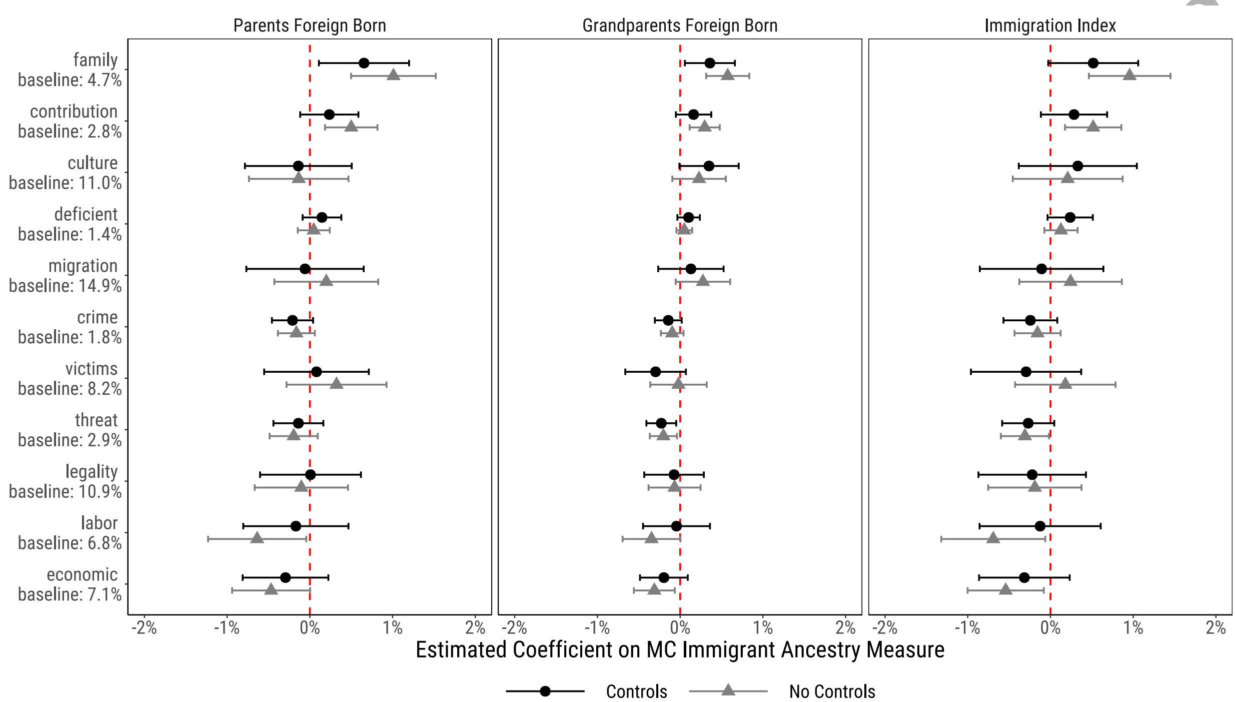
Note: For each measure of family immigration history, we estimate the effect of immigration family history on supporting permissive immigration policies in final passage votes for immigration bills between the 51st and 91st Congresses. The sample is constructed by focusing on elections in which one candidate possessed an immigrant family history and one candidate did not. In this case, candidates with an immigrant family history are determined based on surname. Each dot represents the share of candidates who voted pro immigration in a given vote share bin. We present 40 bins on either side of the discontinuity using the mimicking variance evenly-spaced method from Calonico et al. (2017). We identify the effect by using close elections in which a candidate with an immigrant family history narrowly won or narrowly lost the election. Across all three measures of family history, we observe a significant and positive effect on support for permissive immigration legislation.

Figure IV: RDD Robustness Check: Sensitivity of Estimates to Surname Score Cutoff Donut for Treatment Assignment (Optimal BW)



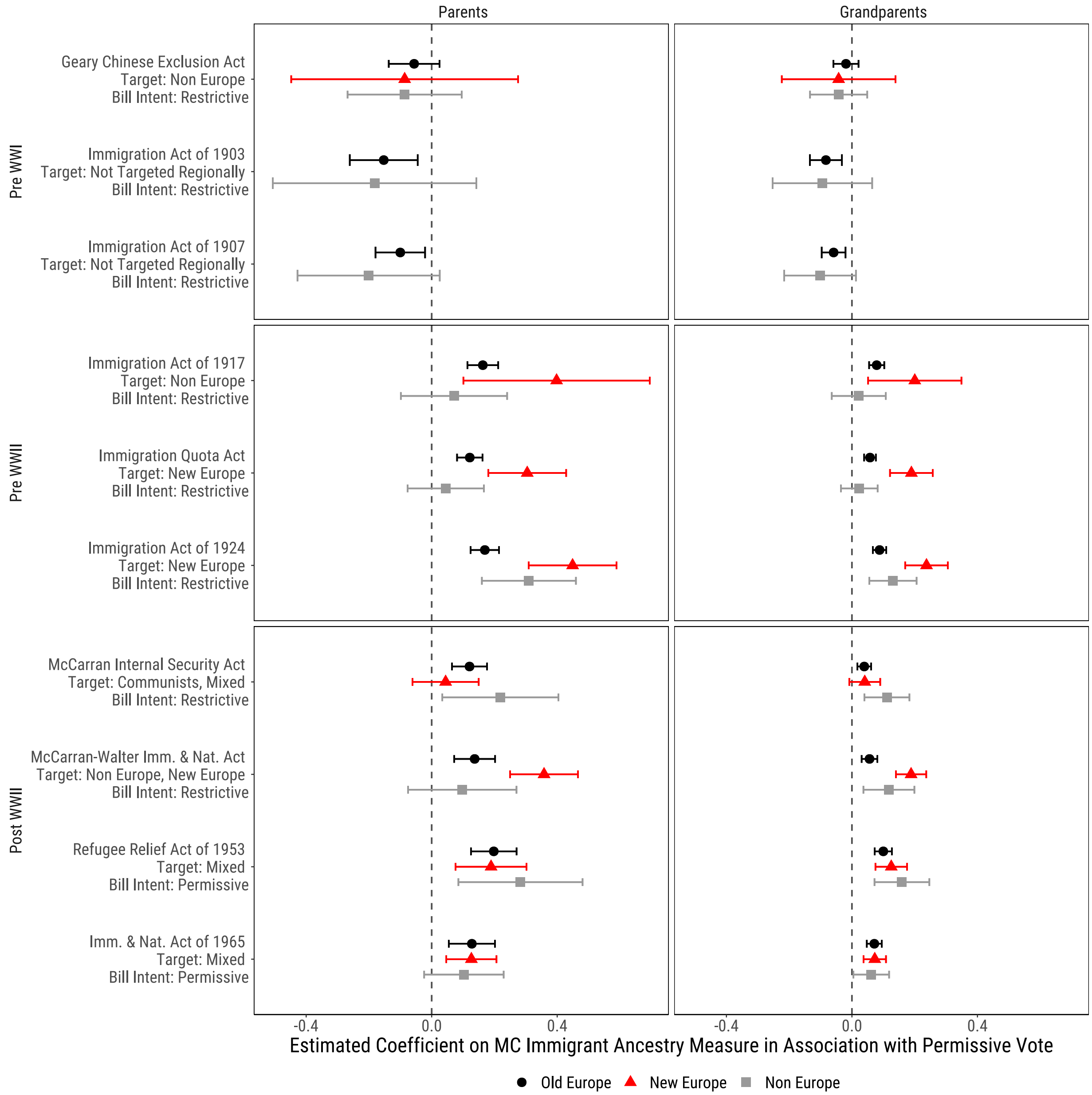
Note: This figure reports RDD estimates for different cutoffs in determining the threshold for classifying a surname as denoting foreign-born. Moving from left to right along the x-axis varies the threshold calculation used to determine when the binary variable indicating an immigrant family history takes a value equal to one. For example, when $x = 0$ individuals with a Surname Score higher than the 50th percentile are classified as having a family immigration history and individuals whose Surname Score is below the 50th percentile are not. When $x = 10$, then individuals with a Surname Score higher than the 60th percentile are classified as having a family immigration history equal to one and individuals with a Surname Score less than or equal to the 40th percentile are assigned a zero; all others would be excluded from the sample. We continued to estimate the RDD results as long as we retained at least 50 effective observations. We perform a local linear regression to estimate the discontinuity and the sample is determined using an algorithm for optimal bandwidth (Calonico, Cattaneo and Titiunik 2014) in the running variable (vote share).

Figure V: Relationship between Family Immigration History and Frames Used for Immigration Speech



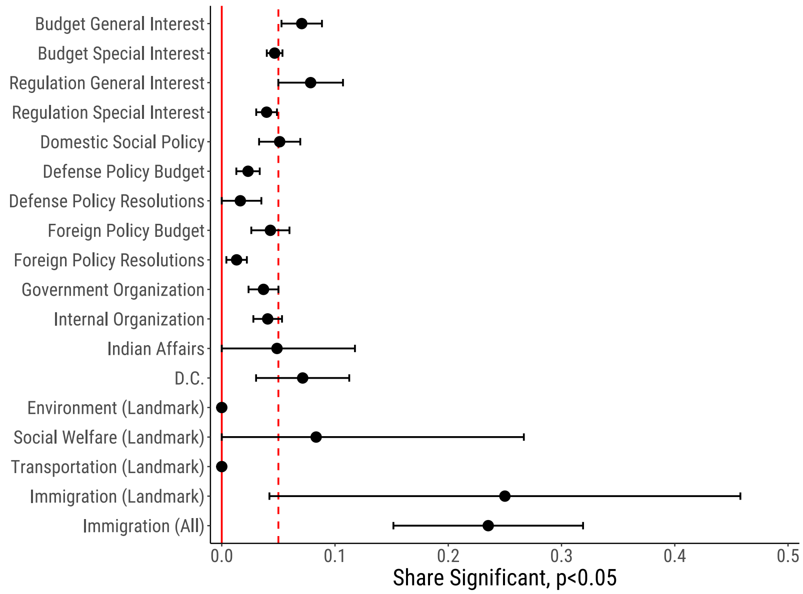
Note: This figure reports the estimated relationship for MCs between family history (measured as number of foreign-born parents or grandparents) and use of specific frames in speeches in Congress about the subject of immigration. The data on frames is calculated as the share of all speeches on the subject of immigration that reference a particular frame. We report here a subset of possible frames based upon those that had a significant (or close to significant) relationship with family history of immigration. Under each frame identified with a y-axis label we report the baseline mean for the frame (e.g., what share of the time did the average MC with no family history of immigration employ the given frame when speaking about immigration?).

Figure VI: Relationship between Family Immigration History and Permissive Immigration Voting, by Nation of Origin



Note: This figure reports the estimated relationship for MCs between family history (measured as number of foreign-born parents or grandparents) and casting permissive votes on landmark immigration legislation. Each bill is coded so that a permissive vote is the positive outcome. MCs' family history is decomposed by nation of origin into those with "Old Europe", "New Europe" and "Non Europe" heritage. For each bill under consideration, we also report the group or groups primarily targeted by the legislation (relatively speaking) as well as if the legislation itself was primarily permissive or restrictive.

Figure VII: Immigration History and Permissive/Liberal Votes for Placebo Topics, 51st–91st Congresses



Note: This figure reports estimates for the coefficient on the immigrant family history variable in regressions with outcomes being a range of placebo topic roll call votes during the 51st–91st Congresses. For each topic (as defined by Peltzman (1984)), we identified all votes in our time period where conflict existed—based on whether majorities of each party opposed one another—and then for each bill we regressed vote choice on Immigration Index, district composition and all other covariates included in our main specifications. We then plot the share of regressions for each topic in which the coefficient for Immigration Index is statistically significant ($p < 0.05$) for vote choice. While family history is a frequent and strong predictor of roll call voting on all Immigration final passage votes, as well as major legislation affecting immigration policy (as defined by Stathis (2014)), family history is not a frequent significant predictor of voting in almost every other area. For the bottom four rows in the figure, we performed a similar exercise for major legislation in the policy areas of immigration, transportation, the environment and social welfare.

Table I: Landmark Immigration Bills

Congress	Bill		Roll Call #	Pro Immigrant	Yea	Nay
52	HR6185	Geary Chinese Exclusion Act				
		House	96	Nay	188	27
		Senate	42	Nay	30	16
52		Gresham-Yang Treaty				
		Senate	447	Nay	51	25
57	HR12199	Immigration Act of 1903				
		House	170	Nay	140	68
59	S4403	Immigration Act of 1907				
		House	110	Nay	194	101
		Senate	110	Nay	15	30
64	HR10384	Immigration Act of 1917				
		House	121	Nay	309	117
		Senate	324	Nay	65	22
67	HR4075	Immigration Quota Act (1921)				
		House	21	Nay	285	41
		Senate	21	Nay	90	2
68	HR7995	Immigration Act of 1924 (Johnson-Reed Act)				
		House	90	Nay	319	72
		Senate	126	Nay	72	11
80	S2242	Displaced Persons Act of 1948				
		House	N/A (no final roll-call vote)			
		Senate	198	Yea	75	17
81	HR9490	McCarran Internal Security Act (1950)				
	S4037	House	264	Nay	302	56
		Senate	444	Nay	77	12
82	HR5678	McCarran-Walter Immigration and Nationality Act (1952)				
		House	165	Nay	284	116
		Senate	298	Nay	60	31
83	HR6481	Refugee Relief Act of 1953				
		House	64	Yea	225	189
		Senate	82	Yea	63	30
89	HR2580	Immigration and Nationality Act of 1965				
		House	177	Yea	330	79
		Senate	232	Yea	80	20

Note: This table reports landmark immigration legislation. We coded each piece of legislation based on whether a Yea or Nay vote aligned with a more permissive (more pro immigrant) stance. The totals for Yeas and Nays include announced votes and paired votes. There is no bill number for the Gresham-Yang Treaty. We use the veto override votes for the Immigration Act of 1917, the McCarran Internal Security Act, and the McCarran-Walter Immigration and Nationality Act.

Table II: Immigration History and MC Vote Choice

Panel A. Pro Immigration Vote in Landmark Bill Sample

	MC Immigrant Ancestry Measured as: Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.078***	0.075***	0.053***	0.037***	0.037***	0.026***	0.065***	0.065***	0.047***
	(0.012)	(0.011)	(0.010)	(0.006)	(0.006)	(0.005)	(0.012)	(0.011)	(0.011)
Log Foreign Born Population in Congressional District	0.056***	0.046***	0.048***	0.082***	0.052***	0.053***	0.085***	0.053***	0.054***
	(0.005)	(0.008)	(0.008)	(0.007)	(0.010)	(0.010)	(0.007)	(0.010)	(0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,901	3,901	3,901	2,714	2,714	2,714	2,714	2,714	2,714
Adjusted R^2	0.28	0.31	0.36	0.35	0.38	0.42	0.35	0.38	0.42

Panel B. Pro Immigration Vote in All Immigration Bill Sample

	MC Immigrant Ancestry Measured as: Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.045***	0.045***	0.033***	0.022***	0.023***	0.016***	0.040***	0.041***	0.030***
	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.006)	(0.005)	(0.005)
Log Foreign Born Population in Congressional District	0.038***	0.038***	0.039***	0.044***	0.037***	0.039***	0.046***	0.038***	0.039***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,390	19,390	19,390	14,119	14,119	14,119	14,119	14,119	14,119
Adjusted R^2	0.34	0.35	0.37	0.35	0.36	0.37	0.35	0.36	0.37

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports results from regressing an indicator for pro immigration roll call votes on family immigration history, congressional district foreign-born population, congressional district total population, and other covariates. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 to 3, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 4 to 6, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 7 to 9, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index. In the table, each column includes bill fixed effects and a variable indicating whether the member was in the House or in the Senate. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. Other CD controls include census region fixed effects and log Black population. Other MC controls include party fixed effects and quadratics in age and tenure. Standard errors clustered at the MC level.

Table III: Regression Discontinuity: Imputed Immigration History and Vote Choice, All Bills Pooled

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.095***	0.100***	0.097***	0.129***	0.179***	0.177***	0.090***	0.109***	0.106***
	(0.027)	(0.035)	(0.026)	(0.030)	(0.042)	(0.029)	(0.027)	(0.036)	(0.025)
N	5316	5316	5316	4770	4770	4770	5393	5393	5393
N (Effective)	2404	1428	2558	2202	1301	2281	2330	1532	2648
Bandwidth	$\pm$9.07	$\pm$5	$\pm$10	$\pm$9.49	$\pm$5	$\pm$10	$\pm$8.3	$\pm$5	$\pm$10

	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.091***	0.082***	0.130***	0.089***	0.078**	0.109***	0.071***	0.077**	0.105***
	(0.022)	(0.030)	(0.022)	(0.027)	(0.036)	(0.026)	(0.025)	(0.034)	(0.025)
N	5610	5610	5610	5294	5294	5294	5538	5538	5538
N (Effective)	3065	1764	2996	2602	1568	2744	2811	1690	2909
Bandwidth	$\pm$10.32	$\pm$5	$\pm$10	$\pm$9.15	$\pm$5	$\pm$10	$\pm$9.39	$\pm$5	$\pm$10

	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.107***	0.116***	0.115***	0.102***	0.151***	0.134***	0.115***	0.119***	0.133***
	(0.027)	(0.034)	(0.025)	(0.027)	(0.041)	(0.029)	(0.026)	(0.034)	(0.025)
N	5382	5382	5382	4783	4783	4783	5414	5414	5414
N (Effective)	2336	1465	2600	2516	1308	2283	2471	1563	2665
Bandwidth	$\pm$8.55	$\pm$5	$\pm$10	$\pm$11.41	$\pm$5	$\pm$10	$\pm$8.88	$\pm$5	$\pm$10

	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.071***	0.076**	0.099***	0.121***	0.094***	0.134***	0.086***	0.076**	0.100***
	(0.024)	(0.031)	(0.023)	(0.027)	(0.036)	(0.025)	(0.025)	(0.033)	(0.024)
N	5665	5665	5665	5479	5479	5479	5648	5648	5648
N (Effective)	2853	1759	3031	2484	1634	2862	2825	1748	2983
Bandwidth	$\pm$9.03	$\pm$5	$\pm$10	$\pm$8.19	$\pm$5	$\pm$10	$\pm$9.18	$\pm$5	$\pm$10

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Each panel presents results from different methods of predicting ancestry based on surnames (regional or national, simple shares or an f-index measure). Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ± 5, and ± 10) for the running variable vote share. Standard errors are clustered at the MC level. The positive and statistically significant estimates across all specifications suggest that electing MCs with a family history of immigration increases the probability of casting a vote in favor of permissive immigration policy.

Table IV: Immigration History and Immigration Speeches: Tone

	Card Tone on Immigration Speech								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.023***	0.020***	0.018***	0.010***	0.008***	0.008***	0.018***	0.014***	0.013***
	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Log Foreign Born Population in Congressional District	0.022***	0.028***	0.021***	0.026***	0.032***	0.023***	0.027***	0.033***	0.023***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	No	Yes	No	No	Yes	No	No	Yes
Other MC Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,720	9,720	9,720	6,599	6,599	6,599	6,599	6,599	6,599
Adjusted R^2	0.13	0.14	0.15	0.14	0.16	0.16	0.14	0.16	0.16

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports the relationship between the key measures of family immigration history and the tone of MC immigration speech. A higher value reflects more positive tone. Specifically, tone is calculated in Card et al. (2022) by subtracting the share of negative tone speeches from positive tone speeches, where each speech is classified via a human-trained machine learning classifier. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 to 3, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 4 to 6, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 7 to 9, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index.

Table V: Regression Discontinuity: Imputed Immigration History (Surname Score) and Speech, Card Tone

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.057*	0.191***	0.103***	0.027	0.069	0.051	0.069**	0.161***	0.086***
	(0.031)	(0.043)	(0.031)	(0.032)	(0.047)	(0.034)	(0.031)	(0.041)	(0.030)
N	2598	2598	2598	2376	2376	2376	2692	2692	2692
N (Effective)	1242	710	1280	1235	647	1155	1281	757	1347
Bandwidth	±9.6	±5	±10	±10.83	±5	±10	±9.2	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.032	0.107***	0.041	0.073**	0.150***	0.086***	0.058*	0.141***	0.074***
	(0.029)	(0.038)	(0.027)	(0.033)	(0.039)	(0.028)	(0.032)	(0.040)	(0.028)
N	2789	2789	2789	2716	2716	2716	2833	2833	2833
N (Effective)	1363	880	1481	1092	809	1408	1229	869	1480
Bandwidth	±8.78	±5	±10	±7.13	±5	±10	±7.7	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.058*	0.184***	0.101***	0.054	0.095**	0.072**	0.076**	0.204***	0.099***
	(0.030)	(0.042)	(0.031)	(0.035)	(0.045)	(0.033)	(0.032)	(0.041)	(0.030)
N	2631	2631	2631	2392	2392	2392	2689	2689	2689
N (Effective)	1323	724	1300	1034	654	1165	1161	767	1338
Bandwidth	±10.23	±5	±10	±8.59	±5	±10	±8.28	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.034	0.091**	0.050*	0.076**	0.128***	0.094***	0.033	0.085**	0.051*
	(0.029)	(0.039)	(0.028)	(0.031)	(0.038)	(0.027)	(0.027)	(0.036)	(0.026)
N	2819	2819	2819	2792	2792	2792	2890	2890	2890
N (Effective)	1443	894	1506	1229	853	1463	1477	925	1537
Bandwidth	±9.31	±5	±10	±7.79	±5	±10	±9.34	±5	±10

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election on the tone of immigration speeches given. Each panel presents results from different methods of predicting ancestry based on surnames (regional or national, simple shares or an f-index measure). Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level. The positive estimates across most specifications suggest that electing MCs with a family history increases the chances for giving more positive speeches about immigration, although the statistical significance varies depending on the specification.

Table VI: Immigration History and MC Vote Choice: All Bills Pooled, Family Migration History Controls

	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.077***	0.080***	0.056***	0.037***	0.041***	0.028***	0.065***	0.073***	0.053***
	(0.012)	(0.012)	(0.011)	(0.007)	(0.007)	(0.006)	(0.013)	(0.012)	(0.012)
MC Migrant Ancestry	0.012	0.023**	0.017*	0.005	0.011	0.005	0.008	0.023	0.015
	(0.011)	(0.011)	(0.010)	(0.008)	(0.008)	(0.008)	(0.015)	(0.015)	(0.014)
Log Foreign Born Pop in Congressional District	0.064***	0.054***	0.055***	0.088***	0.055***	0.055***	0.092***	0.055***	0.055***
	(0.006)	(0.009)	(0.008)	(0.007)	(0.011)	(0.011)	(0.007)	(0.011)	(0.011)
Log Migrant Pop in Congressional District	−0.059***	−0.042***	−0.034**	−0.055***	−0.017	−0.012	−0.059***	−0.026	−0.018
	(0.012)	(0.015)	(0.014)	(0.015)	(0.018)	(0.018)	(0.016)	(0.019)	(0.018)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,881	3,881	3,881	2,697	2,697	2,697	2,697	2,697	2,697
Adjusted R^2	0.29	0.31	0.36	0.35	0.38	0.42	0.35	0.38	0.42
p-value Hyp Test: Immigrant Coef = Migrant Coef	<0.001	<0.001	0.001	<0.001	<0.001	0.001	<0.001	<0.001	0.005

	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.046***	0.049***	0.037***	0.024***	0.026***	0.017***	0.039***	0.044***	0.031***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)
MC Migrant Ancestry	0.007	0.013***	0.012***	0.005	0.008**	0.003	0.001	0.009	0.004
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.007)	(0.007)	(0.006)
Log Foreign Born Pop in Congressional District	0.041***	0.042***	0.041***	0.047***	0.039***	0.039***	0.049***	0.040***	0.039***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)
Log Migrant Pop in Congressional District	−0.026***	−0.022***	−0.013**	−0.024***	−0.012	−0.003	−0.023***	−0.013	−0.004
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,329	19,329	19,329	14,045	14,045	14,045	14,045	14,045	14,045
Adjusted R^2	0.35	0.35	0.37	0.35	0.36	0.37	0.35	0.36	0.37
p-value Hyp Test: Immigrant Coef = Migrant Coef	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates Table II but includes an additional control for domestic migrant family history in addition to our key variable, international immigrant family history. We define migrant history comparably to immigrant family history but where migration identifies people who move across states (within the U.S.) rather than across countries. An MC is a migrant if he or she represents a state in Congress that is not his or her birthstate. An MC's parent is defined as a migrant if the MC was born in a different state from the parent, and an MC's grandparent is defined as a migrant if the MC's parent was born in a different state from the grandparent. As with immigration, we count the number of migrant parents and grandparents each MC has. In the table, the controls match the controls used in Table II; we also add a control for the log of the migrant population in a district, parallel to our control for the log of the foreign-born population. In Panel A, the sample includes votes on the key immigration legislation listed in Table I, while Panel B includes all immigration votes. The bottom row of each panel reports the p-value from a

Table VII: Targeted Immigration Legislation and MC Vote Choice

	Parents				Grandparents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MC Immigrant Ancestry	0.084***	0.080***	0.061***		0.038***	0.037***	0.027***	
	(0.013)	(0.012)	(0.012)		(0.006)	(0.006)	(0.006)	
MC Immigrant Ancestry × Target of Legislation	0.098***	0.073**	0.059**	0.100**	0.059***	0.049***	0.041***	0.058***
	(0.034)	(0.032)	(0.030)	(0.039)	(0.015)	(0.014)	(0.013)	(0.017)
Log Foreign Born Population	0.095***	0.070***	0.070***	-0.175***	0.098***	0.063***	0.064***	-0.219***
	(0.005)	(0.008)	(0.008)	(0.042)	(0.006)	(0.009)	(0.009)	(0.047)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other MC Controls	No	No	Yes	Yes	No	No	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MC FE	No	No	No	Yes	No	No	No	Yes
Observations	3,134	3,134	3,134	3,134	2,408	2,408	2,408	2,408
Adjusted R^2	0.38	0.41	0.44	0.62	0.39	0.42	0.45	0.61

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports estimates from pooled regressions of Landmark immigration bills after World War I's onset from Table I. Columns 1-3 and 5-7 replicate the standard specifications but include an additional term interacting the number of immigrant parents or grandparents with an indicator variable that takes a value of one if the MC's parent or grandparent was of an immigrant group targeted by the legislation. Columns 4 and 8 include individual fixed effects, which absorb each member's family immigration history. Belonging to an immigrant group targeted by legislation varies by bill within member; that variation allows us to estimate the coefficient for the interaction of MC Immigrant History and the target indicator. We omitted the three pre-World War I Landmark bills because they either did not differentially target an immigrant group or they targeted groups, such as people of Chinese heritage, with no members in Congress at the time. Standard errors are clustered at the MC level.

Table VIII: Immigration History and MC Childrens' Names

	Outcome: F-Index Percentile of Child's Name								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	1.95^{***}	2.09^{***}	2.01^{***}	0.90^{***}	1.10^{***}	1.08^{***}	1.99^{***}	2.37^{***}	2.32^{***}
	(0.61)	(0.59)	(0.59)	(0.33)	(0.31)	(0.32)	(0.70)	(0.68)	(0.69)
Log Foreign Born Population in Congressional District	0.17	0.96^{**}	0.98^{**}	0.64^{*}	1.21^{**}	1.21^{**}	0.64^{*}	1.20^{**}	1.22^{**}
	(0.25)	(0.39)	(0.39)	(0.33)	(0.52)	(0.53)	(0.33)	(0.52)	(0.53)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Child Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,504	9,504	9,504	5,512	5,512	5,512	5,512	5,512	5,512
Adjusted R^2	0.005	0.02	0.02	0.005	0.02	0.02	0.005	0.02	0.02
Dependent variable mean	44.1	44.1	44.1	44.5	44.5	44.5	44.5	44.5	44.5

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table uses the full individual census sample data from 1880-1940 to estimate the relationship between Immigrant Ancestry and F-Index Percentile of a Child's Name. The f-index is a likelihood ratio measuring the relative foreignness of a name calculated for each name as in Equation 2 by sex. Child controls include age, sex, the interaction of age and sex, and census year. We limit our sample to MC children who are born before their parent enters Congress.

“Descended from Immigrants and Revolutionists:” How Family History Shapes Immigration Policymaking

James Feigenbaum Maxwell Palmer Benjamin Schneer

For Online Publication Appendix

A Supplementary Analysis

A.1 Robustness Tables and Figures

Table A.1: Summary Statistics for Key Variables: Voting MCs Matched to Census Data

	Panel A. Landmark Bills			
	N	Mean	St. Dev.	Median
Foreign Born MC	4274	0.03	0.17	0
Parents Foreign Born	3914	0.36	0.72	0
Grandparents Foreign Born	2721	1.45	1.77	0
Immigration Index	2721	0.66	0.91	0
At Least One Foreign Born Parent	3914	0.21	0.41	0
At Least One Foreign Born Grandparent	2721	0.45	0.50	0
All Foreign Born Parents	3914	0.15	0.35	0
All Foreign Born Grandparents	2721	0.29	0.45	0
Surname Foreign Born MC	4275	0.08	0.10	0.05
Surname Parents Foreign Born MC	4270	0.33	0.38	0.19
Surname Grandparents Foreign Born MC	4238	1.02	1.02	0.75
Democrat	4286	0.52	0.50	1
Republican	4286	0.48	0.50	0
Other Party	4286	0.01	0.09	0
House	4286	0.80	0.40	1
Nonwhite	3841	0.01	0.08	0
Northeast	4286	0.25	0.43	0
Midwest	4286	0	0	0
West	4286	0.12	0.32	0
South	4286	0.32	0.46	0
CD Foreign Born Population (1000s)	4269	72.88	227.45	20.80
Age	4286	52.30	10.14	52
Tenure	4286	7.44	7.04	5
	Panel B. All Immigration Bills			
	N	Mean	St. Dev.	Median
Foreign Born MC	20793	0.04	0.19	0
Parents Foreign Born	19470	0.40	0.75	0
Grandparents Foreign Born	14158	1.51	1.79	0
Immigration Index	14158	0.69	0.94	0
At Least One Foreign Born Parent	19470	0.24	0.43	0
At Least One Foreign Born Grandparent	14158	0.46	0.50	0
All Foreign Born Parents	19470	0.16	0.37	0
All Foreign Born Grandparents	14158	0.30	0.46	0
Surname Foreign Born MC	20783	0.08	0.10	0.05
Surname Parents Foreign Born MC	20772	0.35	0.39	0.23
Surname Grandparents Foreign Born MC	20643	1.08	1.02	0.82
Democrat	20823	0.53	0.50	1
Republican	20823	0.46	0.50	0
Other Party	20823	0.01	0.10	0
House	20823	0.88	0.32	1
Nonwhite	18963	0.01	0.07	0
Northeast	20823	0.25	0.44	0
Midwest	20823	0	0	0
West	20823	0.11	0.31	0
South	20823	0.31	0.46	0
CD Foreign Born Population (1000s)	20733	62.98	208.99	19.89
Age	20823	52.24	10.14	52
Tenure	20823	7.34	6.94	5

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports summary statistics, including number, mean, standard deviation, and median, for the key variables in our data. In Panel A, the sample is comprised of members of Congress who cast votes on one or more of the landmark immigration bills in our sample. In Panel B, the sample is comprised of all members of Congress between the 51st and 91st Congresses. In both panels, we report data at the bill level, so members who cast votes on multiple bills are up-weighted and variables that change over time (like age or tenure) are recorded as of each bill in the data.

Table A.2: Immigration History and MC Vote Choice: Excluding Foreign Born MCs

Panel A. Pro Immigration Vote in Landmark Bill Sample

	MC Immigrant Ancestry Measured as: Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.093***	0.087***	0.063***	0.041***	0.039***	0.027***	0.093***	0.088***	0.063***
	(0.013)	(0.012)	(0.011)	(0.006)	(0.006)	(0.006)	(0.014)	(0.013)	(0.013)
Log Foreign Born Population in Congressional District	0.056***	0.045***	0.047***	0.081***	0.051***	0.051***	0.082***	0.050***	0.051***
	(0.005)	(0.008)	(0.008)	(0.007)	(0.010)	(0.010)	(0.007)	(0.010)	(0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,776	3,776	3,776	2,589	2,589	2,589	2,589	2,589	2,589
Adjusted R^2	0.29	0.32	0.36	0.36	0.39	0.42	0.36	0.39	0.42

Panel B. Pro Immigration Vote in All Immigration Bill Sample

	MC Immigrant Ancestry Measured as: Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.052***	0.051***	0.038***	0.024***	0.024***	0.018***	0.057***	0.056***	0.042***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.006)
Log Foreign Born Population in Congressional District	0.038***	0.036***	0.038***	0.044***	0.035***	0.037***	0.044***	0.035***	0.036***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,634	18,634	18,634	13,363	13,363	13,363	13,363	13,363	13,363
Adjusted R^2	0.35	0.35	0.37	0.36	0.36	0.38	0.36	0.36	0.38

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates the paper's main results but excludes foreign-born MCs from the sample, illustrating that the relationship between family immigration history and vote choice is not driven only by members who immigrated to the United States after birth. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 to 3, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 4 to 6, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 7 to 9, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index. In the table, each column includes bill fixed effects and a variable indicating whether the member was in the House or in the Senate. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. Other CD controls include census region, log total population and log Black population. Other MC controls include party fixed effects and quadratics in age and tenure. Standard errors clustered at the MC level.

Table A.3: Immigration History and MC Vote Choice: Robust to Controlling for District Immigrant Ancestry Constructed Via Census Linking

	Panel A. Pro Immigration Vote in Landmark Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Foreign Born	0.053***	0.045***	0.045***	0.036***	0.033***	0.040***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)
Log Foreign Born Population in Congressional District	0.048***					
	(0.008)					
CD Share Foreign Born		0.696***			1.770***	
		(0.096)			(0.391)	
CD Share Parents Foreign Born			0.339***		−2.234***	
			(0.050)		(0.309)	
CD Share Grandparents Foreign Born				0.374***	1.444***	
				(0.040)	(0.158)	
CD Immigration Index						0.149***
						(0.018)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,901	3,881	3,881	3,881	3,881	3,881
Adjusted R^2	0.36	0.36	0.36	0.36	0.38	0.36
	Panel B. Pro Immigration Vote in All Immigration Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Foreign Born	0.033***	0.029***	0.028***	0.025***	0.024***	0.026***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Foreign Born Population in Congressional District	0.039***					
	(0.004)					
CD Share Foreign Born		0.521***			0.960***	
		(0.045)			(0.176)	
CD Share Parents Foreign Born			0.262***		−1.067***	
			(0.023)		(0.147)	
CD Share Grandparents Foreign Born				0.243***	0.719***	
				(0.019)	(0.077)	
CD Immigration Index						0.105***
						(0.009)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,390	19,329	19,329	19,329	19,329	19,329
Adjusted R^2	0.37	0.37	0.37	0.37	0.37	0.37

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates the results in Table II column 3 but rather than simply measure CD ancestry as the log foreign-born population, we construct CD ancestry via census linking to parallel our MC Ancestry measure. For more details see Appendix C.3.

Table A.4: Immigration History and MC Vote Choice: Robust to Controlling for District Immigrant Ancestry Constructed Via Census Linking

	Panel A. Pro Immigration Vote in Landmark Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Grandparents Foreign Born	0.026*** (0.005)	0.022*** (0.005)	0.022*** (0.005)	0.018*** (0.005)	0.017*** (0.005)	0.020*** (0.005)
Log Foreign Born Population in Congressional District	0.053*** (0.010)					
CD Share Foreign Born		0.888*** (0.113)			1.764*** (0.422)	
CD Share Parents Foreign Born			0.425*** (0.061)		−1.487*** (0.346)	
CD Share Grandparents Foreign Born				0.398*** (0.049)	0.874*** (0.182)	
CD Immigration Index						0.174*** (0.022)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,714	2,705	2,705	2,705	2,705	2,705
Adjusted R^2	0.42	0.42	0.42	0.43	0.43	0.42
	Panel B. Pro Immigration Vote in All Immigration Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Grandparents Foreign Born	0.016*** (0.002)	0.015*** (0.002)	0.014*** (0.002)	0.012*** (0.002)	0.012*** (0.003)	0.013*** (0.002)
Log Foreign Born Population in Congressional District	0.039*** (0.004)					
CD Share Foreign Born		0.550*** (0.053)			0.905*** (0.190)	
CD Share Parents Foreign Born			0.272*** (0.028)		−0.788*** (0.156)	
CD Share Grandparents Foreign Born				0.242*** (0.023)	0.517*** (0.085)	
CD Immigration Index						0.107*** (0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,119	14,087	14,087	14,087	14,087	14,087
Adjusted R^2	0.37	0.38	0.37	0.38	0.38	0.38

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Note: This table replicates the results in Table II column 6 but rather than simply measure CD ancestry as the log foreign-born population, we construct CD ancestry via census linking to parallel our MC Ancestry measure. For more details see Appendix C.3.

Table A.5: Immigration History and MC Vote Choice: Robust to Controlling for District Immigrant Ancestry Constructed Via Census Linking

	Panel A. Pro Immigration Vote in Landmark Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration Index	0.047***	0.038***	0.038***	0.031***	0.030***	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log Foreign Born Population in Congressional District	0.054***					
	(0.010)					
CD Share Foreign Born		0.886***			1.761***	
		(0.115)			(0.421)	
CD Share Parents Foreign Born			0.425***		−1.536***	
			(0.062)		(0.346)	
CD Share Grandparents Foreign Born				0.402***	0.914***	
				(0.049)	(0.181)	
CD Immigration Index						0.175***
						(0.023)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,714	2,705	2,705	2,705	2,705	2,705
Adjusted R^2	0.42	0.42	0.42	0.42	0.43	0.42
	Panel B. Pro Immigration Vote in All Immigration Bill Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration Index	0.030***	0.026***	0.026***	0.023***	0.022***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log Foreign Born Population in Congressional District	0.039***					
	(0.004)					
CD Share Foreign Born		0.547***			0.901***	
		(0.053)			(0.189)	
CD Share Parents Foreign Born			0.272***		−0.815***	
			(0.028)		(0.155)	
CD Share Grandparents Foreign Born				0.242***	0.540***	
				(0.023)	(0.084)	
CD Immigration Index						0.107***
						(0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,119	14,087	14,087	14,087	14,087	14,087
Adjusted R^2	0.37	0.37	0.37	0.38	0.38	0.38

$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Note: This table replicates the results in Table II column 9 but rather than simply measure CD ancestry as the log foreign-born population, we construct CD ancestry via census linking to parallel our MC Ancestry measure. For more details see Appendix C.3.

Table A.6: Relative Explanatory Power of Immigration History and Foreign-Born Population and Political Party: Standardized Regressions

	Panel A. Pro Immigration Vote (Standardized) in Landmark Bill Sample					
	MC Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry (Standardized)	0.184***	0.186***	0.264***	0.267***	0.254***	0.256***
	(0.018)	(0.017)	(0.021)	(0.021)	(0.023)	(0.022)
Foreign Born Population in Congressional District (Standardized)	0.062***	0.076***	0.055***	0.064***	0.055***	0.063***
	(0.016)	(0.016)	(0.019)	(0.018)	(0.018)	(0.017)
Democrat (Standardized)		0.118***		0.095***		0.091***
		(0.017)		(0.021)		(0.021)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,901	3,901	2,714	2,714	2,714	2,714
Adjusted R^2	0.26	0.27	0.30	0.31	0.29	0.30

	Panel B. Pro Immigration Vote (Standardized) in All Immigration Bill Sample					
	MC Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry (Standardized)	0.116***	0.120***	0.155***	0.160***	0.148***	0.153***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.011)	(0.010)
Foreign Born Population in Congressional District (Standardized)	0.040***	0.048***	0.040***	0.046***	0.040***	0.045***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Democrat (Standardized)		0.070***		0.066***		0.064***
		(0.008)		(0.009)		(0.009)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,390	19,390	14,119	14,119	14,119	14,119
Adjusted R^2	0.33	0.34	0.34	0.34	0.34	0.34

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports results for the standardized regression of casting a pro immigration vote on a measure of family immigration history and the district-level foreign-born population and the MC's party. All variables in the model are standardized by subtracting each observation by the variable's mean and dividing by the standard deviation. Panel A covers landmark immigration bills while Panel B covers all immigration bill. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 and 2, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 3 and 4, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 5 and 6, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index.

Table A.7: Relative Explanatory Power of Immigration History and District Foreign-Born Ancestry and Political Party: Standardized Regressions

	Panel A. Pro Immigration Vote (Standardized) in Landmark Bill Sample					
	MC Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry (Standardized)	0.183***	0.185***	0.261***	0.264***	0.253***	0.255***
	(0.018)	(0.017)	(0.021)	(0.020)	(0.023)	(0.022)
CD Parents Foreign Born (Standardized)	0.070***	0.084***				
	(0.015)	(0.016)				
CD Grandparents Foreign Born (Standardized)			0.072***	0.082***		
			(0.017)	(0.017)		
CD Immigration Index (Standardized)					0.070***	0.079***
					(0.017)	(0.017)
Democrat (Standardized)		0.119***		0.099***		0.095***
		(0.017)		(0.021)		(0.021)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,881	3,881	2,705	2,705	2,705	2,705
Adjusted R^2	0.25	0.27	0.30	0.31	0.29	0.30
	Panel B. Pro Immigration Vote (Standardized) in All Immigration Bill Sample					
	MC Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry (Standardized)	0.116***	0.120***	0.154***	0.159***	0.148***	0.153***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.011)	(0.010)
CD Parents Foreign Born (Standardized)	0.043***	0.051***				
	(0.009)	(0.010)				
CD Grandparents Foreign Born (Standardized)			0.043***	0.050***		
			(0.010)	(0.010)		
CD Immigration Index (Standardized)					0.043***	0.050***
					(0.010)	(0.011)
Democrat (Standardized)		0.070***		0.067***		0.065***
		(0.008)		(0.009)		(0.009)
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,329	19,329	14,087	14,087	14,087	14,087
Adjusted R^2	0.33	0.34	0.34	0.34	0.34	0.34

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports results for the standardized regression of casting a pro immigration vote on a measure of family immigration history and the district-level family immigration history and the MC's party. It replicates Table A.6 but rather than use foreign-born population to measure district ancestry, we use a census linking-based measure of ancestry that parallels how we measure family history of immigration for MCs. See Appendix C.3 for details.

Table A.8: Immigration History and MC Vote Choice: Chernozhukov et al. (2018) Double Machine Learning Results

	Panel A. Baseline Controls in Feature Set					
	Landmark Bill Sample			All Immigration Bill Sample		
	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound
1+ Foreign-Born Parent	0.077	0.040	0.114	0.051	0.032	0.071
Both Foreign-Born Parents	0.038	−0.002	0.079	0.037	0.017	0.058
1+ Foreign-Born Grandparent	0.070	0.036	0.104	0.053	0.034	0.071
2+ Foreign-Born Grandparent	0.080	0.045	0.115	0.054	0.035	0.072
3+ Foreign-Born Grandparent	0.075	0.038	0.112	0.059	0.039	0.078
All Foreign-Born Grandparents	0.066	0.029	0.104	0.054	0.035	0.074
Immigration Index	0.064	0.025	0.103	0.050	0.030	0.070
	Panel B. Extended Controls in Feature Set					
	Landmark Bill Sample			All Immigration Bill Sample		
	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound
1+ Foreign-Born Parent	0.048	0.013	0.083	0.040	0.021	0.060
Both Foreign-Born Parents	0.028	−0.009	0.066	0.035	0.014	0.056
1+ Foreign-Born Grandparent	0.024	−0.009	0.058	0.028	0.009	0.047
2+ Foreign-Born Grandparent	0.035	0.001	0.068	0.031	0.012	0.050
3+ Foreign-Born Grandparent	0.039	0.003	0.075	0.035	0.015	0.055
All Foreign-Born Grandparents	0.036	0.000	0.071	0.038	0.018	0.058
Immigration Index	0.047	0.011	0.083	0.038	0.018	0.058

Note: This table presents results from the double or debiased machine learning procedure proposed by Chernozhukov et al. (2018). We present estimated coefficients along with 95% confidence interval upper and lower bounds for our landmark bills sample and all bills samples. We use a random forest, though the results are robust to other ML model choices. In short, we "learn" very flexible mappings from our set of control variables to our variable of interest (MC immigrant ancestry) and to our roll call outcomes with a random forest model. In Panel A, we use only our baseline controls (as in column 3 of Table II) and in Panel B we include controls for local newspaper sentiment, local economic conditions, and local immigrant ancestry source countries. Our results are robust with two exceptions: in Panel A when the measure of MC immigrant ancestry is a dummy for whether or not both parents are foreign-born or in Panel B when the measure of MC immigrant ancestry is a dummy for 1 or more foreign-born parent (but only in the Landmark Bills sample). One difference between these results and those reported in Table II is that here we measure MC immigrant ancestry with indicator variables only. For example, rather than count the number of foreign-born grandparents, we create indicators for having one or more foreign-born grandparents, two or more, three or more, and an indicator for having all four grandparents foreign-born. The measure of immigration index is likewise an indicator for an immigration index larger than 1.5. We use the `DoubleML` package in R (Bach et al. 2021).

Table A.9: Immigration History and MC Vote Choice: Cinelli and Hazlett (2020) Sensitivity Analysis:
How strong would the unobserved confounder have to be (relative to the observed covariate) to reduce the coefficient on MC Ancestry to 0?

	Landmark Bill Sample		All Immigration Bill Sample	
	Unobserved confounder strength relative to observed covariate:			
Table II Specification	Log FB Pop	Party FE	Log FB Pop	Party FE
1	1.5		1.1	
2	4.4		3.2	
3	3.0	2.3	2.3	2.8
4	0.8		0.7	
5	3.4		2.7	
6	2.4	2.0	1.9	2.3
7	0.8		0.7	
8	2.9		2.5	
9	2.1	2.1	1.9	2.6

Note: This table presents results from the sensitivity analysis proposed by Cinelli and Hazlett (2020). We benchmark how strong unobserved confounders would have to be (relative to the observed covariates) to reduce our estimated coefficients of interest (on our measures of MC Ancestry) to 0. We do this for both the landmark and all bills samples. We choose two observed confounders as benchmarks. First, we use our key measure of district demographics, the log of the foreign-born population. Second, we use party fixed effects (which are only included in specifications 3, 6, and 9 of Table II). These results imply that the unobserved confounders would have to be quite a bit stronger or more important than either party or foreign-born population to overturn our results. We use the `sensemakr` package in R (Cinelli, Ferwerda and Hazlett 2020).

Table A.10: Immigration History and MC Vote Choice: Democrats Only

	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.105***	0.073***	0.073***	0.064***	0.043***	0.043***	0.116***	0.081***	0.081***
	(0.017)	(0.017)	(0.017)	(0.010)	(0.010)	(0.010)	(0.020)	(0.019)	(0.020)
Log Foreign Born Population in Congressional District	0.108***	0.052***	0.051***	0.108***	0.050***	0.048***	0.115***	0.051***	0.049***
	(0.007)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)	(0.009)	(0.011)	(0.011)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,984	1,984	1,984	1,361	1,361	1,361	1,361	1,361	1,361
Adjusted R^2	0.47	0.51	0.51	0.47	0.51	0.51	0.46	0.51	0.51
	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.065***	0.052***	0.051***	0.035***	0.027***	0.027***	0.069***	0.057***	0.056***
	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)
Log Foreign Born Population in Congressional District	0.060***	0.034***	0.034***	0.057***	0.031***	0.031***	0.059***	0.031***	0.030***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,163	10,163	10,163	7,340	7,340	7,340	7,340	7,340	7,340
Adjusted R^2	0.39	0.39	0.40	0.37	0.38	0.38	0.37	0.38	0.38

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates the paper's main results but includes only Democrats in the sample, illustrating that the relationship between family immigration history and vote choice is not driven only by members of one party. In the table, each column includes bill fixed effects and a variable indicating whether the member was in the House or in the Senate. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation.

Table A.11: Immigration History and MC Vote Choice: Republicans Only

	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.022*	0.032***	0.033***	0.003	0.010*	0.012*	0.007	0.020*	0.026**
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.012)
Log Foreign Born Population in Congressional District	0.088***	0.084***	0.082***	0.106***	0.086***	0.082***	0.105***	0.085***	0.080***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)	(0.011)	(0.013)	(0.012)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,892	1,892	1,892	1,334	1,334	1,334	1,334	1,334	1,334
Adjusted R^2	0.47	0.49	0.49	0.50	0.52	0.52	0.50	0.52	0.52

	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.012**	0.016***	0.016***	0.005*	0.008***	0.008***	0.009*	0.013**	0.015***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
Log Foreign Born Population in Congressional District	0.051***	0.050***	0.049***	0.055***	0.050***	0.050***	0.055***	0.050***	0.049***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,026	9,026	9,026	6,604	6,604	6,604	6,604	6,604	6,604
Adjusted R^2	0.48	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates the paper's main results but includes only Republicans in the sample, illustrating that the relationship between family immigration history and vote choice is not driven only by members of one party. In the table, each column includes bill fixed effects and a variable indicating whether the member was in the House or in the Senate. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. Standard errors clustered at the MC level.

Table A.12: Immigration History and MC Vote Choice: State Fixed Effects

Panel A. Pro Immigration Vote in Landmark Bill Sample

	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.070***	0.064***	0.040***	0.032***	0.030***	0.018***	0.053***	0.050***	0.031***
	(0.011)	(0.011)	(0.010)	(0.006)	(0.006)	(0.005)	(0.011)	(0.011)	(0.010)
Log Foreign Born Population in Congressional District	0.037***	0.026**	0.022**	0.045***	0.030**	0.028**	0.045***	0.031**	0.028**
	(0.012)	(0.011)	(0.011)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,901	3,901	3,901	2,714	2,714	2,714	2,714	2,714	2,714
Adjusted R^2	0.32	0.34	0.38	0.40	0.42	0.45	0.40	0.41	0.45

Panel B. Pro Immigration Vote in All Immigration Bill Sample

	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.042***	0.040***	0.027***	0.021***	0.020***	0.013***	0.036***	0.034***	0.023***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.006)	(0.005)	(0.005)
Log Foreign Born Population in Congressional District	0.038***	0.031***	0.027***	0.037***	0.030***	0.027***	0.038***	0.031***	0.027***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,390	19,390	19,390	14,119	14,119	14,119	14,119	14,119	14,119
Adjusted R^2	0.35	0.36	0.37	0.36	0.37	0.38	0.36	0.37	0.38

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates the paper's main results but includes fixed effects for states in all columns. Otherwise, the specification remains the same as in Tabel II. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. Standard errors clustered at the MC level.

Table A.13: Immigration History and MC Speech: Chernozhukov et al. (2018) Double Machine Learning Results

	Panel A. Baseline Controls in Feature Set		
	Card et al. (2022) Tone		
	Estimate	Lower Bound	Upper Bound
1+ Foreign-Born Parent	0.025	0.010	0.040
Both Foreign-Born Parents	0.033	0.017	0.049
1+ Foreign-Born Grandparent	0.020	0.006	0.034
2+ Foreign-Born Grandparent	0.023	0.009	0.037
3+ Foreign-Born Grandparent	0.025	0.010	0.040
All Foreign-Born Grandparents	0.025	0.010	0.040
Immigration Index	0.029	0.013	0.044
	Panel B. Extended Controls in Feature Set		
	Card et al. (2022) Tone		
	Estimate	Lower Bound	Upper Bound
1+ Foreign-Born Parent	0.017	0.002	0.033
Both Foreign-Born Parents	0.025	0.009	0.041
1+ Foreign-Born Grandparent	0.013	−0.001	0.028
2+ Foreign-Born Grandparent	0.017	0.002	0.032
3+ Foreign-Born Grandparent	0.018	0.003	0.034
All Foreign-Born Grandparents	0.015	0.000	0.031
Immigration Index	0.020	0.004	0.035

Note: This table presents results from the double or debiased machine learning procedure proposed by Chernozhukov et al. (2018). We present estimated coefficients along with 95% confidence interval upper and lower bounds for our measure of speech tone from Card et al. (2022). We use a random forest, though the results are robust to other ML model choices. In short, we "learn" very flexible mappings from our baseline set of control variables to our variable of interest (MC immigrant ancestry) and to our speech outcome with a random forest model. In Panel A, we use only our baseline controls (as in column 3 of Table IV) and in Panel B we include controls for local newspaper sentiment, local economic conditions, and local immigrant ancestry source countries. Our results are robust. One difference between these results and those reported in Table IV is that here we measure MC immigrant ancestry with indicator variables only. For example, rather than count the number of foreign-born grandparents, we create indicators for having one or more foreign-born grandparents, two or more, three or more, and an indicator for having all four grandparents foreign-born. The measure of immigration index is likewise an indicator for an immigration index larger than 1.5. We use the `DoubleML` package in R (Bach et al. 2021).

Table A.14: Immigration History and MC Speech Tone: Cinelli and Hazlett (2020) Sensitivity Analysis:
How strong would the unobserved confounder have to be (relative to the observed covariate) to reduce the coefficient on MC Ancestry to 0?

	Card et al. (2022) Tone	
	Unobserved confounder strength relative to observed covariate:	
Table IV Specification	Log FB Pop	Party FE
1	1.2	
2	3.4	
3	2.7	4.3
4	0.8	
5	2.9	
6	2.1	2.4
7	0.7	
8	2.4	
9	1.8	2.6

Note: This table presents results from the sensitivity analysis proposed by Cinelli and Hazlett (2020). We benchmark how strong unobserved confounders would have to be (relative to the observed covariates) to reduce our estimated coefficients of interest (on our measures of MC Ancestry) to 0. We choose two observed confounders as benchmarks. First, we use our key measure of district demographics, the log of the foreign-born population. Second, we use party fixed effects (which are only included in specifications 3, 6, and 9 of Table IV). These results imply that the unobserved confounders would have to be quite a bit stronger or more important than either party or foreign-born population to overturn our results. We use the `sensemakr` package in R (Cinelli, Ferwerda and Hazlett 2020).

Table A.15: Family Immigration Origins and MC Vote Choice, Pre-WWI

	Panel A. Pre-WWI Immigration Votes					
	Geary Chinese Exclusion Act (1891)		Immigration Act of 1903		Immigration Act of 1907	
	(1)	(2)	(3)	(4)	(5)	(6)
Old Europe Parents	−0.056 (0.041)		−0.153*** (0.055)		−0.100** (0.040)	
New Europe Parents	−0.086 (0.184)					
Non Europe Foreign Born Parents	−0.086 (0.092)		−0.182 (0.164)		−0.201* (0.115)	
Old Europe Grandparents		−0.019 (0.020)		−0.083*** (0.026)		−0.058*** (0.019)
New Europe Grandparents		−0.042 (0.092)				
Non Europe Foreign Born Grandparents		−0.042 (0.046)		−0.094 (0.081)		−0.102* (0.058)
Constant	0.172*** (0.024)	0.170*** (0.024)	0.364*** (0.035)	0.373*** (0.035)	0.380*** (0.030)	0.389*** (0.030)
Observations	258	258	205	205	294	294
Adjusted R^2	−0.0007	−0.005	0.03	0.04	0.02	0.03

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table decomposes MC family immigration history by region of origin. For each of seven landmark immigration bills, we have estimated the relationship between immigration sources and casting a vote that is permissive on immigration policy. The codings used to classify country of origin into groups (e.g., "Old Europe", "New Europe") are available in Appendix C.6. Explanatory variables referring to Parents count how many parents an MC has from the listed region; explanatory variables referring to Grandparents count how many grandparents an MC has from the listed region. Bills that most explicitly imposed or maintained restrictions on New Europe immigrants included: the Immigration Quota Act, Johnson-Reed Act, and McCarran-Walter Immigration and Nationality Act. These bills also exhibit the largest gaps in support between MCs with Old versus New Europe origins, though overall a family history of immigration, no matter the source region, predicted support for the more permissive position on landmark legislation.

Table A.16: Family Immigration Origins and MC Vote Choice, Post-WWI

	Panel A. Pre-WWII Immigration Votes					
	Immigration Act (1917)		Immigration Quota Act (1921)		Johnson-Reed Act (1924)	
	(1)	(2)	(3)	(4)	(5)	(6)
Old Europe Parents	0.163***		0.121***		0.169***	
	(0.025)		(0.021)		(0.023)	
New Europe Parents	0.398***		0.305***		0.449***	
	(0.151)		(0.063)		(0.071)	
Non Europe Foreign Born Parents	0.071		0.045		0.310***	
	(0.086)		(0.062)		(0.076)	
Old Europe Grandparents		0.079***		0.058***		0.088***
		(0.012)		(0.010)		(0.011)
New Europe Grandparents		0.200***		0.189***		0.238***
		(0.076)		(0.035)		(0.035)
Non Europe Foreign Born Grandparents		0.022		0.023		0.131***
		(0.044)		(0.030)		(0.038)
Constant	0.204***	0.199***	0.055***	0.049***	0.102***	0.086***
	(0.021)	(0.022)	(0.016)	(0.016)	(0.018)	(0.018)
Observations	512	512	418	418	473	473
Adjusted R^2	0.08	0.08	0.11	0.13	0.17	0.19

	Panel B. Post-WWII Immigration Votes							
	McCarran Internal Security Act (1950)		McCarran-Walter Immigration and Nationality Act (1952)		Refugee Relief Act (1953)		Immigration & Nationality Act (1965)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Old Europe Parents	0.121***		0.137***		0.198***		0.128***	
	(0.028)		(0.033)		(0.037)		(0.037)	
New Europe Parents	0.044		0.358***		0.189***		0.126***	
	(0.054)		(0.055)		(0.058)		(0.041)	
Non Europe Foreign Born Parents	0.219**		0.098		0.283***		0.103	
	(0.094)		(0.088)		(0.101)		(0.064)	
Old Europe Grandparents		0.039***		0.056***		0.100***		0.071***
		(0.011)		(0.013)		(0.014)		(0.012)
New Europe Grandparents		0.041		0.188***		0.125***		0.073***
		(0.025)		(0.025)		(0.026)		(0.018)
Non Europe Foreign Born Grandparents		0.111***		0.118***		0.159***		0.062**
		(0.037)		(0.041)		(0.044)		(0.029)
Constant	0.117***	0.099***	0.237***	0.203***	0.499***	0.440***	0.768***	0.723***
	(0.018)	(0.020)	(0.022)	(0.024)	(0.024)	(0.025)	(0.019)	(0.021)
Observations	445	445	489	489	505	505	507	507
Adjusted R^2	0.04	0.04	0.10	0.13	0.07	0.13	0.04	0.08

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table decomposes MC family immigration history by region of origin. For each of seven landmark immigration bills, we have estimated the relationship between immigration sources and casting a vote that is permissive on immigration policy. The codings used to classify country of origin into groups (e.g., "Old Europe", "New Europe") are available in Appendix C.6. Explanatory variables referring to Parents count how many parents an MC has from the listed region; explanatory variables referring to Grandparents count how many grandparents an MC has from the listed region. Bills that most explicitly imposed or maintained restrictions on New Europe immigrants included: the Immigration Quota Act, Johnson-Reed Act, and McCarran-Walter Immigration and Nationality Act. These bills also exhibit the largest gaps in support between MCs with Old versus New Europe origins, though overall a family history of immigration, no matter the source region, predicted support for the more permissive position on landmark legislation.

Table A.17: Immigration History and MC Vote Choice: Bills Related to Chinese Exclusion

	Pro Immigration Vote in All Immigration Bill Sample					
	51-64 Congresses			Full Period		
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry	0.052^{***}	0.054^{***}	0.044^{***}	0.047^{***}	0.047^{***}	0.035^{***}
	(0.014)	(0.014)	(0.012)	(0.006)	(0.005)	(0.005)
MC Immigrant Ancestry × Related to Chinese Exclusion	-0.061^{***}	-0.057^{**}	-0.066^{***}	-0.091^{***}	-0.084^{***}	-0.082^{***}
	(0.022)	(0.023)	(0.025)	(0.018)	(0.018)	(0.020)
Log Foreign Born Population in Congressional District	-0.019^{***}	0.031^{***}	0.041^{***}	0.038^{***}	0.038^{***}	0.039^{***}
	(0.005)	(0.009)	(0.008)	(0.002)	(0.004)	(0.004)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,955	2,955	2,955	19,390	19,390	19,390
Adjusted R^2	0.26	0.28	0.32	0.34	0.35	0.37

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table matches columns 1, 2, and 3 of Table II but with an interaction between an indicator for legislation targeting Chinese immigrants and MC Immigrant Ancestry.

Table A.18: Hypothesis Tests of Relationship between Family Immigration History and Immigration Voting by Nation of Origin: Supplement to Figure VI

Bill	Target	Hypothesis Test	p-Values	
			Parents	Grandparents
Geary Chinese Exclusion Act	Non Europe	Non vs. Old Europe	0.762	0.638
		Non vs. New Europe	1.000	1.000
Immigration Act of 1903	Not Targeted Regionally	Placebo: Non vs. Old Europe	0.865	0.893
Immigration Act of 1907	Not Targeted Regionally	Placebo: Non vs. Old Europe	0.400	0.475
Immigration Act of 1917	Non Europe	Non vs. Old Europe	0.299	0.205
		Non vs. New Europe	0.059	0.041
Immigration Quota Act	New Europe	New vs. Old Europe	0.005	0.000
		New vs. Non Europe	0.003	0.000
Immigration Act of 1924 (Johnson-Reed Act)	New Europe	New vs. Old Europe	0.000	0.000
		New vs. Non Europe	0.178	0.036
McCarran Internal Security Act	Mixed	Placebo: Non vs. Old Europe	0.312	0.056
		Placebo: New vs. Old Europe	0.201	0.953
McCarran-Walter Immigration and Nationality Act	Non & New Europe	Non vs. Old Europe	0.669	0.148
		New vs. Old Europe	0.000	0.000
Refugee Relief Act of 1953	Mixed	Placebo: Non vs. Old Europe	0.419	0.195
		Placebo: New vs. Old Europe	0.897	0.359
Immigration and Nationality Act of 1965	Mixed	Placebo: Non vs. Old Europe	0.729	0.751
		Placebo: Old vs. Non Europe	0.977	0.945

Note: This table presents p-values from hypothesis tests comparing the estimates of the relationship between pro-immigration voting and Non Europe, New Europe, and Old Europe ancestry, based on the estimates reported in Figure VI and Appendix Tables A.15 and A.16.

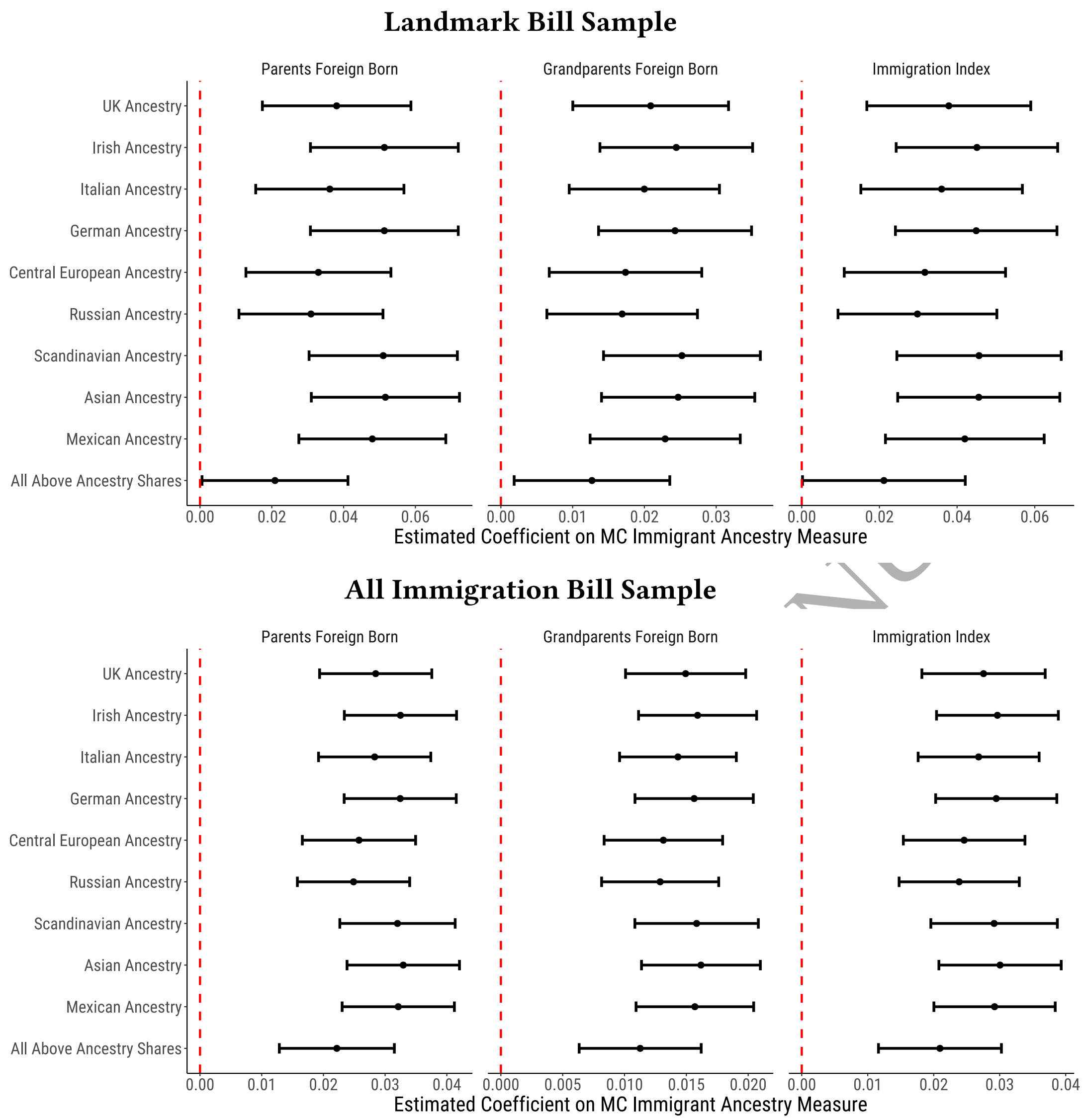
Table A.19: Immigration History and Intergenerational Mobility

	Panel A. Pro Immigration Vote in Landmark Bill Sample			
	(1)	(2)	(3)	(4)
MC Immigrant Ancestry	0.0458***	0.0635**	0.0427***	0.0427*
	(0.0107)	(0.0261)	(0.0106)	(0.0250)
IGM Rank (Overall)	0.0042***	0.0047***		
	(0.0013)	(0.0014)		
IGM Rank (Immigrants)			0.0039***	0.0039***
			(0.0009)	(0.0010)
MC Immigrant Ancestry × IGM Rank (Overall)		-0.0006		
		(0.0008)		
MC Immigrant Ancestry × IGM Rank (Immigrants)				0.0000
				(0.0008)
Log Foreign Born Population in Congressional District	0.0434***	0.0429***	0.0565***	0.0566***
	(0.0111)	(0.0111)	(0.0101)	(0.0101)
All CD and MC Controls	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes
Observations	2,604	2,604	2,604	2,604
Adjusted R^2	0.42	0.42	0.43	0.43
	Panel B. Pro Immigration Vote in All Immigration Bill Sample			
	(1)	(2)	(3)	(4)
MC Immigrant Ancestry	0.0291***	0.0349***	0.0279***	0.0180*
	(0.0048)	(0.0121)	(0.0047)	(0.0109)
IGM Rank (Overall)	0.0019***	0.0020***		
	(0.0006)	(0.0006)		
IGM Rank (Immigrants)			0.0014***	0.0013***
			(0.0004)	(0.0004)
MC Immigrant Ancestry × IGM Rank (Overall)		-0.0002		
		(0.0004)		
MC Immigrant Ancestry × IGM Rank (Immigrants)				0.0003
				(0.0003)
Log Foreign Born Population in Congressional District	0.0341***	0.0340***	0.0399***	0.0395***
	(0.0050)	(0.0050)	(0.0045)	(0.0045)
All CD and MC Controls	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes
Observations	13,604	13,604	13,604	13,604
Adjusted R^2	0.38	0.38	0.38	0.38

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

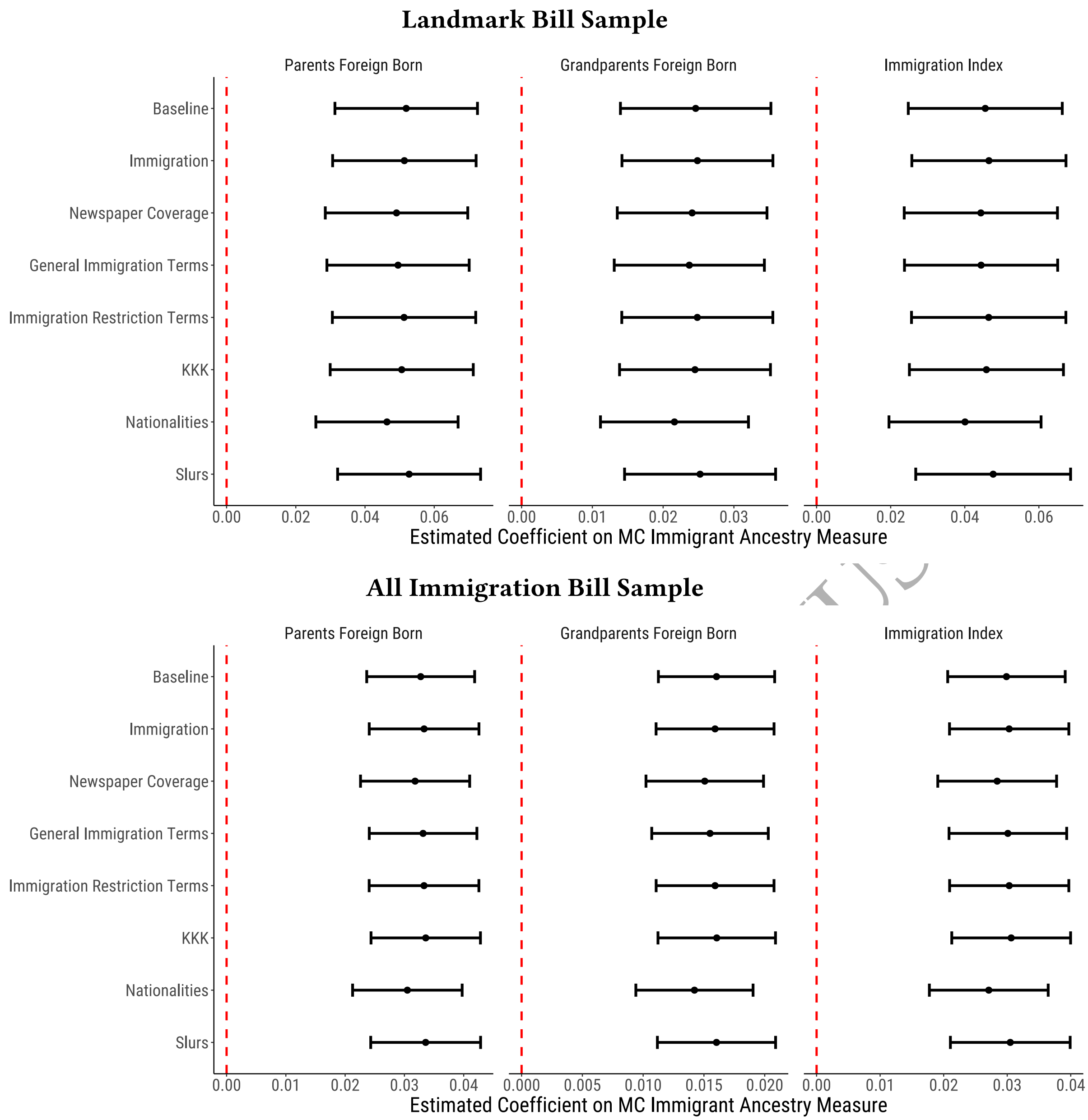
Note: This table investigates the relationship between MC support for immigration, MC family immigration history, and local intergenerational mobility. The specification matches that of Table II column 9 with Immigration Index as our measure of MC Immigrant Ancestry but with additional independent variables measuring local rates of intergenerational mobility. IGM Rank reports the state's rank in terms of intergenerational mobility, measured either overall or only among the foreign-born. We also interact this rank with the MC's own immigration history. The state with ranking 1 has the highest rate of mobility. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. Standard errors are clustered at the MC level.

Figure A.1: Robustness of Immigration History and MC Vote Choice: District-Level Ancestry Shares by Country of Origin



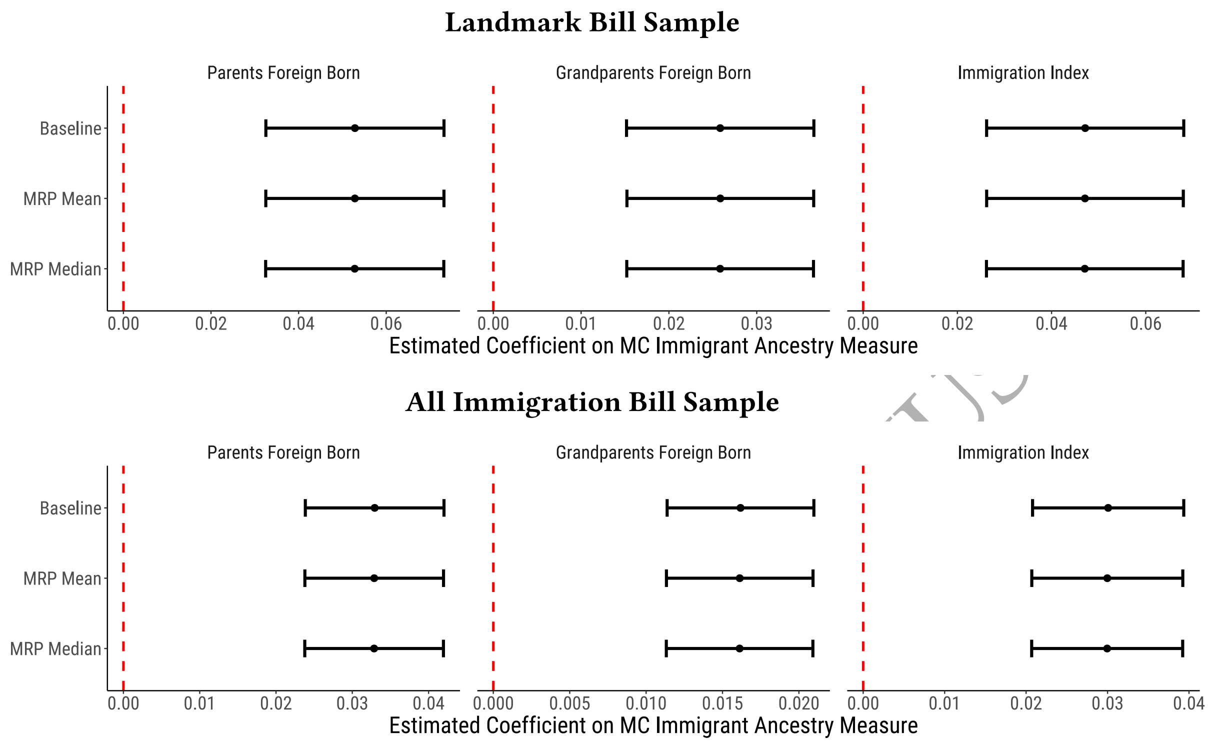
Note: This figure reports results from regressing an indicator for pro immigration roll call votes on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. In the first row (baseline), the estimates include bill fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row and on, we add controls for the ancestry composition of each district's residents, using data from Fulford, Petkov and Schiantarelli (2020). This county-level data captures the share of ancestry from various sending countries, allowing us to account for differences in political engagement or views on future immigration among different ancestry groups. Standard errors are always clustered at the MC level.

Figure A.2: Robustness of Immigration History and MC Vote Choice: District-Level Newspaper Content Measures



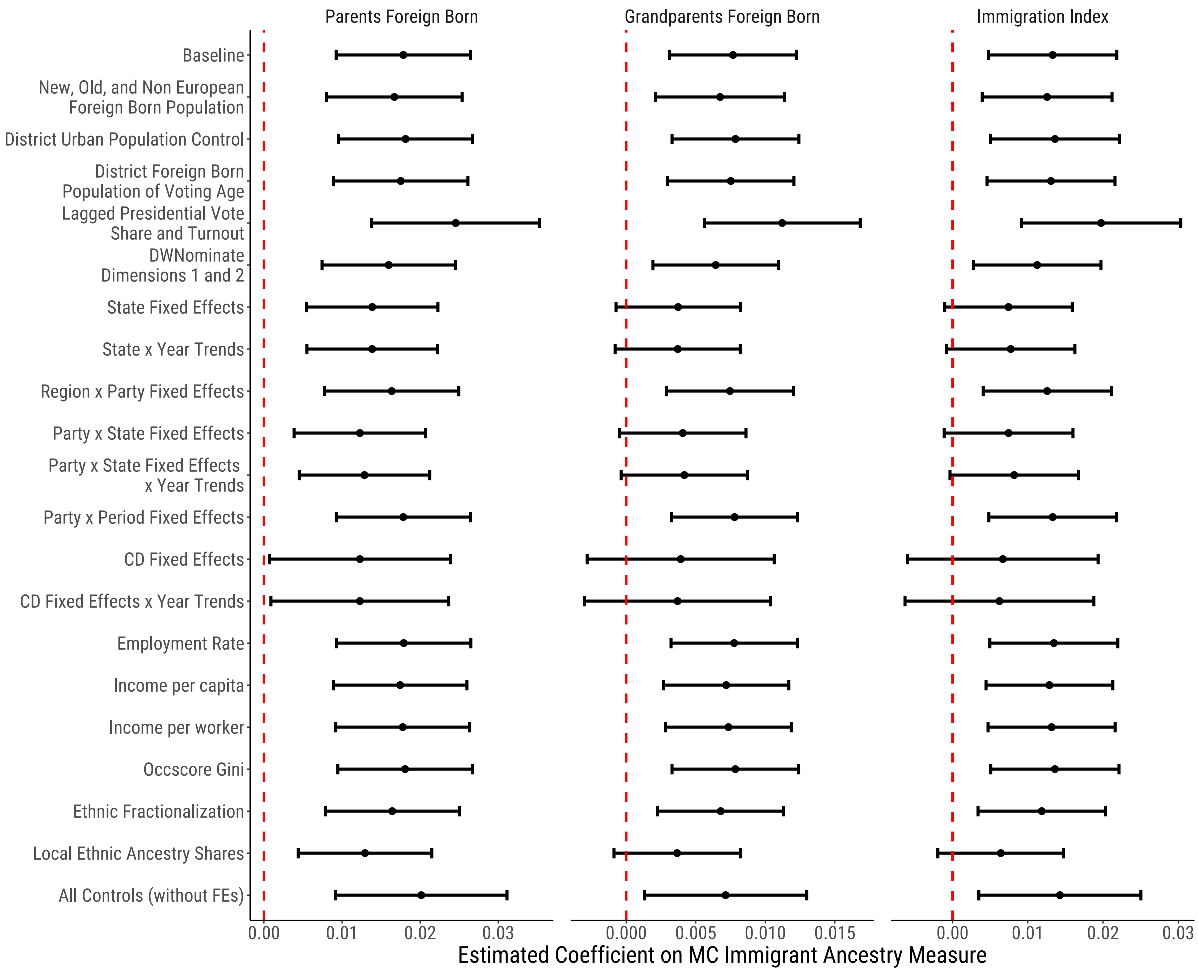
Note: This figure reports results from regressing an indicator for pro immigration roll call votes on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. In the first row (baseline), the estimates include bill fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. We then add controls for local sentiment towards immigration derived from newspaper content, following the strategy of Fouka, Mazumder and Tabellini (2022). We collect data from newspapers.com for our entire sample period and construct normalized counts at the district-by-year level for various terms related to immigration, such as general interest in immigration topics, terms about immigration restriction, terms about prominent ethnicities and religions of immigrants, ethnic slurs, and KKK-related terms. The stability of the primary coefficients of interest on MC ancestry after including these newspaper-based controls suggests that the relationship between MC ancestry and roll call voting is robust to accounting for local sentiment towards immigration as captured by newspaper content. Standard errors are always clustered at the MC level.

Figure A.3: Robustness of Immigration History and MC Vote Choice: MRP



This figure reports results from regressing an indicator for pro immigration roll call votes on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. In the first row (baseline), the estimates include bill fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. We then add controls for historical constituency preferences estimated using multilevel regression with post-stratification (MRP). The MRP estimates are based on data from 8 Gallup polls conducted between 1951 and 1965, which include questions about attitudes towards immigration. The polls are combined with detailed demographic information from the complete count census data to predict local immigration attitudes at the state by urban/rural level. The specific poll questions, coded from least to most supportive of future immigration, are available in Table C.3. Our MRP output allows us to measure both the mean and median score of pro immigrant sentiment in each constituency. The consistency of the main result across specifications with and without the MRP-based controls suggests that the relationship between MC immigration background and legislative behavior is not driven solely by constituency preferences.

Figure A.4: Robustness of Immigration History and MC Speech Tone



Note: This figure reports results from regressing immigration speech tone from Card et al. (2022) on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford, Petkov and Schiantarelli (2020). Next, we show that our results are robust to controlling for local ethnic fractionalization and then local ethnic population shares. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

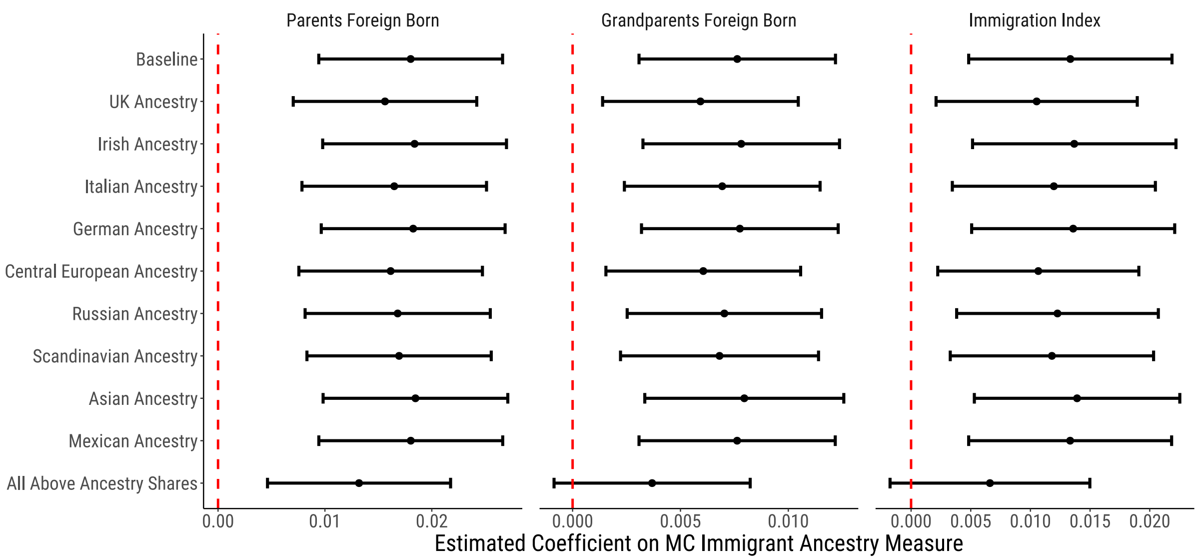
Table A.20: Relative Explanatory Power of Immigration History and Foreign-Born Population and Political Party on Speech Tone: Standardized Regressions

	Card Tone on Immigration Speech (Standardized)					
	MC Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
MC Immigrant Ancestry (Standardized)	0.100***	0.100***	0.125***	0.127***	0.118***	0.119***
	(0.012)	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
Foreign Born Population in Congressional District (Standardized)	0.036***	0.039***	0.044***	0.048***	0.044***	0.048***
	(0.010)	(0.010)	(0.013)	(0.014)	(0.013)	(0.015)
Democrat (Standardized)		0.028**		0.057***		0.056***
		(0.012)		(0.015)		(0.015)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,720	9,720	6,599	6,599	6,599	6,599
Adjusted R^2	0.12	0.12	0.13	0.14	0.13	0.13

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

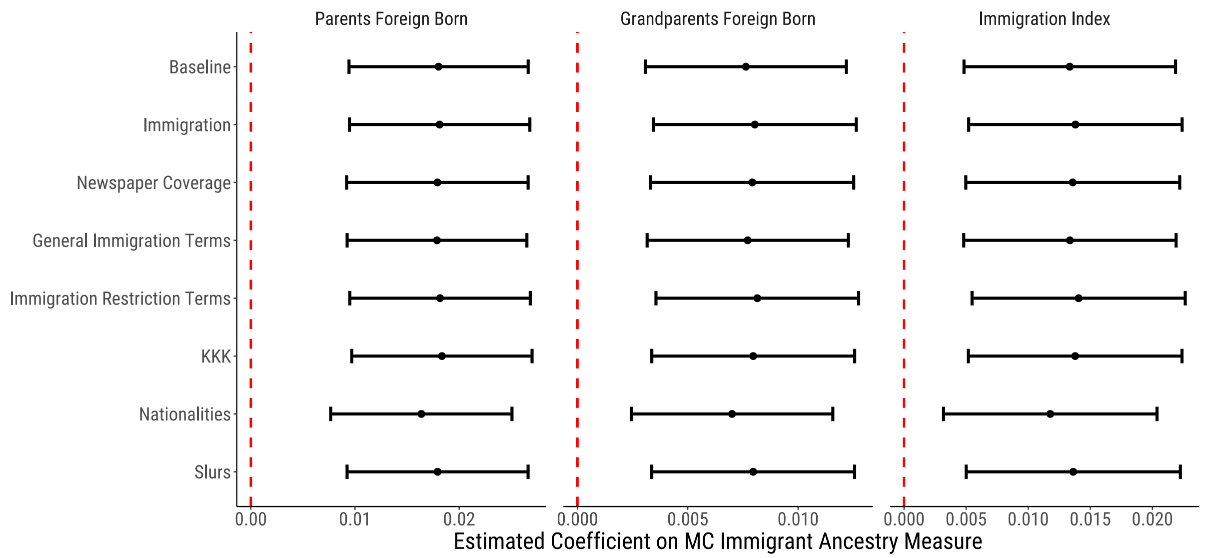
Note: This table reports the standardized relationship between the key measures of family immigration history and the tone of MC immigration speech. A higher value reflects more positive tone. Specifically, tone is calculated in Card et al. (2022) by subtracting the share of negative tone speeches from positive tone speeches, where each speech is classified via a human-trained machine learning classifier. All variables in the model are standardized by subtracting each observation by the variable's mean and dividing by the standard deviation. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 to 3, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 4 to 6, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 7 to 9, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index.

Figure A.5: Robustness of Immigration History and MC Speech Tone: District Ancestry Shares from Fulford et al (2020)



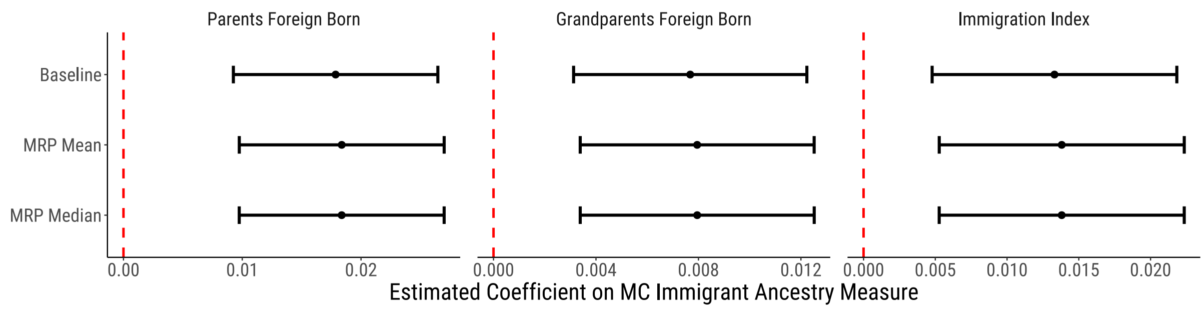
Note: This figure reports results from regressing immigration speech tone from Card et al. (2022) on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row and on, we add controls for the ancestry composition of each district's residents, using data from Fulford, Petkov and Schiantarelli (2020). This county-level data captures the share of ancestry from various sending countries, allowing us to account for differences in political engagement or views on future immigration among different ancestry groups. Standard errors are always clustered at the MC level.

Figure A.6: Robustness of Immigration History and MC Speech Tone: Newspaper



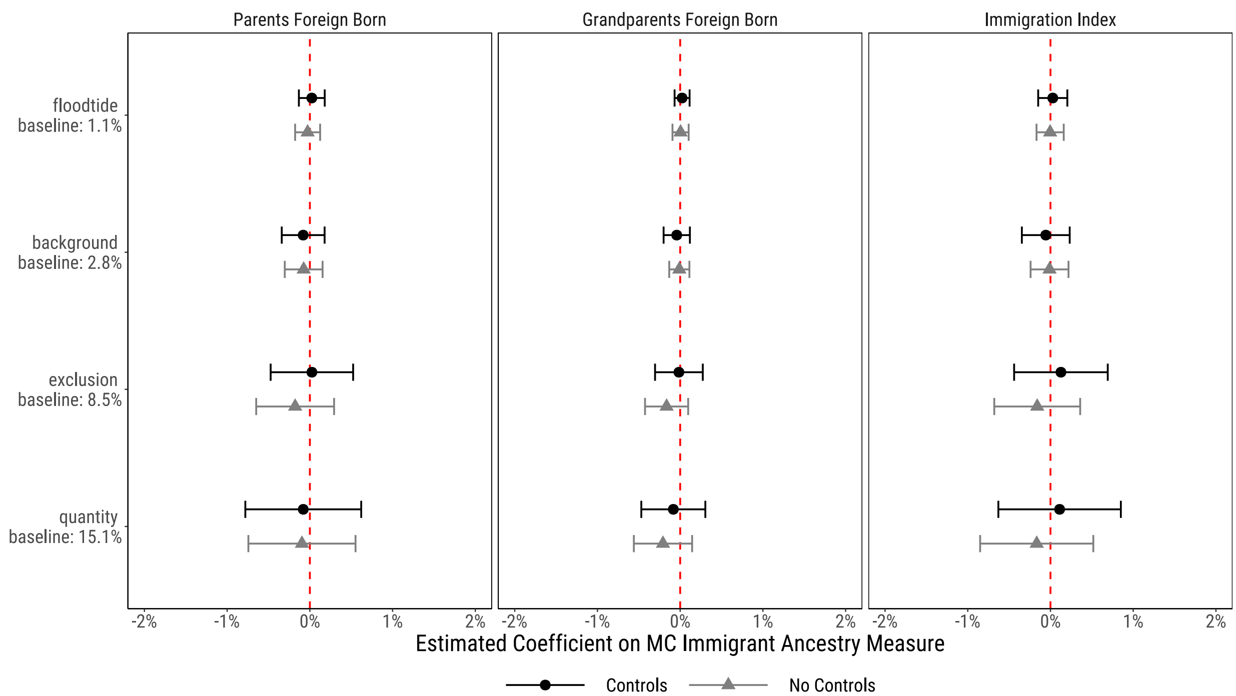
Note: This figure reports results from regressing immigration speech tone from Card et al. (2022) on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. We then add controls for local sentiment towards immigration derived from newspaper content, following the strategy of Fouka, Mazumder and Tabellini (2022). We collect data from newspapers.com for our entire sample period and construct normalized counts at the district-by-year level for various terms related to immigration, such as general interest in immigration topics, terms about immigration restriction, terms about prominent ethnicities and religions of immigrants, ethnic slurs, and KKK-related terms. The stability of the primary coefficients of interest on MC ancestry after including these newspaper-based controls suggests that the relationship between MC ancestry and roll call voting is robust to accounting for local sentiment towards immigration as captured by newspaper content. Standard errors are always clustered at the MC level.

Figure A.7: Robustness of Immigration History and MC Speech Tone: MRP



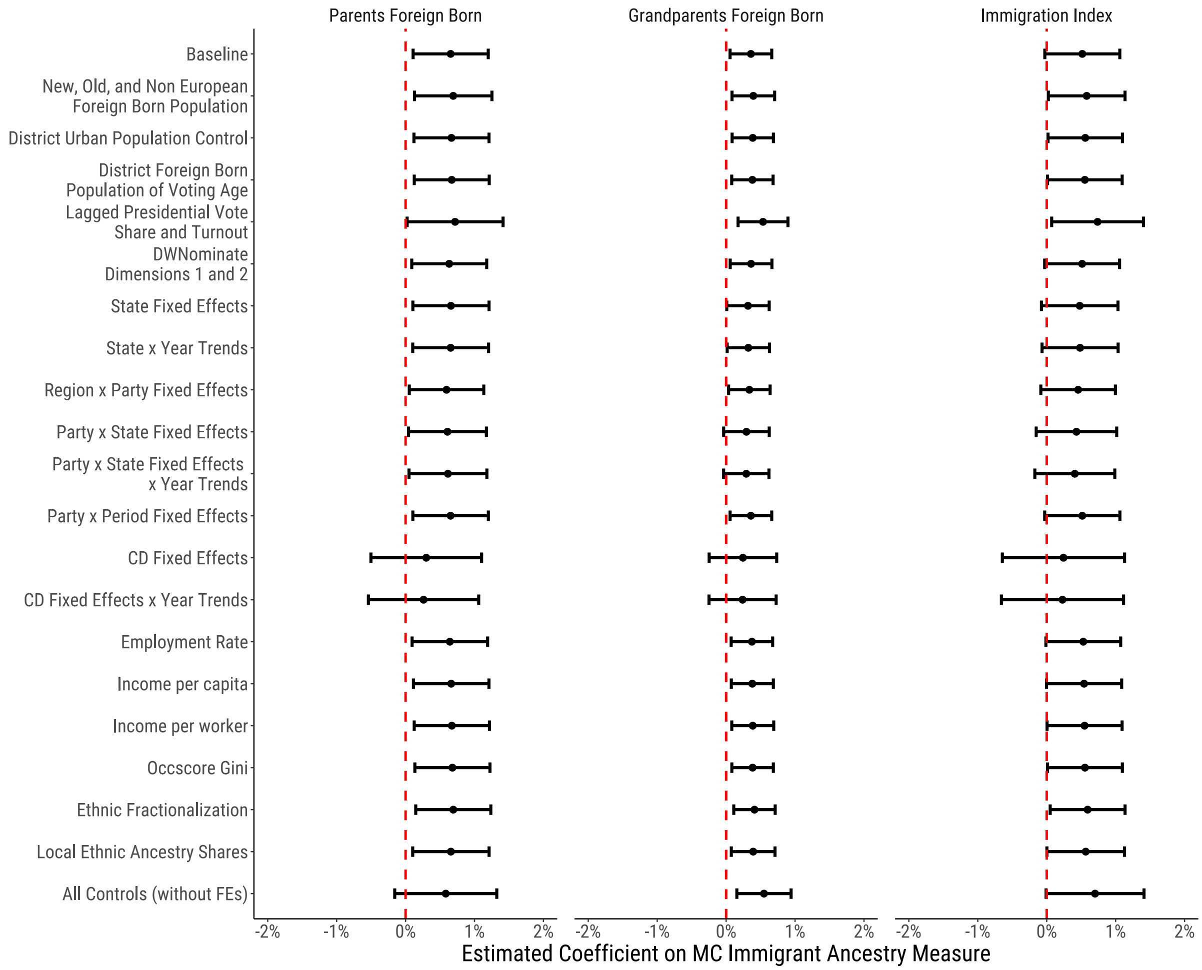
This figure reports results from regressing immigration speech tone from Card et al. (2022) on family immigration history. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. We then add controls for historical constituency preferences estimated using multilevel regression with post-stratification (MRP). The MRP estimates are based on data from 8 Gallup polls conducted between 1951 and 1965, which include questions about attitudes towards immigration. The polls are combined with detailed demographic information from the complete count census data to predict local immigration attitudes at the state by urban/rural level. The specific poll questions, coded from least to most supportive of future immigration, are available in Table C.3. Our MRP output allows us to measure both the mean and median score of pro immigrant sentiment in each constituency. The consistency of the main result across specifications with and without the MRP-based controls suggests that the relationship between MC immigration background and congressional speech tone is not driven solely by constituency preferences.

Figure A.8: Relationship between Family Immigration History and Additional/Other Frames Used for Immigration Speech



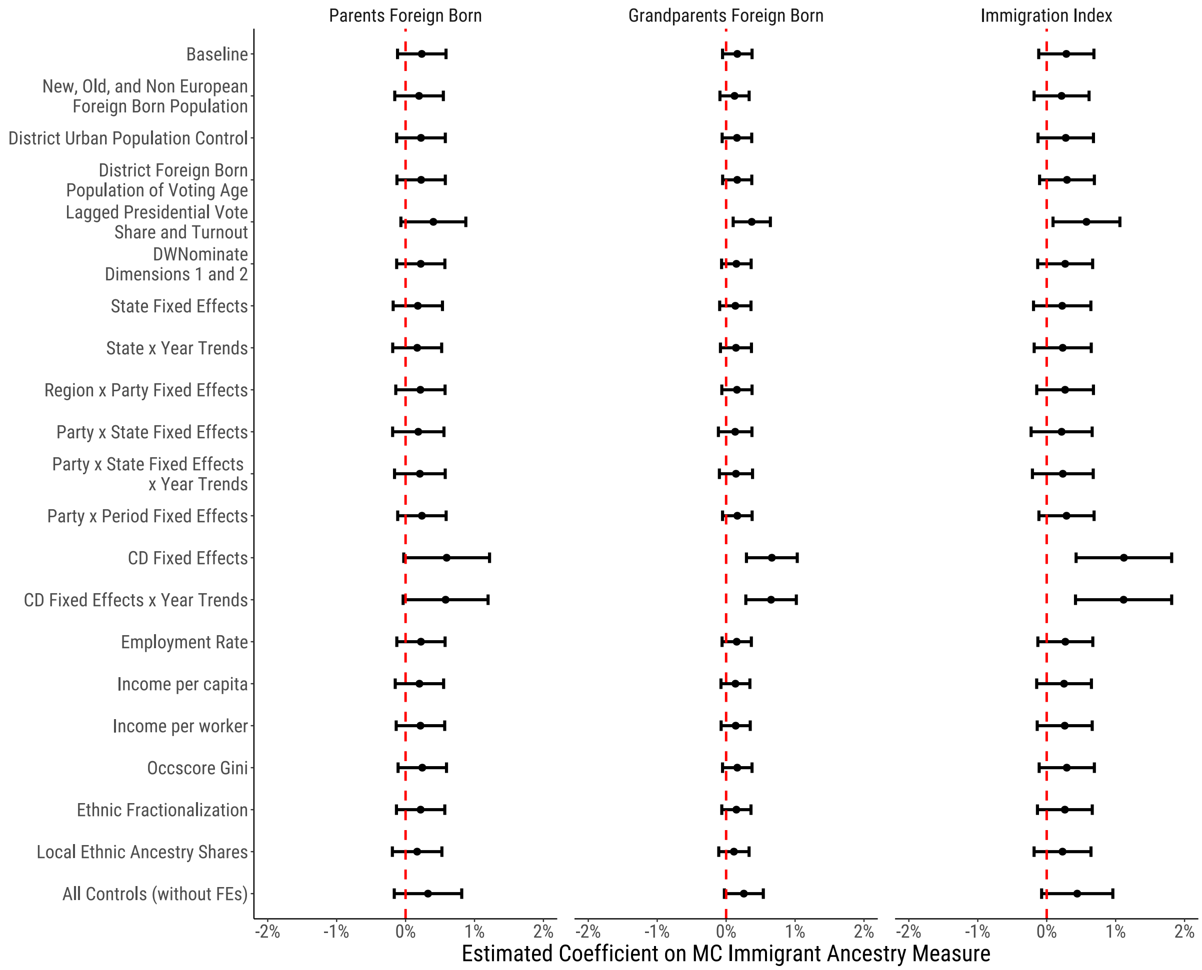
Note: This figure reports the estimated relationship for MCs between family history (measured as number of foreign-born parents or grandparents) and use of other frames, besides the key frames of interest, in speeches in Congress about the subject of immigration. The data on frames is calculated as the share of all speeches on the subject of immigration that reference a particular frame. We report here a subset of possible frames based upon those that had a significant (or close to significant) relationship with family history of immigration. Under each frame identified with a y-axis label we report the baseline mean for the frame (e.g., what share of the time did the average MC with no family history of immigration employ the given frame when speaking about immigration?).

Figure A.9: Robustness of Immigration History and MC Speech Tone: Family Frame



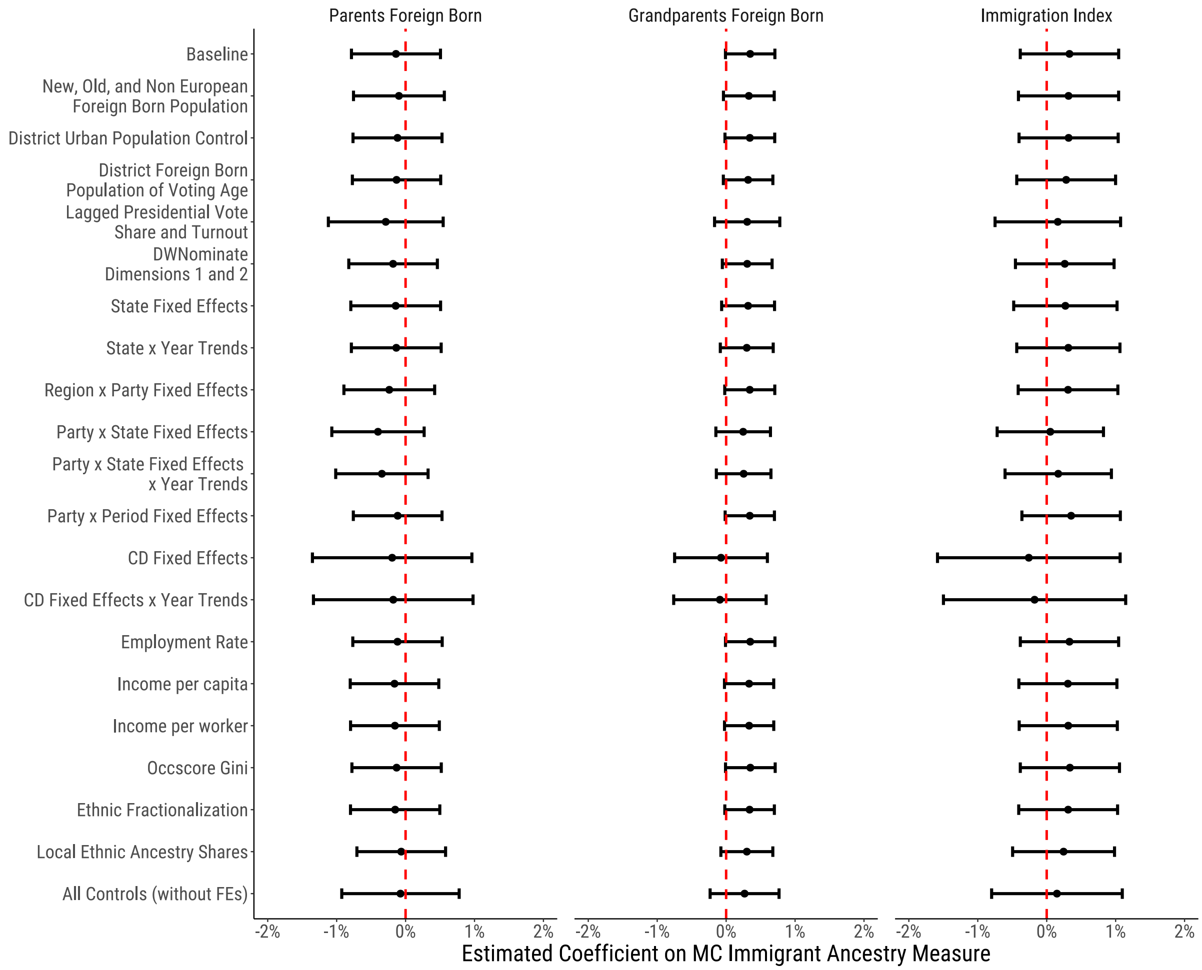
Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Family frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Figure A.10: Robustness of Immigration History and MC Speech Tone: Contribution Frame



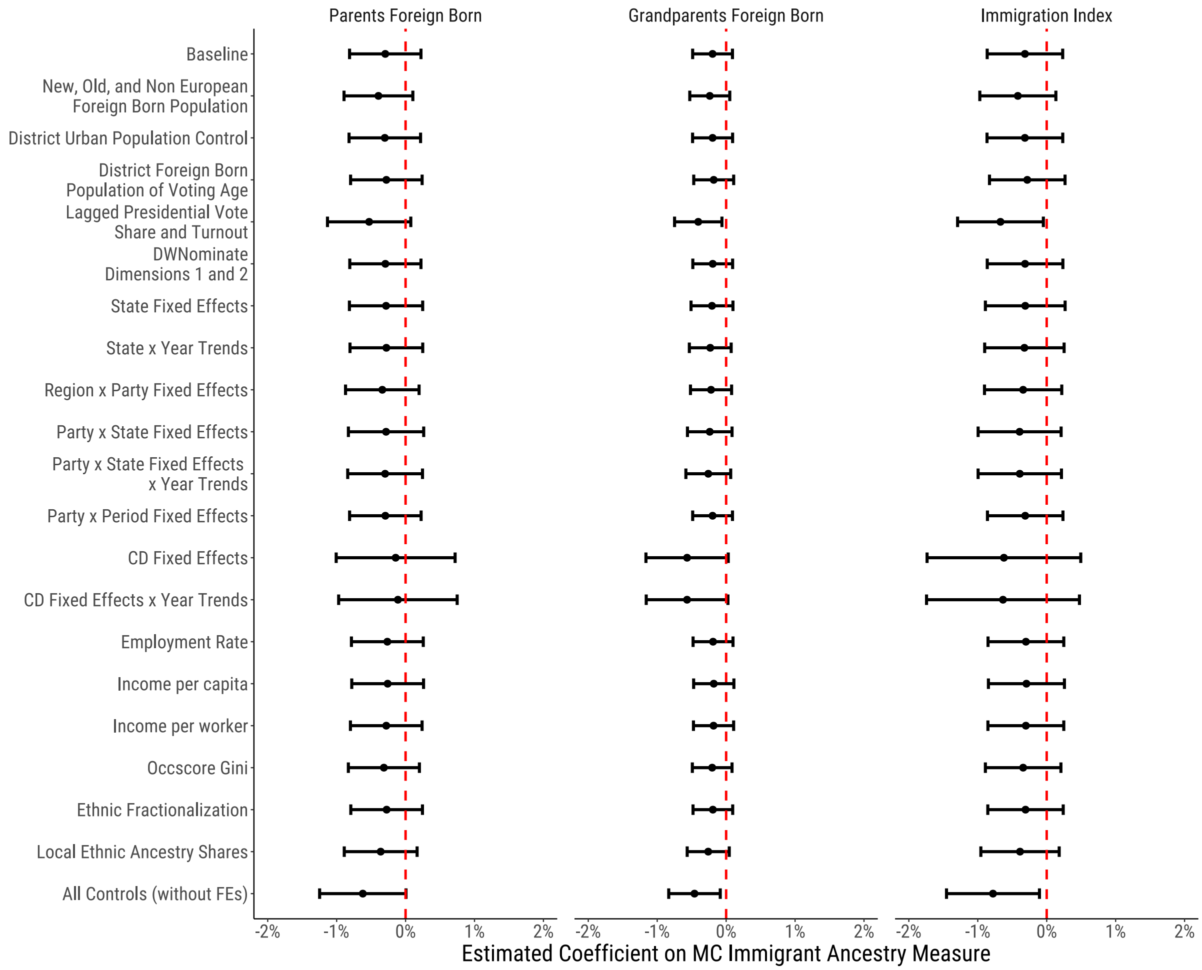
Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Contribution frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Figure A.11: Robustness of Immigration History and MC Speech Tone: Culture Frame



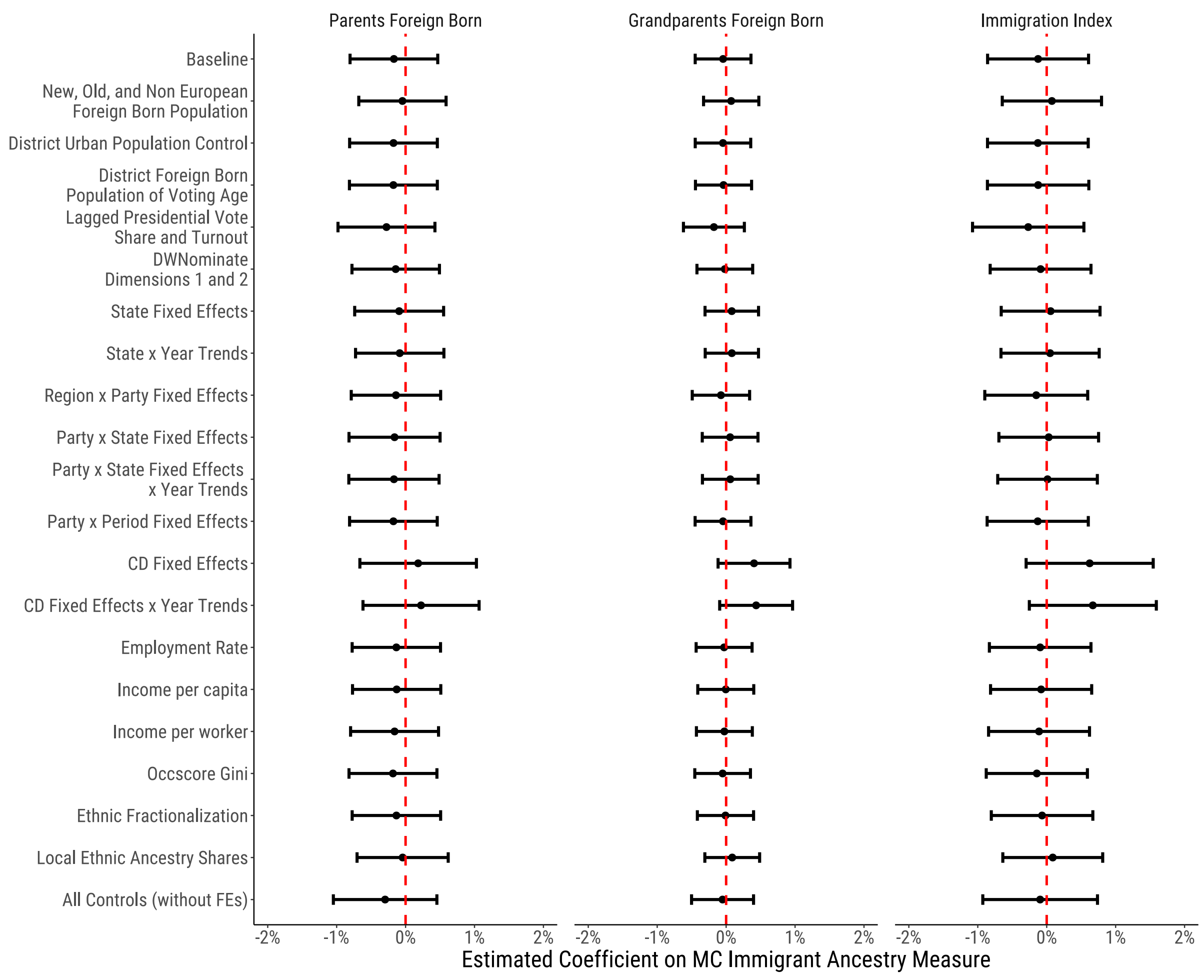
Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Culture frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Figure A.12: Robustness of Immigration History and MC Speech Tone: Economic Frame



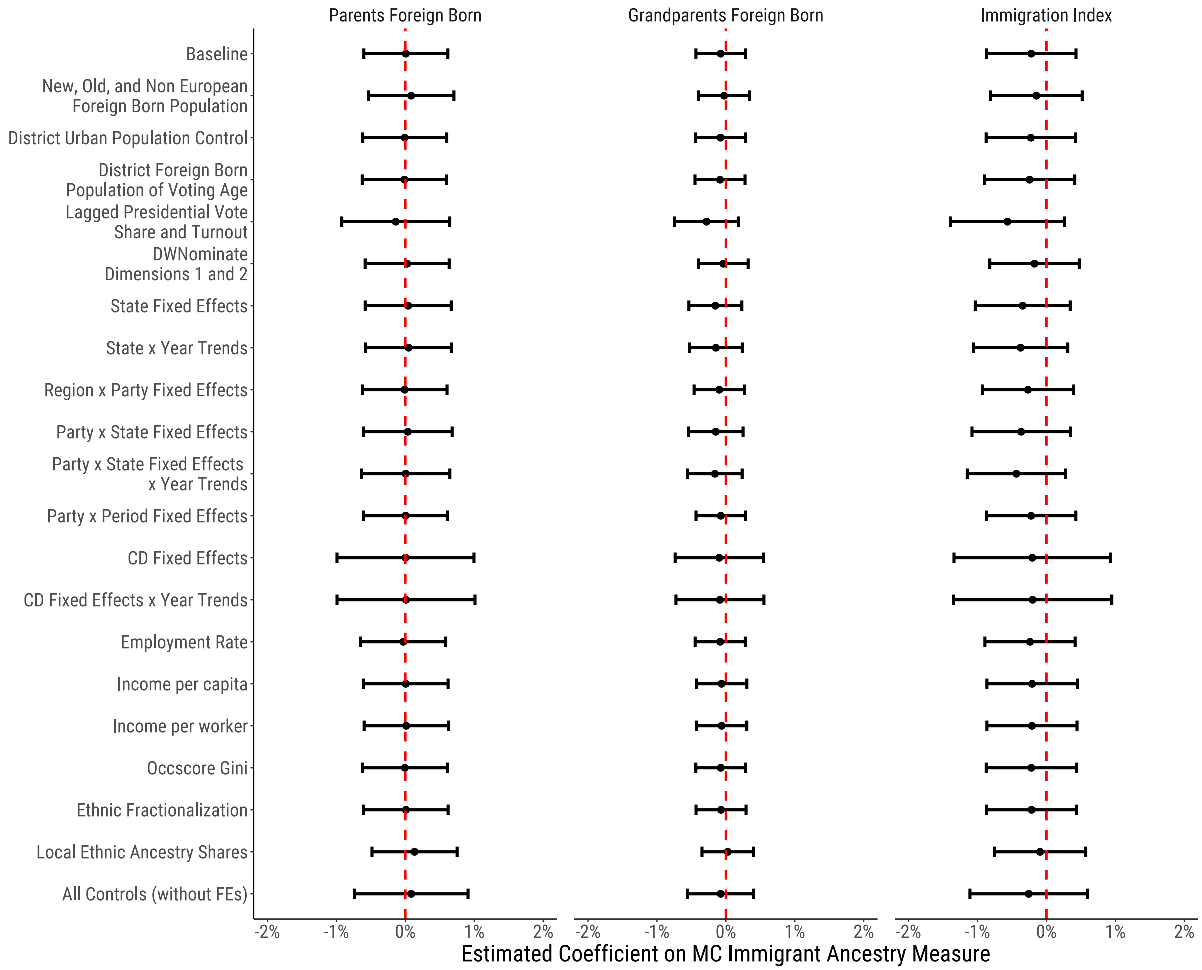
Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Economic frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Figure A.13: Robustness of Immigration History and MC Speech Tone: Labor Frame



Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Labor frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Figure A.14: Robustness of Immigration History and MC Speech Tone: Legality Frame



Note: This figure reports results from regressing immigration speech tone on family immigration history, focusing on the Legality frame. We report the coefficient on the MC immigration history variable with 95% confidence intervals. In the first row (baseline), the estimates include Congress fixed effects and a variable indicating whether the member was in the House or in the Senate, as well as congressional district foreign-born population, total population, MC party, census region, and quadratics in age and tenure. The baseline controls are included in all results. In the second row, we include three controls for the log of the population of foreign-born from New Europe, Old Europe, and Non-Europe in each district. In the third row, we include controls for the log of the urban population in each district. In the fourth row, we include a control for the size of the foreign-born voting age population. Next, we include a control for the vote share for the Democratic candidate in the most recent Presidential election to control for district political preferences (along with controls for Presidential turnout). Next, we include controls in the first and second dimensions of DW-Nominate scores for MCs. Next, we include state fixed effects; local time trends by interacting state fixed effects with year; region by party and state by party fixed effects; state by party fixed effects interacted with year trends (which help control for base or primary constituency); and congressional district fixed effects both on their own and interacted with year trends. We also show that our results are robust to controlling for local economic conditions like the employment rate, income per capita and per worker, and inequality, all using data from Fulford et al. (2020). Finally, we show that our results are robust to controlling for local ethnic fractionalization. Finally, we include a specification controlling for all substantive covariates used in previous rows in the Figure (e.g., variables other than fixed effects and time trends). Standard errors are always clustered at the MC level.

Table A.21: Immigration History and Childrens' Names, Full Census Individual Samples 1880-1940

	Outcome: F-Index Percentile of Child's Name					
	Immigrant Ancestry Measured as:					
	Parents Foreign Born		Grandparents Foreign Born		Immigration Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant Ancestry	9.36***	2.62***	2.14***	1.25***	4.91***	2.63***
	(0.00)	(0.53)	(0.00)	(0.27)	(0.01)	(0.58)
Immigrant Ancestry × Non-MC Sample		6.74***		0.89***		2.28***
		(0.53)		(0.27)		(0.58)
Child Controls x Sample	No	Yes	No	Yes	No	Yes
Child Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147,107,415	147,117,928	32,540,940	32,547,114	32,540,940	32,547,114
Adjusted R^2	0.10	0.10	0.02	0.02	0.03	0.03
Dependent variable mean	43.6	43.6	38.3	38.3	38.3	38.3

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table uses the full individual census sample data from 1880-1940 to estimate the relationship between Immigrant Ancestry and F-Index Percentile of a Child's Name. The f-index is a likelihood ratio measuring the relative foreignness of a name calculated for each name as in Equation 2 by sex. Child controls include age, sex, the interaction of age and sex, and census year. See Table VIII for more details on the specifications.

Table A.22: Immigration History and MC Childrens' Names, MC Ancestry against MC Name-Score

	Outcome: F-Index Percentile of Child's Name								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry Actual	0.83	1.40**	1.35**	0.30	0.71**	0.71**	0.74	1.55**	1.53**
	(0.66)	(0.66)	(0.66)	(0.35)	(0.35)	(0.35)	(0.76)	(0.77)	(0.78)
MC Immigrant Ancestry Name Score	5.62***	3.29***	3.26***	2.53***	1.48***	1.45***	4.71***	2.77**	2.74**
	(1.14)	(1.20)	(1.21)	(0.51)	(0.55)	(0.55)	(1.02)	(1.12)	(1.13)
Log Foreign Born Population in Congressional District	0.10	0.84**	0.88**	0.47	1.09**	1.11**	0.47	1.06**	1.09**
	(0.25)	(0.39)	(0.39)	(0.33)	(0.52)	(0.53)	(0.33)	(0.52)	(0.52)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Child Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,495	9,495	9,495	5,466	5,466	5,466	5,507	5,507	5,507
Adjusted R^2	0.010	0.02	0.02	0.01	0.03	0.03	0.01	0.03	0.03
Dependent variable mean	44.1	44.1	44.1	44.6	44.6	44.6	44.5	44.5	44.5

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table uses the full individual census sample data from 1880-1940 to estimate the relationship between Immigrant Ancestry and F-Index Percentile of a Child's Name. The f-index is a likelihood ratio measuring the relative foreignness of a name calculated for each name as in Equation 2 by sex. Child controls include age, sex, the interaction of age and sex, and census year. We limit our sample to MC children who are born before their parent enters Congress.

Table A.23: Immigration History versus Visible Foreign Surnames and MC Vote Choice

	Panel A. Pro Immigration Vote in Landmark Bill Sample		
	MC Immigrant Ancestry Measured as:		
	Parents Foreign Born	Grandparents Foreign Born	Immigration Index
	(1)	(2)	(3)
Actual MC Immigrant Ancestry	0.044***	0.021***	0.041***
	(0.012)	(0.006)	(0.012)
Surname Predicted MC Immigrant Ancestry	0.042*	0.021**	0.028
	(0.024)	(0.010)	(0.020)
Log Foreign Born Population in Congressional District	0.047***	0.051***	0.053***
	(0.008)	(0.010)	(0.010)
Log Total Population	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes
Observations	3,885	2,675	2,705
Adjusted R^2	0.36	0.41	0.42
	Panel B. Pro Immigration Vote in All Immigration Bill Sample		
	MC Immigrant Ancestry Measured as:		
	Parents Foreign Born	Grandparents Foreign Born	Immigration Index
	(1)	(2)	(3)
Actual MC Immigrant Ancestry	0.025***	0.011***	0.021***
	(0.005)	(0.003)	(0.005)
Surname Predicted MC Immigrant Ancestry	0.035***	0.020***	0.035***
	(0.010)	(0.004)	(0.009)
Log Foreign Born Population in Congressional District	0.038***	0.036***	0.037***
	(0.004)	(0.004)	(0.004)
Log Total Population	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes
Observations	19,341	13,961	14,083
Adjusted R^2	0.37	0.37	0.37

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports results measuring how visible indicators of a family history of immigration (surname) and actual family history correlate with roll call voting on immigration legislation. For example, the Parents Foreign Born variable refers to the number of foreign-born parents an MC has, while the Surname Parents Foreign Born variable refers to the average number of foreign-born parents for a person with the same surname and located in the same region as the MC. Controls are parallel to Table II. Standard errors clustered at the MC level.

Table A.24: Immigration History versus Visible Foreign Surnames and Speech (Card Tone)

	Card Tone		
	MC Immigrant Ancestry Measured as:		
	Parents Foreign Born	Grandparents Foreign Born	Immigration Index
	(1)	(2)	(3)
Actual MC Immigrant Ancestry	0.016***	0.005**	0.010**
	(0.005)	(0.003)	(0.005)
Surname Predicted MC Immigrant Ancestry	0.009	0.009**	0.014*
	(0.009)	(0.004)	(0.008)
Log Foreign Born Population in Congressional District	0.021***	0.021***	0.022***
	(0.003)	(0.004)	(0.004)
Log Total Population	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes
Congress FE	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes
Observations	9,679	6,478	6,572
Adjusted R^2	0.14	0.16	0.16

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports results measuring how visible indicators of a family history of immigration (surname) and actual family history correlate with immigration speech tone from Card et al. (2022). For example, the Parents Foreign Born variable refers to the number of foreign-born parents an MC has, while the Surname Parents Foreign Born variable refers to the average number of foreign-born parents for a person with the same surname and located in the same region as the MC. Controls are parallel to Table IV Panel A. Standard errors clustered at the MC level.

Table A.25: Family Immigration Origins and MC Vote Choice, Quota Exposure

	Panel A. Pre-WWII Immigration Votes							
	Immigration Quota Act (1921)				Johnson-Reed Act (1924)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Old Europe Parents	0.121***				0.169***			
	(0.021)				(0.023)			
New Europe Parents	0.305***				0.449***			
	(0.063)				(0.071)			
Non Europe Foreign Born Parents	0.045				0.310***			
	(0.062)				(0.076)			
Old Europe Grandparents		0.058***				0.088***		
		(0.010)				(0.011)		
New Europe Grandparents		0.189***				0.238***		
		(0.035)				(0.035)		
Non Europe Foreign Born Grandparents		0.023				0.131***		
		(0.030)				(0.038)		
Quota-Exposed Parents			0.380***				0.295***	
			(0.061)				(0.065)	
Non-Quota-Exposed Parents			0.108***				0.194***	
			(0.020)				(0.023)	
Quota-Exposed Grandparents				0.235***				0.148***
				(0.037)				(0.037)
Non-Quota-Exposed Grandparents				0.055***				0.099***
				(0.011)				(0.013)
Constant	0.055***	0.049***	0.053***	0.041*	0.102***	0.086***	0.097***	0.081***
	(0.016)	(0.016)	(0.016)	(0.025)	(0.018)	(0.018)	(0.018)	(0.027)
Observations	418	418	408	250	473	473	462	297
Adjusted R^2	0.11	0.13	0.13	0.19	0.17	0.19	0.16	0.19

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table decomposes MC family immigration history by region of origin and by quota exposure. For the two quota bills of the 1920s, we have estimated the relationship between immigration sources and casting a vote that is permissive on immigration policy. MCs with more ancestry from quota-exposed sources are more likely to oppose the quota acts compared to MCs with US-born ancestry. MCs with more ancestry from non-quota-exposed sources also oppose the quota acts, but to a lesser extent. Although the Old/New Europe divide does not perfectly correlate with the relative effects of restrictive immigration policy, particularly the 1921 and 1924 quotas, there is a strong overlap between quota exposure and the Old/New Europe distinction, given the history of the quotas and the construction of the Old/New partition.

Table A.26: Immigration History and MC Vote Choice: Interaction with English-Speaking Origins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
MC Immigrant Ancestry	0.077***	0.077***	0.056***	0.031***	0.034***	0.024***	0.070***	0.074***	0.052***
	(0.018)	(0.015)	(0.014)	(0.008)	(0.007)	(0.007)	(0.017)	(0.015)	(0.014)
MC Immigrant Ancestry × Any UK, Canadian, or Irish Ancestry	0.031	0.020	0.013	0.018**	0.010	0.007	0.045**	0.028	0.022
	(0.024)	(0.021)	(0.019)	(0.009)	(0.008)	(0.007)	(0.021)	(0.019)	(0.018)
Log Foreign Born Population in Congressional District	0.056***	0.045***	0.047***	0.081***	0.051***	0.052***	0.081***	0.050***	0.051***
	(0.005)	(0.008)	(0.008)	(0.007)	(0.010)	(0.010)	(0.007)	(0.010)	(0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,776	3,776	3,776	2,589	2,589	2,589	2,589	2,589	2,589
Adjusted R^2	0.29	0.32	0.36	0.36	0.39	0.42	0.36	0.39	0.42
	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.051***	0.055***	0.045***	0.023***	0.026***	0.021***	0.053***	0.058***	0.047***
	(0.008)	(0.007)	(0.006)	(0.004)	(0.003)	(0.003)	(0.008)	(0.007)	(0.007)
MC Immigrant Ancestry × Any UK, Canadian, or Irish Ancestry	0.003	−0.007	−0.014*	0.002	−0.004	−0.007*	0.008	−0.003	−0.011
	(0.011)	(0.010)	(0.009)	(0.004)	(0.004)	(0.003)	(0.010)	(0.009)	(0.008)
Log Foreign Born Population in Congressional District	0.038***	0.036***	0.038***	0.043***	0.035***	0.037***	0.043***	0.035***	0.036***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,634	18,634	18,634	13,363	13,363	13,363	13,363	13,363	13,363
Adjusted R^2	0.35	0.35	0.37	0.36	0.36	0.38	0.36	0.36	0.38

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table II but includes interactions with origins from English-speaking source countries, specifically the UK, Ireland, or Canada. The Any UK, Irish, or Canadian indicator is based on having a parent or grandparent born in the UK, Ireland, or Canada. In the top panel, the sample includes votes on the key immigration legislation listed in Table I. In the bottom panel, the sample includes votes on all immigration legislation. The results show that even MCs with immigrant ancestry from English-speaking countries are more likely to support pro-immigration legislation, suggesting that an overarching immigrant identity matters. Standard errors clustered at the MC level.

Table A.27: Immigration History and Immigration Speeches: Ash and Gennaro (2022) Affect

	Ash and Gennaro (2022) Affect on Immigration Speech								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.010**	0.009*	0.010**	0.005**	0.004*	0.005**	0.011***	0.011**	0.012***
	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Log Foreign Born Population in Congressional District	0.003	0.005**	0.005	0.003	0.004	0.005	0.003	0.004	0.004
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	No	Yes	No	No	Yes	No	No	Yes
Other MC Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,971	2,971	2,971	2,211	2,211	2,211	2,211	2,211	2,211
Adjusted R^2	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.03	0.03

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports the relationship between the key measures of family immigration history and the emotional affect of MC speech about immigration. Gennaro and Ash (2022) study emotional and logical argumentation in Congress, identifying which speeches made by MCs are more or less emotional. They measure emotionality with a text embedding approach, measuring the semantic similarity between words with two poles anchoring their space: emotion versus reason. They find low and stable emotionality over time but significant increases in the 1970s. A higher value of our outcome variable here reflects a more emotional affect in speech. We measure MC Immigrant Ancestry in three ways with the measure indicated in the column header. In columns 1 to 3, Parents Foreign Born ranges between 0 and 2 and counts the number of foreign-born parents. In columns 4 to 6, Grandparents Foreign Born ranges between 0 and 4 and counts the number of foreign-born grandparents. In columns 7 to 9, Immigration Index ranges between 0 and 3 with each generation (self, parents, and grandparents) contributing one third of the weight to the index.

Table A.28: Immigration History and MC Vote Choice: All Bills Pooled, Family Migration History Controls

	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.077***	0.080***	0.056***	0.035***	0.039***	0.025***	0.046**	0.056***	0.048***
	(0.012)	(0.012)	(0.011)	(0.007)	(0.007)	(0.007)	(0.018)	(0.018)	(0.017)
MC Migrant Ancestry	0.043**	0.042**	0.034**	0.014	0.014	0.013	0.048*	0.042	0.036
	(0.018)	(0.017)	(0.016)	(0.016)	(0.015)	(0.015)	(0.025)	(0.026)	(0.025)
MC Migrant Ancestry × Migration Distance 500-1K Miles	−0.043**	−0.027	−0.025	−0.009	−0.005	−0.010	−0.048**	−0.023	−0.028
	(0.022)	(0.022)	(0.020)	(0.018)	(0.018)	(0.017)	(0.024)	(0.025)	(0.024)
MC Migrant Ancestry × Migration Distance 1K+ Miles	−0.037*	−0.023	−0.019	−0.013	−0.005	−0.010	−0.020	−0.007	−0.007
	(0.020)	(0.020)	(0.019)	(0.014)	(0.014)	(0.014)	(0.024)	(0.026)	(0.024)
Log Foreign Born Pop in Congressional District	0.064***	0.055***	0.056***	0.089***	0.055***	0.057***	0.074***	0.032**	0.038***
	(0.006)	(0.009)	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)	(0.012)	(0.012)
Log Migrant Pop in Congressional District	−0.059***	−0.045***	−0.037***	−0.054***	−0.017	−0.014	−0.047**	−0.021	−0.019
	(0.012)	(0.015)	(0.014)	(0.016)	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,869	3,869	3,869	2,481	2,481	2,481	1,960	1,960	1,960
Adjusted R^2	0.29	0.32	0.36	0.34	0.37	0.41	0.30	0.32	0.34

	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.046***	0.049***	0.037***	0.023***	0.026***	0.017***	0.029***	0.032***	0.024***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.007)
MC Migrant Ancestry	0.021**	0.024***	0.023***	0.002	0.001	0.000	0.008	0.006	0.003
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
MC Migrant Ancestry × Migration Distance 500-1K Miles	−0.012	−0.009	−0.011	0.003	0.008	0.005	−0.006	0.003	−0.001
	(0.011)	(0.011)	(0.010)	(0.008)	(0.007)	(0.007)	(0.011)	(0.011)	(0.010)
MC Migrant Ancestry × Migration Distance 1K+ Miles	−0.021**	−0.017*	−0.014	0.003	0.008	0.004	−0.004	0.000	0.000
	(0.009)	(0.010)	(0.009)	(0.006)	(0.006)	(0.006)	(0.011)	(0.012)	(0.011)
Log Foreign Born Pop in Congressional District	0.041***	0.042***	0.041***	0.048***	0.040***	0.041***	0.040***	0.026***	0.030***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)
Log Migrant Pop in Congressional District	−0.025***	−0.023***	−0.014**	−0.025***	−0.010	−0.004	−0.013	−0.004	0.000
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,260	19,260	19,260	12,945	12,945	12,945	10,092	10,092	10,092
Adjusted R^2	0.35	0.35	0.37	0.35	0.36	0.37	0.36	0.36	0.37

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates Table VI but accounts for the distance of internal migration based on distance categories.

Table A.29: Immigration History and MC Vote Choice: Robust to Controlling for Father's SES

	Panel A. Pro Immigration Vote in Landmark Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.104***	0.095***	0.069***	0.050***	0.047***	0.033***	0.120***	0.110***	0.079***
	(0.016)	(0.016)	(0.014)	(0.007)	(0.007)	(0.007)	(0.017)	(0.016)	(0.015)
Father's Economic Status	−0.013	−0.022	−0.010	−0.028	−0.037*	−0.024	−0.021	−0.031	−0.021
	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Log Foreign Born Population in Congressional District	0.085***	0.049***	0.048***	0.078***	0.042***	0.044***	0.078***	0.041***	0.043***
	(0.007)	(0.010)	(0.010)	(0.008)	(0.010)	(0.010)	(0.008)	(0.010)	(0.010)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,254	2,254	2,254	2,180	2,180	2,180	2,180	2,180	2,180
Adjusted R^2	0.37	0.39	0.42	0.37	0.39	0.42	0.37	0.39	0.42
	Panel B. Pro Immigration Vote in All Immigration Bill Sample								
	MC Immigrant Ancestry Measured as:								
	Parents Foreign Born			Grandparents Foreign Born			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MC Immigrant Ancestry	0.060***	0.057***	0.042***	0.027***	0.026***	0.019***	0.066***	0.064***	0.046***
	(0.008)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.007)
Father's Economic Status	−0.012	−0.017**	−0.009	−0.020**	−0.025***	−0.016*	−0.017**	−0.023***	−0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
Log Foreign Born Population in Congressional District	0.047***	0.035***	0.036***	0.043***	0.031***	0.034***	0.043***	0.031***	0.033***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Other MC Controls	No	No	Yes	No	No	Yes	No	No	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,379	11,379	11,379	11,125	11,125	11,125	11,125	11,125	11,125
Adjusted R^2	0.37	0.37	0.39	0.37	0.37	0.38	0.37	0.37	0.38

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates Table II, but includes controls for each MC's father's socio-economic status. We measure MC's father's status using a score based on the father's census occupation coded following Song et al. (2020) and Ward (2023). The methods allow occupations to vary in status over cohorts, regions, and race. We see that our main results are robust to including this control. Also evident in the table, once we control for family immigration history, there is little to no correlation between father's economic status and how his future-MC child votes on immigration legislation. Standard errors clustered at the MC level.

A.2 Miscast Votes

Family history of immigration also helps us explain ideologically-surprising or "miscast" votes on immigration issues. Specifically, we examine bills where (1) an MC was predicted to vote pro immigration based on their ideological position (as measured by both dimensions of DW-NOMINATE) but instead voted anti immigration; and, (2) an MC was predicted to vote anti immigration but instead voted pro immigration.

For every bill, Voteview (which provides DW-NOMINATE scores and data) calculates a "cut line" that best divides the Yea and Nay votes (Poole 2005). A miscast vote is one that is on the "wrong" side of the line: any MC whose actual vote is the opposite of their most likely predicted vote. "Miscast vote" is defined as a binary variable, such that positive coefficients are associated with a higher likelihood of voting differently than one's ideological prediction (or others with similar DW-NOMINATE scores), and negative coefficients are associated with a lower probability of differing from one's ideological prediction. These "miscast" votes allow us to examine instances where immigration history led MCs to depart from what would be predicted by their overall political ideology. This approach moves beyond simply controlling for party, as in Table II, which is useful because restrictionist ideologies cut across both parties, for example by bringing together Southern Democrats and some Western Republicans.

To implement this test, we divided our data into sub-samples: (1) Individuals predicted to cast a "pro" immigration vote; and, (2) individuals predicted to cast an "anti" immigration vote. Within each sub-sample, we then coded all individuals with a "miscast" vote with a 1 and those who voted according to expectations with a 0. Table A.30 reports the results. Focusing on Panel B, in all cases, the directions of the coefficients accord with our expectations. First, immigration history predicts a reduced rate of diverging from pre-existing ideology when an MC is predicted to vote in favor of immigration. We estimate that an additional foreign-born parent is associated with a reduction of 3 percentage points; and a 1.5 percentage point change for additional foreign-born grandparents. We also observe a positive relationship between immigration history and casting a pro vote despite having an overall political ideology that would predict casting an anti vote, with coefficcient sizes similar to the prior case, but in the opposite direction.

A.3 Replicating Main Results Using Surname Scores

It is possible that the pattern of missing data—particularly for foreign-born grandparents—might somehow bias our results. In particular, missingness for this measure occurs in our earliest sample years. As one check against this possibility, we re-estimate our core results using estimated immigration histories based on surname, which has the advantage of no missingness (though measures everyone's immigration history with some error). Table A.31 replicates the results from Table II using only foreign-born scores derived from an MCs surname and finds similar results as to when we measured immigration history using individual level census data.

Table A.30: Immigration History and Miscast Votes

	Panel A. Landmark Bills					
	Predicted Pro but Voted Against			Predicted Against but Voted For		
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Foreign Born	−0.018			0.032***		
	(0.013)			(0.011)		
Grandparents Foreign Born		−0.006			0.016***	
		(0.007)			(0.006)	
Immigration Index			−0.015			0.034***
			(0.015)			(0.011)
Log Foreign Born Population in Congressional District	−0.060***	−0.047***	−0.047***	0.025***	0.025***	0.024***
	(0.013)	(0.018)	(0.018)	(0.006)	(0.008)	(0.008)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,204	952	952	2,605	1,721	1,721
Adjusted R^2	0.13	0.10	0.10	0.08	0.09	0.09
	Panel B. All Immigration Bills					
	Predicted Pro but Voted Against			Predicted Against but Voted For		
	(1)	(2)	(3)	(4)	(5)	(6)
Parents Foreign Born	−0.027***			0.019***		
	(0.006)			(0.006)		
Grandparents Foreign Born		−0.015***			0.009***	
		(0.004)			(0.003)	
Immigration Index			−0.030***			0.018***
			(0.007)			(0.006)
Log Foreign Born Population in Congressional District	−0.021***	−0.021***	−0.020***	0.028***	0.027***	0.027***
	(0.006)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
Log Total Population	Yes	Yes	Yes	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,119	5,532	5,532	10,895	7,652	7,652
Adjusted R^2	0.08	0.09	0.09	0.09	0.10	0.10

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table splits the sample depending on whether an MC's ideological score (DW-Nominate) would predict a pro- or anti-immigration roll call vote. Columns 1 through 3 are instances where the outcome variable takes a value of 1 if an MC was predicted to vote Pro but voted Anti, and 0 if they were predicted to vote Pro and did so. Columns 4 through 6 are instances where the outcome variable takes a value of 1 if an MC was predicted to vote Anti but in fact voted Pro, and 0 if they were predicted to vote Anti and did so. Each column includes bill and chamber fixed effects as well as MC controls (party, region, age and tenure) and CD controls (log foreign-born population, log total population, and log black population). Standard errors clustered at the MC level.

Table A.31: Immigration History using Visible Foreign Surname Measure and MC Vote Choice

	Panel A. Pro Immigration Vote in Landmark Bill Sample		
	MC Immigrant Ancestry Measured as:		
	Parents Foreign Born	Grandparents Foreign Born	Immigration Index
	(1)	(2)	(3)
Surname Predicted MC Immigrant Ancestry	0.078***	0.036***	0.062***
	(0.021)	(0.008)	(0.016)
Log Foreign Born Population in Congressional District	0.050***	0.048***	0.049***
	(0.007)	(0.007)	(0.007)
Log Total Population	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes
Observations	4,253	4,222	4,258
Adjusted R^2	0.35	0.35	0.36
	Panel B. Pro Immigration Vote in All Immigration Bill Sample		
	MC Immigrant Ancestry Measured as:		
	Parents Foreign Born	Grandparents Foreign Born	Immigration Index
	(1)	(2)	(3)
Surname Predicted MC Immigrant Ancestry	0.055***	0.024***	0.045***
	(0.009)	(0.003)	(0.007)
Log Foreign Born Population in Congressional District	0.041***	0.040***	0.041***
	(0.003)	(0.003)	(0.003)
Log Total Population	Yes	Yes	Yes
Other CD Controls	Yes	Yes	Yes
Other MC Controls	Yes	Yes	Yes
Bill FE	Yes	Yes	Yes
Chamber FE	Yes	Yes	Yes
Observations	20,682	20,555	20,693
Adjusted R^2	0.37	0.37	0.37

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates the main results in the paper using Surname Scores (i.e., imputed family immigration history based on average immigration levels for people with the same name and in the same region) rather than individual immigration histories based on census matching. All columns include bill and chamber fixed effects. Standard errors clustered at the MC level.

B Supplementary Historical Information

B.1 Immigration Bills

In this appendix section, we describe the landmark immigration legislation (see Table I for the full list). The Geary Chinese Exclusion Act, passed in 1892, extended the 10-year term of the 1882 Chinese Exclusion Act and added new requirements for both Chinese immigrants and Chinese people who had already immigrated to the United States. The Gresham-Yang Treaty, ratified by the Senate in 1894, prohibited any new Chinese immigration. The Immigration Act of 1903, also called the "Anarchist Exclusion Act," prohibited anarchists and other groups deemed undesirable from immigrating, and also allowed for the deportation of people who had not immigrated legally. The Immigration Act of 1907 added additional restrictions on who could immigrate.

The Immigration Act of 1917 was the first major bill designed to restrict European immigration into the United States that ultimately went into law. Passed by Congress over Woodrow Wilson's veto at the end of the 64th Congress, the act imposed a literacy test on European immigrants, and barred immigrants from Asian countries. The Immigration Quota Act (also called the Emergency Immigration Act of 1921 or Immigration Act of 1921) capped the number of immigrants and set quotas for immigration based on the number of people of each nationality already residing in the United States. The Immigration Act of 1924 (the Johnson-Reed Act) further lowered the number of immigrants allowed each year and heavily favored Northern European immigrants over those from Southern or Eastern Europe.[55] All three bills passed each chamber by large margins.

A second cluster of immigration acts followed WWII. The Displaced Persons Act of 1948 and Refugee Relief Act of 1953 temporarily increased the number of immigrants admitted due to the vast number of refugees in Europe after the war.[56] The McCarran-Walter Immigration and Nationality Act, passed by Congress in 1952 over the veto of Harry Truman, reorganized and consolidated immigration laws while preserving strict nationality quotas limiting immigration. Finally, the Immigration and Nationality Act of 1965 overhauled the immigration system once again, eliminating the nationality-based quota system and replacing it with a multi-category system that prioritized special skills or having relatives already residing in the United States. The long-term effect of the bill was to end the preference for Northern European immigrants and allow for increased immigration from the rest of the world. Abramitzky and Boustan (2017) suggest that the 1965 bill led to a new era of Mass Migration, albeit with very different source countries than the previous one.

B.2 Race and Immigrant Experience

The relationship between race and immigrant experience also marks a complex point of comparison between our period of study and today's Congress. Most of the immigrant MCs in our historical sample are white, echoing both the history of race in U.S. politics and the fact that immigration to the US from most non-European countries was nearly impossible for the late 19th and early 20th centuries. The shares from Europe were over 80% from 1850 to 1950, with immigrants from Canada making up another substantial share (Abramitzky and Boustan 2017). Immigration to the US from Asia was banned entirely for much of

[55] For a detailed account of the politics of immigration reform, see Tichenor (2002).

[56] The House of Representatives did not hold a final roll call vote on the Displace Persons Act of 1948; we only include the Senate vote in our analysis.

the period. But as scholars (for example, Painter (2011) and Roediger (2006)) have documented extensively, the concept of race and whiteness in the early 20th century was contested in U.S. society. The contestation of race and whiteness extended to Congress. See Tichenor (2002) for detailed accounts of how Congress relied on racial tropes and discredited pseudo-science from groups such as the Immigration Restriction League when formulating immigration policy. U.S. society, and lawmakers, did not always view European immigrants, especially those from southern and eastern Europe, as belonging to the same racial group as "whites" (Guglielmo 2003). Thus, while the analysis of historical legislative behavior in our study may not speak directly to the racial dynamics at play in today's immigration debates, ideas about race still had bearing on the immigration policies applied to European immigrants in the early and mid 20th Century.

B.3 Mechanisms Affecting Group Boundaries

Processes that make immigrant group identity a more salient boundary for MCs include group consciousness and/or linked fate. The concept of "group consciousness" involves "identification with a group and a political awareness or ideology regarding the group's relative position in society along with a commitment to collective action aimed at realizing the group's interests" (Miller et al. 1981). The concept of "linked fate" suggests that some political beliefs and actions taken by people who belong to minority ethnic or racial groups can be explained by their perceptions of racial group interests. Most famously, researchers have posited that linked fate helps explain the political cohesion of black voters in the US (Dawson 1995). But notions of linked fate have since been shown to operate for groups based on race, ethnicity, gender, class and religion (Gay, Hochschild and White 2016).

For lawmakers who belong to a relevant group, these processes may link the interests of the group to those of the lawmaker. In traditional applications of group consciousness and linked fate, researchers have found that these concepts explain increased rates of political participation as well as more liberal views towards public policy (Verba and Nie 1987; Dawson 1995). The core logic underlying these empirical relationships is that individuals exhibiting group consciousness or a sense of linked fate *are more likely to engage in political behaviors advantageous to "their" group*. Extending this theory to a legislative context would suggest that, when these mechanisms are present, legislators with family histories of immigration would be more likely to prefer immigration policies seen as advantageous to their group.

C Supplementary Data Details

C.1 Census Linking Overview

The complete 1880, 1900, 1910, 1920, 1930, and 1940 Federal Censuses have recently been digitized by a joint effort of Ancestry.com and the Minnesota Population Center. The restricted-access version of the data, managed by IPUMS (Ruggles et al. 2020) and housed at the National Bureau of Economic Research (NBER), includes transcribed names that enable us to link to external data sources at the individual-level. We search for each member in each of the decennial Federal Censuses from 1880 to 1940 to link MCs to census records. Individuals' names as enumerated in the US Federal Census are restricted for 72 years following the census for privacy reasons, so we stop with the 1940 census, released publicly in 2012.

Recent advances in historical record linking make this work possible. See Abramitzky et al. (2021b) and Bailey et al. (2017) for more details. We turn to the Feigenbaum (2018) census linking method for three key reasons. First, in a recent review of historical census linking methods, Abramitzky et al. (2021b) finds that the most commonly used methods trace out a frontier, trading off false positives and false negatives in linking. The Feigenbaum method, by replicating the hand links a trained researcher would make, does particularly well at minimizing false negatives or records for which a true match exists but is not recovered. Because we link from high quality source data (the Congressional Biographical Directories including middle names and exact dates of birth) and link into *five* censuses, we believe we are creating a linked sample that is unlikely to have many false positives as well. Second, Abramitzky et al. (2021b) also note that choice of exact historical linking method, among those commonly used by recent economic historians working with the complete count census, tends not to affect research conclusions. Third, because we are linking from a non-census source into the census, we cannot use the off-the-shelf, census-to-census links like Abramitzky, Boustan and Rashid (2020) or the IPUMS-linked samples.[57]

Noise in our data makes exact matching—requiring an MC to report his or her first and last name, year of birth, and state of birth exactly the same in the census as in our congressional data—impractical and potentially biased (Abramitzky et al. 2021b). While hand linking records might be able to distinguish between subtle errors in two records identifying the same person or distinguishing two different people, it is not practical to apply hand linking to large samples and—even with clear instructions on how to make links—not replicable. Instead, the machine learning algorithm we use learns how to trade off discrepancies in record features. These include errors in first names or last names or how large a penalty to apply to potential matches with one or two years off in the year of birth.[58] The algorithm uses a wide range of record linkage features to build predictions for matches including Jaro-Winkler string distance and Soundex agreement on first and last name, absolute difference in year of birth, agreement on first and last characters of names, as well as name commonness and state of birth.

[57] `https://usa.ipums.org/usa/linked_data_samples.shtml`

[58] Errors in years of birth may be surprising, but are very common. For one, censuses record age, not date or even year of birth. Because censuses are taken on different days in each wave (June 1 in 1900, April 15 in 1910, January 1 in 1920, and April 1 in 1930 and 1940), these ages are noisy. With our data on MCs, we observe birthdate exactly, so we can calculate expected age as of the census. However, censuses were taken by enumerators asking questions of one respondent per household, and ages were often estimated or heaped on the nearest round number or simply misstated. In addition, the transcription process for age may be especially noisy because there are no context clues to help a transcriber determine between a poorly written 2 or 3, for example. See Ghosh, Hwang and Squires (2023) for more on the role census enumerator handwriting plays in record linkage.

Table C.1: Examples of Family Background from Census Data

	Carl Albert	Clinton Anderson	James Michael Curley
Birthplace	Oklahoma	South Dakota	Massachusetts
Mother	Texas	South Dakota	Ireland
Father	Missouri	Sweden	Ireland
Maternal	Missouri	Illinois	Ireland
Grandparents	Kansas	Wisconsin	Ireland
Paternal	Missouri	Sweden	Ireland
Grandparents	Texas	Sweden	Ireland

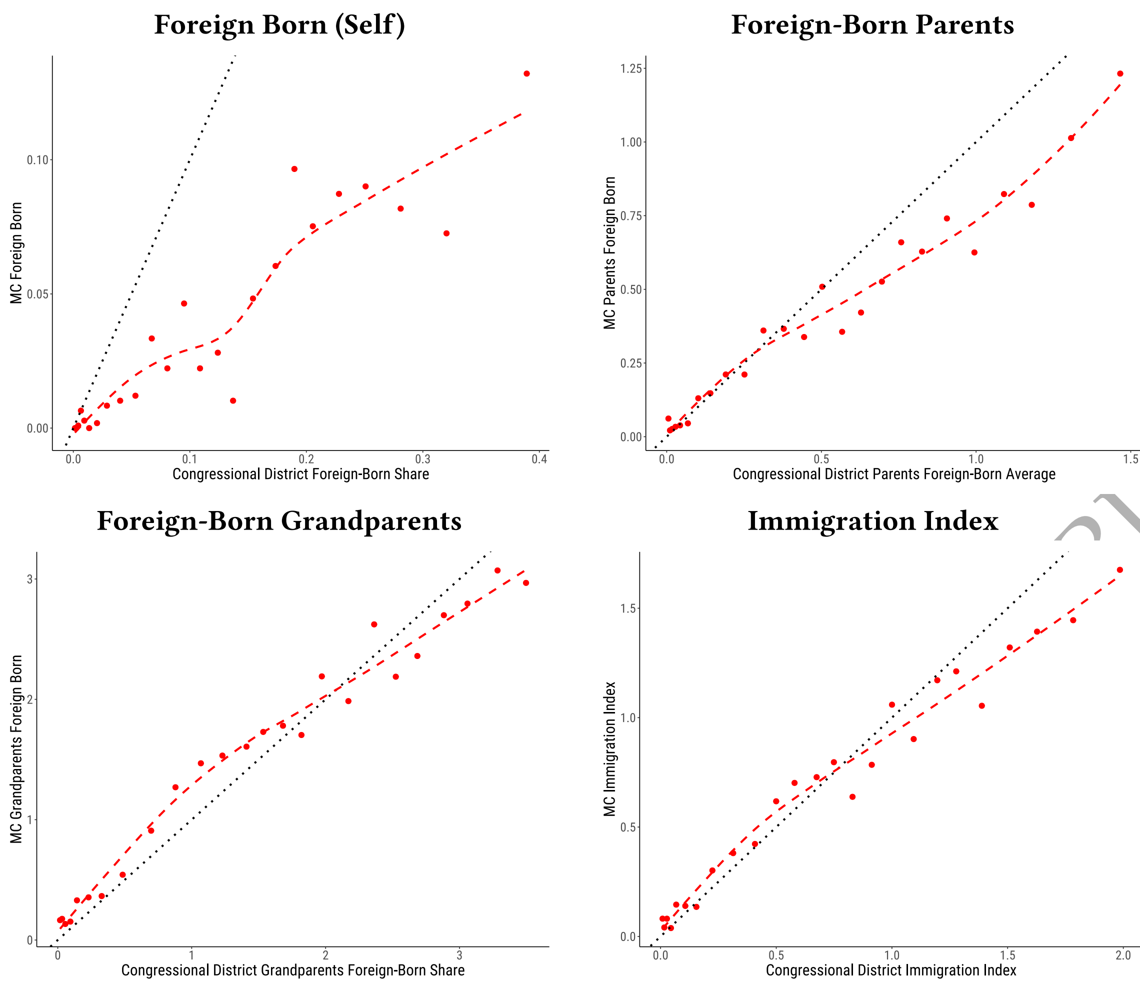
Note: This table illustrates varying family backgrounds for three members who served in Congress during our sample period: Carl Albert, Clinton Anderson, and James Michael Curley. All three are white males and are US-born, but have very different family histories that we can recover by linking to the complete count census.

Table C.2: Family Immigration History for MCs by Party and Chamber

	Overall			House			Senate		
	Total	Dem	Rep	Total	Dem	Rep	Total	Dem	Rep
Share Foreign-Born	0.04	0.03	0.05	0.04	0.03	0.05	0.04	0.02	0.05
Mean Number of Foreign-Born Parents	0.40	0.38	0.40	0.41	0.40	0.41	0.31	0.26	0.32
Mean Number of Foreign-Born Grandparents	1.60	1.57	1.60	1.64	1.61	1.63	1.40	1.28	1.44
Share with 1+ Foreign-Born Parent	0.24	0.23	0.24	0.25	0.24	0.25	0.18	0.16	0.19
Share with 1+ Foreign-Born Grandparent	0.49	0.46	0.51	0.50	0.47	0.52	0.44	0.40	0.46
Share with Both Parents Foreign-Born	0.16	0.15	0.16	0.17	0.16	0.16	0.12	0.10	0.13
Share with All Grandparents Foreign-Born	0.32	0.33	0.31	0.33	0.34	0.31	0.28	0.26	0.29
N	4593	2346	2166	3837	1966	1810	756	380	356

Note: This table reports summary statistics for family immigration history for MCs in the 51st to 91st Congresses by chamber and by party. Members who held office in multiple congresses in the sample are counted once (per chamber), in slight contrast to Table A.1 which summarized our MCs data at the bill level. Members from third parties are included in totals.

Figure C.1: Relationship between MC Immigration Family History and CD Immigration Family History



Note: This figure displays the relationship between the actual immigration family history of an MC and the district represented by the MC. Each bin represents 1/25th of the data and the dots present the average within each bin. The label above each plot denotes the specific measure used. As is evident from the plot, the relationship between foreign-born population shares at the CD-level and foreign-born ancestry at the MC-level is positive and close to linear.

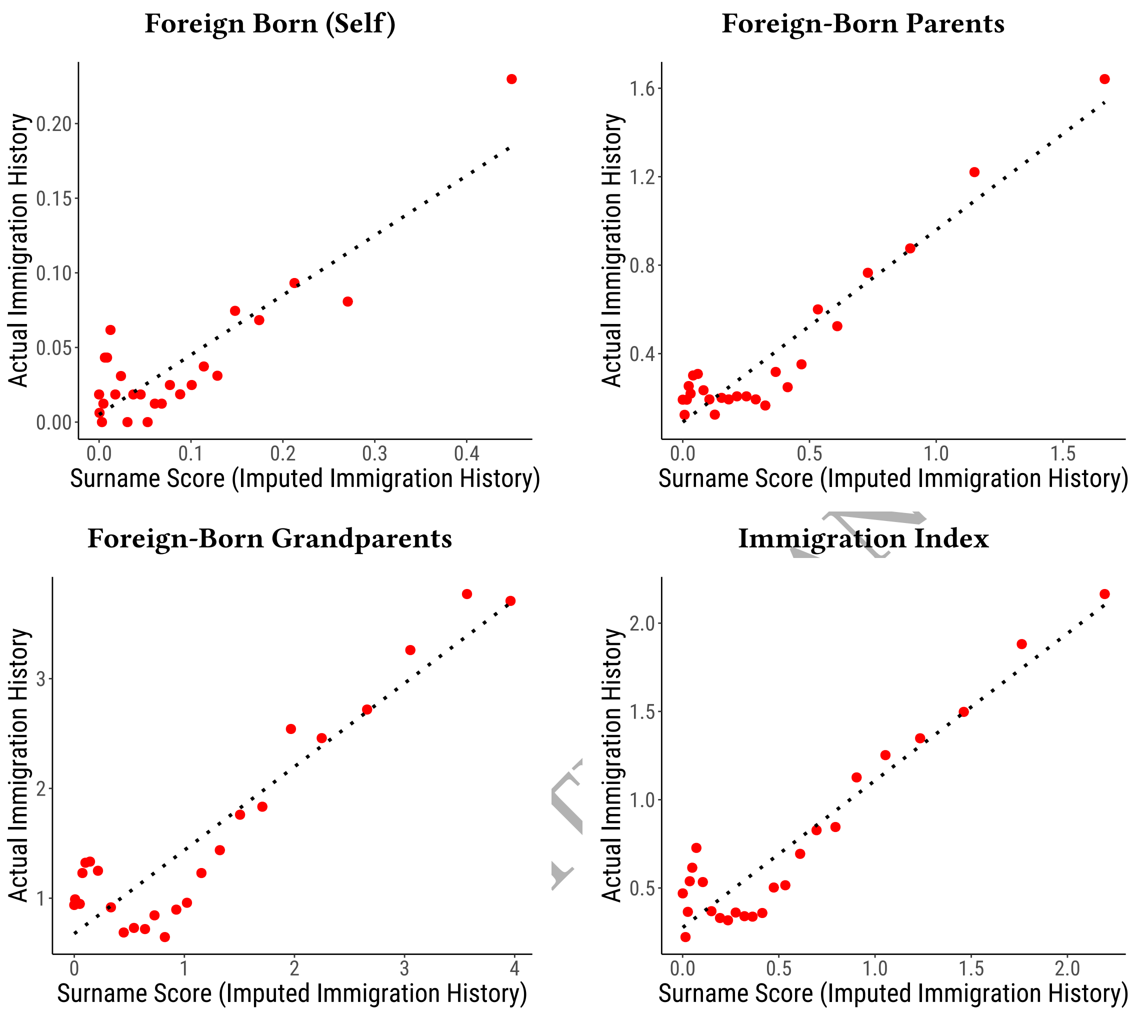
C.2 Surname Scores

Surname-based measures are useful for individuals for whom we have less available information. This includes older MCs who we are unlikely to find residing at home with their parents. In addition, it is extremely difficult to census link failed candidates for Congress: for these challengers, we rarely observe either year of birth or place of birth, two variables key to census linking. Surname scores allow us to proxy for immigration histories of these challengers. And, in subsequent analyses, they provide a measure for public perceptions or visibility of immigrant background since they report the average immigration background for an individual based on surname alone.

While not a one to one correspondence, the correlation between actual immigration family history and surname score is very high. We view immigration history based on surname as measuring the variable of interest, Immigration History$_i$, but with some error—that is, Immigration History$_i$ = Surname Score$_i + \varepsilon_i$. The error term can be thought of as the difference for each individual between the average immigration background of someone with that surname and the actual immigration background of the individual under study.

Figure C.2 illustrates the correspondence between Immigration History$_i$ and Surname Score$_i$ for Members of Congress. We present the data in a binned scatterplot with 25 bins in surname score. Each bin represents 1/25th of the data and the dots present the average within each bin. We also plot the best linear fit.

Figure C.2: Comparison of Actual Foreign-Born Status to Imputed Foreign-Born Status (Surname Scores), Members of Congress



Note: This figure displays the relationship between surname score, which is an imputed measure of family immigration history based on surname, and the actual immigration history of an MC. We present the data in a binned scatterplot with 25 bins in surname score. Each bin represents 1/25th of the data and the dots present the average within each bin. The label above each plot denotes the specific measure used. For example, Foreign-Born Grandparents captures the number of grandparents born abroad as non-citizens. We also plot the best linear fit.

C.3 Constructing Linked Sample Based Measures of District Demographics

In our main analysis, we use district foreign-born population to control for district demographics. However, our measure of ancestry for our MCs is much more precise, using census linking to recover not just if MCs are foreign-born but to count their foreign-born parents and foreign-born grandparents. In this appendix section, we describe a parallel construction of CD level ancestry which we use in several robusntess tables (see Table A.7).

We construct these parallel measures of ancestry CD by CD and Congress by Congress. To do this, we draw on the complete count census data, as we did for the MCs. To be as parallel as possible with our measures of MC ancestry, we use census linking but do so at scale for everyone in each congressional district, not just the MC who represents the district. We use off-the-shelf census links from the Census Linking Project (Abramitzky, Boustan and Rashid 2020). For every person we observe in any given census, we use their forward and backward CLP links to find them in other censuses and thus find their family members (primarily their parents but also their grandparents) in other censuses. This gives us information on whether or not the person is foreign-born, how many of their parents are foreign-born, and how many of their grandparents are foreign-born, using both the mother and father birthplace answers in most censuses and the birthplace answers of relatives seen in a household. This is exactly parallel to how we construct ancestry for our MC sample. We then aggregate these measures to the county-level (and then convert to district-level data).[59]

C.4 Opinion Polls for MRP Robustness

The polling data used for the MRP analysis is drawn from the Roper iPoll Gallup archive. We focus on 8 different polls conducted between 1951 and 1965. These polls all feature questions about respondents' feelings on immigration. The polls also asked respondents their state and urban status, age, sex, race, occupation, and level of education. We use all of these features in our MRP analysis. Though the specific poll questions vary, we recode each from least to most supportive of future immigration. The full text of the poll questions is included in Table C.3. The sample sizes of these polls range from 1403 to 2532. Because the polls asked respondents their state and urban status (and not their county or congressional district), we construct measures of attitude at the state by urban/rural level.

[59]Without complete count data in 1890 or in 1950 or after, we interpolate or extrapolate from the closest census with data.

Table C.3: Historical Poll Questions Used in MRP Robustness Analysis

Roper ID	Date	Sample Size	Poll Question
31087455	Feb 1951	1403	A U.S. senator has suggested that the United States give a million German, Polish, Czech and other European citizens a chance to enlist as part of the United States forces in Europe. After 5 years' service, they and their families would be allowed to come to this country and become citizens of the United States. Would you approve or disapprove of this?
31087466	Nov 1951	2019	Recently many persons have escaped from Russia and Russian-controlled countries. Do you think they should or should not be allowed to come to the United States?
31087502	Jul 1953	1532	Millions of people have come to West Germany from the Eastern Zone of Germany, Poland, and Czechoslovakia to get away from the communists. President Eisenhower has asked Congress to let about 200,000 of these people enter this country. Would you approve or disapprove of this?
31087531	May 1955	1504	Would you approve or disapprove of having a few families from Europe come to this neighborhood to live?
31087559	Nov 1956	1502	Should the laws of the U.S. (United States) be changed to make it easier for refugees to come here from communist-held countries such as Hungary and Poland?
31087586	Jul 1958	1621	In Europe there are still one hundred and sixty thousand refugees who left Hungary to escape the communists. It has been suggested that the U.S. permit sixty-five thousand of these people to come to this country. Would you approve or disapprove of this plan?
31092366	Sep 1964	1611	Do you think the number of immigrants allowed to enter the U.S. each year should be increased somewhat, decreased somewhat, or kept at about the present level?
31087694	Jun 1965	2534	Should immigration be kept at its present level, increased, or decreased?

Note: To measure constituency preferences historically, we draw data from the Roper iPoll Gallup archive from 8 different polls conducted between 1951 and 1965. These polls all feature questions about feelings on immigration. We recode answers to measure support or opposition to more immigration. Because the polls asked respondents their state and urban status (and not their county or congressional district), we construct measures of attitude at the state by urban/rural level. We use multilevel regression with post stratification (MRP) to estimate the opinions of constituencies. MRP combines constituency-level characteristics and individual-level characteristics to estimate the outcome variable (responses to a specific poll question, usually; see Lax and Phillips (2009)) even when only a handful of observations for each constituency are available in the original data. Because we have access to the complete count census data, our measurement of the demographics of each constituency are quite precise and we include several individual traits (sex, race, education, occupation, and age). We follow Hanretty (2020) in constructing our MRP estimates of immigration attitudes.

C.5 Tone of Speech

Card et al. (2022) analyzes congressional speeches on immigration in order to understand how attitudes towards immigration have shifted since the late 1800s. Their findings are descriptive; they argue that the aggregate tone of speech about immigration in Congress has covaried with immigration policymaking over time. For example, the "gradual loosening of immigration laws in the 1940s" was "mirrored by congressional tone toward immigration, which began improving in the 1940s, eventually becoming net positive on average in the 1950s" (Card et al. 2022, p. 6).

In their study, Card et al. (2022) collected all congressional speeches since 1880, identified which speeches pertained to immigration, and use text analysis methods to identify the tone (pro-immigration, anti-immigration, or neutral) of each speech. The authors also analyzed how different MCs frame their speeches (e.g. family, crime, legality, threat, etc.) and how the usage of these frames has changed over time.

Card et al. (2022) scores each speech on immigration in three parts: pro, anti, and neutral. We use these speeches to calculate a *tone* metric for member for each congress. Specifically, we use a measure of tone that ranges from -1 to 1 (with positive values indicating more positive tone).

For example, in the 64th Congress (in which the Immigration Act of 1917 was passed), Rep. Augustus Gardner (R-MA) made 52 speeches pertaining to immigration. Of these, the algorithm used by Card et al. (2022) classifies one as positive, 32 as neutral, and 19 and against immigration. The speech below is an example of one classified as anti-immigration in tone:

> Now . Mr. Chairman . my objection to this bill is that in ordinary times it will only cut down immigration by 300.000 . or thereabouts . If I had my way . I should be glad to vote for a bill that would either suspend immigration altogether for the next 10 years or come mighty near it . There are 20.000.000 men mobilized in Europe . In the course of this year or next they are going to start to demobilize those 20.000.000 men . They are going to project 20.000.000 men on the ruined industries of Europe . and I have an idea that those demobilized men are going to try to come over here in vast numbers .

In contrast, Rep. Martin Foster (D-IL), in the same Congress, gave a speech classified as pro-immigration in tone:

> I can not believe that the gentleman from Massachusetts represents the true sentiment of the people of Massachusetts In his charge against the people of this country who are of German birth . Let us hope in the American Congress such an attack will never again be made and that the country will not believe that the American Congress does countenance or indorse such statements . We have reason to believe from past experience when our country was in peril and it became necessary to engage in war that these men of foreign birth or their descendants have been among the first of those to enlist and offr their services and their lives . if necessary . to sustain the flag .

Treating tone of speech as a form of legislative behavior raises a broader conceptual question of whether measures based on text should be thought of in a manner similar to direct measures of member ideology such as roll call votes. That is, can measures derived from speech data yield reliable indicators of policy preferences in specific policy domains? High dimensional text data is incredibly promising and scholars increasingly use text-based measurements to track a variety of outcomes including policy preferences. However, the validity of these measures is often difficult to establish. While the connection between roll call voting (or legislator ideology) and congressional floor speech is assumed for much past work (for example, Gentzkow and Shapiro (2010) score the ideologies of newspapers based on textual similarity with MC speech by party) and researchers often employ speech as a dependent variable, the use of speech to construct good measures of MC-specific policy preferences is not well established.

Ultimately, one contribution of this paper is to illustrate robust correlations between important MC-level covariates and both speech and roll call based measures of policy preferences. To our knowledge, we are also the first to document similar effects on speech and roll call voting for the same treatment using our close election RDD strategy. This focus on a particular (and important and divisive) policy area like immigration helps validate the use of speech to measure legislator preferences. This contribution is important because, as Ash and Hansen (2023) note in their recent review, "Text Algorithms in Economics", the "challenge of validating algorithmic output" is a key limitation in the literature. The results established here help to bridge these two distinct forms of legislative behavior, providing a proof of concept that speech data can be used to construct reliable measures of preferences for specific policy areas.

Finally, yet another dimension of congressional speech data related to immigration is the *frame* adopted by the speaker. Table C.4 reports a selection of examples, drawn from the Card et al. (2022) speech data, illustrating frames adopted by MCs in their speeches.

Table C.4: Examples of Speech Frames

Frame	Example Speech
Background	STONE (R-PA; 1896): Mr. Speaker. the broad statement that the Germans of this country are opposed to restricting immigration is a libel on the German citizens resident in our country . No more loyal . patriotic class of people exist within the borders of the United States than our German population . They are not opposed . in any sense of the word . to restricting immigration in a proper way
Contribution	PHEIFFER (R-NY; 1942): These are cases that do not come to the county clerks in ordinary times . This is simply to recognize the loyalty . the patriotism . and the devotion to our institutions these aliens show by enlisting in the Army . This simply gives them a short cut to citizenship .
Deficient	FORD (R-CA; 1940): Mr. Speaker . hearings are being held on the bill for the deportation of undesirable aliens . I have taken the stand that the committees of the House and this House itself can defend this country just as well as our Army . our Navy . and our air force can by deporting those who may be part of a " fifth column . " I believe that if this country Is destroyed by undesirable aliens who bore from within it . is just as much destroyed as if it is destroyed through the loss of our Army and our Navy . I think it is high time we took it unto ourselves at least to throw these people out of the country . if we do not put them in jail .
Economic	JONAS (R-NC; 1965): I was interested in the comments of the distinguished chairman of the Committee on the Judiciary about respective immigrants from one country having to compete with others . I assume reference was made to cornpeting on the basis of skill . Is that correct ?
Exclusion	ANDRESEN (R-MN; 1953): It seems to me it is up to the Immigration Service to prevent those wetbacks from coming over .
Flood/Tide	JOHNSON (D-TX; 1940): Let me conclude with this thought : There are a great many hobgoblins conjured up in the brains of certain Members . They are afraid we are going to have a flood of foreigners descend upon us . They are afraid it is goingto get us into war . This bill does not affect the immigration and naturalization laws . It will not bring in a single person or individual who is not now permitted to come in under the immigration and naturalization laws . It will not be effective unless all governments consent in advance thereto . I have no sympathy with the plea that because all children can not be saved . none should be saved .
Labor	ANDRESEN (R-MN; 1950): This proposal began during the World War when it was not possible to get American labor to go out and do this kind of stoop work . I may say very frankly that I would prefer to employ American labor if we could get it . We can not get it today . and I doubt very much if we shall be able to get American labor to go out and work in the fields to do this stoop labor.
Legality	KING (R-HI; 1937): The purpose is to grant the same exemptions . under existing law . to alien wives of American citizens that are now granted in the case of Chinese wives of American citizens . The total number affected by this bill is about 25 . some of whom are residents of my district . The exemption only applies to marriages that occurred prior to the passage of the immigration law of 1924 . It would not apply to any marriages subsequent to that time .
Migration	KALANIANAOLE (R-HI; 1908): If any Americans there are being driven out . it is not by Europeans . but by Asiatic cheap labor . Now . we . as American citizens . want to do away with these conditions as they are there today . We want more laborers who are citizens or eligible to become citizens.
Quantity	TEMPLE (R-PA; 1917): If so . there is probable trouble ahead of us . To illustrate : In western Pennsylvania there are a great many thousands of foreigners . In the district I represent there were . according to the census . of 1910 . about 90.000 men over 21 . Of those men over 21 . 38.000 were foreign born . A great many of them are not citizens of the . United States . sono have taken out their first papers . Our mines and our steel mills are partly dependent upon those men .
Threat	PHEIFFER (R-NY; 1942): During the past week end . we have learned that that probability has . with dramatic suddenness and stark and vidid realism . emerged into the realm of fact . Had not the F. B. I. so promptly and efficiently rounded up the eight Nazi rattlesnakes who were landed from submarines on the coasts of Florida and Long Island . they would even now doubtless be sheltered and aided In their nefarious work by Nazi sympathizers in this country . The existing statutes do not adequately cope with this grave problem.
Threat	GRIFFIN (R-MI; 1958): Mr. Chairman . as the representatve of counties in western Michigan which are great producers of fruit and other agricultural products . I know the importance of the pending legislation . I am particularly aware of the problems which cherry growers would face if they were not authorized by this legislation to secure Mexican nationals . in sufficient numbers and at the right times . to harvest their annual crop . As it has been pointed out . this law does not permit Mexican nationals to displace domestic labor . On the contrary . the legislation specifically protects the prior job rights of domestic workers if they are willing and available to perform the work of harvesting those crops .
Victims	Mr. MARTIN J. KENNEDY (D-NY; 1940): I am anxious to have the RECORD show that we are going to welcome the children of all nations . that it is not for the benefit of any one country . It would be well for the chancelors of Europe to know that what we are now doing is not to favor one particular nation or to punish another . but only to show our affection for all children .

Note: This table presents select examples of speeches associated with frames as identified in Card et al. (2022).

C.6 Coding Places of Origin into Regions

We identify regions of origin using IPUMS birthplace coding.

Old Europe: Denmark, Faroe Islands, Finland, Iceland, Lapland, Norway, Svalbard and Jan Meyen, Svalbard, Jan Meyen, Sweden, England, Channel Islands, Guernsey, Jersey, Isle of Man, Scotland, Wales, United Kingdom, Ireland, Northern Ireland, Northern Europe, Belgium, France, Alsace-Lorraine, Alsace, Lorraine, Liechtenstein, Luxembourg, Monaco, Netherlands, Switzerland, Western Europe, Austria, Austria-Hungary, Austria-Graz, Austria-Linz, Austria-Salzburg, Austria-Tyrol, Austria-Vienna, Austria-Kaernten, Austria-Neustadt, Bulgaria, Czechoslovakia, Bohemia, Bohemia-Moravia, Slovakia, Czech Republic, Germany, Berlin, West Berlin, East Berlin, West Germany, Baden, Bavaria, Braunschweig, Bremen, Hamburg, Hanover, Hessen, Hesse-Nassau, Lippe, Lubeck, Oldenburg, Rheinland, Schaumburg-Lippe, Schleswig, Sigmaringen, Schwarzburg, Westphalia, Wurttemberg, Waldeck, Wittenberg, Frankfurt, Saarland, Nordrhein-Westfalen, East Germany, Anhalt, Brandenburg, Kingdom of Saxony, Mecklenburg, Saxony, Thuringian States, Sachsen-Meiningen, Sachsen-Weimar-Eisenach, Probable Saxony, Schwerin, Strelitz, Prussia, Hohenzollern, and Niedersachsen.

New Europe: Albania, Andorra, Gibraltar, Greece, Dodecanese Islands, Turkey Greece, Macedonia, Italy, Malta, Portugal, Azores, Madeira Islands, Cape Verde Islands, St. Miguel, San Marino, Spain, Vatican City, Southern Europe, Hungary, Poland, Austrian Poland, Galicia, German Poland, East Prussia, Pomerania, Posen, Prussian Poland, Silesia, West Prussia, Russian Poland, Romania, Transylvania, Yugoslavia, Croatia, Montenegro, Serbia, Bosnia, Dalmatia, Slovonia, Carniola, Slovenia, Kosovo, Central Europe, Eastern Europe, Estonia, Latvia, Lithuania, Baltic States, Other USSR/Russia, Byelorussia, Moldavia, Bessarabia, Ukraine, Armenia, Azerbaijan, Republic of Georgia, Kazakhstan, Kirghizia, Tadzhik, Turkmenistan, Uzbekistan, Siberia, USSR, Europe.

C.7 Constructing Linked Samples and Intergenerational Mobility to Test Information Mechanism

The second possible mechanism we explore in the main paper is information. In contrast to MCs with no (recent) foreign-born ancestry, MCs with a family history of immigration might possess more accurate information about immigration (and thus about the effects of restricting or liberalizing immigration policy). These MCs have first-hand experience that could make them more empathetic to the plight of new immigrants. They might better understand the efficiency gains from immigration. Or, as a particularly successful descendant of immigrants, they might recognize, through introspection, the (high) potential upward mobility of immigrants to the US (Abramitzky et al. 2021a).

To assess whether knowledge about the potential upward mobility of immigrants affected policymaking, we constructed measures of intergenerational mobility throughout our sample. Our approach echoes the linked samples and mobility analysis in (Abramitzky et al. 2021a), but extends the sample to many more census-to-census links. We start with all sons aged 0-16 living with their fathers in the 1850, 1860, 1870, 1880, 1900, 1910, and 1920 censuses. We link these sons ahead to their adult-selves 20 or 30 years later using Census Linking Project crosswalk files (Abramitzky, Boustan and Rashid 2020). For each father-son pair, we record their occupation, age, race, and location. We focus on the white sample given the racial demographics of immigrants during our period. Like (Abramitzky et al. 2021a), we identify families as immigrant or not based on the birthplace of the father. We measure economic status using an adjusted version of Song et al. (2020) scores proposed by Ward (2023). These scores are based on human capital averages by occupation but vary by cohort, region, and race to account for changes in occupations (and their relative social status) over time.[60] The scores run from 0 to 100 and represent a given occupation's place in the human capital distribution for each cohort, region, and race.

We then regress the economic status of the son as an adult on the economic status of the father 20 or 30 years earlier. We do this both overall and for just the sample with immigrant fathers. Following (Abramitzky et al. 2021a), we focus on one particular measure of intergenerational mobility: the expected ranked outcome of a son with a father at the 25th percentile. We run this regression for each origin state by outcome census pair to generate a measure of mobility; that is, a single regression would include all sons found in 1940 who were observed in Massachusetts in either 1910 or 1920 (30- and 20-year links) and would tell us the expected economic status of a son in 1940 from Massachusetts with a father at the 25th percentile. We then rank the rates of mobility within each outcome census—the state with ranking 1 has the highest rate of mobility (specifically the best expected outcome for sons starting at the 25th percentile)—and use these rankings in our analysis.

[60]Our results are robust to using standard occupation scores from IPUMs or the unadjusted Song scores.

D RDD Robustness

The RDD approach in our paper follows the standards for employing a regression discontinuity design in an electoral setting (Lee 2008). The key assumption hinges on the notion that winning a very close election occurs largely due to random factors. As an election grows closer, a candidate's chance of landing narrowly on one side or the other of the 50% vote threshold, which determines the winner, begins to resemble a coin flip. By comparing the gap in vote choices between winners and losers at the 50% threshold we obtain an estimate of the effect of immigration background on vote choice. Crucially, this regression discontinuity approach relies on the continuity of the conditional mean function as we approach the threshold from at least one side (Lee and Lemieux 2010). We employ several robustness checks to provide additional evidence that (1) there are not jumps in the outcome at thresholds other than 50%, and (2) the assignment mechanism at the threshold is close to random.

Table D.1: RDD Robustness Check with Placebo Outcome Variables at District Level: Running Variable is Imputed Immigration History (Surname Score)

	Estimate	SE	P-Value	N (Effective)	Bandwidth
Region					
South	0.033	0.038	0.386	1865	7.25
Midwest	-0.049	0.047	0.293	1908	7.48
West	-0.010	0.024	0.666	2794	12.50
Northeast	0.036	0.044	0.412	1815	7.01
Political Outcomes					
Presidential Vote Share	0.012	0.014	0.373	2207	14.54
Presidential Turnout	0.021	0.013	0.105	1541	7.82
District Demographics					
Log Foreign-Born Population	-0.109	0.126	0.385	2079	8.53
Log Black Population	0.119	0.157	0.449	1824	7.14
Log Female Population	-0.004	0.053	0.934	2230	9.26
Log Male Population	-0.002	0.053	0.963	2160	8.95
Log Farms	-0.021	0.208	0.918	1844	7.95
Log Total Population	-0.003	0.053	0.949	2196	9.10
Log Urban Population	-0.116	0.108	0.283	2893	13.40
Foreign-Born Share	-0.005	0.009	0.551	2134	8.82
Black Share	0.008	0.008	0.317	1699	6.63
Female Share	0.001	0.002	0.723	2078	8.53
Male Share	-0.001	0.002	0.724	2078	8.53
Urban Share	-0.018	0.026	0.502	2139	8.86
Fulford Ancestry					
UK Ancestry Share	-0.009	0.017	0.610	2218	9.19
Irish Ancestry Share	0.000	0.006	0.982	2092	8.62
Italian Ancestry Share	0.003	0.005	0.472	1886	7.47
German Ancestry Share	-0.001	0.010	0.879	2028	8.22
Central European Ancestry Share	0.002	0.004	0.685	2092	8.64
Russian Ancestry Share	0.003	0.003	0.384	1914	7.60
Scandinavian Ancestry Share	-0.002	0.005	0.648	2490	10.73
Asian Ancestry Share	0.001	0.001	0.489	2639	11.72
Mexican Ancestry Share	0.001	0.003	0.661	2044	8.32
Fulford Economic					
Fulford Employment Rate	-0.002	0.004	0.706	2024	8.22
Fulford Income Per Capita	-123.450	227.056	0.587	1910	7.56
Fulford Income Per Worker	-566.019	466.410	0.225	1848	7.27
Fulford Gini Coefficient	-0.002	0.004	0.582	2179	9.04
Fulford Fractionalization	-0.013	0.011	0.235	1857	7.32

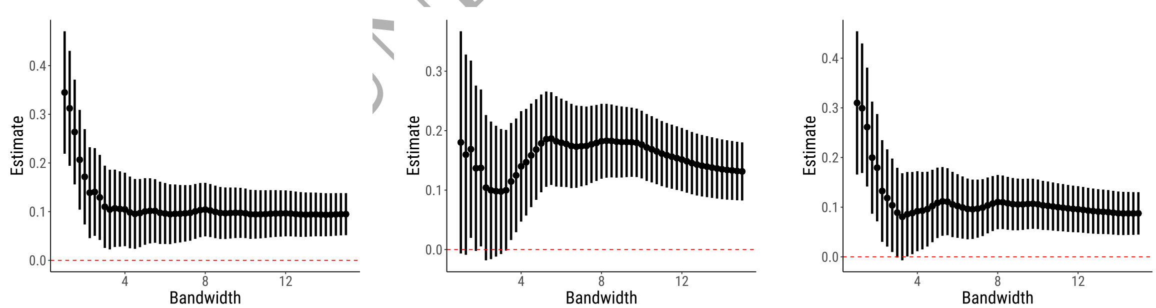
Note: This table shows that our measures at the district level are balanced across close elections won or lost by the immigrant descended candidate. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for our immigration index measure of family history using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.2: RDD Robustness Check with Placebo Outcome Variables at the MC Level: Running Variable is Imputed Immigration History (Surname Score)

	Estimate	SE	P-Value	N (Effective)	Bandwidth
Lagged MC Outcomes					
Age (Lagged)	1.700	1.103	0.123	1606	8.50
Years in Congress (Lagged)	0.102	0.538	0.849	1437	7.38
Democrat (Lagged)	0.056	0.060	0.349	3424	20.99
Bundled Treatment MC Outcomes					
Age	-1.512	0.975	0.121	2085	8.47
Years in Congress	-1.823	0.427	0.000	1726	6.68
Democrat	0.215	0.043	0.000	2339	9.76
Lagged DW Nominate					
DW Nominate Dim 1 (Lagged)	-0.064	0.056	0.252	2896	22.78
DW Nominate Dim 2 (Lagged)	-0.016	0.049	0.751	1756	9.45
DW Nominate Dim 1 (Lagged) Alt	-0.080	0.053	0.133	2907	23.13
DW Nominate Dim 2 (Lagged) Alt	-0.041	0.046	0.372	1611	8.53
DW Nominate					
DW Nominate Dim 1	-0.040	0.064	0.524	2917	15.82
DW Nominate Dim 2	-0.006	0.043	0.896	2062	8.35
DW Nominate Dim 1 Alt	-0.057	0.062	0.361	2939	16.08
DW Nominate Dim 2 Alt	-0.004	0.042	0.921	2110	8.67
Speech					
Card Tone (Lagged)	-0.023	0.045	0.605	822	11.27
Card Speech Count (Lagged)	0.197	0.460	0.668	1362	6.88
Card Speech Positive Count (Lagged)	-0.054	0.084	0.522	1413	7.22
Card Speech Negative Count (Lagged)	0.132	0.148	0.371	1456	7.51

Note: This table shows balance (and imbalance) in our measures at the MC level across close elections won or lost by the immigrant descended candidate. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for our immigration index measure of family history using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. The results for DW Nominate Dimensions 1 and 2 refer to the Nokken-Poole estimates, which allow for ideal points to change Congress to Congress. Standard errors are clustered at the MC level.

Figure D.1: RDD Robustness Check: Bandwidth Robustness for Roll-Call Votes



(a) Foreign-Born Parents **(b)** Foreign-Born Grandparents **(c)** Immigration Index

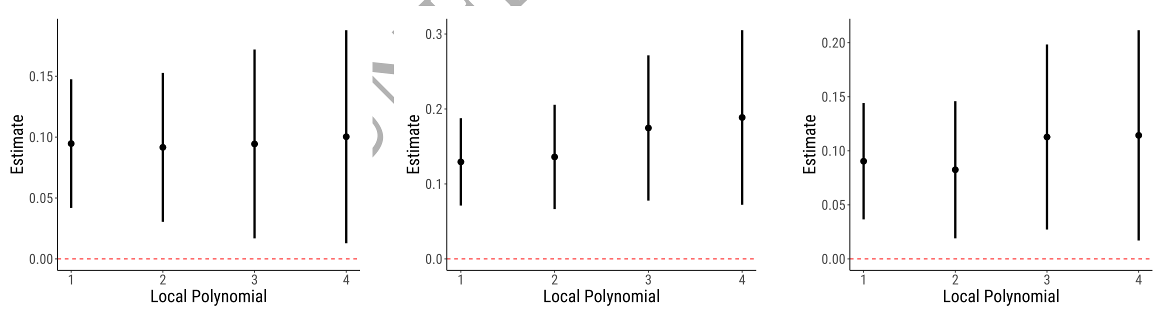
Note: This figure replicates our RDD from Table III, estimating the effect of electing an MC with foreign-born ancestors on permissive immigration roll call votes, but varies the bandwidth between 1 and 15 points by 0.25 points. Results are shown for our regional share surname measure of family history.

Table D.3: RDD Robustness Check with Placebo Outcome Variables based on Local Newspaper Coverage: Running Variable is Imputed Immigration History (Surname Score)

	Estimate	SE	P-Value	N (Effective)	Bandwidth
Newspaper Hits					
Immigrant	0.054	0.142	0.702	2006	8.35
Immigration	0.104	0.213	0.624	2092	8.85
Alien	0.512	0.584	0.381	1933	7.94
Quota	0.441	0.458	0.336	1856	7.51
Refugee	-0.038	0.143	0.790	1942	7.99
Foreigner	0.069	0.216	0.750	2027	8.50
Catholic	0.164	1.663	0.922	2012	8.39
Chinese	-0.002	1.064	0.998	2012	8.39
Irish	0.657	1.157	0.570	2011	8.37
Italian	0.487	1.988	0.807	1966	8.12
Jew	0.073	0.419	0.862	2001	8.32
Jewish	0.029	1.259	0.982	2005	8.34
Mexican	0.735	0.633	0.246	2020	8.46
KKK	0.035	0.071	0.623	1997	8.29
Klan	0.077	0.127	0.544	1959	8.07
Dago	0.018	0.014	0.202	2015	8.42
Kike	-0.006	0.024	0.820	2070	8.73

Note: This table shows that our measures of local sentiment based on newspaper terms are balanced across close elections won or lost by the immigrant descended candidate. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for our immigration index measure of family history using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Figure D.2: RDD Robustness Check: Polynomial Robustness for Roll-Call Votes



(a) Foreign-Born Parents **(b)** Foreign-Born Grandparents **(c)** Immigration Index

Note: This figure replicates our RDD from Table III, estimating the effect of electing an MC with foreign-born ancestors on permissive immigration roll call votes, but changes the local polynomial order. Results are shown for our regional share surname measure of family history using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share.

Table D.4: RDD Robustness: Imputed Immigration History (Surname Score) and Vote Choice, All Bills Pooled and Controlling for the Party and Tenure of the Candidate with Higher Imputed Immigration History

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.100***	0.104***	0.104***	0.126***	0.181***	0.179***	0.095***	0.115***	0.112***
	(0.027)	(0.034)	(0.026)	(0.029)	(0.043)	(0.030)	(0.027)	(0.036)	(0.026)
N	5142	5142	5142	4610	4610	4610	5225	5225	5225
N (Effective)	2264	1358	2451	2198	1244	2191	2274	1459	2545
Bandwidth	±8.92	±5	±10	±10.02	±5	±10	±8.47	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.088***	0.083***	0.129***	0.091***	0.079**	0.112***	0.070***	0.070**	0.103***
	(0.023)	(0.030)	(0.023)	(0.027)	(0.036)	(0.025)	(0.025)	(0.034)	(0.025)
N	5423	5423	5423	5122	5122	5122	5357	5357	5357
N (Effective)	2866	1680	2882	2501	1506	2647	2720	1619	2804
Bandwidth	±9.9	±5	±10	±9.11	±5	±10	±9.47	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.115***	0.118***	0.124***	0.103***	0.157***	0.137***	0.123***	0.129***	0.140***
	(0.026)	(0.034)	(0.025)	(0.029)	(0.042)	(0.029)	(0.027)	(0.034)	(0.025)
N	5200	5200	5200	4626	4626	4626	5238	5238	5238
N (Effective)	2173	1390	2487	2257	1250	2193	2308	1487	2559
Bandwidth	±8.24	±5	±10	±10.25	±5	±10	±8.54	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.065***	0.079**	0.096***	0.124***	0.104***	0.136***	0.085***	0.082**	0.102***
	(0.024)	(0.031)	(0.023)	(0.028)	(0.035)	(0.025)	(0.024)	(0.033)	(0.024)
N	5472	5472	5472	5287	5287	5287	5447	5447	5447
N (Effective)	2822	1664	2907	2362	1550	2751	2786	1655	2853
Bandwidth	±9.52	±5	±10	±8.09	±5	±10	±9.67	±5	±10

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table replicates our RDD from Table III but includes additional covariates controlling for party and for tenure. As in Table III, we report estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. We predict ancestry based on regional surnames using simple shares. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.5: RDD Robustness Check: Imputed Immigration History and Vote Choice, Landmark Bills Only

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.098	0.021	0.034	0.140*	−0.041	0.089	0.090	0.006	0.000
	(0.072)	(0.103)	(0.074)	(0.074)	(0.106)	(0.074)	(0.069)	(0.105)	(0.072)
N	1154	1154	1154	1066	1066	1066	1179	1179	1179
N (Effective)	607	337	585	532	326	534	651	368	610
Bandwidth	±10.53	±5	±10	±9.92	±5	±10	±11.15	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates our RDD from Table III but focusing only on our sample of landmark roll call legislation. As in Table III, we report estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. We predict ancestry based on regional surnames using simple shares. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ± 5, and ± 10) for the running variable vote share. Standard errors are clustered at the MC level. The positive estimates across all specifications suggest that MCs with a family history of immigration are more likely to vote in favor of immigration but underscore that there is simply not enough sample when limited to landmark bills to draw any strong conclusions.

Table D.6: RDD Robustness Check: Election Threshold Continuity Check for Imputed Immigration History (Surname Score) and Vote Choice, 51st–91st Congress

	Artificial Winner Threshold:				
	40	45	50	55	60
	(1)	(2)	(3)	(4)	(5)
Estimate	−0.041	−0.021	0.090***	−0.057*	−0.003
	(0.033)	(0.025)	(0.027)	(0.030)	(0.040)
N	5393	5393	5393	5393	5393
N (Effective)	2147	2559	2330	1915	944
Bandwidth	±9.09	±9.16	±8.3	±8.19	±5.95

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table checks for continuity in the running variable. In each case, we recalculate treatment status based on an artificial threshold for vote share, different from the true threshold. In reality, the threshold distinguishing winners from losers is 50. As a result, there should not be discontinuities at other vote shares. Each column lists the threshold used. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.7: RDD Robustness Check: Election Closeness Donut for Imputed Immigration History (Surname Score) and Vote Choice, 51st–91st Congress

	MC Immigrant Ancestry Measured as: Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.101***	0.082***	0.098***	0.147***	0.134***	0.173***	0.094***	0.077***	0.102***
	(0.027)	(0.028)	(0.031)	(0.031)	(0.032)	(0.036)	(0.028)	(0.029)	(0.032)
N	5288	5255	5170	4749	4724	4650	5366	5331	5240
N (Effective)	2487	2395	2260	1987	1982	1794	2251	2279	2074
Bandwidth	±9.73	±9.4	±9.08	±8.43	±8.54	±7.87	±8.02	±8.36	±7.77
Election Donut	±0.25	±0.5	±1	±0.25	±0.5	±1	±0.25	±0.5	±1

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates our main estimates but imposing a "donut" for vote shares at the threshold between winning and losing an election. Elections with vote shares within a given donut are dropped from the sample. The size of the donut is listed in the row at the bottom of the table. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.8: RDD Robustness Check: Actual and Imputed Immigration History (Actual Immigration for MCs and Surname Score for Losing Candidates) and Vote Choice, All Bills Pooled

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.125***	0.087**	0.125***	0.091***	0.119***	0.131***	0.115***	0.145***	0.145***
	(0.031)	(0.036)	(0.028)	(0.028)	(0.037)	(0.027)	(0.028)	(0.036)	(0.027)
N	6258	6258	6258	4667	4667	4667	4795	4795	4795
N (Effective)	2432	1727	3126	2336	1386	2440	2330	1385	2448
Bandwidth	±7.23	±5	±10	±9.38	±5	±10	±9.23	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.099***	0.076**	0.109***	0.066**	0.039	0.072**	0.093***	0.088**	0.103***
	(0.029)	(0.036)	(0.028)	(0.030)	(0.041)	(0.029)	(0.026)	(0.040)	(0.028)
N	5788	5788	5788	4131	4131	4131	4217	4217	4217
N (Effective)	2718	1727	3124	2190	1289	2274	2597	1315	2285
Bandwidth	±8.25	±5	±10	±9.36	±5	±10	±11.92	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.137***	0.095**	0.139***	0.100***	0.104***	0.125***	0.122***	0.143***	0.152***
	(0.032)	(0.037)	(0.028)	(0.029)	(0.037)	(0.027)	(0.028)	(0.036)	(0.027)
N	6260	6260	6260	4662	4662	4662	4787	4787	4787
N (Effective)	2516	1738	3138	2115	1375	2421	2263	1392	2443
Bandwidth	±7.52	±5	±10	±8.44	±5	±10	±8.94	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.126***	0.069*	0.117***	0.101***	0.046	0.098***	0.110***	0.097**	0.117***
	(0.033)	(0.037)	(0.028)	(0.031)	(0.041)	(0.029)	(0.027)	(0.039)	(0.028)
N	5857	5857	5857	4197	4197	4197	4295	4295	4295
N (Effective)	2228	1755	3165	2065	1278	2275	2394	1341	2328
Bandwidth	±6.45	±5	±10	±8.64	±5	±10	±10.38	±5	±10

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not. For winning candidates (who become MCs) we use actual ancestry; for losing candidates we use surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Each panel presents results from different methods of predicting ancestry based on surnames (regional or national, simple shares or an f-index measure). Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level. As in Table III, the positive and statistically significant estimates across all specifications suggest that electing MCs with a family history of immigration increases the probability of casting a vote in favor of permissive immigration policy.

Table D.9: RDD Robustness: Imputed Immigration History and Vote Choice, All Bills Pooled, Full Names

	Candidate Ancestry Measured from Regional Full Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.159***	0.155***	0.149***	0.086***	0.046	0.066**	0.145***	0.127***	0.142***
	(0.030)	(0.032)	(0.026)	(0.029)	(0.038)	(0.028)	(0.028)	(0.032)	(0.026)
N	4387	4387	4387	4125	4125	4125	4419	4419	4419
N (Effective)	1583	1241	2153	1877	1196	2044	1875	1301	2199
Bandwidth	±6.62	±5	±10	±8.91	±5	±10	±7.84	±5	±10

	Candidate Ancestry Measured from National Full Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.101***	0.068*	0.112***	0.139***	0.121***	0.137***	0.138***	0.124***	0.155***
	(0.028)	(0.035)	(0.026)	(0.029)	(0.036)	(0.025)	(0.027)	(0.034)	(0.024)
N	4510	4510	4510	4436	4436	4436	4603	4603	4603
N (Effective)	2029	1322	2325	1816	1285	2308	1936	1343	2338
Bandwidth	±8.23	±5	±10	±7.35	±5	±10	±7.71	±5	±10

	Candidate Ancestry Measured from Regional Full Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.144***	0.155***	0.130***	0.084***	0.050	0.066**	0.124***	0.132***	0.128***
	(0.030)	(0.032)	(0.026)	(0.030)	(0.038)	(0.028)	(0.028)	(0.032)	(0.025)
N	4412	4412	4412	4193	4193	4193	4487	4487	4487
N (Effective)	1583	1259	2180	1844	1208	2066	1872	1326	2271
Bandwidth	±6.47	±5	±10	±8.42	±5	±10	±7.51	±5	±10

	Candidate Ancestry Measured from National Full Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.125***	0.103***	0.134***	0.124***	0.132***	0.116***	0.122***	0.129***	0.131***
	(0.028)	(0.035)	(0.025)	(0.031)	(0.037)	(0.026)	(0.028)	(0.033)	(0.024)
N	4569	4569	4569	4318	4318	4318	4615	4615	4615
N (Effective)	1923	1323	2344	1765	1267	2267	1832	1373	2414
Bandwidth	±7.63	±5	±10	±7.13	±5	±10	±6.96	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table III but using full names rather than surnames to impute ancestry for candidates.

Table D.10: RDD Robustness: Imputed Immigration History and Vote Choice, All Bills Pooled, First Names

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Candidate Ancestry Measured from Regional First Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.039	0.080**	0.033	0.030	0.092***	0.035	0.030	0.070**	0.031
	(0.024)	(0.032)	(0.023)	(0.024)	(0.034)	(0.025)	(0.023)	(0.032)	(0.023)
N	5924	5924	5924	6074	6074	6074	6049	6049	6049
N (Effective)	2834	1689	2985	3173	1678	2973	2921	1667	2991
Bandwidth	±9.24	±5	±10	±10.8	±5	±10	±9.71	±5	±10
	Candidate Ancestry Measured from National First Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.070***	0.113***	0.070***	0.034	0.031	0.015	0.066***	0.109***	0.068***
	(0.024)	(0.034)	(0.024)	(0.022)	(0.033)	(0.023)	(0.023)	(0.033)	(0.024)
N	5586	5586	5586	6353	6353	6353	5666	5666	5666
N (Effective)	2853	1574	2807	3553	1839	3261	3105	1606	2838
Bandwidth	±10.18	±5	±10	±11.34	±5	±10	±11.29	±5	±10
	Candidate Ancestry Measured from Regional First Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.036	0.088***	0.034	0.027	0.095***	0.038	0.014	0.061*	0.008
	(0.024)	(0.032)	(0.023)	(0.024)	(0.035)	(0.025)	(0.024)	(0.033)	(0.023)
N	5993	5993	5993	6057	6057	6057	5962	5962	5962
N (Effective)	2788	1704	3009	3243	1679	2972	2689	1654	2930
Bandwidth	±8.94	±5	±10	±11.17	±5	±10	±8.82	±5	±10
	Candidate Ancestry Measured from National First Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.077***	0.103***	0.065***	0.056**	0.042	0.038	0.080***	0.120***	0.092***
	(0.023)	(0.033)	(0.024)	(0.022)	(0.033)	(0.023)	(0.025)	(0.036)	(0.025)
N	5608	5608	5608	6070	6070	6070	5172	5172	5172
N (Effective)	3010	1606	2830	3304	1751	3081	2760	1495	2617
Bandwidth	±10.84	±5	±10	±10.94	±5	±10	±10.58	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table III but using first names rather than surnames to impute ancestry for candidates.

Table D.11: RDD Robustness: Imputed Immigration History and Vote Choice, All Bills Pooled, Triangular Kernel

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.096***	0.104***	0.096***	0.140***	0.170***	0.176***	0.094***	0.110***	0.105***
	(0.026)	(0.035)	(0.026)	(0.031)	(0.043)	(0.030)	(0.027)	(0.037)	(0.026)
N	5316	5316	5316	4770	4770	4770	5393	5393	5393
N (Effective)	2589	1428	2558	2194	1301	2281	2533	1532	2648
Bandwidth	±10.09	±5	±10	±9.44	±5	±10	±9.24	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.100***	0.082***	0.128***	0.091***	0.066*	0.107***	0.078***	0.073**	0.107***
	(0.024)	(0.031)	(0.023)	(0.027)	(0.038)	(0.027)	(0.026)	(0.035)	(0.025)
N	5610	5610	5610	5294	5294	5294	5538	5538	5538
N (Effective)	2894	1764	2996	2667	1568	2744	2859	1690	2909
Bandwidth	±9.35	±5	±10	±9.5	±5	±10	±9.71	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.109***	0.122***	0.115***	0.107***	0.144***	0.135***	0.115***	0.121***	0.131***
	(0.026)	(0.035)	(0.026)	(0.027)	(0.043)	(0.030)	(0.026)	(0.035)	(0.026)
N	5382	5382	5382	4783	4783	4783	5414	5414	5414
N (Effective)	2473	1465	2600	2664	1308	2283	2652	1563	2665
Bandwidth	±9.29	±5	±10	±12.2	±5	±10	±9.9	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.074***	0.073**	0.099***	0.122***	0.088**	0.132***	0.089***	0.081**	0.101***
	(0.024)	(0.032)	(0.024)	(0.028)	(0.037)	(0.026)	(0.025)	(0.034)	(0.025)
N	5665	5665	5665	5479	5479	5479	5648	5648	5648
N (Effective)	2923	1759	3031	2581	1634	2862	2927	1748	2983
Bandwidth	±9.37	±5	±10	±8.61	±5	±10	±9.75	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table III but using a triangular kernel rather than an Epanechnikov kernel to assign weights to observations around the cutoff in the RDD. Triangular kernels give more weight to observations near the cutoff than a uniform kernel but not as much as the Epanechnikov kernel.

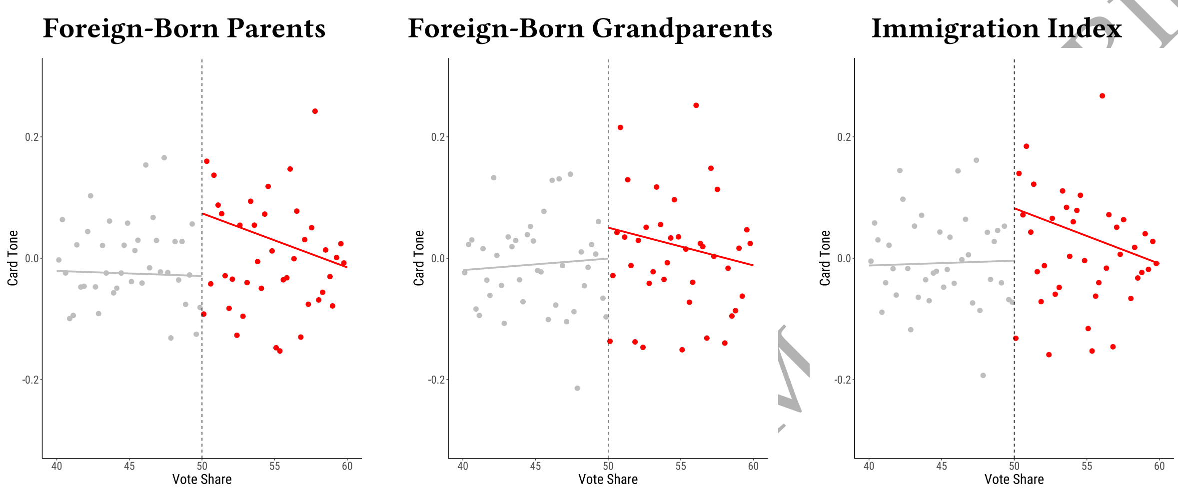
Table D.12: RDD Robustness: Imputed Immigration History and Vote Choice, All Bills Pooled, Uniform Kernel

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.095**	0.113***	0.093***	0.150***	0.214***	0.153***	0.102***	0.126***	0.098***
	(0.044)	(0.034)	(0.025)	(0.034)	(0.039)	(0.028)	(0.029)	(0.034)	(0.025)
N	5316	5316	5316	4770	4770	4770	5393	5393	5393
N (Effective)	826	1428	2561	1575	1301	2284	1930	1532	2651
Bandwidth	±2.67	±5	±10	±6.25	±5	±10	±6.48	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.103***	0.103***	0.111***	0.096***	0.110***	0.103***	0.071***	0.111***	0.083***
	(0.025)	(0.029)	(0.022)	(0.028)	(0.034)	(0.024)	(0.027)	(0.032)	(0.024)
N	5610	5610	5610	5294	5294	5294	5538	5538	5538
N (Effective)	2262	1764	2999	2103	1568	2747	2268	1690	2912
Bandwidth	±6.75	±5	±10	±7.03	±5	±10	±7.04	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.112***	0.123***	0.108***	0.114***	0.183***	0.112***	0.141***	0.136***	0.126***
	(0.029)	(0.033)	(0.024)	(0.031)	(0.038)	(0.028)	(0.042)	(0.032)	(0.024)
N	5382	5382	5382	4783	4783	4783	5414	5414	5414
N (Effective)	1810	1465	2603	1806	1308	2286	1042	1563	2668
Bandwidth	±6.29	±5	±10	±7.22	±5	±10	±3.13	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.086***	0.101***	0.082***	0.136***	0.124***	0.134***	0.078***	0.094***	0.088***
	(0.028)	(0.029)	(0.022)	(0.029)	(0.033)	(0.024)	(0.027)	(0.031)	(0.023)
N	5665	5665	5665	5479	5479	5479	5648	5648	5648
N (Effective)	2034	1759	3034	2041	1634	2865	2249	1748	2986
Bandwidth	±6.01	±5	±10	±6.45	±5	±10	±6.84	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

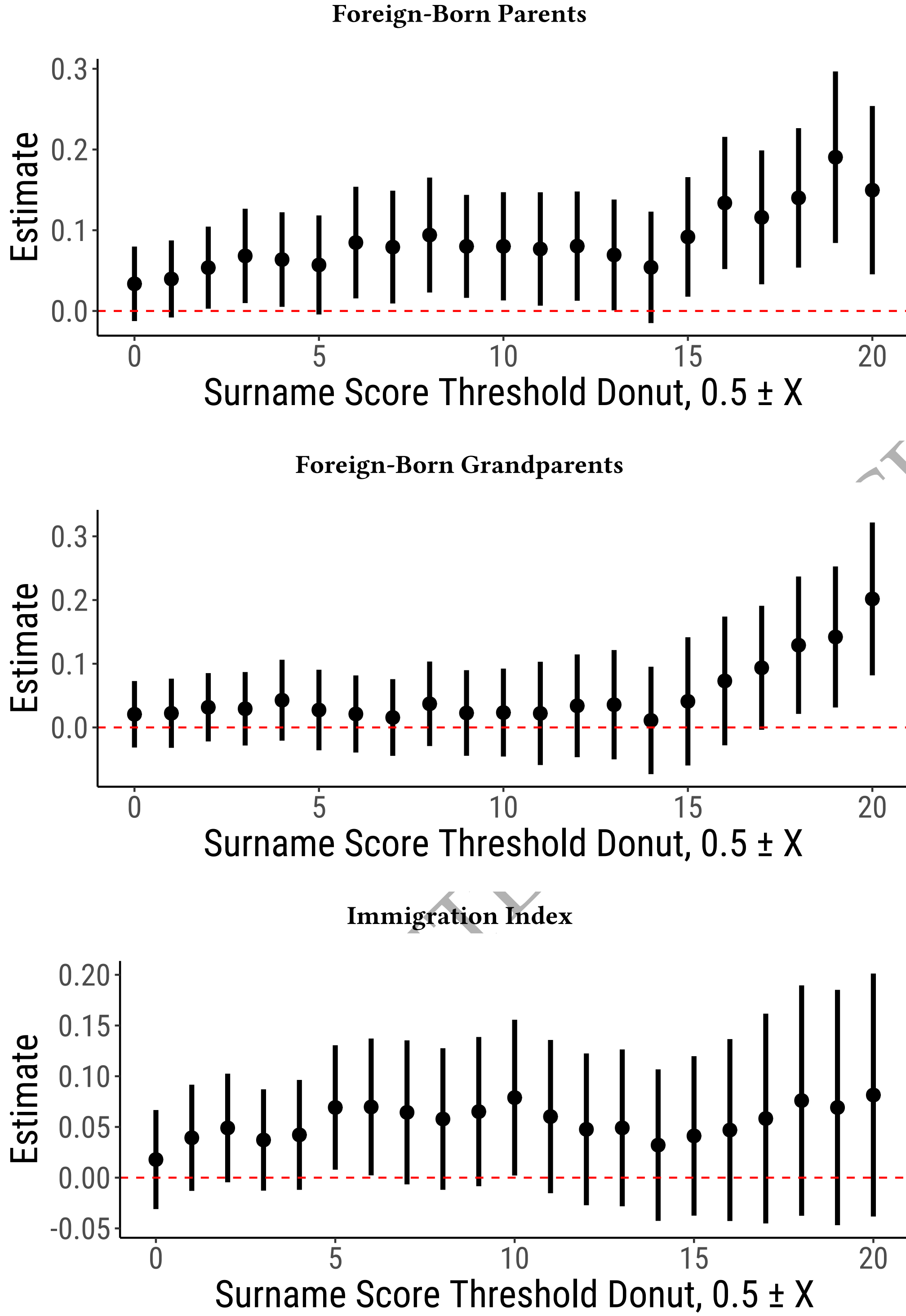
Note: This table replicates Table III but using a uniform kernel rather than an Epanechnikov kernel to assign weights to observations around the cutoff in the RDD. Triangular kernels give more weight to observations near the cutoff than a uniform kernel but not as much as the Epanechnikov kernel.

Figure D.3: RDD: Effect of MC Immigration History (Surname Score) on Immigration Speech Tone, 51st–91st Congresses



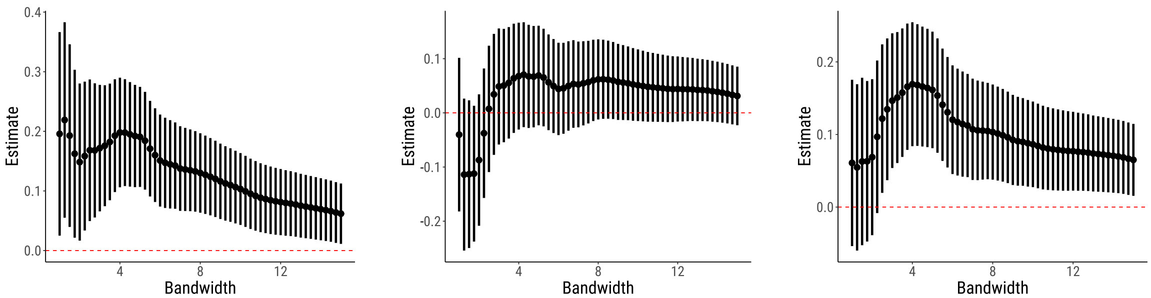
Note: For each measure of family immigration history, we estimate the effect of immigration family history on using more positive tone in speech about immigration between the 51st and 91st Congresses. The sample is constructed by focusing on elections in which one candidate possessed an immigrant family history and one candidate did not. In this case, candidates with an immigrant family history are determined based on surname. Each dot represents the share of candidates who voted pro immigration in a given vote share bin. We present 40 bins on either side of the discontinuity using the mimicking variance evenly-spaced method from Calonico et al. (2017). We identify the effect by using close elections in which a candidate with an immigrant family history narrowly won or narrowly lost the election.

Figure D.4: RDD Robustness Check: Sensitivity of Card et al Speech Tone Estimates to Surname Score Cutoff Donut for Treatment Assignment (Optimal BW)



Note: This figure reports RDD estimates for different cutoffs in determining the threshold for classifying a surname as denoting foreign-born. Moving from left to right along the x-axis varies the threshold calculation used to determine when the binary variable indicating an immigrant family history takes a value equal to one. For example, when $x = 0$ individuals with a Surname Score higher than the 50th percentile are classified as having a family immigration history and individuals whose Surname Score is below the 50th percentile are not. When $x = 10$, then individuals with a Surname Score higher than the 60th percentile are classified as having a family immigration history equal to one and individuals with a Surname Score less than or equal to the 40th percentile are assigned a zero; all others would be excluded from the sample. We continued to estimate the RDD results as long as we retained at least 50 effective observations. We perform a local linear regression to estimate the discontinuity and the sample is determined using an algorithm for optimal bandwidth (Calonico, Cattaneo and Titiunik 2014) in the running variable (vote share).

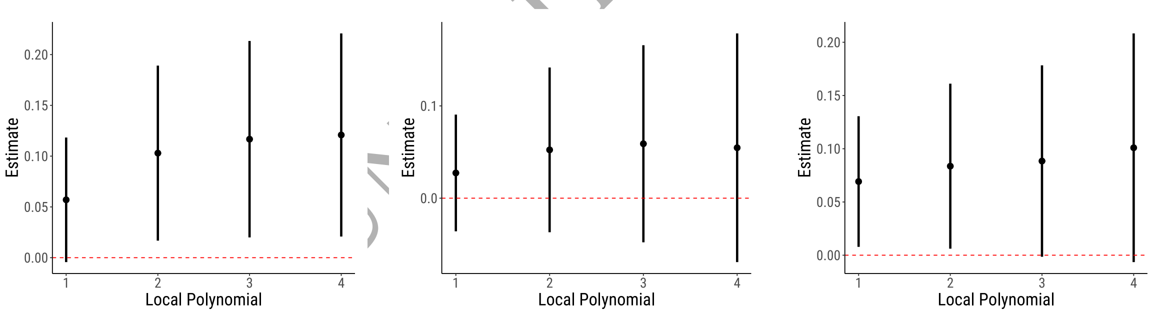
Figure D.5: RDD Robustness Check: Bandwidth Robustness for Speech Tone



(a) Foreign-Born Parents **(b)** Foreign-Born Grandparents **(c)** Immigration Index

Note: This figure replicates our RDD from Table V, estimating the effect of electing an MC with foreign-born ancestors on tone of immigration-related speeches, but varies the bandwidth between 1 and 15 points by 0.25 points. Results are shown for our regional shares names measure of family history.

Figure D.6: RDD Robustness Check: Polynomial Robustness for Speech Tone



(a) Foreign-Born Parents **(b)** Foreign-Born Grandparents **(c)** Immigration Index

Note: This figure replicates our RDD from Table V, estimating the effect of electing an MC with foreign-born ancestors on tone of immigration-related speeches, but changes the local polynomial order. Results are shown for our regional shares names measure of family history using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share.

Table D.13: RDD Robustness Check: Election Threshold Continuity Check for Imputed Immigration History (Surname Score) and Speech Tone, 51st–91st Congress

	Artificial Winner Threshold:				
	40	45	50	55	60
	(1)	(2)	(3)	(4)	(5)
Estimate	−0.010	−0.018	0.069**	−0.063**	0.004
	(0.033)	(0.027)	(0.031)	(0.032)	(0.034)
N	2692	2692	2692	2692	2692
N (Effective)	863	1497	1281	1060	583
Bandwidth	±7.22	±11.73	±9.2	±8.95	±6.69

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table checks for continuity in the running variable. In each case, we recalculate treatment status based on an artificial threshold for vote share, different from the true threshold. In reality, the threshold distinguishing winners from losers is 50. As a result, there should not be discontinuities at other vote shares. Each column lists the threshold used. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.14: RDD Robustness Check: Election Closeness Donut for Imputed Immigration History (Surname Score) and Speech Tone, 51st–91st Congress

	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.070**	0.078**	0.011	0.026	0.053	0.031	0.078**	0.092***	0.047
	(0.033)	(0.035)	(0.029)	(0.031)	(0.036)	(0.034)	(0.032)	(0.035)	(0.033)
N	2579	2564	2532	2364	2351	2319	2673	2660	2621
N (Effective)	1151	1068	1388	1238	1050	1176	1197	1092	1221
Bandwidth	±8.84	±8.16	±11.81	±11.07	±9.07	±10.8	±8.74	±7.94	±9.43
Election Donut	25	50	100	25	50	100	25	50	100

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates our main estimates but imposing a "donut" for vote shares at the threshold between winning and losing an election. Elections with vote shares within a given donut are dropped from the sample. The size of the donut is listed in the row at the bottom of the table. The table estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not based on surnames. All results use predictions of ancestry based on regional surnames shares. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and using optimal bandwidths (Calonico, Cattaneo and Titiunik 2014) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.15: RDD Robustness Check: Actual and Imputed Immigration History (Actual Immigration for MCs and Surname Score for Losing Candidates) and Speech Tone

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.057*	0.133***	0.069**	0.050	0.067	0.057*	0.026	0.026	0.030
	(0.032)	(0.043)	(0.029)	(0.033)	(0.046)	(0.032)	(0.029)	(0.044)	(0.030)
N	2968	2968	2968	2180	2180	2180	2232	2232	2232
N (Effective)	1361	869	1521	1109	656	1136	1257	659	1149
Bandwidth	±8.62	±5	±10	±9.56	±5	±10	±11.24	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.068**	0.121***	0.080***	0.056*	0.148***	0.073**	0.039	0.088*	0.056*
	(0.029)	(0.043)	(0.029)	(0.032)	(0.047)	(0.032)	(0.034)	(0.047)	(0.032)
N	2811	2811	2811	1980	1980	1980	2021	2021	2021
N (Effective)	1593	877	1532	1075	607	1063	1006	624	1084
Bandwidth	±10.68	±5	±10	±10.19	±5	±10	±9.07	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.065**	0.141***	0.078***	0.051*	0.065	0.055*	0.025	0.029	0.024
	(0.033)	(0.044)	(0.030)	(0.030)	(0.045)	(0.031)	(0.030)	(0.045)	(0.031)
N	2974	2974	2974	2170	2170	2170	2212	2212	2212
N (Effective)	1356	876	1534	1167	644	1119	1162	658	1136
Bandwidth	±8.51	±5	±10	±10.55	±5	±10	±10.27	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.080**	0.114***	0.089***	0.067**	0.118***	0.083***	0.005	0.008	0.021
	(0.035)	(0.044)	(0.030)	(0.034)	(0.044)	(0.032)	(0.030)	(0.039)	(0.029)
N	2866	2866	2866	2006	2006	2006	2037	2037	2037
N (Effective)	1222	902	1572	982	633	1074	1006	652	1095
Bandwidth	±7.2	±5	±10	±8.72	±5	±10	±8.96	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not. For winning candidates (who become MCs) we use actual ancestry; for losing candidates we use surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. Each panel presents results from different methods of predicting ancestry based on surnames (regional or national, simple shares or an f-index measure). Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level. As in Table V, the positive and statistically significant estimates across all specifications suggest that electing MCs with a family history of immigration increases the probability of speaking with a positive tone about immigration policy.

Table D.16: RDD Robustness: Imputed Immigration History and Speech Tone, Full Names

	Candidate Ancestry Measured from Regional Full Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.097**	0.203***	0.103***	0.089**	0.199***	0.114***	0.053	0.157***	0.060
	(0.045)	(0.051)	(0.036)	(0.041)	(0.048)	(0.035)	(0.046)	(0.052)	(0.037)
N	2129	2129	2129	2060	2060	2060	2154	2154	2154
N (Effective)	780	614	1074	844	624	1051	808	644	1099
Bandwidth	±6.59	±5	±10	±7.31	±5	±10	±6.57	±5	±10
	Candidate Ancestry Measured from National Full Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.078**	0.194***	0.104***	0.133***	0.225***	0.146***	0.107***	0.176***	0.124***
	(0.035)	(0.045)	(0.031)	(0.039)	(0.044)	(0.031)	(0.036)	(0.043)	(0.031)
N	2223	2223	2223	2212	2212	2212	2240	2240	2240
N (Effective)	1012	680	1166	836	672	1171	939	692	1163
Bandwidth	±8.29	±5	±10	±6.4	±5	±10	±7.48	±5	±10
	Candidate Ancestry Measured from Regional Full Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.081*	0.198***	0.094***	0.076*	0.186***	0.106***	0.083**	0.159***	0.091***
	(0.042)	(0.052)	(0.036)	(0.040)	(0.049)	(0.036)	(0.042)	(0.047)	(0.034)
N	2157	2157	2157	2069	2069	2069	2202	2202	2202
N (Effective)	880	625	1086	895	619	1046	773	640	1111
Bandwidth	±7.57	±5	±10	±7.91	±5	±10	±6.32	±5	±10
	Candidate Ancestry Measured from National Full Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.068*	0.172***	0.086***	0.131***	0.218***	0.137***	0.060*	0.145***	0.083***
	(0.037)	(0.046)	(0.033)	(0.045)	(0.050)	(0.034)	(0.033)	(0.043)	(0.031)
N	2238	2238	2238	2179	2179	2179	2270	2270	2270
N (Effective)	980	681	1171	808	668	1170	1086	714	1199
Bandwidth	±7.85	±5	±10	±6.22	±5	±10	±8.65	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table V but using full names rather than surnames to impute ancestry for candidates.

Table D.17: RDD Robustness: Imputed Immigration History and Speech Tone, First Names

	Candidate Ancestry Measured from Regional First Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.014	0.091**	0.009	0.013	0.064	0.034	−0.012	0.046	−0.018
	(0.034)	(0.045)	(0.031)	(0.032)	(0.044)	(0.031)	(0.029)	(0.047)	(0.031)
N	2863	2863	2863	2906	2906	2906	2917	2917	2917
N (Effective)	1298	855	1481	1357	832	1462	1667	842	1498
Bandwidth	±8.32	±5	±10	±9.12	±5	±10	±11.82	±5	±10
	Candidate Ancestry Measured from National First Name Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.054	0.143***	0.069**	0.028	0.061	0.030	0.036	0.112**	0.060**
	(0.034)	(0.045)	(0.031)	(0.030)	(0.041)	(0.028)	(0.030)	(0.044)	(0.030)
N	2692	2692	2692	3061	3061	3061	2714	2714	2714
N (Effective)	1213	800	1406	1462	902	1598	1419	792	1397
Bandwidth	±8.32	±5	±10	±8.87	±5	±10	±10.24	±5	±10
	Candidate Ancestry Measured from Regional First Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.001	0.062	−0.009	0.019	0.070	0.036	0.006	0.036	−0.001
	(0.034)	(0.045)	(0.031)	(0.033)	(0.044)	(0.031)	(0.032)	(0.047)	(0.031)
N	2882	2882	2882	2913	2913	2913	2908	2908	2908
N (Effective)	1302	852	1484	1340	841	1468	1475	844	1496
Bandwidth	±8.35	±5	±10	±8.86	±5	±10	±9.82	±5	±10
	Candidate Ancestry Measured from National First Name F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.031	0.125***	0.047	0.021	0.053	0.029	0.061*	0.113**	0.080***
	(0.031)	(0.044)	(0.030)	(0.031)	(0.044)	(0.030)	(0.035)	(0.045)	(0.030)
N	2680	2680	2680	2945	2945	2945	2577	2577	2577
N (Effective)	1308	783	1386	1445	882	1546	1085	750	1331
Bandwidth	±9.22	±5	±10	±9.13	±5	±10	±7.71	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table V but using first names rather than surnames to impute ancestry for candidates.

Table D.18: RDD Robustness: Imputed Immigration History and Speech Tone, Triangular Kernel

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.067**	0.189***	0.112***	0.028	0.065	0.053	0.072**	0.160***	0.093***
	(0.032)	(0.044)	(0.032)	(0.032)	(0.047)	(0.035)	(0.031)	(0.041)	(0.031)
N	2598	2598	2598	2376	2376	2376	2692	2692	2692
N (Effective)	1251	710	1280	1301	647	1155	1335	757	1347
Bandwidth	±9.68	±5	±10	±11.79	±5	±10	±9.84	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.036	0.102***	0.047*	0.082**	0.148***	0.093***	0.065**	0.138***	0.081***
	(0.030)	(0.039)	(0.028)	(0.034)	(0.041)	(0.029)	(0.033)	(0.041)	(0.029)
N	2789	2789	2789	2716	2716	2716	2833	2833	2833
N (Effective)	1402	880	1481	1112	809	1408	1250	869	1480
Bandwidth	±9.17	±5	±10	±7.28	±5	±10	±7.91	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.066**	0.186***	0.109***	0.057	0.093**	0.075**	0.083**	0.201***	0.109***
	(0.031)	(0.043)	(0.032)	(0.035)	(0.045)	(0.034)	(0.033)	(0.042)	(0.030)
N	2631	2631	2631	2392	2392	2392	2689	2689	2689
N (Effective)	1337	724	1300	1109	654	1165	1199	767	1338
Bandwidth	±10.38	±5	±10	±9.27	±5	±10	±8.67	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.037	0.085**	0.053*	0.084***	0.125***	0.098***	0.037	0.082**	0.054**
	(0.030)	(0.041)	(0.029)	(0.032)	(0.039)	(0.028)	(0.027)	(0.036)	(0.027)
N	2819	2819	2819	2792	2792	2792	2890	2890	2890
N (Effective)	1475	894	1506	1225	853	1463	1499	925	1537
Bandwidth	±9.66	±5	±10	±7.77	±5	±10	±9.64	±5	±10

$^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$

Note: This table replicates Table V but using a triangular kernel rather than an Epanechnikov kernel to assign weights to observations around the cutoff in the RDD. Triangular kernels give more weight to observations near the cutoff than a uniform kernel but not as much as the Epanechnikov kernel.

Table D.19: RDD Robustness: Imputed Immigration History and Speech Tone, Uniform Kernel

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.036	0.174***	0.082***	0.022	0.074	0.042	0.066**	0.141***	0.076***
	(0.029)	(0.041)	(0.029)	(0.035)	(0.045)	(0.031)	(0.032)	(0.040)	(0.028)
N	2598	2598	2598	2376	2376	2376	2692	2692	2692
N (Effective)	1260	710	1281	985	647	1156	1107	757	1348
Bandwidth	±9.76	±5	±10	±8.17	±5	±10	±7.74	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.032	0.095***	0.033	0.050	0.147***	0.070***	0.041	0.136***	0.057**
	(0.024)	(0.036)	(0.025)	(0.032)	(0.037)	(0.027)	(0.030)	(0.037)	(0.026)
N	2789	2789	2789	2716	2716	2716	2833	2833	2833
N (Effective)	1562	880	1482	1031	809	1409	1250	869	1481
Bandwidth	±10.79	±5	±10	±6.69	±5	±10	±7.89	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.045	0.168***	0.088***	0.047	0.094**	0.058*	0.061*	0.181***	0.085***
	(0.029)	(0.040)	(0.029)	(0.036)	(0.043)	(0.030)	(0.032)	(0.039)	(0.028)
N	2631	2631	2631	2392	2392	2392	2689	2689	2689
N (Effective)	1249	724	1301	930	654	1166	1092	767	1339
Bandwidth	±9.5	±5	±10	±7.34	±5	±10	±7.56	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.027	0.095***	0.045*	0.053*	0.135***	0.074***	0.028	0.083**	0.039
	(0.030)	(0.037)	(0.026)	(0.028)	(0.036)	(0.025)	(0.025)	(0.034)	(0.024)
N	2819	2819	2819	2792	2792	2792	2890	2890	2890
N (Effective)	1236	894	1507	1295	853	1464	1444	925	1538
Bandwidth	±7.55	±5	±10	±8.42	±5	±10	±9.13	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates Table V but using a uniform kernel rather than an Epanechnikov kernel to assign weights to observations around the cutoff in the RDD. Triangular kernels give more weight to observations near the cutoff than a uniform kernel but not as much as the Epanechnikov kernel.

Table D.20: RDD Robustness: Imputed Immigration History (Surname Score) and Speech, Card Tone: Controlling for the Party and Tenure of the Candidate with Higher Imputed Immigration History

	Candidate Ancestry Measured from Regional Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.078**	0.194***	0.101***	0.008	0.046	0.023	0.058*	0.152***	0.079**
	(0.037)	(0.045)	(0.032)	(0.036)	(0.048)	(0.035)	(0.033)	(0.044)	(0.032)
N	2488	2488	2488	2274	2274	2274	2581	2581	2581
N (Effective)	954	660	1203	1032	600	1085	1201	702	1265
Bandwidth	±7.29	±5	±10	±9.3	±5	±10	±9.23	±5	±10
	Candidate Ancestry Measured from National Surname Shares								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.038	0.097**	0.043	0.062*	0.127***	0.079***	0.055*	0.127***	0.075***
	(0.028)	(0.040)	(0.028)	(0.033)	(0.041)	(0.029)	(0.032)	(0.041)	(0.029)
N	2688	2688	2688	2615	2615	2615	2731	2731	2731
N (Effective)	1419	828	1408	1112	761	1337	1239	820	1410
Bandwidth	±10.09	±5	±10	±7.78	±5	±10	±8.33	±5	±10
	Candidate Ancestry Measured from Regional Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.067*	0.179***	0.096***	0.022	0.064	0.038	0.062*	0.190***	0.089***
	(0.036)	(0.045)	(0.032)	(0.036)	(0.046)	(0.034)	(0.034)	(0.044)	(0.031)
N	2520	2520	2520	2291	2291	2291	2581	2581	2581
N (Effective)	1037	672	1222	994	606	1095	1117	714	1258
Bandwidth	±8.04	±5	±10	±8.9	±5	±10	±8.52	±5	±10
	Candidate Ancestry Measured from National Surname F-Index								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.031	0.081**	0.046	0.064**	0.104***	0.084***	0.032	0.074**	0.046*
	(0.027)	(0.041)	(0.029)	(0.030)	(0.040)	(0.028)	(0.027)	(0.037)	(0.027)
N	2708	2708	2708	2688	2688	2688	2775	2775	2775
N (Effective)	1595	835	1428	1260	799	1392	1433	865	1455
Bandwidth	±11.7	±5	±10	±8.72	±5	±10	±9.8	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates our RDD from Table V but includes additional covariates controlling for party and for tenure. As in Table V, we report estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election. We predict ancestry based on regional surnames using simple shares. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.21: Regression Discontinuity: Imputed Immigration History (Surname Score) and Speech, Log Counts by Sentiment

	Total Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	−0.066	−0.141	−0.069	−0.047	−0.154	−0.126*	−0.133*	−0.182**	−0.164**
	(0.070)	(0.090)	(0.067)	(0.072)	(0.098)	(0.071)	(0.068)	(0.091)	(0.067)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2547	1525	2723	2396	1394	2475	2781	1608	2836
Bandwidth	±9.06	±5	±10	±9.52	±5	±10	±9.65	±5	±10
	Pro Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.025	0.030	0.028	0.007	−0.079	−0.040	−0.004	0.014	−0.019
	(0.040)	(0.048)	(0.035)	(0.037)	(0.051)	(0.037)	(0.033)	(0.047)	(0.035)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2157	1525	2723	2462	1394	2475	2996	1608	2836
Bandwidth	±7.33	±5	±10	±9.88	±5	±10	±10.71	±5	±10
	Anti Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	−0.053	−0.152**	−0.093**	−0.050	−0.123**	−0.090**	−0.117***	−0.158***	−0.137***
	(0.044)	(0.059)	(0.043)	(0.047)	(0.062)	(0.044)	(0.044)	(0.058)	(0.040)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2566	1525	2723	2211	1394	2475	2506	1608	2836
Bandwidth	±9.15	±5	±10	±8.64	±5	±10	±8.46	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election on the logged count of immigration speeches given (Panel A: all, Panel B: Pro Immigration, Panel C: Anti Immigration) with sentiment coding from Card et al. (2022). All results use predictions of ancestry based on regional surnames shares. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level.

Table D.22: Regression Discontinuity: Imputed Immigration History (Surname Score) and Speech, Inverse Hyperbolic Sine Counts by Sentiment

	Total Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	−0.081	−0.171	−0.081	−0.053	−0.179	−0.149*	−0.160*	−0.227**	−0.198**
	(0.086)	(0.110)	(0.082)	(0.089)	(0.119)	(0.087)	(0.083)	(0.112)	(0.082)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2534	1525	2723	2399	1394	2475	2770	1608	2836
Bandwidth	±9.02	±5	±10	±9.53	±5	±10	±9.62	±5	±10
	Pro Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	0.030	0.036	0.033	0.006	−0.103	−0.053	−0.007	0.013	−0.026
	(0.052)	(0.061)	(0.045)	(0.047)	(0.065)	(0.047)	(0.043)	(0.061)	(0.044)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2160	1525	2723	2456	1394	2475	3020	1608	2836
Bandwidth	±7.35	±5	±10	±9.84	±5	±10	±10.85	±5	±10
	Anti Immigration Speeches								
	MC Immigrant Ancestry Measured as:								
	Parents			Grandparents			Immigration Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate	−0.064	−0.191**	−0.115**	−0.061	−0.154**	−0.112**	−0.146***	−0.202***	−0.172***
	(0.055)	(0.074)	(0.053)	(0.059)	(0.078)	(0.055)	(0.055)	(0.072)	(0.050)
N	5358	5358	5358	4954	4954	4954	5531	5531	5531
N (Effective)	2572	1525	2723	2204	1394	2475	2505	1608	2836
Bandwidth	±9.18	±5	±10	±8.61	±5	±10	±8.45	±5	±10

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Note: This table replicates our RDD from Table D.21 but changes the outcome from a log-transformed outcome to one transformed using inverse hyperbolic sines. It reports estimates from a regression discontinuity design where the sample is constructed by focusing on close elections in which one candidate is predicted to have an immigrant family history and the other is not, based on surnames. The coefficients represent the effect attributable to the candidate with a family history of immigration winning the election on the inverse hyperbolic sine count of immigration speeches given (Panel A: all, Panel B: Pro Immigration, Panel C: Anti Immigration) with sentiment coding from Card et al. (2022). All results use predictions of ancestry based on regional surnames shares. Results are shown for three different measures of immigration history (parents, grandparents, and an immigration index) and across various bandwidths (Calonico, Cattaneo and Titiunik (2014) optimal, ±5, and ±10) for the running variable vote share. Standard errors are clustered at the MC level.

E Prediction Model Analysis

We have documented a statistically significant relationship between an MC's family history of immigration and (1) their voting record on landmark immigration votes, (2) their voting record on an expanded set of additional immigration votes, and (3) their tone in speeches about immigration on the floor of Congress. However, questions remain about the relative importance for immigration policymaking of MCs' family backgrounds both historically and under counterfactual scenarios such as a Congress composed of additional MCs descended recently from immigrants. To address these questions and place family immigration history in context, we take a machine-learning approach and build a prediction model of immigration roll call voting and immigration speech. After describing how we build the model using a Ridge Logistic Regression, we analyze the wide set of possible predictors, or features, of the model and compare the variable importance of family immigration history to other key features when predicting voting and speech patterns. Overall, we find that family immigration history ranks among the most important explanatory variables in our data—as important as an MC's party and more important than region, age, gender, and many other district- and individual-level characteristics, though family history is less important only than an MCs' ideological score. We then compute legislative vote outcomes under different counterfactuals.

E.1 Building the Prediction Model

We begin by building a model using a range of covariates used in our main specifications and robustness checks (over 30 variables) to predict immigration voting. We omit member and district fixed effects since our purpose for this exercise is to compare variable importance across substantive member- and district-level variables. Since we are interested in comparing the explanatory power of immigration history to other variables, we elected to employ a ridge regression, which penalizes non-zero coefficient estimates using L2 regularization. In effect, this pushes the magnitude of coefficients towards zero but, unlike a LASSO model, does not limit the number of non-zero coefficient estimates. Additionally, while LASSO models sometimes exhibit instability in coefficient estimates for highly co-linear variables across data subsamples, Ridge regressions suffer less from this issue.

To fit the model, we created a training set (85%) and a test set (15%) of roll call votes, partitioning the set of all votes for which we had a non-missing immigration vote and immigration index variable and standardizing all predictors. Using the training set data, we minimize the function:

$$\sum_{ib}(y_{ib} - \alpha - \delta \cdot \text{Immigration History}_i - X \cdot \beta)^2 + \lambda \sum_{ib} ||\alpha^2 + \delta^2 + \beta^2||_2^2$$

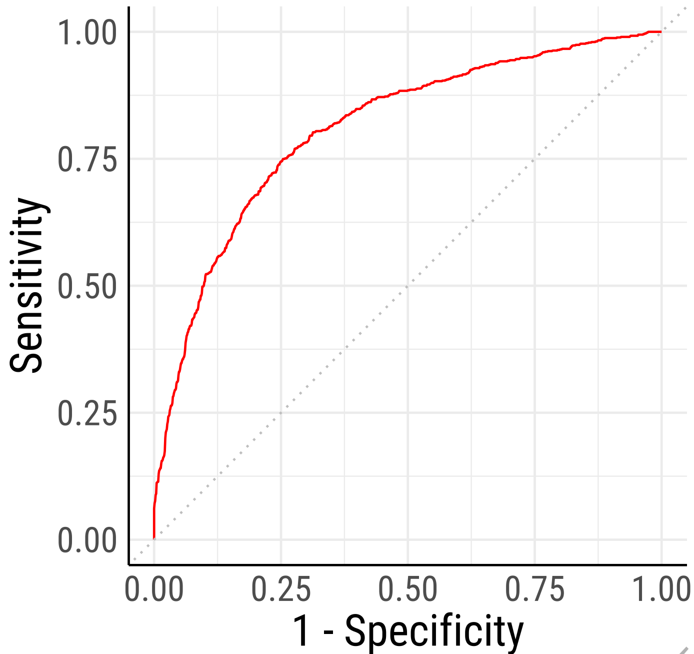
where variable and coefficient definitions are identical to our main specification but with a host of additional variables included in the matrix of predictors X.[61] We choose the largest penalty term λ within one standard error of the λ that minimizes prediction error based on three-fold cross validation within partitions of the training set; we determine the optimal threshold for classifying "yea" versus "nay" votes through this cross-validation process as well. With the model results in hand, we can then assess model performance by making out of sample predictions in the test set.

Figure E.1 reports the Receiver Operating Characteristic (ROC) Curve, which displays the trade-off

[61] We include in X the variables included in Figures II, A.1, and A.2.

between sensitivity and specificity for different thresholds. Table E.2 reports the performance statistics for the out of sample predictions based on the optimal threshold. Overall, the prediction model retains an accuracy of 75%. Precision is 72% (true positives divided by true and false positives, sensitivity or recall is 66% (true positives divided by all actual positives), and specificity is 82% (probability of true negatives divided by all actual negatives). Finally, Table E.1 reports the confusion matrix for the model's out of sample predictions. These performance statistics show that as a prediction tool the model performs reasonably well even out of sample.

Figure E.1: Predicting Permissive Immigration Votes: Ridge (Logistic) Regression Model, ROC Curve



Note: This figure plots the ROC curve from the out of sample predictions in a test set based on a ridge regression prediction model. It portrays the performance at each possible threshold

Table E.1: Ridge Regression Prediction Model for Immigration Roll Call Votes, Performance Statistics, Confusion Matrix

Response	Truth	
	pro	anti
pro	588	226
anti	307	1003

Note: This table reports the confusion matrix for the predictive model for Landmark and Other Immigration votes in our sample. The predictions are based on first fitting the model on a training set comprised of 85% of the data and then making predictions on a test set comprised of 15% of the data.

Table E.2: Ridge Regression Prediction Model for Immigration Roll Call Votes, Performance Statistics

Accuracy	Precision	Recall	Specificity
0.749	0.722	0.657	0.816

Note: This table captures the quality of the predictive model for Landmark and Other Immigration votes in our sample. The statistics are derived from first fitting the model on a training set comprised of 85% of the data and then making predictions on a test set comprised of 15% of the data.

E.2 Variable Importance in Prediction Model

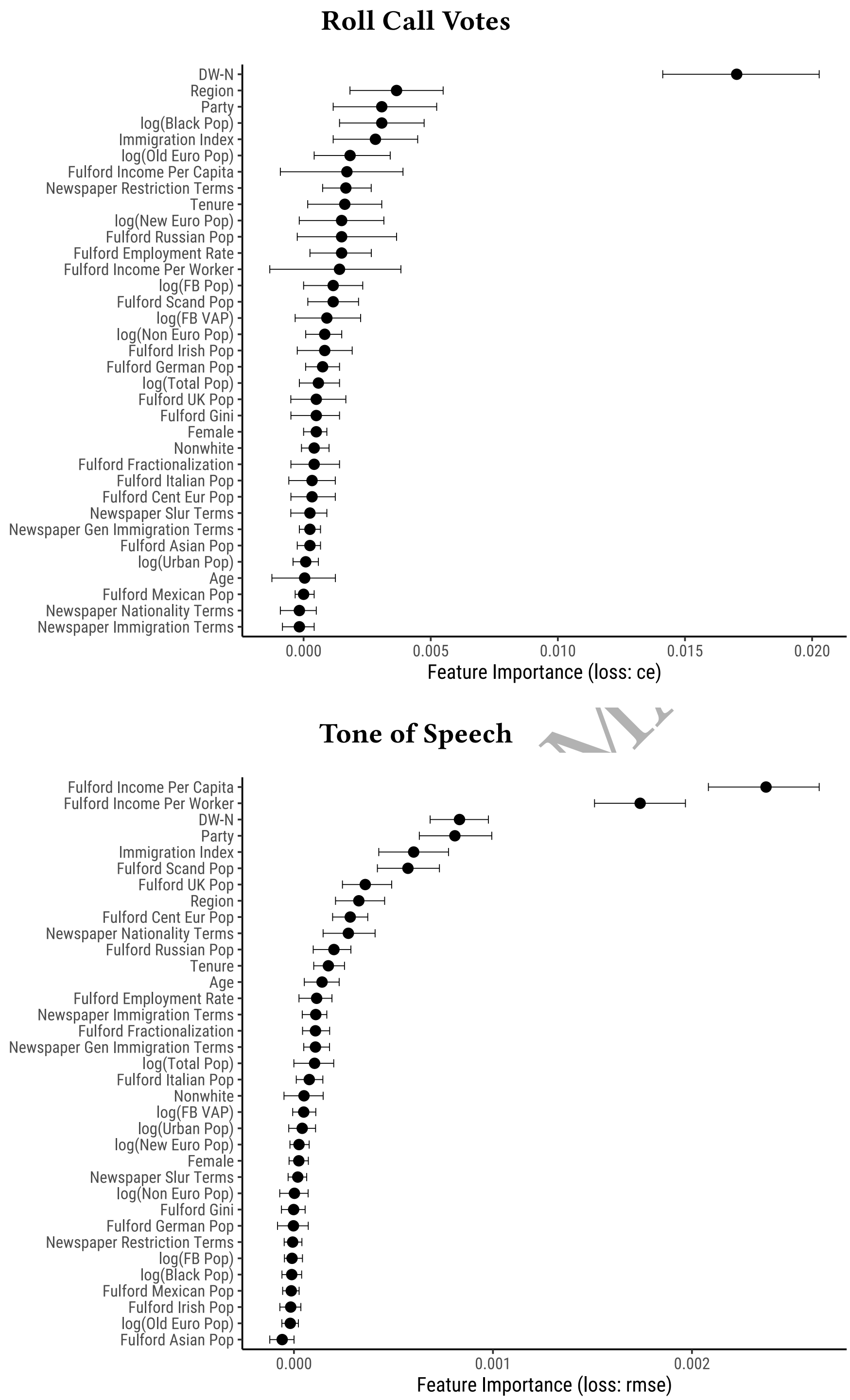
Given this performance, we now use the model to compare variable performance for the purposes of prediction of immigration votes. We use a standard variable importance approach: for each predictor we compare the model performance in terms of classification error for the fully-specified model versus the error when a given predictor is shuffled randomly, making it independent from the outcome of interest (Fisher, Rudin and Dominici 2019). We repeated this shuffling five-hundred times. We plot the results for the features of our prediction model, omitting Congress, chamber and state indicator variables, in Panel A of Figure E.2. The figure illustrates that immigration index is in the top handful of features in terms of variable importance. Direct measures of ideology appear most important for purposes of prediction, where the Nokken-Poole DW-Nominate estimates are the first dimension ideological scores for an MC in the Congress in which the vote took place.[62] This is followed by Region, party, black population, and then immigration history. Importantly, for a variable to exhibit any predictive power at all in this exercise already crosses a relatively high threshold since congressional term itself explains a substantial part of the variation in voting.

We perform a similar modeling exercise with the tone of MCs' floor speeches on immigration as the outcome in Panel B of Figure E.2. In this case, since the tone of speech is a continuous variable, we tune the model using mean-squared error as the key performance metric. Again, member family immigration history ranks highly among the set of explanatory variables available to us, lagging behind only some district-level economic variables, ideology and party.

Importantly, with this exercise we do not seek to claim that family immigration history is always the most important explanatory factor in MC voting or expression in Congress. Such a claim would be implausible, as well-known factors such as political ideology and party clearly structure a large part of member behavior. Instead, this predictive exercise shows that with regard to lawmaking and legislative behavior on immigration policy in Congress, family immigration background rises to a point of importance where it may begin to approach other well-studied characteristics that help to explain member behavior.

[62]Ideology may absorb some of the explanatory power of immigration history itself. Furthermore, it may be slightly problematic to include in a model predicting vote choice since ideology is determined from the set of all votes cast by members in a given Congress.

Figure E.2: Ridge Regression Prediction Model for Immigration Roll Call Votes and Tone of Immigration Floor Speeches, Variable Importance



Note: This figure reports the difference in classification errors (Roll Calls Votes) and mean-square errors (Tone of Speech), on average across 500 draws, between the full prediction model and models that randomly permute a given feature.

E.3 How Pivotal was MC Ancestry for Roll-Call Votes and Tone of Speech

Next, we explore the extent to which family immigration history could prove pivotal for immigration policymaking. Specifically, we benchmark family immigration history against other MC-level features from our main specification to offer a sense of its importance for bill passage. Making predictions based on our model estimates suggests that large changes in the immigrant composition of Congress could coincide with a flip in the outcome of roughly 16% of the landmark bill votes in our sample and roughly 14% of the full set of immigration bills that we examined.

Fundamentally, this is a different approach to assessing variable importance that incorporates the context of our study. While the model is trained to predict the outcome of individual MC roll call votes, we know that those roll call votes are aggregated up to determine whether or not each bill passes the full chamber. Thus, we examine how often a variable could matter for changing actual legislative outcomes in terms of bill passage. For this exercise, we again use the ridge regression with the baseline set of features to fit a model on the full set of bills.[63]

We seek to explore possible counterfactual scenarios as we vary the composition of Congress along one feature while holding other features fixed. For numeric variables, we evaluate them at their observed maximum and minimum values. We evaluate categorical variables at each possible category. Thus, for each observed value of a variable, we set all observations equal to that value while leaving all other variables unchanged and then make a prediction using the fitted model based on this counterfactual. We then sum up the new counterfactual vote totals for each bill based on these predictions and assess whether the vote totals cross a majority threshold in comparison to the vote totals when holding all features at their observed values.

Such an approach explores the bounds on changes in immigration policymaking that could plausibly coincide with shifts in key explanatory variables. Of course, such an exercise deserves several words of caution. First, a meaningful change in the composition of Congress would likely change the entire policymaking agenda—a different set of bills would be brought to the floor and a different set of issues might be debated in Congress. Counterfactual exercises such as this one do not capture these types of important dynamics. Second, a prediction exercise such as this one has no bearing on causal interpretations; indeed, we think rather than focus on marginal changes this prediction model provides insights primarily about plausible bounds on legislator behavior and policy changes associated with changes in a feature of Congress.

To make this exercise more concrete, consider our findings for the Immigration Index variable. The maximum value for Immigration Index is three; the minimum is zero. The mean is 0.69 and the standard deviation is 0.94. When we examine an increase in the Immigration Index (e.g., set Immigration Index to 3), we predict a significant change in the composition of bill passage rates: the outcome for roughly 10.5% of Landmark and 12.4% of all immigration bills in our sample would be predicted to change from anti- to pro-immigration. For a more modest one standard deviation increase in the immigrant composition of Congress, we predict that 9% of bill outcomes would change. Furthermore, the changes in bill passage rates for immigration generally surpass changes in some other MC-level characteristics such as age and tenure, with the exception of the counterfactual of setting tenure to its maximum. We present the results

[63] Model performance statistics, calculated here based on in-sample predictions given the nature of this exercise, are similar to those in the previous section but with model accuracy slightly degraded (from 75% to 74%) since we use a narrower set of predictors.

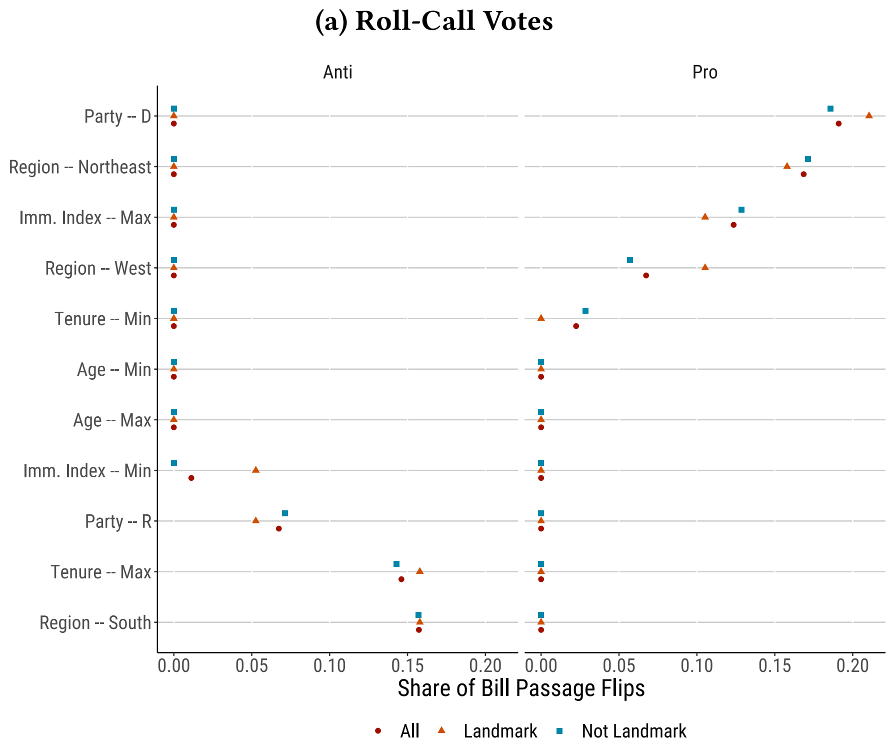
of these counterfactuals in Figure E.3 Panel A.

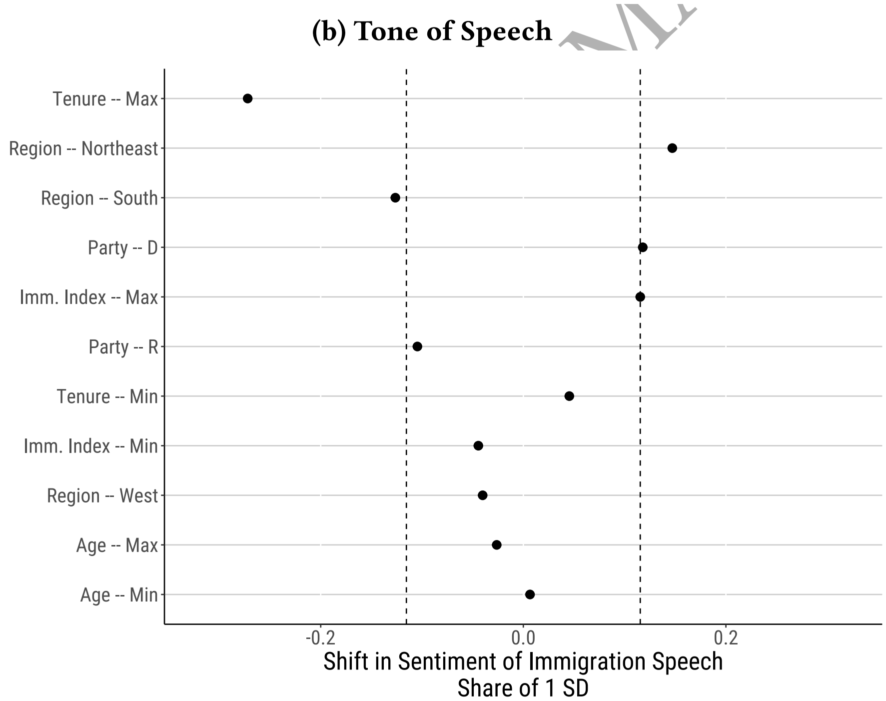
Next, we evaluate roll call voting on immigration under the counterfactual that no members of Congress were immigrants or descended from immigrants (e.g., we set the value to zero). *Note that in practice this represents a less than one standard deviation decrease in the immigration index.* When evaluating how the model predicts member voting under this counterfactual, we estimate that the outcome of 5.26% of the Landmark bills in our sample would change (from a pro- to an anti-immigration outcome). Across all immigration bills in the sample, we estimate that the outcome for 1.1% of bills would change. For Landmark legislation, this estimate registers a magnitude equivalent to the change in predicted vote outcomes for the extreme counterfactual of a fully Republican Congress. This more modest finding for decreases in the number of immigrants in Congress arises based on a combination of the estimated probability thresholds required for members to change their vote, the vote margins of the immigration bills under consideration, and the magnitude of the estimated coefficient for the Immigration Index variable.[64]

Following a similar approach, we also estimate the shift in tone of floor speeches, in aggregate, predicted by counterfactual changes in the composition of Congress. Figure E.3 Panel B reports the results. The model suggests a counterfactual scenario of a Congress with no family history of immigration predicts a shift in immigration speech towards a more negative tone by 4.4% of a standard deviation. A Congress with full family immigration histories predicts a shift towards a more positive tone on the order of 11.5% of a standard deviation. Similarly to the bill passage results, party stands out as another very strong predictor of shifts in tone of immigration speeches.

[64]In this context we estimate a coefficient of 0.14 for Immigration Index.

Figure E.3: Immigration Bill Passage Changes and Tone of Speech Changes Predicted by Changes in the Composition of Congress





Note: This figure reports the predicted changes in bill passage and in the tone of floor speech predicted by changes in the composition of Congress for a set of MC-Level variables. In Panel A, we report the share of bills that would switch from failure to passage or passage to failure for changes in each variable.

F Assessing Intrinsic versus Extrinsic Motivations

Across the mechanisms we consider, explanations related to identity as part of an immigrant in-group appear to stand up best to empirical scrutiny. This mechanism raises a further question: Do intrinsic or extrinsic factors motivate those MCs engaging in pro-immigrant legislative behavior consistent with in-group identity? This question matters insofar as behavior related to social identity could arise from an MC's own tastes, from efforts to appeal to an electoral constituency (e.g., the preference of a district-level median voter), or from efforts to appeal to a narrower primary or base constituency (e.g., the preference of a narrower constituency median from the set of an MCs' key supporters).

Our earlier analysis somewhat pushes against the extrinsic explanations. In addition to the RDD separating district-level concerns from MC ideology (Table III), robustness checks that separately include fixed effects for region by party, state by party, and state by party interacted with year trends all help account for the composition and tastes of each MCs' base or primary supporters (Figure II). Now we consider additional empirical tests to examine whether accounting for varying salience of extrinsic factors alters the empirical relationships we have observed thus far.

F.1 Visibility of Immigrant Background and Visibility of MC Behavior

There are several pathways by which an MC with a visible immigrant background might act differently than an MC with the same family history but a less visible immigrant identity. Consider the case of MC surnames denoting an immigrant background. When MCs have surnames visibly identifying their family histories of immigration, their primary constituencies might view them as "descriptive representatives" and expect them to take pro-immigrant positions on legislation. An immigrant surname might boost the election chances of an MC in a district with immigrant constituents, in turn reinforcing a role as a descriptive representative. This extrinsic motivation would explain broadcasting their in-group identity. A second possibility is that a surname denoting a family history of immigration influences an MC's sense of group boundaries and personal preferences. This would lead to different legislative behaviors but would be more in line with an MC's intrinsic motivations for expressing their in-group identity.

While we can never disentangle a member's intrinsic versus extrinsic motives entirely, whether a member's immigrant status and actions regarding immigration policy are more or less visible provides a starting point: pro-immigrant behavior even with less visible indicators of immigrant status and less visible choices related to immigration and cultural identity may suggest stronger intrinsic motivation. In this subsection, we assess the relative importance of these explanations by examining outcomes highly "visible" to the primary or base constituency as well as an outcome less prone to pressures from such groups; at the same time, we decompose immigrant identity into actual ancestry and the visibility or salience of that ancestry (as measured from surnames).

This approach splits family immigration history into an MC's actual family history and public perception of family immigration history based on names. Consider an MC who has one foreign-born parent but a surname that does not indicate a recent family history of immigration (for example, "Smith" averaged 0.03 foreign-born parents among people in the South in 1930). Now compare this to someone who also has one foreign-born parent but who possesses a surname suggesting a high probability of an immigrant background (for example, "Sundstrom" indicated on average 1.56 foreign-born parents for someone born at the turn of the century in the Northeast). Both have the same actual immigrant ancestry but public perceptions based on surnames are likely very different.

We start by examining the naming decisions of future MCs for their children in Table A.22; we control for the more visible trappings of immigrant status through surname, and we focus on the less visible element of actual immigrant identity. Similarly, the outcome of interest—child naming—is also less visible as compared to a speech or a vote and reflects a choice unlikely to reflect strategic political motives, especially because we restrict to the sample of children born before their MC parents entered Congress. While not every specification reaches statistical significance in Table A.22—actual ancestry and name-predicted ancestry are highly correlated—in many cases, we observe a positive relationship between actual as well as perceived immigrant ancestry and naming choices. We cannot reject nulls for different magnitudes of these estimates, though in the majority of cases the name score variable appears larger. Given that we continue to observe positive and significant relationships between actual identity and foreignness of a child's name, the results suggest MCs chose more immigrant-sounding names not purely for strategic motives such as catering to a future base constituency.

Next, we examine how actual immigrant background correlates with an MC's decision-making on immigration roll call votes and speech, holding *visible* immigration history constant. Compared to child naming, these represent more visible policy choices (with speeches as most visible), influenced by strategic motives to varying degrees. As we see in Table A.23 (roll call) and Table A.24 (speech tone), across all specifications, the coefficient on the actual immigration history variable registers as statistically significant.[65] Both actual and predicted immigrant ancestry matter regardless of the visibility of the action taken, suggesting that intrinsic motivations are at play.

F.2 Roll Call Voting by District Composition

We also examine whether variation in the immigrant composition of districts coincides with observable differences in the magnitude of the correlation of MC immigrant family history with legislative behavior. We split the sample based upon whether immigrant populations (proxied for by district foreign-born share) comprised 0-10%, 10-20%, 20-30% or 30% or more of the district, following Goldin (1994). Again, this approach may help tease out intrinsic versus extrinsic motivations related to immigrant group identity. If the association between immigrant family history and support for permissive immigration policies is stronger for members from districts with higher immigrant shares (and disappears in districts with low immigrant shares), that might suggest that MCs with immigrant backgrounds supported permissive policies to cater to the preferences of their base constituencies (especially immigrants in their district). That would be evidence for extrinsic motivations. Alternatively, if the association does not move dramatically across district compositions, that would be more consistent with intrinsic factors.

In Figure F.1, we present the results for landmark legislation (upper panel) and for all immigration bills (lower panel). While there is some variation in uncertainty around the estimates, due to small sample sizes in some subsamples, the point estimates appear generally stable. We cannot reject the null of no difference in the estimates for any of the varying district compositions. Thus we do not observe evidence consistent with strategic concerns about the preferences of a member's base constituency driving legislative behavior

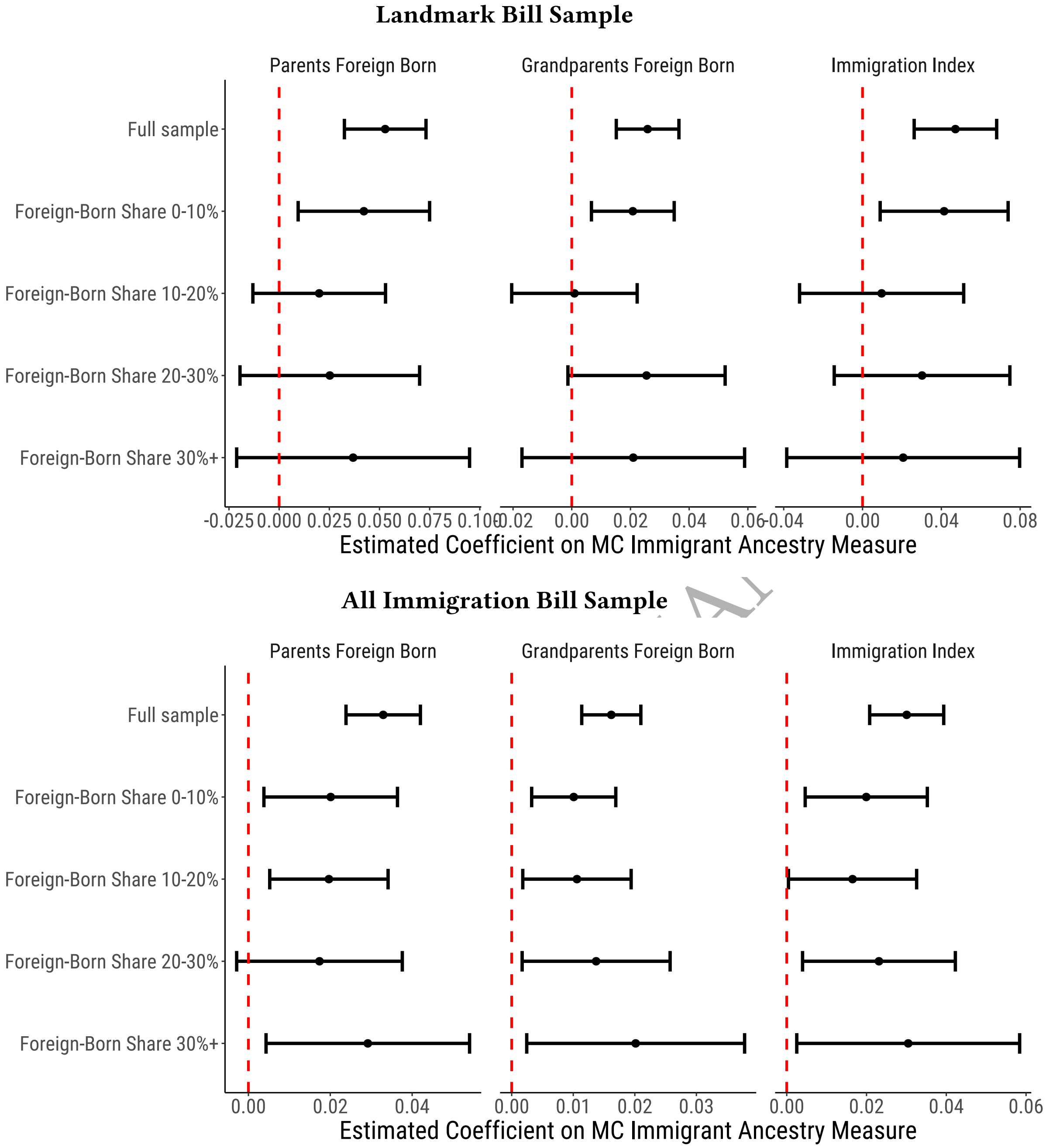
[65]The coefficient for surname-predicted ancestry is also positive. But the relative sizes reveal an interesting pattern. In the most visible votes (e.g., landmark votes), actual MC Immigrant Ancestry appears to matter more than perceived ancestry. In the less visible votes (e.g., all bills), both coefficients are highly statistically significant and the predicted ancestry coefficients are larger in magnitude. Meanwhile for speech tone, predicted ancestry coefficients are generally larger in magnitude.

related to immigration. This appears broadly consistent with research finding relative stability of member ideological ratings on issue-specific policies regardless of district electoral competitiveness (Fowler et al. 2016), and highlights the role of intrinsic motivation for member behavior in this context.

To summarize this subsection and the previous one, across differing levels of district composition, differing levels of visibility of MC actions, and accounting for differing levels of visibility of immigrant background, actual immigration history retains a relatively stable and significant relationship with downstream outcomes, consistent with an intrinsic group identity motive. While a sense of group identity can matter whether it arises from intrinsic (e.g., internal) or extrinsic motives (e.g., strategic motives related to base constituency), our analyses suggest that intrinsic factors play a role. Our results do not suggest that extrinsic factors do not matter at all. However, across these empirical exercises designed to tease apart intrinsic from extrinsic factors, personal MC preferences hold up quite robustly as a factor.[66]

[66] Again, this finding aligns well with other research that has found stability in MC ideological preferences in practice, such as work noting how ideological change in Congress often comes from member replacement rather than member adaptation (Lee, Moretti and Butler 2004) and that personal preferences outweigh any other factor for member ideology (Levitt 1996).

Figure F.1: Robustness of Immigration History and MC Vote Choice: By District Foreign-Born Share Bin



Note: The figure presents the association between an MC's immigrant family history and their support for permissive immigration policies, stratified by the share of immigrants in their district. The upper panel shows the results for landmark legislation, while the lower panel includes all immigration bills. Despite some variation in the uncertainty of the estimates due to small sample sizes, the point estimates remain generally stable across different district compositions, suggesting that the relationship between immigrant background and legislative behavior on immigration is not significantly influenced by the demographics of the district.

G Alternative Approaches to Estimating the Effects of Family Immigration History on Roll Call Voting for Immigration and Other Bills

The share of bill-by-bill regressions where family immigration history is a significant explanatory factor is much higher for immigration legislation than for other legislation. Averaging across bill topics, Table G.1 reports that family immigration history is statistically significant in roughly 4% of regressions for other legislation; for immigration legislation, family immigration history is statistically significant at $p < 0.05$ about 24% of the time.

The results from this placebo exercise withstand several additional robustness checks. First, in order to determine the direction of a vote (e.g., whether supporting a bill is a liberal/permissive position or not), we counted the coefficient on family immigration history as significant only if both the direction of the estimate aligned with the liberal/permissive vote and if the estimate's p-value registered below 0.05. We can relax this approach by not placing any restriction on the direction of the vote. In this manner, we test whether family immigration history was a statistically significant predictor of voting on a set of bills, regardless of the direction of the vote. Figure G.1 reports the results when implementing this approach. As the figure illustrates, relaxing this restriction does lead to a higher share of votes on other topics being explained by family immigration history. However, as one might expect, family immigration history still has by far the strongest statistical relationship with bills on immigration policy.

Second, while the method we employ based on Washington (2009) examines only bills where a majority of the members of the major political parties opposed each other (e.g., omitting bills where this level of partisan conflict did not exist), we can also relax this restriction. To do so, we define the direction of a vote based on the party voting yea or nay at a higher rate, e.g., the *party plurality*. For non-immigration bills, the party plurality approach will also by construction include a larger share of the total roll call votes taken in Congress because partisan conflict is no longer required for inclusion in the sample. For immigration legislation, a permissive position could in theory differ from a "liberal" position if a greater share of Democratic versus Republican members of Congress supported the anti-immigration position. As a reference we therefore also include the immigration estimates based on our original qualitative codings.

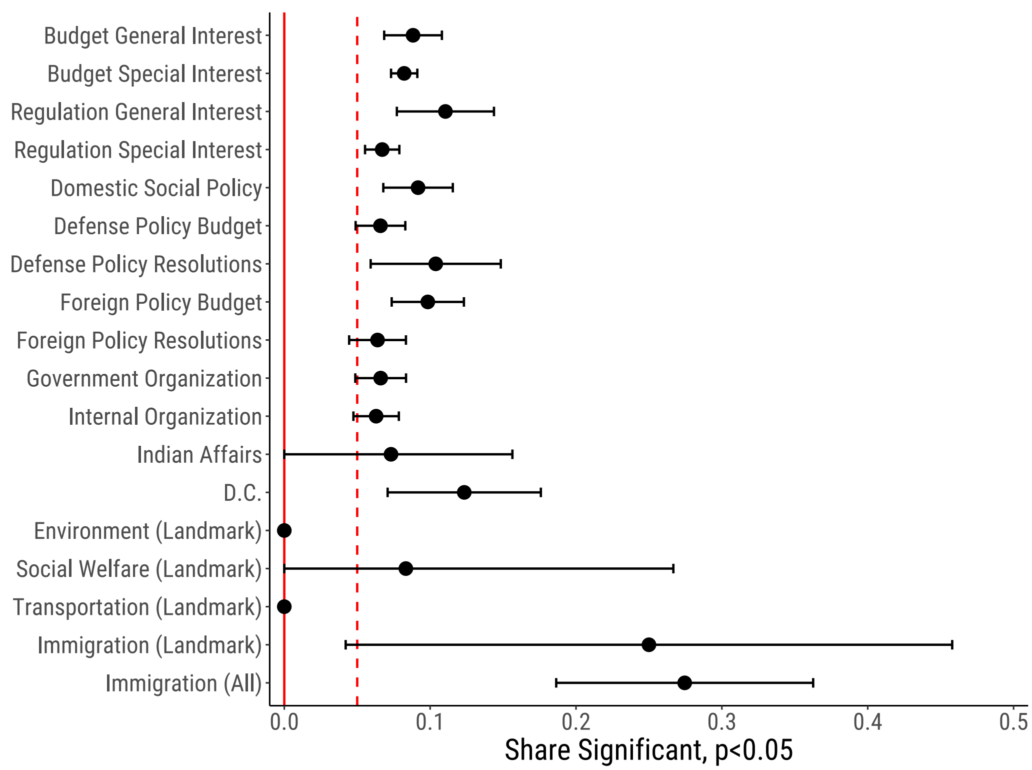
Figure G.2 reports the results from this alternative approach. For each topic, the point estimate reflects the share of individual bill-by-bill regressions where family immigration history registered as statistically significant. The estimates with the gray dots and confidence intervals are based on the sample of bills constructed based on party plurality; the black points and confidence intervals reflect the original estimates for immigration legislation. Overall, the results are largely unchanged when we take this approach. For non-immigration bills, a comparison of this figure with the original Figure VII shows that the more inclusive approach does not meaningfully alter conclusions regarding what topics having voting patterns meaningfully correlated with family history. For legislation related to immigration, family history continues to register as significant in a larger share of votes for roll call votes on immigration than for any other topic, though the share of significant votes does shift downward slightly. One interpretation of this shift is that family immigration history is a better predictor of "permissive" immigration votes (based on the qualitative codings) than on "partisan" immigration votes (based on the party plurality codings).

Table G.1: Share of Statistically Significant (p<0.05) Regressions for Immigration versus Other Topics

	Not Significant	Significant
Other Legislation	95.66% (10,654)	4.34% (483)
Immigration Legislation	76.23% (93)	23.77% (29)

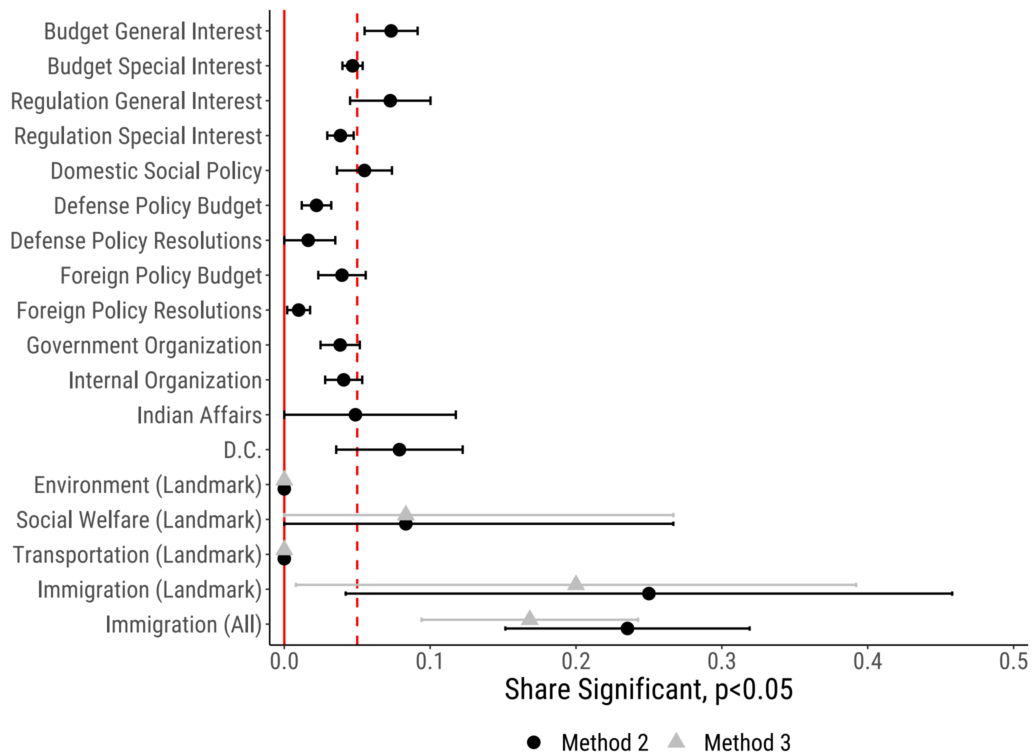
Note: This table reports the share of bill-by-bill regressions from Figure VII for which family immigration history is statistically significant, breaking out the results by immigration legislation versus other legislation.

Figure G.1: Robustness Check for Effect of Immigration History on Permissive/Liberal Vote for Placebo Topics, No Restriction on the Direction of the Vote



Note: This figure reports the effects of an immigrant family history across a range of placebo topics on roll call votes during the 51st–91st Congresses. For each topic (as defined by Peltzman (1984)) and each vote, we determined if family immigration history was a statistically significant predictor of voting, regardless of the direction of the vote. This approach contrasts with our main approach in the body of the paper where we focused on how family immigration history predicted liberal/permissive voting on bills. We then regressed vote choice on Immigration Index, district composition and other covariates included in our main specifications. We plot the share of regressions for each topic in which the coefficient for Immigration Index has a statistically significant ($p<0.05$) effect on vote choice. We performed a similar exercise for major legislation in the policy areas of immigration, transportation, the environment and social welfare.

Figure G.2: Robustness Check for Effect of Immigration History on Permissive/Liberal Vote for Placebo Topics, Alternative Approach to Identifying Direction of Vote



Note: This figure reports the effects of an immigrant family history across a range of placebo topics on roll call votes during the 51st–91st Congresses. For each topic (as defined by Peltzman (1984)) and each vote, we (1) identified the more liberal position based upon the share of each party supporting a bill for the non-immigration topics, and (2) for immigration votes (a) we used our qualitative immigration codes (with the effects reported with the black points and confidence intervals), and (b) used the same approach as in (1) (with the effects reported with the gray points and confidence intervals). This approach contrasts with our main approach in the body of the paper where the votes included are restricted to those for which a majority of each party oppose each other and the liberal direction of the vote is determined based on which side is supported by a majority of Democrats. We then regressed vote choice on Immigration Index, district composition and other covariates included in our main specifications. We plot the share of regressions for each topic in which the coefficient for Immigration Index has a statistically significant ($p < 0.05$) effect on vote choice. We performed a similar exercise for major legislation in the policy areas of immigration, transportation, the environment and social welfare.

H Using the Jones and Olken (2005) approach to estimate individual leader effects

We also assess the importance of family history using an alternative approach inspired by Jones and Olken (2005). In Jones and Olken (2005), the authors devised a method for determining the importance of a country's leadership on GDP growth by examining moments of leadership turnover. Focusing on plausibly exogenous turnovers due to leader deaths, the authors regressed GDP on pre and post indicators for each leader in the sample. Under the null of leaders having no effect on growth, the change in growth rate (e.g., $\widehat{POST} - \widehat{PRE}$ for each turnover event) has percentile rank r distributed uniformly on a unit interval (e.g., $r \sim \text{Unif}(0,1)$). Based on the properties of the uniform distribution, the authors compute a test-statistic K where $K = \frac{\sum(y-1/4)}{\sqrt{Z/48}}$ with $y = |r - 1/2|$ and Z equalling the number of leaders in the sample. With this test statistic in hand, the authors perform a one-sided hypothesis test to assess the probability of observing a K as large as they computed under the null of leadership not mattering for growth.

We set out to follow a similar approach to assessing the importance of family immigration history on legislative behavior. Our setting has some important commonalities and differences when compared to the case of leadership and growth. We specifically seek to understand the question of whether family histories of immigration matter for immigration policy voting. One key point of difference is that, whereas Jones and Olken (2005) seek to determine whether a leader's identity matters broadly speaking, we are focused primarily on examining an individual characteristic: family immigration history. In a regression context the comparison is not dissimilar to the comparison of estimating an individual fixed effect versus estimating the coefficient for an explanatory variable. Thus, whereas Jones and Olken (2005) examine variation from any one leader to another, we focus instead on instances where a change in family immigration history occurs due to the turnover. Furthermore, in the context of the Senate and the House, many turnovers due to death are filled with a family member or with someone seen as an ideological successor to the previous member. Thus, for our context of congressional turnovers, even if the timing of a turnover due to death is plausibly random the person replacing the former member is often not.

This restriction, in tandem with the fact that not many MCs die in office, dramatically shrinks the number of turnovers we can examine. As a result, this exercise presents a very high bar for finding a significant relationship between roll call voting and family history. Following the Jones and Olken (2005) approach also raises the question of how much of a change in family immigration history need occur in order to signify a meaningful break or change in family background. To take a neutral stance on this, we examine instances where (1) a change from no family history of immigration to some family immigration history (or vice versa) occurs, (2) any change in family history of immigration occurs (e.g., a turnover leads to a different number of foreign-born parents for each member), and (3) a change occurs from no family history of immigration to a full family history of immigration.

We begin by processing the congressional data so as to identify moments of member turnover. We identify the last term served by members of Congress (e.g., when the turnover occurred) and then proceed to match each member who turns over to the subsequent member (from the same district for House members and from the same state for Senators). We identify turnovers due to death based on those deaths occurring in either a member's last congressional term or before a new member has assumed office in the next term; this approach includes members who fell sick during their last term, left office, and were then replaced shortly before dying. Following the approach of creating a pre- and post-turnover time window from Jones and Olken (2005), we limit the sample to up to five congressional terms before the turnover occurred as well as up to five congressional terms for the member who subsequently filled the role after the turnover. We exclude the Congress in which the turnover occurred since the voting records for members in that Congress will often be minimal and incomplete. For each of these sequences, we further determine whether a change in family immigration history coincided with the personnel change brought about by the turnover. Next, we estimate the pre- and post-turnover effects for this subsample of the data and construct the test statistics as described above. We calculate p-values by determining the place of the test statistic K in a null distribution generated via 1,000 random draws.

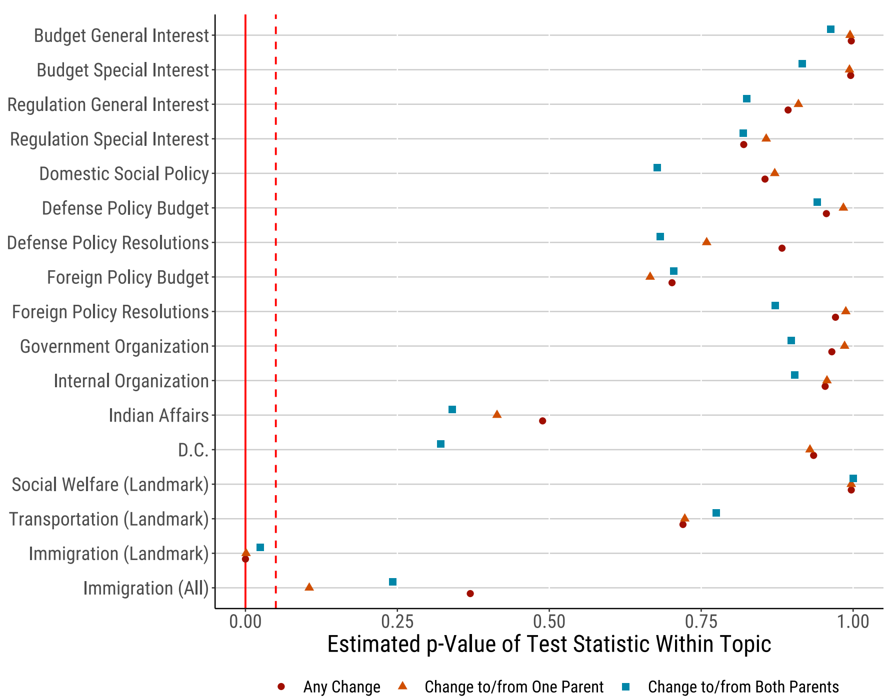
Table H.1 presents results from this approach when examining how turnover due to death may or may not be related to roll call voting on immigration policy. For Landmark legislation we estimate that there is a meaningful break in immigration voting records associated with turnover leading to changes in family immigration history in 3 of our 3 specifications. Turning to breaks in the roll call voting for all immigration legislation, we calculate p-values of 0.10 for one of our three specifications. So, while for our broader set of immigration legislation we cannot reject the null at a level of $p = 0.05$, the results are nonetheless suggestive. Finally, when replicating this exercise for roll calls on other topics, we find that no other topics register as having anything close to a statistically significant relationship with roll call voting. Figure H.1 illustrates the p-values estimated from the Jones and Olken (2005) procedure for turnovers due to death across all topics. Only Immigration (Landmark) registers a meaningful shift when examining turnovers due to death. Immigration (All) is the only other topic with p-values below $p = 0.25$.

Table H.1: Member Turnover Method for Assessment of whether Family History Matters for Roll-Call Vote Ideology

	Z	K	p-Value	Topic
Immigrant Parent (Any Change, Turnover Death)	20	3.36	0.00	Immigration (Landmark)
Immigrant Parent (At Least One), Turnover Death)	20	3.36	0.00	Immigration (Landmark)
Immigrant Parent (Both, Turnover Death)	13	2.01	0.02	Immigration (Landmark)
Immigrant Parent (Any Change, Turnover Death)	89	0.31	0.37	Immigration (All)
Immigrant Parent (At Least One), Turnover Death)	78	1.04	0.10	Immigration (All)
Immigrant Parent (Both, Turnover Death)	59	0.65	0.24	Immigration (All)

Note: This table reports the test statistics and p-values from an estimation approach that seeks to determine whether member identity with respect to family history matters for roll call voting ideology based on the method from Jones and Olken (2005). Z refers to the number of members in the sample; K refers to the value for the test statistic calculated from the procedure. Rows with a p-value below 0.05 allow us to reject the null hypothesis that a family history of immigration has no effect on roll-call ideology.

Figure H.1: Member Turnover Method for Assessment of whether Family History Matters for Roll Call Voting on Immigration and Other Topics



Note: This figure reports the p-values from an estimation approach that seeks to determine whether member identity with respect to family history matters for roll call voting based on the method from Jones and Olken (2005). We perform this test based on changes in the pattern of voting behavior on a given topic for a member and for their replacement after their death.

I Text Analysis of Congressional Speeches on Immigration

Here we describe the analysis of the free text of congressional speeches on the subject of immigration. As our source material, we employ data from the replication materials of the paper Card et al. (2022), which captures speeches on the subject of immigration given by members of Congress. Restricting the data to our time period under study, we process the text of each speech by stemming the words, removing punctuation, removing stop words and tokenizing the text into trigrams (e.g., three-word phrases).

After preparing this speech data, we then perform a simple descriptive exercise where we calculate the term frequency–inverse document frequency (tf-idf) (Ramos et al. 2003) for each trigram by immigration status. The tf-idf provides a measure of the relative informativeness of a given term by reweighting how often a term appears in each document (term frequency) based upon how many documents it appears across (inverse document frequency). Phrases that are frequent both within and across documents, such as definite articles or other common words, are thereby weighted downwards. The result is a standard method for trying to understand term importance, such as words related to the subjects of a speech, essay or conversation.

Figure I.1 reports the results for the top 10 phrases with the highest tf-idf scores calculated for members with family histories of immigration and for those without. We exclude references to Congress, the House, the Senate, the Speaker and other officials. We use time periods following those applied in Card et al. (2022), who split their sample depending on era of immigration.

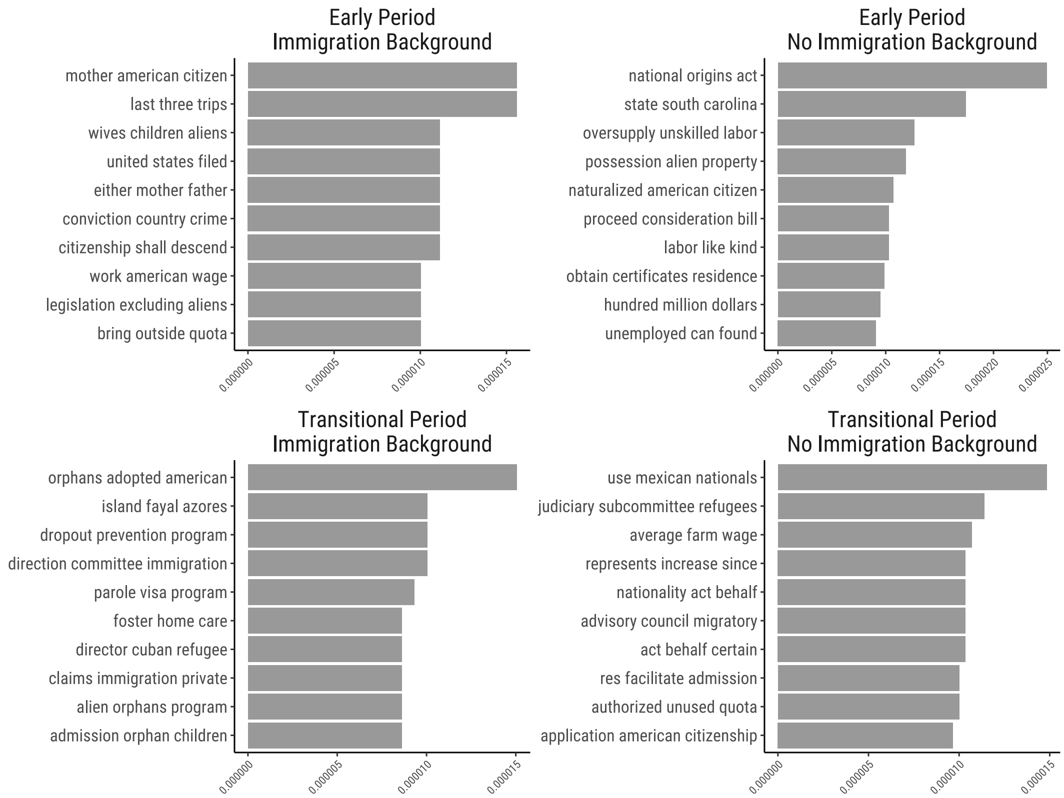
Even using just this relatively rudimentary descriptive exercise, several key differences across immigration background immediately stand out. Members without an immigration background often appear to use phrases related to employment and the economy such as "oversupply unskilled labor", "labor like kind", "unemployed can found", "average farm wage", "use mexican nationals" (the last phrase also related to farm labor). For example, Caleb Powers (R-KY), in a speech related to literacy tests and the Immigration Act of 1907, spoke:

> Men who were then opposing the literacy test, as men are opposing the literacy test now, opposed a bill similar in character to the bill now under consideration, and succeeded in having a commission appointed to investigate the whole subject of immigration [. . .] And after four years of investigation by them in this country and in Europe the commission came to the unanimous conclusion that there was an oversupply of unskilled labor in this country, and that the foreign Immigration should be largely curtailed.[67]

In this quote, Powers advocates for the view that there was an oversupply of unskilled labor and therefore a literacy test might dampen unskilled immigration. On the other hand, we find that members with an immigration background have only one term related to labor in their top 10 most frequently used terms in either time period—"work american wage"—used primarily in language advocating for immigrants to have the right to work for an American wage. Rather than frames related to labor, many of the terms spoken by MCs descended from immigrants involve references to family, including trigrams such as "mother american citizen", "wives children aliens", "either mother father", "orphans adopted american", and "admission orphan children". Many of these relate to humanitarian efforts. For example, after earthquakes in Italy, Robert Giaimo (D-CT) whose parents were both born in Italy, introduced legislation to "authorize the

[67] Quotation from: Caleb Powers. "Immigration." *Congressional Record*, vol. 49, part 1, p. 674, December 14, 1912.

Figure I.1: Top 10 Most Informative Phrases (trigrams) in Immigration Speeches by Family History of Immigration



Note: This table reports the tf-idf scores for each trigram listed. These represent the top 10 trigrams based on calculation of this metric in member speeches on immigration for MCs with and without foreign-born parents.

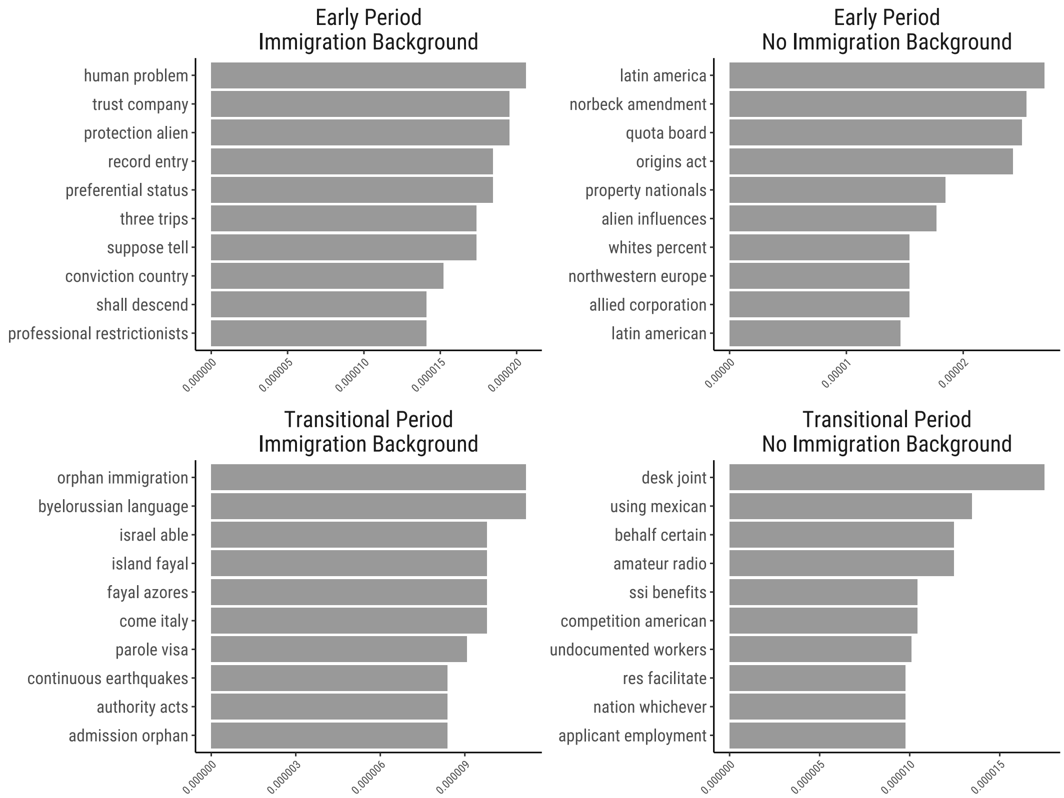
immediate entry into the United States of aliens who have been displaced as a result of the catastrophic earthquakes in Sicily earlier this month," with the legislation making available non-quota immigrant visas to "the wives and children of such aliens".[68]

Such comparisons based upon the text of speeches are necessarily impressionistic, but they do help suggest possible differences in the frames used by members when speaking about immigration. Members descended from immigrants appear more likely to emphasize positive elements of the immigrant experience ("work american wage") or the family and/or humanitarian aspects of immigration, depending on the time period. Members with no such background appear more likely to adopt frames in which the interests of native-born domestic citizens are protected, including economic interests.

We also replicate this approach using bigrams (e.g., two-word phrases) rather than trigrams. Figure I.2 reports the top 10 bigrams by era of immigration across those members with and without family histories of immigration. As before, the results appear broadly consistent with the notion that the most distinctive terms spoken by MCs with an immigration background differ from the terms spoken by those with no immigration background. Furthermore, the terms spoken by those with no family history of immigration include terms likely associated with restrictive frames, including the phrases "ssi benefits", "undocumented

[68]Quotation from: Giaimo, Robert. "Legislation for Special Visas for Earthquake Victims." *Congressional Record*, vol. 114, part 2, p. 1508, January 30, 1968.

Figure I.2: Top 10 Most Informative Phrases (bigrams) in Immigration Speeches by Family History of Immigration



Note: This table reports the tf-idf scores for each bigram listed. These represent the top 10 bigrams based on calculation of this metric in member speeches on immigration for MCs with and without foreign-born parents.

workers”, “applicant employment”, and “alien influences”.

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