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Labor market demand and attitudes toward immigration*

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Abstract

Western labor markets have undergone major transformations, while anti-immigrant constituencies have expanded and diversified. Yet the causal links between labor market dynamics and immigration attitudes remain contested. We argue that labor market demand is a strong and overlooked driver of immigration attitudes. We analyze 60 million job postings at the occupation-region level linked with panel data in Germany (2014-2022), and exploit the opening of the Tesla Gigafactory in Berlin-Brandenburg as an exogenous demand shock using a difference-in-differences design. Our results show that: 1) labor demand in the form of high-quality occupational exit options mitigates concerns about immigration by reducing perceptions of economic risk and foreign competition; 2) vacancy rates reveal egocentric and prospective mechanisms rather than sociotropic ones; 3) firms' labor demand drives immigration attitudes over and above immigrant labor supply and aggregate economic shocks; 4) effects are strongest among highly educated workers, helping explain the diversification of anti-immigrant coalitions.

Keywords: Labor market; job vacancies; attitudes toward immigration; panel data; difference-in-differences; Germany.

Wordcount: 10,825.

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Introduction

Anti-immigrant coalitions in Western democracies have both expanded and diversified in recent years. While lower-educated, working-class constituencies remain disproportionately represented among radical right electorates (Oesch and Rennwald, 2018), anti-immigrant narratives have increasingly permeated mainstream political spaces and gained traction among less likely social groups (Akkerman et al., 2016; Alizade, 2023). In parallel, labor markets in Western democracies have undergone profound transformations in the last 30 years. While technological change and automation reduce labor demand in low- and mid-skilled occupations (Kurer and Gallego, 2019; Gallego et al., 2022; Gallego and Kurer, 2022), post-COVID labor markets and developments in artificial intelligence are also affecting groups that were traditionally more sheltered (Autor et al., 2023; Webb, 2019).

Are the growth and diversification of anti-immigrant coalitions causally linked to these unprecedented employment fluctuations? Although the connection seems intuitive, the relationship between labor market dynamics and immigration attitudes remains highly contested. A prominent strand of existing research on the determinants of attitudes towards immigration has focused on studying the role of labor supply, namely the share or increase of immigrant workers. These studies have only found limited evidence for the idea that labor market competition influences immigration attitudes (Hainmueller and Hiscox, 2010; Hainmueller and Hopkins, 2014; Malhotra et al., 2013). More recent accounts have further complemented these insights by highlighting that national or local economic shocks may heighten anti-immigrant sentiments, but typically through mechanisms not directly related to individuals' own economic circumstances (Colantone and Stanig, 2018a,b; Finseraas and Nyhus, 2025; Margalit, 2019). The joint consensus emerging from these literature streams has been that sociotropic rather than egotropic considerations shape immigration concerns.

We argue that this conclusion is premature as existing accounts have disregarded or conflated a labor market dimension that is critical in shaping self-interest-driven concerns about immigration: firms' labor demand. Specifically, we contend that the availability of high-quality exit options within one's occupation reduces perceptions of economic risk and competition with foreign workers. Building on this, we argue that labor demand reduces immigration concerns and theorize two conditions that moderate this relationship. First, the effect should be most pronounced when job vacancies are of high quality, such as when firms offer permanent contracts. Second, it should be strongest where competition with immigrants is more likely, namely in occupations with a high share of immigrant workers.

These mechanisms remain blurred in existing accounts. The literature on immigrant labor supply typically treats labor demand as fixed, while the literature on economic shocks focuses on broader aggregates (e.g., regions or industries), where shocks affect multiple factors simultaneously, one of which is labor demand. While the theoretical relevance of labor demand has not gone unnoticed (see especially Pardos-Prado and Xena, 2019), previous tests have relied on occupational unemployment rates, which are a function not only of firms' demand but also of general workforce supply.

To test our argument empirically, we leverage novel data on 60 million unique job postings and full-population administrative records on the number of immigrant workers to create occupation-specific regional aggregates of firms' labor demand and immigrant labor supply. This allows us to overcome limitations that have previously complicated empirically disentangling the two. By combining these data with the German Socio-Economic Panel (GSOEP) from 2014 to 2022, we provide robust individual-level evidence consistent with our argument on the role of labor demand for workers' immigration concerns. Our within-individual longitudinal models incorporate period, regional, and occupational fixed effects, accounting for a wide range of unobserved heterogeneity and contemporaneous confounders. We find that higher levels of occupation-specific labor demand substantially reduce anti-immigration concerns. The standardized effect of occupational vacancies is sizable and comparable to canonical predictors of anti-immigrant sentiment, such as education and regional immigration growth, and is in fact larger and more statistically significant than income, immigration levels, or occupational unemployment rates.

Furthermore, our results support the idea that job quality and immigrant worker prevalence moderates the link between labor demand and individuals' concerns about prospective job competition with foreigners. We find that the effect attenuates in occupational environments with high shares of temporary and precarious job postings. This indicates that workers do not merely attend to the availability of exit options but also to *how good* they are. The effects are especially pronounced in occupations with medium and high levels of immigrant presence, that is, in occupational contexts where competitive threats from immigrant workers are most plausible. These findings underscore the importance of egotropic concerns as a channel shaping immigration attitudes. Additional heterogeneity analyses further reveal that highly educated workers, including managers and socio-cultural professions, are especially reactive to changes in job vacancies. This highlights the potential for anti-immigrant narratives to gain traction beyond traditionally socially conservative constituencies during periods of labor market turbulence.

To causally assess the relationship between labor demand and anti-immigrant attitudes, we complement our analysis with a second quasi-experimental study. Specifically, we implement a difference-in-differences design to exploit the 2019 announcement of the opening of a so-called Gigafactory by the American automotive company Tesla in the regions of Berlin and Brandenburg. The granularity of our data allows us to identify for which specific occupations Tesla opened a position, documenting a sharp increase in Tesla job postings in the affected regions. The results reveal substantial and statistically significant declines in anti-immigrant attitudes among workers exposed to positive labor demand shocks. Strikingly, these effects are confined to workers in high-demand occupations and do not extend to residents of the affected regions more generally, further substantiating self-interested mechanisms rather than broader sociotropic effects that stem from increased regional economic activity.

This paper makes four contributions. First, it disentangles labor demand from labor supply, which allows us to demonstrate that workers' access to high-quality exit options is a powerful driver of attitudes toward immigration. This qualifies the mainstream position in the literature that environmental shocks shaping immigration attitudes are only sociotropic or tied to national-level conditions (Colantone and Stanig, 2018b; Hopkins, 2010; Finseraas and Nyhus, 2025). Unlike most studies on immigration concerns, we identify mechanisms driven by firms' labor demand, rather than by regional economic shocks that evoke sociotropic concerns or by immigrant labor supply shocks that increase job or wage competition.

Second, by focusing on and isolating labor demand, the paper examines a more pervasive source of individuals' perceptions of their labor market situation than those typically considered in the literature, such as occupational unemployment (Pardos-Prado and Xena, 2019) or the risk of job loss (Hopkins et al., 2024; Trubowitz, 2026). Surprisingly perhaps, job loss is a relatively rare and occupationally concentrated experience compared to the share of workers actively considering alternative employment across the occupational hierarchy. Indeed, according to a survey conducted by Stepstone, more than two thirds of employees in Germany recently considered changing their job, highlighting how overlooked but potentially consequential the availability of occupational exit options are for economic and political preferences.[1] This contrasts with job loss risk—according to the latest available wave of the German Socioeconomic Panel, around 75% of respondents perceived that their probability to be dismissed in the next two years was zero, while less than 5% stated that it was 50% or higher.

The focus on labor demand is so widespread across the labor force that it can help to better explain the formation of broad anti-immigration coalitions, including the mobilizing power of immigrant-skeptic narratives among highly educated workers typically associated with more progressive values. While prior work emphasizes that education reduces cultural concerns about immigration (e.g., Cavaille and Marshall, 2019), we show that this relationship depends on labor demand within workers' occupations. This suggests that some highly educated individuals' liberal values are more conditional than often assumed, following a "food comes first, then morals" logic, consistent with evidence that economic shocks shape attitudes beyond the most economically vulnerable (Hopkins et al., 2024; Serrano-Serrat, 2026).

Third, we advance the study of the economic determinants of political preferences by leveraging novel data and an empirical strategy that measures labor demand at a granular level. This approach enables us to examine the micro-foundations of individuals' political attitudes, which are often obscured in more aggregate analyses of local shocks. By tracking the specific occupations for which firms post vacancies in a given region, we capture firm-level behavior as a central driver of labor market conditions and, in turn, politically relevant immigration preferences. In doing so, we also highlight the role of firms as key actors in shaping political attitudes, contributing to a small but growing body of research in political economy and political behavior that places the structure and behavior of firms at the center of their analyses (see, for example, Ansell and Gingrich, 2021; Andersson and Dehdari, 2021; Giannoni, 2025).

Finally, disentangling labor supply and demand sharpens our understanding of anti-immigrant

[1] https://www.thestepstonegroup.com/english/newsroom/press-releases/willingness-to-change-jobs-reaches-new-high-development-opportunities-and-purpose-become-top-priorities/ (06/08/2026).

views and their policy implications. Sentiments driven by perceptions of labor market prospects (labor demand) differ fundamentally from those rooted in direct job competition (immigrant labor supply), implying distinct policy responses. Our findings point to two implications that diverge from those that would follow from accounts centered on labor supply. First, place-based policies or incentives that stimulate regional labor demand in specific occupations can weaken the appeal of anti-immigrant narratives. Second, immigration systems that prioritize the targeted admissions of immigrants with occupational profiles that are high in demand can foster public acceptance of newcomers (Kawakami et al., 2025) while avoiding substantial political backlash, even at high levels of immigration and irrespective of the immigrants' skill levels.

Theoretical Considerations and Expectations

There is a long tradition of studies assessing the economic drivers of anti-immigrant sentiment in public opinion. In this section we review two prominent strands of research dominating the debate in recent times, namely labor market competition caused by immigrant labor supply and the sociotropic effects of local-level economic shocks. We then provide a demand-side perspective on anti-immigration sentiments and articulate our basic expectation and how they advance the debate.

Supply-side perspectives and local economic shocks

Labor market competition has been a longstanding perspective on public attitudes toward migrants (Pecoraro and Ruedin, 2020a). The canonical *factor-proportions* model theorizes that, in closed economies, an inflow of foreign workers of a given skill level increases labor supply and therefore decreases wages (Scheve and Slaughter, 2001). This model was famously discredited by Hainmueller and Hiscox (2010), who showed that high-skilled immigrants are always preferred over low-skilled immigrants for reasons that have less to do with economic competition and more with cultural predispositions proxied by educational attainment. Although other influential studies have subsequently found significant labor market competition effects in specific occupational environments (Malhotra et al., 2013) or in sectors undergoing economic contractions (Dancygier and Donnelly, 2013), the broader conclusion drawn was that hostility toward economic migrants competing for similar jobs or at similar skill levels as domestic workers is not a particularly prevalent source of anti-immigrant sentiments (Malhotra et al., 2013), and that the role of material self-interest is limited (Hainmueller and Hopkins, 2014).

The more recent debate has rather been dominated by a second strand of research showing that local economic performance is closely linked to various types of political attitudes and behavior (Carreras et al., 2019; Broz et al., 2021; Vasilopoulou and Talving, 2023; Arzheimer et al., 2024). A number of regional economic dynamics have been analyzed, including long-term processes of decline (Carreras et al., 2019), import competition in global economies (Colantone and Stanig, 2018a; Choi et al., 2024), automation (Anelli et al., 2021; Baccini and Weymouth, 2021), or fiscal adjustments and social services erosion (Fetzer, 2019; Cremaschi et al., 2024; Dal Bo' et al., 2023). In all, there is substantial causal evidence that deteriorating local economies drive anti-immigrant and/or populist success.

The joint consensus emerging from this research is that sociotropic concerns are behind the rise of hostility toward economic migrants. Yet, other strands of research have pointed to the importance of egotropic considerations. These studies have shown that different labor market features like occupation-specific human capital, long-term incentives to improve wage conditions, and communication-intensive tasks can insulate natives from external competition (Ortega and Polavieja, 2012; Polavieja, 2016). Workers with highly transferable skills across occupations have also been hypothesized to be less anxious about immigrant competition (Pardos-Prado and Xena, 2019; Serrano-Serrat, 2026). Similarly, occupational immobility (understood as the costs to switch jobs in a given industry or geographical location) has been shown to increase anti-globalization sentiments in contexts of high exposure to import competition (Bisbee and Rosendorff, 2025).

A demand-side perspective on anti-immigration sentiment

The advances made by previous research strands are indisputable. However, they obscure firms' labor demand as an important driver of individual-level perceptions of labor market prospects and competitive threats from foreign workers. The research strands summarized above either assume labor demand to be fixed when focusing on immigrant types and inflows (i.e. supply-side dynamics) or treat regions as relatively homogeneous aggregate units. This masks important individual-level variation in the responses to immigrant worker supply or local economic shocks that stem from diverging patterns of occupation-specific labor demand, which remains under-theorized or empirically entangled in existing accounts.

While immigrants employed in high-demand occupations have been found to enjoy greater public acceptance (Kawakami et al., 2025), the extent to which occupational demand alleviates perceptions of economic risk and reduces anxieties about immigration among native workers has not yet been systematically examined. Where the role of labor demand in shaping anti-immigrant sentiments has been recognized more explicitly, it has remained empirically confounded by supply-side dynamics. For example, the study of perceptions of prospective risk and their role in shaping anti-immigrant attitudes (Pardos-Prado and Xena, 2019) focused on occupation-specific unemployment rates that measure the share of individuals actively seeking work but unable to find employment, which is the outcome of an interplay between both, demand and supply. Importantly, unemployment and vacancies capture distinct labor market dynamics and need not move together. For instance, while technological change has been shown to drive the decline of routine occupations, this decline is not explained by increased unemployment, but rather by occupational switches, coupled with reduced labor market demand (Kurer and Gallego, 2019; Gallego and Kurer, 2022).

Our approach instead centers on a demand-side perspective by analyzing job openings—that is, vacant positions employers are actively attempting to fill. Understanding labor demand as employers' need for workers within specific occupations and regions, high labor demand signals favorable employment opportunities, long-term economic prospects, and insurance from potential economic shocks. More specifically, we argue that the relationship between labor market demand and attitudes toward immigration can operate through instrumental concerns about labor market competition. When employment opportunities are scarce, immigrant workers are more likely to be perceived as direct competitors, potentially worsening perceived risks of wage suppression or job loss. This suggests a prospective theoretical mechanism grounded in future income-maximization and insurance-based motives. When job opportunities within one's occupation are abundant, individuals are likely to anticipate favorable wages and perceive greater exit options in the event of unemployment. This interpretation aligns with a well-established literature emphasizing risk and insurance as key determinants of policy preferences and political behavior (Iversen and Soskice, 2001; Rehm, 2009). The implication of this argument is that, holding immigrant labor supply constant, individuals' access to exit options in the labor market affects their attitudes towards immigration:

H1: *Higher levels of labor market demand within a given occupation reduce anti-immigration concerns.*

While the proposed argument establishes a general relationship between labor market demand and anti-immigration concerns, our theoretical framework implies that the strength of this effect likely varies across contexts. First, the proposed effect of labor market demand on anti-immigrant attitudes assumes an egocentric and prospective utilitarian mechanism. This means that if vacancies signal future economic returns and security, not all vacancies are equally consequential. As research has extensively shown, both employment status and contract type are critical in explaining political preferences and behavior (Rueda, 2005, 2007). Insiders with long-term contracts face relatively low probabilities of job loss, while outsiders with fixed-term or non-standard contracts are much more exposed to economic risks. Following this line of research, we argue that job vacancies matter most when the occupational labor market provides stable, long-term, and high-quality employment rather than temporary or precarious contracts. This is because more stable job postings provide more credible signals of long-term labor market stability. This leads to our second hypothesis:

H2: *Higher levels of labor market demand within a given occupation reduce anti-immigration concerns, particularly when the share of permanent, long-term contracts is high.*

Moreover, we expect the relationship between labor demand and anti-immigration attitudes to depend on levels of immigrant concentration in specific occupations. Our theory posits that weak labor demand triggers fears of labor market competition with immigrants, while high labor demand alleviates them. However, the salience and credibility of immigrants as a competitive threat depends critically on whether they are seen as plausible competitors. In occupations with very few migrants or none at all, the connection between labor market dynamics and prospective immigration threats will be less likely. We claim that when immigrants constitute a substantial share of an occupation's workforce, weak labor demand makes the threat of displacement and competition with immigrants more tangible and immediate. This implies that the positive effects of labor demand are especially pronounced in contexts with high levels of immigrant worker supply:

H3: *Higher levels of labor market demand within a given occupation reduce anti-immigration concerns, particularly when immigrant worker supply is high (i.e., when prospective competition with migrants is more plausible).*

Data and Empirical Strategy

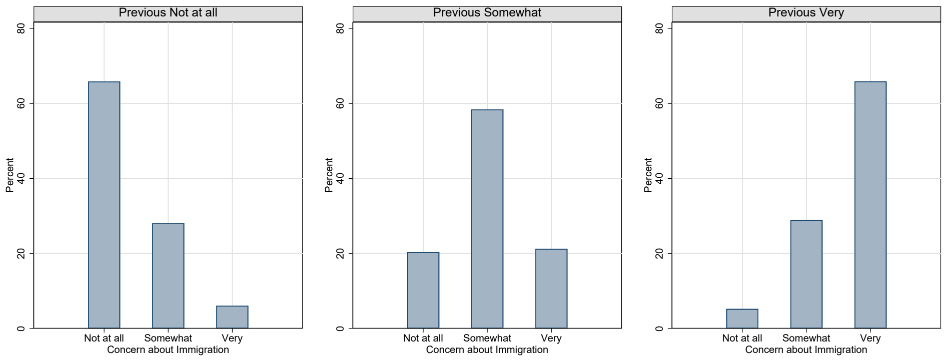
In this section we introduce our main variables of interest and empirical strategy. We begin by describing the main set of dependent variables, as well as how we operationalize job vacancies. We then discuss the empirical specification and how we circumvent the main threats to causal identification. Control variables are discussed in Appendix A.1.2.

Data sources and variables

Concerns over immigration (main dependent variable). We measure individual concerns over immigration using data from the German Socio-Economic Panel (GSOEP). Each year, respondents are asked: "How concerned are you about immigration to Germany?" with three possible answers: "Very concerned," "Somewhat concerned," or "Not at all concerned." We code responses as 0 if individuals report that they are not concerned and as 1 if they express immigration concerns. Since the same individuals are interviewed repeatedly, we can track within-individual changes in immigration concerns.

One potential problem in this setting would be that individuals' immigration preferences are largely stable over time (Kustov et al., 2021; Lancaster, 2022). Figure 1 explores this possibility displaying the distribution of immigration concerns broken down by their response in the previous year. The figure shows that only about 60% of respondents maintain the same level of concern from one year to the next, with the rest gradually shifting between categories. In addition, Appendix A.1.3 documents significant changes in the average level of immigration concerns over the years, with a clear peak during the so-called "refugee crisis" of 2015–2016. While this dependent variable could also capture variation in the public saliency of immigration debates, its strong correlation with pure attitudinal items asked in specific waves suggests that it also captures attitudinal dispositions (Cohen and Pardos-Prado, 2025).

Figure 1: How individuals change their concerns over immigration



Job vacancies (explanatory variable). To measure the number of job vacancies, we use job posting data from Lightcast, a company that aggregates information from over 160,000 sources — including job advertisements, government reports, skills databases, and professional profiles. They provide the almost complete universe of online job vacancies, with more than 60 million unique job postings for the period studied.[2] We operationalize this measure as the number of job postings at the ISCO4d–NUTS1–year level spanning 2014 to 2022. When deciding at which level to aggregate the number of job vacancies, there is the classic bias-variance trade-off: using more detailed variation tends to produce less biased results but increases variance because the number of vacancies is smaller. Since our argument is primarily occupational, we aggregate the data at the most detailed occupational level (about 400 occupations), leaving regional variation at the federal level (16 regions).

This measure of vacancies is assigned to respondents based on their GSOEP occupational and regional identifiers, yielding approximately 100,000 individual observations. As the raw distribution of job vacancies is highly skewed, we apply a logarithmic transformation, adding one to avoid losing observations (see Appendix A.1.1 to explore its distribution and evolution

[2]In some instances firms decide to post the same job offer in different platforms. We use unique job postings.

over time). Appendix A.2 shows that the results remain unchanged with or without that transformation.

We have theorized that vacancies are analytically different from other measures commonly used in the literature. Specifically, we claim that they are different from other measures capturing supply-side dynamics like occupational unemployment and immigration rates. To explore this, we use data from the German Federal Agency of Employment, which provides occupational unemployment and immigration rates from administrative data. Lightcast and the Federal Agency use different occupational identifiers. While Lightcast uses ISCO codes, the Federal Agency uses KLDB (a German-specific occupation classification). Since the GSOEP contains both identifiers, we link job vacancy data using ISCO codes, and these other occupational dimensions using KLDB codes.

Figure 2 explores the relationship between our measure of job vacancies with these other variables, showing the results of a least squares binscatter after subtracting individual, year, occupation and year fixed effects (Cattaneo et al., 2024). Dots are 50 equally-sized bins, and the dashed orange lines display the linear relationship between the variables. Occupation unemployment rates are marginally negatively related to our measure of job vacancies ($b = -0.017$), and only explain a small portion of the variation in job vacancies (within $R^2 = 0.001$). On the other hand, occupational immigration rates are positively associated with the measure of vacancies ($b = 0.06$), consistent with the idea that immigrants tend to self-select into sectors with high demand and opportunity. Crucially, however, the amount of variation in vacancies explained by occupational immigration rates is very small (within $R^2 = 0.003$).

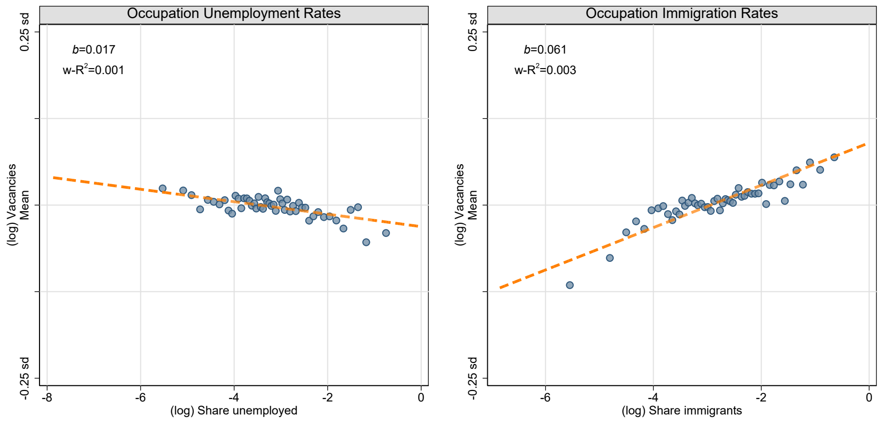
Specification

We explore the relationship between the number of vacancies and immigration concerns by means of the following linear regression model:

$$Y_{i,t} = \beta Vac_{o,r,t} + \delta' X_{i,t} + \gamma' Z_{r,t} + \varphi' W_{o,r,t} + \alpha_i + \lambda_t + \sigma_o + \rho_r + e_{i,t} \tag{1}$$

where $Y_{i,t}$ is immigration concerns of individual i in year t, and $Vac_{o,r,t}$ is the (log) of the

Figure 2: Least Squares Binscatters: Association of Unemployment and Immigration Rates with Job Vacancies



number of vacancies in occupation o in region r and year t.[3] β is the parameter of interest, and it identifies how a 1 percent increase in occupational vacancies changes concerns about immigration.

While we control for unobserved time-invariant factors at the individual (α_i), occupation (σ_o) and region levels (ρ_r), as well as aggregated shocks (λ_t), there are time-varying factors that may confound the relation of interest. To address this concern, we include a set of time-varying controls: $X_{i,t}$ captures individual time-varying characteristics, $Z_{r,t}$ controls for regional conditions that vary over time, and $W_{o,r,t}$ includes variables that vary at the occupation-region-year level. $e_{i,t}$ is the random error. Since we observe the same individuals over time and the treatment varies at the occupation-region level, we allow the error term to be correlated at the individual *and* at the occupation-region level (Abadie et al., 2023; Cameron et al., 2011).[4] We explore different fixed effects (FEs) and cluster structures in the robustness section.

[3]Specifically, o and r are functions that link each individual i in year t to an occupation and region, respectively (that is, $o(i,t), r(i,t)$). Thus, the number of vacancies varies at the occupation-region-year level, where the occupation and the region are a function of the individual and the year.

[4]Clustering standard errors exclusively at the individual level would imply that the error terms of workers employed in the same occupation–region are independent, an assumption that is not realistic. Conversely, clustering only at the level of occupation–region would mean that the error terms for individuals who change either occupation or region are independent. To address both concerns, we use two-way clustering (Cameron et al., 2011).

Variation exploited and threats to identification

Understanding the type of variation exploited in Equation 1 is key to assessing the main threats to identification. In particular, we are leveraging within individual variation in the number of vacancies, controlling for the fact that when individuals change occupation/region the mean levels of vacancies and immigration concerns are different in the new occupation/region. Moreover, year FEs account for aggregate shocks occurring at the national level. This accounts, for example, for the overall increase in the number of vacancies posted online over the years, as well as for the national changes in immigration saliency. Broadly speaking, this implies that we analyze changes in vacancies due to: *i)* individuals changing occupations (occupation movers), *ii)* individuals changing region (region movers), and/or *iii)* variation in the number of vacancies in a given region and occupation.

The main threat to identification when analyzing occupational (or regional) movers is that changing occupations may be correlated with many factors other than the vacancies themselves. First, there may be unobserved time-varying individual factors that explain the change in occupation and immigration concerns (e.g., a person who becomes more risk averse becomes more concerned about immigration and decides to move to a "safer" occupation). Second, people who change occupations may not completely assimilate into their class of destination, and occupation FEs do not fully capture these dynamics (Ares, 2020). Related, changing region may affect immigration concerns for factors unrelated to vacancies (Consiglio and Kurer, 2025; Gallego et al., 2016). To deal with these potential threats to identification, in the robustness section we run models exploiting variation in the number of vacancies that is unrelated to individuals' changing occupations or regions. Moreover, we include a second empirical study that exploits a quasi-random demand shock, alleviating some self-selection and endogeneity concerns.

Furthermore, even though the last source of variation — the number of vacancies in a given occupation and region — is not driven by individuals' actions, there may be other factors that could explain both the number of vacancies and immigration concerns. For example, the number of vacancies in an occupation may reflect broader occupational developments, such as technological change, which could have an effect on immigration concerns beyond that of vacancies itself. In the main specification, we control for a number of regional controls, as well as two dimensions that are usually tested in the literature: occupational unemployment and immigration rates (Pecoraro and Ruedin, 2020b; Pardos-Prado and Xena, 2019). Moreover, to make sure that time-varying factors at the occupation or regional level are not biasing our results, in the robustness section we run a specification with region-year and occupation-year FEs yielding similar results.

Evidence

Job Vacancies and Immigration Concerns

Table 1 presents models testing the association between job vacancies and immigration concerns.[5] Each column sequentially adds different control variables and FEs.[6] In all specifications, higher levels of vacancies are associated with lower concerns over immigration. This supports the main expectation in H1, namely that higher levels of occupational demand reduce anti-immigration concerns. In Column 1, when only introducing two-way fixed effects (TWFE) (i.e., individual and year FEs), a 1 percent increase in the number of vacancies is associated with a decrease in the probability of being concerned about immigration by 0.29 percentage points (pp). The coefficient remains highly stable when introducing individual and regional controls, and drops to -0.39 when adding occupation-region controls, which include occupational unemployment and immigration rates. The most pronounced change in the estimated coefficient occurs when occupation FEs are included, reducing the estimate to -1.28. This indicates that occupations with lower levels of online postings are the ones less concerned about immigration. The coefficient remains fairly constant when introducing region FE. In our preferred and strictest specification, a 1 percent increase in job vacancies decreases the probability of expressing concerns about immigration by 1.19 pp.

To better understand this relationship, we explore the predicted probability of being concerned about immigration as a function of the number of vacancies. We estimate flexible models that do not assume a linear relationship between vacancies and immigration concerns. Specifically, we estimate an OLS specification in which the relationship is approximated by a

[5] See Appendix A.5 for full results for all the tables and figures presented in this section.

[6] We keep the sample from the last specification. The main differences between samples would arise because individual FEs absorb all the variation for individuals who responded in only one round.

Table 1: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
(log) Vacancies	-0.287**	-0.293**	-0.323**	-0.393***	-1.278***	-1.188***
	(0.134)	(0.134)	(0.134)	(0.141)	(0.438)	(0.456)
TWFE	✓	✓	✓	✓	✓	✓
Ind. Controls		✓	✓	✓	✓	✓
Region Controls			✓	✓	✓	✓
Reg.-Occ. Controls				✓	✓	✓
Occupation FE					✓	✓
Region FE						✓
Observations	100649	100649	100649	100649	100649	100649
R^2	0.597	0.597	0.597	0.597	0.600	0.600

Standard errors clustered at the occupation and individual level in parentheses.

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

cubic spline with three knots, and we complement this with the non-parametric least squares binscatter with 20 bins (Cattaneo et al., 2024).[7] Both approaches suggest a monotonic negative relationship between the two variables which is relatively strong: while around 80% of respondents express concerns about immigration at low levels of vacancies, this share declines to about 65% at high levels.

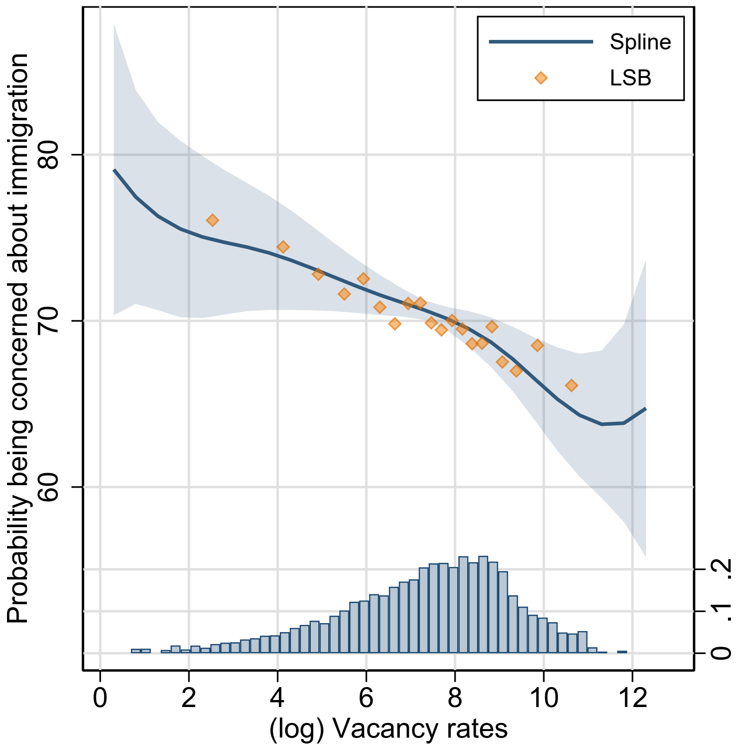
Finally, we turn to analyze the substantive size of the relationship between job vacancies and immigration concerns, comparing it to other variables usually considered in the literature.[8] To do so, we standardize all variables after subtracting the FEs included in the main specification to analyze shifts in explanatory variables that are typical for individuals in the sample (Mummolo and Peterson, 2018). In particular, while results in Table 1 show the effects associated with a 1 percent increase in job vacancies, results in Table 2 show the coefficients associated with a within-FEs standard deviation increase.

This exercise shows that the effect of labor demand captured through job vacancies on immigration concerns are substantial. For instance, they amount to 60% of the size associated with education and regional immigration growth rates, which are considered key factors explaining immigration attitudes. Indeed, a Wald test comparing these coefficients indicates they are not statistically different from each other (with p-values of 0.15 and 0.27, respectively).

[7] In Appendix A.2.1 we show the marginal effect of one unit increase in (log) vacancies at different values of vacancies from the spline specification.

[8] It is worth emphasizing that the aim is not to compare causal magnitudes, but merely to show evidence of the magnitude of different conditional associations (Keele et al., 2020).

Figure 3: Predicted Values: Spline and Least Square Binscatter



Moreover, vacancy effects are twice as large as those of income, albeit the differences between the coefficients is not statistically significant. When analyzing occupation-region variables, we find that occupational unemployment and immigration rates are not associated with immigration concerns, while the quality of job postings reduces concerns about immigration.[9] Overall, this confirms the main expectation in H1 and indicates that, for a given level of immigrant labor supply and unemployment rates, the number of job postings is an important predictor of immigration concerns.

[9]The absence of a relationship between occupational unemployment rates and immigration concerns contrasts with recent findings in the literature. We argue that this discrepancy is due to differences in the level of aggregation and the type of variation exploited, which in turn affects how individuals assess the probability of becoming unemployed. For example, Pardos-Prado and Xena (2019) and Serrano-Serrat (2026) document a negative relationship between occupational unemployment rates and immigration concerns by relying on aggregate occupational business cycle. Similarly, Cohen and Pardos-Prado (2025) find such a relationship using more fine-grained regional variation. Taken together, this evidence suggests that individuals derive unemployment risk in their occupation either from general occupational business cycles or from more localized labor market conditions.

Table 2: Substantive effects: comparison with other factors

	$\hat{\beta}$	95% Confidence Intervals
Panel A: Main Effects		
Vacancies	-0.289***	[-0.507,-0.072]
Panel B: Individual		
Education years	-0.523***	[-0.786,-0.259]
Tenure	0.058	[-0.154,0.269]
Income	-0.184*	[-0.381,0.014]
Panel C: Regional		
Unemployment rates	-0.247**	[-0.489,-0.004]
Immigration growth rates	0.458***	[0.223,0.692]
Panel D: Occupation-Region		
Unemployment rates (occupational)	-0.164	[-0.387,0.059]
Immigration rates (occupational)	-0.149	[-0.390,0.092]
% Temporary vacancies	0.374***	[0.160,0.588]

Note: Coefficients represent the effect of a one standard deviation increase on the probability of being concerned about immigration. 95% confidence intervals computed from standard errors clustered at the individual and region-occupation level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Probing mechanisms

The previous section presented evidence of significant, robust, and large effects of vacancies depressing anti-immigration concern, with magnitudes statistically indistinguishable from important predictors like education levels and regional immigration growth rates. In this section we further explore the nature of the effects found. Since the argument stated that job vacancies improved economic prospects and fear of immigrant competition, we test whether the effects are moderated by the quality of jobs (H2) and immigrant labor supply (H3), respectively.

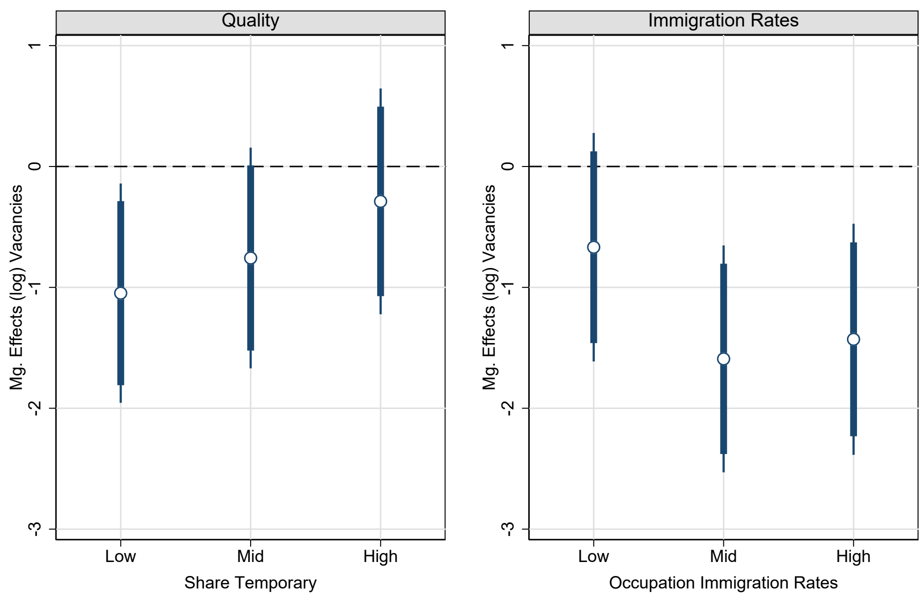
Figure 4 reports the effects of vacancies on anti-immigration concerns depending on the share of temporary contracts (left) and the share of immigrants in that given occupation (right). All occupational conditioning variables used in this section are measured at the occupation-region-year level.[10]

The left panel in Figure 4 tests the expectation that the effect of vacancies is stronger when the prevalence of low-quality jobs within individuals' occupation and region is low (H2). Validating this conditional relationship would support the self-interested mechanism at the core of our argument: labor demand reduces immigration anxieties as long as it meaningfully

[10]The definition of these variables is provided in Appendix A.1.2, and the specification used is discussed in Appendix A.3.1.

signals future economic returns and job security. When the share of temporal jobs is low, greater job vacancies lead to lower immigration concerns, while the relationship is close to zero and not statistically significant when the share of temporal job postings is high. Indeed, the difference between the coefficient at high and low levels of the moderator is significant. This supports H2, in that labor market demand reduces anti-immigration concerns but only when the prevalence of long-term contracts is high. This implies that the attenuation of immigration concerns is conditional on the quality of the exit options workers have access to.

Figure 4: Interaction job vacancies with occupational variables



Note: Figures display marginal effects from models interacting job vacancies with terciles of each moderating occupational dimension. All control variables are also interacted with the moderator (Hainmueller et al., 2019). Models include individual, year, occupation, and region fixed effects. The blue dots and spikes are the point estimates and the associated 90% and 95% confidence intervals computed from clustered standard errors at the individual and region-occupation level. The difference at low and high levels of the moderator is significant at 5% level in both cases.

We further expected that the effect of higher levels of labor demand should be particularly pronounced when the share of immigrants at the occupational level is high (H3). More specifically, the association between labor market fluctuations and perceived competition with migrants is more likely to occur in occupations where migrant competition is plausible, rather than in occupational labor market segments to which migrants have little or no access.

The right panel in Figure 4 provides evidence for this: the effect if job vacancies is especially pronounced when the share of immigrants in the occupation is at middle or high levels.

When the share of immigrants is low, there is no significant relationship between job vacancies and concerns about immigration. At highest levels, a 1 percent increase in job vacancies decreases concerns about immigration by 1.5 pp and the difference in coefficients at high and low immigration rate levels is statistically significant, indicating the presence of interactive effects (Hainmueller et al., 2019). These results support H3—changes in job vacancies are especially relevant when the share of immigrants in the occupation is large. This has important implications. Even if migrants self-select into occupational environments with high vacancy levels, this does not necessarily lead to an increase in anti-immigrant sentiments among the workers in these occupations. Moreover, further assessing contextual drivers of the proposed effects, we show that they hold at distinct levels of occupational unemployment rates (Figure A.11). This indicates that the interactive effects found in Figure 4 are specific about immigrant labor supply and not driven by general labor market slack.

In sum, the heterogeneous effects presented in this section provide evidence supporting an utilitarian and self-interested mechanism. Dynamic labor markets reduce concerns about economic competition with migrants, as long as exit options are good enough to genuinely reduce risks and competition with migrants is plausible. The economic character of this mechanism is further substantiated in Appendix A.4, examining whether labor market demand shapes workers' subjective assessments of their economic situation. Using GSOEP data on different measures of subjective economic evaluations and regressing our main specification, we find that higher levels of vacancies are associated with lower economic concerns, which is consistent with our theoretical framework.

Heterogeneity across educational and skill levels

We next examine heterogeneity in the effects across education and occupational class to assess how broadly our findings extend across the workforce and what they imply for the formation of anti-immigrant coalitions.

First, prior research highlights anti-immigrant attitudes among lower-educated individuals, while the highly educated are typically associated with more liberal cultural values. Yet even this group is not immune to certain economic concerns (see also Pardos-Prado and Xena, 2019). More liberal immigration attitudes among the highly educated may instead be conditional on the availability of valuable exit options in the labor market.

To shed light on this, Figure 5 presents the marginal effects of vacancies conditional on education levels. The results indicate that vacancies suppress anti-immigration concerns especially among highly educated individuals, while they are statistically insignificant among the low and medium educated. These findings may be explained by two factors. First, anti-immigrant views among lower-educated individuals may be more entrenched and thus less responsive to changing labor market conditions. Second, highly educated individuals make substantial upfront investments in human capital, which are tied to expectations of future returns. When these expectations are not realized or become uncertain, concerns about prospective competition from immigrants are more likely to arise even among this group, diluting otherwise more liberal cultural attitudes. The results are unlikely to be driven by a heterogeneous level or increase of job postings across skill levels. Appendix A.1.1 shows that the growth in online job postings is substantial and comparable across most occupational groups and subgroups (ISCO 1- and 2-digit).[11]

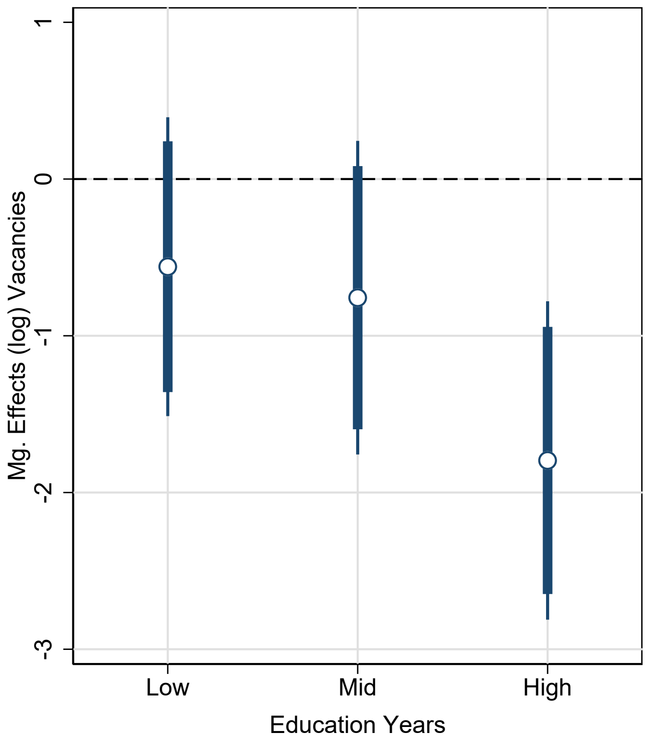
Second, and in addition to education, there may be further nuances in the ways different occupational class groups react to changes in labor demand. We therefore estimate the effect of vacancies for six different Oesch classes (Ares, 2020; Oesch, 2006).[12] Figure 6 plots the marginal effects of the interaction between job vacancies and each occupational class group. The horizontal dashed orange line depicts the average marginal effect estimated in Column 6 of Table 1. In terms of magnitude, the results seem to broadly hold for across occupational classes with the exception of Clerks and Service Workers, which tend to be low-skilled occupations (Oesch, 2006). Indeed, the fact that we find significant effects for Managers and Sociocultural professionals aligns with the above findings on heterogeneous effects by education. Together, they suggest that workers with higher levels of education and skills are "conditionally liberal" in the sense that their more permissive immigration attitudes are contingent on perceived labor market prospects determined by the availability of high-quality exit options.

Appendix A.3.2 provides further support for these findings using alternative measures that

[11] The only noticeable exceptions are 'skilled agricultural' jobs, even of they constitute a small share of the German workforce—job posting growth is flat over time, and the the level of postings is not negligible but moderately low compared to other groups.

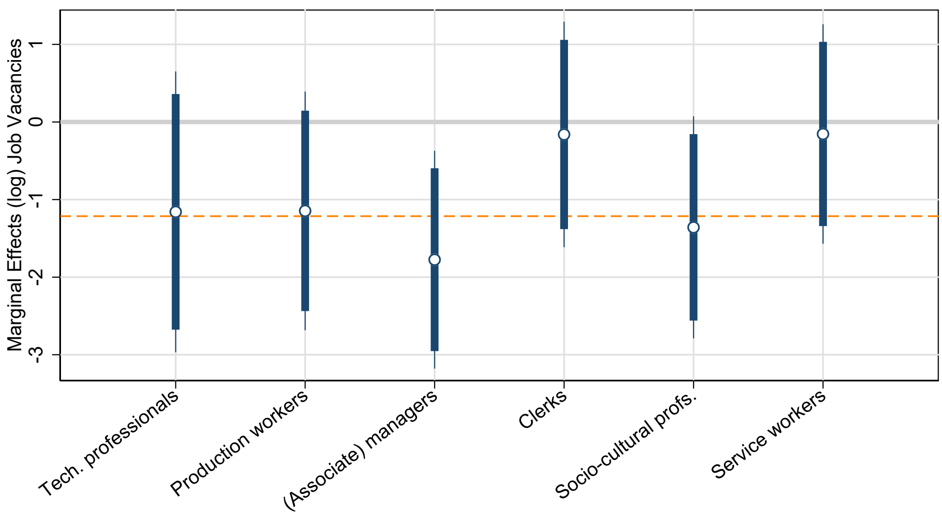
[12] We aggregate Oesch classes based on the 4-digit ISCO information and drop the self-employed. The detailed logic of this classification can be found in Appendix A.1.4.

Figure 5: Heterogeneous effects by levels of education



Note: Education levels correspond to education year terciles.

Figure 6: Heterogeneous effects by Oesch class schema



Note: Coefficients associated with each Oesch class schema, and 90/95% confidence intervals. Orange line states for the average marginal effect estimated in Column 6 of Table 1.

tap into vertical dimensions of social class more specifically. We examine the direct distinction between low and high marketable skills proposed by Oesch (2006). This hierarchical approach captures the competitive advantage that employers assign to employees based on their marketability and productivity (Erikson and Goldthorpe, 1993). Consistent with the above argument, the effects are stronger for highly skilled workers. This stands in contrast to the results we obtain from analyses of horizontal dimensions of social class, which distinguish occupations across interpersonal, organizational, and technical work logics (Ares, 2020; Oesch, 2006). In this case we do not find effect heterogeneity, reinforcing the notion that demand effects are conditional on high vs. low skills but persistent across different types of work logic, and regardless of whether they rely on more communication-intensive or technical skills among others.

Robustness tests and further analyses

The results are robust to a large set of further tests described in Appendix A.2. First, since we are dealing with a binary dependent variable, we run a logit specification with a Mundlak formulation to deal with incidental parameter problem—the bias that arises in non-linear models when estimating individual fixed effects with a limited number of time periods (Mundlak, 1978; Wooldridge, 2010). Since respondents can provide three possible answers (not at all concerned, somewhat concerned, or very concerned), we also run an ordered logit specification using this Mundlak formulation. In all these models, high vacancy rates remain consistent predictors of anti-immigration concerns. Moreover, we show similar results using different dependent variables from the European Social Survey.

The results are also robust to using different operationalizations of the number of vacancies and when creating a measure of vacancy rates (i.e., dividing the number of vacancies by the number of unemployed workers). In all these alternative operationalizations, vacancies consistently behave like in our main models. Furthermore, we construct an indicator variable that captures whether an individual has experienced a sharp increase or decrease in the number of job vacancies, using different thresholds. The results suggest that the effects are driven by increases, not decreases, in job vacancies. We also use a separate database to calculate the number of vacancies. Specifically, we calculate occupational vacancies from the company Textkernel rather than from Lightcast, with job vacancies at the occupational level of the German classification (KldB) instead of ISCO for 2014, 2017, and 2021. This allows us to make sure that our results are not sensitive to different ways of extracting and processing job ads from online platforms, or to different occupational identifiers and levels of aggregation.

We find that the results are robust to clustering the standard errors in different ways and to more demanding specifications, including a broad set of FEs, such as individual-occupation and individual-region FEs, or occupation-year and region-year FEs. Moreover, we provide evidence that unobserved confounders are unlikely to drive the relationship studied (Cinelli and Hazlett, 2020), and that the results hold when including job vacancies at the industry level and industry FEs.

We also perform a placebo test to further validate that we are not finding a spurious relationship between the variables of interest. Specifically, we run a regression that includes not only contemporaneous job vacancies, but also their future values (Elwert and Pfeffer, 2022). We show that while contemporaneous job vacancies are negatively related to immigration concerns, this is not the case for future number of vacancies.

In Appendix A.3.2, we further study if the effects found are unique to any specific period, showing that the coefficients are fairly constant for all years in the sample. This suggests that we are not capturing aggregate national trends of politicization of anti-immigration discourse (Hopkins, 2010).

Case study: Tesla Berlin-Brandenburg Gigafactory

Our main analyses suggest that rising job vacancies reduce individuals' concerns about immigration. However, as mentioned above, it is difficult to establish causality in this setting. To further strengthen our argument, we turn to a specific case that provides a plausible exogenous demand shock: the opening of the Tesla Berlin-Brandenburg Gigafactory within the time span covered by our data. By means of a difference-in-differences (DiD) design we show evidence consistent with our argument. It is important to note that while this evidence provides greater internal validity than the analyses in previous sections, it estimates the average treatment effect on the treated (ATT) rather than the average marginal effects for the entire population.

This section is structured as follows. First, we describe the case study and show descriptive evidence consistent with our claims. We then discuss the main specification used to estimate the causal effects of the Gigafactory opening on concerns about immigration. Finally, we present the main results.

Context

Tesla's Berlin–Brandenburg Gigafactory is the company's first full-scale manufacturing campus in continental Europe. Announced in late 2019, the facility was located in Grünheide (Brandenburg), about a 40-minute drive southeast of central Berlin. It was designed for the production of battery cells and the assembly of Model Y vehicles for the European market. The plant was officially inaugurated in March 2022 and started vehicle production in spring of the same year.

Although the opening was planned for 2022, Tesla advertised and filled a large number of positions in 2020 and 2021. This early recruitment was likely driven by the required time to recruit and provide on-the-job training, as well as to start the pilot production (Welle, 2022). In terms of location, Grünheide was chosen because it offered a mix of logistical connectivity, expansion opportunities, and a pool of skilled labor. The occupational mix ranged from unskilled and semi-skilled production workers to highly specialized battery and process engineers, reflecting the plant's heterogeneity. Appendix A.6.1 shows a description of the share of treated occupations at the ISCO 2-digit level, indicating that highly skilled occupations were more demanded than low-skilled occupations.[13]

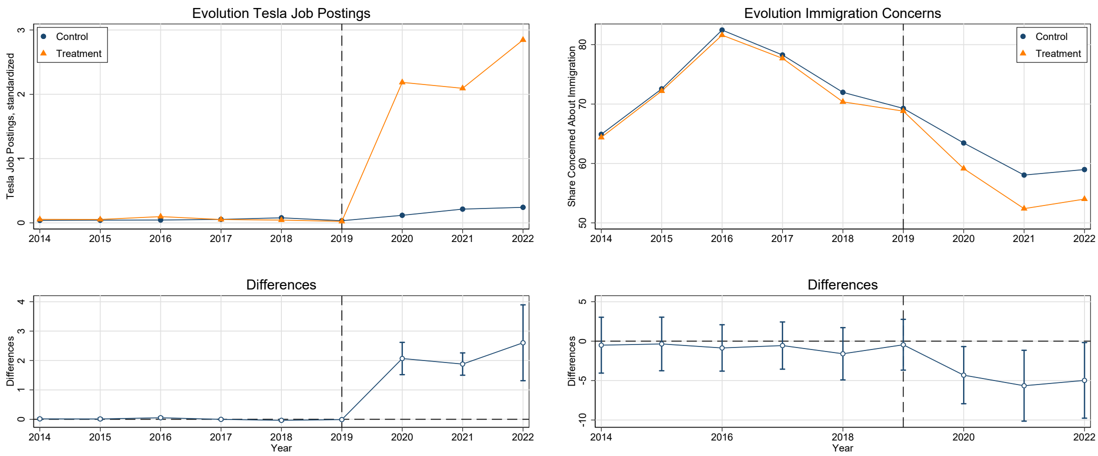
Thus, from the announcement of the plant opening at the end of 2019 to the start of production in 2022, we expect a significant increase in job postings across a wide range of occupations in Berlin and Brandenburg. Fortunately, using the Lightcast database, we can track the job postings advertized specifically by Tesla and actually see if there was an increase in job postings and which occupations were demanded. In the left panel of Figure 7, we can observe the increase in Tesla's job postings from 2020 onwards in Berlin and Brandenburg (blue dots), but not in other regions and occupations (orange triangles). The differences in means, with the 95% confidence intervals are displayed in the bottom panel.

Turning to analyze the expected responses in terms of concerns about immigration, the

[13] In fact, 45% of Professional occupations are treated, for Elementary Occupations this share drops to 26%. Examples of treated occupations include 1211-Human Resource Managers, and 8131-Chemical Products Plant and Machine Operators.

right panel of Figure 7 shows the evolution of the proportion of people showing some degree of concern about immigration. Indeed, not only control and treated individuals followed similar trends before the shock, but also they were similar in levels. This was the case even though this was a period of high volatility of immigration concerns, increasing our confidence that in the absence of the opening, immigration concerns would have follow the same trends (Kahn-Lang and Lang, 2020). In line with our expectations, a divergence can be observed after the opening of the Gigafactory, with immigration concerns declining more for the treated occupations in Berlin and Brandenburg.

Figure 7: Evolution Tesla Job Postings in Treated and Control Regions



Empirical Strategy

To formally explore the causal effect of this shock, we employ a difference-in-differences (DiD) strategy. The logic of this approach is to study how the differences between the treatment and the control group (first difference) changes after the opening of the Gigafactory (second difference). To test this, we estimate the following specification:

$$Imm_{i,t} = \beta Treated_i \times Post_t + \alpha_i + \lambda_t + \sigma_o + \rho_r + e_{i,t} \quad (2)$$

where the coefficient of interest, β, identifies the ATT, measuring the causal impact of the Gigafactory opening on those affected by it.

The main threat to identification is violation of the parallel trends assumption, which states that in the absence of the shock, immigration concerns of the treatment and the control group would have evolved similarly. In this regard, properly defining the treatment groups is crucial for identification. One approach is to classify as treated all individuals who, at any point after the opening, worked in Berlin or Brandenburg in an occupation for which the Gigafactory advertised positions. However, this strategy—using contemporaneous region-occupation to define treatment status—risks including individuals who "moved to opportunity", that is, those who relocated to a treated region-occupation specifically because of the Gigafactory opening. If such endogenous mobility occurred, immigration concerns for movers could have already been evolving differently from the control group prior to treatment. To address this concern, our preferred specification defines treatment status based on individuals' occupation-region *prior* to the shock, exploiting the GSOEP's panel structure. This approach ensures that $Treated_i$ varies only at the individual level and is absorbed by individual fixed effects, eliminating concerns about time-varying selection into treatment.[14]

Moreover, the parallel trend assumption would not hold if Tesla selected Berlin-Brandenburg partly due to skilled labor availability or other characteristics correlated with the evolution of immigration attitudes. For example, if tech-sector workers in the region were becoming more cosmopolitan independent of the Gigafactory, our estimates would conflate pre-existing trends with treatment effects. We perform two exercises to address these concerns. First, we augment Equation 2 to directly control for the possibility that treated region-occupations were already experiencing economic expansion or shifts in immigration attitudes independent of Tesla's opening. Following Hall et al. (2021), we compute deciles of job vacancies and average immigration concerns at the occupation-region level for the pre-treatment period, and interact these deciles with year FE (the specification is discussed in Appendix A.6.2). This approach ensures that we compare treated and control occupations with a similar evolution of labor market conditions and immigration attitudes in the pre-treatment period. Second, we run an event study specification to test whether treated individuals were already experiencing a different

[14] We also estimate specifications using contemporaneous treatment status. Then, the treatment status is defined as $Treated_{o(i,t),r(i,t)} = 1$ if individual i works in a treated occupation-region at time t, and zero otherwise (where $o(i,t)$ and $r(i,t)$ are functions that map individual-year observations into their occupation and region of residence, respectively). In these models, we include a time-varying control for working in a treated occupation-region to account for the fact that treatment status can change. We compare coefficients across these specifications below. Appendix A.6.3 shows the results for non-movers. However, it should be noted that this approach may be problematic as the sample is affected by the treatment (Cinelli et al., 2024).

evolution of immigration concerns compared to control individuals prior to the treatment.

Another potential threat to identification is the violation of the Stable Unit Treatment Value Assumption (SUTVA). The core implication for this study is the no interference condition, which implies that control units are not affected by the treatment.[15] This empirical assumption is of theoretical interest, as it entails how we expect the Gigafactory opening to affect distinct individuals. For instance, SUTVA would be violated if individuals working on untreated occupations in treated regions were affected (as recently found by Finseraas and Nyhus (2025)). For this reason, we consider two control groups. First, we filter all workers in occupation-regions not affected by the opening. Second, we restrict the control group to be all workers in occupations affected by the opening (i.e. occupations demanded by the Tesla opening) but who were in other regions. Moreover, to directly assess whether the plant opening affected untreated individuals in treated regions, we examine whether residing in Berlin-Brandenburg influences immigration attitudes among workers in occupations not targeted by Tesla. Finding no such effect would provide evidence against regional spillovers and support our interpretation that the effects operate through occupation-specific labor demand rather than general regional sentiment.

Main Results

This section presents the results of this exercise. As has been stated above, the main identification assumption underlying our design is that, absent of the treatment, the treatment and control groups would have evolved similarly (i.e., the parallel trends assumption). As a first exercise, Appendix A.6.3 shows that the treated and control groups were not (linearly) diverging before the treatment (Kahn-Lang and Lang, 2020), especially when adding controls and accounting for the possibility that individuals may move to opportunity (Consiglio and Kurer, 2025).

Table 3 presents the main results of this analysis using different specifications. Specifically, we present the results using various definitions of the treatment and the sample considered, both

[15] A second component of SUTVA is treatment consistency, meaning the treatment (the Gigafactory opening) is defined identically for all treated units. We acknowledge that the intensity of the Gigafactory's impact may vary depending on the share of total vacancies posted by Tesla and present results that use variation in treatment intensity.

with and without controls. Column 1 reports estimates considering those individuals as treated who live in Berlin or Brandenburg and work in treated occupations after the treatment—that is, including individuals who move to opportunity. The control group consists of all other individuals. The estimated ATT is -2.3 (p-value$<$0.1), indicating that treated individuals experienced a decrease in concerns about immigration about 2.3 pp, compared to the case of not having been treated. In Column 2, we introduce pre-treatment deciles of immigration concerns and job vacancies interacted with year FE, finding more highly significant effects, with a coefficient of -2.7 (p-value$<$0.05).

Columns 3 and 4 show the results of a similar exercise but defining treated individuals as those who, in the year prior to the Gigafactory opening, worked in treated occupations while residing in Berlin or Brandenburg. Column 3 shows the results without and column 4 with controls. The results are similar to those in the first two columns, suggesting that moving to opportunity was not especially important. In column 5, we restrict the sample to treated occupations, i.e., we compare treated individuals (who lived in Berlin or Brandenburg at *t-1*) and how their concerns about immigration differ after the Gigafactory opened, compared to other individuals who worked in the exact same treated occupations but lived in other regions. When we use this control group, the coefficient decreases, indicating that among treated occupations, being in a treated region after the opening of the Gigafactory led to a decrease in immigration concerns of about 3.4 pp (p-value$<$0.05).

Finally, in Column 6 we explore the possibility that previous results were capturing regional effects rather than vacancies at the occupational level (Finseraas and Nyhus, 2025). Specifically, we analyze whether being in a treated region is associated with lower concerns about immigration for those individuals who did not work in occupations affected by the Gigafactory opening. When analyzing only control occupations, being in a treated region is not significantly related to anti-immigration concerns. This indicates that the effects are driven by direct material considerations, and that for this specific mechanism there are no spillover effects at the regional level. It also highlights that egotropic rather than sociotropic considerations drive the main finding.

So far, we have distinguished between treated and control occupations using a binary classification. However, this approach obscures important variation, as the intensity of the treatment

Table 3: Main Results Difference-in-Differences

	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-2.263*	-2.708**	-2.309*	-2.933**	-3.470**	-0.949
	(1.282)	(1.301)	(1.338)	(1.351)	(1.378)	(1.648)
Treatment	Contemp.	Contemp.	Pre-treat.	Pre-treat.	Pre-treat.	Pre-treat.
Sample	All	All	All	All	Treat.Occ	Control Occ.
Controls × Year FE	No	Yes	No	Yes	Yes	Yes
Observations	113606	111718	112325	111503	69350	42122
R^2	0.593	0.600	0.591	0.595	0.600	0.596

Standard errors clustered at the individual and occupation-region level in parentheses

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

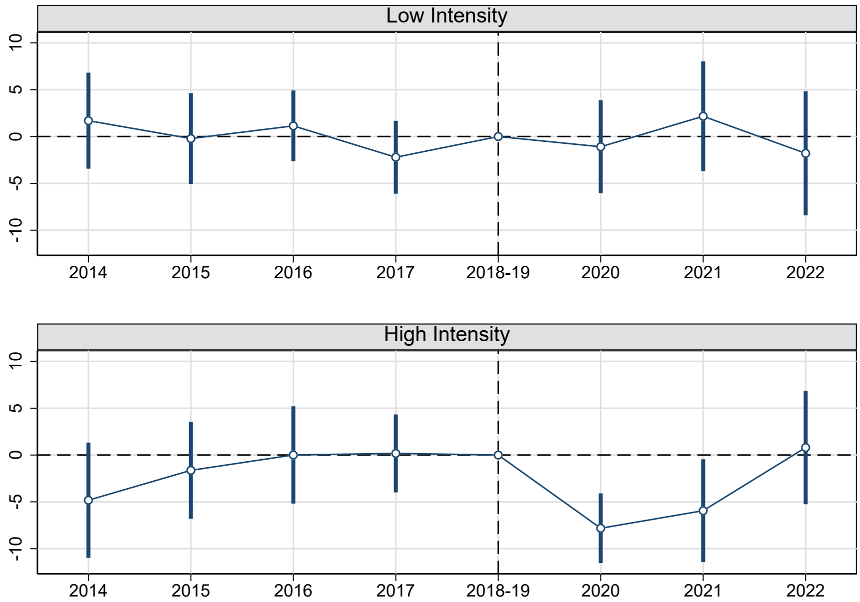
differed substantially across occupations. To capture this heterogeneity, we present dynamic DiD specifications that divide treated occupations into two groups based on treatment intensity. Specifically, we define treatment intensity as the share of Tesla postings relative to total vacancies in each occupation. Figure 8 reports results separately for low-intensity occupations (below-median intensity) and high-intensity occupations (above-median intensity). In these event studies, coefficients for years prior to the reference period serve as placebo tests for the parallel trends assumption.[16] Reassuringly, pre-treatment coefficients are close to zero and jointly not statistically significant at both intensity levels (Wald test p-values > 0.5).

The treatment effect emerges in the year Tesla began hiring. Treated individuals—in particular, those in highly exposed occupations—experienced a meaningful reduction in immigration concerns. Specifically, concerns among individuals in high-intensity occupations declined by approximately 5 pp in the two years following the start of the hiring process.

In Appendix A.6.3 we assess the sensitivity of the findings to different empirical decisions. First, while we document that linear trends may not be particularly problematic in our setting, we assess whether introducing diverging trends between treatment status and a linear trend changes the results (Hassell and Holbein, 2025; Strezhnev, 2024). As is common when introducing these trends, the effects are estimated less precisely but remain significant and, if anything, are larger in magnitude than in our main model. Second, we perform the same

[16]Following Miller (2023), we aggregate years in the reference period to increase precision. This addresses concerns that the absence of pre-trends may reflect insufficient statistical power or reliance on a single reference year.

Figure 8: Event Study



exercise separately for Berlin and Brandenburg, using different control groups for each case, and generally find sizable effects in both cases.

We also check for the possibility that we may be capturing dynamics related to COVID-pandemic. For instance, booming cities, such as Berlin, may fare better compared to other regions when the pandemic started. However, note that this is not very plausible given the evidence shown in the last column in Table 3: for non-treated occupations, being in a treated region is not related to concerns about immigration. To further investigate this possibility, in Appendix A.6.3 we explore the role played by COVID-related industries. Specifically, we show similar results when we: *i)* control for differential post-pandemic trends in COVID-related industries (i.e., pharmaceutical manufacturing, biotechnology R&D, and medical practice activities) or, *ii)* exclude these industries from the sample.

Moreover, we show similar evidence using synthetic DiD estimates (Arkhangelsky et al., 2021). For this analysis, we created a stacked database where the unit of analysis is the region-occupation rather than the individual. We also find negative effects of our treatment on immigration concerns in the two years after the opening.

Finally, in Appendix A.6.4, we show that only highly educated workers are affected by the treatment. This aligns with our earlier findings on effect heterogeneity and further substantiates that workers with higher education levels are more "conditionally liberal" than often assumed.

Discussion and Conclusion

Recent scholarship has largely converged on the view that immigration attitudes are primarily shaped by sociotropic concerns, with egotropic considerations playing a limited role. This conclusion, however, rests on empirical approaches that either focus narrowly on immigrant labor supply or fail to disentangle labor supply- from demand-side dynamics. As a result, a central dimension of individuals' labor market conditions has remained under-theorized and empirically obscured.

This article centers on labor demand and shows that it is a key determinant of immigration attitudes. We set out to argue that occupation-specific labor demand shapes workers' perceived exit options and, in turn, their perceptions of economic risk and competition with immigrant workers. When labor demand is high, credible exit options reduce perceived vulnerability, thereby attenuating anti-immigration sentiments.

Leveraging novel German data on job vacancies and administrative records on immigrant employment, combined with panel survey data, we provide robust evidence that labor demand exerts strong effects on immigration attitudes, with higher levels of occupation-specific labor demand reducing concerns about immigration. Crucially, these effects depend on both the employment stability offered by available jobs and the level of immigrant worker supply. The findings imply that labor demand attenuates perceived competition only when vacancies offer credible high-quality exit options. Moreover, whether immigrant co-worker presence is perceived as threatening depends on whether workers face a dynamic labor market that offers viable alternatives. Our results suggest that in such contexts, even high levels of immigrant presence do not necessarily translate into heightened concerns about competition. This implies that prevalent hiring practices that favor immigrant employment in understaffed occupations or in contexts of expected labor shortages (Mergener and Maier, 2019) do not inherently generate political backlash, even among workers in those very same occupations.

We further establish causality by exploiting a localized labor demand shock generated by the opening of Tesla's Gigafactory in Berlin-Brandenburg. Using granular occupational and regional variation, we show that an increase in labor demand causally reduces anti-immigration concerns, with effects confined to directly affected occupations. The effects are not visible among the very same occupations in other regions not benefiting from the Tesla demand shock, or among other occupations in the same region benefiting from potential spillover effects. This pattern provides strong evidence for egotropic mechanisms and stands in contrast to dominant accounts emphasizing sociotropic channels.

Our analysis of heterogeneous effects further reveals that labor demand is particularly consequential for highly educated and skilled workers. This challenges conventional views that such groups are largely insulated from anti-immigrant sentiment due to their more liberal cultural orientations. Instead, we show that these are not unconditional: support for immigration among the highly educated depends on favorable labor market conditions.

This finding and interpretation aligns with emerging evidence on radical right party support among "apprehensive voters"—–individuals who are materially secure but pessimistic about their future prospects (Häusermann et al., 2023). Our findings reinforce this argument by showing that even individuals typically associated with favorable labor market positions respond to signals about future labor market opportunities with changes in their views on immigration.

The article's findings carry important policy implications. First, concerns about immigration are not driven solely by exposure to immigrant workers but are conditional on the broader labor market context. Policies that generate stable, high-quality employment can mitigate anti-immigrant sentiment by reducing perceived economic vulnerability. Second, immigration systems that align admissions with labor market needs by targeting occupations with high demand can foster public acceptance of newcomers while avoiding substantial political backlash, even at high levels of inflows.

In sum, this article demonstrates that labor demand and firm behavior are a central but previously underexplored determinant of immigration attitudes. By disentangling labor demand from labor supply and tracing its effects on individuals' perceived economic prospects, we show that egotropic concerns play a more important role than commonly assumed. Understanding how economic opportunities shape political attitudes is thus crucial for explaining contemporary patterns of immigration politics and for designing policies that promote both economic prosperity and social cohesion.

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Appendix

A.1 Data

A.1.1 Job Vacancies

Figure A.1 illustrates the logic of taking the logarithm of the number of vacancies. The left panel shows the untransformed distribution of vacancies in the GSOEP sample, while the right panel displays the distribution after the log transformation.

Figure A.1: Histogram Job Vacancies

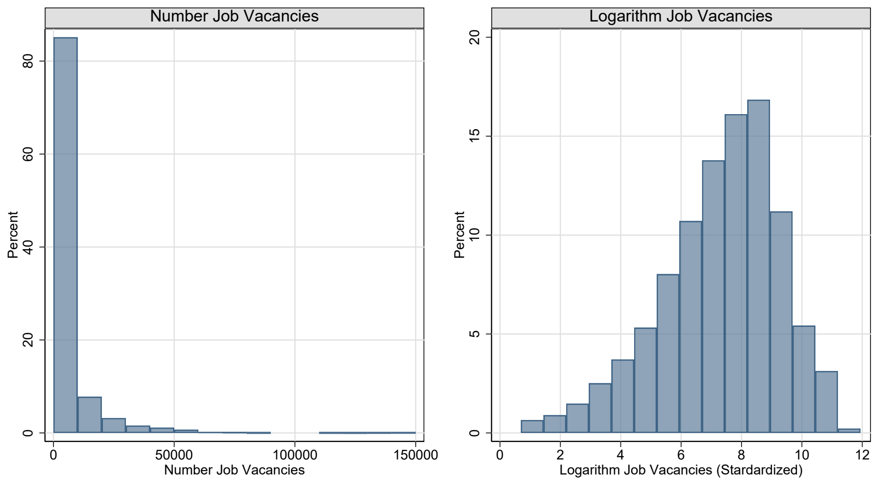


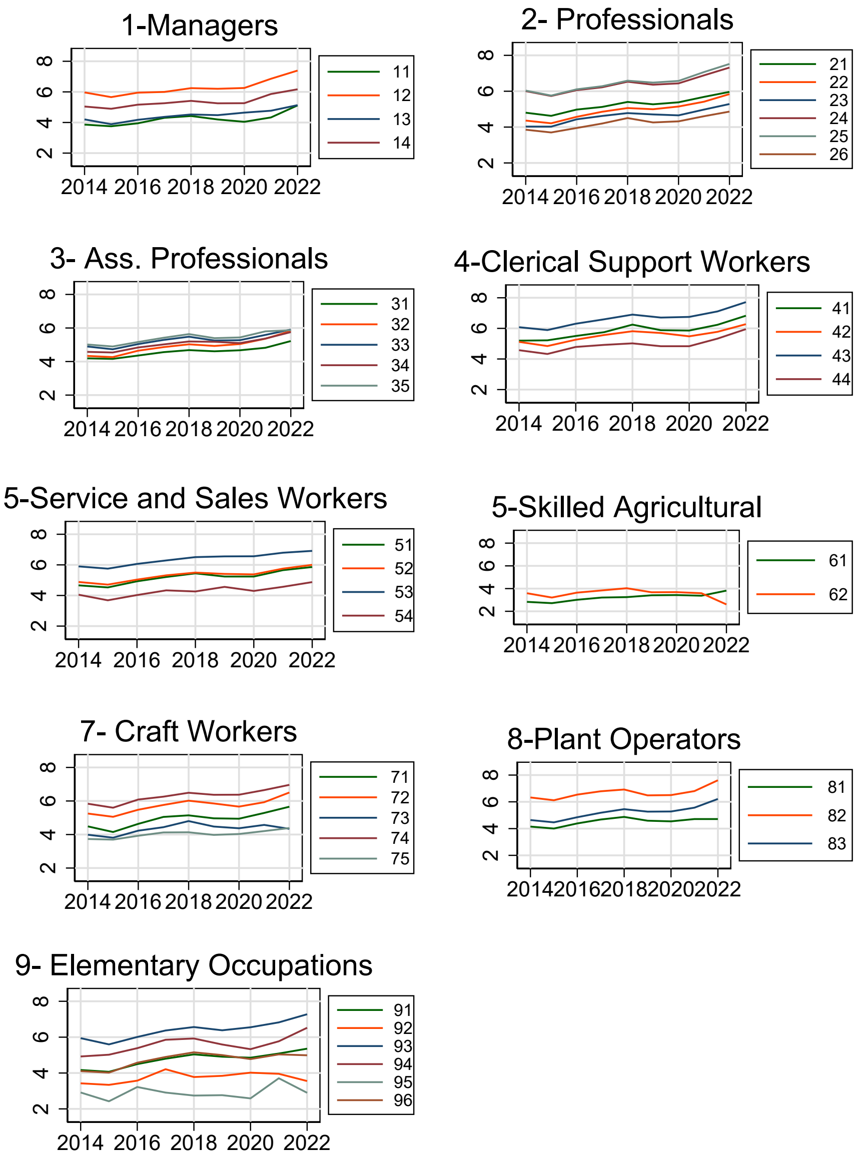
Figure A.2 shows the evolution of our measure of job vacancies over time for different occupations aggregated at the ISCO 2-digits level.

A.1.2 Controls

Individual controls:

- **Education Years.** To capture general skills is the number of years of formal education that the individual has.
- **Firm tenure.** We aim to capture the level fo attachment between the individual and the firm.

Figure A.2: Evolution Job Vacancies



- **Manual Worker (unskilled/skilled).** Even though we control for occupation FE, according to EGP class schema, some occupations might be manual within ISCO 2-digits. We introduce dummies capturing whether the individual enters an occupation that is considered manual. We distinguish between unskilled and skilled manual workers.

- **Age.** It could be that age is associated with occupation and with higher concerns about immigration.

- **Unemployed.** This is a dummy variable that takes the value of one if the individual is unemployed and zero otherwise. This is intended to capture realized risk as an independent channel of risk exposure.

- **Income.** To capture current economic situation of the individual we use the logarithm of the current net labor income.

Regional controls:

- **Regional unemployment rates.**
- **Regional GDP per capita.**
- **Regional change in immigration rates.**

Occupation-region controls:

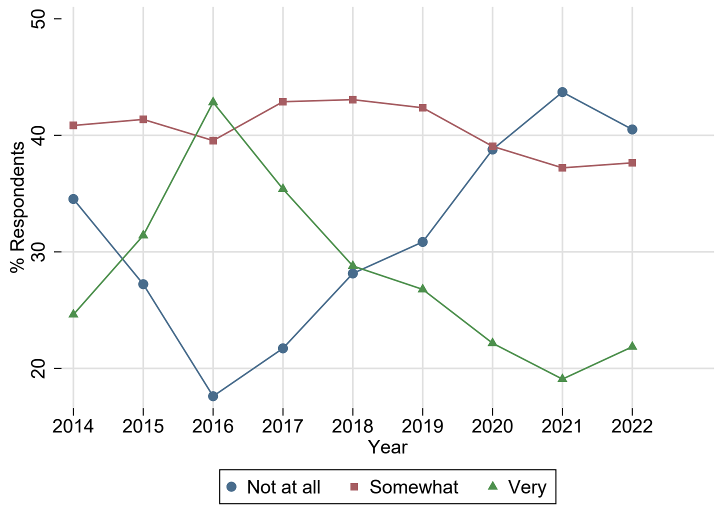
- **Quality Vacancies.** Share of jobs postings that offer temporal contracts in a given occupation-region. It has been obtained from Lightcast. The occupational identifier is ISCO 4-digits.

- **Occupation Size.** Number of workers in the occupation (in logs). Obtained from German Federal Agency of Employment, aggregate numbers at the occupation-region from administrative data. The occupational identifiers is KLDB at 3-digits plus the "niveau" (which is an indicator of the skill level of the occupation).

- **Occupation Unemployment Rates.** share of unemployed workers in the occupation (in logs). Obtained from German Federal Agency of Employment, aggregate numbers at the occupation-region from administrative data. The occupational identifiers is KLDB at 3-digits plus the "niveau". Missing values filled with linear interpolation.

- **Occupation Immigration Rates.** Share of immigrant workers in the occupation (in logs). Obtained from German Federal Agency of Employment, aggregate numbers at the occupation-region from administrative data. The occupational identifiers is KLDB at 3-digits plus the "niveau". Missing values filled with linear interpolation.

Figure A.3: Evolution share respondents with different concerns about immigration



A.1.3 Evolution Immigration Concerns

A.1.4 Oesch class schema

Oesch's original class schema distinguishes 16 occupational categories that allows for a very detailed differentiation of positions based on employment type, skill level and organizational size. While this level of detail is theoretically precise, it presents a practical challenge for empirical analyses: Many categories contained relatively few cases, and broader patterns of social stratification could be obscured by fine-grained distinctions.

To overcome these limitations, Oesch proposed an 8-category version of the schema that groups similar occupations together while retaining the essential structure of social stratification. Specifically, the simplification retains the two main dimensions of class:

- **Vertical dimension (skill level):** This dimensions captures the social standing of occupations in terms of skills and life chances. The 8-category scheme distinguish between high- and low-skill level occupations. High-skilled occupations include Technical Professionals, (Associate) Managers, and Socio-cultural Professionals.

- **Horizontal dimension (employment logic/work content):** This axis captures differences in the nature and organization of work. Distinctions between technical, organizational, and interpersonal are made in the simplified version of the scheme.

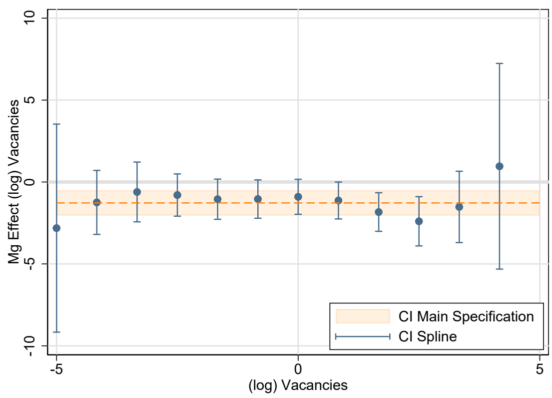
There is a bias-variance trade-off when deciding between the full detailed version with 16 categories or the reduced one. By reducing the number of categories from 16 to 8, the scheme strikes a balance between detail and usability. In this sense, the 8-category version preserves the conceptual integrity of Oesch's classification while improving its practical applicability.

A.2 Further Analyses & Robustness

A.2.1 Marginal effects across vacancies levels

Figure A.4 shows the effects associated with a unit increase in (log) vacancies at different levels of vacancies. These marginal effects are computed from the spline specification of Figure 3. In blue are the results from this exercise, and in orange the results and confidence intervals of a linear specification. Overall the results suggest that the results are relatively constant for all levels of job vacancies, and resemble the linear model.

Figure A.4: Marginal effects of (log) vacancies at distinct values of (log) vacancies

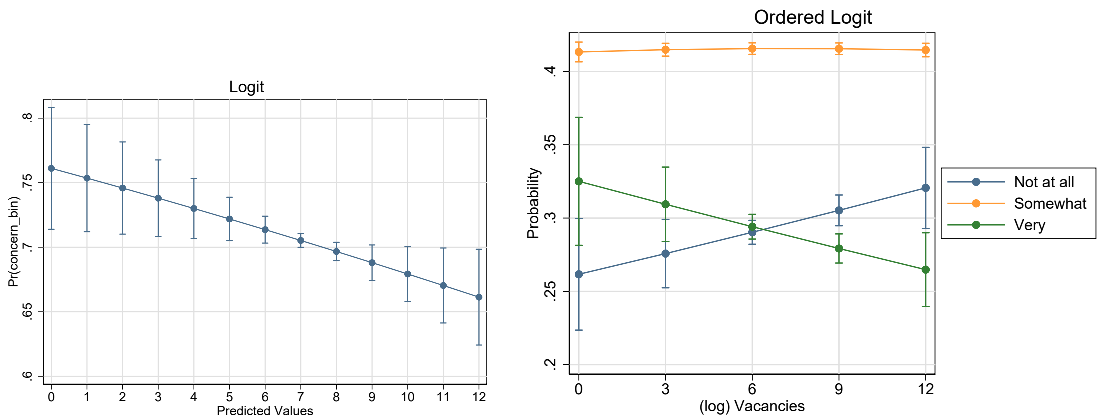


A.2.2 Robustness

Changes in the Dependent Variable.

Non-linear models. Estimating non-linear models, such as a logit or an ordered logit model with unit FEs is problematic due to the incidental problem (when the number of units is large but the number of time periods is small, as in this setting) . In such a models, average marginal effects depend on all covariates, and the model cannot unbiasedly estimate the parameters

Figure A.5: Different Models: Logit and Ordered Logit



Note: Predicted values and associated 90% confidence intervals from clustered standard errors at the individual level.

associated with the FEs (Mundlak, 1978; Wooldridge, 2010). For this reason, we run logit and ordered logit specifications using a Mundlak specification (as defined above). In these instances, two-way clustering standard errors cannot be estimated, thus, they are clustered at the individual level. We obtain similar results to the main analysis when estimating the logit model. For ordered logit, we observe a decrease in those highly concerned and an increase in those not at all concerned. Those somewhat-concerned remain stable.

European Social Survey. We also use data from the European Social Survey which contains different questions that tap into concerns about immigration. Specifically, there is a question about whether the respondent think that immigration is good or bad for ones' country economy (Economy), whether it enriches or harms one's country culture (Culture), whether it makes the country a better place to live (Place). We also create a PCA with the three dimensions. All re-scales from 0 to 100.

These data is a pool cross-section for Germany from the last fifth rounds (from 2014 onwards), and compare between individuals with different levels of vacancies. We use introduce a set of demographic controls (gender, education, income satisfaction, trade union membership, and employment relationshio) as well as ISCO 4-digits, NUTs-1, and year FEs. The coefficient is specially large for economic concerns. The results are also significant for cultural concerns, albeit is smaller in size (p-value<0.1), but not for immigrants making a country a better place to live. The variable of the PCA is also of negative sign and significant (p-value<0.1).

Table A.1: Results with ESS data

	(1) Economy	(2) Culture	(3) Place	(4) PCA
Vacancies	-1.740***	-1.210*	-0.238	-0.997*
	(0.631)	(0.680)	(0.645)	(0.561)
Observations	13807	13849	13802	13665
Observations	13645	13689	13642	13509
R^2	0.153	0.148	0.135	0.168

Standard errors clustered at the occupation-NUTS1 level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Different operationalization of job vacancies. In the main text we have argued that since the number of vacancies was very skewed, we use the logarithmic transformation (with the results displayed in the first column in Table A.2). Figure A.2 shows that the results are robust to different transformations of the variable.

In Column 2 we show the results winsorizing the variable (setting the minimum and maximum values of vacancies at the 5th/95th percentile, respectively), finding a slight decrease in the coefficient. In Column 3 we use the untransformed measure of the number of vacancies, without taking the logarithm, and in Column 4 we transform the variable as a percentile. Finally, in the last two columns we use a measure of vacancy rates, dividing the number of vacancies (measured using ISCO codes) by the number of unemployed (measured using KLDB codes), with and without taking the logarithm.

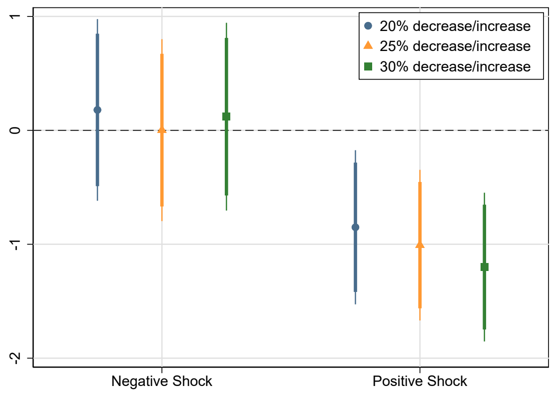
Table A.2: Different Vacancy Measures

	(1) log Vac	(2) Winsord.	(3) Untrans.	(4) Perc.	(5) Vac.Rates	(6) log Vac.Rates
Vacancies	-0.289***	-0.264**	-0.190**	-0.239**	-0.167**	-0.623**
	(0.111)	(0.110)	(0.0958)	(0.113)	(0.0764)	(0.276)
Observations	100649	100649	100649	100649	100275	100275
R^2	0.600	0.600	0.600	0.600	0.600	0.600

Standard errors clustered at the individual and region-occupation level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Moreover, it could be interesting to test whether the effects are symmetric in the direction. For instance, analyzing how income was related to redistribution preferences, Ahrens (2022) shows that while negative shocks on income were not related to redistribution preferences, positive income shocks decreased redistribution preferences. We code an individual as receiving a positive (negative) shock, if the number of vacancies experienced a sufficiently large increase (decrease) in the number of vacancies. Specifically, we use three thresholds: 20, 25 and 30% increase (decrease).[17] In both cases the reference category are those individuals who have experienced neither a positive nor a negative shock. The results are summarized in Figure A.6, in blue, yellow and green for the different intensities. In all cases there is evidence that the effects are driven by increases in job vacancies decreasing concerns about immigration.

Figure A.6: Looking for asymmetries: negative and positive shocks



Vacancy Rates from Textkernel

Rather than Lightcast, we use Textkernel data from election years in 2014, 2017 and 2021 (Consiglio and Kurer, 2025). Importantly, here job postings are classified according to the KLDB occupation classification. Panel A in Table A.3 shows the results using Textkernel data, and Panel B using Lightcast data for the same period studied. Reassuringly, results in Panel A are similar to the main results. Despite that without occupation FE the results are not significant, the size of the coefficients are similar to our main specification. The fact that the results are non-significant is not surprising given that the number of observations is much smaller (25,000 rather than 100,000). Indeed, when using the same sample with Lightcast data, we obtain non-significant results when not introducing occupation FEs.

When adding occupation FE the results become more negative and highly significant, and they remain fairly constant when adding region FE. Indeed, when adding all FEs the coefficient is much larger than than in our main specification. This is in part explained by the sample studied: when studying the same sample with Lightcast data, the coefficient from the main specification increases from 1.18 to 2.63.

[17] It should be taken into account that since we take the differences in job vacancies to create this variable we lose observations, $N = 85,673$.

Table A.3: Results with Textkernel data

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Textkernel						
log Vacancies	-0.224	-0.255	-0.249	-0.439	-3.632***	-4.047***
	(0.352)	(0.358)	(0.371)	(0.511)	(0.953)	(1.041)
Panel B: Lightcast						
(log) Vacancies	-0.0998	-0.211	-0.313	-0.315	-2.890***	-2.626**
	(0.217)	(0.232)	(0.268)	(0.280)	(0.996)	(1.064)
TWFE	✓	✓	✓	✓	✓	✓
Ind. Controls		✓	✓	✓	✓	✓
Region Controls			✓	✓	✓	✓
Reg.-Occ. Controls				✓	✓	✓
Occupation FE					✓	✓
Region FE						✓
Observations	26952	25728	25113	24409	24371	24371
R^2	0.673	0.674	0.676	0.675	0.683	0.683

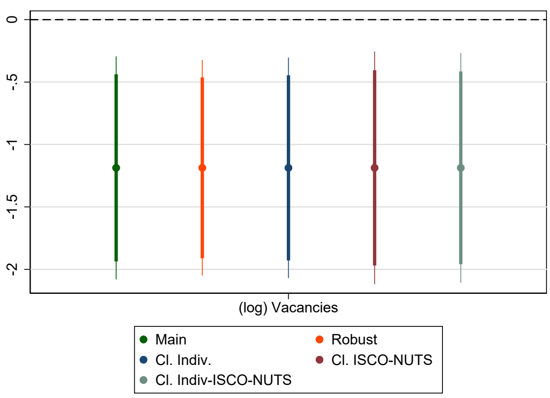
Standard errors in parentheses

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

Different Assumptions about the Error Term

In the main text we show the results allowing the error terms to be correlated within individuals *and* within occupations. Figure A.7 shows that we obtain similar conclusions when employing other assumptions about the error term. Regardless of whether we assume the error term to be independently distributed between individuals, we allow them to be correlated within individuals (but not at the occupation-region), to be correlated within occupation-region (but not at the individual), or to be correlated to individual-occupation-region, the results are almost identical.

Figure A.7: Different Assumptions Error Term

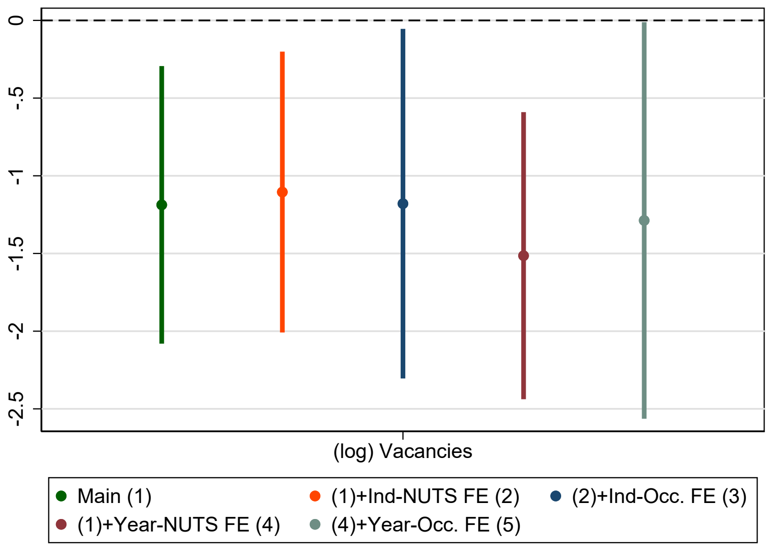


Different Specifications and Fixed Effects

Figure A.8 displays the results with different FE specifications. In green there are the results of the main specification in Column 6 in Table 1, and we subsequently add fixed effects. In orange the are the results when including individual-region FE, thus, exploiting only variation of individual-spells that are in the same region. In blue are the results adding also individual-occupation FE, which implies that we exploit variation that is not driven either by region or occupation movers. The point estimates are very similar to the main specification.

Next, we turn to explore the role played by regional time-varying factors. In maroon are the results of the main specification adding year-nuts FE. This implies that we account for all NUTS1 time-varying factors that may be affecting both vacancies and immigration concerns. This accounts to *all* regional economic factors that may co-evolve with job vacancies and that also explain immigration concerns, such as the China Shock. In light blue are the results adding occupation-year FE, that is, accounting for all occupation time-varying factors. For instance, this captures the fact that the number of job postings may have increased differently for different occupations (Blair and Deming, 2020).

Figure A.8: Different Fixed Effects Specifications



Sensitivity analysis. To further assess how sensitive are the results to omitted variables, we use the approach of Cinelli and Hazlett (2020). This approach assesses how large should be unobserved variables (affecting immigration concerns and job vacancies) to make the proposed effect to be equal to zero. This methodology uses control variables as benchmarks in a way to assess how plausible it is that unobserved confounders (c) are driving the results. In Table A.4 we should what would be the estimated coefficient (and the associated standard errors) in case that the unobserved factors were three time as important as all individual controls, all regional controls, and all occupation-region controls, respectively.[18] Moreover, the table shows what would be the partial R^2 of unobserved confounders and our measure of vacancies, after subtracting all other controls and fixed effects (the $R^2_{c,x}$).

The main takeaway from this analysis is that unobserved factors that were three times as important as the controls used in the main specification, would make our results more *stronger*.

Table A.4: Sensitivity Analysis (Cinelli and Hazlett, 2020)

	$\hat{\beta}$	s.e.	$R^2_{c,x}$
Individual	-1.38	0.566	0.0021
Region	-2.17	0.58	0.05
Occ.-Region	-1.57	0.569	0.01

Industry Vacancies

We also introduce the number of job postings at the industry level, and industry FE. We compute occupations at NACER 2-digits which is the maximum level of detail in Lightcast and SOEP data. We obtain similar results, indicating that the story is occupational, not at the industry level.

Table A.5: Results considering industry variables

	(1)	(2)	(3)
(log) Vacancies	-1.187***	-1.135**	-1.384***
	(0.456)	(0.460)	(0.466)
Vacancies Industry		✓	✓
FE Industry			✓
Observations	100649	99036	99035
R^2	0.600	0.600	0.601

Standard errors clustered at the occupation-NUTS1 in parentheses

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

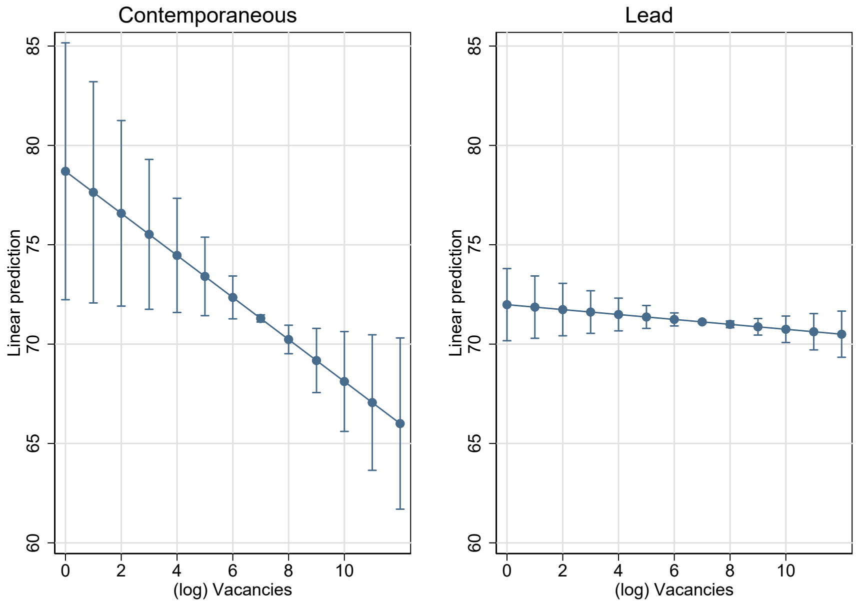
Placebo: lead job vacancies

We perform a placebo test, looking whether *future* job vacancies predict current anti-immigration attitudes when controlling for their current levels. Figure A.9 shows the results.

[18]Standard errors are assumed to be homoscedastik and independent across observations.

The left panel indicates that while contemporaneous job vacancies are clearly related to concerns about immigration (left panel), this is not the case for future job vacancies, rendering support to our specification. The result on contemporaneous vacancies is less precisely estimated than in the main text (p-value$< .1$) as there is a 25% drop in the number of observations. The coefficient is similar in magnitude.

Figure A.9: Results lead vacancies



A.3 Heterogeneity

A.3.1 Specification

In this section we discuss the specification used in the heterogeneity part of the analysis. Since we aim to study how job vacancies are related to immigration concerns at different levels of other moderating variables ($M_{i,t}$), we rely on interactive models. However, simply introducing the interaction between job vacancies and the moderators may be problematic. First, it could be that control variables are differently related to immigration concerns at different levels of the moderator, leading to omitted interaction bias (Blackwell and Olson, 2022). Second, when using continuous moderators, we would be assuming linear interactive effects, an assumption that it is not theoretically grounded (Hainmueller et al., 2019). To avoid these problems we run a specification where the relationship between vacancies and immigration concerns may be different at different terciles of the moderator, and that interacts control variables with moderator's terciles. In particular, we run the following specification:

$$Imm_{i,t} = \sum_{j \in \{L,M,H\}} \beta_j Vac_{o,r,t} \times 1_j(M_{i,t}) + \delta' \dot{X}_{i,t} + \gamma' \dot{Z}_{r,t} + \varphi' \dot{W}_{o,r,t} + \alpha_i + \lambda_t + \sigma_o + \rho_r + e_{i,t} \quad (3)$$

where $1_j(M_{i,t})$ is an indicator function equal to one if the moderator $M_{i,t}$ falls into tercile $j \in \{L, M, H\}$ (low, medium, or high), and zero otherwise. β_j are the parameters of interest and estimate the conditional average marginal effect of job vacancies at each tercile of the moderator. Following Hainmueller et al. (2019) we define interactive effects as the difference between the coefficient at the highest and the lowest tercile (i.e., $\beta_H - \beta_L$). $\dot{X}_{i,t}$ denotes individual control variables interacted with the terciles of the moderator, with analogous interactions defined for regional controls ($\dot{Z}_{r,t}$) and occupation–region controls ($\dot{W}_{o,r,t}$).

For the cases where the moderator is discrete (when studying vertical and horizontal dimensions of occupations), we similarly show the conditional average marginal effect of job vacancies at each level of the moderator, and interact the controls with the moderator.

A.3.2 Further Analyses

Results by year. We interact job vacancies with a dummy for each year, finding that the results are highly stable over time. This suggests that the role of job vacancies does not depend on the nationalization of anti-immigration discourse — see Figure A.3 (Hopkins, 2010).

Heterogeneous effects by levels of occupation unemployment rates. In the main text we have shown that our measure of vacancies diminishes immigration concerns specially when the share of immigrants in the occupation is large. In Figure A.11, we show that this is specific about immigration share, not general unemployment rates. Indeed, there are no interactive effects of job vacancies at distinct occupational unemployment rates levels.

Continuous moderators. While in the main specification we use terciles of the moderators, in Figure A.12 we show the results assuming linear interactive effects. Indeed, the results

Figure A.10: Results by year

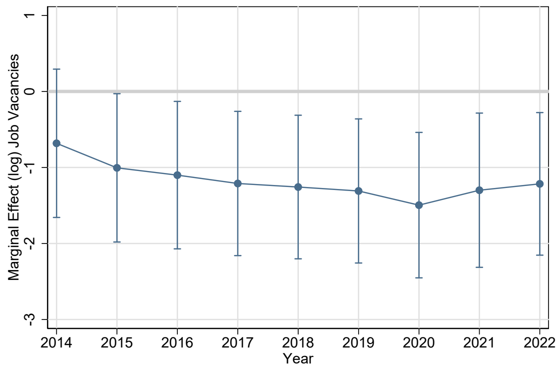
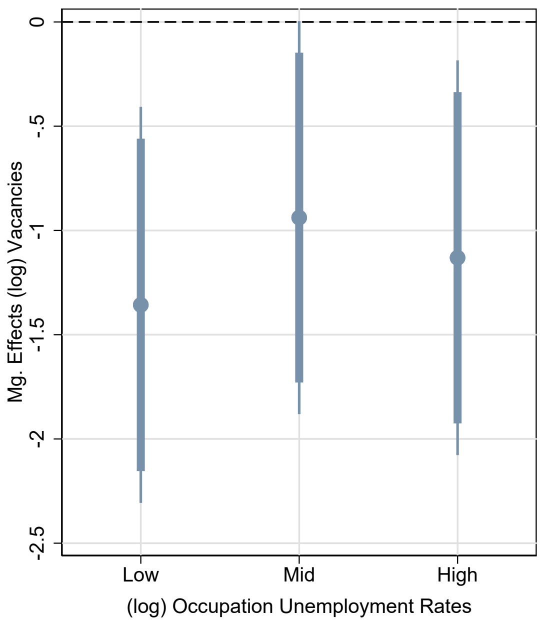


Figure A.11: Heterogeneous by Occupational Unemployment



discussed in the main text are essentially replicated when using a specification with linear moderating effects. Figure A.13 shows the results performing the same exercise for education years.

Other vertical dimensions of class. In this section we explore whether the interactive results hold for other variables that capture the vertical dimensions of social class. Specifically, we distinguish between vertical and horizontal dimensions of social class (Ares, 2020; Oesch, 2006). The left panel in Figure A.14 shows the results by different vertical dimensions of social class. The main takeaway is that the results are driven by individuals with higher occupational

Figure A.12: Heterogeneous effects with continuous moderators

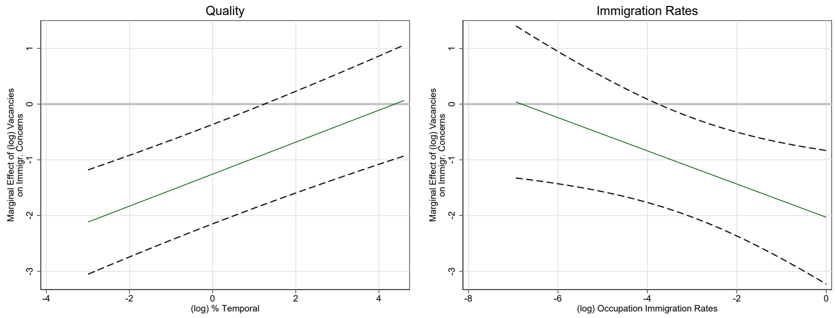
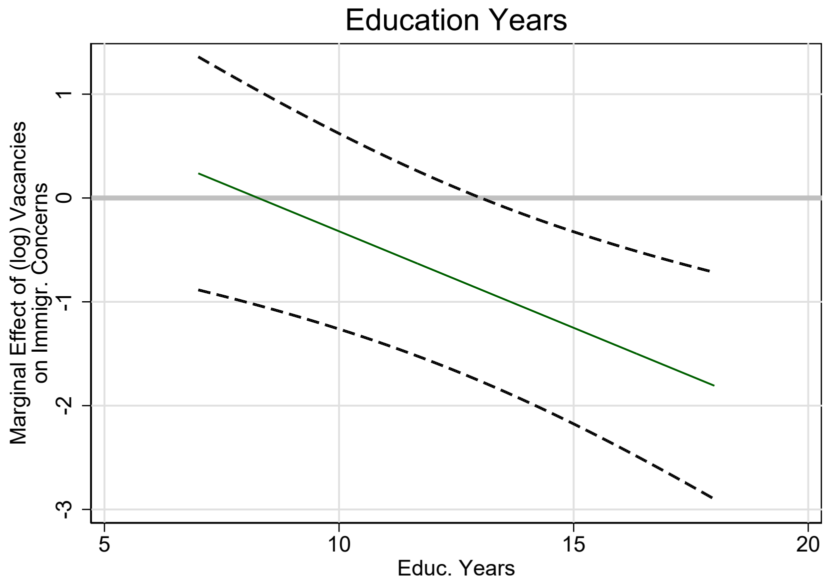


Figure A.13: Heterogeneous effects by other vertical dimensions of skills

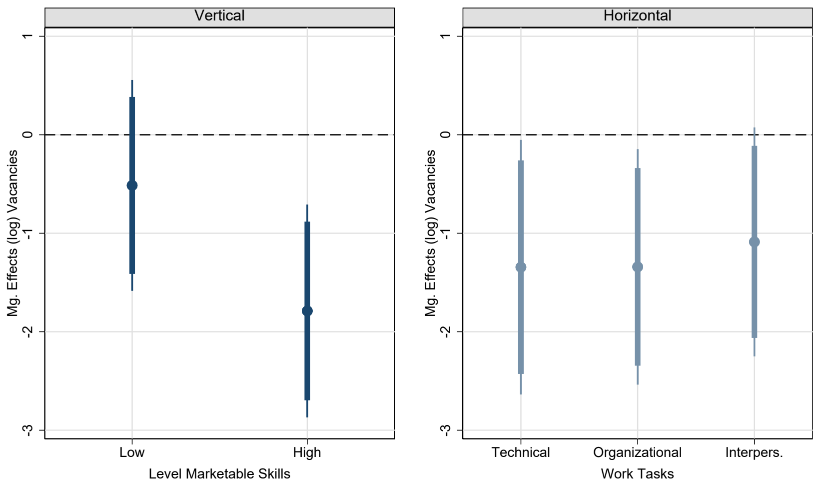


skills. For those working in occupations requiring low levels of skills, the relationship between vacancies and immigration concerns is not statistically significant (with a coefficient of -0.5). For those with high skills, job vacancies are substantially and negatively related to immigration concerns, with an estimated coefficient of -1.75. Indeed, the difference between the coefficients is highly significant.

The right panel in Figure A.14 shows the effect of vacancies across a horizontal dimension distinguishing between types, rather than levels of skills. This horizontal distinction refers to work logics, which are defined by the setting of the work process and whether the orientation is focused on technical, organizational, or interpersonal work among others (Oesch, 2006). Occupational work logics have been suggested to be drivers of political preferences- either by mediating the effect of personality traits pushing people to self-select into certain occupations, or by exogenously creating those preferences (Kitschelt and Rehm, 2014).

Even if relevant to explore as potential drivers of social and political preferences, the theoretical effect of horizontal work logics and vacancy rates on immigration attitudes is ambiguous, and therefore not part of our hypotheses. On the one hand, interpersonal work logics focused on the interaction with people are theoretically associated with more liberal attitudes than more rigid environments focused on the manipulation of objects. The previous rationale behind conditional liberalism would expect that while anti-immigrant predispositions are culturally more entrenched, labor market demand should have a stronger effect among workers operating in interpersonal work logics. On the other hand, however, communication-intensive tasks that are more prevalent in interpersonal work logics have also proven insulate workers from foreign competition (Polavieja, 2016). This would imply a weaker effect of labor demand on anti-immigrant attitudes. The theoretical ambiguity of horizontal work skills is reflected in the right panel of Figure A.14. The results indicate that they play a less prominent moderating role, with job vacancies equally affecting distinct occupations regardless of the type of skills.

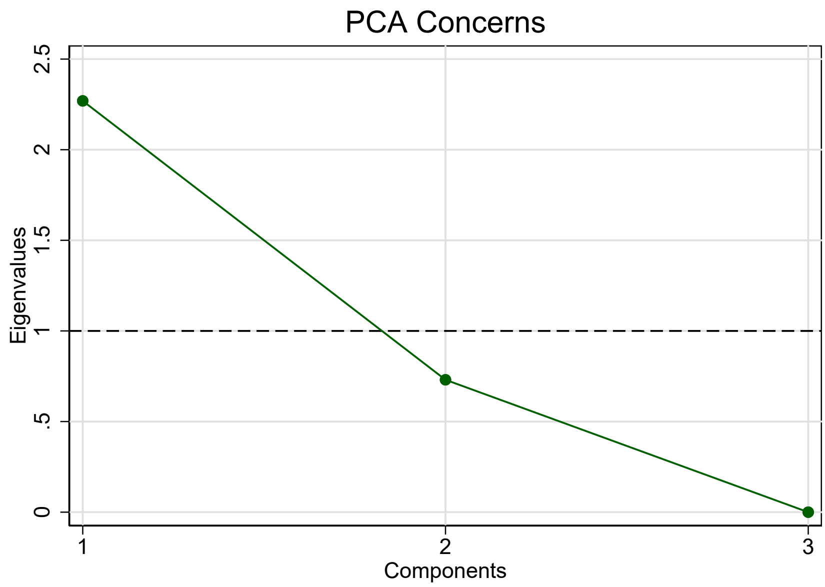
Figure A.14: Heterogeneous by Vertical and Horizontal dimensions of skills



A.4 Further Assessing the Mechanism: Subjective Economic Evaluations

In this section we explore whether job vacancies shape subjective economic evaluations. To do so, we draw on a sets of survey questions capturing economic concerns. Specifically, respondents are asked "How concerned are you about the following issues?". We focus on three dimensions that are most relevant for our analysis: *i)* job security, *ii)* one's own economic situation, and *iii)* the economy in general. Responses are coded as 1 if individuals report being "not worried" and as 0 if they indicate being "somewhat" or "very worried", that is, positive values means being less concerned about the economy. In addition to these specific questions, we also summarize the different latent dimensions captured by these items using principal component analysis (PCA).[19] The Eigenvalues are displayed in Figure A.15.

Figure A.15: Eigenvalues Principal Component Analysis Subjective Economic Evaluations



Our argument states that the number of job vacancies in a given occupation–region provides individuals with relevant information that influences their subjective economic evaluations. However, while the labor economics literature provides extensive evidence on how job vacancies affect economic outcomes (e.g., Modestino et al. (2020)), much less is known about how they relate to individuals' subjective assessments of the economy. This section aims to fill this gap,

[19]The loadings take the following values: job loss: 0.42, own economy: 0.64, and general economy 0.64.

with the results summarized in Table A.6.

The results show that a 1 percent increase in the number of vacancies is associated with a 1.09 percentage point (pp) increase in the probability of being concerned about job loss, and a 1.2 pp increase in the probability of showing concerns about one's own economic situation. There is also a positive association with concerns about the national economy. The combined PCA measure also shows a positive and highly significant relationship. Overall, this means that more job vacancies leads to more optimistic subjective economic evaluations.

Table A.6: Vacancies and Subjective Economic Evaluations

	(1) Job Security	(2) Own Eco.	(3) Agg. Eco.	(4) PCA
(log) Vacancies	-1.086**	-1.203**	-1.158**	-0.0432***
	(0.500)	(0.485)	(0.510)	(0.0152)
Observations	99391	100533	91180	89997
R^2	0.553	0.566	0.601	0.637

Note: Regressions with individual, year, occupation and region FEs, as well as all controls defined in Appendix A.1.2. Standard errors clustered at the individual and occupation-region level in parentheses. * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$

A.5 Tables Results Main Text with Controls

Table A.7: Tables 1 and 2

	(1)	(2)	(3)	(4)	(5)	(6)
(log) Vacancies	-0.287**	-0.293**	-0.323**	-0.393***	-1.278***	-1.188***
	(0.134)	(0.134)	(0.134)	(0.141)	(0.438)	(0.456)
Educ. Years		-2.437***	-2.406***	-2.427***	-2.234***	-2.179***
		(0.562)	(0.562)	(0.563)	(0.559)	(0.560)
Manual Un-skilled		-0.175	-0.219	0.169	-0.0574	-0.0411
		(0.785)	(0.783)	(0.820)	(1.318)	(1.320)
Manual Skilled		0.325	0.289	0.395	0.175	0.183
		(0.909)	(0.908)	(0.912)	(1.203)	(1.205)
Tenure		0.433	0.431	0.445	0.294	0.263
		(0.485)	(0.485)	(0.484)	(0.493)	(0.492)
Unemployed		-0.284	-0.143	-0.0484	-0.140	-0.127
		(1.286)	(1.285)	(1.288)	(1.287)	(1.290)
(log) Income		-0.493**	-0.504**	-0.523**	-0.446*	-0.441*
		(0.242)	(0.241)	(0.242)	(0.242)	(0.242)
Unemp. Rate			-0.422	-0.447	-0.455	-0.614**
			(0.292)	(0.295)	(0.294)	(0.308)
GDP			0.0000829	0.0000820	0.000151	-0.0000945
			(0.000122)	(0.000122)	(0.000122)	(0.000283)
Immigr.			335.6***	335.0***	349.2***	342.1***
			(87.86)	(87.81)	(87.94)	(89.33)
(log) OUR				-0.0930	-0.501	-0.457
				(0.267)	(0.314)	(0.317)
(log) OIR				-0.400	-0.615	-0.629
				(0.402)	(0.496)	(0.518)
(log) Size Occ.				-0.0339	-0.357	-0.402*
				(0.180)	(0.228)	(0.231)
(log) % Temporal				0.432***	0.527***	0.524***
				(0.146)	(0.153)	(0.153)
Constant	72.36***	107.4***	103.7***	103.0***	104.6***	113.3***
	(0.974)	(7.372)	(8.615)	(8.680)	(9.386)	(12.97)
Observations	100649	100649	100649	100649	100649	100649
R^2	0.597	0.597	0.597	0.597	0.600	0.600

Standard errors in parentheses

Note that all coefficients not shown in Table 2 are the same as in Table 1.

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

Table A.8: Figure 3: Spline

(log) Vacancies	-9.256
	(13.97)
(log) Vacancies^2	-2.016
	(3.384)
(log) Vacancies^3	-0.156
	(0.260)
Spline (knot $= -3.82$)	0.199
	(0.330)
Spline (knot $= -1.02$)	-0.124
	(0.144)
Spline (knot $= 1.78$)	0.348
	(0.275)
Educ. Years	-2.173***
	(0.560)
Manual Un-skilled	-0.0482
	(1.318)
Manual Skilled	0.169
	(1.205)
Tenure	0.243
	(0.493)
Unemployed	-0.147
	(1.292)
(log) Income	-0.441*
	(0.242)
Unemp. Rate	-0.541*
	(0.310)
GDP	-0.0000774
	(0.000284)
Immigr.	334.5***
	(89.38)
(log) OUR	-0.446
	(0.317)
(log) OIR	-0.648
	(0.518)
(log) Size Occ.	-0.400*
	(0.231)
(log) % Temporal	0.506***
	(0.155)
Constant	93.13***
	(21.68)
Observations	100649
R^2	0.600

Standard errors in parentheses

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

Table A.9: Figure 4 Left Panel: Interaction Quality Vacancies

Low	-1.048**
	(0.463)
Mid	-0.757
	(0.466)
High	-0.289
	(0.476)
Low	0
	(.)
Mid	-12.17***
	(4.686)
High	-12.28**
	(4.829)
(log) % Temporal	0.0638
	(0.264)
Low × (log) % Temporal	0
	(.)
Mid × (log) % Temporal	1.101*
	(0.619)
High × (log) % Temporal	1.337**
	(0.638)
Low × Educ. Years	0
	(.)
Mid × Educ. Years	0.673***
	(0.131)
High × Educ. Years	0.269**
	(0.130)
Low × Manual Un-skilled	0
	(.)
Mid × Manual Un-skilled	-0.400
	(0.983)
High × Manual Un-skilled	0.987
	(1.225)
Low × Manual Skilled	0
	(.)
Mid × Manual Skilled	0.590
	(1.071)

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High × Manual Skilled	3.011**
	(1.301)
Low × Tenure	0
	(.)
Mid × Tenure	-0.442
	(0.287)
High × Tenure	-0.360
	(0.278)
Low × Unemployed	0
	(.)
Mid × Unemployed	1.831
	(2.219)
High × Unemployed	0.417
	(2.685)
Low × (log) Income	0
	(.)
Mid × (log) Income	0.472
	(0.385)
High × (log) Income	0.868**
	(0.372)
Low × Unemp. Rate	0
	(.)
Mid × Unemp. Rate	0.0510
	(0.295)
High × Unemp. Rate	0.657**
	(0.289)
Low × GDP	0
	(.)
Mid × GDP	-0.0000440
	(0.0000525)
High × GDP	-0.0000736
	(0.0000563)
Low × Immigr.	0
	(.)
Mid × Immigr.	-24.89
	(67.06)

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High × Immigr.	22.64
	(134.2)
Low × (log) OUR	0
	(.)
Mid × (log) OUR	-0.529
	(0.409)
High × (log) OUR	-0.216
	(0.407)
Low × (log) Size Occ.	0
	(.)
Mid × (log) Size Occ.	-0.268
	(0.197)
High × (log) Size Occ.	-0.373*
	(0.203)
Low × (log) OIR	0
	(.)
Mid × (log) OIR	0.0291
	(0.352)
High × (log) OIR	0.227
	(0.382)
Educ. Years	-2.421***
	(0.560)
Manual Un-skilled	-0.112
	(1.481)
Manual Skilled	-1.012
	(1.404)
Tenure	0.498
	(0.509)
Unemployed	-0.828
	(1.861)
(log) Income	-0.865***
	(0.323)
Unemp. Rate	-1.007***
	(0.356)
GDP	-0.000154
	(0.000289)

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Immigr.	308.7***
	(102.5)
(log) OUR	-0.163
	(0.409)
(log) Size Occ.	-0.125
	(0.266)
(log) OIR	-0.744
	(0.576)
Constant	119.5***
	(13.31)
Observations	100649
R^2	0.600

Standard errors in parentheses

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

Table A.10: Figure 4 Right Panel: Interaction Occ. Immigration Rates

Low	-0.668
	(0.482)
Mid	-1.591***
	(0.479)
High	-1.430***
	(0.488)
Low	0
	(.)
Mid	-1.941
	(7.926)
High	-2.323
	(8.392)
(log) OIR	-0.194
	(0.798)
Low × (log) OIR	0
	(.)
Mid × (log) OIR	-1.159
	(1.468)
High × (log) OIR	-0.335
	(1.263)
Low × Educ. Years	0
	(.)
Mid × Educ. Years	-0.223
	(0.209)
High × Educ. Years	-0.113
	(0.269)
Low × Manual Un-skilled	0
	(.)
Mid × Manual Un-skilled	0.777
	(1.977)
High × Manual Un-skilled	1.633
	(1.977)
Low × Manual Skilled	0
	(.)
Mid × Manual Skilled	3.243*
	(1.920)

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High × Manual Skilled	5.002**
	(2.053)
Low × Tenure	0
	(.)
Mid × Tenure	0.725
	(0.470)
High × Tenure	0.968
	(0.598)
Low × Unemployed	0
	(.)
Mid × Unemployed	1.286
	(3.470)
High × Unemployed	5.896*
	(3.073)
Low × (log) Income	0
	(.)
Mid × (log) Income	-0.133
	(0.503)
High × (log) Income	0.243
	(0.556)
Low × Unemp. Rate	0
	(.)
Mid × Unemp. Rate	0.288
	(0.371)
High × Unemp. Rate	-0.282
	(0.453)
Low × GDP	0
	(.)
Mid × GDP	0.000153
	(0.000102)
High × GDP	0.000146
	(0.000118)
Low × Immigr.	0
	(.)
Mid × Immigr.	39.12
	(69.70)

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High × Immigr.	-7.510
	(68.27)
Low × (log) OUR	0
	(.)
Mid × (log) OUR	0.0516
	(0.528)
High × (log) OUR	0.354
	(0.601)
Low × (log) Size Occ.	0
	(.)
Mid × (log) Size Occ.	0.132
	(0.291)
High × (log) Size Occ.	0.321
	(0.359)
Low × (log) Qualification	0
	(.)
Mid × (log) Qualification	0.0955
	(0.150)
High × (log) Qualification	-0.205
	(0.153)
Educ. Years	-2.011***
	(0.568)
Manual Un-skilled	-1.530
	(2.176)
Manual Skilled	-3.011
	(1.852)
Tenure	-0.324
	(0.583)
Unemployed	-3.628
	(2.690)
(log) Income	-0.480
	(0.416)
Unemp. Rate	-0.640*
	(0.367)
GDP	-0.000211
	(0.000297)

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Immigr.	317.7***
	(94.76)
(log) OUR	-0.588
	(0.434)
(log) Size Occ.	-0.545*
	(0.289)
(log) Qualification	0.409***
	(0.129)
Constant	115.0***
	(14.14)
Observations	100649
R^2	0.600

Standard errors in parentheses

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

Table A.11: Figure 5: Interaction Education

Low	-0.559
	(0.486)
Mid	-0.757
	(0.510)
High	-1.796***
	(0.518)
Low × Educ. Years	0
	(.)
Mid × Educ. Years	0.870
	(0.830)
High × Educ. Years	1.598**
	(0.762)
Low × Manual Un-skilled	0
	(.)
Mid × Manual Un-skilled	-4.151**
	(2.016)
High × Manual Un-skilled	-3.951
	(3.735)
Low × Manual Skilled	0
	(.)
Mid × Manual Skilled	-3.712
	(2.468)
High × Manual Skilled	1.840
	(3.610)
Low × Tenure	0
	(.)
Mid × Tenure	-0.933
	(1.216)
High × Tenure	-1.228
	(1.158)
Low × Unemployed	0
	(.)
Mid × Unemployed	2.445
	(4.045)
High × Unemployed	-6.788
	(5.032)

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Low × (log) Income	0
	(.)
Mid × (log) Income	0.289
	(0.677)
High × (log) Income	-0.374
	(0.540)
Low × Unemp. Rate	0
	(.)
Mid × Unemp. Rate	-0.530
	(0.505)
High × Unemp. Rate	-2.328***
	(0.505)
Low × GDP	0
	(.)
Mid × GDP	-0.000133
	(0.000188)
High × GDP	-0.000219
	(0.000187)
Low × Immigr.	0
	(.)
Mid × Immigr.	4.384
	(72.11)
High × Immigr.	-137.0**
	(63.91)
Low × (log) OUR	0
	(.)
Mid × (log) OUR	0.517
	(0.593)
High × (log) OUR	-0.366
	(0.631)
Low × (log) Size Occ.	0
	(.)
Mid × (log) Size Occ.	-0.225
	(0.420)
High × (log) Size Occ.	0.200
	(0.449)

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Low × (log) % Temporal	0
	(.)
Mid × (log) % Temporal	-0.182
	(0.220)
High × (log) % Temporal	0.00302
	(0.202)
Educ. Years	-2.004*
	(1.030)
Manual Un-skilled	0.781
	(1.339)
Manual Skilled	0.645
	(1.287)
Tenure	0.826
	(0.673)
Unemployed	0.0968
	(1.383)
(log) Income	-0.377
	(0.391)
Unemp. Rate	0.308
	(0.392)
GDP	-0.00000695
	(0.000298)
Immigr.	381.7***
	(93.44)
(log) OUR	-0.619*
	(0.372)
(log) Size Occ.	-0.400
	(0.309)
(log) OUR	0
	(2.64e-09)
(log) % Temporal	0.538***
	(0.180)
Constant	100.1***
	(15.34)

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Observations	100649
R^2	0.600

Standard errors in parentheses

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

Table A.12: Figure 6 Right Panel: Interaction Oesch

Technical (semi-)professionals × (log) Vacancies	-1.158
	(0.923)
Production workers × (log) Vacancies	-1.146
	(0.785)
(Associate) managers × (log) Vacancies	-1.775**
	(0.716)
Clerks × (log) Vacancies	-0.161
	(0.741)
Socio-cultural (semi-)professionals × (log) Vacancies	-1.358*
	(0.730)
Service workers × (log) Vacancies	-0.154
	(0.722)
Technical (semi-)professionals × Educ. Years	0
	(.)
Production workers × Educ. Years	-0.243
	(0.621)
(Associate) managers × Educ. Years	0.156
	(0.444)
Clerks × Educ. Years	-0.0881
	(0.482)
Socio-cultural (semi-)professionals × Educ. Years	-0.0942
	(0.545)
Service workers × Educ. Years	0.322
	(0.516)
Technical (semi-)professionals × Manual Un-skilled	0
	(.)
Production workers × Manual Un-skilled	-4.367
	(15.51)
(Associate) managers × Manual Un-skilled	0
	(0.00000895)
Clerks × Manual Un-skilled	-2.665
	(16.50)
Socio-cultural (semi-)professionals × Manual Un-skilled	0
	(0.00000283)
Service workers × Manual Un-skilled	-0.199
	(15.62)

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Technical (semi-)professionals × Manual Skilled	0
	(.)
Production workers × Manual Skilled	-3.378
	(7.594)
(Associate) managers × Manual Skilled	0
	(0.000000480)
Clerks × Manual Skilled	0
	(0.000000181)
Socio-cultural (semi-)professionals × Manual Skilled	0
	(0.00000984)
Service workers × Manual Skilled	-2.578
	(8.015)
Technical (semi-)professionals × Tenure	0
	(.)
Production workers × Tenure	-0.0315
	(0.932)
(Associate) managers × Tenure	-0.941
	(0.866)
Clerks × Tenure	-1.236
	(0.901)
Socio-cultural (semi-)professionals × Tenure	-1.681
	(1.032)
Service workers × Tenure	0.637
	(0.999)
Technical (semi-)professionals × Unemployed	0
	(.)
Production workers × Unemployed	-0.0843
	(8.113)
(Associate) managers × Unemployed	-0.681
	(8.659)
Clerks × Unemployed	-6.648
	(7.896)
Socio-cultural (semi-)professionals × Unemployed	-0.358
	(8.176)
Service workers × Unemployed	-4.831
	(7.146)

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Technical (semi-)professionals × (log) Income	0
	(.)
Production workers × (log) Income	0.350
	(1.012)
(Associate) managers × (log) Income	-0.491
	(0.827)
Clerks × (log) Income	-0.354
	(0.987)
Socio-cultural (semi-)professionals × (log) Income	0.0653
	(0.757)
Service workers × (log) Income	0.0191
	(0.829)
Technical (semi-)professionals × Unemp. Rate	0
	(.)
Production workers × Unemp. Rate	0.438
	(0.713)
(Associate) managers × Unemp. Rate	-0.551
	(0.655)
Clerks × Unemp. Rate	1.160*
	(0.688)
Socio-cultural (semi-)professionals × Unemp. Rate	-0.0581
	(0.678)
Service workers × Unemp. Rate	1.135*
	(0.681)
Technical (semi-)professionals × GDP	0
	(.)
Production workers × GDP	-0.000227
	(0.000172)
(Associate) managers × GDP	-0.000249
	(0.000169)
Clerks × GDP	0.00000135
	(0.000174)
Socio-cultural (semi-)professionals × GDP	0.0000388
	(0.000190)
Service workers × GDP	-0.0000499
	(0.000177)

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Technical (semi-)professionals × Immigr.	0
	(.)
Production workers × Immigr.	104.5
	(102.8)
(Associate) managers × Immigr.	97.65
	(99.90)
Clerks × Immigr.	-149.1
	(101.8)
Socio-cultural (semi-)professionals × Immigr.	31.84
	(95.24)
Service workers × Immigr.	93.29
	(99.31)
Technical (semi-)professionals × (log) OUR	0
	(.)
Production workers × (log) OUR	-1.459
	(1.185)
(Associate) managers × (log) OUR	-1.510
	(1.271)
Clerks × (log) OUR	-0.0263
	(1.113)
Socio-cultural (semi-)professionals × (log) OUR	-1.510
	(1.319)
Service workers × (log) OUR	-0.824
	(1.170)
Technical (semi-)professionals × (log) OIR	0
	(.)
Production workers × (log) OIR	3.202**
	(1.277)
(Associate) managers × (log) OIR	1.553
	(1.322)
Clerks × (log) OIR	1.634
	(1.378)
Socio-cultural (semi-)professionals × (log) OIR	0.294
	(1.458)
Service workers × (log) OIR	0.939
	(1.311)

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Technical (semi-)professionals × (log) Size Occ.	0
	(.)
Production workers × (log) Size Occ.	0.734
	(0.667)
(Associate) managers × (log) Size Occ.	0.956
	(0.649)
Clerks × (log) Size Occ.	1.212*
	(0.687)
Socio-cultural (semi-)professionals × (log) Size Occ.	0.503
	(0.715)
Service workers × (log) Size Occ.	1.318**
	(0.638)
Technical (semi-)professionals × (log) % Temporal	0
	(.)
Production workers × (log) % Temporal	0.574*
	(0.342)
(Associate) managers × (log) % Temporal	0.726**
	(0.332)
Clerks × (log) % Temporal	-0.157
	(0.376)
Socio-cultural (semi-)professionals × (log) % Temporal	0.228
	(0.351)
Service workers × (log) % Temporal	0.102
	(0.346)
Educ. Years	-2.206***
	(0.670)
Manual Un-skilled	3.169
	(15.45)
Manual Skilled	3.516
	(7.512)
Tenure	0.846
	(0.808)
Unemployed	3.550
	(7.032)
(log) Income	-0.377
	(0.664)

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Unemp. Rate	-0.896
	(0.598)
GDP	0.00000658
	(0.000316)
Immigr.	296.2**
	(117.8)
(log) OUR	0.200
	(0.984)
(log) OIR	-1.889*
	(1.100)
(log) Size Occ.	-1.181**
	(0.490)
(log) % Temporal	0.145
	(0.303)
Constant	109.6***
	(13.07)
Observations	100649
R^2	0.600

Standard errors in parentheses

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

A.6 Application: Tesla Berlin-Brandenburg Gigafactory

A.6.1 Description treated occupations

Table A.13: Share treated occupations by ISCO 2-digits groups

Occupation	Share Treated
11.Chief Executives, Senior Officials	0.5
12.Administrative and Commercial Managers	.714
13.Production and Specialized Services	.583
14.Hospitality, Retail and Other	.6
21.Science and Engineering Professionals	.458
22.Health Professionals	.143
23.Teaching Professionals	.167
24.Business and Administration Professionals	.909
25.Information and Communications Tech.	.889
26.Legal, Social and Cultural Professionals	.381
31.Science and Engineering Associate Profs.	.458
32.Health Associate Professionals	.063
33.Business and Administration Assoc.	.292
34.Legal, Social, Cultural Associate Profs.	.364
35.Information and Communications Tech.	.5
41.General and Keyboard Clerks	.25
42.Customer Services Clerks	.4
43.Numerical and Material Recording Clerks	.667
44.Other Clerical Support Workers	.333
51.Personal Services Workers	.353
52.Sales Workers	.462
53.Personal Care Workers	.2
54.Protective Services Workers	.4
61.Market-oriented Skilled Agricultural	0
62.Market-oriented Skilled Forestry,	.333
71.Building and Related Trades Workers	.313
72.Metal, Machinery and Related Trades	.583
73.Handicraft and Printing Workers	.083
74.Electrical and Electronic Trades Workers	.8
75.Food Processing, Woodworking, ...	.158
81.Stationary Plant and Machine Operators	.423
82.Assemblers	.667
83.Drivers and Mobile Plant Operators	.273
91.Cleaners and Helpers	.167
92.Agricultural, Forestry and Fishery	.2
93.Mining, Construction, Manufacturing	.571
94.Food Preparation Assistants	0
95.Street and Related Sales and Services	0.5

A.6.2 Specification with controls

In the main text we show the results expanding the main specification to include controls. The main problem when introducing controls in DiD settings is that the variable may be post-treatment, biasing the results. To avoid this type of problem, we follow Hall et al. (2021) and take deciles of the control variables before the treatment (in our case for the reference years used in the event study), and interact these deciles with year FE.

Specifically, being $Vac^{10}_{o,r,19}$ and $Imm^{10}_{o,r,19}$ the deciles of number of job postings and average immigration concerns of occupation o in region r for individuals working in this region-occupation before the Tesla opening, the specification is the following:

$$Imm_{i,t} = \beta Treated_i \times Post_t + \sum_{j=2014}^{2022} \delta_j^{vac} Vac^{10}_{o,r,19} \times 1\{t = j\} + \sum_{j=2014}^{2022} \delta_j^{vac} Imm^{10}_{o,r,19} \times 1\{t = j\} +$$

$$+\alpha_i + \lambda_t + \sigma_o + \rho_r + e_{i,t} \tag{4}$$

A.6.3 Robustness Checks & Further Analyses: Difference in Differences

Checking for Linear Pre-trends. The main identification assumption of the DiD analysis is that, in the absence of treatment, the treated and control groups would have followed parallel trends. While this cannot be directly tested because it involves counterfactuals, it is common to assess whether the treated and control groups were already on divergent linear trends before the treatment occurred (Kahn-Lang and Lang, 2020). Specifically, for the pre-treatment periods, a model is estimated with immigration concerns as the dependent variable and the interaction between the treated group and linear trends as the main explanatory variable. FEs and controls are included as in the main regression table in the main text (Table 3).

The results of this test are shown in Table A.14. Reassuringly, they suggest that there were no significant linear pre-trend differences between the treated and control groups. Only without controls and with contemporaneous treatment are the differences in trends significant at the 10 percent level. In any case, the direction of the trends goes against finding a negative coefficient, as the treated group was, if anything, becoming more concerned about immigration than the control group.

Controlling for Pre-trends. Besides checking for statistically significant linear pre-

Table A.14: Test for Linear Pre-trends

	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Trend	1.238*	0.556	1.069	0.513	0.421	-0.517
	(0.735)	(0.739)	(0.716)	(0.716)	(0.724)	(0.298)
Treatment	Contemp.	Contemp.	Pre-treat.	Pre-treat.	Pre-treat.	Pre-treat.
Sample	All	All	All	All	Treat.Occ	Control Occ.
Controls × Year FE	No	Yes	No	Yes	Yes	Yes
Observations	82246	80796	82351	80755	49963	30761
R^2	0.601	0.609	0.601	0.608	0.609	0.615

Standard errors clustered at the individual and occupation-region level in parentheses

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

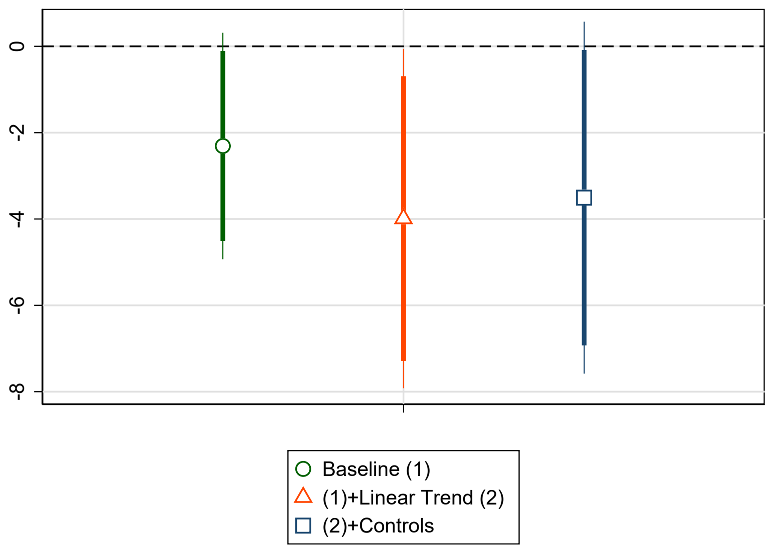
trends, it is usually advisable to directly control for them (Hassell and Holbein, 2025; Kahn-Lang and Lang, 2020; Strezhnev, 2024). However, when there are multiple post-treatment periods, adding the interaction between treatment status and a linear trend may bias the results (see, e.g., Strezhnev (2024)). In this case, rather than simply introducing the interaction between being in the treatment group and a post-period dummy, one needs to introduce the interaction between being in the treatment group and a dummy for each post-treatment period. In our case, this implies estimating the following specification:

$$Imm_{i,t} = \sum_{k=\{20,21,22\}} \beta_k Treated_i \times 1(t=k) + \theta Treated_i \times Year_t + \alpha_i + \lambda_t + \sigma_o + \rho_r + e_{i,t} \quad (5)$$

where $1(t=k)$ takes the value of one when the time period of the observation is equal to k and zero otherwise and $\theta Treated_i \times Year_t$ is the interaction between being in the treatment group and a linear time-trend. β_k are the parameters of interest, and the quantity of interest to be estimated is the average of these three coefficients (Strezhnev, 2024).

The results of this exercise are shown in Figure A.16. The green dot represents the baseline result without controls (column 3 in Table 3), the orange triangle indicates the specification that adds the linear trend interacted with treatment group status, and the blue square represents the specification that also includes controls interacted with the fixed effects. As is common when adding such controls, statistical power decreases, as indicated by the larger 95% confidence intervals. Reassuringly, the coefficients remain significant at least at the 0.1 level, and the point estimates are somewhat larger.

Figure A.16: Estimates controlling for linear trends

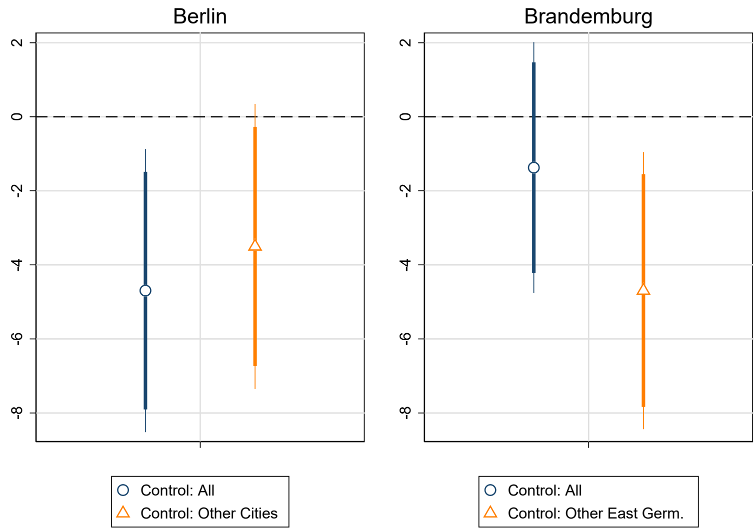


Separating Berlin and Brandenburg. In the main analysis, we have two relatively distinct treated regions: Berlin and Brandenburg. Berlin is the capital of Germany, with a population density of about 4,000 persons per km^2, while Brandenburg is mainly rural, with a population density of about 90 persons per km^2. Moreover, Brandenburg was compared to regions of East Germany, which may be problematic. In Figure A.17, we present the results separately for Berlin (left panel) and Brandenburg (right panel), using different control groups to account for their differences.

The results for Berlin show a large and negative effect of the Gigafactory opening on immigration concerns. The blue dot represents the result using all other region-occupations as the control group, as in the main specification, while the orange triangle represents the result when using other municipalities classified as urban as the control group. In the latter case, the coefficient is substantively large but only significant at the 0.1 level. We conduct a similar analysis for Brandenburg: the blue dot uses all other regions as controls, while the orange triangle uses other regions of East Germany. In this case, significant and substantially large effects of the Gigafactory opening on immigration concerns are observed only when comparing to more similar regions.

Non-movers. In the main DiD specification that we use, we consider as treated those

Figure A.17: Effects by Berlin and Brandenburg



individuals who were working in Berlin or Brandenburg before the opening of the Gigafactory. In this way we were ruling out the possibility of individuals self-select into and out of the treatment. We also show the results using the "contemporaneous" treatment — defined as whether the individual was working in a treated region in a treated occupation in a post-treatment year.

Diversely, in Table A.15 we show the results for non-movers. The results are similar in size to the main specification (with a small reduction between 5 and 7%), albeit a bit less precisely estimate due to the drop in observations (in the main text there are 15% more observations). Moreover, these results should be read with caution as the sample is a function of the treatment, potentially leading to post-treatment bias Cinelli et al. (2024).

COVID. Since the results of the event study suggest that the effects are driven by 2020, a potential concern is that the results are driven by the COVID pandemics. In this section we try to address these concerns.

Specifically, using the NACE 2-digits code we identify the three main industries related with the COVID pandemics: 21 — Manufacture of basic pharmaceutical products and pharmaceutical preparations, 72 - Scientific research and development (which includes "Research and experimental development on biotechnology"), and 86 - Human health activities. In columns 1 to 4 of Table A.16, we show similar results when excluding these industries. In columns 5 and 6

Table A.15: Results Non-Movers

	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	-2.201	-2.627*	-2.201	-2.571*	-2.785*	-0.667
	(1.365)	(1.389)	(1.365)	(1.379)	(1.428)	(1.770)
Treatment	Contemp.	Contemp.	Pre-treat.	Pre-treat.	Pre-treat.	Pre-treat.
Sample	All	All	All	All	Treat.Occ	Control Occ.
Controls × Year FE	No	Yes	No	Yes	Yes	Yes
Observations	98880	97696	98880	98216	61968	36248
R^2	0.603	0.608	0.603	0.607	0.608	0.607

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

we create a treatment variable using as treatment status working in a COVID-related industry (rather than in a industry affected by the Gigafactory opening). Our results remain negative and significant, while the ATT for COVID industries is non-significant, and if anything with the opposite sign.

Table A.16: Results considering COVID-related industries

	(1)	(2)	(3)	(4)	(5)	(6)
ATT Tesla	-2.633**	-3.145**	-2.730**	-3.225**	-2.461*	-2.877**
	(1.284)	(1.320)	(1.376)	(1.381)	(1.344)	(1.348)
ATT Covid					3.244	2.801
					(2.004)	(2.025)
Treatment	Contemp.	Contemp.	Pre-treat.	Pre-treat.	Pre-treat.	Pre-treat.
Sample	No-COVID	No-COVID	No-COVID	No-COVID	All	All
Controls	No	Yes	No	Yes	No	Yes
Observations	99743	99743	65881	65881	112325	69708
R^2	0.592	0.592	0.596	0.596	0.591	0.596

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Columns 1 to 4 drop all individuals working in COVID-related industries.

Continuous treatment. In Table A.17, we present the results using the intensity of the treatment instead of a dummy variable indicating whether the occupation-region is treated. The results are consistent with those in the main text.

Synthetic Difference in Differences. As a last robustness we regress a synthetic DiD model (Arkhangelsky et al., 2021). In this case we create a (balanced) dataset were the unit

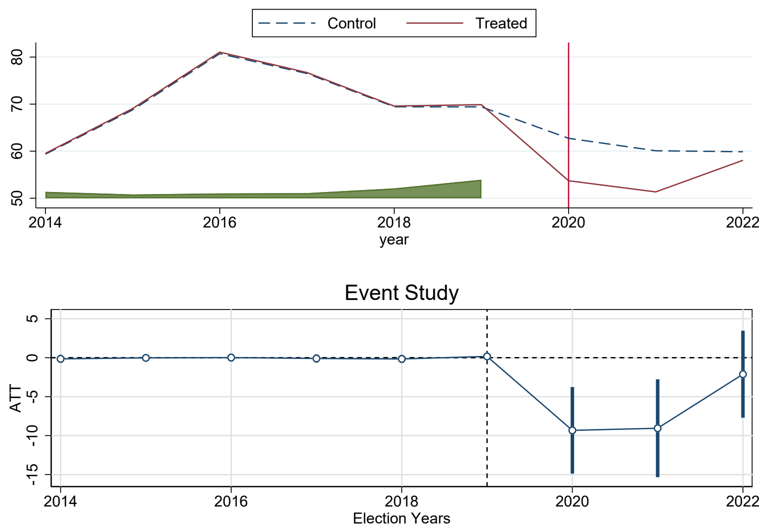
Table A.17: DiD with Continuous Treatment

	(1)	(2)	(3)	(4)	(5)
ATT	-2.401	-3.707**	-1.603*	-1.855**	-1.898**
	(1.637)	(1.667)	(0.861)	(0.841)	(0.897)
Treatment	Contemp.	Contemp.	Pre-treat.	Pre-treat.	Pre-treat.
Sample	All	All	All	All	Treat.Occ
Controls × Year FE	No	Yes	No	Yes	Yes
Observations	113606	109881	112325	111503	69350
R^2	0.593	0.598	0.591	0.595	0.600

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of analysis is the occupation-region.[20] We compute average immigration concerns for each occupation-region, assigning the treatment at the occupation-region level, as in our main analysis. Figure A.18 displays the results of this analysis. The top panel shows the average immigration concerns for treated (red) and the estimated immigration concerns for the synthetic control group. This exercise documents a large decrease in immigration concerns after the Gigafactory started the hiring process. The bottom panel shows the estimates an event study version of the synthetic DiD Ciccia (2024), which quantifies a significant negative effect.

Figure A.18: Synthetic Difference in Differences



[20]Should be noted that this means that small occupation-regions receive the same weight as large ones.

A.6.4 Heterogeneity by education levels

In this section, we examine how the opening of the Gigafactory affects the immigration concerns depending on individuals' education level. The results are displayed in Figure A.19 and show how the Gigafactory had specially an effect on the highly educated, which is consistent with our conditionally liberal hypothesis.

Figure A.19: Heterogeneity by skill levels