Lost in Translation: Artificial Intelligence and the Demand for Foreign Language Skills

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Abstract

Rapid advancements in artificial intelligence (AI) have sparked debate over its employment effects, yet evidence on AI's labor market impacts remains scant. This study investigates the labor market effects of machine translation (MT) on a) employment and wages in the translation profession; and b) the demand for foreign language skills across occupations and industries. Taking advantage of the heterogeneity in the use of MT across 695 local labor markets in the United States, we analyze its effects post-2010, when Google Translate was released as an app. Doing so, we document a negative relationship between Google Translate adoption and translator employment, corroborated by an instrumental variable approach, and a host of placebo regressions. Similarly, improvements in MT reduced the demand for all foreign language skills investigated, including for Spanish, Chinese, Japanese, French, and German.

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I Introduction

Rapid advances in artificial intelligence (AI) have caused much debate over its employment effects in the U.S. and other developed economies (Autor, 2015; Brynjolfsson and McAfee, 2014; Frey, 2019; Mokyr et al., 2015). However, while a number of studies have pointed to the labor displacing effects of industrial robots (Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Chen et al., 2022a), evidence of the labor market impacts of AI remains scant. Indeed, most studies have focused on the *potential* exposure of jobs to AI rather than its actual employment effects (Frey and Osborne, 2017; Brynjolfsson et al., 2018; Felten et al., 2019; Eloundou et al., 2023). A noteworthy exception is Acemoglu et al. (2022), who found no noticeable impact of AI on employment or wages at the occupation or industry level.

In this paper, we zoom in on the labor market impacts of one of the most widespread AI technologies: machine translation (MT). While the U.S. translation industry has experienced some growth over the past decade, increasing from 33.5 billion USD in 2012 to 37 billion USD by 2021 (American Translation Association, 2021), there is much popular concern over the future employment prospects of translators. According to a 2024 survey, more than three-quarters of translators believe that generative AI will negatively impact their future incomes.[1] Meanwhile, others have questioned the continued value of foreign language skills more generally. For example, *The Economist* recently opined that "AI could make it less necessary to learn foreign languages," a sentiment reinforced by OpenAI's recent demonstration of Sky, when it seamlessly translated speech between Italian and English in real-time.

Advancements in machine translation, however, have a longer history. The IBM701, the first MT system, was launched in 1954 through a collaboration between IBM and Georgetown University. Another milestone was the advent of free online translation services in the late 1990s and early 2000s, with tools like Babel Fish in 1997 and Google Translate in 2006. But it was only with the launch of Google Translate as an app on Android and iOS in 2010—when it was also integrated into browsers such as Chrome—that the technology gained widespread use. As documented in Figure 1 , searches for "Google Translate" jumped around this time, while searches for the word

[1] https://www2.societyofauthors.org/2024/04/11/soa-survey-reveals-a-third-of-translators-and-quarter-of-illustrators-losing-work-to-ai/

"Translator" dropped in tandem.

In our empirical analysis, we turn to formally probe the labor market impacts of machine translation software after 2010, focusing on (a) job displacement and wage effects among translators and interpreters; and (b) the demand for foreign language skills across the economy as a whole. To do so, our analysis combines three sources of data. First, we measure the use of MT software across the United States using search engine data from Google Trends to capture the differences in treatments across local labor markets (see Figure 2), which we interchangeably refer to as "cities". Matched with local occupational-level employment data, we explore the impact of tools like Google Translate on employment among translators and interpreters. Third, we construct a city-level dataset of hiring patterns using comprehensive information on U.S. online job vacancy postings and their detailed skill requirements from Lightcast (formerly Burning Glass Technologies), covering the years 2010 through to 2023. This allows us not only to measure the labor demand for translators and interpreters, but also to capture the demand for foreign language skills.

We start by documenting a negative relationship between translator employment and the adoption of Google Translate, controlling for demographic composition and trade patterns to account for migration and changes in foreign commerce that might influence local demand for language skills. To isolate the impact of machine translation from potential confounds—particularly the rise of remote human translation services—we further incorporate controls for online searches related to human translation services. Moreover, we exploit the growth and consolidation of the Google "brand" during the analysed period to construct an instrumental variable. We use the internet searches for "Google Drive", since this app performs a completely different task from MT and is therefore plausibly exogenous to translator employment. Our baseline estimate indicates that a 1 percentage point increase in the use of Google Translate reduced translator employment growth by 0.71 percentage points. A counterfactual scenario suggests that approximately 28,000 fewer translator positions were created as a consequence of machine translation technology relative to the broader growth trajectory of the profession. In contrast, we find that while wage growth slowed following the adoption of Google Translate, it began to recover around 2016, resulting in no statistically significant impact on wages over the full sample period. We note that the initial drop contradicts theories like wage rigidity; it is more likely to be explained by the increasing demand for higher-skilled translation tasks that machine translation cannot easily replace, leading to the eventual rebound in compensation.

We next reaffirm that the previously documented negative relationship between the use of Google Translate and the demand for translators, this time using our job postings dataset. Reassuringly, we find that labor markets with more searches for Google Translate experienced a significant slowdown in the growth of translator job postings—again using "Google Drive" as an instrument. Additionally, we run a range of placebo regressions on similar occupations that are unlikely to be directly impacted by machine translation technology. These include: editors, proofreaders and copy markers, technical writers, and desktop publishers. As expected, we find no impact on the labor demand for these professions.

In the second part of our analysis, we turn to estimate the impact of machine translation on the demand for language skills for the five most common foreign languages in the United States: Spanish, Chinese, Japanese, German, and French. Based on the empirical approach outlined above, we find that the rise in internet searches for Google Translate corresponded with a decrease in demand for all languages spoken by the United States top five trading partners. Our baseline IV estimates suggest Spanish-speaking workers were the most affected by machine translation, with a -1.4 percentage point reduction in job posting growth for the analysed period, while demand for Chinese and German speakers declined by -1.3 and -0.8 percentage points, respectively. The impact on job postings for Japanese speakers is also significant, although less pronounced, with reductions of less than 0.6 percentage points. It stands to reason that these effects will only intensify as machine translation technology continues to improve, particularly in speech translation, which could similarly impact interpreters as well as the value of foreign language skills for in-person communication.

Our study is related to two literatures. First, we build on an extensive body of work exploring the labor market impacts of new technologies in general, and AI in particular. This strand of research shows that automation displaces some workers (Acemoglu and Restrepo, 2020; Bessen et al., 2023; Chen et al., 2022a; Feigenbaum and Gross, 2024), but the effects vary across technologies, time, and place (Chen and Frey, 2024; Dauth et al., 2021; Graetz and Michaels, 2018; Acemoglu et al., 2020). Related to AI, studies have documented declines in labor demand in a few individual tasks, like writing and translation, among freelancers on online platforms (Hui et al., 2023; Yilmaz et al., 2023). But while these studies are informative about the impact of AI on workers in individual tasks (Peng et al., 2023; Noy and Zhang, 2023; Brynjolfsson et al., 2023), they are silent on potential displacement effects. An exception is Acemoglu et al. (2022), who found no noticeable impact of AI exposure on employment or wages at the occupation or industry level. To the best of our knowledge, this study is the first to document the displacement effect of AI at the occupational level.

Second, we add to a large literature on the returns to skill arising from the complementarity between technology and high-skilled labor, known as skill-biased technological change (SBTC) (Acemoglu and Autor, 2011; Katz and Murphy, 1992; Juhn et al., 1993; Goldin and Katz, 2009; Bound and Johnson, 1992). A strand of this literature shows that as computers replaced labor in middle-skill routine tasks, they complemented high-skilled labor, leading to job polarization (Autor et al., 2006, 2003; Goos et al., 2009; Autor and Dorn, 2013; Michaels et al., 2014). However, Beaudry et al. (2016) document that around the year 2000, the demand for skills, particularly for cognitive tasks typically associated with higher educational attainment, experienced a reversal. Similarly, Castex and Kogan Dechter (2014) find smaller returns to cognitive test scores in the 2000s compared to the 1980s—possibly reflecting AI broadening the range of tasks machines can perform to skilled work, such as automated tax preparation, legal e-discovery, and cancer diagnosis and treatment (Brynjolfsson and McAfee, 2014). Meanwhile, skills that cannot be replaced by automation are typically complemented by it, and social interaction has so far proven hard to automate (Autor, 2015; Frey and Osborne, 2017), explaining the extraordinary increase in demand for social skills (Deming, 2017). We add to this literature by documenting a relatively recent phenomenon: despite the increase in the demand for social skills over the 2010s, and continued globalisation in services (Baldwin, 2022), we have seen a decline in the demand for skills that facilitate interaction in terms of foreign languages.

The remainder of this paper is organized as follows. Section 2 provides an overview of the history of machine translation, the translation profession, and foreign language education in the United States. Section 3 describes the data and measurement approaches used in our analysis. Section 4 examines the impact of machine translation on translator employment and job postings across U.S. cities. Section 5 extends the analysis to investigate its effects on the demand for bilingual workers proficient in Spanish, French, German, Chinese, or Japanese. Finally, Section 6 presents our conclusions and outlines potential directions for future research.

II Background: Technology, Translation, and Language Skills

In this section, we provide an overview of the translator profession and the state of foreign language education in the United States. We then examine recent advancements in machine translation, setting the stage for our empirical analysis of its labor market impacts.

II.A Translator Profession in the United States

The translation and interpretation industry in the U.S. is largely unregulated, with employment requirements determined primarily by individual employers and agencies (Department of State, 2019). While ISO standards exist and certain agencies offer certification, like the American Translation Association, these are not legally required to be employed (American Translators Association, 2021).

As of today, human translation remains a significant operation. Translation and interpretation professionals maintain significant presence across diverse institutional settings—spanning professional and technical services, legal systems, government agencies, educational institutions, and healthcare services throughout all levels of government (Bureau of Labor Statistics, 2023b). Overall, the U.S. translation industry has grown since the release of Google Translate—from 33.5 billion USD in 2012, to 37 billion USD by 2021 (American Translators Association, 2021), and the Bureau of Labor Statistics (BLS) predicts a steady growth in the employment outlook of the industry as well (with around 4 percent growth predicted till 2032, on par with the national average). It further estimates that about 68,700 people were employed as translators and interpreters in 2022 (Bureau of Labor Statistics, 2023b). With some 21 percent of them being self-employed, the BLS has statistics on around 51,000 people (Bureau of Labor Statistics, 2023a) employed as translators and interpreters in the U.S., which is the data we exploit in our empirical analysis. Among these, the majority (around 34,000) work in the private sector, earning an average annual wage of 63,080 USD, while around 17,000 are employed at various levels of government.[2]

Meanwhile, foreign language education remains widespread in the United States, although it

[2] Federal Government spending on Translation and Interpretation services, while down from the 2000s, still fluctuates around 300 million USD per year from 2020 onwards (usaspending.gov 2024). The Department of Defence and Department of Justice take up most of these funds.

operates within a decentralized, state-led framework without a national foreign language policy (Met, 1994). This is in contrast to most G7 and EU states, which stipulate compulsory study hours in their centralised curricula for learning at least one (up to three) foreign languages over the course of schooling (Eurydice Network, 2024).[3] In the United States, the first comprehensive survey of students enrolled in foreign language courses, the *National Foreign Language Enrollment Survey of US K-12 Public Schools*, was made in 2008. Its latest revision in 2017, which included private schools, revealed that around 10.6 million (19.66) percent of American school students were enrolled in one or multiple foreign language courses—up from 8.9 million (18.51 percent) in 2007-8 (FLE Report, 2017).

II.B History of Translation Software

The first machine translation (MT) system, IBM701, was deployed in 1954, as a culmination of a partnership between IBM and Georgetown University. This machine translated Russian into English via a slow, word-for-word replacement process. This year also saw the inaugural issue of *Machine Translation*, the first journal in the field (Gaspari, 2024; Chan, 2023).[4] Yet despite significant investments and research, the early 'rule-based' MT systems were slow and unreliable, leading to a revaluation of MT investments by the U.S. government, under the Automatic Language Processing Advisory Committee (ALPAC). This Committee was asked to evaluate advances in MT, compare it with the costs and state of human translation, and whether public financial support for MT research should continue. Its report, published in 1966, declared that "... we do not have useful machine translation. Further, there is no immediate or predictable prospect of useful machine translation" (ALPAC, 1966, p. 32). The ALPAC report reined in expectations from MT, and resulted in most U.S. federal funding being discontinued, with only a few privately funded projects continuing between the 1960s-80s (Gaspari, 2024). Rule-based MT, with the exception of the Canadian Meteo system of translating weather forecasts from English to French, would give way

[3]Fellow G7 states like Germany, Italy and France, for example, stipulate up to ~190, 165 and 198 yearly hours respectively for foreign language learning in secondary schooling.

[4]Cold War concerns made investments into MT a 'multimillion dollar affair', with large contributions (6.5 million USD by the National Science Foundation to various universities, 1.3 million USD by the CIA, and 11.9 million USD by the U.S. Department of Defence) by the US government from the 1950s to 1964 (see ALPAC, 1966, appendix 16). While this sum has been contested (to around 11-12 million USD instead), that still remains a significant investment (Hutchins, 2003).

to other, more efficient systems in the 1980s.

With the developments in personal computing and the Internet in the 1980s and 90s, companies became interested in marketing translation software towards individuals, opening up a new market for MT (Gaspari, 2024). Computer-aided translation companies like Trados (Germany) and Star Group (Switzerland) were established in 1984, which developed products like TED (eventually, Translator's Workbench) and Transit 1.0. The 1990s saw regional expansion of translation software—IBM's Translation Manager, the Russian PROMT, the UK's SDL International, etc. This set up a rapid expansion of available commercial translation systems, from 3 in 1993, to 20+ by 2003, aided by more built-in functions, support for more document formats and languages, among other things (Chan, 2023).

The mid-90s boom in MT was also partially driven by the new data-driven approaches to MT—called statistical machine translation (SMT). Moving away from the extensive investment in developing rule-based systems, SMT systems were trained on 'parallel corpora' of translated source and target texts. SMT superseded rule-based systems due to them being cost-effective and quicker to update (Gaspari, 2024). The late 1990s and early 2000s saw the emergence of free online translation services like Babel Fish (1997) and Google Translate (2004), as well as more and more countries in Europe and Asia developing their own translation software.

Since 2014, Statistical Machine Translation (SMT) systems have increasingly been replaced by Neural Machine Translation (NMT) systems. SMT relies on statistical models and aligned bilingual corpora, breaking sentences into smaller units and translating these units based on learned probabilities. While effective, SMT often produces more literal translations due to its fragmentary approach. In contrast, NMT systems leverage deep learning with unified neural network architectures, processing entire sentences as sequences to generate more fluent and natural translations. NMT systems, utilizing encoder-decoder structures with attention mechanisms, excel at capturing context and handling long-range dependencies. However, they require substantial computational resources for training. While SMT systems remain more flexible for incorporating rules and domain-specific knowledge, NMT systems demonstrate superior adaptability and generalization when trained on large datasets, making them the preferred choice for modern machine translation applications.

Google Chrome and Google Translate: In 2008, after developing various tools that complemented its newly-found dominance in the Search Engine market (Statista, 2025), Google released a web browser called Google Chrome. Despite being faced by more established competitors such as Microsoft's Internet Explorer and Mozilla Firefox, it only took them five years to become the most widely used browsing app. During this time, they also harnessed the data compiled via Google Books and their large user base of 'hundreds of millions of people' to develop a SMT system called Google Translate. To retrieve accurate translations, Google's computing clusters were initially trained on 'the largest corpus of bilingual and monolingual text ever assembled' composed of UN documents, international treaties, and multilingual corporate websites (Ramati and Pinchevski, 2018, p. 2556). The resulting software was officially released in 2010, introduced both as an Android application and integrated into Google Chrome, allowing webpages to be translated directly while browsing.

Google Translate's mission remains "to enable everyone, everywhere to understand the world and express themselves across languages," hinting at targeting a more broad-based, casual user base (Pitman, 2021). This can be confirmed via the rapid adoption of its mobile application—jumping from a 100 million downloads by 2014, to 750+ million by 2019, and over a billion by March 2021 (Pitman, 2021). Growing from a few language offerings to 133 (Caswell, 2022), Google Translate was used by over 500 million users with over 100 billion words translated per day, as of 2016 (Turovsky, 2016). Revised numbers in 2018 took the volume to 143 billion words per day (Windeler, 2024), and over a billion users in 2023 (Gu, 2023).

Google Translate shifted to Neural MT in 2016 (Le and Schuster, 2016), boosting its performance and with a research paper suggesting to have nearly indistinguishable results between Google's NMT and human translation of Chinese (Wu, 2016). While varying language to language, two studies of similar contexts and languages (communication of medical phrases) can be compared. A 2014 study concluded only 57.7 percent accuracy for Google Translate (Patil and Davies, 2014); by 2021, the average accuracy of translated medical communication was 82.5 percent (Taira et al., 2021). Despite still being inaccurate for a complete reliance on Google Translate, this jump shows considerable improvement in less than a decade of work. Indeed, as shown by Yilmaz et al. (2023), the introduction of Google's NMT reduced postings of translation tasks online.

However, as we will see, machine translation was having a material impact on translation work long before then, even at the occupational level. We next turn to explore the impact of machine translation on the demand for foreign language skills in general and translator employment thus far.

III Data and Methodology

We start by building a city-level dataset using individual data from the 2010–2022 American Community Survey (ACS), which includes annual 1-in-100 samples of the U.S. population. We then merge this dataset with information on a) the geographical spread of Google Translate; b) job postings data from Lightcast; and c) local employment and wage statistics for translators and interpreters from the Occupational Employment and Wage Statistics (OEWS) series. This allows us to assess the impact of machine translation on human translators and the demand for language skills in local labor markets.

III.A Data

For our empirical analysis, we draw upon search engine data from Google Trends to identify the varying interest in various emerging platforms and technologies, such as Google Drive and Google Translate across geographies. Doing so, we follow an emerging literature relying on the search intensity for digital technologies to investigate their labor market impacts. For example, Berger et al. (2018) uses Google Trends to measure the effect of the proliferation of Uber on employment and wages in taxi services, noting that city-level data obtained from Google Trends is highly correlated with the number of active Uber drivers per capita in a city, underlining its reliability.[5] In our case, in order to explore the geographic variation in the use of machine translation (see Figure A1), we transform Google's designated market areas (DMAs) into 2990 U.S. counties which we then map onto the 2000 communing zones (CZs) drawn by the U.S. Department of Agriculture. These represent local labor markets as they are based on actual commuting patterns from the 2000 census (USDA, 2024). For each city and year, the relative search intensity for "Google Translate"

[5] More broadly, since its initial release in 2006, Google Trends data has been used to measure investor's attention (Da et al., 2011), unemployment (Choi and Varian, 2012), demand in specific industries such as tourism (Jun et al., 2018), and the spread of disease (Ginsberg et al., 2009).

is compared to other related keywords such as "translator" and "translation". This means that the maximum value possible for this indicator is 100 (see Fig. 1).

For each CZ, we next map on data from the American Community Survey (ACS), which reports workers' occupation and industry, educational attainment, location of residence, and demographic characteristics, like age and ethnic background.[6] This allows us to control for factors that might shape the demand for language skills other than technology, including changes in the total number of native speakers of languages other than English, and other changes in the composition of the local population. Moreover, since the demand for language skills can also be influenced by changing patters of international trade, we also map on trade data from the Economic Indicators Division of the U.S. Census Bureau. Specifically, we add controls of state-level trade (imports plus exports) with countries that speak any of the analysed languages (Spanish, Chinese, German, French or Japanese).

Next, to obtain reliable wage data employment for translators and interpreters, we use the Occupational Employment and Wage Statistics (OEWS) series compiled by the BLS. This series draws from over a million firm and establishment surveys to provide employment and income estimates for approximately 830 occupations. Since this data is available only at the state and metropolitan area (MSA) levels, we adjust our specifications accordingly. This data, it must be noted, excludes about 21 percent of translators and interpreters that are self-employed, meaning that our analysis focuses on the full population of wage-employed translators. We also note that interpreters are less likely to be affected by machine translation, and the OEWS data does not allow us to distinguish between translators and interpreters. The inclusion of interpreters likely dilutes the overall observed impact on the more affected group (translators). Therefore, our estimates may understate the true extent of the impact on translator employment specifically.

Finally, to capture the demand for language skills as well as translators, we use a rich database provided by Lightcast (previously known as Burning Glass). This dataset consists of more than 180 million job postings in the U.S. between 2010 and 2023 based on 40,000 job boards and company websites (Acemoglu et al., 2022; Babina et al., 2024). By leveraging the standardised skill taxonomy used by Lightcast to cluster these postings, we also identify job openings that require

[6] For our analysis, we restrict our sample to the working population, aged 18–65, outside of Puerto Rico and Hawaii.

one of the languages used by the top-5 trading partners of the US: Spanish, Chinese, German, French or Japanese (see Figure A2). Again, this job postings data is collapsed to have estimates of changes in the demand for translators and language skills at the CZ level. Also in this case, translator and interpreter employment is bundled into one occupation, meaning that we are unable to disentangle the differential impact of machine translation on these activities.

III.B Empirical Strategy

In 2010 Google Translate first gained traction as it was launched as an app on Android and iOS, and was integrated into browsers such as Chrome. Thus, taking 2010 as time t, we can estimate:

$$\Delta L_{ij,t+h} = \alpha_h + \gamma_h \Delta GT_{jh} + \beta \Delta \mathbf{X}'_{ijh} + \varepsilon_{ijh} \tag{1}$$

Where the change in employment of labor market i in designated market area (DMA) j in relative time h ($\Delta L_{ij,t+h}$) is a function of the market-area change in interest for Google Translate (ΔGT_{jh}), plus the change in a vector of labor market-specific controls ($\Delta \mathbf{X}'_{ijh}$) and year fixed effects (α_h). Given that changes in interest for Google Translate can be driven by other factors that could simultaneously affect local demand for language skills or for translators and interpreters, in the $\Delta \mathbf{X}'_{ijh}$ vector of control variables, we consider (a) the change in the total number of native speakers of various languages;[7] (b) the change in trade with partners such as Latin America, Europe, Japan, and China; and (c) changes in population, average salary, and the total number of non-translator job postings (see Table 1). Standard errors are clustered at the communing zone level unless otherwise stated.

Of course, it is still possible that some unobserved factors are simultaneously driving changes in translator employment and the use of Google Translate: economic shocks can reduce the local supply of translators while increasing the reliance on MT tools, or local policies may promote the use of digital platforms to aid the learning of foreign languages. Nonetheless, as discussed in Section II, the advancements in the translation capabilities of Google Translate were very much tied to the growth of Google within the internet browser market and, more generally, with the consolidation of a "brand" of Google products. We rely on this fact to construct an instrumental

[7] We use the ACS sample information on language spoken at home which is clustered into Spanish, Indo-European, and Asian Languages.

variable that allows us to isolate the variation in the use of Google Translate that is driven by the growth and eventual market dominance of Google within various markets.

Besides developing a useful MT software, Google has been quite successful in expanding and eventually capturing the market for other digital products such as web browsing (Google Chrome), web analytics (Google Analytics), email management (Gmail), media players (YouTube), and mobile maps (Google Maps). Recent research shows that digital products are "experience goods," meaning their quality cannot be assessed before use; consumers depend on brand reputation to decide whether or not to try them (Barwise and Watkins, 2018). This dynamic creates economies of scale that further enhance the returns of maintaining a strong brand associated with reliable, high-quality products (Chen et al., 2022b). We take advantage of this fact and use the geographical variation in the reputation of the Google brand as an instrumental variable (IV) for the use of Google Translate.

To generate an indicator of brand reputation that varies over time and across geographical areas, we use internet searches for another digital product developed by Google to compete in the cloud storage market: Google Drive[8]. This personal cloud storage software, announced in 2011 and released in 2012, has been used and installed by many households and businesses as an effective way of storing and sharing back-up copies of their computer files. We choose this particular application since (a) it was released around the same time as Google Translate and (b) while performing a completely different task from a MT software, it is still likely to be adopted by households and firms due to the reputation Google had built with their previously released products.

Formally, we instrument the change in interest in Google Translate (i.e. the ΔGT_{jh} of Eq. 1) with the market-area h change of interest in Google Drive (ΔGD_{jh}):

$$\Delta GT_{jh} = \alpha_h + \theta_h \Delta GD_{jh} + \beta \Delta \mathbf{X}'_{ijh} + \varepsilon_{ijh} \tag{2}$$

This IV strategy builds on the intuition that the change in interest in another widely used Google product (Google Drive in this case) captures the variation in the use of Google Translate that is driven by changes in Google's brand reputation and *not* by some unobserved factors that may

[8]Note that we could not use the evolution of Google's stock price as a proxy for reputation since its value does not vary by geographical area.

simultaneously affect the demand for translators and the use of a MT software.

Figure 2 plots the changes in the key variables of interests across local labor markets between 2010 and 2023, revealing several noteworthy patterns. First, as expected, *all* labour markets have increased their use of Google Translate (Panel (c)), and Google Drive (Panel (d)). However, reassuringly for our purposes, we observe significant variation in both variables across space, which we exploit in our empirical analysis. Third, Spanish, which is the most widely spoken foreign language in the U.S., is mainly spoken in the South, which has seen the largest increase in the demand for Spanish language skills according to our job postings data (Panel (b)). The geographic demand for translators, however, follows a different pattern, falling in numerous communing zones where the demand for Spanish language skills increased, pointing to other significant variables at work. In the below, we explore the role of machine translation in explaining such declines in employment.

IV Machine Translation, Translator Jobs, and Wages

Based on the empirical strategy outlined above, we begin by implementing model 1 to estimate the effect of Google Translate on a) translator and interpreter employment and wages, based on establishment survey data from the Occupational Employment and Wage Statistics (OEWS) series; and b) labor demand for translators and interpreters, using job postings from Lightcast.

Column 1 of Table 2 provides a baseline OLS estimation using the stacked differences for the full sample period (2010-2023). Our analysis reveals a robust negative correlation between metro-area adoption of machine translation and growth in translator employment. This relationship persists after incorporating both year fixed-effects and our comprehensive set of control variable. Next, in Column 2, we report a Reduced Form estimation, showing that the increase in the use of Google Drive has coincided with a decline in the local number of translator jobs across cities. Even though this correlation is purely descriptive and does not imply that the access to cloud storage services is displacing translators and interpreters, it underlines the validity of out instrument in that it could be influencing the outcome *through* the variable we are instrumenting (in our case the change in interest in Google Translate). We note that the instrument is also relevant, as reflected in the First Stage (FS) of the Two-Stage Least Squares (2SLS) regression needed for implementing our empirical strategy. Moreover, the first coefficient reported in Column 3 shows a clear and statistically significant association between the use of Google Drive and the number of internet searches for Google Translate at the metro area level.

Column 4 reports the results from our IV estimate. We note that the coefficient gains in statistical significance and magnitude relative to our OLS estimate. Reassuringly, we also note that the First Stage effective F-Statistic is well above the customary critical value of 10. In order to calculate the implied effect of machine translation on translator employment, we multiply the IV coefficient by the observed change in interest in Google Translate between 2010 and 2023 and by the partial R-squared of the First Stage. We take this latter number as a valid estimate of the variance in the use of Google Translate that is driven by the instrument.[9] This yields a reduction in the growth rate of of -0.8 ($= -0.84 \times 0.86 \times 0.98$) percentage points. Taking the actual observed change in translator vacancies as a reference point, we estimate that Google Translate more than *halved* the potential growth of translator employment over the sample period. Similarly, if we take the 2010 number of translators as a baseline, we can also compare the implied effect to a counterfactual scenario in which Google Translate was never developed. Our estimates indicate that machine translation adoption moderated translator employment growth, resulting in approximately 28,000 fewer positions created relative to the counterfactual growth trajectory absent this technological change. Indeed, overall, total employment in the U.S. grew around 13 percent between 2010 and 2023, while translator and interpreter employment only grew by 3 percent.

We next turn to explore the impact of Google Translate on translator wages, using, as before, the instrumented version of model 1 for all the individual years after 2010 that are included in our metro-area sample. The resulting γ coefficients are organised in Figure A3 . We note that wage growth slowed down in the early years of adoption of Google Translate but it recovered from 2016 onward. Thus, when we stack all the differences relative to 2010 there is no statistically significant impact on translator wages over the full sample period. While we are unable to fully disentangle the mechanisms behind the initial slowdown in wage growth and its subsequent rebound, this pattern could reflect wage rigidity, which has been documented for both incumbent workers and new hires (Grigsby et al., 2021; Hazell and Taska, 2023), or a gradual compositional shift toward higher-skill translation tasks that are less susceptible to automation. Wage rigidity would explain why nominal

[9] This particular method to weight the coefficient of a 2SLS regression has been widely used in research on labor markets. See for example Autor et al. (2013) and Acemoglu et al. (2016).

wages did not decline outright, while the delayed wage recovery suggests that the transition toward more specialized, higher-paying roles did not occur immediately. Both firms and translators may have required some time to adjust to the evolving demand for human translation skills.

To probe our baseline findings further, we proceed to estimate the effect of Google Translate on translator labor demand using the near-universe of U.S. job postings. Although not informative about job displacement, job postings permit us to create a more granular measure of labour demand while extending the geographical reach of our empirical analysis beyond metropolitan areas, which excludes around 14% of the U.S. population that lives in micropolitan and low-density areas (Census Bureau, 2019). To that end, we create a panel of commuting zones (CZs), comprising the whole of the United States, except for Puerto Rico and Hawaii. These geographic areas are based on actual commuting patterns, and have been widely used in the literature to map the exposure of local labour markets to various economic and technological shocks (Autor et al., 2013; Acemoglu et al., 2016; Autor et al., 2021), much like the one we are observing.

Table 3 summarises the results of our main specification for the full sample period. Again, using OLS, we document a statistically significant negative relationship between local machine translation intensity and the number of jobs advertised across cities (column 1), which increases in statistical and economic significance with our IV strategy (column 4). Taking the IV coefficient at face value, a 10 percentage point increase in the interest in Google Translate led to a 0.17 percentage point reduction in the growth rate of translator job postings. Since here we are dealing with vacancies (we do not observe actual hires), it should not come as a surprise that this effect is substantially larger than the impact we observed on employment (see section V.A). Based on the the 2010-2023 increase in local searches for Google Translate multiplied by the partial R-squared of the First Stage, we estimate that the actual reduction in translator job posting growth to be -1.09 ($= -1.74 \times 0.89 \times 0.70$) percentage points. This, compared to a counterfactual scenario in which Google Translate was never adopted, implies a loss of nearly 10,000 translator vacancies over the sample period.

IV.A Robustness and heterogeneity

We next turn to probe the robustness of our findings in several ways. First, as a way of testing if our empirical strategy is correctly identifying a reduction in demand growth driven by the rise of Google Translate and *not* by other potentially confounding trends or shocks, we implement the instrumented version of model 1 on the job postings growth rates of similar occupations (see Table 4). These occupations have been selected based their proximity in the O*NET's Specific Vocational Preparation (SVP) score, and the technology skills they require—which machine translation technology cannot replace. Reassuringly, we find that all these other jobs, Desktop Publishers, Technical Writers, Editors, and Copywriters were left unaffected by advances in the use of machine translation software.

Second, while the coefficients of Table 3 represent the average effect for the whole 2010-2023 period, we also estimate model 1 for all the years included in our sample to see the the cumulative effect relative to 2010. As shown in Figure A4 , it is not until 2017 that the γ effect on the demand for translators becomes significant. We note that this follows Google Translate's shift to Neural MT in 2016 (Le and Schuster, 2016), which significantly boosted its performance, making results between Google's NMT and human translation indistinguishable (Wu, 2016). It hovers around -2 until 2019, when it interacts with a major shock—the COVID-19 pandemic. This event, which expanded the sheer number of remote and hybrid jobs, might also have led employers to increasingly rely on technologies such as Machine Translation and other forms of AI (Acemoglu et al., 2022). Finally, for the last 3 years included in our analysis, the effect stabilises around -4. Once again, the larger magnitude of this coefficient vis-à-vis the one retrieved from the BLS employment data imply a greater sensitivity of job postings to changes in hiring and staffing strategies due to emerging technologies.

Third, in Figure A5 we document that there are no significant pretrends. Specifically, we estimate the relationship between machine translation and translator employment, imputing for the pre-2010 years the average metro-area level change in Google Translate use between 2011 and 2023. Our results show that there is no statistically significant relationship between MT intensity and and pre-2010 changes in translator employment. We also note that, similarly to the analysis using job postings (Fig. A4), the effect only becomes significant after Google Translate starts to rely on Neural Machine Translation systems in 2016.

Fourth, we explore the heterogeneity of the impacts of machine translation on translators specialising in different language pairs. Specifically, in Table 5, we estimate instrumented versions of specification 1 for translators of the languages spoken by two key trading partners of the United

States: China and Latin America. As shown in Column 1, the impact is largest for Spanish translators, where we can infer a 0.96 ($= -1.54 \times 0.89 \times 0.70$) percentage point reduction in the growth rate of related job postings. Similarly, Chinese translators experienced a reduction in demand of around 0.5 percentage points. In the next section, we turn to explore the impact of machine translation on various language skills across the labour market as a whole.

V The Demand for Foreign Language Skills

For the second part of our analysis, we take advantage of the detailed skills taxonomy developed by Lightcast, which flags job postings that include particular language skills as part of the job requirements. As before, we take the near universe of job postings and collapse them onto commuting zones, giving us significant variation in the demand for the five most common foreign language skills in the United States across space.

To that end, Table 6 shows the coefficients retrieved from the 2SLS estimation of model. 1. As expected, the rise in internet searches for Google Translate led to a decrease in demand growth for all of the languages spoken by the top-5 trading partners of the U.S., though we note that in the case of French, the coefficient is not statistically significant. We note that the demand for Spanish-speaking workers declined the most, with a growth rate reduction of -1.37 ($= -2.19 \times 0.89 \times 0.70$) percentage points. The demand for Chinese and German language skills also saw a sizeable decline of -1.26 and -0.81 percentage points, respectively, while the growth slowdown for jobs emphasising the need for Japanese language skills was somewhat more modest (-0.6).

V.A Robustness and heterogeneity

To investigate the role of improvements in machine translation over time, we next estimate these effects year by year over the sample period. Doing so, we find that machine translation reduced the demand for foreign language skills well before the introduction of neural machine translation (NMT) in 2016. Figure A6 shows that already by 2013 the rise of Google Translate had stunted demand growth for Spanish-speaking workers. The same is true of the demand for Chinese language skills, which began to fall in relative terms in local labour markets relying more on Google Translate already in 2015—also before US-China trade relations deteriorated under the Trump administration (see Figure A7). In similar fashion, the demand for French language skills fell already in 2014, while the effect for German and Japanese language skills is negative, albeit statistically insignificant in most years. This is probably due to the generally lower demand for such language skills as shown in Figure 3.

Of course, it is still possible that foreign language skills matter more in some settings than in others. To that end, we next probe the impact of machine translation on foreign language skills across major occupational groups. The results from this exercise are shown in Table 7. Turning first to Spanish, we observe an economically and statistically negative effect across all occupational categories, albeit to varying degree: the effect is particularly pronounced in healthcare, food and farming, as well as industry, relative to more skilled roles in management, IT, sciences and engineering. We further note that the estimated coefficients are negative across all languages and occupational groups, though not statistically significant in a few rare instances. One noteworthy example is the negligible impact on Japanese for in IT, sciences and engineering (Column 2), where language skills are likely to have been particularly important, as underlined by the literature on the role of language in technology transfer (Juhász et al., 2024). The impact of German and French language skills, in contrast, is more muted in business and management (Column 3), possibly pointing towards the continued relevance of these languages in international commerce and other business settings.

Finally, to test the robustness of these results, we also estimate the effect of Google Translate on the demand for comparable skills that require specialised training but that should not be affected by the greater availability of machine translation software. Specifically, we implement our main specification on the change in job postings of the four most demanded software skills in the United States: Java, Oracle, SQL, and Microsoft Excel. As shown in Table 8, greater exposure to Google Translate did not lead to a statistically significant reduction in the demand for any of these skills.

Taken together, our findings lead us to conclude that machine translation has reduced the demand for foreign language skills across all investigated language pairs, in most professional settings.

VI Conclusion

There has been much concern over the employment impacts of AI. Yet in a recent study, Acemoglu et al. (2022) conclude that "aggregate effects of AI, if present, are not yet detectable—plausibly because AI technologies are still in their infancy and have spread to only a limited part of the US economy." In this paper, we zoom in on one particular AI application which has seen considerable progress over the past decade: machine translation. Exploiting the variation in the use of machine translation across local labor markets in the United States, we show that the adoption of Google Translate contributed to a 0.71 percentage point reduction in translator employment growth, translating into an estimated loss of more than 28,000 jobs over the 2010-2023 period. Second, while there was a short-lived decline in translator compensation right after Google Translate was released, the subsequent rebound indicates that downward wage rigidities forced employers to use other methods to adjust demand.

Third, we assess the broader labour market implications of machine translation in terms of its impact on the demand for foreign language skills. Across specifications, we consistently find significant declines in the demand for workers proficient in the five most commonly spoken foreign languages in the United States—Spanish, Chinese, Japanese, German, and French—with the largest impact observed on Spanish language skills. These findings are robust across broader occupational categories with some exceptions. For example, we find that the negative impact on the demand for Chinese language skills to be relatively muted in IT, science and engineering, possibly reflecting the continued importance of language for technology transfer.

Finally, although the observed effects have been moderate thus far, they are likely to intensify as machine translation technologies continue to advance, particularly in the realm of simultaneous speech interpretation. Indeed, historically, the work of interpreters has been less vulnerable to automation. However, recent developments, such as OpenAI's demonstration of Sky, suggest that translation software is beginning to penetrate these areas as well. These trends carry significant implications for education policy, especially considering that nearly 20 percent of students in American schools are currently enrolled in one or more foreign language courses. We consider the labor market impacts of real-time voice translation to be a fruitful avenue for future inquiry.

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Table 1: Google Trends and Job Postings Data

	Mean	SD	p25	Median	p75
A. Search Engine Data					
Δ Interest in Google Translate	0.95	0.16	0.88	0.93	1.00
Δ Interest in Google Drive	2.23	1.30	1.28	1.57	3.00
B. Job Postings Data					
Δ Translator Job Postings	0.71	0.87	0.00	0.69	1.39
Δ Other job postings	1.20	0.44	0.89	1.20	1.49
Δ Avg. Salary	0.39	0.95	0.16	0.30	0.45
C. Demographic Data					
Δ Spanish Speakers	0.02	0.56	-0.07	0.06	0.17
Δ Other Indo-European Languages Speakers	-0.03	0.66	-0.22	0.02	0.21
Δ Asian Languages Speakers	0.07	0.81	-0.11	0.09	0.30
Δ Population	0.04	0.09	-0.03	0.02	0.09
D. Trade Data					
Δ Trade with Latin America	0.63	0.27	0.45	0.66	0.80
Δ Trade with Europe	0.61	0.27	0.43	0.63	0.76
Δ Trade with Japan	0.38	0.52	0.08	0.34	0.69
Δ Trade with China	0.25	0.36	0.08	0.26	0.46

Note: This table reports the average 2010-2023 log change for all the commuting zones (CZ) included in the analysis. Search Engine Data comes from Google Trends, while the source for Job Postings is Lightcast Data. Demographic Data comes from the American Community Survey (ACS), and information on Trade comes from the Economic Indicators Division of the US Census Bureau.

Table 2: Effect of Google Translate on Translator Jobs, 2010-2023

	(1) OLS	(2) RF	(3) FS	(4) IV
Δ Interest in Google Translate	-0.394**			-0.839***
	(0.123)			(0.238)
Δ Interest in Google Drive		-0.174***	0.208***	
		(0.047)	(0.019)	
Δ Employment in Other Occupations	0.697**	0.619**	-0.059	0.569**
	(0.209)	(0.222)	(0.077)	(0.218)
Δ Population	-0.158	-0.104	-0.127*	-0.210
	(0.120)	(0.121)	(0.063)	(0.129)
Δ Avg. income	-0.515	-0.315	-0.086	-0.387
	(0.421)	(0.431)	(0.219)	(0.417)
Year Fixed Effects	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes
Observations	2600	2600	2600	2600
Metro Areas	200	200	200	200
First Stage F-statistic				213

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents estimates of the effect of searches for Google Translate on translator employment. The sample is composed of US Metro Areas included in the Occupational Employment and Wage Statistics (OEWS) series. The outcome variable is the stacked growth rates of translator employment relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed employment counts reported by the OEWS. The main variable of interest is the market area growth in internet searches for Google Translate. This is also approximated with log-differences relative to 2010, when Google Translate was launched as an App and integrated into browsers such as Chrome. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. Column 1 organises the main OLS coefficients. Column 2 reports a Reduced Form specification in which the main regressor is the change in searches for Google Drive. Column 3 shows the First Stage of our instrumental variable strategy, where we instrument change in interest in Google Translate with searches for Google Drive. Finally, Column 4 reports the main results of the two-stage least squares (2SLS) estimation. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Metro Area.

Table 3: Effect of Google Translate on Demand for Translators, 2010-2023

	(1) OLS	(2) RF	(3) FS	(4) IV
Δ Interest in Google Translate	-0.272*			-1.744***
	(0.121)			(0.515)
Δ Interest in Google Drive		-0.064***	0.036***	
		(0.016)	(0.006)	
Δ Other job postings	0.264***	0.261***	0.007	0.273***
	(0.041)	(0.040)	(0.010)	(0.044)
Δ Population	2.868***	2.891***	-0.293**	2.379***
	(0.358)	(0.347)	(0.092)	(0.380)
Δ Avg. Salary	-0.067**	-0.060**	-0.007	-0.072***
	(0.022)	(0.022)	(0.004)	(0.018)
Year Fixed Effects	Yes	Yes	Yes	Yes
Related Searches Controls	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes
Observations	9048	9048	9048	9048
Commuting Zones	696	696	696	696
First Stage F-statistic				28

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents estimates of the effect of searches for Google Translate on translator job postings. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of translator job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is also approximated with log-differences relative to 2010, when Google Translate was launched as an App and integrated into browsers such as Chrome. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; Related Internet Searches; and State-level changes in trade with Europe, Japan, China, and Latin America. Column 1 organises the main OLS coefficients. Column 2 reports a Reduced Form specification in which the main regressor is the change in searches for Google Drive. Column 3 shows the First Stage of our instrumental variable strategy, where we instrument change in interest in Google Translate with searches for Google Drive. Finally, Column 4 reports the main results of the two-stage least squares (2SLS) estimation. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

Table 4: Effect of Google Translate on Demand for Placebo Occupations, 2010-2023

	(1) Desktop Publishers	(2) Technical Writers	(3) Editors	(4) Copywriters
Δ Interest in Google Translate	0.168	-1.047	1.126	0.328
	(0.195)	(0.556)	(0.586)	(0.508)
Δ Avg. Salary	0.001	-0.048**	-0.024	0.006
	(0.003)	(0.015)	(0.018)	(0.018)
Δ Population	-0.048	0.981*	1.525***	-3.541***
	(0.148)	(0.395)	(0.383)	(0.449)
Δ Other job postings	0.023	0.300***	0.262***	0.307***
	(0.014)	(0.042)	(0.042)	(0.048)
Year Fixed Effects	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes
Observations	9048	9048	9048	9048
Commuting Zones	696	696	696	696
First Stage F-statistic	15	15	15	15

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents estimates of the effect of searches for Google Translate on occupations that are similar to that of Translators and Interpreters. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is instrumented with change in interest in Google Drive in the same period. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

Table 5: Effect of Google Translate on Demand for Translators of Specific Languages, 2010-2023

	(1) OLS	(2) RF	(3) FS	(4) IV
A. Spanish				
Δ Interest in Google Translate	-0.139			-1.540***
	(0.071)			(0.431)
Δ Interest in Google Drive		-0.056***	0.036***	
		(0.013)	(0.006)	
Δ Other job postings	0.197***	0.196***	0.007	0.206***
	(0.030)	(0.029)	(0.010)	(0.033)
Δ Population	2.464***	2.451***	-0.293**	1.999***
	(0.318)	(0.303)	(0.092)	(0.324)
Δ Avg. Salary	-0.037	-0.031	-0.007	-0.042**
	(0.019)	(0.018)	(0.004)	(0.015)
B. Chinese				
Δ Interest in Google Translate	-0.087			-0.840***
	(0.045)			(0.248)
Δ Interest in Google Drive		-0.031***	0.036***	
		(0.007)	(0.006)	
Δ Other job postings	0.053**	0.052**	0.007	0.058**
	(0.018)	(0.018)	(0.010)	(0.020)
Δ Population	1.507***	1.504***	-0.293**	1.257***
	(0.265)	(0.255)	(0.092)	(0.252)
Δ Avg. Salary	-0.018	-0.015	-0.007	-0.021*
	(0.011)	(0.011)	(0.004)	(0.009)
Observations	9048	9048	9048	9048
Metro Areas	696	696	696	696
First Stage F-statistic				28

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents 2SLS estimates of the effect of searches for Google Translate on job postings of translators of specific languages. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is instrumented with change in interest in Google Drive in the same period. Covariates include Commuting-Zone growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

Table 6: Effect of Google Translate on Demand for Language Skills, 2010-2023

	(1) Spanish	(2) Chinese	(3) Japanese	(4) German	(5) French
Δ Interest in Google Translate	-2.189***	-2.020***	-0.922**	-1.301*	-0.827
	(0.583)	(0.557)	(0.322)	(0.539)	(0.511)
Δ Other job postings	0.510***	0.147**	0.080**	0.322***	0.355***
	(0.054)	(0.045)	(0.026)	(0.051)	(0.049)
Δ Population	1.306***	3.001***	1.209***	1.228**	1.762***
	(0.314)	(0.440)	(0.284)	(0.391)	(0.405)
Δ Avg. Salary	-0.086***	-0.057**	-0.025**	-0.047**	-0.029
	(0.017)	(0.020)	(0.010)	(0.015)	(0.017)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Related Searches Controls	Yes	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes	Yes
Observations	9048	9048	9048	9048	9048
Commuting Zones	696	696	696	696	696
First Stage F-statistic	28	28	28	28	28

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents 2SLS estimates of the effect of searches for Google Translate on job postings that require specific Language Skills. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is instrumented with change in interest in Google Drive in the same period. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

Table 7: Effect on Demand for Specific Languages within Occupational Groups

	(1) Food & Farming	(2) Business & Management	(3) IT, Sciences & Engineering	(4) Care & Community	(5) Law, Arts & Education	(6) Healthcare	(7) Industry
A. Spanish							
Δ Interest in Google Translate	-3.394***	-3.113***	-2.127**	-3.323***	-2.231**	-3.616***	-3.877***
	(0.815)	(0.773)	(0.670)	(0.894)	(0.690)	(0.921)	(1.014)
B. Chinese							
Δ Interest in Google Translate	-0.554***	-2.131***	-0.883***	-0.850***	-1.288***	-0.915***	-0.627***
	(0.167)	(0.530)	(0.262)	(0.239)	(0.371)	(0.278)	(0.176)
C. French							
Δ Interest in Google Translate	-0.891***	-0.263	-1.052**	-0.718**	-1.726***	0.573	-0.404
	(0.266)	(0.401)	(0.370)	(0.268)	(0.488)	(0.304)	(0.337)
D. German							
Δ Interest in Google Translate	-0.308*	-1.104*	-1.301**	-0.304*	-0.751**	-0.259	-0.895**
	(0.124)	(0.435)	(0.412)	(0.140)	(0.274)	(0.156)	(0.277)
E. Japanese							
Δ Interest in Google Translate	-0.206**	-0.744**	-0.174	-0.158*	-0.597**	-0.118*	-0.282**
	(0.074)	(0.257)	(0.131)	(0.067)	(0.212)	(0.049)	(0.102)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9048	9048	9048	9048	9048	9048	9048
Commuting Zones	696	696	696	696	696	696	696
First Stage F-statistic	15	15	15	15	15	15	15

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents 2SLS estimates of the effect of searches for Google Translate on job postings that require specific Language Skills by Large Occupational Group. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is instrumented with change in interest in Google Drive in the same period. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

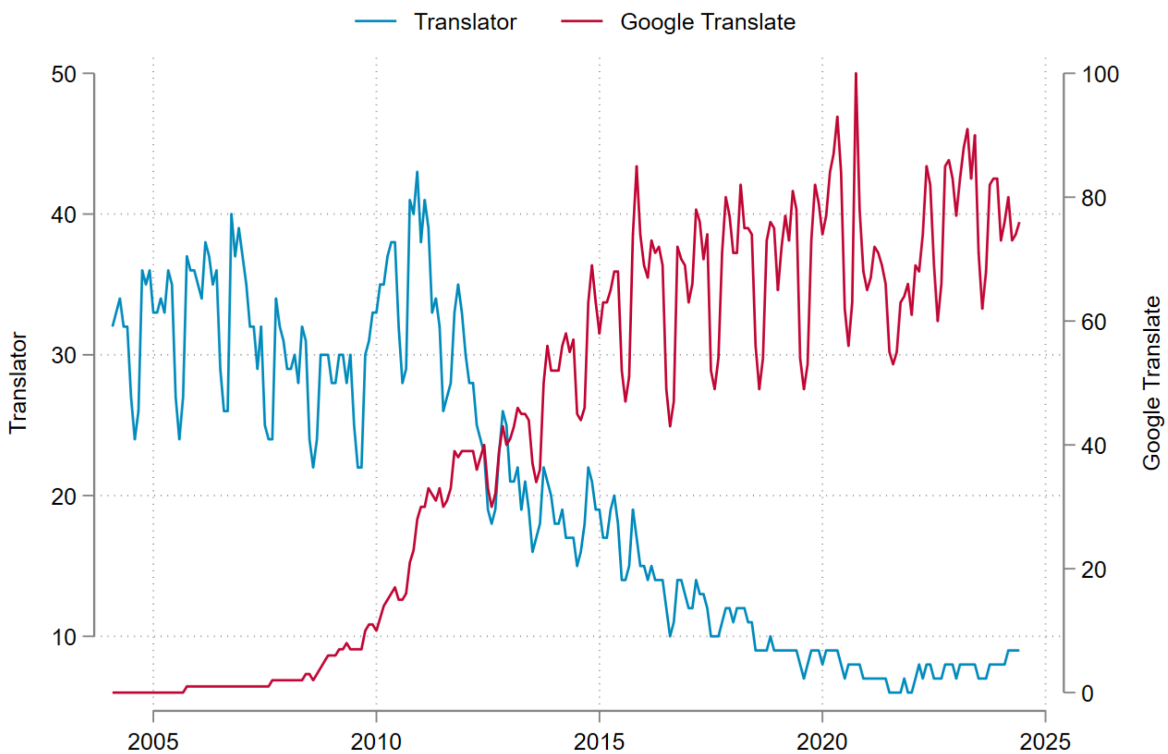
Table 8: Effect of Google Translate on Demand for Software Skills, 2010-2023

	(1) Java	(2) Oracle	(3) SQL	(4) Excel
Δ Interest in Google Translate	-0.946	-0.826	-0.185	-0.850
	(0.605)	(0.536)	(0.557)	(0.459)
Δ Avg. Salary	-0.080***	-0.053***	-0.069**	-0.092***
	(0.018)	(0.015)	(0.022)	(0.026)
Δ Population	0.980*	0.616	0.935	0.202
	(0.460)	(0.424)	(0.478)	(0.327)
Δ Other job postings	0.497***	0.368***	0.493***	0.639***
	(0.068)	(0.053)	(0.069)	(0.060)
Year Fixed Effects	Yes	Yes	Yes	Yes
Foreign Language Speakers Controls	Yes	Yes	Yes	Yes
Trade Controls	Yes	Yes	Yes	Yes
Observations	9048	9048	9048	9048
Commuting Zones	696	696	696	696
First Stage F-statistic	28	28	28	28

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

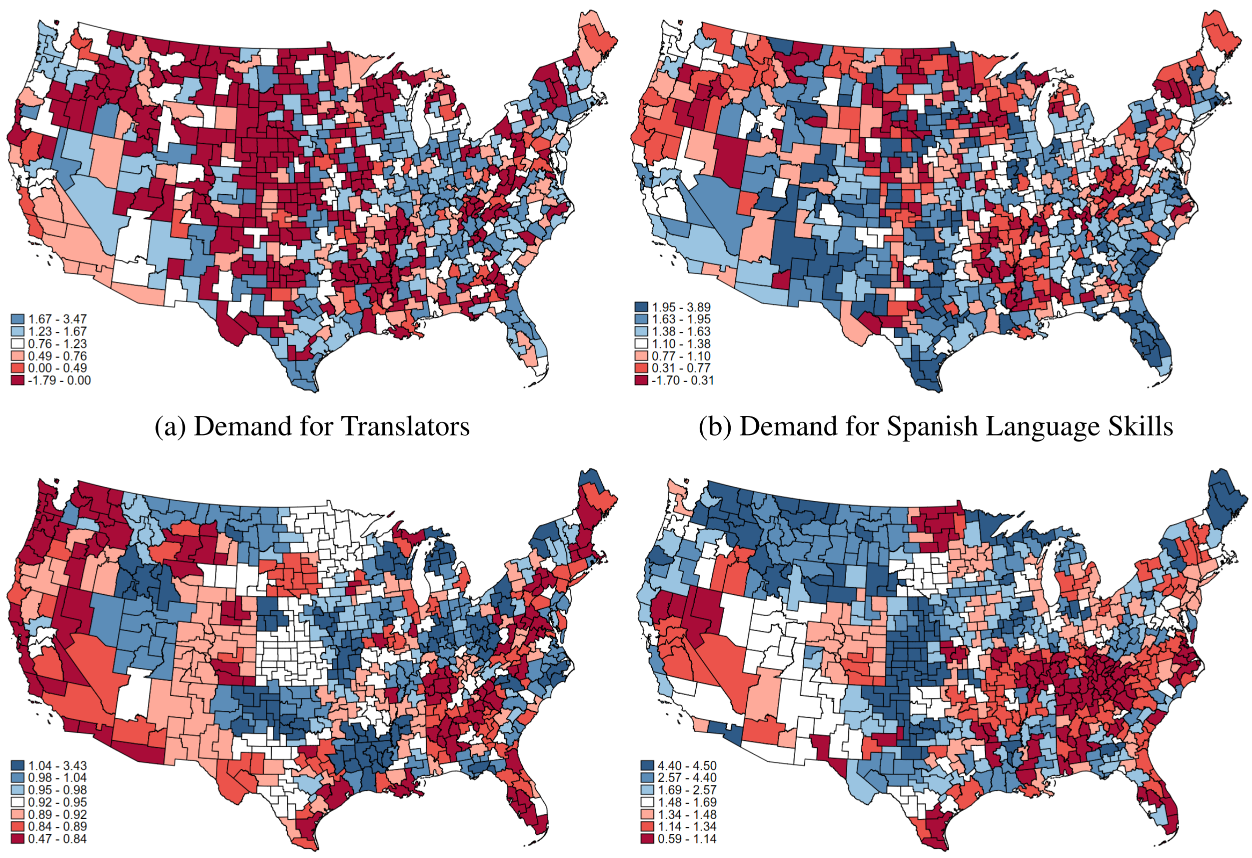
Note: This table presents 2SLS estimates of the effect of searches for Google Translate on Software Skills. The sample is composed of US Commuting Zones. The outcome variable is the stacked growth rates of job postings relative to 2010 between 2011 and 2023. We approximate these rates with the differences in the log-transformed counts reported by Lightcast Data. The main variable of interest is the market area growth in internet searches for Google Translate. This is instrumented with change in interest in Google Drive in the same period. Covariates include Metro Area growth in population; average income; employment in other occupations; number of people that speak Spanish, Asian, or European languages at home; and State-level changes in trade with Europe, Japan, China, and Latin America. All specifications include Year Fixed Effects. Standard errors (in parenthesis) are clustered by Commuting Zone.

Figure 1 : Google Searches for “Translator” and “Google Translate” (2004-2024)



Note: This graph plots monthly “interest” in two Google search terms: “Translator” (on the left axis) and “Google Translate” (right axis). The interest index is calculated by Google Trends using an unbiased sample of searches for different time periods and geographies.

Figure 2 : Changes in US labor Markets and Interest in Google Products (2010-2023)



(a) Demand for Translators

(b) Demand for Spanish Language Skills

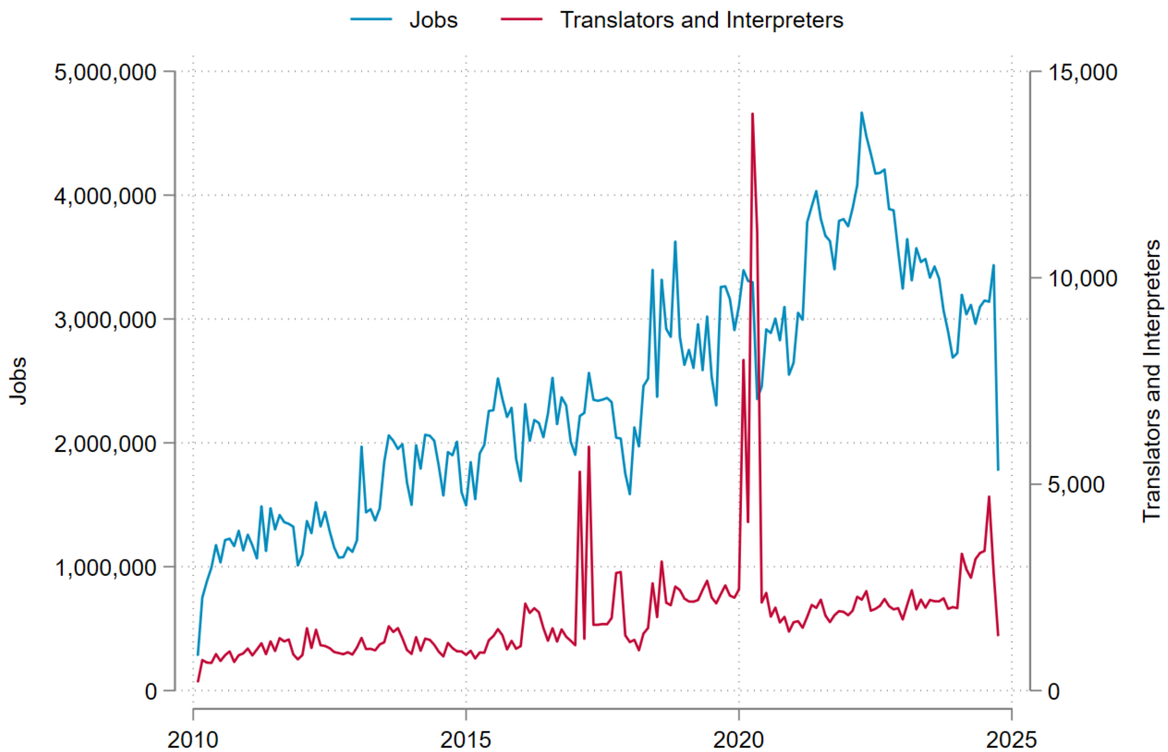
(c) Interest in Google Translate

(d) Interest in Google Drive

Note: These four maps report the 2010-2023 log change in four variables of interest: translator job postings, job postings requiring any level of Spanish skills, internet searches for Google Translate, and internet searches for Google Drive. Changes are reported at the Commuting Zone (CZ) level.

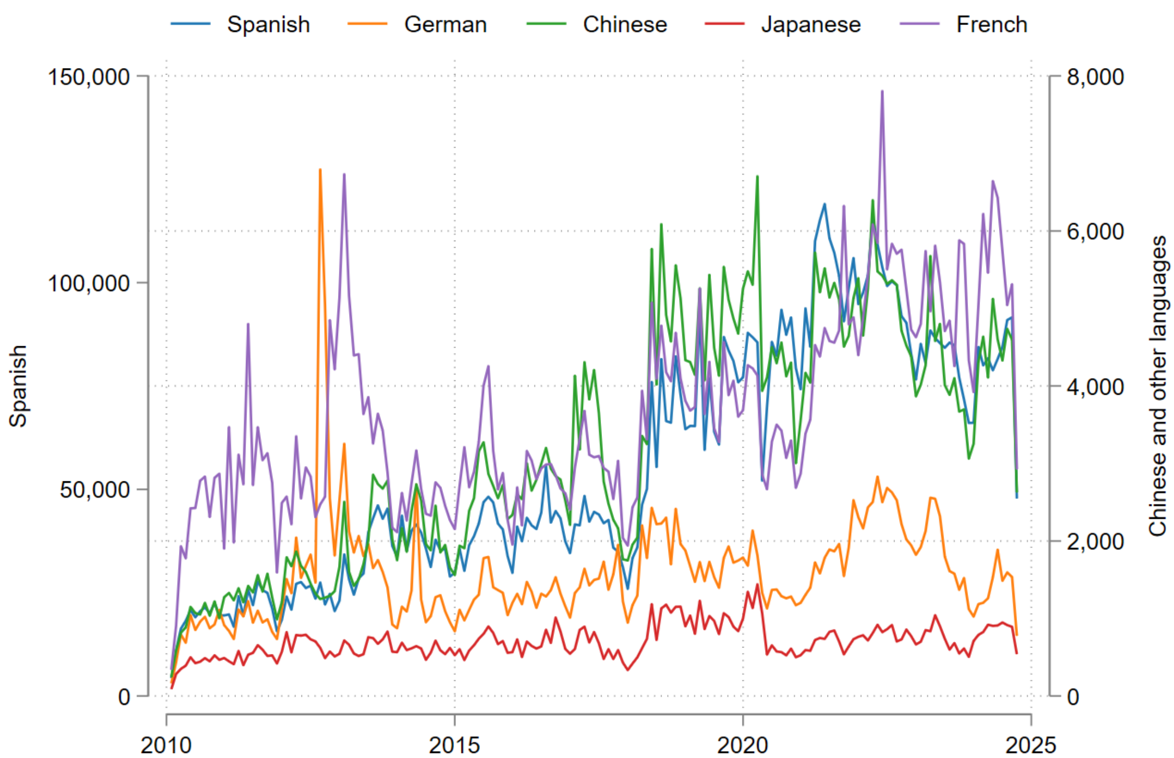
Appendix

Figure A1 : Translator and Total Job Postings (2010-2023)



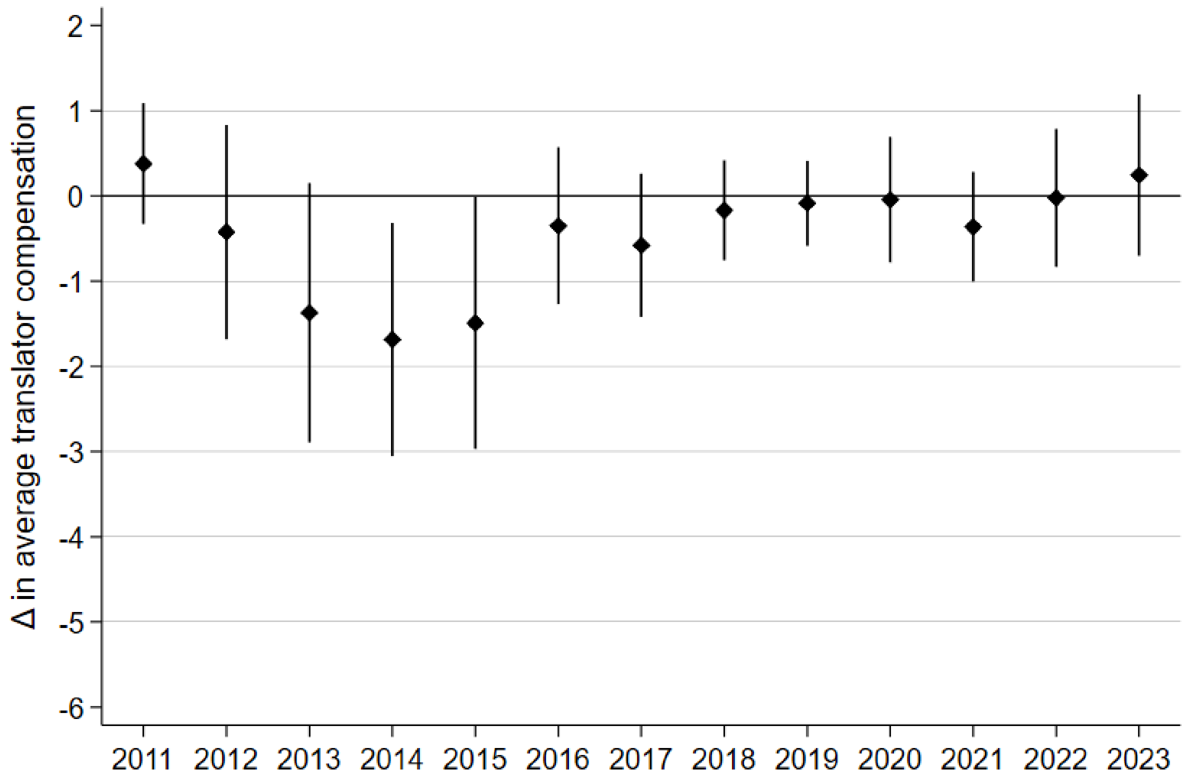
Note: This graph plots on the left axis all the US job postings available in the Lightcast Data (formerly known as *Burning Glass*), and on the right axis those specifically classified as “Translator and Interpreter” Jobs.

Figure A2 : Job Postings Requiring Specific Languages (2010-2023)



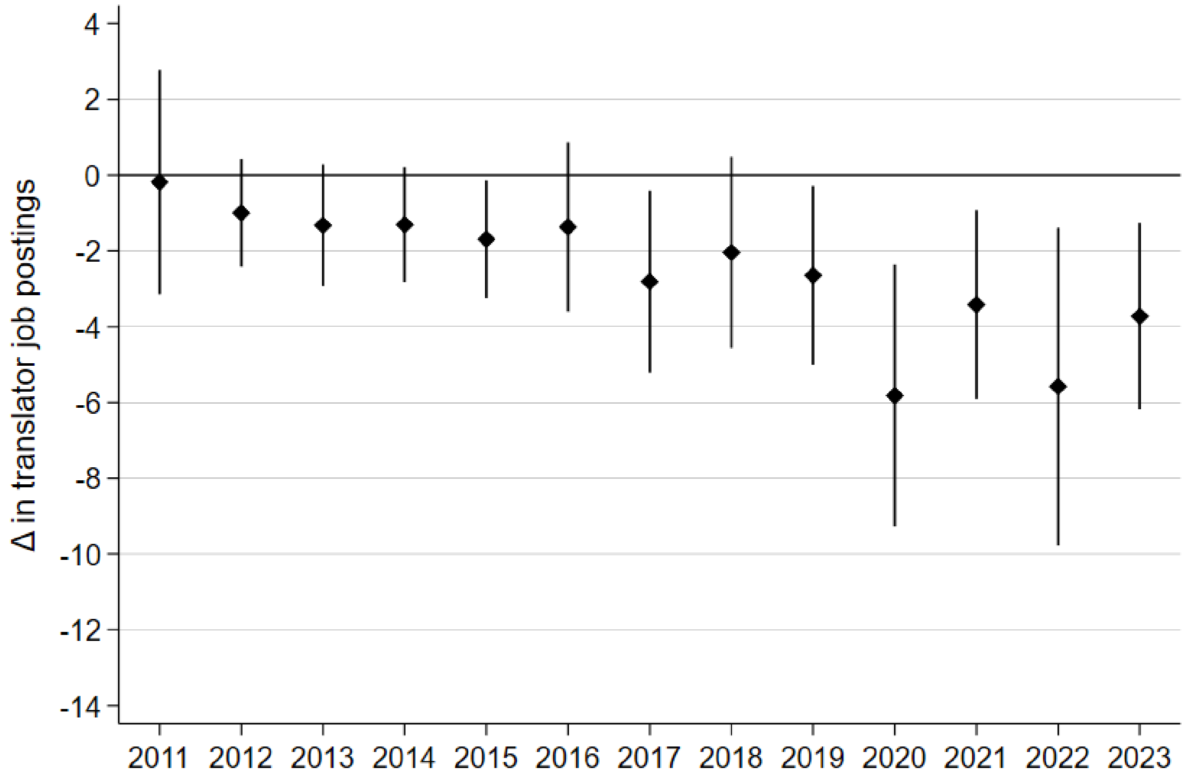
Note: This graph plots the all the US job postings in Lightcast Data (formerly known as *Burning Glass*) that ask for specific language skills.

Figure A3 : Effect on Translator Compensation



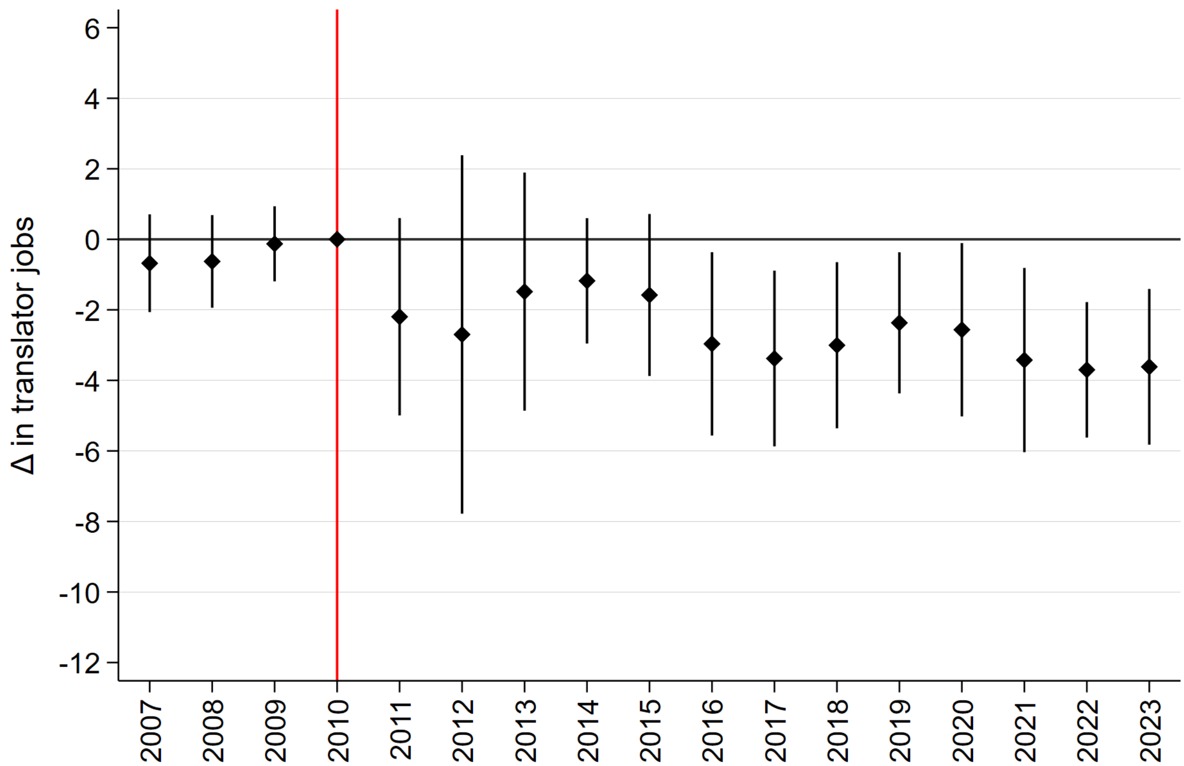
Note: This graph plots the γ_h coefficients of 12 separate 2SLS regressions as specified by Eq. 1. Spikes indicate 95% confidence intervals. Controls include changes in population, economic dynamism, demographic composition, and international trade with countries that speak languages other that English.

Figure A4 : Effect on the Demand for Translators



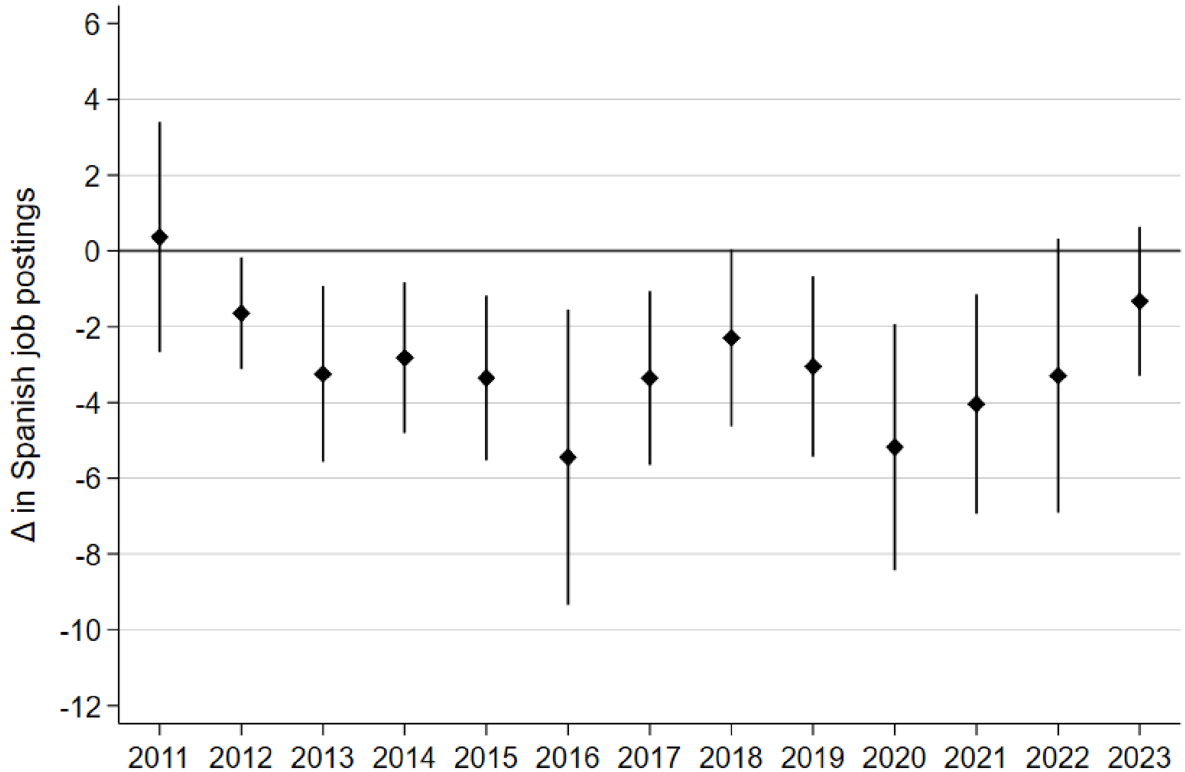
Note: This graph plots the γ_h coefficients of 12 separate 2SLS regressions as specified by Eq. 1. Spikes indicate 95% confidence intervals. Controls include changes in population, economic dynamism, demographic composition, and international trade with countries that speak languages other that English.

Figure A5 : Effect on Translator Employment (Metro Areas)



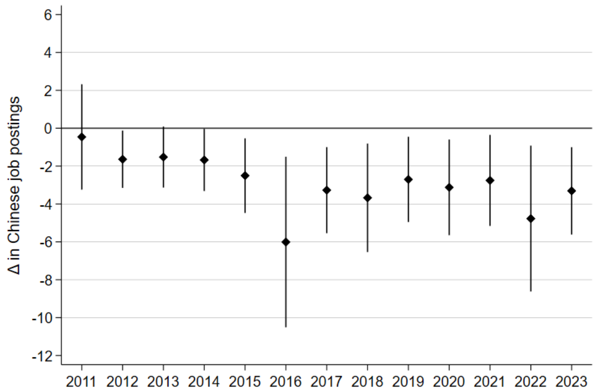
Note: This graph plots the γ_h coefficients of 17 separate 2SLS regressions as specified by Eq. 1. Spikes indicate 95% confidence intervals. Controls include changes in economic dynamism. For the years prior to the release of Google Translate (2010), we input the average change in the interest indicator between 2011 and 2023.

Figure A6 : Effect on the Demand for Spanish Skills

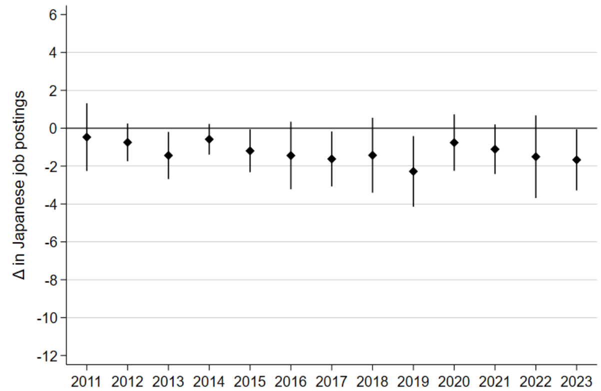


Note: This graph plots the γ_h coefficients of 12 separate 2SLS regressions as specified by Eq. 1. Spikes indicate 95% confidence intervals. Controls include changes in population, economic dynamism, demographic composition, and international trade with countries that speak languages other that English.

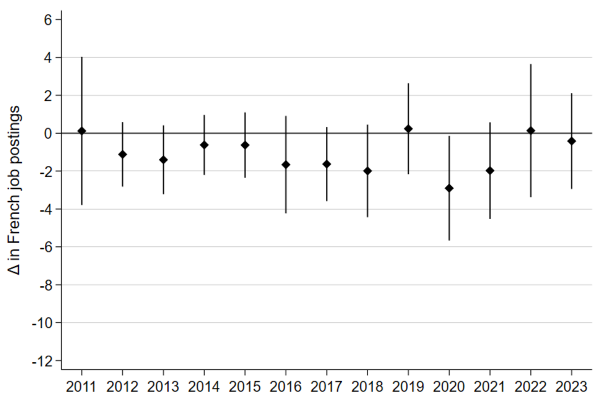
Figure A7 : Effect on the Demand for Other Languages



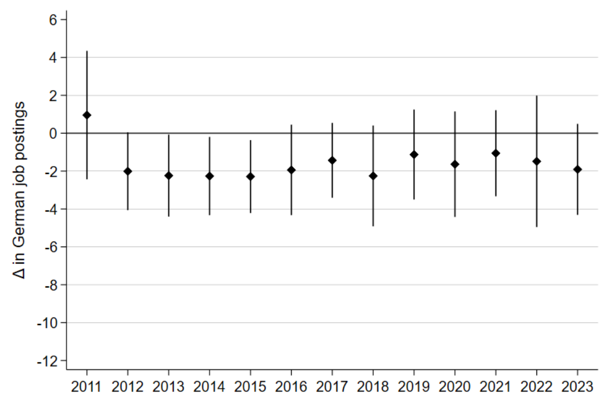
(a) Chinese



(b) Japanese



(c) French



(d) German

Note: All graphs plot the γ_h coefficients of 12 separate 2SLS regressions as specified by Eq. 1. Spikes indicate 95% confidence intervals. Controls include changes in population, economic dynamism, demographic composition, and international trade with countries that speak languages other that English.