Globalized Arts: International Migration and Stylistic Diversity among Artists (1400-2024)

Keywords: Sociology of Art, International Migration, Large Language Model, Vision transformer model, Causal Inference, Propensity Score

Extended Abstract

Research Question

This research would like to answer the long-standing questions in Sociology and Art history, through a migration perspective: **How did stylistic diversity of artists change through time? How would international migration experience influence individual stylistic diversity?**

Social theories have long discussed on how migration would shape artistic expressions. Basch et al. (2005) introduced transnationalism, explaining how migrants maintain cultural and artistic ties across borders. Similarly, the theory of identity by Hall (1990) suggests that art is a form of cultural representation shaped by historical and political contexts. More fundamentally, the decolonial theory by Fanon (2002) argues that displaced artists challenge dominant aesthetic paradigms by introducing alternative narratives. Empirical results also showed grounded evidence to these theories. Moelyono (2025) examines how choreographers working in multicultural environments blend movement vocabularies from different regions, resulting in hybrid dance forms. Some scholars even found a new phenomenon of ”global decentering” of art, which is due to the international migration of early generation artists (Lee et al., 2024), indirectly supporting the idea of migration effect on artistic diversity.

Data

The data from WikiArt.org, an open-access digital repository of paintings that provides metadata on artists and artworks, would be leveraged to address our questions. To enrich this dataset, additional demographic information—including international immigration status, education, and gender—was extracted by Large Language Models from Wikipedia.[1] To answer our research question, we would like to first quantify the artistic styles of artists from their artworks, and then use causal inference techniques to test how international migration would influence artistic diversity. The detailed research pipeline is shown in Fig. 1.

Predicting Stylistic Diversity

Following some previous attempts on ”measuring” art history (Dumoulin et al., 2017; Elgammal et al., 2018; Mezina & Burget, 2025), we employ a deep learning approach to predict the style diversity of artists. We used *contrastive learning* within a CLIP-based framework trained on over 171,430 paintings from over 2,752 artists to recognize style patterns. *CLIP* (Contrastive Language–Image Pre-training; Radford et al., 2021) jointly learns visual and textual representations by aligning images with corresponding textual descriptions. In our work, we adapt this

[1]We used GPT 4o-turbo to summarize the long wikipedia texts, and extracted the information by few-shot chain-of-thoughts prompts towards GPT 3.5

approach by fine-tuning the CLIP model on artworks to capture subtle stylistic cues. Specifically, each artwork's image is encoded via a pre-trained CLIP image encoder, and concurrently, a rich textual representation of the artist's social and demographic background is constructed by concatenating multiple columns from the artist dataset. Through contrastive learning using an InfoNCE-based loss (Oord et al., 2019), our dual-branch network is optimized to pull together the image embeddings and the associated artist text embeddings for artworks sharing similar stylistic labels while pushing apart those from different styles.

From the fine-tuned contrastive learning model, we could output the probability of each artists belonging to each styles, and compute the stylistic diversity by the variance of the probabilities. Fig. 2 shows the trend of style diversity in each period related to international migration. The diversity scores increased through the 19th and 20th century, especially around year of 1900. There is also a slight difference between high and low international migration rates years-the year of low international migration have lower style diversity than the others, specifically from about 1850 to 2000. Further, the style diversity for each artists would be standardized by their Z-score to a normal distribution.

International Immigration Effect on Stylistic Diversity

Accordingly, this study investigates the causal effect of international migration on the stylistic diversity of artists. International migration here is treated as a binary treatment variable (D), and demographic covariates such as education and gender serve as confounders (X). To address potential confounding, we adopt a causal inference framework based on propensity score estimation. Specifically, we first fit a logistic regression model predicting the probability of international migration given the covariates. The resulting propensity scores are then used to divide the sample into 10 subclasses (bins). Within each bin, a simple OLS regression of the style diversity outcome on the treatment is performed, and the bin-specific treatment effects are aggregated using a weighted average—yielding an overall average treatment effect (ATE).

Our subclassification approach produces an estimated ATE of 0.0340, indicating that international migration is associated with a slight increase in the diversity of artistic style as measured by our proxy. To assess the robustness and statistical significance of this effect, we perform a bootstrap procedure with 500 resamples. The bootstrap analysis yields a standard error of approximately 0.0062 and a 95% confidence interval ranging from 0.0022 to 0.0460, which does not include zero (see Fig.3). This suggests that the observed effect, albeit numerically small, is statistically significant. Furthermore, a randomization test is conducted by shuffling the treatment assignment within each propensity score subclass. The resulting null distribution of the ATE confirms that the observed effect is unlikely to arise by chance. While the effect size is modest, these findings contribute to the understanding of how international migration might influence artistic expression.

Future Directions

The current causal inference analysis was conducted at the artist level, comparing the treatment group (artists who immigrated) with the control group (artists who did not immigrate). For future research, given that we have timestamps for when each artwork was created and when each artist immigrated, a Difference-in-Differences (DiD) analysis could be implemented. This approach would allow us to compare an artist's style diversity before and after immigration while controlling for broader temporal trends, providing a more robust estimation of the causal impact of migration on artistic diversity.

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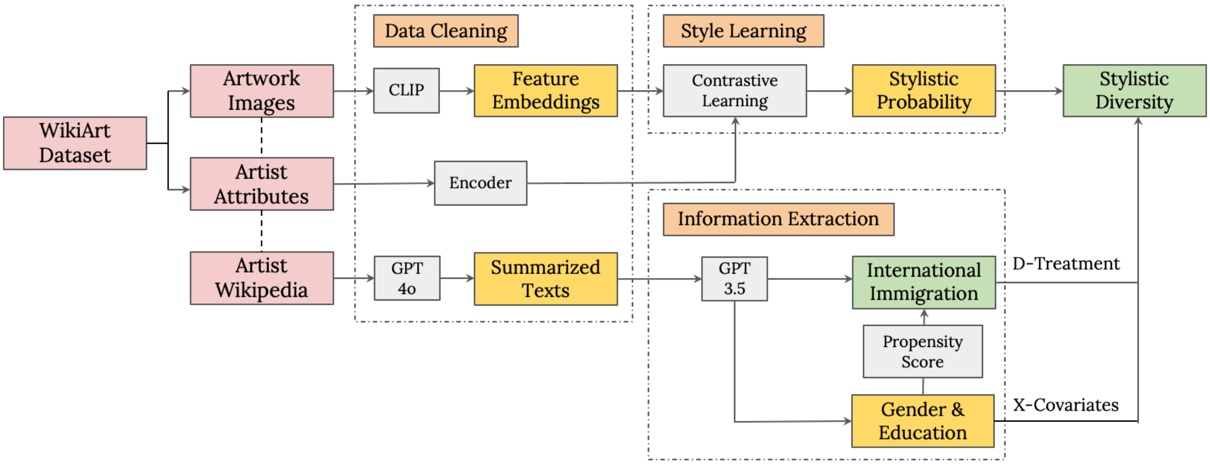

Figure 1: Research Pipeline

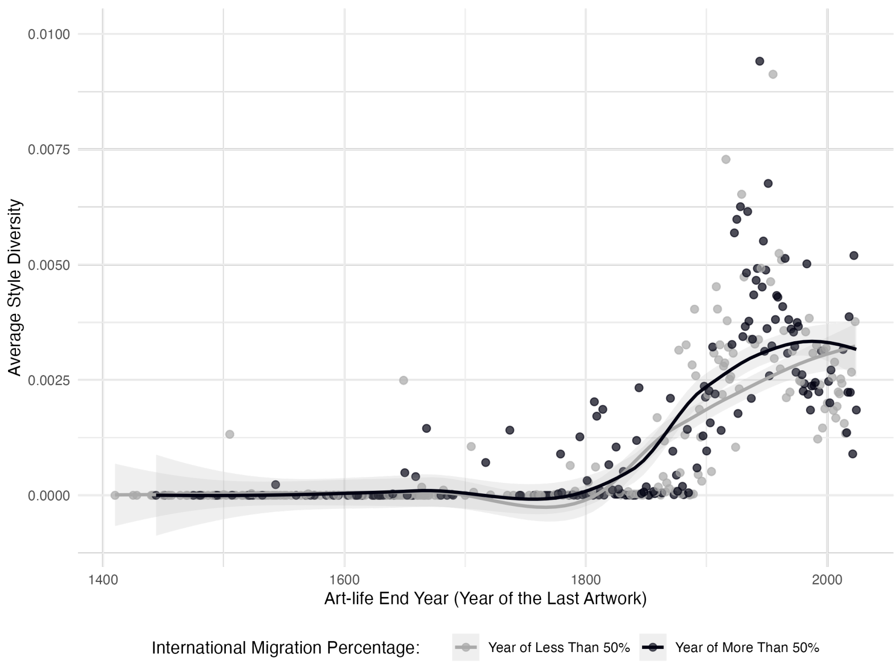

Figure 2: Average Style Diversity by Art-life End Year

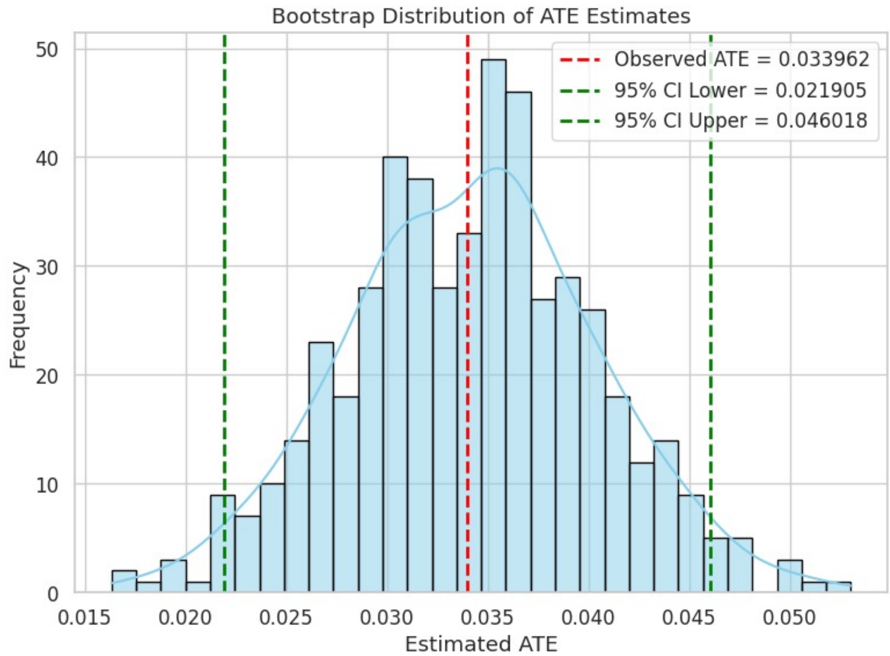

Figure 3: Bootstrap Distribution of ATE Estimates