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The Relationship Between Social Media Trends and Trade Flows: Analysing the Global Matcha Trend

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Abstract

This study aims to investigate how social media trends affect international trade through a study on the relationship between the global matcha tea trend and Japanese green tea exports. The study is performed in two steps, due to limitations in social media data access. Firstly, a time-series regression is used to analyse the relationship between global TikTok views and Google search intensity for matcha, finding a strong and economically meaningful positive association. Secondly, a gravity model of Japanese green tea exports to 148 countries over the period 2010-2025 is estimated using Google search intensity as a proxy for the social media trend. The regression is estimated with a Poisson Pseudo Maximum Likelihood estimator as well as importer and year-month fixed effects. The results from the preferred gravity specification do not show a statistically significant relationship between Google search intensity and exports. However, alternative specifications with less fixed effects reveal a positive association with statistical significance, suggesting that the matcha trend operates primarily as a global demand shifter rather than through importer-specific demand responses. The research performed and the model applied are new additions to literature on international economics, and the results highlight the relevance of future research with improved models to increase the understanding of social media trends' effects on trade flows.

Keywords: *Google Trends, Gravity Model, Japan, Matcha, TikTok, Trade, Social Media, Trend, Poisson Pseudo Maximum Likelihood, Fixed Effects*

List of Abbreviations

CEPII - Centre d'Etudes Prospectives et d'Informations Internationales

FE - Fixed Effects

GDP - Gross Domestic Product

HAC - Heteroskedasticity and Autocorrelation Consistent

IMF - International Monetary Fund

OLS - Ordinary Least Squares

PPML - Poisson Pseudo-Maximum Likelihood

SE - Standard Errors

UNPD - United Nations Population Division

HS - Harmonized System

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1 Introduction

How is it that a tea traditionally consumed by Japanese monks in ceremonial contexts, often described by first-time drinkers as tasting like “liquid grass”, has become one of the most popular beverages in cafés across the world? How has a green tea that, until recently, was largely unknown outside Japan evolved into one of the country’s fastest-growing export commodities?

Since their introduction to the world, social media platforms have evolved from digital spaces for personal interaction to powerful arenas of global influence, shaping consumer preferences, cultural exchange, and economic behavior. Today, social media is widely recognized as a factor influencing consumption patterns and the diffusion of trends. However, the extent to which social media can affect consumers’ interest in specific products, and how this interest translates into international trade, remains an open question in economic research. The global rise of matcha makes a compelling case to study this phenomenon through.

Matcha, a finely ground green tea with deep cultural roots in Japan, has in recent years become a prominent feature of global food and lifestyle trends, receiving substantial attention on social media platforms. Simultaneously, Japanese ministries have reported rapidly increasing exports, whilst prices are rising and concerns about limited supplies are emerging (Chia, 2025). This development raises broader questions about how digitally driven trends can influence trade patterns and export performance.

The purpose of this thesis is to investigate if a correlation between social media trends and international trade flows can be found through economic modelling, using the case of matcha tea exports from Japan. More specifically, the study examines to what degree increased consumer interest associated with social media trends has contributed to higher Japanese green tea exports. Focusing on matcha provides a context with strong product-country associations, making it well suited for analyzing how social media trends translate into observable changes in trade flows. The research question addressed is hence stated as followingly: “Do social media trends affect international trade flows?”, which is examined by the more specific question, “To what degree has the social media matcha trend affected Japanese green tea exports?”.

The empirical analysis follows a two-step quantitative approach. In the first step, a time-series regression is used to examine the relationship between social media exposure, proxied by TikTok views, and consumer interest, measured by Google searches. This step aims to motivate the use of Google Trends search data as a proxy for the social media trend in the following step, since TikTok data is available only over a limited timespan.

In the second step, a gravity model of trade is estimated to analyze the relationship between consumer interest and trade patterns, more specifically Japanese green tea exports. Google Trends data and export data from 148 importing countries over the period January 2010 to November 2025 are combined with standard gravity variables. This constitutes, to the knowledge of the author, the most comprehensive empirical analysis of matcha trade to date in terms of country coverage and time span. Furthermore, it adds to broader literature on social media's impact on consumer behavior, and the role of information access in international trade, by linking the two together. While the analysis is constrained by data limitations, it aims to offer a new perspective on how demand-side forces driven by social media may affect international trade flows, and initiate future research on the topic.

The main results indicate that social media exposure highly correlates with consumer interest, but further analysis shows a non-significant relationship between consumer interest as a trend proxy and Japanese green tea exports. However, alternative specifications with less fixed effects reveal a positive association with statistical significance, suggesting that the matcha trend operates primarily as a global demand shock rather than through importer-specific demand responses.

Following this introduction, the thesis proceeds as follows. Section 2 provides background on matcha and its recent global diffusion. Section 3 outlines the theoretical framework linking social media influence to consumer demand and trade. Section 4 reviews relevant literature. Section 5 describes the data and empirical strategy. Section 6 presents the results, followed by a discussion in Section 7. Section 8 concludes.

2 Background: Introducing the matcha case

This chapter aims to give a solid background to the research topic by providing an informative background on matcha tea, the social media trend, and matcha export developments.

2.1 What is matcha?

Matcha is a powdered green tea that has been a part of Japanese tradition for centuries. The tea is distinguished by its powdered form, stemming from China brought to Japan by Buddhist monks, and that the tea leaves used to create the powder, Tencha, are grown in shadow, giving the tea its distinct flavour (Iro, 2025) and its characterizing bright green colour (Tea & Coffee Trade Journal, 2024).

Ever since the 16th century, matcha tea has served as a ceremonial drink in the Japanese tea ceremony “Cha-No-Yu” (Iro, 2025), making the tea deeply cultural to the Japanese people. Except for its cultural value, the tea is drunk for its supposed health benefits and awakening effects, bearing high levels of antioxidants and more caffeine than other green teas (Tea & Coffee Trade Journal, 2024).

2.2 The matcha trend

Up until mid 2010’s, matcha tea was mostly consumed in Japan and a few other Asian countries, and limited amounts were exported internationally. But over the past decade, both production and exports have drastically increased. According to a BBC article, the Japanese agricultural ministry has reported that matcha production almost tripled between 2010 and 2023, and that green tea exports, including matcha, increased by 25% during 2024 (Chia, 2025). Today, the tea has become a standard product at cafés all over the world. Additionally, matcha is increasingly used in ways other than drinking, for example as an ingredient in cooking, baking and even beauty products (The Economist, 2025; Fukuyama, 2025).

Figure 1. Gwyneth Paltrow's Instagram post showing her drinking a matcha latte in 2015. Source: Paltrow, G (2026).

The increase in production and exports have been connected to the covid-pandemic, health food interest, increased tourism to Japan, and social media trends (Chia, 2025; Enjoji, 2025). During the Covid-19 pandemic, demand for health supplements and nutritional food increased, and post-pandemic the Japanese Yen has decreased in value - opening up for a tourist-boom in Japan (Chia, 2025). Meanwhile this is deemed to have contributed to the matcha trend, social media is often mentioned as the key contributor. Figure 1 (Paltrow, 2026) shows an Instagram post from 2015 made by actor and health entrepreneur Gwyneth Paltrow, cited as a pivotal moment in matcha's early expansion beyond Japan (Hari, 2024). Today, influencers as well as amateur social media users promote matcha-drinking by sharing recipes, matcha vendor reviews, and creative ways to use matcha by uploading pictures and videos of the eye-catching drink. Figure 2 (TikTok, 2026) illustrates examples of how this is displayed on TikTok. All videos have an amount of views ranging between 26,3 thousand and 3,9 million, and between 975 and 288 thousand likes, indicating high exposure on the platform.

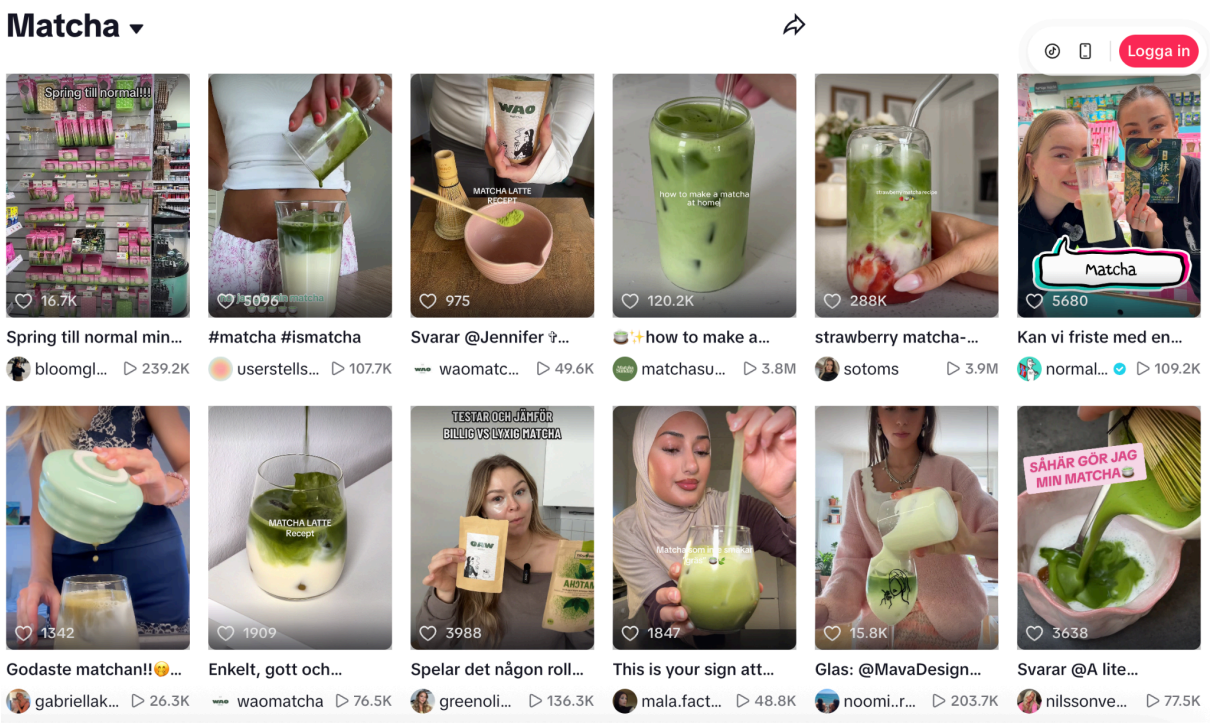

Figure 2. A screenshot of TikTok's page for posts related to keyword "Matcha", illustrating examples of the content that accumulates to the trend. Source: TikTok (2026).

In December 2025, 9.8 million posts using the hashtag "matcha" have been uploaded to Instagram, and similar hashtags such as "matchalover", "matchatea", and "matchalatte" have been used on tens of millions of posts on the platform (Instagram, 2025). On TikTok, 283 million posts associated with matcha have been uploaded (TikTok, 2026), aggregating over 15 billion views in total (The Economist, 2025). Figure 3 (Exolyt, 2025) illustrates a part of this, showing the development of posts and views on TikTok between January 2024 and December 2025.

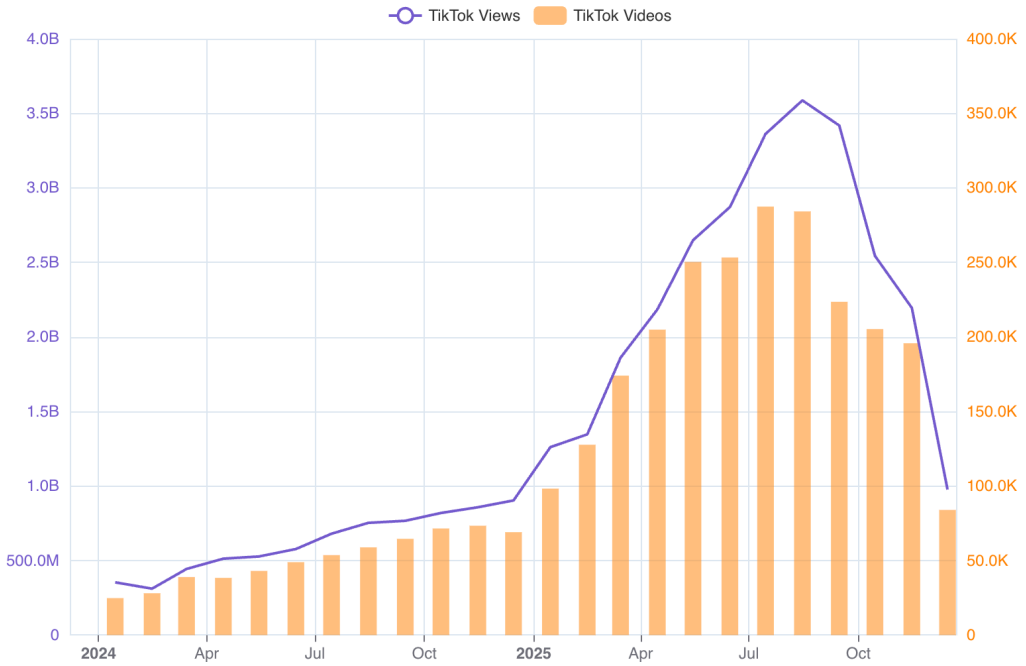

Figure 3. Diagram showing the amount of posted videos to TikTok with the hashtag "matcha", and their amount of views, between January 2024 and December 2025. Source: Exolyt (2025).

In media (The Economist, 2025; Chia, 2025; Enjoji, 2025), TikTok is mentioned as the social media platform where the trend is most widespread, aligning with data from Google Trends (2025) enhanced by Glimpse.[1] According to this data, TikTok is the social media platform where the term "matcha" is most frequently used, far beyond the average for a social media platform. This strongly speaks for TikTok being the most important social media for the matcha trend.

Furthermore, a trend can be seen on Google's search statistics, showing a clearly increasing consumer interest for the green tea. The word "matcha" was searched 23 million times in August 2025, compared to 10 million times in August 2024, 5,3 million times in August 2020, and 3 million times in August 2015 (Google Trends, 2025). Figure 4 (Google Trends, 2025) illustrates the global Google Trends index[2] for the word "matcha" over the period January 2010-November 2025, showing a clear upward sloping trend over time.

[1] Glimpse is a Chrome enhancer for Google Trends, providing deeper insights to data.
[2] The Google Trends index measures Google searches in an index from 0-100. Google Trends (2025) explains the index as followingly: "Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term".

Figure 4. Global Google Trends index for word “matcha” between January 2010-November 2025. Source: Google Trends (2025).

The interest for matcha is widely spread over the world. Figure 5 (Google Trends, 2025) illustrates the global interest, from which it can be concluded that the interest is highest in South East Asia, Australia, large parts of Europe and North America.

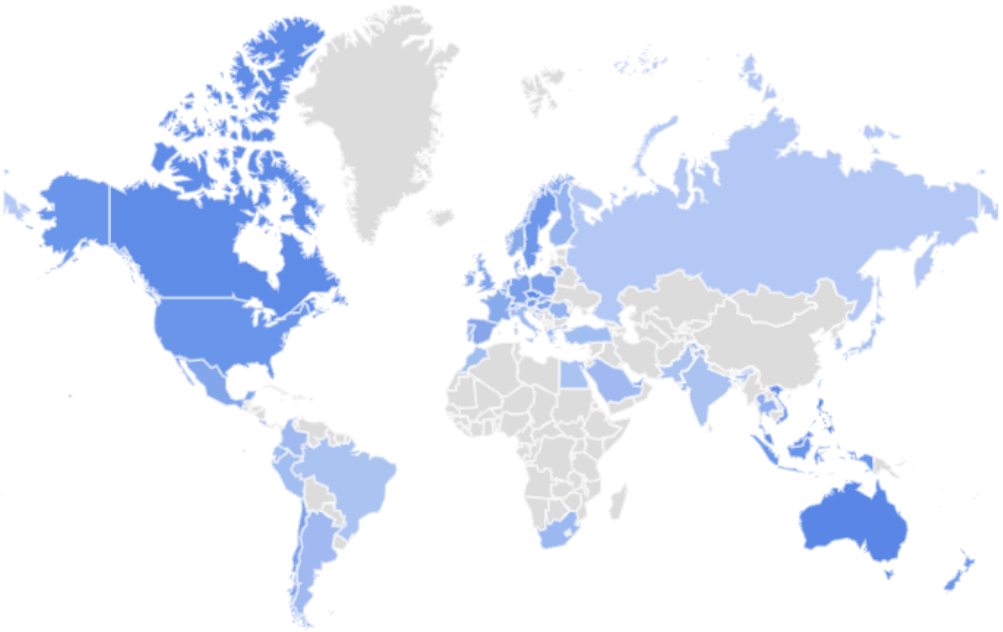

Figure 5. World map where a darker blue colour indicates a higher ratio of Google searches for word “matcha” out of total domestic Google searches. Source: Google Trends (2025).

The surging global demand is already meeting obstacles in Japan. Due to an aging farmer population, climate changes and increased U.S. tariffs, difficulties to meet the surging demand

are becoming increasingly prominent, pushing up prices in both Japan and globally (Chia, 2025).

It is clear that the powdered green tea has gone from being a ceremonial speciality mostly drunk domestically in Japan and parts of Asia, to a globally sought after commodity. This provokes an interest to economically analyse the relationship between the TikTok-trend and the effects on Japanese exports, to gain broader insights on how social media trends can affect international trade flows.

3 Theoretical framework: the link between social media trends and trade flows

In international economics and trade theory, bilateral trade flows are explained by a combination of economic size, trade costs and supply- and demand conditions. Classical trade theories, such as those by Ricardo and Heckscher & Ohlin, focus on supply-side factors such as comparative advantage and factor endowments, whilst more modern theories increasingly point to the relevance of demand-side forces in trade (van Marrewijk, 2017).

In consumer theory, the demand for a commodity depends on income, prices and preferences. Whilst income and prices are intuitively measured through Gross Domestic Product (GDP) and price indexes, preferences are harder to directly observe. According to newer theory by e.g. Krugman, consumer demands are not only affected by prices and income, but also from product differentiation (van Marrewijk, 2017). Economic theory, especially within advertising, also recognises that information and awareness affects consumer preferences. When consumers are exposed to a lot of information about a product, the chances they consume the product increase, and hence creates demand shifts (Bagwell, 2007).

The Cambridge Dictionary defines a trend as “a general development or change in a situation or in the way that people are behaving” (Cambridge University Press & Assessment, 2026). From an economic perspective, trends arise through social interaction, information diffusion and coordination in preferences. This paints a case of consumers forming preferences in collectives, being influenced by the behaviour and choices of others, rather than forming individual preferences. Banerjee (1992) and Bikhchandani, Hirshleifer & Welch (1992) have analysed this through models on herd behavior and informational cascades; a phenomenon where individuals mimic the actions of others, either ignoring to act on their own information or simply not seeking information of their own. These behaviours and mechanisms are described as a key force behind a certain type of trend formation, called social learning. Once a large number of consumers buy or endorse a product, consummation becomes self-reinforcing, which could be interpreted as trend-creation.

Later work on consumer preferences emphasizes that individuals are not merely passive imitators of others’ behavior. In the Friedkin-Johnsen model, individuals develop their

opinions through a combination of their initial beliefs and the behavior of others (Friedkin & Johnsen, 1999). Unlike pure herding frameworks, this model allows for individual preferences while still allowing for coordinated shifts in behavior, creating trends. Increased visibility of others' choices, such as through social media, can therefore shape consumer attention and demand, reinforcing trends without eliminating individual differences in tastes.

Further, social media trends can be seen as demand-side preference shocks, changing consumption patterns over time. In an international trade context, such preference shocks can increase import demand for products from specific exporting countries, continuingly affecting bilateral trade flows. This aligns with models of monopolistic competition and differentiated goods by Krugman, where demand shifts translate into changes in export volumes rather than prices alone (van Marrewijk, 2017).

This thesis builds on these theoretical insights by empirically examining whether a social media trend is associated with higher consumer interest and affected bilateral trade flows of Japanese matcha.

4 Previous research

Extensive research has been done on the relationship between social media content and consumer behaviour, primarily within the fields of marketing and consumer psychology. A large part of this research focuses on how firms and brands can use social media platforms to influence consumer's purchasing decisions, and usually rely on survey data, interviews or experimental approaches, rather than analysing market and social media data.

Stephen (2016) provides a comprehensive overview of how social media influences the consumer decision-making process, and emphasizes the role of user interaction and user-generated content in shaping consumer preferences. Other empirical studies similarly find that exposure to products on social media is associated with increased purchase intentions and consumption, particularly for lifestyle-oriented and experience goods. For example, Varghese & Agrawal's (2021) survey-based analysis finds that consumers being exposed to goods through social media are willing to spend more money on purchases, and purchase more impulsively, than in cases where social media has not been an influence.

While this marketing focused research demonstrates a clear link between social media and consumer behavior, it does not involve or analyse international trade outcomes. In contrast, a separate branch of research in international economics studies how information and communication technologies affect trade flows. Early studies, e.g. those by Freund and Weinhold (2004) as well as Clarke and Wallsten (2006), find that increased internet availability and digital connectivity is associated with larger bilateral trade volumes, primarily through reduced information frictions and search costs. This has been further confirmed by following studies, for example that by Vissner (2019) showing that increased internet penetration and broadband coverage stimulates trade and decreases trade costs. A more recent study by Bailey et. al. (2021) furthermore find that strong connections over social media platforms increase bilateral trade flows, by analysing Facebook and bilateral trade data between 170 countries. These contributions suggest that improved access to information can be enough to stimulate increased trade flows, even if trade costs remain the same.

However, research explicitly studying the relationship between social media trends and observed international trade flows, is new ground. Existing trade-focused studies often use broad measures of internet access or digital infrastructure, or focus on general social media

connections rather than trends. As a result, social media-driven preference shocks and their influence on trade flows is an area of study to be further developed, hopefully initiated by this first study.

In the context of Japanese matcha, prior research has mainly been qualitative or descriptive. A study by Farahiyah, Oceanie and Janah (2025) report how matcha has been pictured as a health product and lifestyle symbol on the social media platforms Instagram and TikTok, often promoted by influencers and wellness communities. The study similarly to this one applies data from Exolyt,[3] but does not relate their analysis to a perspective on trade.

When looking at strategies to proxy consumer interest and demand, a growing number of studies have begun to use Google Trends data. Choi and Varian (2012) demonstrate that search intensity can predict concurrent economic activity, and later research has used Google Trends to e.g. predict tourism flows (Wen et al., 2021) and private consumption (Vosen & Schmidt, 2011). This literature supports the use of search data as an observable indicator of underlying consumer interest.

This thesis contributes to the existing literature by empirically connecting social media trends, consumer interest to international trade flows within a gravity framework. By combining TikTok data, Google Trends data and bilateral export data from Japan, the analysis bridges insights from marketing-oriented research on consumer behavior with economic models of trade. Rather than focusing on firm-level strategies, this study examines whether aggregate measures of consumer attention are systematically associated with export performance across countries over time. In doing so, the thesis extends prior research on information frictions and demand shifters in international trade, while also contributing to the literature that uses data from digital platforms to study economic behavior. The specific focus on matcha allows for an application where product-country associations are strong, making it a suitable case for analyzing how social media trends may translate into observably changing or emerging trade flows.

[3] Exolyt is a platform providing data and analyses of TikTok-content. See further discussions about Exolyt in chapter 5.3.2.

5 Empirical strategy

To investigate the research question, a quantitative study is performed through a two step analysis aiming to make the social media matcha trend and its effects measurable. Because of its high impact on the social media trend, TikTok is the social media platform observed in this study. Due to the lack of extensive data from TikTok,[4] the first step in the empirical strategy is to investigate the correlation between TikTok-views and Google Trends index, to validate usage of the latter as a proxy for the social media trend in the main model.

The second step of the strategy presents the main model. Here, a gravity framework is applied to analyse the relationship between consumer interest and trade, by using Japanese bilateral matcha exports as the dependent variable and data on Google Trends index together with standard gravity model variables as explanatory variables.

The empirical model is an object for estimation issues, which are accounted for later in this chapter. Followingly, the applied data and sample is presented, and its limitations discussed.

5.1 Empirical model

5.1.1. Step 1: The relationship between trend and consumer interest

In the first step, the correlation between the trend on TikTok and Google searches is tested. In other words; an analysis of the relationship between trend and consumer interest. The following linear model is defined:

$$(1)\ Google_t = \beta_0 + \beta_1 \ln(TikTok_t) + \varepsilon_t$$

$Google_t$ represents the Google Trends index for matcha in the world at time t, and β_0 is a constant term capturing the baseline level of the index. $TikTok_t$ represents amount of views on posts labeled "#matcha" on TikTok at time t, and is logged to limit the influence of extreme observations and allow for more intuitive interpretation of β_1. β_1 will be interpreted as a semi-elasticity, translating into the point change in Google Trend index when TikTok views

[4] Sample and data for TikTok is presented and discussed further in chapter 5.3.2.

increase by one percent. Lastly, the error term ε_t accounts for variations in the dependent variable that are not explained by the explanatory variable.

The hypotheses tested in this model are stated as followingly:

- The null hypothesis (H_0): There is no significant relationship between Google Trends index and number of TikTok views ($\beta_1 = 0$).
- The alternative hypothesis (H_A): Google Trends index increases with the number of TikTok views ($\beta_1 > 0.$).

According to the theoretical framework and previous research connecting social media influence to increased consumer interest, β_1 is expected to be positive. This would indicate a positive relationship between TikTok views and the Google Trends index, and hence that the TikTok-trend has a strong correlation with the consumer interest of matcha. This would mean we can reject the null hypothesis, and motivates the use of the Google Trends index as a proxy for the TikTok trend in the following step.

5.1.2 Step 2: The relationship between consumer interest and trade flows

Step 2, the main model, is performed with a Gravity model used to explain the relationship between the consumers' matcha interest and Japanese matcha exports. The Gravity model of trade is a standard empirical framework in international economics, stemming from Tinbergen (1962). The model explains bilateral trade flows as a function of economic size and trade costs, predicting that trade between two countries increases with their economic mass, commonly measured by GDP, population and/or GDP per capita, and decreases with trade frictions such as transport and coordination costs, proxied by geographic distance. The model by Tinbergen has later been added to with theoretical cementing by Anderson and van Wincoop (2003), making the model widely used in contemporary international economics (Yotov et al., 2016). Yotov et al. (2016) provide an extensive practical guide on the applications of the gravity model, which at large is the base for this section's empirical model.

To capture variation in demand affected by the social media trend, the model adds Google Trends index, capturing consumer interest, as a proxy for the trend. The main estimation of

the main model is performed with a Poisson Pseudo-Maximum Likelihood (PPML) estimator.[5] The regression is hence expressed accordingly:

$$(2)\ Ex_{jt} = \exp(\beta_0 + \beta_1 Google_{jt} + \beta_2 \ln(GDP_{jt}) + \beta_3 \ln(Population_{jt}) + \lambda_j + \gamma_t + \varepsilon_{jt})$$

Ex_{jt} represents the exports of green tea from Japan to importer j at time t, and β_0 is a constant term capturing the baseline level of exports. $Google_{jt}$ represents the Google Trends index for "matcha" in importer j at time t, GDP_{jt} the size of the economy in importer j at time t, and $Population_{jt}$ is the size of the importer j at time t.

The explanatory variables GDP and population are logged to simplify interpretation, according to gravity model and PPML estimation standards (Santos Silva & Tenreyro, 2006). Since the dependent variable is kept in levels, according to PPML requirements (Santos Silva & Tenreyro, 2006), β_2 and β_3 are hence interpreted as elasticities where the coefficient represents the percent change in exports per 1-percent change in GDP and population, respectively. The explanatory variable Google is kept in levels to assure zero values in data are kept in the analysis, which makes β_1 be interpreted as a semi-elasticity: per 1-point index change, exports will change by $100 \times \beta_1$ percent.

Fixed effects (FE) are included in the regression to account for otherwise not observed explanatory factors.[6] λ_j captures the importer FE, γ_t captures the year-month FE,[7] and ε_{jt} represents the error term capturing variations in the dependent variable that are not explained by the explanatory variables.

The hypotheses tested in this model are stated as followingly:

- The null hypothesis (H_0): There is no significant relationship between exports and Google Trends index ($\beta_1 = 0$).
- The alternative hypothesis (H_A): Exports increase with Google Trends index ($\beta_1 > 0$).

[5] The PPML estimator is in this case mainly used to preserve zero values in trade flows, but serves multiple purposes (Yotov et al., 2016). See Section 5.2.2 for further discussion on PPML.
[6] The purpose of FE is further explained and discussed in chapter 5.2.2.
[7] Year-month FE refers to fixed effects for each year-month combination, e.g. February 2018, February 2019 etc, common for all importing countries.

β_1 is expected to be positive, since the theoretical framework can be interpreted as the trend being a demand shifter, implying increased trade flows. Also β_2 and β_3 are expected to be positive, since higher GDP and larger populations tend to lead to increased trade flows according to gravity theory (Yotov et al., 2016).

As a first robustness check, results with a log-linear ordinary least squares (OLS) estimator will be reported for the main model. This is *not* the main nor preferred estimator for the model, but is performed to compare the results to the more standardized estimator. The regression adapted to OLS is expressed as followingly:

$$(3)\ \ln Ex_{ijt} = \beta_0 + \beta_1 Google_{jt} + \beta_2 \ln(GDP_{jt}) + \beta_3 \ln(Population_{jt}) + \lambda_j + \gamma_t + \varepsilon_{jt}$$

Additionally, robustness checks including the variable $Distance_j$ and excluding importer FE, will be performed with both OLS and PPML estimators. In regression (2) and (3), a variable for distance is excluded since importer FE absorbs all time-invariant country characteristics, including geographic distance to Japan. The opposite choice could have been done; omitting importer FE and including distance in the regression, but importer FE was kept since it accounts for a large variety of trade costs, whilst distance accounts for one, in itself. The PPML adapted regression with distance is expressed as followingly:

$$(4)\ Ex_{jt} = \exp(\beta_0 + \beta_1 Google_{jt} + \beta_2 \ln(GDP_{jt}) + \beta_3 \ln(Population_{jt}) + \beta_4 \ln(Distance_j) + \gamma_t + \varepsilon_{jt})$$

Where $Distance_j$ is the geographic distance between Japan and the importer j. β_4 is interpreted as an elasticity where the coefficient represents the percent change in exports per 1-percent change in distance. β_4 is expected to be negative, since increased bilateral distance tends to decrease trade flows (Yotov et al., 2016).

Lastly, a robustness test including lagging of the Google Trends index by one month will be performed. This is performed to account for delays between observed Google searches and observed Japanese exports, which may arise both from consumers taking time between information-seeking and actual purchasing, as well as logistical frictions in reporting exports. The regression with lagged Google Trends index is stated as followingly:

$$(5)\ Ex_{jt} = \exp(\beta_0 + \beta_1 Google_{j(t-1)} + \beta_2 \ln(GDP_{jt}) + \beta_3 \ln(Population_{jt}) + \lambda_j + \gamma_t + \varepsilon_{jt})$$

5.2 Estimation issues and applied approaches

The empirical models and data presented come with certain estimation issues, which together with the applied approaches to handle them, are accounted for in this chapter.

5.2.1 Estimations issues and approaches in Step 1

The regression in Step 1 is estimated using heteroskedasticity and autocorrelation consistent (HAC) standard errors (SE) to account for the time-series nature of the data.[8] Monthly observations of TikTok views and Google Trends index may exhibit serial correlation, as shocks to social media activity and consumer interest can persist across continuous months. In addition, periods of viral activity can generate heteroskedastic error variance over time. HAC standard errors provide valid statistical inference in the presence of both heteroskedasticity and autocorrelation, and hence acts as the applied approach towards the issue (Newey and West, 1987).

The HAC standard errors are computed using the Newey-West estimator. The lag length is chosen according to the rule of thumb $L = 0{,}75T^{1/3}$, a simplified rule originating from literature by Newey and West (1994), where T represents the number of time periods. With a sample size of 23 monthly observations, the rule of thumb suggests a lag length of 3, which is the length applied to the estimation.[9]

5.2.2 Estimations issues and approaches in Step 2

A key insight from the structural gravity framework provided by Anderson and van Wincoop (2003) is the importance of multilateral resistance. The idea of multilateral resistance acknowledges that trade between two countries is not only affected by their direct relationship, but also by the trade costs and opportunities with all other countries, creating complex, interconnected patterns in international trade. Failing to account for these so called multilateral resistance terms can lead to omitted variable bias. This is typically accounted for through the inclusion of country fixed effects and time fixed effects (Yotov et al., 2016), as in

[8] See chapter 5.3.6 for a discussion on the limitations in the TikTok data, including the unavailability of cross-sectional data.
[9] The result of the rule of thumb should be rounded upwards. $0{,}75*23^{1/3} = 2{,}1329$ which rounded upwards indicates usage of lag length 3.

this empirical model. In this study, they are specifically referred to as importer FE and year-month FE. Importer FE absorbs all time-invariant country characteristics affecting trade with Japan, including geographic distance, cultural ties, and persistent trade policies. Year-month FE captures global shocks and common trends, such as changes in world demand, shipping conditions, or economic cycles for each specific year-month combination. Standard models also suggest using exporter FE (Yotov et al., 2016), but since Japan is the sole exporter in this study, importer FE are the equivalent of pair FE; accounting for the relationship between two countries. Followingly, export FE are already captured by the importer FE.

A critique against the usage of FE, in this case especially the year-month FE, is that they can absorb much of the variation caused by social media trends. As stated in the theoretical framework, social media trends spread over country borders and could be seen as global demand shifters. Simultaneously, global shocks is one of the factors time FE absorbs. Therefore, results without FE will be reported and analysed in comparison with the FE-including estimations.

Furthermore, the main estimation is performed with a Poisson Pseudo-Maximum Likelihood (PPML) estimator together with robust and clustered standard errors. The usage of an PPML estimator became standard practice after the release of an influential paper by Santos Silva & Tenreyro (2006). Their research highlights that PPML is a robust approach for two common estimation issues in trade data: heteroskedasticity and zero values. International trade data is characterized by heteroskedasticity, meaning that the variance of export flows increases with their magnitude of export flows. The previous standard with OLS estimates did not solve this issue, since it requires the dependent variable to be logged, creating biased estimates of coefficients (Santos Silva & Tenreyro, 2006). The PPML estimator can on the other hand be applied to the levels of trade data, estimating the multiplicable form of the gravity model, providing constant estimates of coefficients. Furthermore, PPML accounts for zero values, which is frequent in trade data. Logging the dependent variable, as demanded by OLS, excludes zero values which might result in biased results, since zero trade flows could be systematically related to explanatory variables. Because of the PPML estimator's ability to keep data in levels, zeros are kept in the sample and hence accounted for in the estimates. This approach has been used in a number of estimations of gravity equations, and is recommended by Yotos et al. (2016) in their substantial guide.

Statistical inference is furthermore based on robust standard errors clustered at the importer level. Robust standard errors are used to account for potential differences in the variability of trade flows, while clustering at the importer level accounts for correlation in the error terms within importing countries over time. This approach provides more reliable measures of statistical significance given the panel structure of the data.

5.3 Data and sample

In this chapter, the applied data, sample and sources are presented. Furthermore, limitations in the data and sample are discussed, since they affect the interpretation of the result.

5.3.1 Sample

The sample varies over the two models. In model 1, observations are made monthly between January 2024 and November 2025. This time span was chosen since TikTok-data was only available for this period when the data was collected.[10] The sample is furthermore on data on a worldwide-level.[11]

In model 2, the sample includes 148 importer countries.[12] The set is determined by the intersection of the countries available in the UN Comtrade-database and those for which Google Trend index was available over the sample period presented further below. Countries for which Google Trends data were unavailable were excluded from the main specification, as search interest, the trend, cannot be observed. In the context of this thesis, such data is crucial for the research. Countries for which export data is missing are excluded according to the same logic. A small number of countries[13] were excluded from the sample due to substantial missing data in GDP, a core variable in the gravity framework. Rather than running the regression without GDP for these countries, which could result in measurement errors, the analysis prioritizes data consistency over the potential risk for bias.

Observations are made monthly from January 2010 to November 2025. The start in January 2010 is chosen to cover a period of time pre-trend, fully capturing the development of the

[10] In December 2025.
[11] See chapter 5.3.6 for a discussion on the limitations in the TikTok data, including the unavailability of cross-sectional data.
[12] See Appendix 1 for the full set of countries analysed.
[13] Afghanistan, Bhutan, Cuba, Lebanon, Syria, Sri Lanka & Yemen.

trend and its effects. Data is observed up until November 2025, which is as recent data observations were available in Google Trends at the time of retrieving data.[14] The large sample approach reduces selection bias and allows for a systematic analysis of the trend-trade relationship.

5.3.2 TikTok

TikTok is the variable used to represent the social media trend in the first model, and represents monthly data on the number of views on posts with the hashtag "matcha" uploaded to TikTok. The data on views specifically was chosen over e.g. data on the amount of uploaded posts related to matcha, since views are deemed to more accurately capture the level of trend outreach. Social media posts can be made by a small number of people, but the number of views capture how large the outreach of these posts have been, hence, how widespread the matcha-trend is.

TikTok-data is a necessity in this study since it is the social media platform that has been most influential in the matcha trend (Google Trends, 2025), and is therefore a suitable option to represent the trend. The concrete and real-time data furthermore provides a way to quantitatively measure the social media trend's scope.

The data was retrieved from Exolyt (2025), a platform providing data and analyses of TikTok-content. Data on total values of monthly TikTok views was manually collected from the platform. Attempts were made to retrieve data from the primary source, but such efforts failed because of the lack of publicly available data. The choice to use a secondary source was made in relation to the importance of the usage of TikTok-data, where the latter was deemed important enough to motivate the use of a non-primary source.

5.3.3 Google Trends index

The variable *Google* is present in both steps: as the dependent variable in regression 1, and an independent variable, proxying the social media trend, in regression 2 and 3. *Google* represents consumer interest through the Google Trends index for the word "matcha", provided from Google Trends (2025). This data is crucial for the analysis since it provides us

[14] In December 2025.

with a measurable level of consumer interest, and has available data for a longer time span and a larger set of countries than TikTok.

The Google Trends dataset for regression 1 was downloaded from Google Trends (2025). The dataset for regression 2 and 3 was manually created by downloading index-datasets from Google Trends (2025) for each individual importer country analysed, and furthermore compiling them.

5.3.4 Japanese exports

Ex is the variable used to represent the Japanese exports of matcha, the dependent variable in the main model (Step 2). The variable includes data on Japan's reported net weight (kg) of green tea exports, where matcha tea is included, to the 148 sample countries. The data is retrieved from the UN Comtrade database by the United Nations Statistics Division (2025). The database categorizes commodities by the Harmonized System (HS), where green tea (matcha included), is categorized in two sub-groups.[15] It is the combined exported weight within these two groups of commodities that are included in the variable. Both sub-groups are included to cover the full scope of matcha-exports, which is of relevance to answer the research question. Exports are measured using net weight (kg) in order to capture changes in physical trade volumes and avoid confounding effects from price variation, quality upgrading, and exchange rate movements.

While mirror import data sometimes differ from Japan's exporter-reported flows, e.g. Nicaragua reporting matcha-imports from Japan but Japan not reporting matcha-exports to Nicaragua, a single reporting side is used consistently to avoid measurement inconsistency. Missing export observations are therefore indirectly treated as zero trade flows.

5.3.5 Macroeconomic variables

The latter explanatory variables used in the second step are included based on Gravity model-standards (Bacchetta et al., 2012). Gross Domestic Product (GDP) is included to capture the market size of the countries importing matcha from Japan. Population is included

[15] The two HS sub-groups are **0902-10** "Green tea (not fermented) in immediate packings of a content not exceeding 3 kg", and **0902-20** "Other green tea (not fermented)" (i.e. green tea packings of a content exceeding 3 kg).

to control for matcha importing countries sizes, and Distance represents a measure on bilateral trade costs when importer FE are excluded.

The data on both GDP and Population was retrieved on a yearly level for years 2010-2024 from the World Bank (2025). At the time for data retrieval[16] the World Bank did not provide data on GDP nor population for the year of 2025. Hence, 2025 projections from the International Monetary Fund (IMF) (2025) and United Nations Population Division (UNPD) (2024) were used as complementary data, and were integrated to the World Bank datasets. Distance-data was retrieved from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) (2016), where the distances are calculated following a great circle formula, using latitudes and longitudes of the most important cities (population-wise). This distance variable was used since it more accurately captures trading distances than the capital-distances, e.g. because not all countries see the capital as their main trading centre.

Both the World Bank, IMF, UNPD and CEPII are well established sources for Gravity-model data (Yotov et al., 2016), making their datasets optimal for use in the main model of this research paper. The used datasets[17] provided data to cover all countries included in the sample, leaving the aggregated panel dataset without any missing data.

5.3.6 Limitations

The data used in this study are subject to several limitations that should be considered when interpreting the results. First, the analysis relies on data from a single social media platform, TikTok, and therefore does not capture the full scope of social media activity related to matcha. Other platforms such as Instagram, YouTube, or X may also influence consumer awareness and purchasing behavior, but are due to the combination of time- and data availability constraints beyond the scope of this thesis. This implies that the measured social media effect may understate the broader influence of social media trends. TikTok is nonetheless chosen as the studied platform given its documented importance in the matcha trend (Google Trends, 2025).

[16] In December 2025
[17] See Appendix 2 for exact datasets and variable definitions.

The most prominent data limitation concerns the restricted time coverage of the TikTok data and the lack of matcha-specific export data. At the time of data collection,[18] TikTok data were only available on a worldwide level and for a relatively short period of approximately two years. This substantially reduces statistical power and constrains the scope for modeling, hence making it unsuitable for the main regression. Instead, a separate time-series regression is estimated (Step 1) to examine the relationship between TikTok activity and Google search intensity, thereby motivating the use of Google Trends as a proxy for the social media trend (step 2). Had TikTok data been available over a longer period, this variable would have been included directly in the main gravity specification. The limitations in the TikTok data do not disappear when implementing the two-step model, but are prominent in both, which is now discussed further.

In Step 1, the lack of country specific TikTok data causes limitations. Ideally, this step would benefit from cross-sectional variation across countries, allowing the analysis to analyse differences in exposure to social media trends and effects on consumer behavior over time. Such variation would enable the inclusion of fixed effects and reduce concerns related to serial dependence in a short time series. Since country specific TikTok data was not available the analysis in step 1 is restricted to a single aggregate time series. As a result, the estimation relies solely on time-related variation, making robust inference particularly important.

In Step 2, it is acknowledged that Google Trends does not perfectly proxy the TikTok trend. Even though Step 1 is used to motivate the use of the proxy, limitations remain. For example, not all exposure to TikTok content leads consumers to actively seek information through Google, and the relative usage of the platforms might vary across and within countries. Consequently, the results are limited to be interpreted as capturing the effects of TikTok-driven attention as reflected in Google search behavior, rather than exposure to the trend itself.

Finally, export data from UN Comtrade do not distinguish matcha from other types of green tea. The dependent variable therefore captures exports of green tea variations that might not be directly affected by the social media-driven matcha trend, and is most importantly not part of the research specification. This introduces measurement error in the dependent variable and

[18] In December 2025

may reduce the estimated relationship between consumer interest and exports. Other trade databases as well as export reports were examined and sought after for matcha specific export data, but could not be found.

6 Results

This chapter includes the results of the tests run in Stata, as well as a continuous analysis and discussion of the presented results.

6.1 Step 1: The relationship between trend and consumer interest

Table 1 shows the results for the OLS estimate of regression (1), with Robust SE and HAC SE, respectively.

The results show a strong, positive and statistically significant relationship between TikTok views and Google search interest. All results indicate p-values below 0.01, indicating very strong statistical significance. Furthermore, the high R^2 indicates a good fit of the model, where TikTok views explain a large share of the variation in Google searches over the sample period. However, because of the short sample period the R^2 should be interpreted as reflecting strong correlation between the two variables, rather than causality.

The TikTok-coefficient is interpreted as the change in Google Trend index when TikTok views increase by one percent. Applying the results, this means that a 1 percent increase in TikTok views is associated with an increase of approximately 0.26 points in Google Trends index. A 10 percent increase in TikTok views therefore corresponds to an increase of roughly 2.6 index points, and a 100% increase in TikTok exposure is associated with an increase of about 26 points. Given that the index ranges from 0-100, this result indicates that exposure to social media trends leads to economically significant effects on consumer search behaviour and attention. Additionally, comparing column (1) and (2) shows that the estimated coefficient is robust to HAC standard error corrections, suggesting that the result is not driven by heteroskedasticity or autocorrelation in the error term.

The coefficient results imply a rejection of the null hypothesis. Together with the outcomes from the statistical and economic analysis, this leads to the conclusion that increased exposure on social media is associated with higher consumer attention. This is consistent with the previous research by Stephen (2016), connecting social media influences to changed consumer behavior. It should nevertheless be noted that the data used in this step is limited, with both Google and TikTok variables covering a scope of less than two years and is

measured on a global level. Nonetheless, the strong results are deemed as sufficient to motivate the use of Google Trends as a proxy for the social media trend in the following gravity analysis. Given the exploratory nature of this thesis, this approach provides a foundation which future research can hopefully build upon.

Table 1: Results for Step 1

	(1) OLS with Robust SE	(2) OLS with HAC SE lag(3)
TikTok	25.696*** (0.000)	25.696*** (0.000)
Constant	-475.714*** (0.000)	-475.714*** (0.000)
Observations	23	23
R^2	0.932	*not displayed*

Notes: P-values in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

6.2 Step 2: The relationship between consumer interest and trade flows

6.2.1 Main observations

Table 2 shows the PPML estimates with different FE specifications. Column (1) presents the preferred specification including both importer and year-month FE, and shows no statistically significant effect of Google search intensity on Japanese green tea exports. Columns (3) and (4) on the other hand illustrate that the estimated relationship becomes statistically significant when year-month FE are excluded.

The economic significance follows a similar pattern - when year-month FE is removed, the economic significance of Google search intensity in relation to exports increases. In the main estimation (Column (1)) with both importer and year-month FE, the Google-estimate is interpreted as a 1 point increase in Google Trends index leading to 0,2% increased exports, which in this context is not a significant increase. Columns (3) and (4) account for larger economic effects, with 1,1% and 0,6% increased exports for every point of increased Google

Trends index, respectively. In these cases, economic significance is somewhat higher, especially in the estimation with only importer FE (Column (3)). A ten point increase in Google search intensity would translate into a 11% increase of exports, which is a noticeable increase.

The estimations of the independent variables GDP, population and distance generally follow the expected pattern. GDP and population show positive relationships with exports, except for GDP in Column (1), which is statistically insignificant, and population in Column (2) & (4), where importer FE are removed. Distance, where included, also follows expected results with negative relationships to exports.

The results imply that the positive association between consumer interest and Japanese green tea exports is primarily driven by global demand shifts and cross-country variation, rather than within-country changes over time. In the preferred specification in Column (1), which includes both importer and year-month fixed effects, the coefficient on the Google Trends index is economically small and statistically insignificant. This indicates that once importer-specific characteristics and global shocks are controlled for, there is no evidence of a within-country relationship between consumer interest and exports. In contrast, specifications that include only one or no fixed effects yield positive and statistically significant coefficients for the Google Trends index. This pattern implies that the estimated relationship reflects global trends and common demand shocks that affect multiple countries simultaneously, which are absorbed by year-month fixed effects in the preferred model. This result seems consistent with the matcha trend being global and spread across borders through social media, and could be the factor explaining the found results. However, specifications excluding fixed effects allow for greater omitted variable bias, and should therefore not be heavily relied upon.

The results provide insight into how global consumer trends may coincide with increased export flows and highlight the importance of model specification when studying social media-driven trade flows in the future.

Table 2: Results for Step 2 - PPML estimates with varying FE specifications

	(1)	(2)	(3)	(4)
Google	0.002 (0.612)	-0.008 (0.221)	0.011*** (0.000)	0.006*** (0.000)
ln(GDP)	-0.029 (0.651)	1.497*** (0.000)	0.058 (0.388)	1.488*** (0.000)
ln(Population)	1.038 (0.593)	-0.581** (0.019)	4.760*** (0.001)	-0.574*** (0.000)
ln(Distance)	*omitted*	-0.211 (0.718)	*omitted*	-0.163*** (0.001)
Constant	-7.764 (0.829)	-7.764 (0.829)	-79.270*** (0.002)	-21.363*** (0.000)
Year-month FE	Yes	Yes	No	No
Importer FE	Yes	No	Yes	No
Observations	18,050	28,120	18,145	28,268
R^2	0.945	0.727	0.931	0.713

Notes: Standard Errors clustered by importer. P-values in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

6.2.2 Robustness tests

To assess the robustness of the main observations, two robustness tests are reported below. Table 3 shows OLS estimations with the same FE specifications as presented above, whilst Table 4 shows PPML estimations with lagged Google Trends index.

The OLS estimations are based on a significantly lower amount of observations. This is consistent with the fact that OLS does not allow for zero values, which are excluded from both export and Google data. In large, the estimates mirror the results of the PPML estimates, where results are non significant except for when year-month FE are excluded (Column (3)). This means, the estimated relationship between Google search intensity and exports is sensitive to how much variation is absorbed by fixed effects, rather than to the estimator itself. It should be noted that the results under OLS are even less robust than with PPML according to the over-all higher p-values, strengthening the choice of PPML as preferred estimator.

Table 3: Results for Step 2 - Robustness test with OLS estimates with varying FE specifications

	(1)	(2)	(3)	(4)
Google	0.001 (0.722)	-0.006 (0.445)	0.017*** (0.000)	0.001 (0.722)
ln(GDP)	0.741*** (0.000)	0.867*** (0.000)	0.001 (0.989)	0.741*** (0.000)
ln(Population)	0.012 (0.939)	-0.078 (0.623)	3.507*** (0.003)	0.012 (0.939)
ln(Distance)	*omitted*	-1.363* (0.073)	*omitted*	-1.255* (0.091)
Constant	-2.060 (0.676)	-2.784 (0.569)	-53.186*** (0.007)	-2.060 (0.676)
Year-month FE	Yes	Yes	No	No
Importer FE	Yes	No	Yes	No
Observations	7,231	7,239	7,231	7,239
R^2	0.792	0.778	0.328	0.299

Notes: Standard Errors clustered by importer. P-values in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 4 presents a robustness check where the Google Trends index is lagged by one month, to account for potential delays between consumer interest and observed trade flows. The results closely mirror those of the main specification. In the preferred model, including both importer and year-month fixed effects, the lagged Google Trends coefficient is small and statistically insignificant, indicating that past consumer interest does not explain within-importer changes in exports. Identical to previous results, specifications excluding year-month FE generate statistically significant coefficients, suggesting that the association between the matcha trend and exports is driven primarily by global movements in interest rather than importer-specific demand shifts. It can additionally be noted that the results for the lagged Google variable in Column (3) and (4) are identical to those in the same columns in Table 2. Also results in columns (1) and (2) are very similar to those of Table 2. This implies that the estimated relationship between consumer interest and exports is not sensitive to

short-run timing delays. Concludingly, lagging the Google Trends variable does not alter the main conclusion of the analysis.

Table 4: Robustness check - PPML estimates with one month-lagged Google Trends and varying FE specifications

	(1)	(2)	(3)	(4)
Google (t-1)	0.004 (0.298)	-0.007 (0.249)	0.011*** (0.000)	0.006** (0.013)
ln(GDP)	-0.035 (0.599)	1.484*** (0.000)	0.055 (0.424)	1.476*** (0.000)
ln(Population)	0.997 (0.606)	-0.571** (0.019)	4.722*** (0.001)	-0.566** (0.023)
ln(Distance)	*omitted*	-0.205 (0.726)	*omitted*	-0.164 (0.774)
Constant	-6.869 (0.848)	-20.529*** (0.002)	-78.466*** (0.002)	-21.166*** (0.001)
Year-month FE	Yes	Yes	No	No
Importer FE	Yes	No	Yes	No
Observations	16,530	25,752	16,625	25,900
R^2	0.945	0,7251	0.933	0.711

Notes: Standard Errors clustered by importer. P-values in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

7 Summary and Conclusion

How is it that a tea traditionally consumed by Japanese monks in ceremonial contexts, often described by first-time drinkers as tasting like “liquid grass”, has become one of the most popular beverages in cafés across the world? How has a green tea that, until recently, was largely unknown outside Japan evolved into one of the country’s fastest-growing export commodities? If the answer lies in the global social media trend, this thesis cannot fully answer. Nonetheless, this thesis has despite uncertain results shed light on an unexplored area of study, hopefully inspiring future research on an increasingly relevant economic topic.

The purpose of this thesis was to study the relationship between social media trends and trade flows, through the specific case of the global matcha trend. The study applied a two-step model specifically designed for the data available, where Step 1 studied the relationship between the trend, as through TikTok views, and consumer interest, as through Google Trends index. The strong relationship found served as a motivator to use Google Trends as a proxy for the social media trend in Step 2, where the relationship between Japanese green tea exports and Google Trends index was studied through a gravity model. The results from the preferred model of Step 2 showed no statistically significant relationship between Google Trends index and Japanese exports, whilst models including less strict fixed effects did show statistical significance. This result was consistent over multiple robustness tests, including estimations with OLS and estimating Google search intensity with a one month lag. This indicates that social media trend’s relation to trade flows lies in global shocks and cross-country variation, rather than intra-country demand shifts. The results highlight that further research needs to be performed in the area of study to improve the model where global trends are accounted for, whilst still generating reliable results.

Even though the research questions couldn’t be clearly answered, this thesis has contributed to international economics by initiating studies of a new area - that of social media trends’ link to trade flows. As social media continues to grow and internet access increases over the world, it is an area of study that could and should be further studied. In future studies, focus could preferably lie in accessing deeper data on social media, analysing countries more directly affected by a trend, performing control group-tests and exploring models accounting for classic estimation issues whilst allowing to study global demand shocks.

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Appendix

Appendix 1: Countries analysed

Importers				n = 148
Albania	Colombia	Honduras	Mauritius	Sierra Leone
Algeria	Comoros	Hong Kong	Mexico	Singapore
Andorra	Congo Brazzaville	Hungary	Moldova	Slovakia
Angola	Congo Kinshasa	Iceland	Mongolia	Slovenia
Argentina	Costa Rica	India	Montenegro	South Africa
Armenia	Croatia	Indonesia	Morocco	Spain
Australia	Cyprus	Iran	Mozambique	Sudan
Austria	Czechia	Iraq	Namibia	Suriname
Azerbaijan	Denmark	Ireland	Nepal	Sweden
Bahamas	Djibouti	Israel	Netherlands	Switzerland
Bahrain	Dominican Republic	Italy	New Zealand	Tajikistan
Bangladesh	Ecuador	Jamaica	Nicaragua	Tanzania
Barbados	Egypt	Jordan	Nigeria	Thailand
Belarus	El Salvador	Kazakhstan	Norway	Trinidad and Tobago
Belgium	Equatorial Guinea	Kenya	Pakistan	Tunisia
Belize	Estonia	Kuwait	Panama	Turkiye
Bolivia	Ethiopia	Kyrgyzstan	Papua New Guinea	Turkmenistan
Bosnia and Herzegovina	Fiji	Laos	Paraguay	Uganda
Botswana	Finland	Latvia	Peru	Ukraine
Brazil	France	Libya	Philippines	United Arab Emirates
Brunei	Gambia	Lithuania	Poland	United Kingdom
Bulgaria	Georgia	Luxembourg	Portugal	United States
Burundi	Germany	Macao	Qatar	Uruguay
Cambodia	Ghana	Madagascar	Romania	Uzbekistan
Cameroon	Greece	Malawi	Russia	Venezuela
Canada	Grenada	Malaysia	Rwanda	Viet Nam
Cabo Verde	Guatemala	Maldives	Saudi Arabia	Zambia
Chad	Guinea	Mali	Senegal	Zimbabwe
Chile	Guinea-Bissau	Malta	Serbia	
China	Guyana	Mauritania	Seychelles	

Appendix 2: Sources and definitions for macroeconomic variables

Variable	Source, dataset and definition
GDP (2010-2024 data)	*Source*: World Bank (2025) *Dataset*: World Development Indicators *Definition*: GDP, current US$
GDP (2025 projection data)	*Source*: International Monetary Fund (2025) *Dataset:* World Economic Outlook (WEO) *Definition*: Gross domestic product (GDP), Current prices, US dollar
Population (2010-2024 data)	*Source*: World Bank (2025) *Dataset*: World Development Indicators *Definition*: Population, total
Population (2025 projection data)	*Source*: United Nations Population Division (2024) *Dataset*: World Population Prospects 2024: Population - Both sexes (median) *Definition*: Total population, both sexes combined, as of 1 July (thousands)
Distance	*Source*: Centre d'Etudes Prospectives et d'Informations Internationales (2016) *Dataset*: GeoDist, dyadic file: dist_cepii *Definition*: Dist: distances calculated following the great circle formula, which uses latitudes and longitudes of the most important cities/agglomerations (in terms of population).

Appendix 3: AI Disclosure

The production of this thesis has been supported by the artificial intelligence (AI) tool ChatGDP from OpenAI. The tool was used to sort large sets of data and text, provide instructions on the usage of Stata and Excel, as well as assistance in generating code for Stata, and suggestions for improved linguistics and grammar. All information retrieved by AI has been carefully reviewed and criticised before it has been used or implemented into the thesis.