Reimagining Endogeneity in Trade and Migration: Using Shift-Share Instruments and Machine Learning

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Declaration of Co-Authorship

I am the sole author of Chapters 1 and 3 of this dissertation. I also declare that I have co-authored Chapter 2 with Professor Laura Brown. I explain the nature of co-authorship for the second chapter below.

Contribution to Chapter 2, titled: Trade and Migration: What Causes What?

I identified the research topic, framed the research questions, and constructed and cleaned the dataset. Furthermore, I developed the methodology, estimated the results, and prepared the first draft and subsequent drafts of the paper for journal submission.

Professor Laura Brown refined the research questions and made significant contributions in writing the introduction and the literature review. Professor Brown introduced new variables and restructured the methodology and results sections. She also reviewed and edited the chapter multiple times.

Professor Brown and I agree that I am most definitely the first author of this publication, but her contribution is significant enough to be recognized as the second author.

Abstract

This dissertation consists of three chapters and focuses on the fields of applied econometrics, international trade, the economics of migration, and regional economics.

Chapter 1 demonstrates how applied researchers can develop, select, and validate Shift-Share Instrumental Variables (SSIVs) in their studies. It introduces a novel SSIV Search Method to estimate the causal effect of interprovincial services trade on interprovincial goods trade in Canada. Using the Poisson Pseudo Maximum Likelihood (PPML) estimator within the gravity model, the results reveal a significant causal effect of services trade on goods trade. SSIV variants with lagged disaggregate shocks and shares outperform literature-suggested SSIVs in empirical validity, predictive accuracy, and bias reduction. Machine Learning techniques (such as Gradient Boosting and Random Forest) and Monte Carlo simulations validate the robustness of these instruments.

Chapter 2 examines the bidirectional causality between interprovincial trade and migration within Canada. It develops 80 SSIVs for interprovincial trade and 4 SSIVs for interprovincial migration to address endogeneity. Using the PPML estimator, the analysis shows that trade (both aggregate and disaggregate), particularly services trade, has a stronger influence on migration than migration does on trade. These findings suggest that reducing trade barriers could influence internal migration patterns in Canada.

Chapter 3 explores the relationship between trade and migration at both interprovincial and international levels. It introduces modified SSIVs as new instruments and finds that both interprovincial and international trade attract migration. The impact of interprovincial trade on interprovincial migration is greater than that of international trade on international migration to Canada. Exports show similar impacts on attracting migrants interprovincially and internationally. Random Forest results demonstrate the superior predictive power of Modified SSIVs compared to traditional ones. This chapter also recommends policies for provinces aiming to attract both interprovincial and international migrants.

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Dedication

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Contents

Introduction

While establishing any causal relationships in regional studies, endogeneity may arise from reverse causality, omitted variables bias and measurement error. Any model estimations in the presence of these problems are inconsistent and biased, leading to unreliable policy recommendations.

A widely recognized solution to this problem is to find a suitable instrumental variable (IV), which must satisfy three important conditions: relevance, exogeneity and exclusion restrictions. An IV meets the relevance condition if it is strongly correlated with the endogenous variable. It is exogenous if it is not correlated with the error term. Finally, the exclusion restriction holds if the instrument influences the dependent variable only through its impact on the endogenous variable.

Country-level empirical studies employ policy variables (such as agreements and memberships) as IVs to establish causal relationships. However, regional studies cannot use those policy variables as IVs due to the lack of variations across provinces, failing to satisfy the relevance condition of a valid IV.

For example, if we want to investigate the causal relationship between interprovincial services and goods trade, we need to address the endogeneity between services and goods trade due to the reverse causality between them. Since policy variables across all provinces will be the same, these variables fail to satisfy the relevance condition of a valid IV. To overcome such challenges in regional studies, this dissertation proposes the application of the Shift-Share Instrumental Variable (SSIV) method.

To tackle endogeneity in provincial settings, the first chapter of this dissertation develops and advances methods to derive SSIVs. Chapter 1 designs an SSIV Search Method with 58 SSIVs using an empirical setting of estimating the causal effect of interprovincial services trade on interprovincial goods trade in Canada. The novel method incorporates both established techniques and innovative modifications to address endogeneity in interprovincial analysis.

Employing the Poisson Pseudo Maximum Likelihood (PPML) within the gravity model, Chapter 1 finds a positive and significant causal effect of interprovincial services trade on goods trade within Canada.

While this chapter utilizes machine learning techniques [such as Gradient Boosting (GB) and Random Forest (RF)] to estimate the predictive scores of all SSIVs, it also applies Monte Carlo simulations to estimate the bias of SSIV estimators for robust estimations. The results indicate that our SSIV variants with lagged disaggregate shocks and shares outperform literature-suggested SSIVs in empirical validity, predictive accuracy, and bias reduction.

Chapter 2 extends the application of SSIVs to investigate the bi-directional causal relationships between interprovincial trade (in aggregate and disaggregate) and migration within Canada. Robust estimations of these causal effects can significantly enhance the precision of evidence-based policies.

Since trade and migration influence each other, we address this endogeneity issue with SSIVs for both analyses. This chapter develops 80 SSIVs for interprovincial trade and 4 SSIVs for interprovincial migration.

The findings reveal that the influence of trade on migration is substantial compared to the impact of migration on trade. Notably, the services trade has a much stronger effect on attracting migrants than the goods trade.

As Canadian provinces engage in interprovincial and international trade, these trade dynamics may influence interprovincial and international migration. Till today, no single study in the literature has explored these dynamics at the provincial level. Chapter 3 is the first one to compare the impact of interprovincial trade on interprovincial migration vs the effect of provinces trading internationally on international migration. It further fills the gap in the literature by examining the influence of exports in both contexts.

Chapter 3 finds that both interprovincial and international trade impact interprovincial and international migration. To address the endogeneity problem between trade and migration, this chapter derives 16 SSIVs and suggests new Modified SSIVs with lagged shocks and shares. It further explores the thought from Bartik (1991) on the potential of export shocks and shares as instruments. Machine learning findings reveal that SSIVs from exports have higher predictive strength than all other SSIVs.

The remainder of the dissertation is organized as follows: Chapter 1 discusses the SSIV Search Method with an empirical trade setting. Chapter 2 shows a comprehensive picture of the bi-directional causality between trade (in aggregate and disaggregate) and migration. Chapter 3 compares the impact of interprovincial trade on interprovincial migration vs the influence of international trade on international migration.

Chapter 1

Shift-Share Instruments: Review, Modification & Application

Abstract

Using an empirical setting to estimate the causal effect of interprovincial services trade on interprovincial goods trade in Canada, we demonstrate how applied researchers can develop, select and validate Shift-Share Instrumental Variables (SSIVs) in their studies. Leveraging a trade dataset for the years 2007 to 2019, we design a novel SSIV Search Method to construct 58 SSIVs, incorporating both established techniques and innovative modifications to address endogeneity in interprovincial analysis. Employing the Poisson Pseudo Maximum Likelihood (PPML) estimator within the gravity model, we find a significant causal effect of interprovincial services trade on interprovincial goods trade across just-identified (JI) and over-identified (OI) IV models. The results reveal that our SSIV variants, particularly those with lagged disaggregate shocks and shares, consistently outperform literature-suggested SSIVs in terms of empirical validity, predictive accuracy, and bias reduction. Evidence from Machine Learning techniques, such as Gradient Boosting and Random Forest models, suggests that our instruments have higher predictive power than literature-suggested instruments. Monte Carlo simulations further validate the low-bias properties of all SSIVs tested, with our variants consistently exhibiting lower bias. Notably, lagged disaggregate shocks and shares enhance the reliability of estimates by capturing regional and sectoral heterogeneity and eliminating potential contemporaneous correlations between the instruments and the outcome variable. Based on our experiment, we recommend using lagged disaggregate shocks and shares to construct SSIVs for the most reliable estimates. Indeed, we prepare a practical prescription for applied researchers to address and solve the endogeneity problem in interprovincial and similar empirical applications.

JEL Codes: C36, C53, F14, F15, F17 & R11.

Keywords: Endogeneity, IV, SSIV, Interprovincial Trade, Machine Learning & Monte Carlo Simulations.

1.1 Introduction

Addressing endogeneity is a fundamental challenge in empirical research, particularly in regional studies. A widely recognized solution to this endogeneity problem is to find a suitable instrumental variable (henceforth, IV). While country-level studies often instrument the endogenous variable with policy changes or agreements, identifying valid instruments in a regional setting becomes considerably challenging. Since federal policies or agreements often lack variation across provinces, they fail to satisfy the relevance condition of a valid instrument. In this study, we address this challenge by reviewing and advancing methods to develop the Shift-Share Instrumental Variables (SSIVs, henceforth).

The remarkable contribution from Timothy J Bartik (1991, 1993) was to introduce the idea of SSIV in economics. Since then SSIV has become one of the convincing solutions to solve the endogeneity problem for regional analysis. It is also known as the Bartik instruments. In his book "Who Benefits from State and Local Economic Development Policies", Bartik (1991) constructs an instrument for local employment growth rate by interacting local industry employment shares with the national industry growth rates. While Blanchard & Katz (1992) were the first to employ this method empirically after Bartik (1991), a significant number of empirical studies followed (Card, 2001, 2009; Autor et al., 2013; Hummels et al., 2014; Acemoglu et al., 2016; Peri, 2016; Goldsmith-Pinkham et al., 2020; Xu, 2023).

Despite its significant applications in causal inference, the SSIV technique faces some limitations such as potential bias from unobserved regional characteristics and the inability of aggregate shocks to fully account for industrial and regional heterogeneity. To tackle these issues, several studies (Autor et al., 2013; Acemoglu et al., 2016; Jaeger et al., 2018; Adão et al., 2019; Goldsmith-Pinkham et al., 2020; Broxterman & Larson, 2020; Borusyak et al., 2022) offer modifications and theoretical foundations to this technique.

In this study, we enhance the quality of SSIVs by designing a SSIV Search Method with our SSIVs and literature-suggested SSIVs. We argue that our variants with disaggregate shocks and shares address regional and industrial heterogeneity better compared to literature-suggested SSIVs with aggregate shocks. Moreover, the application of aggregate shocks in SSIVs may risk the exclusion restriction of SSIVs as they affect the outcome variable indirectly. Therefore, our innovative approach deals with these potential risks using disaggregate shocks and shares. To eliminate any potential contemporaneous correlation between instruments and the endogenous variable, our variants incorporate lag in both shocks and shares of SSIVs to predict the endogenous regressor based on the past economic conditions.

To compare the empirical performance of literature-suggested SSIVs and our SSIVs, this study uses an empirical setting of estimating the causal effect of interprovincial services trade on interprovincial goods trade within Canada for the years 2007 to 2019. Moreover, we apply all these instruments under an empirical setup to examine their empirical performance across just-identified

(JI, henceforth) and over-identified (OI, hereafter) IV models. We investigate whether all the SSIVs produce equivalent results, or which instrument performs best empirically under JI and OI IV models.

Conventionally, we rely on the first stage results, specifically F-statistic and R-squared values, to evaluate the strength of SSIVs. Notably, this study utilizes Machine Learning techniques, such as Gradient Boosting (GB) and Random Forests (RF) models, to identify the strong and weak SSIVs based on higher predictive scores and lower root mean squared errors (henceforth, RMSE). We further apply Monte Carlo simulations to estimate bias of all SSIVs. This study sets the empirical performance benchmark on three key pillars: first-stage results from conventional IV estimations, predictive scores from machine learning results and bias values from Monte Carlo simulations.

This study answers four important questions: [a] Do all derived SSIVs produce equivalent results in JI and OI IV models? [b] Do literature-suggested SSIVs empirically outperform our proposed SSIVs in both JI and OI IV models? [c] Do Machine Learning techniques suggest that literature-suggested SSIVs have stronger predictive power than our SSIVs? [d] Do the Monte Carlo simulations reveal that literature-suggested SSIVs are less biased than our SSIV variants in JI and OI IV models?

Using an interprovincial panel data-set for the years 2007 to 2019, we design our SSIV Search Method with 58 SSIVs to address the endogeneity problem between interprovincial services trade and interprovincial goods trade. We use both [a] aggregate shock and share, and [b] six disaggregate shocks and shares of interprovincial services trade to derive SSIVs in this study. Employing the PPML estimator in the gravity model framework, we find that interprovincial services trade significantly impacts interprovincial goods trade within Canada across all versions of IV models. It is statistically significant at a 1% level across JI and OI IV models.

Conventional IV results indicate that literature-suggested SSIVs and our variants of SSIVs show similar results in estimating the causal effect of interprovincial services trade on interprovincial goods trade. All SSIVs produce very high values of the F-statistic and R-squared in the first stage [FS, hereafter] across both JI and OI models, satisfying the minimum and maximum thresholds for F-statistic values $F \geq 10$ (Stock & Yogo, 2002) and $F \geq 50$ (Keane & Neal, 2021). Our results reveal that all the SSIVs consistently demonstrate strong first-stage relevance with higher F-statistic and R-squared values and perform robustly across both JI and OI settings. This study underscores the flexibility and effectiveness of SSIVs in addressing endogeneity in various empirical contexts.

Our SSIV variants consistently show superior empirical performance with strong first-stage results, higher predictive and lower RMSE values as well as low bias. Our SSIVs, particularly with lagged disaggregate shocks and shares, yield higher values of F-statistic compared to literature-suggested SSIVs. Notably, the OI models with all SSIVs cannot reject the null hypothesis of the Hansen J Statistics and pass the over-identification tests.

The findings from GB and RF models suggest that our instruments show higher predictive scores, and lower RMSE in comparison to literature-suggested instruments. This evidence emphasizes the need for incorporating lags and using disaggregate shares to enhance the strength of the instruments in predictive models. The results from Monte Carlo simulations reveal that all the SSIVs in our dataset are very low in bias. Specially, our instruments consistently yield lower bias values compared to the literature-suggested instruments. It is consistent with larger sample size.

This paper makes three significant contributions. Firstly, it generates a comprehensive set of SSIVs with an SSIV Search Method for robust estimations. Secondly, it proposes a novel modification for constructing SSIVs to account for regional and sectoral heterogeneity. Lastly, the innovative applications of machine learning techniques and Monte Carlo simulation together provide substantial grounds for scholars to be selective about the right IV models.

This study prescribes a way for scholars to derive, select and apply SSIVs in their studies. Moreover, the combination of theoretical innovation with the empirical application of this paper offers a robust framework to address endogeneity in regional studies.

The remainder of the paper is organized as follows: Section 2 presents the empirical application. We provide a review of shift-share instruments in Section 3. In Section 4, we discuss the methodology. We provide a data description in Section 5. The estimated and simulated results are discussed in Section 6. Then, Section 7 concludes. In Section 8, we show robustness. Finally, Section 9 discusses future research.

1.2 Empirical Application

First, we develop an empirical setup where we show the context of endogeneity and the need to solve this problem using SSIVs. Under that empirical setup, we derive SSIVs following the existing methods suggested in the literature and then we show new ways to derive new SSIVs.

In our empirical setting, we estimate the impact of interprovincial services trade on the interprovincial goods trade within Canada. Let's discuss the relationship between the services trade and the goods trade and provide the rationale behind investigating this relationship.

A deeper understanding of the causal relationship between interprovincial services trade and goods trade is essential for shaping effective trade policies and fostering regional economic development in Canada. If the interprovincial services trade boosts interprovincial goods trade, any strategic investment in service-oriented infrastructure can also affect the trade of goods. Provinces with resource-based industries can strengthen their regional competitiveness by integrating services into the goods value chain. To provide valuable insights for achieving this goal, we aim to uncover the interplay between services trade and goods trade in Canada.

Now, we demonstrate how services trade interlinks goods trade with an example in the Canadian context. For instance, an educational institution serves as a hub for services trade. Canadian institutions do exports and imports services. The enrollment of international students in Canada is one example of services exports whereas they import services by hiring foreign faculty members. Most often, we find universities with bookstores and restaurants selling goods to customers. Specifically, bookstores export and import goods by selling books, clothing and so on both online and offline. While our example shows the association between the services trade and the goods trade, our study investigates the existence of a causal effect of services trade on the goods trade at the provincial level within Canada.

This study substantiates the above example with a trend analysis across provincial levels within Canada. Larger trading provinces such as Alberta, British Columbia, and Ontario show consistent growth both in services and goods trades (see, Appendix A). These bigger trading provinces trade among themselves the most in both sectors. If we observe the other provinces such as Quebec, Newfoundland and Labrador, New Brunswick and Nova Scotia, they show a parallel increase in services and goods trade. While we notice an increase in services trade over the years in both Manitoba and Saskatchewan, we see a slight decline in goods trade in these provinces with few trading provinces such as Quebec and Ontario.

We further build our empirical application with a review of the literature on services and goods trade to understand how our work contributes to the literature. Although the literature points out similarities and dissimilarities between services trade and goods trade, a significant number of studies show an association between the services trade and the goods trade (Ariu, 2016; Ariu et al., 2020; Arnold et al., 2011; Breinlich & Criscuolo, 2011; Egger et al., 2012; Hoekman & Shepherd, 2017; Lennon, 2009; Nordås & Rouzet, 2017; Nordås, 2010; Sauve & Mattoo, 2003).

Services trade reform increases the productivity of manufacturing firms (Ariu, 2016; Ariu et al., 2020; Arnold et al., 2011; Breinlich & Criscuolo, 2011; Egger et al., 2012; Hoekman & Shepherd, 2017; Lennon, 2009; Nordås & Rouzet, 2017; Sauve & Mattoo, 2003), while services trade and goods trade show a complementary relationship in production and trade (Nordås, 2010).

Firm-level evidence suggests that firms selling both goods and services obtain a greater share of international trade (Ariu, 2016; Breinlich & Criscuolo, 2011). The services trade and the goods trade are not independent of each other (Ariu et al., 2020). They find that services play the role of demand shifters for goods trade. Their study proposes a theoretical explanation based on the one-way complementary relationship between goods and services. They also mention that we can consume goods alone or with services. They find a positive impact of services on goods export performance. Crozet & Milet (2017) show that French manufacturing firms increase their profitability and total sales of goods with the start of selling services.

Though the literature produces evidence in favour of the complementary relationship between services trade and goods trade, it does not provide a clear answer on the causal relationship between services trade and goods trade. Therefore, our research significantly contributes to this area by examining the causal relationship between services trade and goods trade at the provincial level within Canada for the first time in the literature.

1.2.1 Services Trade and Goods Trade: Endogeneity & IV Approach

Let's consider a simple model of services trade and goods trade before applying IV approach.

$$TG_{ij} = \gamma_0 + \gamma_1 TS_{ij} + \gamma_2\ Controls + \epsilon_{ij} \tag{1.1}$$

Where: TG_{ij} is interprovincial goods trade flow from province i to province j; TS_{ij} is interprovincial services trade flow from province i to province j; $Controls$ is a vector of control variables (such as distance, income, shared border, weather, etc.); ϵ_{ij} is error term.

Empirical evidence shows that goods trade influences services trade (Lennon, 2009). We also find a significant number of examples in favour of this. Car manufacturers such as Toyota, Honda and so on not only sell cars but also offer car loans (Ariu et al., 2020). Tech giants such as Apple, Microsoft and others sell both goods and services. When we purchase an iPhone, we end up buying Apple Care. So, we can state that goods trade may affect services trade. While anecdotal evidence suggests the interplay between goods and services trade, we further test this relationship empirically using the Granger (Non) Causality Test (Dumitrescu & Hurlin, 2012).

We further confirm the likelihood of the reverse causality between services trade and goods trade utilizing the Granger (Non) Causality Test in this panel setup (Dumitrescu & Hurlin, 2012). Before testing for causation, we use the unit root test using Im et al. (2003) to check that the variables are stationary.

Table 1.1 provides evidence in favour of reverse causality between services trade and goods trade. The results from Table 1.1 suggest that both services trade and goods trade have significant bidirectional causality, rejecting the null hypothesis at the 1% level of significance.

Table 1.1: Dumitrescu & Hurlin (2012) Granger Non-Causality Test Results

Direction of Causality	**P-Value**
Services Trade $\longrightarrow$ Goods Trade	0.000
Goods Trade $\longrightarrow$ Services Trade	0.000

Therefore, interprovincial services trade (TS_{ij}) is an endogenous variable for our empirical application, and we cannot use equation (1.1) for this study. We need instruments for interprovincial services trade.

Given the endogeneity of TS_{ij}, equation (1.1) may produce biased and inconsistent estimations. To address this issue, we employ an IV approach, rewritten as follows:

$$TG_{ij} = \gamma_0 + \gamma_1 T\hat{S}_{ij} + \gamma_2 \text{Controls} + \epsilon_{ij}, \tag{1.2}$$

Where, the first-stage equation instruments $T\hat{S}_{ij}$ with Z_{ij}.

$$TS_{ij} = \delta_0 + \delta_1 Z_{ij} + \delta_2 \text{Controls} + \nu_{ij}. \tag{1.3}$$

Here, Z_{ij} represents instruments for TS_{ij}.

The search for instruments is a challenge for this study, and the next section explains why we chose the SSIV method over others to address this challenge.

1.2.2 Why SSIVs?

We need to find appropriate IVs for the endogenous variable (in our case, interprovincial services trade). The IVs have to be relevant, exogenous to goods trade and consistent with the exclusion restriction. Typically, we dive deep into the literature to identify the IVs. Since we are the first ones to study the causal relationship between interprovincial services trade and interprovincial goods trade, the literature leaves the path for innovative solutions here.

Our job of finding IVs would have been slightly less difficult if we had studied our empirical research question at the country level such as (Lennon, 2009)*. She studies the causal relationship between goods trade and services trade and uses IVs such as tariffs and border sharing. However, we cannot use these instruments for our empirical work as her work conducts a country-level analysis. Since these instruments will not have any variations across all the provinces in Canada, the path for innovation continues for us.

Alternatively, provincial agreements or policies can be IVs. However, there is no policy or agreement across Canadian provinces which is specific to the services trade not to the goods trade [check, for example, The New West Partnership Trade Agreement (NWPTA, 2010)]. Also, provincial governments participate in most of the agreements through the federal government and the chance of finding any policy variable becomes narrower. Unfortunately, the flat line continues.

Notably, the remarkable contribution from Bartik (1991, 1993) shows the way to solve the endogeneity problem for our research setting. Following the Bartik instruments construction method, we derive SSIVs for the services trade to establish the causal effect of interprovincial services trade on interprovincial goods trade at the provincial level in Canada.

1.3 Review of Shift Share Instruments

In this section, we discuss the origin of the shift-share instruments. While outlining the contribution of the researchers who offer modifications to this novel technique, we discuss the technique's theoretical aspects.

1.3.1 From Origin to Rise of SSIV

The origin of shift-share analysis goes back to Creamer (1943). Later, Dunn (1960) contributes to this analytical technique by providing a modern accounting identity, showing a clear view of the national economic trends and regional economic changes.

*She instruments goods trade with [a] the average applied import tariff for non-agricultural and non-fuel products and (2) landlocked variable, countries sharing the land border.

It is quite evident that Freeman (1980) uses the decomposition nature and instruments labour demand with the change in industry composition. Timothy J Bartik (1991, 1993) popularizes the idea of shift-share instruments in economics with his strong logic behind using the national growth rate component in his instrument. Since then, it has become a Bartik instrument. The key feature of the Bartik instruments or shift-share instruments is its decomposition approach, which generates exogenous variation and facilitates causal analysis. Later, Blanchard & Katz (1992) contribute appreciably to this area.

Expression (1.4) is the Bartik instruments or the SSIVs derivation method.

$$SSIV_j = \sum_k W_{jt}^k N_t^k \tag{1.4}$$

Here, W_{jt}^k is the local industry [employment] share of location j in k industry and N_t^k is the national growth rate of k industry.

SSIVs rely on some key assumptions: [a] the local industry share is plausibly exogenous. [b] the national industry growth rate is simply a shock at the aggregate level and shocks are exogenous. Any shock at the national level is exogenous to the regional level and the regional share grows rapidly with that shock. [c] The sum of all shares must be 1, by expression $\sum_k W_{jt}^k = 1$.

Bartik (1991, 1993) and Blanchard & Katz (1992) define their instrument as the local employment growth rate, which is constructed by the interacting local industry employment shares with the national industry growth rates. The employment share is plausibly exogenous, and the national industry growth rate represents a shock at the aggregate level and is also exogenous.

SSIVs are fairly simple to derive and possess appealing features. That is why they are popular in economics (Card, 2001, 2009; Autor et al., 2013; Hummels et al., 2014; Acemoglu et al., 2016; Peri, 2016; Goldsmith-Pinkham et al., 2020; Xu, 2023), and particularly in labour economics (Card, 2001, 2009), and international trade (Hummels et al., 2014) for causal inference. The next section highlights the changes in the SSIV derivation method and its relevance in the existing literature.

1.3.2 Modifications & Theoretical Justifications of SSIV

The growing number of works (Autor et al., 2013; Acemoglu et al., 2016; Jaeger et al., 2018; Adão et al., 2019; Goldsmith-Pinkham et al., 2020; Broxterman & Larson, 2020; Borusyak et al., 2022) on this novel technique are opening the "black box", revealing the variations to derive this instrument.

When analyzing the effects of rising China imports on US local labor markets, Autor et al. (2013) instrument the change in US imports from China with the growth rate of Chinese exports to eight other high-income countries. They use exogenous shocks to construct their instruments. Acemoglu et al. (2016) also study the direct effect of rising Chinese import competition on US manufacturing employment, focusing on the job losses in industries most exposed to Chinese imports. They construct their instrument at the national industry level with local labor market outcomes analyzed at the commuting zone level. They lag the share component to avoid any concern related to endogeneity.

Gould et al. (2002) examine the causal effects of income on local crime rates and instrument income using shocks. In migration literature, Jaeger et al. (2018) offer a modification in the shock component following the work of Card (2009), a classic SSIV in labor economics literature. They suggest empirical studies focusing on the impact of immigration should use the lag of the immigration shock. In their study, they use the lag national inflow rates to show the persistent effects of past immigration shocks on local labor markets. They highlight that this method can be handy in distinguishing the effects of current versus past immigration inflows, capturing the ongoing adjustments in the labor market.

When employing SSIV in an empirical setting, care is needed to verify the exogeneity condition of the shock component (Adão et al., 2019). They suggest that researchers should conduct robustness checks using alternative (randomly generated) shocks or placebo tests to confirm that the shock is exogenous. For example, lagging the shock component can differentiate between short-term and long-term effects. In their exercise, they find that studies such as Autor et al. (2013) have overstated the precision of their estimates. Moreover, Borusyak et al. (2022) propose that SSIV identification should come from the quasi-random assignment of shocks, rather than holding the exogeneity on shares.

In another study focusing on the exogeneity of Bartik instruments, Goldsmith-Pinkham et al. (2020) derive their identification from local industry shares, not from national shocks directly. Their instrument's validity relies on the assumption of the exogeneity of shares. They further show that IV estimations with Bartik instruments are numerically equivalent to using local industry shares as instruments within a generalized method of moments (GMM) framework. We outline our contributions to the literature in the next section.

1.3.3 Contribution to the Literature

Several papers fine-tune the SSIV derivation methods in empirical studies, whereas other papers focus on theoretical justification for the exogeneity of SSIVs based on shocks and shares. While Broxterman & Larson (2020) conduct an empirical exercise with alternative versions of Bartik-type instruments using different combinations of national shift and local share variables, Borusyak et al. (2024) provide a structural framework to understand and implement SSIVs. There is no single study which designs a SSIV Search method to derive SSIVs following the up-to-date literature and applying these SSIVs in an empirical study.

We contribute to the literature in several ways. Firstly, we design a SSIV Search Method to generate a comprehensive set of 58 SSIVs. Using the SSIV search approach, our study is the first one in this literature which shows how to derive the SSIVs following the literature-suggested techniques.

Secondly, this study offers modifications to the traditional SSIV derivation technique. Our newly designed instruments capture regional and sectoral heterogeneity more effectively than existing literature-suggested SSIVs.

Thirdly, this study employs machine learning techniques, GB and RF models, to evaluate the performance of the SSIVs. Also, applying Monte Carlo simulations, we contribute by estimating the bias of all the derived SSIVs and solidifying the substantial grounds for applied research in the selection process of SSIVs.

Furthermore, the empirical application of SSIVs to address the endogeneity between interprovincial goods trade and interprovincial services trade offers valuable insights for policymakers and researchers to understand and influence regional trade dynamics.

Lastly, this study provides a robust framework for addressing endogeneity in regional settings by bridging theoretical innovation with empirical application. We set a benchmark for future research in the selection and application of instrumental variables in complex economic settings.

In the next section, we develop the empirical exercise which suffers from the endogeneity problem. Then we offer solutions to this problem using SSIVs and show the causal effect using those instruments.

1.4 Methodology

This section shows the identification strategy for our empirical analysis. First, we introduce the gravity model of trade and explain why we apply this model. Next, we show how we solve the endogeneity problem by deriving and developing instruments for services trade. Finally, we show the causal effect of services trade on goods trade at the provincial level within Canada.

1.4.1 Gravity Model of Trade

The gravity model explains the interplay between services trade and goods trade. Researchers extensively use this model to evaluate trade interlinkages (Ariu, 2016; Ariu et al., 2020; Arnold et al., 2011; Breinlich & Criscuolo, 2011; Egger et al., 2012; Hoekman & Shepherd, 2017; Lennon, 2009; Nordås & Rouzet, 2017; Nordås, 2010; Sauve & Mattoo, 2003). Therefore, we employ the gravity model to estimate the impact of interprovincial services trade on interprovincial goods trade within Canada in a panel setting.

The origin of the gravity model goes back to Newton's universal law of gravitation[†]. Tinbergen (1963) introduces the gravity model of international trade to describe the pattern of bilateral trade flows. While Krugman & Obstfeld (2005) provided a simpler version of the gravity model, the influential work of Silva & Tenreyro (2006) suggested estimating the gravity equation in its multiplicative form, as shown in (1.5). According to the gravity model, trade flow is proportional to

[†]"Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between their centers".

the economic sizes of both regions and inversely proportional to the distance between the trading partners.

$$T_{ij} = \exp\left(\alpha_0 + \alpha_1 \log Y_i + \alpha_2 \log Y_j + \alpha_3 \log D_{ij}\right) + \epsilon_{ij} \tag{1.5}$$

Here, T_{ij} is the trade flow from origin i to destination j; A is a constant of proportionality; Y_i and Y_j are the economic sizes of regions i and j, and besides, these usually represent the Gross Domestic Product (GDP) or Gross National Product (GNP) of each region; D_{ij} captures the distance between two regions i and j, which serves as a proxy for trade costs between trading partners. Also, distance represents impediments to trade such as differences in religions, lack of trade agreements and other barriers.

This study extends the equation (1.5) to analyze the effect of services trade on goods trade. In this empirical setting, our dependent variable is goods trade, whereas the endogenous variable is services trade. We instrument the endogenous services trade with SSIVs. We estimate the impact of services trade on goods trade using the predicted value of services trade and a set of control variables on the right hand side. We explain our identification strategy in details with equations (1.9) and (1.10).

1.4.2 SSIV Derivation Methods

In this section, we first show the usual way to derive the SSIVs. Then we discuss how we derive 58 instruments following the literature and the modifications we offer in this study.

1.4.3 Usual SSIV Derivation Technique

Equation (1.6) presents the derivation technique of SSIV .

$$SSIV^V_{ijt} = N^k_t \times W^k_{ijt} \tag{1.6}$$

Here, $SSIV^V_{ijt}$ are the shift-share instruments for interprovincial services trade and V is the index; N^k_t represents the shift of industry k at time t; W^k_{ijt} denotes the regional trade share of industry k in region j with trading partner i at time t. Notably, k is the number of industries.

To create the SSIV, we first calculate the industry share using the equation (1.7). Then, we estimate the shift or the shock using the expression (1.8).

$$W^k_{ijt} = \frac{T^k_{ijt}}{T_{jt}} \tag{1.7}$$

T^k_{ijt} is the trade flow of industry k from origin i to destination j at time t; T_{jt} is the total trade of destination j at time t.

$$N^k_t = \left[\frac{T^k_t}{T^k_{t-1}}\right] - 1 \tag{1.8}$$

T_t^k is the country-level trade of industry k at time t; T_{t-1}^k is the country-level trade of industry k at time $(t-1)$. Once we estimate the shifts and the share using equations (1.8) and (1.7), we can then calculate the SSIV.

1.4.4 SSIV Search Method for Empirical Setting

This paper introduces the SSIV Search Method to construct and evaluate the effectiveness of various shift-share instruments. Our method systematically examines combinations of aggregate and disaggregate shocks and shares, both with and without lags, to identify SSIVs that balance theoretical rigor and empirical performance.

In our research setting, we design our SSIV Search Method with six service industries alongside the aggregate services industry to derive all the SSIVs for interprovincial services trade. The industries are: [1] Transportation and related services [2] Information and cultural services [3] Telecommunications, broadcasting distribution and related services [4] Education services [5] Arts, entertainment and recreation services and [6] Accommodation and food services.

First, we show how we construct 58 instruments through our SSIV Search Method following the literature and our augmentations. When deriving the instruments suggested by the literature, we also provide our versions with detailed explanations to further unfold the "black box." Table 1.2 shows the comprehensive set of instruments using the SSIV Search Method.

We develop all the instruments using five combinations of shocks and shares from the aggregate services industry and the six disaggregate services industries for this study. The sum of the shares across aggregate and disaggregate services industries is 1. Next, we provide a clear explanation why and how we can construct our instruments.

Table 1.2: SSIV Search Method

Index	Instruments	Construction Method	Components
1–3	$SSIV^1_{AS\star ASR}$; $SSIV^2_{AS\star LASR}$; $SSIV^3_{LAS\star LASR}$	$N^S_{t-q}W^S_{t-r}$, , where $S=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$	Aggregate shocks and shares without & with lag
4–6	$SSIV^4_{ADS\star ADSR}$; $SSIV^5_{ADS\star LADSR}$; $SSIV^6_{LADS\star LADSR}$	$\sum_{k=1}^{6} N^k_{t-q}W^k_{t-r}$, where $k=1,\ldots,6$; $q=0,1$; $r=0,1$; and $q\neq 1$ if $r=0$	Sum of disaggregate shocks and shares without & with lag
7–24	$SSIV^7_{AS\star DSR^1}$ to $SSIV^{12}_{AS\star DSR^6}$; $SSIV^{13}_{AS\star LDSR^1}$ to $SSIV^{18}_{AS\star LDSR^6}$; $SSIV^{19}_{LAS\star LDSR^1}$ to $SSIV^{24}_{LAS\star LDSR^6}$	$N^S_{t-q}W^k_{t-r}$ for $k=1,\ldots,6$; $q=0,1$; $r=0,1$ and $q\neq 1$ if $r=0$	Aggregate shocks with disaggregate shares without & with lag
25–42	$SSIV^{25}_{DS^1\star DSR^1}$ to $SSIV^{30}_{DS^6\star DSR^6}$; $SSIV^{31}_{DS^1\star LDSR^1}$ to $SSIV^{36}_{DS^6\star LDSR^6}$; $SSIV^{37}_{LDS^1\star LDSR^1}$ to $SSIV^{42}_{LDS^6\star LDSR^6}$	$N^k_{t-q}W^k_{t-r}$ for $k=1,\ldots,6$; $q=0,1$; $r=0,1$ and $q\neq 1$ if $r=0$	Disaggregate shocks and shares by industry without & with lag
43–44	$SSIV^{43}_{AS}$; $SSIV^{44}_{LAS}$	N^S_{t-q} for $q=0,1$	Aggregate shocks only without & with lag
45–46	$SSIV^{45}_{ADS}$; $SSIV^{46}_{LADS}$	$\sum_{k=1}^{6} N^k_{t-q}$ for $q=0,1$	Sum of disaggregate shocks across industries without & with lag
47–58	$SSIV^{47}_{DS^1}$ to $SSIV^{52}_{DS^6}$; $SSIV^{53}_{LDS^1}$ to $SSIV^{58}_{LDS^6}$	N^k_{t-q} for $q=0,1$; $k=1,\ldots,6$	Disaggregate shocks by industry

Note: q and r denote the lag on the shock and share, respectively. While S represents aggregate services industry, k indexes the 6 service industries. The condition $q\neq 1$ for $r=0$ excludes lagged shocks with original shares ($N_{t-1}W_t$).

Here: AS and ASR refer to the aggregate shock and share, while LAS and $LASR$ represent their lagged counterparts. ADS and $ADSR$ are aggregated disaggregate shocks and shares, and DS and LDS denote disaggregate shocks without and with lag. DSR and $LADSR$ indicate disaggregate shares without and with lag.

[a] Using Aggregate Services Industry

Using the aggregate services industry, we use the conventional method to derive $SSIV^1_{AS\star ASR}$. To address concerns about the potential endogeneity of the industry share, as highlighted in previous studies (Acemoglu et al., 2016; Algan et al., 2017; Borusyak et al., 2022), we derive $SSIV^2_{AS\star LASR}$ using the lagged share to tackle the minor possibility of the endogeneity in industry share.

As Jaeger et al. (2018) suggested to introduce a lag shock to isolate the current effect from the past effect, we further construct our version of instrument, $SSIV^3_{LAS\star LASR}$, by lagging the shift component of the instrument. To eliminate any potential contemporaneous correlation between instrument and the endogenous variable, our variant of SSIV relies on past industry shifts and regional shares to predict current interprovincial services trade. Our variant builds on the foundational insights of Jaeger et al. (2018) and Acemoglu et al. (2016) by extending the application of lagged variables to both shocks and shares.

Acemoglu et al. (2016) introduced lagging the share component to address its endogeneity, Jaeger et al. (2018) emphasized lagging shocks to disentangle current and historical effects. However, combining a lagged shock with a non-lagged share ($N_{t-1}W_t$) does not fully address endogeneity concerns due to the contemporaneous nature of the share. Therefore, we exclude such combinations, as they do not provide a comprehensive solution to the problem.

[b] Aggregating the Disaggregate Services Industries

We use the six disaggregate services industries to develop three sets of instruments. The first, $SSIV^{4}_{ADS\star ADSR}$, is constructed using the conventional method. Next, we derive $SSIV^{5}_{ADS\star LADSR}$ by lagging only the regional share. Finally, we create $SSIV^{6}_{LADS\star LADSR}$ by lagging both the shocks and shares.

[c] Using Aggregate Shocks & Disaggregate Shares

We derive 18 instruments by combining aggregate shocks with disaggregate shares. First, we follow the conventional approach, pairing aggregate shocks with each disaggregate share to construct six instruments [$SSIV^{7}_{AS\star DSR^1}$ to $SSIV^{12}_{AS\star DSR^6}$]. Next, we lag the disaggregate shares while keeping the aggregate shocks to derive another six instruments [$SSIV^{13}_{AS\star LDSR^1}$ to $SSIV^{18}_{AS\star LDSR^6}$]. Lastly, we lag both the shocks and the shares to generate six additional variants [$SSIV^{19}_{LAS\star LDSR^1}$ to $SSIV^{24}_{LAS\star LDSR^6}$].

[d] Using Disaggregate Shocks & Disaggregate Shares

We construct 18 instruments by combining disaggregate shocks with disaggregate shares. First, we derive six instruments [$SSIV^{25}_{DS^1\star DSR^1}$ to $SSIV^{30}_{DS^6\star DSR^6}$] using the direct combination of shocks and shares. Then, we introduce a lag in the regional shares to develop six additional instruments [$SSIV^{31}_{DS^1\star LDSR^1}$ to $SSIV^{36}_{DS^6\star LDSR^6}$]. Finally, we lag both the shocks and the shares to derive the last six instruments [$SSIV^{37}_{LDS^1\star LDSR^1}$ to $SSIV^{42}_{LDS^6\star LDSR^6}$].

We outline two reasons why we recommend to use disaggreagte shocks and shares to construct SSIVS rather than aggregate shock. First, aggregate shock of the Conventional SSIV can indirectly affect the outcome variable and may weaken the exclusion restriction. Moreover, aggregate shocks may not be able to capture regional and industrial heterogeneity.

On the other-hand, our variants incorporate lag in both shocks and shares to ensure that the endogenous regressor is predicted based on past economic conditions. We also develop our instruments with lag disaggregate shocks and shares to better account for regional and industrial heterogeneity. Therefore, our variants eliminate potential contemporaneous correlations between instruments and the endogenous variable and strengthen the validity of our identification strategy.

[e] Using Aggregate & Disaggregate Shocks

We derive 16 instruments using aggregate and disaggregate shocks, both with and without lags. To address the potential endogeneity of the "regional industry share," we normalize the shares following Goldsmith-Pinkham et al. (2020) and use the shocks as instruments for interprovincial services trade. Using this approach, we construct $SSIV^{43}_{AS}$ using aggregate shocks and $SSIV^{44}_{LAS}$ using lagged aggregate shocks. Similarly, we develop $SSIV^{45}_{ADS}$ using the shocks of six disaggregate industries and $SSIV^{46}_{LADS}$ using their lagged counterparts. By normalizing the disaggregate shares and pairing them with disaggregate shocks, both with and without lags, we construct 12 additional instruments: $SSIV^{47}_{DS^1}$ to $SSIV^{52}_{DS^6}$ and $SSIV^{53}_{LDS^1}$ to $SSIV^{58}_{LDS^6}$.

Thus, we demonstrate the methodology for constructing shock instruments by normalizing regional shares. The following section shows the empirical strategy used to apply these 58 instruments and estimate the causal effect of interprovincial services trade on interprovincial goods trade.

1.4.5 IV Approaches & Comparison

Using Table 1.3, we classify all these instruments into two categories: Literature-Suggested SSIVs and Our SSIVs. Within the literature suggested category, we have two types of instruments: Conventional SSIVs and Modified SSIVs. We derive the Conventional SSIVs using shock and share components, whereas we develop the Modified SSIVs with shock and lag share components.

We construct 58 instruments in this empirical setup and apply these instruments in JI and OI IV models. While setting the benchmark for performance comparisons, we compare our version of instruments to literature-suggested instruments in both versions of IV models.

We use each SSIV independently to instrument the endogenous interprovincial services trade to estimate JI IV models. In contrast, we use more than one instrument to estimate OI IV models. We select the instruments for OI models based on the categories: Our SSIVs vs literature-suggested SSIVs. For instance, Model 1 includes SSIVs derived from aggregate shocks and shares and aggregating disaggregate shocks and shares, while Model 2 incorporates SSIVs built with lagged components.

Our approach in selecting the instruments avoids overlapping instruments across OI models. To provide a clearer performance comparisons of instruments from each category, each OI model examines a different combination of instrument types. Last but not least, this approach also allows us to test the reliability of our results and analyze how different SSIV groups perform under alternative identification frameworks.

Table 1.3: Comparison of Instruments

Literature-Suggested Instruments		Our Instruments
Conventional SSIVs	**Modified SSIVs**	**Our SSIVs**
$\mathrm{SSIV}^{1}_{\mathrm{AS\ast ASR}}$; $\mathrm{SSIV}^{2}_{\mathrm{AS\ast LASR}}$	$\mathrm{SSIV}^{4}_{\mathrm{ADS\ast ADSR}}$; $\mathrm{SSIV}^{5}_{\mathrm{ADS\ast LADSR}}$	$\mathrm{SSIV}^{3}_{\mathrm{LAS\ast LASR}}$; $\mathrm{SSIV}^{6}_{\mathrm{LADS\ast LADRS}}$
$\mathrm{SSIV}^{7}_{\mathrm{AS\ast DSR1}}$, $\mathrm{SSIV}^{8}_{\mathrm{AS\ast DSR2}}$, $\mathrm{SSIV}^{9}_{\mathrm{AS\ast DSR3}}$, $\mathrm{SSIV}^{10}_{\mathrm{AS\ast DSR4}}$, $\mathrm{SSIV}^{11}_{\mathrm{AS\ast DSR5}}$, $\mathrm{SSIV}^{12}_{\mathrm{AS\ast DSR6}}$	$\mathrm{SSIV}^{13}_{\mathrm{AS\ast LDSR1}}$, $\mathrm{SSIV}^{14}_{\mathrm{AS\ast LDSR2}}$, $\mathrm{SSIV}^{15}_{\mathrm{AS\ast LDSR3}}$, $\mathrm{SSIV}^{16}_{\mathrm{AS\ast LDSR4}}$, $\mathrm{SSIV}^{17}_{\mathrm{AS\ast LDSR5}}$, $\mathrm{SSIV}^{18}_{\mathrm{AS\ast LDSR6}}$	$\mathrm{SSIV}^{19}_{\mathrm{LAS\ast LDSR1}}$, $\mathrm{SSIV}^{20}_{\mathrm{LAS\ast LDSR2}}$, $\mathrm{SSIV}^{21}_{\mathrm{LAS\ast LDSR3}}$, $\mathrm{SSIV}^{22}_{\mathrm{LAS\ast LDSR4}}$, $\mathrm{SSIV}^{23}_{\mathrm{LAS\ast LDSR5}}$, $\mathrm{SSIV}^{24}_{\mathrm{LAS\ast LDSR6}}$
		$\mathrm{SSIV}^{25}_{\mathrm{DS1\ast DSR1}}$, $\mathrm{SSIV}^{26}_{\mathrm{DS2\ast DSR2}}$, $\mathrm{SSIV}^{27}_{\mathrm{DS3\ast DSR3}}$, $\mathrm{SSIV}^{28}_{\mathrm{DS4\ast DSR4}}$, $\mathrm{SSIV}^{29}_{\mathrm{DS5\ast DSR5}}$, $\mathrm{SSIV}^{30}_{\mathrm{DS6\ast DSR6}}$
		$\mathrm{SSIV}^{31}_{\mathrm{DS1\ast LDSR1}}$, $\mathrm{SSIV}^{32}_{\mathrm{DS2\ast LDSR2}}$, $\mathrm{SSIV}^{33}_{\mathrm{DS3\ast LDSR3}}$, $\mathrm{SSIV}^{34}_{\mathrm{DS4\ast LDSR4}}$, $\mathrm{SSIV}^{35}_{\mathrm{DS5\ast LDSR5}}$, $\mathrm{SSIV}^{36}_{\mathrm{DS6\ast LDSR6}}$
		$\mathrm{SSIV}^{37}_{\mathrm{LDS1\ast LDSR1}}$, $\mathrm{SSIV}^{38}_{\mathrm{LDS2\ast LDSR2}}$, $\mathrm{SSIV}^{39}_{\mathrm{LDS3\ast LDSR3}}$, $\mathrm{SSIV}^{40}_{\mathrm{LDS4\ast LDSR4}}$, $\mathrm{SSIV}^{41}_{\mathrm{LDS5\ast LDSR5}}$, $\mathrm{SSIV}^{42}_{\mathrm{LDS6\ast LDSR6}}$
$\mathrm{SSIV}^{43}_{\mathrm{AS}}$, $\mathrm{SSIV}^{45}_{\mathrm{ADS}}$		$\mathrm{SSIV}^{44}_{\mathrm{LAS}}$, $\mathrm{SSIV}^{46}_{\mathrm{LADS}}$
$\mathrm{SSIV}^{47}_{\mathrm{DS1}}$, $\mathrm{SSIV}^{48}_{\mathrm{DS2}}$, $\mathrm{SSIV}^{49}_{\mathrm{DS3}}$, $\mathrm{SSIV}^{50}_{\mathrm{DS4}}$, $\mathrm{SSIV}^{51}_{\mathrm{DS5}}$, $\mathrm{SSIV}^{52}_{\mathrm{DS6}}$		$\mathrm{SSIV}^{53}_{\mathrm{LDS1}}$, $\mathrm{SSIV}^{54}_{\mathrm{LDS2}}$, $\mathrm{SSIV}^{55}_{\mathrm{LDS3}}$, $\mathrm{SSIV}^{56}_{\mathrm{LDS4}}$, $\mathrm{SSIV}^{57}_{\mathrm{LDS5}}$, $\mathrm{SSIV}^{58}_{\mathrm{LDS6}}$

1.4.6 Conventional SSIVs

We construct Conventional SSIVs using the mix of pre-determined regional trade shares and their corresponding national growth rates at both aggregate and disaggregate levels. This mechanism leverages regional variation in exposure to exogenous national trade shocks. As the provincial services trade share increases with the national growth rate, all SSIVs become more relevant to interprovincial services trade. Referring to Tables 1.4, 1.5, 1.6, 1.7 and 1.8, the strong first stage results further confirm the relevance of these instruments, consistently exceeding lower threshold of F-statistic [$F \geq 10$] (Bound et al., 1995; Stock & Yogo, 2002) and higher threshold of F-statistic [$F \geq 50$ (Keane & Neal, 2021)] across all version of IV models.

If SSIVs impact goods trade only through services trade then these SSIVs hold the exclusion restrictions. Regional services trade shares are plausibly exogenous to regional goods trade. As Goldsmith-Pinkham et al. (2020) emphasize, the exogeneity of SSIVs depends on the pre-determined nature of the share component. Additionally, the national services shocks are independent of regional goods trade dynamics. A study from Adão et al. (2019) suggests that the exogeneity of SSIVs should rely on the shocks. As the literature backs up the Conventional SSIVs to qualify as instruments, we claim that services trade influences goods trade only through SSIVs. Therefore, Conventional SSIVs satisfy the exclusion restrictions.

Despite having these strengths, Conventional SSIVs encounter two notable limitations. First, regional trade shares may correlate with unobserved regional characteristics. So, any estimations with these instruments may introduce potential bias. Second, aggregate national shocks may indirectly affect goods trade through contemporaneous fluctuations and this may weaken the exclusion restriction. That is why, this instrument development technique requires some modifications and we offer the modifications to this technique in the next section.

1.4.7 Modified SSIVs vs Our SSIVs

With a novel SSIV search framework, we address the limitations of conventional approach and our approach enhances the applicability and robustness of the instruments in our empirical setting. To capture regional and sectoral heterogeneity, our SSIV Search Method systematically explores different combinations of lagged shares and shocks both at aggregate and disaggregate levels to construct our instruments.

Acemoglu et al. (2016) introduced lag share component to address reverse causality in the endogenous share component of shift-share instruments, whereas Jaeger et al. (2018) lagged the shock component to isolate the current effect from the past effect. However, the aggregate shock component in their approach may overlook heterogeneity across industries and regions. It is particularly problematic in trade settings like ours where aggregate shocks may not fully account for heterogeneity across industries and provinces. Additionally, in our study, aggregate shocks may indirectly influence goods trade, leaving a ground for risk with weak exclusion restrictions. Although Jaeger et al. (2018)'s lagging strategy may tackle this weaker exclusion restrictions, this approach still may not be able to capture regional and sectoral heterogeneity.

Relying on the techniques of Acemoglu et al. (2016) and Jaeger et al. (2018), this study designs a comprehensive set of SSIVs through SSIV Search Method. Our granular approach ensures that the instruments can capture regional heterogeneity across industries and improves the quality of instruments. And the strong first stage results from Tables 1.4, 1.5, 1.6, 1.7 and 1.8 show that our SSIVs consistently meet the relevance condition of instruments.

Since our variants include lag in both shares and shocks across aggregate and disaggregate levels, they rely only on past economic conditions. Thereby, our approach eliminates any potential contemporaneous correlations between instruments and goods trade outcomes, strengthening the exclusion restrictions. Thus, our SSIVs influence goods trade only though services trade.

We address the limitations of the conventional approach and argue that our approach enhances the applicability and robustness of the instruments in our empirical setting. It also enhances the quality of instruments in terms of relevance, exogeneity and exclusion restrictions.

1.4.8 Identification Strategy

Since interprovincial services trade is endogenous, we instrument this endogenous variable with SSIVs. Equation (1.9) shows the first stage of the regression, where we instrument the endogenous interprovincial services trade using the SSIVs.

$$TS_{ijt}^{V} = \alpha_0 + \alpha_1 SSIV_{ijt}^{V} + \alpha_2\, Controls_{ij} + \alpha_3\, Controls_{it} + \alpha_4\, Controls_{jt} + \epsilon_{ijt} \tag{1.9}$$

Here, TS_{ijt}^{V} is the interprovincial services trade flow from province i to province j; $SSIV_{ijt}^{V}$ are the Shift-Share Instrumental Variables [SSIVs] derived from the services industries.

$Controls_{ij}$ are D_{ij} and $Border_{ij}$. D_{ij} is the distance between two provinces, and $Border_{ij}$ represents a dummy variable if the two provinces share a border accordingly. $Controls_{it}$ are $GDPC_{it}$, Inc_{it}, Par_{it} and WC_{it}. $GDPC_{it}$ is the GDP Per Capita of province i at time t; Inc_{it} is the annual average income of province i at time t; Par_{it} is the labor participation rate of province i at time t; WC_{it} is the weather conditions of province i at time t in January and February.

$Controls_{jt}$ are $GDPC_{jt}$, Inc_{jt}, Par_{jt} and WC_{jt}. $GDPC_{jt}$ is the GDP Per Capita of province j at time t; Inc_{jt} is the annual average income of province j at time t; Par_{jt} is the labor participation rate in province j at time t; WC_{jt} is the weather conditions of province j at time t in January and February.

In equation (1.9), we instrument interprovincial services trade between two regions by the SSIVs from the services industries, along with controls for distance, Gross Domestic Product [GDP] Per Capita of the two provinces, border sharing, origin and destination provinces' annual average incomes and weather conditions.

We estimate the impact of interprovincial services trade on interprovincial goods trade using Equation (1.10). We incorporate all the right-hand side variables of this equation except interprovincial services trade in Equation (1.9). These variables instrument themselves in the second stage shown in Equation (1.10).

$$\begin{aligned} TG_{ijt} = \exp\Bigg[&\beta_0 + \beta_1 \log \hat{TS}_{ijt}^{V} + \beta_2 \log Controls_{ij} + \beta_3 \log Controls_{it} \\ &+ \beta_4 \log Controls_{jt} + \tau_{it} + \tau_{jt} + \tau_t\Bigg] + \epsilon_{ijt} \end{aligned} \tag{1.10}$$

In the above expression, TG_{ijt} is interprovincial goods trade flow from province i to j; $\hat{TS}_{ijt}^{V}$ are the predicted values of interprovincial services trade flow from province i to j; τ_{it}, τ_{jt}, and τ_t are origin fixed effects, destination fixed effects, and year fixed effects.

From Equation (1.10), we regress interprovincial goods flow between two provinces on the predicted interprovincial services trade flow between the two provinces, the distance between two provinces, the GDP Per Capita, the participation rate, the weather conditions, and average annual income of destination and origin, as well as border sharing between two provinces.

1.4.9 PPML Estimator & The Fixed Effects

We apply the PPML estimator in the gravity model and control unobserved heterogeneity using year-fixed effect, origin and destination-fixed effects. Moreover, we use the Hansen J test to check the validity of overidentifying restrictions for OI IV models.

Conventionally, empirical studies log linearize the gravity equation and they estimate with the 2SLS estimator. However, Silva & Tenreyro (2006) show that log linearizing the gravity equation causes bias and inconsistency if there is heteroskedasticity. They recommend estimating the model in multiplicative form and to use the PPML estimator as it is an efficient estimator. Therefore, our study estimates the equation (1.10) in multiplicative form using the PPML estimator, rather than log-linearizing the equations.

We control unobserved heterogeneity and multilateral resistance terms by introducing year-fixed effects, and origin and destination-fixed effects. Following the work of Anderson & Van Wincoop (2003), the standard practice in the structural gravity model of trade is to account for multilateral resistance terms by incorporating individual dummies for each origin and destination. It is the same as taking fixed effects for origin and destination into the gravity model (Hummels, 1999). Under reasonable assumptions, Fally (2015) shows that only the PPML estimator has the properties to recover the multilateral resistance term using origin and destination fixed effects. Santos Silva & Tenreyro (2022) revisit their estimator and support the findings from Fally (2015).

1.4.10 Machine Learning Approach: A Predictive Strength Analysis of SSIVs

While the conventional IV approach relies on linear first-stage regressions, this study explores the potential of machine learning techniques - Gradient Boosting and Random Forests- as alternative methods for the first-stage regressions. These models are capable of capturing complex and non-linear relationships. his study evaluates the predictive power of the instruments (SSIVs) in explaining the endogenous variable but does not use these predictions in the second-stage IV regressions. The following sections provide an overview of the GB and RF models and outline the empirical strategy applied in this study.

1.4.11 Overview of GB and RF

Friedman (2001) developed the GB model, which builds predictive models through sequential optimization of weak learners. The appealing feature of this technique is to fix the errors from the previous models. The sequential nature of the GB model allows it to capture complex relationships and improve predictive accuracy gradually as it reduces errors from one regression to another. In this study, we apply the GB model to evaluate the predictive strength of the instruments in predicting the endogenous regressor.

Breiman (2001) introduced the RF model, which captures complex and non-linear relationships. It is an ensemble learning technique that combines predictions from multiple decision trees to enhance accuracy and efficiency, specially well known for its high accuracy and efficiency with large datasets (Liaw & Wiener, 2002). We employ the RF model to identify which instruments exhibit superior predictive strength in explaining interprovincial services trade flows.

1.4.12 Data Preparation and Empirical Strategy

This paper applies GB and RF models to assess the predictive strength of 58 SSIVs across both JI and OI models. We construct two matrices- "X" and "Y". Our instruments and control variables include "X" whereas "Y" consists of the dependent variable, interprovincial services trade flow between two regions. Equations (1.11) and (1.12) illustrate the GB prediction and the RF prediction mechanisms.

$$\hat{Y} = \sum_{b=1}^{B} \gamma_b T_b(X) \tag{1.11}$$

Here, $\hat{Y}$ is the predicted interprovincial trade flow, B represents individual trees; $T_b(X)$ shows the prediction of the bth tree based on the instruments and the other control variables, and γ_b denotes the learning rate adjusting each tree's contribution.

$$\hat{Y} = \frac{1}{C} \sum_{i=1}^{C} T_i(X) \tag{1.12}$$

Here, $\hat{Y}$ is the predicted interprovincial trade flow, which we obtain by averaging the outcomes of C individual trees; $T_i(X)$ shows the prediction of the ith tree based on the instruments and the other control variables.

This study outlines the steps to apply GB and RF models. Since we do not have any missing values in our dataset, we first split the dataset into 80% training and 20% testing subsets for validation (James, Witten, Hastie, & Tibshirani, 2013). Next, we fine-tune the parameters such as learning rate, number of estimators, and subsample size using a grid search to optimize model performance (Friedman, 2001; Probst et al., 2019).

We assess the performance of instruments based on variable importance scores and RMSE (Hyndman & Koehler, 2006; Strobl et al., 2007). Lastly, we test the model's ability to predict new data by the cross-validation technique. It evaluates how well it performs on an independent dataset.

We employ $K - fold$ cross-validation and divide the entire dataset randomly by k subsets to validate the model (James, Witten, Hastie, & Tibshirani, 2013). Each iteration consists of one-fold as the testing set, and the remaining $(k-1)$ as the training set. We repeat this process k times and take the average of the results from each fold to generate a single estimation.

After following all the steps mentioned above, we obtain the results from the GB and RF models. We compare the feature scores from the models for all SSIVs and conclude which SSIVs predict interprovincial services trade flow better. While we do not use these predictions in the second-stage IV regressions, the findings exhibit the potential of machine learning techniques to validate and enhance the first-stage regressions in IV analysis.

1.5 Data Description

To investigate how interprovincial services trade impacts interprovincial goods trade for all Canadian provinces, except Prince Edward Island, this research compiles the panel dataset using the following variables: interprovincial goods trade flow, interprovincial services trade flow, consumption tax rate, participation rate, annual yearly income, and gross domestic product (GDP) per capita from CANSIM[‡] for the years 2007 to 2019.

For the implementation of the gravity model, this panel dataset includes distance. This study selects one major city in each Canadian province based on population density as a measure of the distance, and we use the distance[§] between two provinces in the gravity model. If a province shares a border with other provinces, this may increase the probability of migration. Therefore, we include a border dummy variable in the model, with a value of 1 for a province sharing a border with another province, and 0 otherwise. If a province experiences temperatures below $-30°C$ in January and February for the years 2007 to 2019, our study considers that province as having the worst weather conditions as per Environment Canada (2020)'s monthly data. Thus, we set 1 for the worst weather conditions and 0 otherwise.

1.6 Main Results

In this section, we discuss our JI and OI IV results. Next, we explain the results from the GB and the RF estimations. Finally, we show our Monte Carlo simulation results and explain accordingly.

1.6.1 Impact of Services Trade on Goods Trade

Tables 1.4, 1.5, 1.6 and 1.7 show the results from JI IV models, whereas Table 1.8 represents OI IV models. First, we discuss the empirical results using literature-suggested SSIVs and then compare those with our variants. We compare the performance of the instruments based on the values of F-statistics and R-squared from the FS.

1.6.2 Evidence from JI IV Results

Across all versions of IV models, we find that interprovincial services trade positively impacts interprovincial goods trade within Canada, and it is statistically significant at a 1% significance level. If interprovincial services trade increases by 1%, then interprovincial goods trade will increase by more than 1%. The results are robust across all SSIVs. Our empirical finding provides compelling evidence of the causal effect of services trade on goods trade whereas the literature (Ariu, 2016; Ariu et al., 2020; Arnold et al., 2011; Breinlich & Criscuolo, 2011; Egger et al., 2012; Hoekman

[‡]Statistics Canada. *Table 12-10-0088-01: Interprovincial and international trade flows, basic prices, summary level (x 1,000,000).* DOI: 10.25318/1210008801-eng

[§]https://www.distancefromto.net/

& Shepherd, 2017; Lennon, 2009; Nordås & Rouzet, 2017; Nordås, 2010; Sauve & Mattoo, 2003) suggests a positive relationship between services trade and goods.

Table 1.4 represents the estimations of JI IV models with aggregate SSIVs. The coefficient estimates from instruments, aggregate shock and share without lag [$\text{SSIV}^1_{\text{AS}*\text{ASR}}$ and aggregating disaggregate shocks and shares $\text{SSIV}^4_{\text{ADS}*\text{ADSR}}$], and with lag [$\text{SSIV}^2_{\text{AS}*\text{LASR}}$ and $\text{SSIV}^5_{\text{ADS}*\text{LADSR}}$] range from 1.078 to 1.325 and 1.086 to 1.643, respectively. The values of the F-statistic are consistently high across these SSIVs ranging from 207.62 to 222.81. The literature (Bound et al., 1995; Stock & Yogo, 2002) suggests that if the F-statistic of the first stage is 10, the instruments are not weak. It also satisfies a higher threshold of $F \geq 50$ Keane & Neal (2021). Therefore, we claim that all these six aggregate instruments are very strong. We also find that the R-squared values are high across these JI models, ranging from 0.7140 to 0.7860, suggesting strong explanatory power for these models. Among aggregate SSIVs, we observe that aggregating the disaggregate shocks and shares produces higher coefficient values, indicating better quality in capturing variations.

The SSIVs with lag share component slightly perform empirically better than Conventional SSIVs. Notably, the SSIVs with lag share have the biggest advantage over Conventional SSIVs by tackling the endogeneity of the share, and this modification is one of the significant contributions of Acemoglu et al. (2016) in this literature.

Our instruments [$\text{SSIV}^3_{\text{LAS}*\text{LASR}}$ and $\text{SSIV}^6_{\text{LADS}*\text{LADS}}$], which use aggregate shock and share with lag, produce higher coefficients compared to literature-suggested instruments. We observe almost similar first stage F-statistics and R-squared values across these two models, solidifying the strengths of our instruments. Our instruments also effectively handle the endogenous share component and historical data, making them superior to the Conventional SSIVs and equally robust as the modified SSIVs, referring to the instruments of Acemoglu et al. (2016).

Table 1.5 shows the empirical performance of SSIVs using aggregate and disaggregate data, both with and without lag. Conventional SSIVs using aggregate shock and disaggregate share with lag [$\text{SSIV}^7_{\text{AS}*\text{DSR}^1}$ to $\text{SSIV}^{12}_{\text{AS}*\text{DSR}^6}$] perform similarly compared to the modified instruments using aggregate shock and disaggregate share without lag [$\text{SSIV}^{13}_{\text{AS}*\text{LDSR}^1}$ to $\text{SSIV}^{18}_{\text{AS}*\text{LDSR}^6}$]. The models using these SSIVs exhibit the same coefficient values at the second stage, as well as similar F-statistics and R-squared values at the first stage.

On the other hand, IV models using our instruments [$\text{SSIV}^{19}_{\text{LAS}*\text{LDSR}^1}$ to $\text{SSIV}^{24}_{\text{LAS}*\text{LDSR}^6}$; $\text{SSIV}^{25}_{\text{DS}^1*\text{DSR}^1}$ to $\text{SSIV}^{30}_{\text{DS}^6*\text{DSR}^6}$; and $\text{SSIV}^{31}_{\text{DS}^1*\text{LDSR}^1}$ to $\text{SSIV}^{42}_{\text{LDS}^6*\text{LDSR}^6}$] produce higher coefficients, but with similar F-statistics and R-squared values at the FS.

We present the empirical performance of SSIVs derived from disaggregated shocks and shares, both with and without lag, in Table 1.6. The estimations from all JI models indicate that SSIVs in this category yield similar coefficients at the second stage, as well as similar F-statistic and R-squared values at the first stage.

Table 1.7 provides the empirical performance of SSIVs using both aggregate and disaggregate shocks, with and without lag. The results indicate that all instruments, whether aggregate or disaggregate, perform equally well under JI mechanism. These instruments generate similar coefficient estimates at the second stage and comparable F-statistic and R-squared values at the first stage. Figures 1.1, 1.2 and 1.3 offer a visual representation that further compares all the coefficients, F-statistics, and R-squared values across all SSIVs.

The estimated models with Conventional SSIVs do not lose any observations as these instruments do not rely on lagged components. However, models with Modified SSIVs and Our SSIVs, which incorporate lags in the shocks and shares, drop observations due to the construction methods of these instruments.

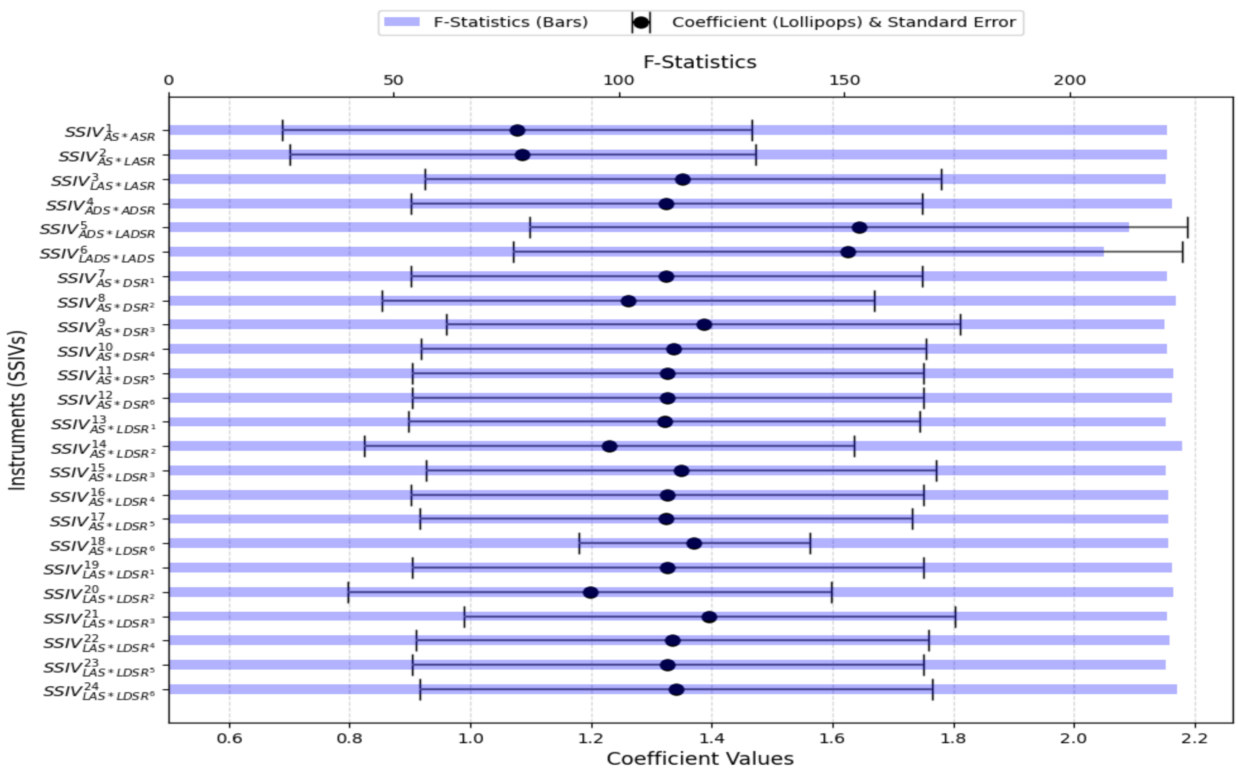

Figure 1.1: Empirical Performance of SSIVs Using Aggregate Shocks & Shifts with Lags and without Lags.

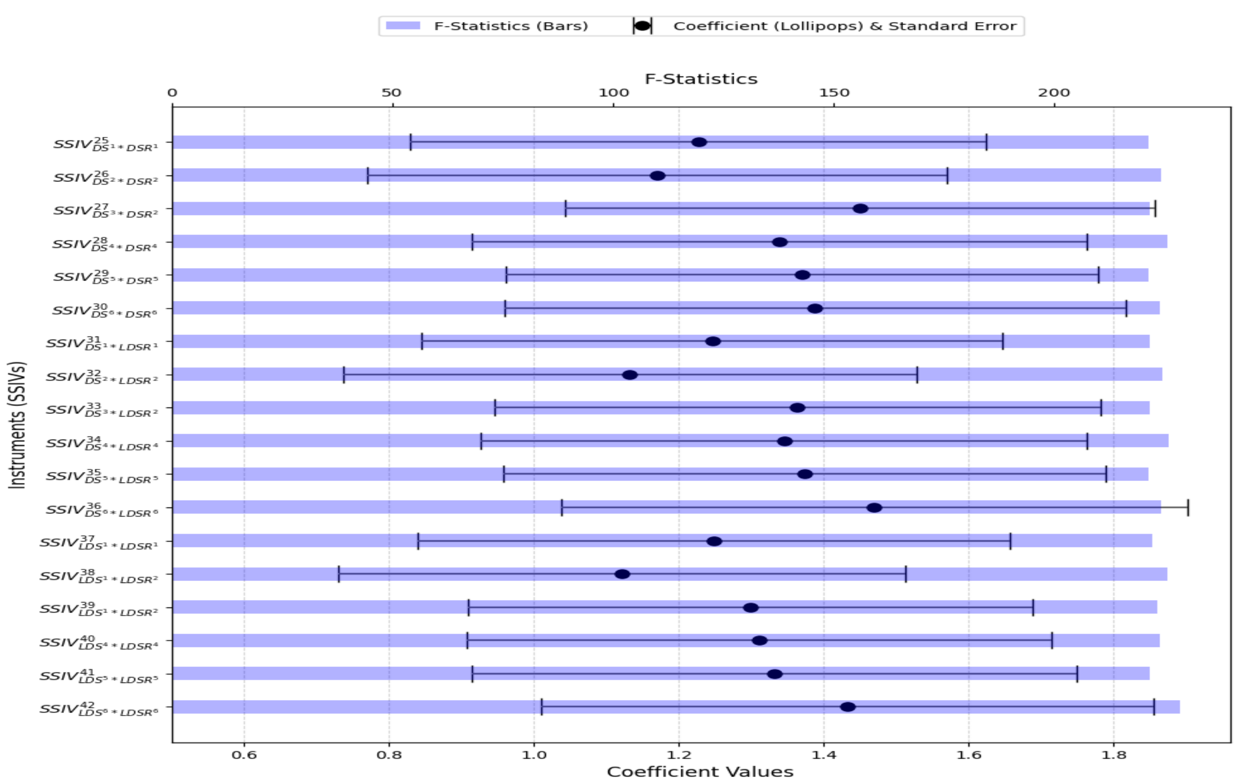

Figure 1.2: Empirical Performance of SSIVs Aggregate and Disaggregate Shifts and Shares without lags and with Lags

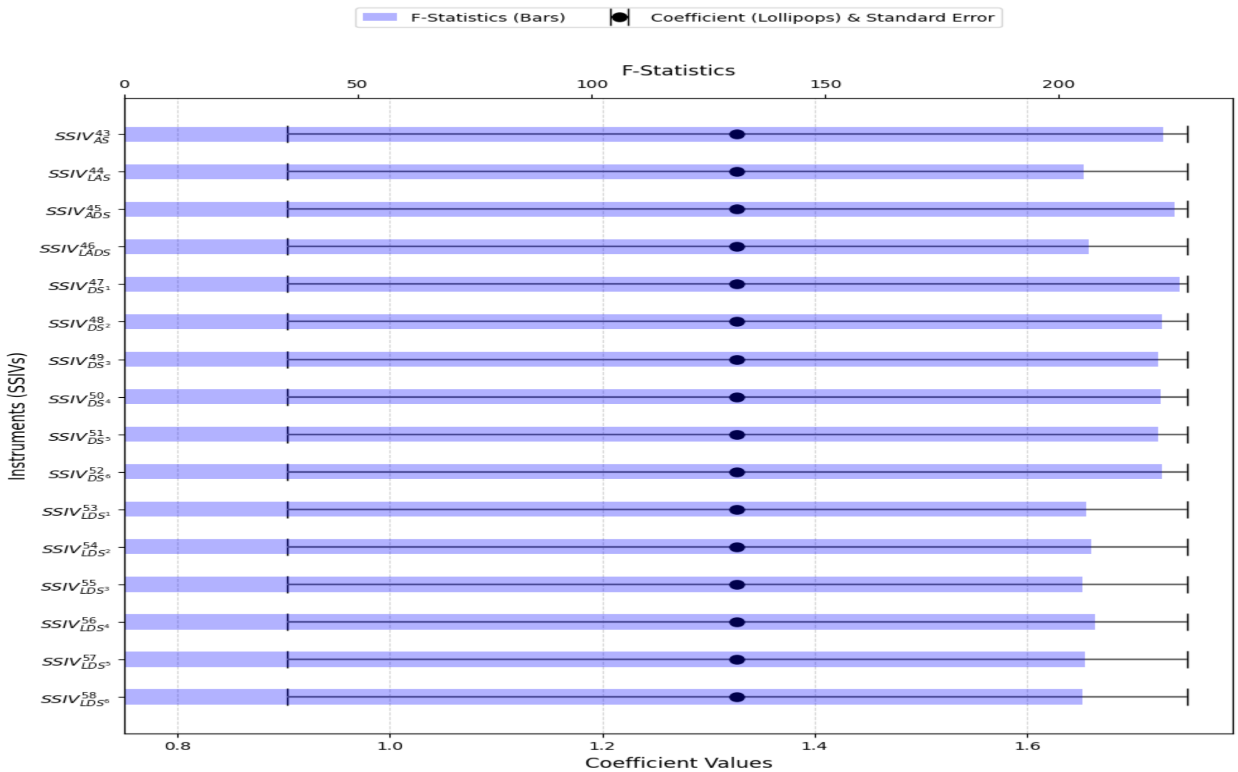

Figure 1.3: Empirical Performance of SSIVs Using Disaggregate Shifts and Shares without lags and with Lags.

Table 1.4: JI IV Results of Services Trade Impact on Goods Trade

Dependent Variable: *Interprovincial Goods Trade [TG_{ijt}]*				
Instruments	$\hat{T}_{S_{yjt}}$	**Obs.**	**F Statistic [FS]**	**R Squared [FS]**
$\mathrm{SSIV}^{1}_{\mathrm{AS*ASR}}$	1.078*** (0.389)	864	221.54	0.7761
$\mathrm{SSIV}^{2}_{\mathrm{AS*LASR}}$	1.086*** (0.386)	864	221.55	0.7140
$\mathrm{SSIV}^{3}_{\mathrm{LAS*LASR}}$	1.352*** (0.427)	792	221.18	0.7758
$\mathrm{SSIV}^{4}_{\mathrm{ADS*ADSR}}$	1.325*** (0.424)	864	222.81	0.7771
$\mathrm{SSIV}^{5}_{\mathrm{ADS*LADSR}}$	1.643*** (0.545)	792	213.08	0.7860
$\mathrm{SSIV}^{6}_{\mathrm{LADS*LADS}}$	1.625*** (0.555)	792	207.62	0.7816
Fixed Effects: Origin, Destination & Year				
Estimator: PPML				
Instrument Development Components: Aggregate and Lagged Shift & Shares				
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

Table 1.5: JI IV Results of Impact of Services Trade on Goods Trade

Dependent Variable: *Interprovincial Goods Trade [TG_{ijt}]*				
Instruments	$\hat{T}_{S_{yjt}}$	**Obs.**	**F Statistic [FS]**	**R Squared [FS]**
$\text{SSIV}^{7}_{\text{AS}*\text{DSR}^1}$	1.325*** (0.424)	864	221.46	0.7760
$\text{SSIV}^{8}_{\text{AS}*\text{DSR}^2}$	1.261*** (0.408)	864	223.68	0.7778
$\text{SSIV}^{9}_{\text{AS}*\text{DSR}^3}$	1.386*** (0.426)	864	221.14	0.7758
$\text{SSIV}^{10}_{\text{AS}*\text{DSR}^4}$	1.336*** (0.418)	864	221.47	0.7761
$\text{SSIV}^{11}_{\text{AS}*\text{DSR}^5}$	1.327*** (0.424)	864	222.87	0.7771
$\text{SSIV}^{12}_{\text{AS}*\text{DSR}^6}$	1.327*** (0.424)	864	222.68	0.7762
$\text{SSIV}^{13}_{\text{AS}*\text{LDSR}^1}$	1.321*** (0.423)	864	221.26	0.7759
$\text{SSIV}^{14}_{\text{AS}*\text{LDSR}^2}$	1.230*** (0.406)	864	224.91	0.7787
$\text{SSIV}^{15}_{\text{AS}*\text{LDSR}^3}$	1.349*** (0.422)	864	221.28	0.7759
$\text{SSIV}^{16}_{\text{AS}*\text{LDSR}^4}$	1.326*** (0.424)	864	221.86	0.7764
$\text{SSIV}^{17}_{\text{AS}*\text{LDSR}^5}$	1.324*** (0.407)	864	221.92	0.7764
$\text{SSIV}^{18}_{\text{AS}*\text{LDSR}^6}$	1.371** (0.192)	864	222.00	0.7765
$\text{SSIV}^{19}_{\text{LAS}*\text{LDSR}^1}$	1.327*** (0.424)	720	222.81	0.7771
$\text{SSIV}^{20}_{\text{LAS}*\text{LDSR}^2}$	1.198*** (0.400)	720	223.04	0.7773
$\text{SSIV}^{21}_{\text{LAS}*\text{LDSR}^3}$	1.396*** (0.407)	720	221.49	0.7761
$\text{SSIV}^{22}_{\text{LAS}*\text{LDSR}^4}$	1.335*** (0.425)	720	222.07	0.7765
$\text{SSIV}^{23}_{\text{LAS}*\text{LDSR}^5}$	1.327*** (0.425)	720	221.22	0.7759
$\text{SSIV}^{24}_{\text{LAS}*\text{LDSR}^6}$	1.341*** (0.425)	720	223.89	0.7779
Fixed Effects: Origin, Destination & Year				
Estimator: PPML				
Instrument Development Components: Aggregate and Disaggregate Shifts and Shares without Lags & with Lags				
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

Table 1.6: JI IV Results of Impact of Services Trade on Goods Trade

Dependent Variable: *Interprovincial Goods Trade [TG_{ijt}]*				
Instruments	$\hat{T}_{S_{yjt}}$	**Obs.**	**F Statistic [FS]**	**R Squared [FS]**
$SSIV^{25}_{DS^1 * DSR^1}$	1.227*** (0.398)	864	221.28	0.7759
$SSIV^{26}_{DS^2 * DSR^2}$	1.170*** (0.400)	864	224.24	0.7782
$SSIV^{27}_{DS^3 * DSR^2}$	1.450*** (0.407)	864	221.51	0.7761
$SSIV^{28}_{DS^4 * DSR^4}$	1.339*** (0.425)	864	225.50	0.7792
$SSIV^{29}_{DS^5 * DSR^5}$	1.370*** (0.409)	864	221.39	0.7760
$SSIV^{30}_{DS^6 * DSR^6}$	1.388*** (0.429)	864	223.79	0.7779
$SSIV^{31}_{DS^1 * LDSR^1}$	1.246*** (0.401)	720	221.44	0.7760
$SSIV^{32}_{DS^2 * LDSR^2}$	1.132*** (0.396)	720	224.45	0.7784
$SSIV^{33}_{DS^3 * LDSR^2}$	1.364*** (0.418)	720	221.46	0.7761
$SSIV^{34}_{DS^4 * LDSR^4}$	1.345*** (0.418)	720	225.72	0.7793
$SSIV^{35}_{DS^5 * LDSR^5}$	1.374*** (0.416)	720	221.34	0.7760
$SSIV^{36}_{DS^6 * LDSR^6}$	1.470*** (0.433)	720	224.18	0.7782
$SSIV^{37}_{LDS^1 * LDSR^1}$	1.248*** (0.409)	648	222.16	0.7766
$SSIV^{38}_{LDS^1 * LDSR^2}$	1.121*** (0.391)	648	225.54	0.7792
$SSIV^{39}_{LDS^1 * LDSR^2}$	1.299*** (0.390)	648	223.17	0.7774
$SSIV^{40}_{LDS^4 * LDSR^4}$	1.311*** (0.404)	648	223.87	0.7779
$SSIV^{41}_{LDS^5 * LDSR^5}$	1.332*** (0.417)	648	221.47	0.7761
$SSIV^{42}_{LDS^6 * LDSR^6}$	1.433*** (0.423)	648	228.41	0.7814
Fixed Effects: Origin, Destination & Year				
Estimator: PPML				
Instrument Development Components: Disaggregate Shifts and Shares without Lags & with Lags				
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

Table 1.7: JI IV Results of Services Trade Impact on Goods Trade

Dependent Variable: *Interprovincial Goods Trade [TG_{ijt}]*				
Instruments	$\hat{T}_{S_{yjt}}$	**Obs.**	**F Statistic [FS]**	**R Squared [FS]**
$\text{SSIV}^{43}_{\text{AS}}$	1.327*** (0.424)	864	222.25	0.7767
$\text{SSIV}^{44}_{\text{LAS}}$	1.327*** (0.424)	720	205.25	0.7797
$\text{SSIV}^{45}_{\text{ADS}}$	1.327*** (0.424)	864	224.83	0.7787
$\text{SSIV}^{46}_{\text{LADS}}$	1.327*** (0.424)	720	206.48	0.7807
$\text{SSIV}^{47}_{\text{DS}^1}$	1.327*** (0.424)	864	225.85	0.7794
$\text{SSIV}^{48}_{\text{DS}^2}$	1.327*** (0.424)	864	222.06	0.7765
$\text{SSIV}^{49}_{\text{DS}^3}$	1.327*** (0.424)	864	221.14	0.7758
$\text{SSIV}^{50}_{\text{DS}^4}$	1.327*** (0.424)	864	221.79	0.7763
$\text{SSIV}^{51}_{\text{DS}^5}$	1.327*** (0.424)	864	221.15	0.7758
$\text{SSIV}^{52}_{\text{DS}^6}$	1.327*** (0.424)	864	222.08	0.7771
$\text{SSIV}^{53}_{\text{LDS}^1}$	1.327*** (0.424)	720	205.74	0.7801
$\text{SSIV}^{54}_{\text{LDS}^2}$	1.327*** (0.424)	720	206.89	0.7801
$\text{SSIV}^{55}_{\text{LDS}^3}$	1.327*** (0.424)	720	204.90	0.7794
$\text{SSIV}^{56}_{\text{LDS}^4}$	1.327*** (0.424)	720	207.77	0.7818
$\text{SSIV}^{57}_{\text{LDS}^5}$	1.327*** (0.424)	720	205.45	0.7798
$\text{SSIV}^{58}_{\text{LDS}^6}$	1.327*** (0.424)	720	205.03	0.7795
Fixed Effects: Origin, Destination & Year				
Estimator: PPML				
Instrument Development Components: Aggregate and Disaggregate Shocks without Lags & with Lags				
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

1.6.3 Evidence from OI IV Results

We compare the empirical performance of OI models' literature-suggested SSIVs to our SSIVs in Table 1.8. We use Figure 1.4 to display the values of the coefficients in the SS, F-statistics and R-squared from the FS for better comparison. We estimate models 1, 3, 4, and 9 using literature-suggested instruments whereas we evaluate models 2, 5, 6, 7, 8, 10, 11 and 12 with our instruments.

Both literature-suggested instruments and our instruments produce positive and statistically significant results at a 1% level, the estimates range from 1.224 to 1.836. This evidence indicates that our estimations are robust across all the models, finding a positive impact of services trade on goods trade. Notably, our estimations show that all the models produce very high values of F-statistic in the FS. We also find high and similar R-squared across all models in the FS, ranging from 0.7179 to 0.7889.

We employ the Hansen J test to examine the validity of the instruments as it ensures that the instruments are uncorrelated with the error term. Therefore, we compare the over-identification test results of the Hansen J statistics across all OI models. The null hypothesis (H_0) of the Hansen J test is that the instruments are valid. The results indicate that we fail to reject the null hypothesis for all OI IV models. Thus, we claim that all the instruments in this study are valid.

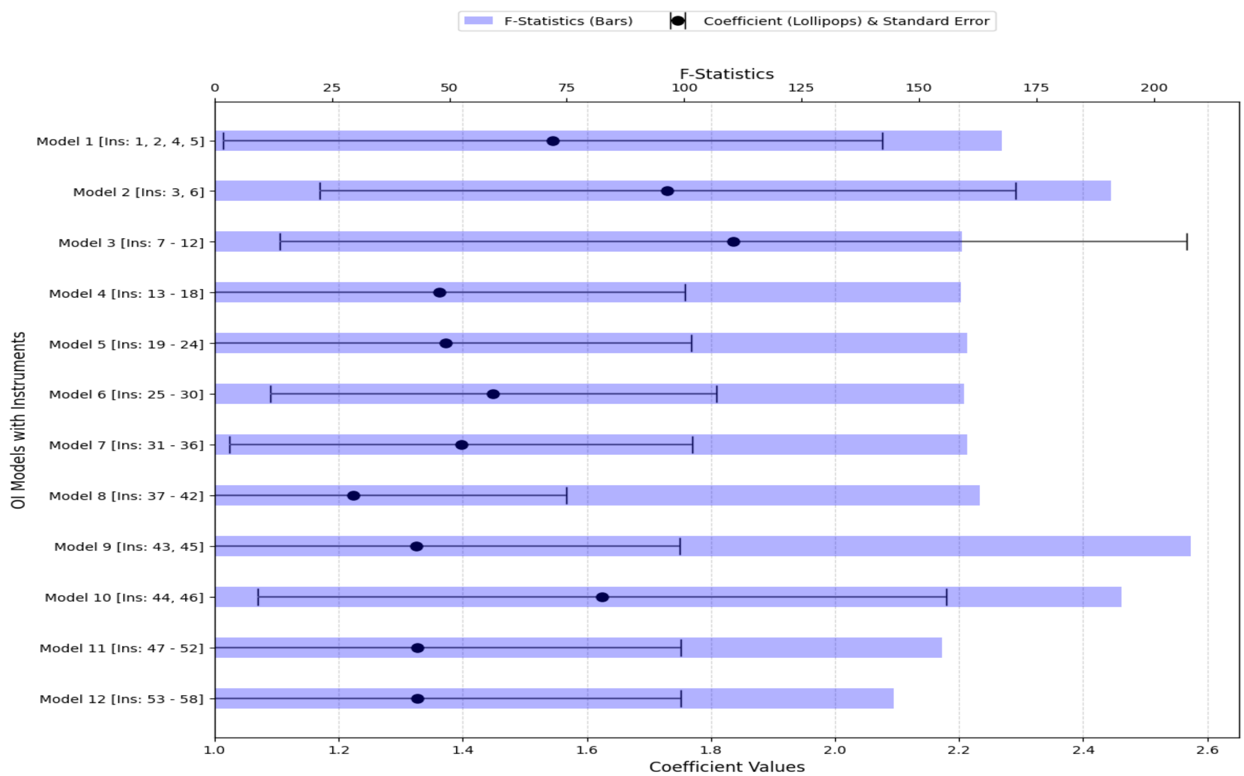

Figure 1.4: Empirical Performance of SSIVs in OI Models Comparing Our Instruments to Literature Suggested Instruments.

Table 1.8: OI IV Results of Impact of Services Trade on Goods Trade

Dependent Variable: *Interprovincial Goods Trade* $[TG_{ijt}]$						
Models	**Instruments**	$\hat{T}_{S_{yjt}}$	**Obs.**	**Hansen J Statistic [P Value]**	**F Stat. [FS]**	**R Squared [FS]**
1	$SSIV^{1}_{AS*ASR}$; $SSIV^{2}_{AS*LASR}$ $SSIV^{4}_{ADS*LADSR}$; $SSIV^{5}_{ADS*LADSR}$	1.545*** (0.531)	864	0.1111	167.76	0.7872
2	$SSIV^{3}_{LAS*LASR}$; $SSIV^{6}_{LADS*LADS}$	1.730*** (0.561)	792	0.2757	190.99	0.7825
3	$SSIV^{7}_{AS*DSR^1}$; $SSIV^{8}_{AS*DSR^2}$; $SSIV^{9}_{AS*DSR^3}$; $SSIV^{10}_{AS*DSR^4}$; $SSIV^{11}_{AS*DSR^5}$; $SSIV^{12}_{AS*DSR^6}$	1.836** (0.731)	864	0.8303	159.08	0.7848
4	$SSIV^{13}_{AS*LDSR^1}$; $SSIV^{14}_{AS*LDSR^2}$ $SSIV^{15}_{AS*LDSR^3}$; $SSIV^{16}_{AS*LDSR^4}$; $SSIV^{17}_{AS*LDSR^5}$; $SSIV^{18}_{AS*LDSR^6}$	1.363*** (0.395)	864	0.6259	159.01	0.7847
5	$SSIV^{19}_{LAS*LDSR^1}$; $SSIV^{20}_{LAS*LDSR^2}$ $SSIV^{21}_{LAS*LDSR^3}$; $SSIV^{22}_{LAS*LDSR^4}$ $SSIV^{23}_{LAS*LDSR^5}$; $SSIV^{24}_{LAS*LDSR^6}$	1.373*** (0.396)	792	0.5996	160.28	0.7861
6	$SSIV^{25}_{DS^1*DSR^1}$; $SSIV^{26}_{DS^2*DSR^2}$ $SSIV^{27}_{DS^3*DSR^3}$; $SSIV^{28}_{DS^4*DSR^4}$; $SSIV^{29}_{DS^5*DSR^5}$; $SSIV^{30}_{DS^6*DSR^6}$	1.449*** (0.359)	864	0.2358	159.70	0.7854
7	$SSIV^{31}_{DS^1*LDSR^1}$; $SSIV^{32}_{DS^2*LDSR^2}$ $SSIV^{33}_{DS^3*LDSR^3}$; $SSIV^{34}_{DS^4*LDSR^4}$; $SSIV^{35}_{DS^5*LDSR^5}$; $SSIV^{36}_{DS^6*LDSR^6}$	1.397*** (0.373)	864	0.1956	160.22	0.7860
8	$SSIV^{37}_{LDS^1*LDSR^1}$; $SSIV^{38}_{LDS^2*LDSR^2}$ $SSIV^{39}_{LDS^3*LDSR^3}$; $SSIV^{40}_{LDS^4*LDSR^4}$; $SSIV^{41}_{LDS^5*LDSR^5}$; $SSIV^{42}_{LDS^6*LDSR^6}$	1.224*** (0.343)	792	0.2597	162.99	0.7889
9	$SSIV^{43}_{AS}$; $SSIV^{45}_{ADS}$	1.325*** (0.424)	864	0.4036	207.80	0.7803
10	$SSIV^{44}_{LAS}$; $SSIV^{46}_{LADS}$	1.625*** (0.555)	864	0.4421	193.09	0.7844
11	$SSIV^{47}_{DS^1}$; $SSIV^{48}_{DS^2}$; $SSIV^{49}_{DS^3}$ $SSIV^{50}_{DS^4}$; $SSIV^{51}_{DS^5}$; $SSIV^{52}_{DS^6}$	1.327*** (0.424)	864	0.4041	154.84	0.7179
12	$SSIV^{53}_{LDS^1}$; $SSIV^{54}_{LDS^2}$ $SSIV^{55}_{LDS^3}$; $SSIV^{56}_{LDS^4}$; $SSIV^{57}_{LDS^5}$; $SSIV^{58}_{LDS^6}$	1.327*** (0.424)	864	0.4041	144.57	0.7851
Fixed Effects: Origin, Destination & Year						
Estimator: PPML						
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*						

1.6.4 Machine Learning Estimations of SSIVs in JI and OI Models

We employ both the GB and the RF models to evaluate the predictive strength and robustness of all the instruments across the JI and OI models in this study. We represent JI estimations from GB and RF models in Tables 9, 10 and 11 whereas Table 12 exhibits OI estimations from these models. We provide visual representations of all these models through Figures 8, 9, 10 and 11.

We evaluate the strength of any instruments based on the predictive score and the RMSE. A higher predictive score means a higher predictive power of the instruments and lower RMSE indicates better model performance. Though estimations using the GB, and the RF models produce similar results, the RF models generate low RMSE, and it is consistent across all SSIVs in JI and OI IV models. The advantage of having low RMSE in the RF models outperforms the estimations from the GB models.

Table 9 and Figure 8 exhibit the performance of SSIVs using Aggregate and Disaggregate Shocks and Shares. All the aggregate SSIVs produce similar predictive scores in both GB and RF models. Among the aggregate SSIVs, two instruments—$\mathrm{SSIV}^{2}_{\mathrm{AS*LASR}}$ [a literature-suggested instrument] and $\mathrm{SSIV}^{6}_{\mathrm{LADS*LADS}}$ [our variant] — demonstrate higher predictive scores and lower RMSE values when using the RF models.

Refer to Table 10 and Figure 9. Utilizing both the GB and RF models, literature-suggested SSIVs with aggregate shocks and disaggregate shares, both with and without lags [$\mathrm{SSIV}^{7}_{\mathrm{AS*DSR^1}}$ to $\mathrm{SSIV}^{12}_{\mathrm{AS*DSR^6}}$ and $\mathrm{SSIV}^{13}_{\mathrm{AS*LDSR^1}}$ to $\mathrm{SSIV}^{18}_{\mathrm{AS*LDSR^6}}$], exhibit similar predictive scores overall compared to our instruments with lagged aggregate shocks and disaggregate shares [$\mathrm{SSIV}^{19}_{\mathrm{LAS*LDSR^1}}$ to $\mathrm{SSIV}^{24}_{\mathrm{LAS*LDSR^6}}$].

All these instruments have overall similar RMSE but show lower RMSE in the RF models compared to the GB model estimations. In Table 11 and Figure 10, we find similar predictive scores across SSIVs using aggregate and disaggregate shocks, with and without lag.

While comparing the performance of all these SSIVs in JI and the OI Models (see, Table 12) using both the GB and the RF techniques, we find similar predictive scores across all versions of models using both literature-suggested SSIVs and our variants of SSIVs in Figure 11. These instruments also produce low RMSE in the RF estimations, showing similar consistency in JI estimations.

Results from conventional IV estimations provide evidence that all the instruments in this study are strong, showing very high values of F-statistic and R-squared in the FS of JI and OI IV models. Moreover, the strength analyses utilizing machine learning techniques also certify that our instruments are robust. Lastly, we present the bias estimations of the instruments using Monte Carlo simulations in the next section to substantiate our claims of strong instruments further.

1.6.5 Bias Estimations from Monte Carlo Simulations

We apply the Monte Carlo simulation framework to estimate the bias of the IV estimator under JI and OI IV models. First, we explain the data generating process (DGP) and then outline how we conduct the Monte Carlo simulation. We estimate the bias of the IV estimator in JI models, where we use one instrument for the endogenous variable (interprovincial services trade flow) in our empirical exercise. We apply ordinary least squares (OLS) to predict the endogenous variable using each SSIV along with controls, and we estimate the second stage using the PPML estimator accordingly. Using this two-stage process, we derive the IV estimates and evaluate the bias of the resulting coefficients. Following the same process, we estimate the bias for OI models using both literature-suggested instruments and our instruments. We again select the instruments in the same way as we estimate our OI models based on the two categories (Our SSIVs and literature-suggested SSIVs).

This study generates regressors from a standard normal distribution, $N(0,1)$, and fixes them across all simulation iterations. We maintain this approach to ensure consistency and comparison of results across 1000 simulation performed over the sample sizes of 1000 and 2000. While generating the synthetic data, we set the true coefficient of the endogenous variable $\beta = 1$ and follow the IV approach. In this study, we report the bias values, standard errors, and 95% confidence intervals.

We independently draw error terms for the first stage and the second stage from $N(0,1)$. Using the first stage equation, we predict the endogenous variable, denoted as interprovincial services trade (TS_{ijt}). The first stage equation includes the instruments and a set of control variables from origin and destination. While constructing the structure of the SSIVs, we also construct the instruments as the product of independent shocks and shares with and without lags and independent shocks with lag and without lags.

While generating the dependent variables and ensuring non-negative trade values, we set (TG_{ijt}) equals the exponential of the predicted trade flow plus an error term (ϵ). This process aligns with the PPML estimator's assumptions. This study sets the coefficients for the controls in both stages to known values ($\beta = 1.0$, $\gamma = 0.5$, $\delta = 0.3$) to evaluate how well the instruments recover the true parameter values.

Employing a PPML estimator, this research uses the fitted values from the first stage regression as an explanatory variable in the second-stage equation and predicts interprovincial goods trade (TG_{ijt}). The second-stage regression includes additional controls such as fixed effects for origin, destination, and year to account for unobserved heterogeneity. Moreover, this research fixes the regressors across iterations to ensure that the results remain robust to sampling variability. We further validate unbiased simulation results by drawing independent error terms. This study estimate the bias of the IV estimator for each model.

Tables 1.9, 1.10 and 1.11 represent the bias estimations for SSIVs in JI IV models, whereas Table 1.12 shows the bias estimations of SSIVs in OI IV models. We also provide visual representations using Figures 1.5 to 1.7 for better comparison across different instruments.

The results from Tables 1.9, 1.10 and 1.11 indicate that all the different SSIVs are very low in bias and close to zero. As we increase the number of sample sizes from 1000 to 2000 over 1000 simulations, the bias values get very close to zero. We also find that an increase in the sample size leads to reducing the standard errors and providing narrow confidence intervals. This shows that instruments are performing well in recovering the true parameter value [$\beta = 1$].

Our SSIV [$\mathrm{SSIV}^{3}_{\mathrm{LAS*LASR}}$] is the least biased among the aggregate instruments using aggregate shock and share, whereas the Modified SSIV [$\mathrm{SSIV}^{2}_{\mathrm{AS*LASR}}$] shows lower bias than the Conventional SSIV [$\mathrm{SSIV}^{1}_{\mathrm{AS*ASR}}$]. While we develop the other three aggregate instruments by aggregating the disaggregate shocks and shares [$\mathrm{SSIV}^{4}_{\mathrm{ADS*ADSR}}$, $\mathrm{SSIV}^{5}_{\mathrm{ADS*LADSR}}$, and $\mathrm{SSIV}^{6}_{\mathrm{LADS*LADRS}}$], these instruments show very low and similar bias. Overall, all these instruments produce lower bias as we increase the sample size [see, Table 1.9].

While the conventional instruments [$\mathrm{SSIV}^{7}_{\mathrm{AS*DSR^{1}}}$ to $\mathrm{SSIV}^{12}_{\mathrm{AS*DSR^{6}}}$] using aggregate shocks and disaggregate shares produce the lowest bias among this category of instruments, our instruments [$\mathrm{SSIV}^{19}_{\mathrm{LAS*LDSR^{1}}}$ to $\mathrm{SSIV}^{24}_{\mathrm{LAS*LDSR^{6}}}$] with lag SSIVs show lower bias than the modified instruments [$\mathrm{SSIV}^{13}_{\mathrm{AS*LDSR^{1}}}$ to $\mathrm{SSIV}^{18}_{\mathrm{AS*LDSR^{6}}}$].

Table 1.10 represents the bias estimations of disaggregate SSIVs using Monte Carlo simulations. In this set of instruments, we develop multiple instruments using disaggregate shocks and shares. Our instruments [$\mathrm{SSIV}^{25}_{\mathrm{DS^{1}*DSR^{1}}}$ to $\mathrm{SSIV}^{30}_{\mathrm{DS^{6}*DSR^{6}}}$] with the conventional estimation technique produce the lowest bias among all the instruments in this category. Moreover, other instruments [$\mathrm{SSIV}^{31}_{\mathrm{DS^{1}*LDSR^{1}}}$ to $\mathrm{SSIV}^{36}_{\mathrm{DS^{6}*LDSR^{6}}}$ and $\mathrm{SSIV}^{37}_{\mathrm{LDS^{1}*LDSR^{1}}}$ to $\mathrm{SSIV}^{42}_{\mathrm{LDS^{6}*LDSR^{6}}}$] also show very low bias. As we increase the sample size, the standard errors tend to decrease, and the confidence intervals become narrower.

Table 1.11 shows the bias estimations of shock instruments applying Monte Carlo simulations. Our instruments using disaggregate shocks [$\mathrm{SSIV}^{47}_{\mathrm{DS^{1}}}$ to $\mathrm{SSIV}^{52}_{\mathrm{DS^{6}}}$] and literature-suggested instruments [$\mathrm{SSIV}^{43}_{\mathrm{AS}}$ and $\mathrm{SSIV}^{45}_{\mathrm{ADS}}$] show very low bias, indicating precise estimations using these instruments. Furthermore, other instruments [$\mathrm{SSIV}^{53}_{\mathrm{LDS^{1}}}$ to $\mathrm{SSIV}^{58}_{\mathrm{LDS^{6}}}$] also have low bias values.

We display the bias estimations of the OI models using literature-suggested instruments and our instruments in Table 1.11. The bias value of OI Model 1 with literature instruments [$\mathrm{SSIV}^{4}_{\mathrm{ADS*ADSR}}$, $\mathrm{SSIV}^{5}_{\mathrm{ADS*LADSR}}$, $\mathrm{SSIV}^{1}_{\mathrm{AS*ASR}}$, and $\mathrm{SSIV}^{2}_{\mathrm{AS*LASR}}$] is slightly lower than that of OI Model 2 with our instruments [$\mathrm{SSIV}^{3}_{\mathrm{LAS*LASR}}$ and $\mathrm{SSIV}^{6}_{\mathrm{LADS*LADS}}$].

We estimate OI Models 3, 4, and 5 using aggregate shocks and shares with and without lag, and these models produce very low and similar bias across all of them, suggesting more accurate estimations. We also find very low and similar bias values across OI Models 6, 7, and 8 using our instruments [$\text{SSIV}^{19}_{\text{LAS}*\text{LDSR}^1}$ to $\text{SSIV}^{24}_{\text{LAS}*\text{LDSR}^6}$; $\text{SSIV}^{25}_{\text{DS}^1*\text{DSR}^1}$ to $\text{SSIV}^{30}_{\text{DS}^6*\text{DSR}^6}$; and $\text{SSIV}^{31}_{\text{DS}^1*\text{LDSR}^1}$ to $\text{SSIV}^{42}_{\text{LDS}^6*\text{LDSR}^6}$]. With an increase in sample size from 1000 to 2000 over 1000 simulations, the bias values and the standard errors decrease.

The bias value of OI Model 9 with literature-suggested instruments [$\text{SSIV}^{43}_{\text{AS}}$ and $\text{SSIV}^{45}_{\text{ADS}}$] is slightly lower than that of OI Model 10 with our instruments [$\text{SSIV}^{44}_{\text{LAS}}$ and $\text{SSIV}^{46}_{\text{LADS}}$]. Models 11 and 12 include our instruments, and they produce very low bias values. The OI Model with disaggregate shocks has lower bias values compared to the OI Model with lagged disaggregate shocks.

All the instruments derived in this paper are very low in bias values and close to zero. These instruments show consistent lower bias values across JI and OI Models, validating the robustness of the estimations using all these instruments. An increase in sample size results in lower bias values and standard errors with narrower confidence intervals.

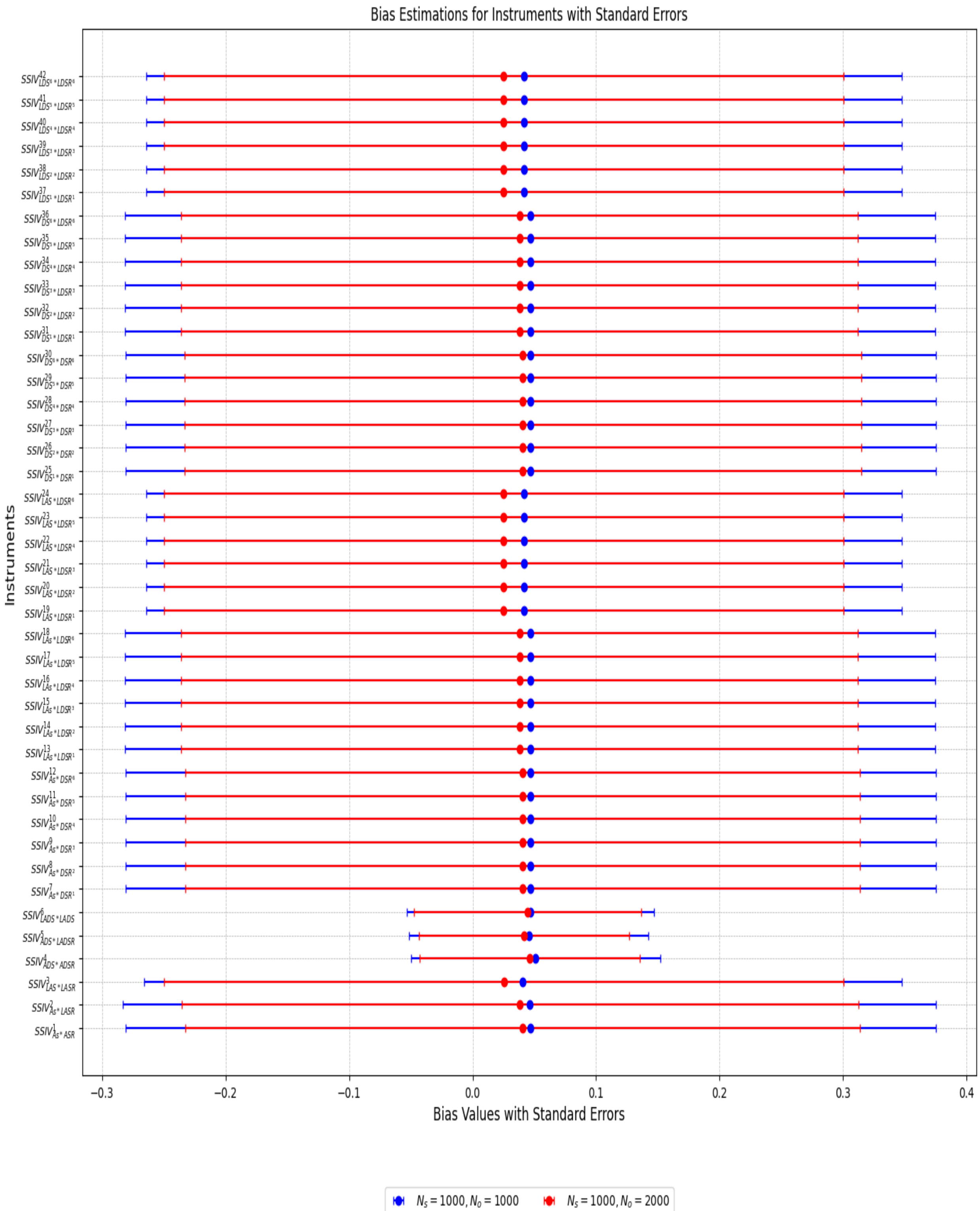

Figure 1.5: Bias Estimations of SSIVs in JI Models from Monte Carlo Simulations

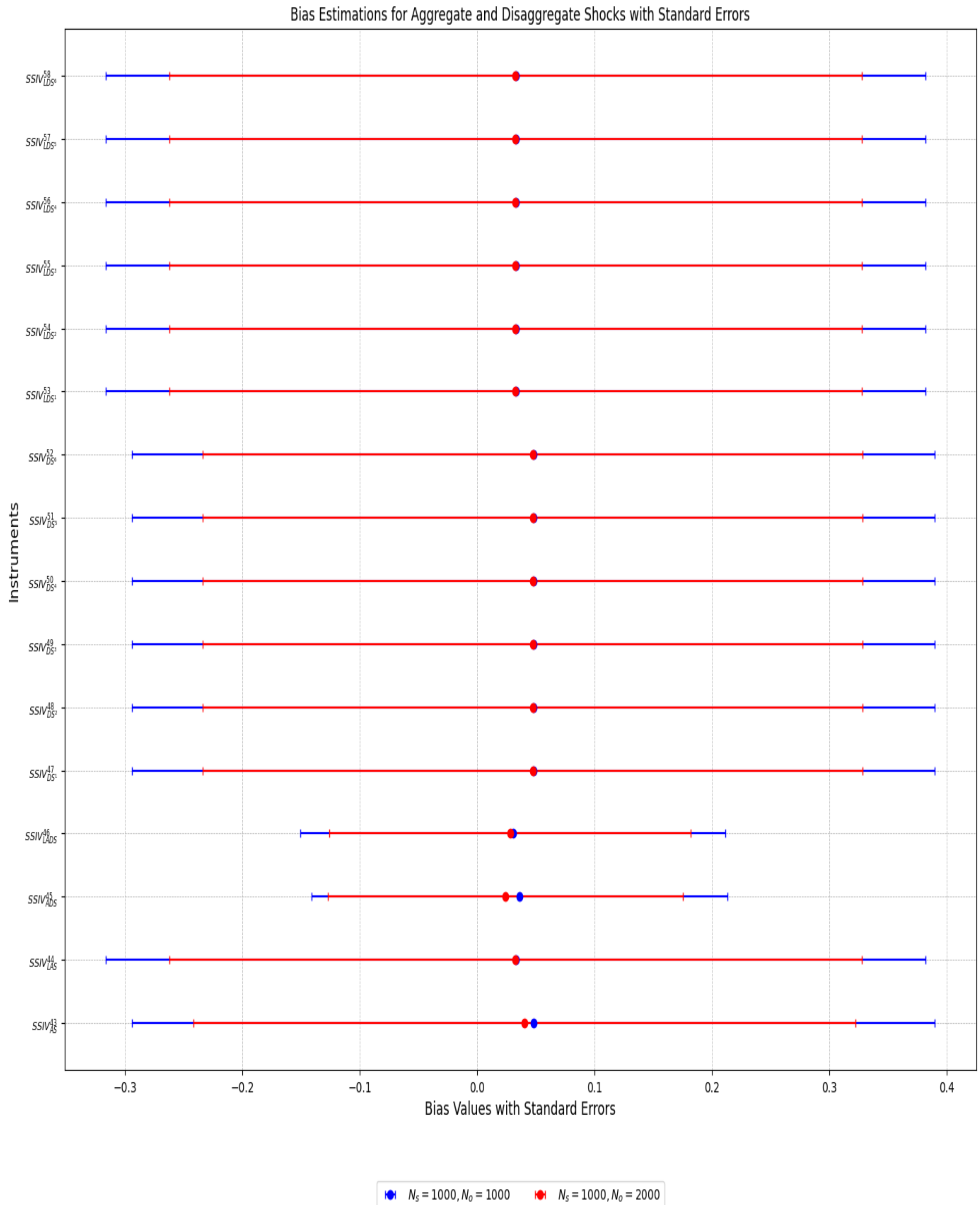

Figure 1.6: Bias Estimations of SSIVs in JI Models from Monte Carlo Simulations

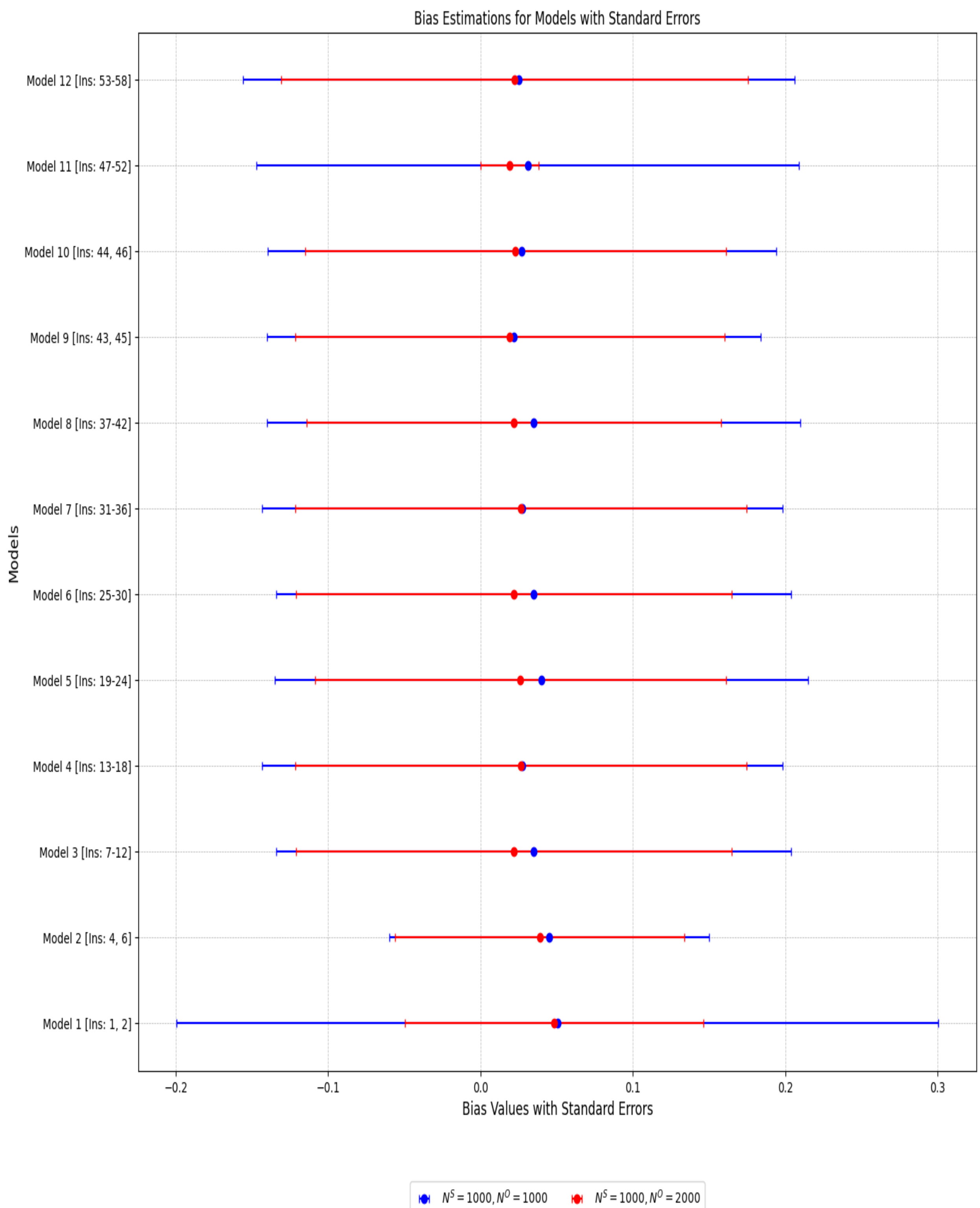

Figure 1.7: Bias Estimations of SSIVs in OI Models from Monte Carlo Simulations

Table 1.9: Table Bias Estimations from Monte Carlo Simulations

Instruments	$N^S = 1000; N^O = 1000$				$N^S = 1000; N^O = 2000$			
	True β	Bias	Std. Err.	CI [95%]	True β	Bias	Std. Err.	CI [95%]
$\mathrm{SSIV}^{1}_{\mathrm{AS*ASR}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0407	0.273	(0.529, 1.589)
$\mathrm{SSIV}^{2}_{\mathrm{AS*LASR}}$	1	0.0460	0.329	(0.425, 1.722)	1	0.0383	0.274	(0.507, 1.628)
$\mathrm{SSIV}^{3}_{\mathrm{LAS*LASR}}$	1	0.0408	0.307	(0.446, 1.645)	1	0.0254	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{4}_{\mathrm{ADS*ADSR}}$	1	0.0511	0.101	(0.876, 1.279)	1	0.0462	0.089	(0.894, 1.238)
$\mathrm{SSIV}^{5}_{\mathrm{ADS*LADSR}}$	1	0.0455	0.097	(0.880, 1.261)	1	0.0418	0.085	(0.910, 1.232)
$\mathrm{SSIV}^{6}_{\mathrm{LADS*LADS}}$	1	0.0470	0.100	(0.879, 1.276)	1	0.0443	0.092	(0.889, 1.266)
$\mathrm{SSIV}^{7}_{\mathrm{AS*DSR^1}}$	1	0.0469	0.328	(0.424, 1.722)	1	0.0407	0.273	(0.529, 1.589)
$\mathrm{SSIV}^{8}_{\mathrm{AS*DSR^2}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.273	(0.529, 1.589)
$\mathrm{SSIV}^{9}_{\mathrm{AS*DSR^3}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0407	0.273	(0.530, 1.589)
$\mathrm{SSIV}^{10}_{\mathrm{AS*DSR^4}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0407	0.273	(0.530, 1.589)
$\mathrm{SSIV}^{11}_{\mathrm{AS*DSR^5}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0407	0.273	(0.530, 1.589)
$\mathrm{SSIV}^{12}_{\mathrm{AS*DSR^6}}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0407	0.273	(0.530, 1.589)
$\mathrm{SSIV}^{13}_{\mathrm{AS*LDSR^1}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{14}_{\mathrm{AS*LDSR^2}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{15}_{\mathrm{AS*LDSR^3}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{16}_{\mathrm{AS*LDSR^4}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{17}_{\mathrm{AS*LDSR^5}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{18}_{\mathrm{AS*LDSR^6}}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\mathrm{SSIV}^{19}_{\mathrm{LAS*LDSR^1}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{20}_{\mathrm{LAS*LDSR^2}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{21}_{\mathrm{LAS*LDSR^3}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{22}_{\mathrm{LAS*LDSR^4}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{23}_{\mathrm{LAS*LDSR^5}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)
$\mathrm{SSIV}^{24}_{\mathrm{LAS*LDSR^6}}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.275	(0.494, 1.586)

Table 1.10: **Bias Estimations from Monte Carlo Simulations**

Instruments	$N^S = 1000; N^O = 1000$				$N^S = 1000; N^O = 2000$			
	True β	**Bias**	**Std. Err.**	**CI [95%]**	**True β**	**Bias**	**Std. Err.**	**CI [95%]**
$\text{SSIV}^{25}_{\text{DS}^1*\text{DSR}^1}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{26}_{\text{DS}^2*\text{DSR}^2}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{27}_{\text{DS}^3*\text{DSR}^3}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{28}_{\text{DS}^4*\text{DSR}^4}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{29}_{\text{DS}^5*\text{DSR}^5}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{30}_{\text{DS}^6*\text{DSR}^6}$	1	0.0469	0.328	(0.424, 1.723)	1	0.0406	0.274	(0.529, 1.589)
$\text{SSIV}^{31}_{\text{DS}^1*\text{LDSR}^1}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{32}_{\text{DS}^2*\text{LDSR}^2}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{33}_{\text{DS}^3*\text{LDSR}^3}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{34}_{\text{DS}^4*\text{LDSR}^4}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{35}_{\text{DS}^5*\text{LDSR}^5}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{36}_{\text{DS}^6*\text{LDSR}^6}$	1	0.0466	0.328	(0.425, 1.720)	1	0.0381	0.274	(0.508, 1.628)
$\text{SSIV}^{37}_{\text{LDS}^1*\text{LDSR}^1}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)
$\text{SSIV}^{38}_{\text{LDS}^2*\text{LDSR}^2}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)
$\text{SSIV}^{39}_{\text{LDS}^3*\text{LDSR}^3}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)
$\text{SSIV}^{40}_{\text{LDS}^4*\text{LDSR}^4}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)
$\text{SSIV}^{41}_{\text{LDS}^5*\text{LDSR}^5}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)
$\text{SSIV}^{42}_{\text{LDS}^6*\text{LDSR}^6}$	1	0.0416	0.306	(0.447, 1.645)	1	0.0252	0.274	(0.494, 1.586)

Table 1.11: Bias Estimations of Aggregate and Disaggregate Shocks from Monte Carlo Simulations

Instruments	$N^S = 1000; N^O = 1000$				$N^S = 1000; N^O = 2000$			
	True β	Bias	Std. Err.	CI [95%]	True β	Bias	Std. Err.	CI [95%]
$\mathrm{SSIV}_{\mathrm{AS}}^{43}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.282	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{LAS}}^{44}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{ADS}}^{45}$	1	0.0361	0.177	(0.728, 1.410)	1	0.0242	0.151	(0.758, 1.342)
$\mathrm{SSIV}_{\mathrm{LADS}}^{46}$	1	0.0306	0.181	(0.709, 1.428)	1	0.0281	0.154	(0.755, 1.339)
$\mathrm{SSIV}_{\mathrm{DS}^1}^{47}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{DS}^2}^{48}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{DS}^3}^{49}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{DS}^4}^{50}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{DS}^5}^{51}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{DS}^6}^{52}$	1	0.0480	0.342	(0.415, 1.798)	1	0.0476	0.281	(0.521, 1.612)
$\mathrm{SSIV}_{\mathrm{LDS}^1}^{53}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{LDS}^2}^{54}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{LDS}^3}^{55}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{LDS}^4}^{56}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{LDS}^5}^{57}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)
$\mathrm{SSIV}_{\mathrm{LDS}^6}^{58}$	1	0.0330	0.349	(0.388, 1.777)	1	0.0328	0.295	(0.448, 1.621)

Table 1.12: **Bias Estimations from Monte Carlo Simulations**

OI Models	Instruments	$N^S = 1000; N^O = 1000$				$N^S = 1000; N^O = 2000$			
		True β	**Bias**	**Std. Err.**	**CI [95%]**	**True β**	**Bias**	**Std. Err.**	**CI [95%]**
1	$\text{SSIV}^1_{\text{AS}*\text{ASR}}$; $\text{SSIV}^2_{\text{AS}*\text{LASR}}$	1	0.0505	0.250	(0.888, 1.286)	1	0.0483	0.098	(0.897, 1.289)
2	$\text{SSIV}^4_{\text{ADS}*\text{ADSR}}$; $\text{SSIV}^6_{\text{LADS}*\text{LADS}}$	1	0.0452	0.105	(0.868, 1.282)	1	0.0389	0.095	(0.884, 1.252)
3	$\text{SSIV}^7_{\text{ADS}*\text{DSR}^1}$; $\text{SSIV}^8_{\text{ADS}*\text{DSR}^2}$; $\text{SSIV}^9_{\text{ADS}*\text{DSR}^3}$; $\text{SSIV}^{10}_{\text{ADS}*\text{DSR}^4}$ $\text{SSIV}^{11}_{\text{ADS}*\text{DSR}^5}$; $\text{SSIV}^{12}_{\text{ADS}*\text{DSR}^6}$	1	0.0351	0.169	(0.727, 1.375)	1	0.0220	0.143	(0.768, 1.334)
4	$\text{SSIV}^{13}_{\text{AS}*\text{LDSR}^1}$; $\text{SSIV}^{14}_{\text{AS}*\text{LDSR}^2}$ $\text{SSIV}^{15}_{\text{AS}*\text{LDSR}^3}$; $\text{SSIV}^{16}_{\text{AS}*\text{LDSR}^4}$ $\text{SSIV}^{17}_{\text{AS}*\text{LDSR}^1}$; $\text{SSIV}^{18}_{\text{AS}*\text{LDSR}^6}$	1	0.0275	0.171	(0.710, 1.396)	1	0.0267	0.148	(0.769, 1.345)
5	$\text{SSIV}^{19}_{\text{LAS}*\text{LDSR}^1}$; $\text{SSIV}^{20}_{\text{LAS}*\text{LDSR}^2}$; $\text{SSIV}^{21}_{\text{LAS}*\text{LDSR}^3}$; $\text{SSIV}^{22}_{\text{LAS}*\text{LDSR}^4}$ $\text{SSIV}^{23}_{\text{LAS}*\text{LDSR}^5}$; $\text{SSIV}^{24}_{\text{LAS}*\text{LDSR}^6}$	1	0.0401	0.175	(0.723, 1.431)	1	0.0263	0.135	(0.784, 1.299)
6	$\text{SSIV}^{25}_{\text{DS}^1*\text{DSR}^1}$; $\text{SSIV}^{26}_{\text{DS}^2*\text{DSR}^2}$ $\text{SSIV}^{27}_{\text{DS}^3*\text{DSR}^3}$; $\text{SSIV}^{28}_{\text{DS}^4*\text{DSR}^4}$ $\text{SSIV}^{29}_{\text{DS}^5*\text{DSR}^5}$; $\text{SSIV}^{30}_{\text{DS}^6*\text{DSR}^6}$	1	0.0351	0.169	(0.727, 1.375)	1	0.0219	0.143	(0.768, 1.334)
7	$\text{SSIV}^{31}_{\text{DS}^1*\text{LDSR}^1}$; $\text{SSIV}^{32}_{\text{DS}^2*\text{LDSR}^2}$ $\text{SSIV}^{33}_{\text{DS}^3*\text{LDSR}^3}$; $\text{SSIV}^{34}_{\text{DS}^4*\text{LDSR}^4}$ $\text{SSIV}^{35}_{\text{DS}^5*\text{LDSR}^5}$; $\text{SSIV}^{36}_{\text{DS}^6*\text{LDSR}^6}$	1	0.0275	0.171	(0.710, 1.369)	1	0.0267	0.148	(0.769, 1.344)
8	$\text{SSIV}^{37}_{\text{LDS}^1*\text{LDSR}^1}$; $\text{SSIV}^{38}_{\text{LDS}^2*\text{LDSR}^2}$ $\text{SSIV}^{39}_{\text{LDS}^3*\text{LDSR}^3}$; $\text{SSIV}^{40}_{\text{LDS}^4*\text{LDSR}^4}$ $\text{SSIV}^{41}_{\text{LDS}^5*\text{LDSR}^5}$; $\text{SSIV}^{42}_{\text{LDS}^6*\text{LDSR}^6}$	1	0.0351	0.175	(0.715, 1.415)	1	0.0221	0.136	(0.777, 1.296)
9	$\text{SSIV}^{43}_{\text{AS}}$; $\text{SSIV}^{45}_{\text{ADS}}$	1	0.02199	0.162	(0.714, 1.378)	1	0.0193	0.141	(0.748, 1.313)
10	$\text{SSIV}^{44}_{\text{LAS}}$; $\text{SSIV}^{46}_{\text{LADS}}$	1	0.0272	0.167	(0.720, 1.365)	1	0.0230	0.138	(0.776, 1.338)
11	$\text{SSIV}^{47}_{\text{DS}^1}$; $\text{SSIV}^{48}_{\text{DS}^2}$ $\text{SSIV}^{49}_{\text{DS}^3}$; $\text{SSIV}^{50}_{\text{DS}^4}$ $\text{SSIV}^{51}_{\text{DS}^5}$; $\text{SSIV}^{52}_{\text{DS}^6}$	1	0.0311	0.178	(0.713, 1.412)	1	0.0193	0.019	(0.752, 1.325)
12	$\text{SSIV}^{53}_{\text{LDS}^1}$; $\text{SSIV}^{54}_{\text{LDS}^2}$ $\text{SSIV}^{55}_{\text{LDS}^3}$; $\text{SSIV}^{56}_{\text{LDS}^4}$ $\text{SSIV}^{57}_{\text{LDS}^5}$; $\text{SSIV}^{58}_{\text{LDS}^6}$	1	0.0252	0.181	(0.704, 1.413)	1	0.0224	0.153	(0.745, 1.340)

1.7 Conclusion

This study shows how applied researchers should derive, develop, and select SSIVs to address the endogeneity problem in interprovincial settings. Using a comprehensive SSIV Search Method, we develop both literature-suggested SSIVs and novel variants of SSIVs to investigate the causal relationship between interprovincial services trade and interprovincial goods trade within Canada from 2007 to 2019.

Our empirical findings reveal a positive and significant causal relationship at a 1% level across both just-identified and over-identified IV models. We find compelling evidence that all SSIVs in this study are strong in the first stage, with very high values of F-statistic and R-squared, solidifying the grounds for strong instruments.

Notably, our variants, especially with lagged disaggregate shocks and shares, consistently outperform Conventional SSIVs in terms of empirical validity, predictive accuracy, and bias reduction. We further confirm the superiority of our instruments with the application of machine learning techniques such as Gradient Boosting and Random Forest models.

The results from Monte Carlo simulations reveal that all the SSIVs in our dataset produce very low bias values closer to zero, providing evidence of precise estimations with these instruments. Importantly, our instruments, particularly those incorporating lagged disaggregate shocks and shares components, exhibit lower bias compared to literature-suggested SSIVs. As we increase the sample size, the bias values decrease and approach zero. The findings indicate that our SSIVs improve predictive power as well as enhance the reliability of causal inference by reducing estimation bias.

While all SSIVs in our dataset show superior empirical performance in estimating the causal effect across JI IV models, this supports the recommendations for using single instrument. Although all the OI models with our instruments and literature-suggested instruments pass the over-identification tests, we see a slight decrease in F-statistics across different models.

Methodologically, this study makes a significant contribution to the literature by introducing a systematic SSIV Search Method for instrument development. By bridging methodological innovation with empirical application, our instruments enhance the quality and robustness of causal inference in interprovincial studies. While investigating an important causal relationship between interprovincial services trade and interprovincial goods trade, we offer a blueprint for aspiring researchers to tackle endogeneity in similar empirical settings in the future. Finally, this study not only advances econometric practice but also enriches the broader understanding of interprovincial trade dynamics.

1.8 Robustness

We design multi-step robustness checks to ensure the reliability and consistency of our estimations based on alternative instrument specifications, machine learning validation, Monte Carlo simulations, and control variable adjustments.

[a] We use different combinations of SSIVs in both JI and OI models, including literature-suggested SSIVs and our novel variants. The results are robust as we find that a consistent positive and significant causal effect of interprovincial services trade on interprovincial goods trade across all SSIVs.

[b] While evaluating the strength of all SSIVs based on the values of the F-statistic and R-squared, we further assess the predictive power of all SSIVs by applying machine learning techniques such as Gradient Boosting (GB) and Random Forest (RF) models. The findings from machine learning methods suggest that all SSIVs have similar predictive scores and low RMSE. With this validation technique, we show that our instruments are superior in terms of explanatory power and capturing sectoral and regional heterogeneity compared to literature-suggested instruments.

[c] We further check the validity of our results by estimating the bias of the instruments using Monte Carlo simulations. Though the results of the simulations indicate that all SSIVs have very low bias values approaching to zero, our instruments consistently yield lower bias than literature-suggested SSIVs. Therefore, empirical estimations with our variants have very high quality in predicting endogenous variable. As we increase the sample size of the simulations, the bias values further tend to reduce and get closer to zero, indicating consistency and high quality.

[d] We test the sensitivity of our results this study by dropping certain control variables. We conduct one robustness check with aggregate instruments by dropping the average annual incomes form origin and destination. The findings show a positive and statistically significant causal effect at the 1% level (check one of our exercises in Table 13).

We find a positive and significant causal effect of interprovincial services trade on interprovincial goods trade across various instruments, estimation techniques, and model specifications. Thus, we conclude that our results are robust through a comprehensive robustness checks.

1.9 Future Research

Applied researchers should employ our variants of SSIVs to check how these SSIVs perform in their datasets. Since our paper shows significant potential for further refinement in OI models, our future work will focus on tackling this.

While we provide a promising direction with the application of machine learning techniques, we plan to create dynamic SSIVs by applying machine learning techniques such as Neural Networks in another paper. This approach could benefit future research in cases of predicting shocks during economic crisis.

This study provides a solid foundation for applied researchers and any work related to ours can benefit empirical scholars applying advanced econometric techniques to develop policy.

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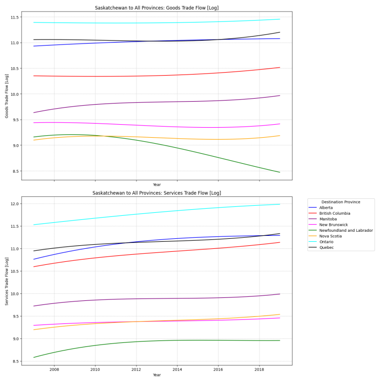
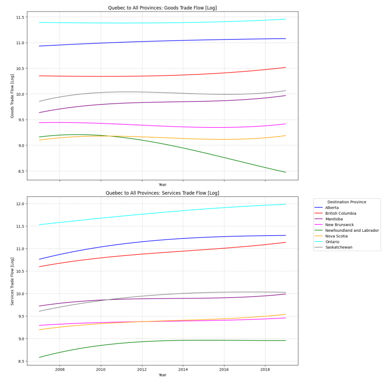
Chapter A

Appendix: Additional Results for Chapter 1

Trend Analyses: Interprovincial Trade Flows of Goods and Services



(a) Saskatchewan to All Provinces



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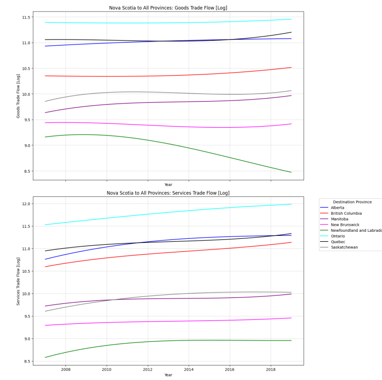

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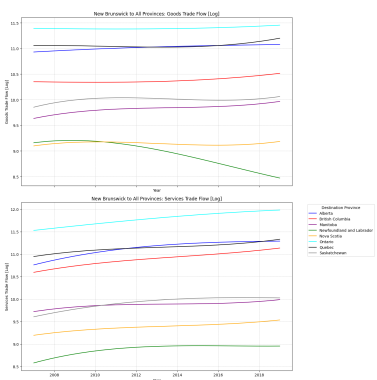
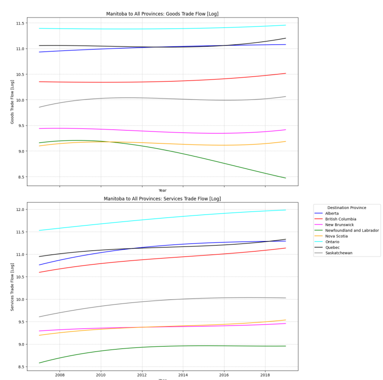


(d) New Brunswick to All Provinces



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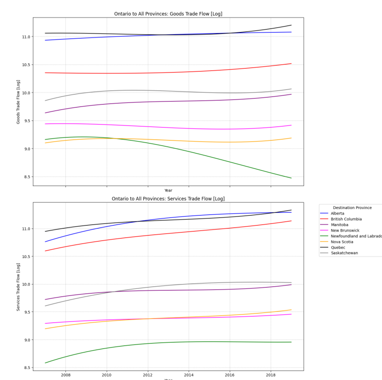
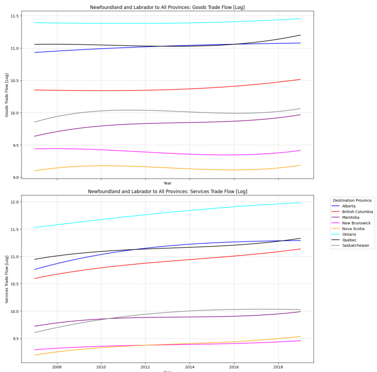
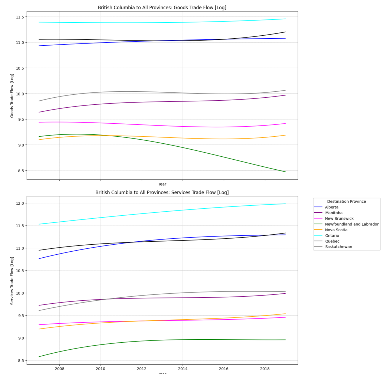


(f) Ontario to All Provinces

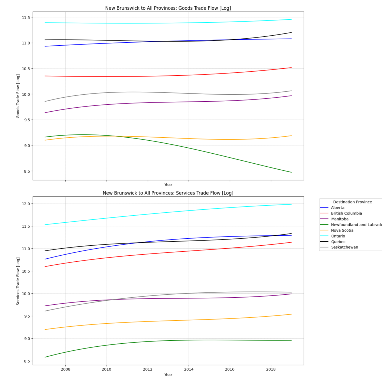
Trend Analyses (continued)



(a) Newfoundland and Labrador to All Provinces



(b) British Columbia to All Provinces



(c) Alberta to All Provinces

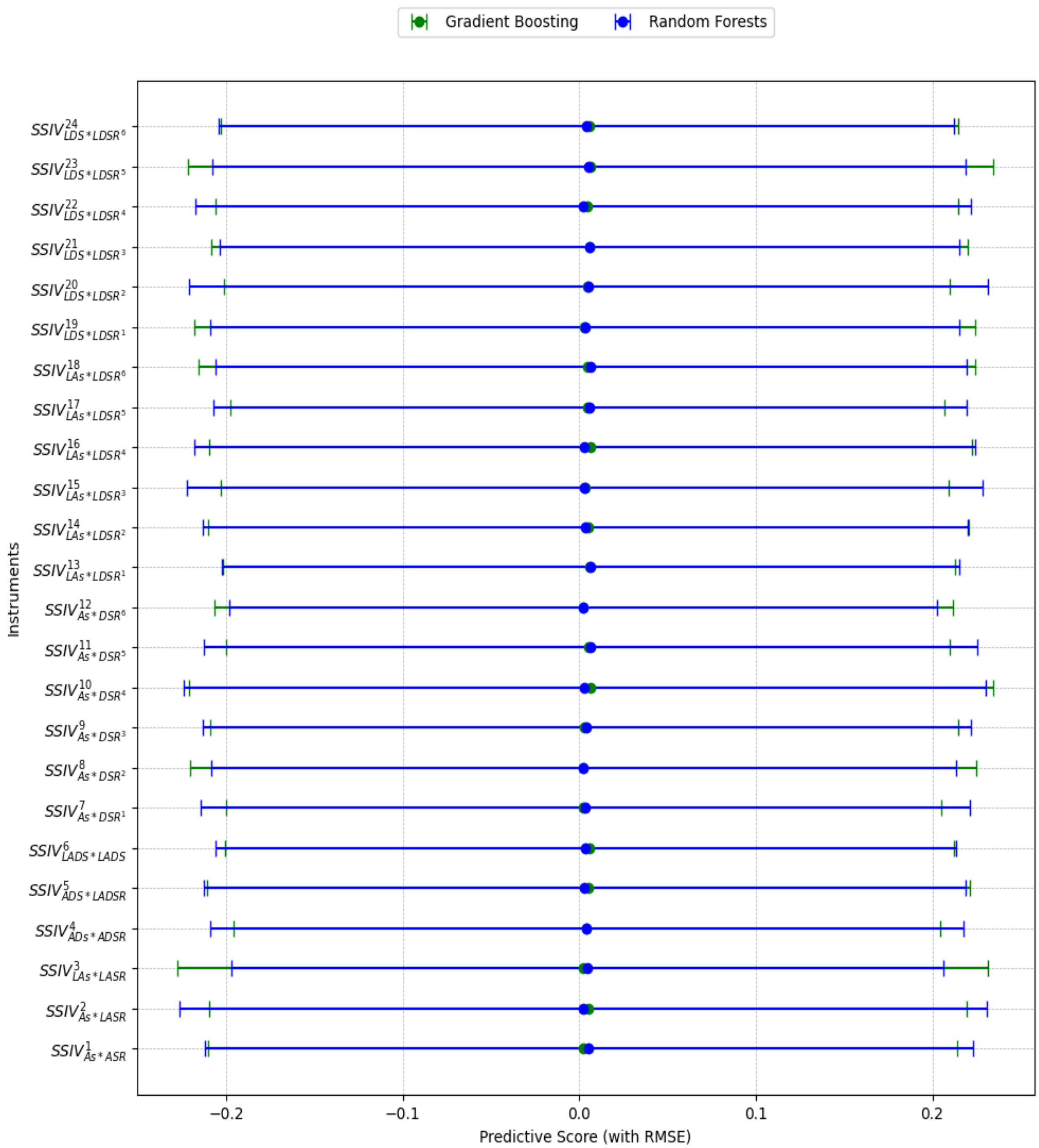


Figure 8: Predictive Scores of SSIVs in JI Models from Machine Learning Estimations.

Table 9: Performance of SSIVs using Aggregate and Disaggregate Shocks & Shares

Dependent Variable: *Interprovincial Services Trade [T_{Sijt}]*				
	Gradient Boosting Model		**Random Forests Model**	
Instruments	**Predictive Score**	**RMSE**	**Predictive Score**	**RMSE**
$\text{SSIV}^{1}_{\text{AS}*\text{ASR}}$	0.002	0.203	0.004	0.217
$\text{SSIV}^{2}_{\text{AS}*\text{LASR}}$	0.003	0.201	0.005	0.211
$\text{SSIV}^{3}_{\text{LAS}*\text{LASR}}$	0.002	0.211	0.002	0.191
$\text{SSIV}^{4}_{\text{ADS}*\text{ADSR}}$	0.002	0.213	0.002	0.203
$\text{SSIV}^{5}_{\text{ADS}*\text{LADSR}}$	0.001	0.209	0.003	0.204
$\text{SSIV}^{6}_{\text{LADS}*\text{LADS}}$	0.002	0.211	0.003	0.196
$\text{SSIV}^{7}_{\text{AS}*\text{DSR}^1}$	0.003	0.220	0.004	0.204
$\text{SSIV}^{8}_{\text{AS}*\text{DSR}^2}$	0.003	0.214	0.007	0.207
$\text{SSIV}^{9}_{\text{AS}*\text{DSR}^3}$	0.003	0.204	0.006	0.196
$\text{SSIV}^{10}_{\text{AS}*\text{DSR}^4}$	0.001	0.212	0.003	0.207
$\text{SSIV}^{11}_{\text{AS}*\text{DSR}^5}$	0.001	0.212	0.003	0.206
$\text{SSIV}^{12}_{\text{AS}*\text{DSR}^6}$	0.002	0.210	0.003	0.199
$\text{SSIV}^{13}_{\text{AS}*\text{LDSR}^1}$	0.002	0.216	0.005	0.209
$\text{SSIV}^{14}_{\text{AS}*\text{LDSR}^2}$	0.004	0.209	0.008	0.197
$\text{SSIV}^{15}_{\text{AS}*\text{LDSR}^3}$	0.003	0.210	0.007	0.209
$\text{SSIV}^{16}_{\text{AS}*\text{LDSR}^4}$	0.001	0.212	0.001	0.202
$\text{SSIV}^{17}_{\text{AS}*\text{LDSR}^5}$	0.002	0.233	0.004	0.211
$\text{SSIV}^{18}_{\text{AS}*\text{LDSR}^6}$	0.003	0.200	0.004	0.214
$\text{SSIV}^{19}_{\text{LAS}*\text{LDSR}^1}$	0.002	0.209	0.002	0.209
$\text{SSIV}^{20}_{\text{LAS}*\text{LDSR}^2}$	0.002	0.212	0.004	0.202
$\text{SSIV}^{21}_{\text{LAS}*\text{LDSR}^3}$	0.004	0.213	0.009	0.201
$\text{SSIV}^{22}_{\text{LAS}*\text{LDSR}^4}$	0.001	0.212	0.001	0.203
$\text{SSIV}^{23}_{\text{LAS}*\text{LDSR}^5}$	0.001	0.212	0.001	0.209
$\text{SSIV}^{24}_{\text{LAS}*\text{LDSR}^6}$	0.001	0.213	0.001	0.213

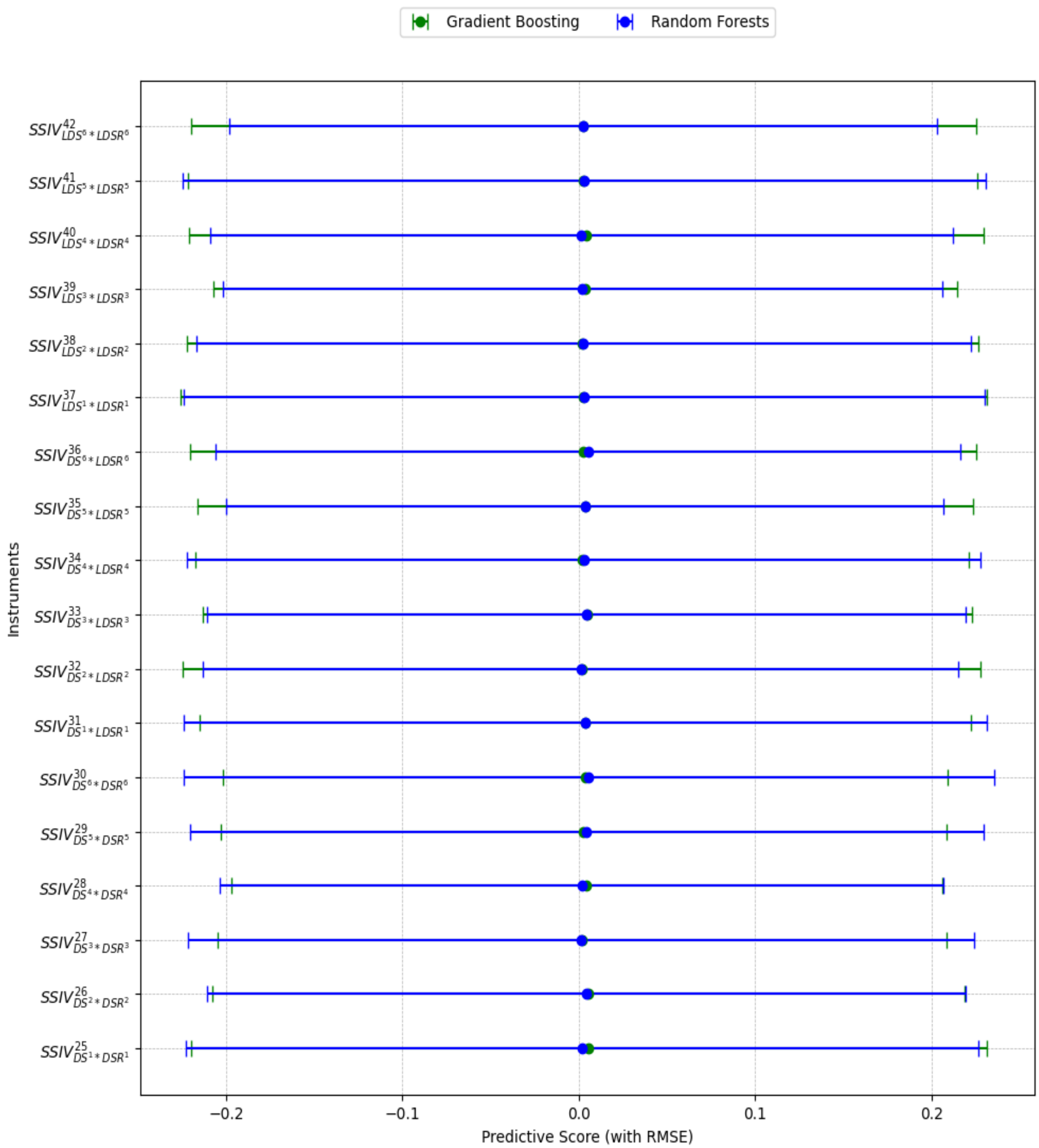


Figure 9: Predictive Scores of SSIVs in JI Models from Machine Learning Estimations.

Table 10: Performance of SSIVs with Aggregate Shocks & Disaggregate Shares

Dependent Variable: *Interprovincial Services Trade [T_{Sijt}]*

	Gradient Boosting Model		Random Forests Model	
Instruments	**Predictive Score**	**RMSE**	**Predictive Score**	**RMSE**
$\text{SSIV}^{25}_{\text{DS}^1*\text{DSR}^1}$	0.001	0.213	0.002	0.213
$\text{SSIV}^{26}_{\text{DS}^2*\text{DSR}^2}$	0.001	0.230	0.005	0.216
$\text{SSIV}^{27}_{\text{DS}^3*\text{DSR}^3}$	0.002	0.213	0.009	0.213
$\text{SSIV}^{28}_{\text{DS}^4*\text{DSR}^4}$	0.001	0.214	0.001	0.196
$\text{SSIV}^{29}_{\text{DS}^5*\text{DSR}^5}$	0.001	0.215	0.002	0.212
$\text{SSIV}^{30}_{\text{DS}^6*\text{DSR}^6}$	0.001	0.214	0.002	0.212
$\text{SSIV}^{31}_{\text{DS}^1*\text{LDSR}^1}$	0.001	0.214	0.002	0.212
$\text{SSIV}^{32}_{\text{DS}^2*\text{LDSR}^2}$	0.003	0.213	0.006	0.199
$\text{SSIV}^{33}_{\text{DS}^3*\text{LDSR}^3}$	0.003	0.213	0.003	0.196
$\text{SSIV}^{34}_{\text{DS}^4*\text{LDSR}^4}$	0.001	0.215	0.002	0.212
$\text{SSIV}^{35}_{\text{DS}^5*\text{LDSR}^5}$	0.001	0.213	0.002	0.201
$\text{SSIV}^{36}_{\text{DS}^6*\text{LDSR}^6}$	0.002	0.211	0.002	0.202
$\text{SSIV}^{37}_{\text{LDS}^1*\text{LDSR}^1}$	0.001	0.214	0.003	0.199
$\text{SSIV}^{38}_{\text{LDS}^2*\text{LDSR}^2}$	0.002	0.211	0.003	0.200
$\text{SSIV}^{39}_{\text{LDS}^3*\text{LDSR}^3}$	0.003	0.216	0.004	0.210
$\text{SSIV}^{40}_{\text{LDS}^4*\text{LDSR}^4}$	0.002	0.213	0.001	0.203
$\text{SSIV}^{41}_{\text{LDS}^5*\text{LDSR}^5}$	0.002	0.215	0.007	0.207
$\text{SSIV}^{42}_{\text{LDS}^6*\text{LDSR}^6}$	0.002	0.212	0.002	0.212

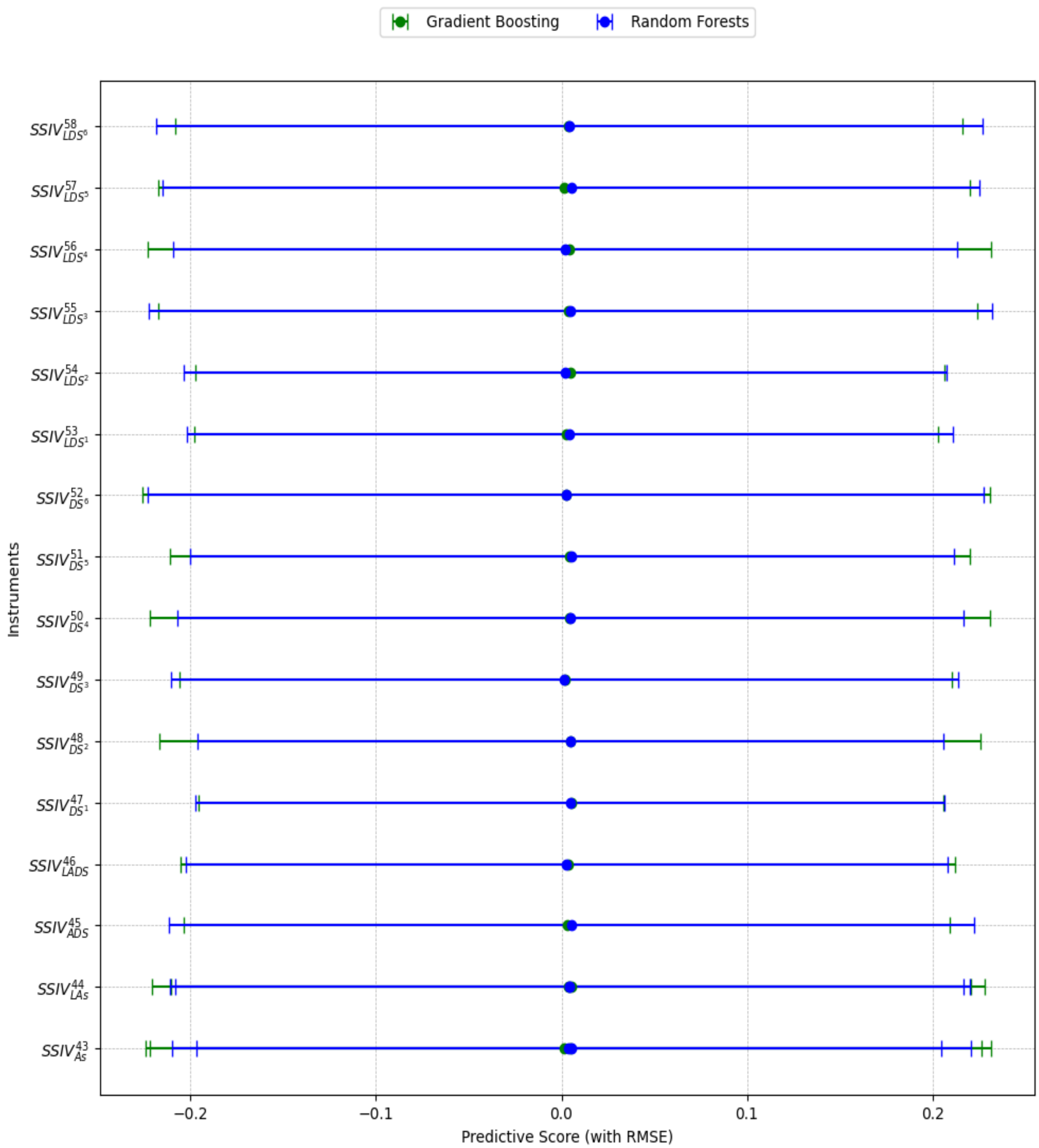


Figure 10: Predictive Scores of SSIVs in JI Models from Machine Learning Estimations.

Table 11: Performance of SSIVs with Disaggregate Shocks & Shares with & without Lag

Dependent Variable: *Interprovincial Services Trade [T_{Sijt}]*				
	Gradient Boosting Model		**Random Forests Model**	
Instruments	**Predictive Score**	**RMSE**	**Predictive Score**	**RMSE**
$\text{SSIV}^{43}_{\text{AS}}$	0.002	0.213	0.006	0.207
$\text{SSIV}^{44}_{\text{LAS}}$	0.001	0.214	0.003	0.200
$\text{SSIV}^{45}_{\text{ADS}}$	0.004	0.209	0.006	0.201
$\text{SSIV}^{46}_{\text{LADS}}$	0.001	0.220	0.004	0.204
$\text{SSIV}^{47}_{\text{DS}^1}$	0.002	0.208	0.002	0.199
$\text{SSIV}^{48}_{\text{DS}^2}$	0.002	0.213	0.004	0.208
$\text{SSIV}^{49}_{\text{DS}^3}$	0.002	0.210	0.004	0.210
$\text{SSIV}^{50}_{\text{DS}^4}$	0.003	0.209	0.003	0.200
$\text{SSIV}^{51}_{\text{DS}^5}$	0.004	0.210	0.004	0.198
$\text{SSIV}^{52}_{\text{DS}^6}$	0.002	0.209	0.002	0.209
$\text{SSIV}^{53}_{\text{LDS}^1}$	0.001	0.223	0.006	0.201
$\text{SSIV}^{54}_{\text{LDS}^2}$	0.001	0.218	0.004	0.200
$\text{SSIV}^{55}_{\text{LDS}^3}$	0.003	0.214	0.006	0.200
$\text{SSIV}^{56}_{\text{LDS}^4}$	0.006	0.230	0.015	0.190
$\text{SSIV}^{57}_{\text{LDS}^5}$	0.002	0.217	0.002	0.202
$\text{SSIV}^{58}_{\text{LDS}^6}$	0.003	0.228	0.007	0.206

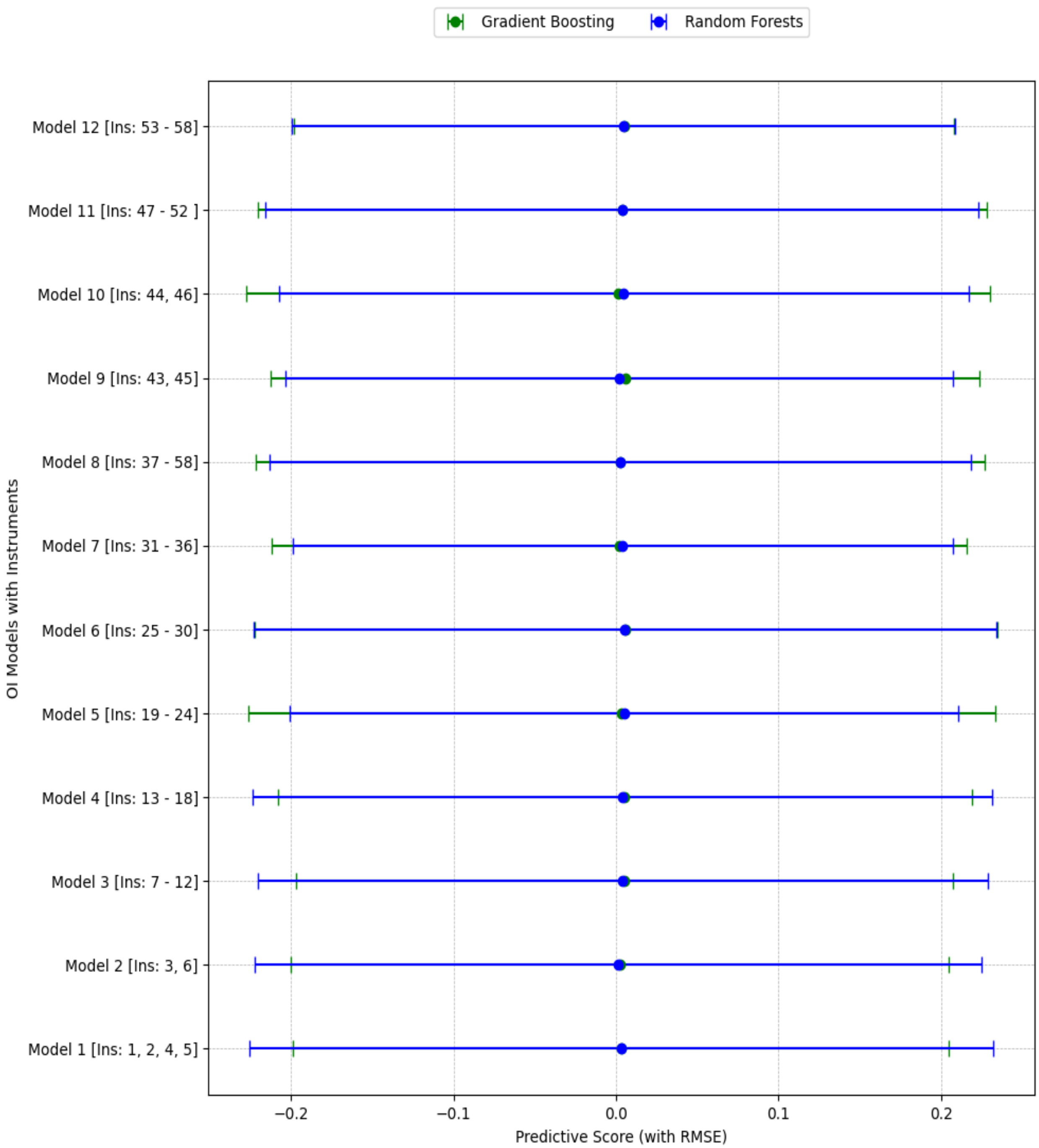


Figure 11: Predictive Scores of SSIVs in OI Models from Machine Learning Estimations.

Table 12: Performance of SSIVs in OI Models

Dependent Variable: Interprovincial Services Trade [$T_{S_{ijt}}$]					
Models	**Instruments**	**Gradient Boosting Model**		**Random Forests Model**	
		Predictive Score	**RMSE**	**Predictive Score**	**RMSE**
1	$SSIV^{1}_{AS*ASR}$	0.002	0.466	0.002	0.461
	$SSIV^{2}_{AS*LASR}$	0.002		0.004	
	$SSIV^{4}_{ADS*ADSR}$	0.001		0.001	
	$SSIV^{5}_{ADS*LADSR}$	0.001		0.002	
2	$SSIV^{3}_{LAS*LASR}$	0.002	0.464	0.002	0.464
	$SSIV^{6}_{LADS*LADS}$	0.003		0.004	
3	$SSIV^{7}_{AS*DSR^1}$	0.001	0.462	0.003	0.445
	$SSIV^{8}_{AS*DSR^2}$	0.003		0.003	
	$SSIV^{9}_{AS*DSR^3}$	0.002		0.004	
	$SSIV^{10}_{AS*DSR^4}$	0.003		0.007	
	$SSIV^{11}_{AS*DSR^5}$	0.001		0.003	
	$SSIV^{12}_{AS*DSR^6}$	0.001		0.002	
4	$SSIV^{13}_{AS*LDSR^1}$	0.003	0.462	0.002	0.460
	$SSIV^{14}_{AS*LDSR^2}$	0.003		0.005	
	$SSIV^{15}_{AS*LDSR^3}$	0.002		0.005	
	$SSIV^{16}_{AS*LDSR^4}$	0.001		0.001	
	$SSIV^{17}_{AS*LDSR^5}$	0.001		0.002	
	$SSIV^{18}_{AS*LDSR^6}$	0.002		0.001	
5	$SSIV^{19}_{LAS*LDSR^1}$	0.001	0.469	0.001	0.460
	$SSIV^{20}_{LAS*LDSR^2}$	0.001		0.003	
	$SSIV^{21}_{LAS*LDSR^3}$	0.002		0.001	
	$SSIV^{22}_{LAS*LDSR^4}$	0.001		0.002	
	$SSIV^{23}_{LAS*LDSR^5}$	0.001		0.003	
	$SSIV^{24}_{LAS*LDSR^6}$	0.001		0.003	
6	$SSIV^{25}_{DS^1*DSR^1}$	0.001	0.472	0.002	0.463
	$SSIV^{26}_{DS^2*DSR^2}$	0.003		0.003	
	$SSIV^{27}_{DS^3*DSR^3}$	0.002		0.003	
	$SSIV^{28}_{DS^4*DSR^4}$	0.002		0.004	
	$SSIV^{29}_{DS^5*DSR^5}$	0.002		0.004	
	$SSIV^{30}_{DS^6*DSR^6}$	0.003		0.002	
7	$SSIV^{31}_{DS^1*LDSR^1}$	0.001	0.472	0.002	0.462
	$SSIV^{32}_{DS^2*LDSR^2}$	0.003		0.005	
	$SSIV^{33}_{DS^3*LDSR^3}$	0.002		0.003	
	$SSIV^{34}_{DS^4*LDSR^4}$	0.001		0.005	
	$SSIV^{35}_{DS^5*LDSR^5}$	0.001		0.001	
	$SSIV^{36}_{DS^6*LDSR^6}$	0.002		0.002	
8	$SSIV^{37}_{LDS^1*LDSR^1}$	0.001	0.474	0.002	0.462
	$SSIV^{38}_{LDS^2*LDSR^2}$	0.001		0.002	
	$SSIV^{39}_{LDS^3*LDSR^3}$	0.003		0.004	
	$SSIV^{40}_{LDS^4*LDSR^4}$	0.002		0.001	
	$SSIV^{41}_{LDS^5*LDSR^5}$	0.001		0.009	
	$SSIV^{42}_{LDS^6*LDSR^6}$	0.002		0.008	
9	$SSIV^{43}_{AS}$	0.002	0.460	0.005	0.459
	$SSIV^{45}_{ADS}$	0.001		0.002	
10	$SSIV^{44}_{LAS}$	0.001	0.220	0.003	0.203
	$SSIV^{46}_{LADS}$	0.001		0.002	
11	$SSIV^{47}_{DS^1}$	0.002	0.459	0.002	0.447
	$SSIV^{48}_{DS^2}$	0.0001		0.002	
	$SSIV^{49}_{DS^3}$	0.0001		0.002	
	$SSIV^{50}_{DS^4}$	0.001		0.003	
	$SSIV^{51}_{DS^5}$	0.003		0.002	
	$SSIV^{52}_{DS^6}$	0.001		0.003	
12	$SSIV^{53}_{LDS^1}$	0.0004	0.468	0.003	0.460
	$SSIV^{54}_{LDS^2}$	0.0007		0.002	
	$SSIV^{55}_{LDS^3}$	0.0009		0.002	
	$SSIV^{56}_{LDS^4}$	0.0042		0.012	
	$SSIV^{57}_{LDS^5}$	0.0004		0.001	
	$SSIV^{58}_{LDS^6}$	0.0009		0.002	

Table 13: Robustness - JI IV Results of Services Trade Impact on Goods Trade

Dependent Variable: *Interprovincial Goods Trade [TG_{ijt}]*

Instruments	$\hat{T}_{S_{yjt}}$	**Obs.**	**F Statistic [FS]**	**R Squared [FS]**
$\text{SSIV}^{1}_{\text{AS}*\text{ASR}}$	1.129*** (0.625)	864	205.77	0.7243
$\text{SSIV}^{2}_{\text{AS}*\text{LASR}}$	1.160*** (0.625)	864	205.80	0.7243
$\text{SSIV}^{3}_{\text{LAS}*\text{LASR}}$	1.419*** (0.624)	792	206.31	0.7248
$\text{SSIV}^{4}_{\text{ADS}*\text{ADSR}}$	1.431*** (0.625)	864	205.79	0.7243
$\text{SSIV}^{5}_{\text{ADS}*\text{LADSR}}$	1.853*** (0.626)	792	199.43	0.7373
$\text{SSIV}^{6}_{\text{LADS}*\text{LADS}}$	1.935*** (0.623)	792	194.56	0.7323

Fixed Effects: Origin, Destination & Year

Estimator: PPML

Instrument Development Components: Aggregate Shift & Shares with and without lags

Dropped Controls: Average Annual Incomes from Origin & Destination

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Chapter 2

Trade & Migration: What Causes What?

Abstract

This paper examines the bi-directional causality between interprovincial trade (in aggregate and disaggregate) and migration within Canada for the years 2007 to 2019. Employing the PPML (Poisson Pseudo Maximum Likelihood) estimator in the gravity model framework, this study finds that both interprovincial trade (in aggregate and disaggregate) and migration significantly impact each other within Canada at a 1% significance level. To address the endogeneity problem between interprovincial trade and migration, we utilize the novel shift-share instrumental variable (SSIV) technique to develop 80 SSIVs for interprovincial trade (in aggregate and disaggregate) and 4 SSIVs for interprovincial migration. While deriving conventional SSIVs, we design our SSIVs with different combinations aggregate and disaggregate shocks and shares without and with lags. The results reveal that all the SSIVs consistently demonstrate strong first-stage relevance with higher F-statistic and R-squared values. We find our estimations are robust across both just-identified and over-identified settings. We argue that our designed SSIVs with lag disaggregate shocks and shares address regional and industrial heterogeneity compared to the conventional SSIVs with aggregate shocks and eliminate any potential contemporaneous correlation between instruments and the endogenous variable. Our results also reveal that the influence of trade on migration is substantial compared to the impact of migration on trade. Notably, the services trade has a much stronger effect on attracting migrants than the goods trade. While migrants significantly influence both goods and services trade, this effect is slightly stronger on goods trade. Our findings suggests that services trade may facilitate migration faster than goods trade.

JEL Codes: C36, C53, F14, F15, F17 & R11.

Keywords: Interprovincial Trade, Goods Trade, Services Trade, Migration, Endogeneity, SSIV & PPML.

2.1 Introduction

Trade and migration are two key drivers of a country's economic landscape. However, while the interplay between trade and migration is often studied from a one-sided view, the other side of the relationship is overlooked within a single framework. This paper investigates the relationship between trade and migration from the Canadian provincial angle, integrating both perspectives under one framework. Dissecting this relationship in the Canadian context can identify the strength and direction of their impact. It is crucial to develop such an understanding to address regional economic disparities and shape evidence-based policies.

We start by asking a fundamental question, what causes what? In other words, this study examines whether trade causes migration or vice-versa. As an increase in trade creates jobs (Coulombe, 2002; Biscourp & Kramarz, 2007), a further boom in trade can induce migrants. If the local labor markets cannot meet the demands of employers, then people outside the labor markets (namely, migrants) will fill the jobs depending on their skills. But the key question is which type of trade (goods or services) influences more migrants. This study addresses these questions too.

When migrants move from one province to another, they significantly impact both goods and services trade at their destination province. Migrants often desire their preferred goods from their home province. This preference can increase imports of their selected goods into their current area if not produced domestically. For instance, a migrant moving to Manitoba from British Columbia may demand wild-caught Pacific salmon. Since Manitoba does not produce such a specialized product, this preference would lead to an increase in imports of wild-caught Pacific salmon to Manitoba. Similarly, if someone from Quebec moves to Manitoba, he or she may influence the demand for French schools or require other services in French. We find similar patterns of influence on trade in goods and services from interprovincial migrants who are also international migrants (Steingress, 2018; Gould, 1994). Therefore, this paper also examines whether interprovincial migrants impact goods or services trade. If migration affects both trade in goods and services, then which is more strongly influenced?

We address three key questions in this study: [1] Does interprovincial trade in aggregate impact interprovincial migration within Canada or vice versa? [2] Does interprovincial goods trade affect migration within Canada or vice versa? [3] Does interprovincial services trade influence migration or vice versa?

To examine the bi-directional causality between interprovincial trade (in aggregate and disaggregate) and migration within Canada, this research compiles a panel dataset for the years 2007 to 2019. First, we examine the causal effects of trade (in aggregate and disaggregate) on migration. To address the endogeneity between interprovincial trade and migration, we develop 80 shift-share instruments for interprovincial trade (in aggregate and disaggregate). We derive 24 instruments from the goods sector using different combinations of shocks and share and derive another 56 instruments from the services sector. To establish the causal effects of interprovincial migration on trade (in aggregate and disaggregate), we address the endogeneity between interprovincial migration and trade by deriving 4 shift-share instruments for interprovincial migration.

Employing the PPML estimator in the gravity model framework, this research finds that both interprovincial trade and migration significantly impact each other within Canada. We find the relationships are statistically significant at a 1% level across all just-identified (JI) and over-identified (OI) IV models. Our results further reveal that the influence of trade on migration is substantial compared to the impact of migration on trade. Notably, the services trade has a much stronger influence in attracting migrants than the goods trade. While interprovincial migrants influence both goods and services trade significantly, migrants affect goods trade slightly more than services trade.

Using the novel shift-share instrumental variable (SSIV) technique, we address the endogeneity problem between interprovincial trade and migration with our designed SSIVs and conventional SSIVs. All SSIVs in this study produce very high values of the F-statistic and R-squared in the first stage (FS, hereafter) across both JI and OI models, satisfying the minimum and maximum thresholds for F-statistic values $F \geq 10$ (Stock & Yogo, 2002) and $F \geq 50$ (Keane & Neal, 2021). Our results reveal that all the SSIVs consistently perform robustly across both JI and OI settings.

This paper argues that our designed SSIVs with lag disaggregate shocks and shares address regional and industrial heterogeneity better compared to conventional SSIVs with aggregate shocks. Moreover, the application of aggregate shocks in SSIVs may risk the exclusion restriction of SSIVs as they affect the outcome variable indirectly. Therefore, our innovative approach deals with these potential risks using disaggregate shocks and shares. To eliminate any potential contemporaneous correlation between instruments and the endogenous variable, our approach incorporates lag in both shocks and shares of SSIVs to predict the endogenous regressor solely based on past economic conditions. We suggest that applied researchers should use a lag aggregate shock if they still want to use an aggregate shock.

This research makes several key contributions to the literature. It provides a comprehensive picture of the bi-directional causality between trade and migration. This study contributes by identifying the sector-specific trade driver for the Canadian provinces' economic landscape and recommends policies to reduce interprovincial trade barriers among provinces. Methodologically, this paper further contributes significantly by developing 84 instruments altogether, including 80 SSIVs for trade in aggregate and disaggregate and 4 SSIVs for migration. Last but not least, it suggests new instruments in the literature and offers refinements in the quality of SSIVs.

The remainder of the paper is arranged as follows: we present the literature review in Section 2, and Section 3 presents the methodology. We provide a data description in Section 4. The estimated results are discussed in Section 5. Then, we outline our policy implications in Section 6. Section 7 concludes. In Section 8, we show robustness. Finally, Section 9 discusses future research.

2.2 Literature Review

The co-movement of trade and migration is not new in the literature, and a significant number of studies have shed light on this phenomenon. We divide the literature into two: trade impacting migration and migration influencing trade.

Trade is the key driver of migration as it creates employment, mostly associated with exports (Coulombe, 2002; Biscourp & Kramarz, 2007). A boost in an economy may create jobs and lead to labor shortages. If the local labour market fails to meet the employers' expectations, people outside the local labor markets often see these opportunities and migrate. Moreover, openness to migration increases job mobility rates independently (Huinink et al., 2014). The neoclassical economic model states that people migrate for higher incomes or jobs (Karemera et al., 2000). Additionally, migrants move with their family members to maximize family income (Mincer, 1978).

The relationship between trade and migration can be either complementary or substitutive. Modern trade theories and extensions support the complementary relationship between trade and migration (Markusen, 2021; Wong, 1983), whereas traditional theories suggest this as substitutive (Mundell, 1957). Theoretically, economists show that trade complements migration using the Heckscher-Ohlin model (Markusen, 2021; Wong, 1983). Empirical studies (Akkoyunlu & Siliverstovs, 2009; Collins et al., 1999; Lopez & Schiff, 1998) also conclude that the relationship between trade and migration is complementary. However, Bruder (2004) shows that trade substitutes the foreign labour force.

As of today, two studies show the causal effect of trade on migration. Firstly, Campaniello (2014) examines the causal relationship between bilateral exports and bilateral migration using a gravity model with OLS and 2SLS techniques for the years 1970 to 2000. She finds that exports and migration from the South to the North show a positive correlation indicating complementarity to one another. Furthermore, Ghani et al. (2020) investigates the causal link between bilateral trade flow and bilateral migration flow for 248 countries over the years 1990 to 2010. They employ the PPML estimator in the gravity model and instrument trade with World Trade Organization (WTO) affiliation and average tariff rates. Their study concludes that trade significantly affects migration.

While looking at the other side of coin, we find empirical evidence in favor of migration impacting trade though various channels. First, Gould (1994) show that U.S. immigrant links foster bilateral trade flows with immigrants' home countries. Studies from Dunlevy & Hutchinson (1999, 2001) further substantiate that migrants impact trade as they prefer goods from home countries. They find a broad pro-import immigrant effect for more finished and more differentiated goods. Moreover, immigrants facilitate bilateral trade and establish trade networks (Lewer & Van den Berg, 2009) through connections and superior market intelligence (Wagner et al., 2002).

Steingress (2018) investigates the causal influence of immigrants on U.S. exports and imports using geographical variation across U.S. states for five years (from 2008 to 2013). His work concludes that an increase in imports into the U.S. from immigrants' home countries is positively associated with an increase in immigrants. The author addresses the endogeneity between trade and migration with the U.S. resettlement program's political refugees. This instrument is exogenous as this polciy deters immigrants from choosing particular states.

Aziz et al. (2023) examine the impact of interprovincial and international net migration on interprovincial trade from 1981 to 2016 for Canadian provinces. They find the relationship between interprovincial and international net migration and interprovincial trade statistically significant and positive. Their work shows that interprovincial net migration influences interprovincial trade more than international net migration. While Aziz et al. (2023)'s study establishes the casual effect of trade on migration in Canada, we criticize their instrumental variable selection. They instrument migration with employment rate and claim that it is a very good instrument. However, we strongly argue that their instrument is not valid and does not meet the necessary conditions of a valid instrument. The validity of any instrument relies on three key criteria: exogeneity, relevance and exclusion restrictions. Although their instrument is relevant, it does not satisfy the other two key criteria: exogeneity and exclusion restrictions. Their instrument, the employment rate, can be still endogenous. If higher employment rates attract migrants, does migration not affect the employment rate? An influx of migrants can increase the employment rate by filling the labor shortages, whereas they can decrease employment by increasing competition. So, the employment rate is not exogenous. Finally, the outcome variable in their study is interprovincial trade, which affects the employment rate directly. Does not the employment rate affect trade? Coulombe (2002) and Biscourp & Kramarz (2007) provide evidence against the validity of Aziz et al. (2023)'s instrument. Thus, their instrument does not hold exclusion restrictions.

This study makes several key contributions. By examining the bi-direction causality between interprovincial trade and migration for the first time in the literature, this study provides a comprehensive overview of trade and migration picture in the Canadian context. We further contribute to the literature by investigating whether the goods trade or the services trade influences interprovincial migration or vice-versa. Methodologically, this paper makes a significant contribution by developing 84 instruments altogether, including 80 SSIVs for trade in aggregate and disaggregate and 4 SSIVs for migration. While we criticize Aziz et al. (2023)'s work, we offer solution to overcome from this criticism by using shift-share instruments in this study. Furthermore, we suggest new instruments in the literature and offer refinements in the quality of SSIVs. Lastly, it recommends policies to reduce interprovincial trade barriers among provinces.

2.3 Methodology

This section introduces introduce the gravity model and explains why we apply this model. Next, we show how we address the endogeneity problem by developing instruments for trade and migration to examine the bi-directional causality. Finally, this paper shows the estimations techniques to estimate the bi-directional causality between interprovincial trade in aggregate and disaggregate and interprovincial migration at the provincial level within Canada.

2.3.1 Gravity Model in Trade and Migration

As the gravity model explains the interplay between trade and migration, we observe a massive application of this gravity model framework in the literature of trade and migration. First, we explain the gravity model of trade and then the gravity model of migration.

Following the scholars such as (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020), we evaluate the relationship between trade and migration applying the gravity model of trade.

The origin of the gravity model comes from Newton's universal law of gravitation *. Tinbergen (1963) introduces the gravity model of international trade to describe the pattern of bilateral trade flows. Krugman & Obstfeld (2005) provide a simpler version of the gravity model shown in equation 2.1. Trade flow is proportional to the economic sizes of both regions and inversely proportional to the distance between the trading partners.

$$T_{ij} = A\frac{Y_i^{\alpha_1} Y_j^{\alpha_2}}{D_{ij}^{\alpha_3}} \tag{2.1}$$

Here, T_{ij} is the trade flow from origin i to destination j; A is a constant of proportionality and it captures factors affecting trade beyond economic size and distance. Y_i and Y_j are the economic sizes of regions i and j, and besides, these usually represent the Gross Domestic Product (GDP) or the Gross National Product (GNP) of each region. D_{ij} captures the distance between two regions i and j, which serves as a proxy for trade costs between trading partners. Also, it represents impediments to trade such as differences in religions, lack of trade agreements and other barriers. Note that α_1, α_2 and α_3 are the parameters.

We extend the equation (2.1) and add interprovincial migration with other control variables to estimate the impact of interprovincial trade in aggregate and disaggregate on migration.

While Ravenstein (1885, 1889) discuss the gravity-type properties of internal migration flow, Zipf (1946) establishes the clear ground of the gravity model in migration with the famous paper discussing the intercity movement within the US. Empirical studies (Gallardo-Sejas et al., 2006; Helliwell, 1997; Ortega & Peri, 2013; Poot et al., 2016; Ramos & Suriñach, 2017; Skeldon, 2014) use

*"Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between their centers".

the gravity model of migration utilizing expression 2.2. Migration flow is proportional to the populations of both places of origin and destination. It has a negative relationship with the distance between origin and destination. An increase in distance increases the cost of migration.

$$M_{ij} = G\frac{P_i^{\gamma_1} P_j^{\gamma_2}}{D_{ij}^{\gamma_3}} \tag{2.2}$$

Here, M_{ij} is the migration flow from origin i to destination j. P_i and P_j denote the populations of provinces i and j. G is a constant of proportionality, reflecting factors influencing migration beyond population size and distance. Also, γ_1, γ_2 and γ_3 are the parameters.

By incorporating our variable of interest (interprovincial trade) with other relevant control variables, we estimate the impact of interprovincial trade (in aggregate and disaggregate) on migration using equation (2.2). The next section addresses the problem of endogeneity between trade and migration and offer solutions to this problem utilizing the SSIV.

2.3.2 Trade and Migration: Endogeneity & IV Approach

While a significant number of scholars study the long standing relationship between trade and migration, the literature provides evidence of reverse causality between trade and migration. Campaniello (2014) and Ghani et al. (2020) demonstrate that trade causes migration whereas other empirical works (Gould, 1994; Dunlevy & Hutchinson, 1999; Aziz et al., 2023) show that migration impacts trade.

Therefore, we examine the bi-directional causality between interprovincial trade (in aggregate and disaggregate) and migration utilizing the Granger (Non) Causality Test in this panel setup (Dumitrescu & Hurlin, 2012). Before testing for causation, we use the unit root test using (Im et al., 2003) to check that the variables are stationary. Results from Tables 5 and 6 further confirm that there is reverse causality between interprovincial trade (in aggregate and disaggregate) and migration. We discuss the results in the main results section.

To estimate the causal effect of interprovincial trade (in aggregate and disaggregate) on migration, we need to instrument the endogenous interprovincial trade. On the other hand, to establish the causal relationship between interprovincial migration and trade, this paper has to instrument the endogenous interprovincial migration. Therefore, we require instruments both for interprovincial trade and migration to establish the causal effects on each other.

2.3.3 Why SSIVs?

This study cannot use the instrumental variables from literature to instrument endogenous interprovincial trade as these do not qualify as instruments in our study. For example, Campaniello (2014) uses two instruments to show the causal impact of trade on migration: average trade tariffs and bilateral exchange rate volatility. Similarly, Ghani et al. (2020) instrument trade with WTO affiliation and average tariff rates to establish the causal impact of trade on migration. However, these instruments do not apply to our study.

Since our study considers how interprovincial trade influences interprovincial migration, instruments such as tariffs, exchange rates, and WTO affiliation lack variation across provinces for any year. Consequently, these variables do not qualify as instruments for this study.

We must find appropriate IVs for trade which are relevant, exogenous to migration and consistent with the exclusion restriction. Thus, this study derives 80 shift-share instrumental variables for interprovincial trade altogether to address the endogeneity problem.

While examining the impact of migration on trade within Canada, Aziz et al. (2023) instrument interprovincial migration with the employment rate. However, we argue that this instrument is not valid. Since trade can impact employment rate directly, it does not hold the exclusion restrictions of IVs. Therefore, we continue searching for instruments.

Using the SSIV technique, Card (2001, 2009) investigated the effects of immigrant inflows on occupation-specific labor market outcomes. Jaeger et al. (2018) later offered a refinement in this method, especially for migration literature. Therefore, to establish the causal relationship between interprovincial migration and trade (in aggregate and disaggregate), this paper constructs 4 SSIVs to instrument interprovincial migration following the literature-suggested techniques (Card, 2001, 2009; Jaeger et al., 2018).

The next section discusses the framework to examine the impact of interprovincial trade (in aggregate and disaggregate) on migration. Then we introduce the identification strategy to estimate the effect of interprovincial migration on interprovincial trade in aggregate and disaggregate.

2.3.4 Impact of Interprovincial Trade on Interprovincial Migration

This study compiles a panel dataset for all Canadian Provinces for the years 2007 to 2019, except Prince Edward Island. It employs the PPML estimator in the gravity model framework to examine the impact of interprovincial trade (in aggregate and disaggregate) on migration.

Since interprovincial trade measures -in total, goods and services- are endogenous variables, this study applies a two-stage approach to address this endogeneity. Next, we introduce SSIV mechanisms and demonstrate how this method can help to address the endogeneity problem. We further outline how we utilize this method to derive instruments for interprovincial trade (in aggregate and disaggregate).

2.3.5 Development of Shift-Share Instruments

Creamer (1943) first introduced the idea of shift-share analysis. While Dunn Jr (1960) refine it with a modern accounting identity, Freeman (1980) uses the decomposition of nature and instruments of labour demand with the change in industry composition.

Timothy J Bartik (1991, 1993) provides a strong rationale for using Shift-Share Instruments in economics. He reintroduces the idea of shift-share instruments by providing the logic of how the national growth rate component captures the shocks. And that is why these are called Bartik Instruments. The key feature of the Bartik Instrument or Shift-Share Instrument is its decomposition approach, which generates exogenous variation and facilitates causal analysis. Later, Blanchard & Katz (1992) contributed remarkably to this area. They define their instrument as the local employment growth rate, which is constructed by the interacting local industry employment shares with the national industry growth rates. The employment share is plausibly exogenous, and the national industry growth rate represents a shock at the aggregate level and is also exogenous. Any shock at the national level is exogenous to the regional level and the regional share grows rapidly with that shock.

These features make shift-share instruments very appealing. Hence, it is popular across various fields of economics (Acemoglu et al., 2016; Autor et al., 2013; Broxterman & Larson, 2020; Card, 2001, 2009; Hummels, 1999; Goldsmith-Pinkham et al., 2020; Peri, 2016; Xu, 2023), and particularly in labour economics (Card, 2001, 2009), and international trade (Hummels et al., 2014) for causal inference.

The growing number of works (Autor et al., 2013; Broxterman & Larson, 2020; Goldsmith-Pinkham et al., 2020) on this novel technique are opening the "black box", revealing the variations of this instrument. We develop our instruments following the works of Autor et al. (2013), Acemoglu et al. (2016), Goldsmith-Pinkham et al. (2020) and Broxterman & Larson (2020).

To estimate the causal effects of interprovincial trade (in aggregate and disaggregate) on migration, this study constructs our SSIVs using the mix of the trade share of regional industry and its national growth rate. Our SSIVs are exogenous to migration and are relevant to interprovincial trade. We further construct new instruments based on previous studies and suggest a new technique for estimating the causal impact of trade on migration.

2.3.6 Constructions of SSIVs for Interprovincial Trade

We estimate the effect of trade on migration in three ways: [i] the impact of interprovincial total trade on interprovincial migration, [ii] the effect of interprovincial goods trade on interprovincial migration and [iii] the impact of interprovincial services trade on interprovincial migration. Hence, this study derives 80 SSIVs from two sectors, goods and services, to instrument interprovincial total trade, interprovincial goods trade and interprovincial services trade.

In this research setting, we derive 24 SSIVs for interprovincial total and goods trades using the aggregate goods sector and two industries of the goods sector: [a] computers and electronic products and [b] plastic and rubber products. Moreover, this study uses six services industries along with the aggregate services sector to derive another 56 SSIVs for interprovincial total and services trades. The services industries are transportation and related services; information and cultural services; telecommunications, broadcasting distribution and related services; education services; arts, entertainment and recreation services; and accommodation and food services.

We first show the conventional method to derive the SSIVs. Then we discuss how we derive 80 instruments following the literature and the modifications we offer in this study.

Expression (2.3) shows the estimation method to construct shift-share instruments. It captures the interaction between the shock of an industry using the national growth rate of that industry and the regional share of that industry. A shock at the country level is exogenous to the regional economy and the share of the regional economy responds to the shock from the country level.

$$SSIV_{ijt}^{V} = N_t^k \times W_{ijt}^k \tag{2.3}$$

Here, $SSIV_{ijt}^{V}$ are the shift-share instruments for interprovincial trade and V is the index; N_t^k represents the shift of industry k at time t; W_{ijt}^k denotes the regional trade share of industry k in region j with trading partner i at time t. Notably, k is the number of industries. The sum of all shares must be 1, by expression $\sum_k W_{ijt}^k = 1$.

To create the SSIV, we first calculate the industry share using the equation (2.4). Then, we estimate the shift or the shock using the expression (2.5).

$$W_{ijt}^k = \frac{T_{ijt}^k}{T_{jt}} \tag{2.4}$$

T_{ijt}^k is the trade flow of industry k from origin i to destination j at time t; T_{jt} is the total trade of destination j at time t.

$$N_t^k = \left[\frac{T_t^k}{T_{t-1}^k}\right] - 1 \tag{2.5}$$

T_t^k is the country-level trade of industry k at time t; T_{t-1}^k is the country-level trade of industry k at time $(t-1)$. Once we estimate the shifts and the share using equations (2.5) and (2.4), we can then calculate the SSIV.

Since we examine bi-directional causality between interprovincial trade and migration, we use two different notations to clearly identify the instruments. Notably, SSIVT represents the shift-share instrumental variable for trade, whereas SSIVM denotes the shift-share instrumental variable for migration. The next two sections demonstrate how this study derives instruments for interprovincial trade.

2.3.7 SSIVs Derived from Goods Sector

Table 1 displays the formation of 24 instruments derived from the goods sector. This section explains the development of all these 24 instruments. The sum of the shares across aggregate and disaggregate goods industries is 1.

Table 1: SSIVs from Goods Sector

Index	Instruments	Construction Method	Components
1–2	$SSIVT^{1}_{AGS\star AGSR}$; $SSIVT^{2}_{LAGS\star LAGSR}$	$N^{G}_{t-q}W^{G}_{t-r}$, , where $G=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks and shares without & with lag
3–4	$SSIVT^{3}_{ADGS\star ADGSR}$; $SSIVT^{4}_{LADGS\star LADGSR}$	$\sum_{k=1}^{2} N^{k}_{t-q}W^{k}_{t-r}$, where $k=1,2$; $q=0,1$; $r=0,1$; and $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Sum of disaggregate shocks and shares without & with lag
5–8	$SSIVT^{5}_{AGS\star DGSR^{1}}$ to $SSIVT^{6}_{AGS\star DGSR^{2}}$; $SSIVT^{7}_{LAGS\star LDGSR^{1}}$ to $SSIVT^{8}_{LAGS\star LDGSR^{2}}$	$N^{G}_{t-q}W^{k}_{t-r}$ for $k=1,2$; $q=0,1$; $r=0,1$ and $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks with disaggregate shares without & with lag
9–12	$SSIVT^{9}_{ADGS\star DGSR^{1}}$ to $SSIVT^{10}_{ADGS\star DGSR^{2}}$; $SSIVT^{11}_{LADGS\star LDGSR^{1}}$ to $SSIVT^{12}_{LADGS\star LDGSR^{2}}$	$N^{G}_{t-q}W^{k}_{t-r}$ for $k=1,2$; $q=0,1$; $r=0,1$ and $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks with disaggregate shares without & with lag
13–16	$SSIVT^{13}_{DGS^{1}\star DGSR^{1}}$ to $SSIVT^{14}_{DGS^{2}\star DGSR^{2}}$; $SSIVT^{15}_{LDGS^{1}\star LDGSR^{1}}$ to $SSIVT^{16}_{LDGS^{2}\star LDGSR^{2}}$	$N^{k}_{t-q}W^{k}_{t-r}$ for $k=1,2$; $q=0,1$; $r=0,1$ and $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Disaggregate shocks and shares by industry without & with lag
17 –18	$SSIVT^{17}_{AGS}$; $SSIVT^{18}_{LAGS}$	N^{S}_{t-q} for $q=0,1$	Aggregate shocks only without & with lag
19–20	$SSIVT^{19}_{ADGS}$; $SSIVT^{20}_{LADGS}$	$\sum_{k=1}^{6} N^{k}_{t-q}$ for $q=0,1$	Sum of disaggregate shocks across industries without & with lag
21–24	$SSIVT^{21}_{DGS^{1}}$ to $SSIVT^{22}_{DGS^{2}}$; $SSIVT^{23}_{LDGS^{1}}$ to $SSIVT^{24}_{LDGS^{2}}$	N^{k}_{t-q} for $q=0,1$; $k=1,6$	Disaggregate shocks by industry

Note: q and r denote the lag on the shock and share, respectively. While G represents aggregate goods industry, k indexes the 2 goods industries. The condition $q\neq 1$ for $r=0$ excludes lagged shocks with original shares ($N_{t-1}W_t$). Also, $q\neq 0$ for $r=1$ excludes lagged shocks with original shares (N_tW_{t-1}).

Here: AGS and $AGSR$ refer to the aggregate goods shock and share, while $LAGS$ and $LAGSR$ represent their lagged counterparts. $ADGS$ and $ADGSR$ are aggregated disaggregate goods shocks and shares, whereas $LADGS$ and $LADGSR$ are aggregated disaggregate goods shocks and shares with lag. DGS and $LDGS$ denote disaggregate shocks without and with lag. $DGSR$ and $LADGSR$ indicate disaggregate shares without and with lag.

[a] Using Aggregate Goods Sector

Using the expressions (2.3), (2.5) and (2.4), we derive $SSIVT^{1}_{AGS\star AGSR}$ from the aggregate goods sector. Following previous empirical studies Acemoglu et al. (2016); Algan et al. (2017); Borusyak et al. (2022); Jaeger et al. (2018), we derive another instrument, $SSIVT^{2}_{LAGS\star LAGSR}$, using the lagged shock and share.

Acemoglu et al. (2016) introduced lag in the share of this technique to address any concerns over the endogeneity of the share component, whereas Jaeger et al. (2018) suggested lagging the shock to isolate current effects from past effects. Therefore, $SSIVT^{2}_{LAGS\star LAGSR}$ relies only on past economic conditions. This lagging strategy improves the exogeneity of our instrument and tackles the possibility of contemporaneous shock effect.

[b] Aggregating Goods Industries

Furthermore, we derive $SSIVT^{3}_{ADGS\star ADGSR}$ conventionally, and $SSIVT^{4}_{LADGS\star LADGSR}$ by lagging both shifts and shares of the two disaggregate goods industries, .

[c] Using Aggregate Shocks & Disaggregate Shares

This paper derives 4 instruments using the combinations of aggregate shocks with disaggregate shares. First, we follow the conventional approach and pair aggregate shocks with each disaggregate share to construct $SSIVT^{5}_{AGS\star DGSR^{1}}$ and $SSIVT^{6}_{AGS\star DGSR^{2}}$. Then, we lag both the shocks and the shares to create two additional variants ($SSIVT^{7}_{LAGS\star LDGSR^{1}}$ and $SSIVT^{8}_{LAGS\star LDGSR^{2}}$).

[d] Aggregating Disaggregate Shocks & Disaggregate Shares

We further develop 4 instruments aggregating the disaggregate shocks with disaggregate shares. Following the conventional approach, we pair aggregating two disaggregate shocks with each disaggregate share to construct $SSIVT^{9}_{ADGS\star DGSR^{1}}$ to $SSIVT^{10}_{ADGS\star DGSR^{2}}$. Then, we get another two instruments ($SSIVT^{11}_{LADGS\star LDGSR^{1}}$ and $SSIVT^{12}_{LADGS\star LDGSR^{2}}$) by lagging both the shocks and the shares.

[e] Using Disaggregate Shocks & Disaggregate Shares

This paper derives 4 instruments aggregating the disaggregate shocks with disaggregate shares. We follow the conventional approach, using aggregating two disaggregate shocks with each disaggregate share to construct $SSIVT^{13}_{DGS^{1}\star DGSR^{1}}$ to $SSIVT^{14}_{DGS^{2}\star DGSR^{2}}$. We further lag both the shocks and the shares to create two additional variants, $SSIVT^{15}_{LDGS^{1}\star LDGSR^{1}}$ and $SSIVT^{16}_{LDGS^{2}\star LDGSR^{2}}$.

[f] Aggregate, Aggregating Disaggregate Shocks & Disaggregate Shocks

This study derives another 8 instruments with the combinations of aggregate, aggregating disaggregate shocks and disaggregate shocks, both with and without lags. This study addresses the potential endogeneity of the "regional industry share by normalizing the shares following Goldsmith-Pinkham et al. (2020) and uses the shocks as instruments for interprovincial trade.

Using this approach, we construct $SSIVT^{17}_{AGS}$ using aggregate shocks and $SSIVT^{18}_{LAGS}$ using lagged aggregate shocks. Similarly, we develop $SSIVT^{19}_{ADGS}$ using the shocks of two disaggregate industries and $SSIVT^{20}_{LADGS}$ using their lagged counterparts.

We further normalize the disaggregate shares and use disaggregate shocks, both with and without lags, as instruments. Therefore, this paper composes 4 additional instruments: $SSIVT^{21}_{DGS^1}$, $SSIVT^{22}_{DGS^2}$; $SSIVT^{23}_{LDGS^1}$ and $SSIVT^{24}_{LDGS^2}$.

Using the literature-suggested techniques and our modifications, this study develops 24 instruments for interprovincial trade. The next section explains how we further derive another 56 instruments from the services sector for interprovincial trade.

2.3.8 SSIVs Derived from Services Sector

In our research setting, we design our SSIVs with six service industries alongside the aggregate services industry to derive all SSIVs for interprovincial trade in aggregate and disaggregate. The industries are: [1] Transportation and related services [2] Information and cultural services [3] Telecommunications, broadcasting distribution and related services [4] Education services [5] Arts, entertainment and recreation services and [6] Accommodation and food services.

First, we show how we construct 54 instruments following the literature and our augmentations. When deriving the instruments suggested by the literature, we also provide our versions with detailed explanations to further unfold the "black box." Table 2 exhibits the comprehensive set of instruments.

We develop all the instruments using five combinations of shocks and shares from the aggregate services industry and the six disaggregate services industries for this study. The sum of the shares across aggregate and disaggregate services industries is 1. Next, we provide a clear explanation why and how we can construct our instruments.

[a] Using Aggregate Services Industry

Using the aggregate services industry, we use the conventional method to derive $SSIV^{25}_{ASS\star ASSR}$. We construct our instrument, $SSIV^{26}_{LASS\star LASSR}$, by lagging both shock and share component following the previous studies (Acemoglu et al., 2016; Algan et al., 2017; Borusyak et al., 2022; Jaeger et al., 2018).

[b] Aggregating the Disaggregate Services Industries

We use the six disaggregate services industries to develop two instruments. We construct $SSIVT^{27}_{ADSS\star ADSSR}$ using the conventional method. Next, we create $SSIVT^{28}_{LADSS\star LADSSR}$ by lagging both the shocks and shares.

Table 2: SSIVs from Services Sector

Index	Instruments	Construction Method	Components
25–26	$SSIVT^{25}_{ASS\star ASSR}$; $SSIVT^{26}_{LASS\star LASSR}$	$N^S_{t-q}W^S_{t-r}$, , where $S=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks and shares without & with lag
27–28	$SSIVT^{27}_{ADSS\star ADSSR}$; $SSIVT^{28}_{LADSS\star LADSSR}$	$\sum_{k=1}^{6} N^k_{t-q}W^k_{t-r}$, where $k=1,\ldots,6$; $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$ and $q\neq 0$ if $r=1$	Sum of disaggregate shocks and shares without & with lag
29–40	$SSIVT^{29}_{ASS\star DSSR^1}$ to $SSIVT^{34}_{ASS\star DSSR^6}$; $SSIVT^{35}_{LASS\star LDSSR^1}$ to $SSIVT^{40}_{LASS\star LDSSR^6}$	$N^S_{t-q}W^k_{t-r}$ for $k=1,\ldots,6$; $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$ and $q\neq 0$ if $r=1$	Aggregate shocks with disaggregate shares without & with lag
41–52	$SSIVT^{41}_{ADSS\star DSSR^1}$ to $SSIVT^{46}_{ADSS\star DSSR^6}$; $SSIVT^{47}_{LADSS\star LDSSR^1}$ to $SSIVT^{52}_{LADSS\star LDSSR^6}$	$N^S_{t-q}W^k_{t-r}$ for $k=1,\ldots,6$; $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$ and $q\neq 0$ if $r=1$	Aggregate shocks with disaggregate shares without & with lag
53–64	$SSIVT^{53}_{DSS^1\star DSSR^1}$ to $SSIVT^{58}_{DSS^6\star DSSR^6}$; $SSIVT^{59}_{LDSS^1\star LDSR^1}$ to $SSIVT^{64}_{LDSS^6\star LDSSR^6}$	$N^k_{t-q}W^k_{t-r}$ for $k=1,\ldots,6$; $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$ and $q\neq 0$ if $r=1$	Disaggregate shocks and shares by industry without & with lag
65–66	$SSIVT^{65}_{ASS}$; $SSIVT^{66}_{LASS}$	N^S_{t-q} for $q=0,1$	Aggregate shocks only without & with lag
67–68	$SSIVT^{67}_{ADSS}$; $SSIVT^{68}_{LADSS}$	$\sum_{k=1}^{6} N^k_{t-q}$ for $q=0,1$	Sum of disaggregate shocks across industries without & with lag
69–80	$SSIVT^{69}_{DSS^1}$ to $SSIVT^{74}_{DSS^6}$; $SSIVT^{75}_{LDSS^1}$ to $SSIVT^{80}_{LDSS^6}$	N^k_{t-q} for $q=0,1$; $k=1,\ldots,6$	Disaggregate shocks by industry

Note: q and r denote the lag on the shock and share, respectively. While S represents aggregate services industry, k indexes the 6 services industries. The condition $q\neq 1$ for $r=0$ excludes lagged shocks with original shares ($N_{t-1}W_t$). Also, $q\neq 0$ for $r=1$ excludes lagged shocks with original shares (N_tW_{t-1}).

Here: ASS and $ASSR$ refer to the aggregate services shock and share, while $LASS$ and $LASSR$ represent their lagged counterparts. $ADSS$ and $ADSSR$ are aggregated disaggregate services shocks and shares, whereas $LADSS$ and $LADSSR$ are aggregated disaggregate services shocks and shares with lag. DSS and $LDSS$ denote disaggregate shocks without and with lag. $DSSR$ and $LADSSR$ indicate disaggregate shares without and with lag.

[c] Using Aggregate Shocks & Disaggregate Shares

We derive 12 instruments by combining aggregate shocks with disaggregate shares. First, we follow the conventional approach, pairing aggregate shocks with each disaggregate share to construct six instruments ($SSIVT^{29}_{ASS\star DSSR^1}$ to $SSIVT^{34}_{ASS\star DSSR^6}$). Then, we lag both the shocks and the shares to generate six variants ($SSIVT^{35}_{LASS\star LDSSR^1}$ to $SSIVT^{40}_{LASS\star LDSSR^6}$).

[d] Aggregating Disaggregate Shocks & Disaggregate Shares

This paper develops 12 instruments aggregating the disaggregate shocks with disaggregate shares. First, we follow the conventional approach, pairing aggregating six disaggregate shocks with each disaggregate share to construct six instruments ($SSIVT^{41}_{ADSS\star DSSR^1}$ to $SSIVT^{46}_{ADSS\star DSSR^6}$). Then, we lag both the shocks and the shares to create six additional variants ($SSIVT^{47}_{LADSS\star LDSSR^1}$ to $SSIVT^{52}_{LADSS\star LDSSR^6}$).

[e] Using Disaggregate Shocks & Disaggregate Shares

Using the combination of disaggregate shocks with disaggregate shares, it constructs 12 instruments. First, we derive six instruments ($SSIVT^{53}_{DSS^1\star DSR^1}$ to $SSIVT^{58}_{DSS^6\star DSR^6}$) with the direct combination of shocks and shares. Furthermore, we lag both the shocks and the shares to derive the last six instruments ($SSIVT^{59}_{LDSS^1\star LDSSR^1}$ to $SSIVT^{64}_{LDSS^6\star LDSSR^6}$).

[f] Using Aggregate & Disaggregate Shocks

This study derives another 12 instruments with the combinations of aggregate and disaggregate shocks, both with and without lags. Following Goldsmith-Pinkham et al. (2020), we use the shocks as instruments for interprovincial trade. Therefore, we create $SSIVT^{65}_{ASS}$ using aggregate shocks and $SSIVT^{66}_{LASS}$ using lagged aggregate shocks. Similarly, we get $SSIVT^{67}_{ADSS}$ using the shocks of six disaggregate industries and $SSIVT^{68}_{LADSS}$ using their lagged counterparts.

This study also uses disaggregate shocks, both with and without lags to construct 12 additional instruments, including $SSIVT^{69}_{DSS^1}$, $SSIVT^{74}_{DSS^6}$, $SSIVT^{75}_{LDSS^1}$ and $SSIVT^{80}_{LDSS^6}$.

The next section shows the empirical strategy to apply these 80 instruments and estimate the causal effect of interprovincial trade (in aggregate and disaggregate) on migration.

2.3.9 Exogeneity and Classification of SSIVs

To estimate the causal effect of interprovincial trade on migration, we construct our instruments using the mix of the trade share of regional industry and its national growth rate. We verify that this SSIV is exogenous to migration and is relevant to interprovincial trade.

A trade shock at the country level is exogenous to provincial trade share. So, the provincial trade share increases as the national growth rate increases. And trade influences migration only through SSIVs.

Regional trade share and the shock at the country level are exogenous to migration. Also, we develop the SSIVs with the combination of these two components (shift and share). Our further lagging strategy in SSIVs addresses any minor possibility of the endogeneity of the share components. As these lagged SSIVs solely depend on past economic events, this lagged decomposition nature eliminates the possibility of any endogeneity concerns in the share component of SSIVs.

Migration does not affect the SSIVs directly nor do the SSIVs affect migration. So, it also holds exclusion restrictions. Thus, the SSIVs satisfy all the criteria to qualify as instruments.

We introduce two types of instruments in this study: conventional SSIVs and modified SSIVs. We develop all the conventional SSIVs using original shocks and shares, whereas modified SSIVs include lagged shocks and shares.

Why our instruments are better?

Since we introduce lag in both shock and share, our version of instruments solely relies on past economic conditions. Our lagging approach isolates any contemporaneous correlation between the instruments and the endogenous variable. We further argue that aggregate shock may indirectly influence interprovincial migration and may weaken the exclusion restriction of an IV. In this case, adopting a lag shock solves the problem.

Aggregate shocks may not be able to capture the regional and sectoral heterogeneity. Therefore, we design our instruments with lag disaggregate shocks and shares to capture these regional and sectoral heterogeneities.

2.3.10 Identification Strategy for Interprovincial Trade

This paper estimates the impact of interprovincial trade on migration following an IV approach. To ensure the robustness and reliability of our estimations, we estimate two types of IV models: just-identified and over-identified. To estimate just-identified IV models, this study instruments interprovincial trade with each of 80 SSIVs derived from the goods and services sectors.

This study further estimates the over-identified IV models using all the SSIVs for interprovincial trade in several ways. This study sets the instruments for over-identified models: [a] using the usual SSIVs derived from the goods and the services sectors [b] instrumenting the shocks from these two industries [c] utilizing the modified SSIVs from the goods and services sectors and [d] employing the lagged shocks

Equation (2.6) shows the first stage of regression. We instrument interprovincial trade (both aggregate and disaggregate) with shift-share instrumental variables (SSIVs) derived from the goods and services sectors. It also controls for variables, including the distance and border sharing between two provinces, the participation rate, Gross Domestic Products (GDP) Per Capita, annual average income, and weather conditions in both origin and destination provinces.

$$T^{U}_{ijt} = \alpha_0 + \alpha_1\,\mathrm{SSIVT}^{V} + \alpha_2\,\mathrm{Controls}_{ij} + \alpha_3\,\mathrm{Controls}_{it} + \alpha_4\,\mathrm{Controls}_{jt} + \varepsilon_{ijt} \tag{2.6}$$

Here, T^{U}_{ijt} denotes the interprovincial trade flow from province i to province j at time t; U represent the form of trade. T^{TT}_{ijt}, T^{TG}_{ijt} and T^{TS}_{ijt} are interprovincial total trade, interprovincial goods trade and interprovincial services trade[†]. SSIVT^{V} are the shift-share instrumental variables (SSIVs) derived from the goods and the services industries for interprovincial trade.

$Controls_{ij}$ are D_{ij} and $Border_{ij}$. D_{ij} is the distance between two provinces, and $Border_{ij}$ represents a dummy variable if the two provinces share a border accordingly. $Controls_{it}$ are $GDPC_{it}$, Inc_{it}, Par_{it} and WC_{it}. $GDPC_{it}$ is the GDP Per Capita of province i at time t; Inc_{it} is the annual average income of province i at time t; Par_{it} is the labor participation rate of province i at time t; WC_{it} is the weather conditions of province i at time t in January and February.

$Controls_{jt}$ are $GDPC_{jt}$, Inc_{jt}, Par_{jt} and WC_{jt}. $GDPC_{jt}$ is the GDP Per Capita of province j at time t; Inc_{jt} is the annual average income at province j at time t; Par_{jt} is the labor participation rate at province j at time t; WC_{jt} is the weather conditions at province j at time t in January and February.

Using equation (2.7), this study estimates the impact of interprovincial trade in aggregate and disaggregate on migration. It incorporates all the control variables of the first-stage into this second-stage regression except interprovincial trade in equation (2.7). These variables instrument themselves in the second stage as shown in equation (2.7).

$$\begin{aligned} M_{ijt} = \exp\Big[&\beta_0 + \beta_1 \log\left(\hat{T}^{U}_{ijt}\right) + \beta_2 \log(\mathrm{Controls}_{ij}) + \beta_3 \log(\mathrm{Controls}_{it}) \\ &+ \beta_4 \log(\mathrm{Controls}_{jt}) + \tau_{it} + \tau_{jt} + \tau_t\Big] + \varepsilon_{ijt} \end{aligned} \tag{2.7}$$

Here, M_{ijt} is interprovincial migration flow from province i to province j; $\hat{T}^{U}_{ijt}$ are the predicted provincial (total, goods and services) trade flows from province i to j; τ_{it}, τ_{jt} and τ_t are origin fixed effects, destination fixed effects, and year fixed effects, respectively.

We regress interprovincial migration flow between two provinces on the predicted provincial trade flows between two provinces, the distance between two provinces, the GDP Per Capita, the participation rate, the weather conditions, and average annual income of both provinces and border sharing between two provinces.

2.3.11 The Impact of Migration on Trade

To compare the impact of migration on trade, we estimate the effects of interprovincial migration on trade in three ways: [i] the impact of interprovincial migration on interprovincial total trade,

[†]**Note**: TT, TG and TS are total trade, goods trade and services

[ii] the effect of interprovincial migration on interprovincial goods trade and [iii] the impact of interprovincial migration on interprovincial services trade.

To estimate the impact of interprovincial migration on interprovincial trade in aggregate and disaggregate for the years 2007 to 2019, this paper applied the PPML estimator in the gravity model following the IV approach.

The next section shows the derivation of instruments for interprovincial migration following the SSIV framework.

2.3.12 SSIVs Derivation for Interprovincial Migration

Since interprovincial migration is an endogenous variable for this part of our study, we instrument interprovincial migration with various combinations of SSIVs. While scholars extensively use different variants of SSIVs in their studies (Card, 2001, 2009; Felbermayr et al., 2015; Gould, 1994; Peri, 2016; Wagner et al., 2002), Card (2001, 2009) formally established this technique in labor economics.

Following Card (2001, 2009), equation (2.8) shows the conventional SSIV derivation method for interprovincial migration. This technique creates an exogenous instrument for interprovincial migration by capturing the interaction between the national migration shock and the regional migration share.

$$\mathrm{SSIVM}_{ijt}^{V} = \mathrm{NM_t} \times \mathrm{WM_{ijt}} \tag{2.8}$$

Here, SSIVM^{V} is the SSIV for interprovincial migration; $\mathrm{NM_t}$ represents the migration shock at time t; $\mathrm{WM_{ijt}}$ denotes the regional migration share from region i to region j at time t.

Expressions (2.9) and (2.10) show the calculation techniques for migration shock and share.

$$\mathrm{NM_t} = \frac{M_t}{P_t} \tag{2.9}$$

In this equation, M_t is the total national migration inflow at time t, and P_t is the country-level total population at time t.

$$\mathrm{WM_{ijt}} = \frac{M_{ijt}}{P_{jt}} \tag{2.10}$$

Here, M_{ijt} is the migration flow from province i to province j at time t; P_{jt} is the total population of destination j at time t.

Therefore, we develop instruments for interprovincial migration using expressions (2.8), (2.9) and (2.10). Table 3 provides an overview of our instruments for interprovincial migration.

Table 3: SSIVs for Interprovincial Migration

Index	Instruments	Construction Method	Components
1–2	$SSIVM^1_{AMS\star AMSR}$; $SSIVM^2_{LAMS\star LAMSR}$	$NM_{t-q}WM_{t-r}$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks and shares without & with lag
3–4	$SSIVM^3_{AMS}$; $SSIVM^4_{LAMS}$	NM_{t-q} for $q=0,1$	Aggregate shocks only without & with lag

Note: q and r denote the lag on the shock and share, respectively. The condition $q \neq 1$ for $r = 0$ excludes lagged shocks with original shares ($NM_{t-1}WM_t$). Also, $q \neq 0$ for $r = 1$ excludes lagged shocks with original shares (NM_tWM_{t-1}).

Here: AMS and $AMSR$ refer to the aggregate migration shock and share, while $LAMS$ and $LAMSR$ represent their lagged counterparts.

Following the conventional method, we create our first instrument, $\text{SSIVM}^1_{AMS*AMSR}$, for interprovincial migration.

Now assume that the migration share is endogenous. In this case, we can lag the share component or normalize the share component of equation (2.8). We use both techniques and derive two more instruments for our study. Firstly, following Jaeger et al. (2018) and Acemoglu et al. (2016), we take lags in both the shock and the share to derive another instrument $\text{SSIVM}^2_{LAMS*LAMSR}$. After normalizing the migration share, we derive another two instruments SSIVM^3_{AMS} and SSIVM^4_{LAMS}.

In this section, we show how we develop our instruments for interprovincial migration. The next section offers a discussion of how these instruments are exogenous to interprovincial trade.

2.3.13 Exogeneity and Classification of SSIVs

We construct the SSIV combining the migration share of a regional economy with its national growth rate. Our instruments are relevant to interprovincial migration and are exogenous to interprovincial trade. The regional migration share increases as the national migration growth rate increases. Nor does the migration shock or the share influence interprovincial trade directly. Migration affects trade only through the SSIVs.

The national migration shock and the regional migration share are exogenous to trade. We introduce lag into SSIV derivation to address any potential concerns about the endogeneity concerns related to the share component. With the lagging strategy, this study makes sure that the SSIVs are solely derived from past economic conditions.

SSIVs do not directly affect migration, nor migration does not directly influence SSIVs. It also satisfies the exclusion restriction. So, SSIVs influence interprovincial trade only through migration. Thus, all the SSIVs in this part of this study also meet the criteria of instruments.

Again, we classify the instruments for this part of the study into two. $SSIVM^1_{AMS\star AMSR}$ is Conventional SSIV for migration, whereas Modified SSIV includes $SSIVM^2_{LAMS\star LAMSR}$. Other two are literature-suggested shocks, $SSIVM^3_{AMS}$ and $SSIVM^4_{LAMS}$.

2.3.14 Identification Strategy for Interprovincial Migration

Using an IV approach, we estimate the impact of interprovincial migration on trade in aggregate and disaggregate. This study further ensures the robustness and reliability of the findings using both types of IV models: just-identified and over-identified.

The just-identified IV models instrument interprovincial migration with each of 4 derived SSIVs, whereas the over-identified IV models use two combination: [a] usual SSIV and modified SSIV and [b] shocks and lag shocks together.

Equation (2.11) instruments interprovincial migration with SSIVs and controls for variables, including the distance and border sharing between two provinces, the participation rate, Gross Domestic Products (GDP) Per Capita, the annual average income, and weather conditions in both origin and destination provinces.

$$M_{ijt} = \gamma_0 + \gamma_1 \,\mathrm{SSIVM}^V_{ijt} + \gamma_2 \,\mathrm{Controls}_{ij} + \gamma_3 \,\mathrm{Controls}_{it} + \gamma_4 \,\mathrm{Controls}_{jt} + \varepsilon_{ijt} \tag{2.11}$$

Where, M_{ijt} is interprovincial migration flow from province i to province j; $SSIVM^V_{ijt}$ are the shift-share instrumental variables for interprovincial migration derived from migration shock and share.

Using equation (2.12), we estimate the causal effect of interprovincial migration on trade in aggregate and disaggregate. The second-stage incorporates all the control variables of the first-stage as these instrument themselves as shown in equation (2.12).

$$\begin{aligned} T^U_{ijt} = \exp \Bigg[&\lambda_0 + \lambda_1 \log\left(\hat{M}_{ijt}\right) + \lambda_2 \log(\mathrm{Controls}_{ij}) + \lambda_3 \log(\mathrm{Controls}_{it}) \\ &+ \lambda_4 \log(\mathrm{Controls}_{jt}) + \tau_{it} + \tau_{jt} + \tau_t \Bigg] + \varepsilon_{ijt} \end{aligned} \tag{2.12}$$

Here, $\hat{M}_{ijt}$ is the predicted provincial migration flow from province i to j. This paper regresses interprovincial trade in aggregate and disaggregate on the predicted migration flow between two provinces, the distance between two provinces, the GDP Per Capita, the participation rate, the weather conditions, and the average annual income of both provinces and border sharing between two provinces.

2.3.15 PPML Estimator & The Fixed Effects

This study employs the PPML estimator in the gravity model framework and controls unobserved heterogeneity using year-fixed effect, origin and destination-fixed effects. Moreover, we check the validity of over-identifying restrictions for OI IV models using the Hansen J test.

Silva & Tenreyro (2006) show that log linearizing the gravity equation causes bias and inconsistency if there is heteroskedasticity. They recommend estimating the model in multiplicative form and to use the PPML estimator as it is an efficient estimator. Therefore, our study estimates the equations (2.7) and (2.12) in multiplicative form using the PPML estimator, rather than log-linearizing the equations.

Following the work of Anderson & Van Wincoop (2003), the standard practice in the structural gravity model of trade is to account for multilateral resistance terms by incorporating individual dummies for each origin and destination. It is the same as taking fixed effects for origin and destination into the gravity model (Hummels, 1999). In migration studies, Ortega & Peri (2012, 2013) also popularize the multilateral resistance term, which captures the decisions to migrate to possible destinations. Destination and origin fixed effects control the influencing factors of migration decisions that do not change over time, such as institutions, culture and attributes. These factors change slowly within a country (Ortega & Peri, 2012).

Hence, it is important to control this multilateral resistance term. We control the multilateral resistance term by applying a PPML estimator in the gravity model with origin and destination fixed effects (Fally, 2015). His remarkable work sheds light on the missing link of whether these fixed effects capture the multilateral resistance terms. He shows that estimating the gravity equation with the PPML estimator with origin and destination fixed effects recovers the multilateral resistance indexes. Under reasonable assumptions, Fally (2015) shows that only the PPML estimator has the properties to satisfy these conditions. Santos Silva & Tenreyro (2022) revisit their estimator and support the findings from Fally (2015).

2.4 Data Description

To examine the bi-directional causality between interprovincial trade (in aggregate and disaggregate) and migration for all Canadian provinces, except Prince Edward Island, this study compiles the panel dataset using the following variables: interprovincial total trade flow, interprovincial goods trade flow, interprovincial services trade flow[‡], participation rate, annual yearly income, and gross domestic product (GDP) per capita from CANSIM for the years 2007 to 2019. This paper also uses interprovincial migration flow data from CANSIM[§].

For the implementation of the gravity model, this panel dataset includes distance. This study selects one major city in each Canadian province based on population density as a measure of the

[‡]Statistics Canada. *Table 12-10-0088-01: Interprovincial and international trade flows, basic prices, summary level (x 1,000,000).* DOI: 10.25318/1210008801-eng.

[§]Statistics Canada. *Table 17-10-0022-01 Estimates of interprovincial migrants by province or territory of origin and destination, annual* DOI: 10.25318/1710002201-eng.

distance, and we use the distance[¶] between two provinces in the gravity model. If a province shares a border with other provinces, this may increase the probability of migration. Therefore, we include a border dummy variable in the model, with a value of 1 for a province sharing a border with another province, and 0 otherwise. If a province experiences temperatures below $-30°C$ in January and February for the years 2007 to 2019, our study considers that province as having the worst weather conditions as per Environment Canada (2020)'s monthly data. Thus, we set 1 for the worst weather conditions and 0 otherwise.

2.5 Main Results

This section explains the summary statistics, the Granger non-causality results and our regression estimations.

2.5.1 Summary Statistics

Table 4 represents the summary statistics for this study. The dataset has 864 observations. A Canadian province's interprovincial trade volume is, on average, \$71,755.59 million. The minimum amount of interprovincial trade is \$3,640 million, and the maximum amount is \$257,400 million.

On average, 2,929.276 persons migrate to a province within Canada annually. The yearly provincial averages range from a minimum of 78 migrants to a maximum of 29,304 persons.

Table 4: Summary Statistics for Interprovincial Trade and Migration

Variables	Mean	Min	Max
Interprovincial Total Trade Flow (In Millions)	79,258.10	12,646.60	257,484
Interprovincial Goods Trade Flow (In Millions)	35,312.44	5,033.7	96,654.2
Interprovincial Services Trade Flow (In Millions)	44,838.44	5,998.2	160,829.7
Interprovincial Migration Flow	2,292.276	78	29,304
GDP (In Millions)	193.78	28.8	752.39
Population (In Thousands)	3,864.476	509.055	14,544.70
Average Yearly Income (In Dollars)	46,089.74	37,600	61,900
Participation Rate (%)	65.91	58.4	74.7
Distance (km)	2,063.942	140.83	4,431.78
Total Number of Observations	**864**		

[¶] https://www.distancefromto.net/

2.5.2 Granger Causality Test Results

Table 5 exhibits the Granger non-causality test results of whether interprovincial trade (in aggregate and disaggregate) causes migration. Before assessing the reverse causality between trade and migration, Im et al. (2003) test results confirm that the variables are stationary. The null hypothesis of this test is that interprovincial trade does not Granger-cause interprovincial migration. The results indicate that interprovincial (in aggregate and disaggregate) cause interprovincial migration as we reject the null hypothesis at a 1% significance level.

Table 6 displays the Granger non-causality test results of examining the causal direction of interprovincial migration on trade (in aggregate and disaggregate). We find strong evidence in favour of reverse causality as we reject the null hypothesis at a 1% significant level.

Table 5: Granger Non-Causality Test Results for Interprovincial Trade

Direction of Causality	P-Value
Interprovincial Total Trade → Interprovincial Migration	0.000
Interprovincial Goods Trade → Interprovincial Migration	0.001
Interprovincial Services Trade → Interprovincial Migration	0.002

Table 6: Granger Non-Causality Test Results for Interprovincial Migration

Direction of Causality	P-Value
Interprovincial Migration → Interprovincial Total Trade	0.000
Interprovincial Migration → Interprovincial Goods Trade	0.003
Interprovincial Migration → Interprovincial Services Trade	0.001

2.5.3 Impact of Interprovincial Trade on Migration

Tables 7 to 10 and Tables 11 to 12 display JI and OI results for the impact of total trade on migration, respectively. Similarly, Tables 13 to 18 represent the JI estimations for the impact of goods trade on migration, whereas Table 19 shows the OI results. While Tables 20 to 29 exhibit the estimated JI results for the impact of services trade on migration, Tables 30 to 31 present the OI findings.

This research employs instruments (1 – 4), (17 – 20), (25 – 28) and (65 – 68) in JI models to analyze the impact of interprovincial total trade on interprovincial migration. OI models include different combinations these instruments: (1, 2), (3, 4), (17, 18), (19, 20), (25, 26), (27, 28), (65, 66), and (67, 68).

To evaluate the impact of interprovincial services trade on migration, we use all the instruments (1 to 24) derived from the goods sector for JI estimation. Furthermore, OI models incorporate various combinations of these instruments, including (1 – 4), (5 – 8), (9 – 12), (13 – 16), (17 – 20) and (21 – 24).

Finally, to ensure robust estimations for analyzing the impact of services trade on migration, we also instrument services trade using all instruments from 25 to 80. The JI models include each of these instruments, whereas the OI model incorporate instruments in groups: (25 – 28), (29 – 34), (35 – 40), (41 – 46), (47 – 52), (53 – 58), (59 – 64), (65 – 68), (69 – 74), and (75 – 80).

The results indicate that interprovincial trade in aggregate and disaggregate impacts interprovincial migration significantly across JI and OI IV models. The relationships are statistically significant at a 1% level. Empirical works such as (Campaniello, 2014; Ghani et al., 2020) find similar results. The findings are consistent across all types of SSIVs from the goods and services sectors. If total trade overall increases by 1% between provinces, interprovincial migration will increase by 1.5%.

While both goods and services trade influence interprovincial migration, services trade has a stronger effect on migration than goods trade. A 1% increase in goods trade attracts migrants by more than 1%, whereas a 1% percent increase in services trade increases interprovincial migration by more than 2.5%. Therefore, the services trade attracts migrants 1.5% higher than the goods trade.

The results are robust across all SSIVs in all versions of IV models. The instruments we introduce in this study are very strong as per the first-stage results relying on the values of F-statistics and R-squared. All the SSIVs produce very high values of F-statistic ranging from 169.87 to 346.49, and these satisfy the minimum [$F \geq 10$ (Bound et al., 1995; Stock & Yogo, 2002)] and maximum [$F \geq 50$ (Keane & Neal, 2021)] thresholds of F-statistic values to be a reliable instrument. The R-squared values ranging from 0.8817 to 0.8048 further validate the strength of all the instruments in this study.

Now we compare the over-identification test results of Hansen J Statistics across all OI models. Looking at Tables 8, 9, 16, 27 and 28, we could not reject the null hypothesis of Hansen J tests. Therefore, we claim that all the instruments in this study pass the over-identification tests and are valid. While looking at the control variables both from origin and destination, we find similar results compared to the literature. For example, the relationship between migration and distance is negative and statistically significant at 1% in all IV models. More distance will discourage migrants from moving as larger distance increases migration costs. This supports the works of Campaniello (2014); Ghani et al. (2020); Karemera et al. (2000).

An increase in labor force participation in the destination negatively affects interprovincial migration from the origin province. It is statistically significant across all models. A higher labor force participation rate may lead to fewer opportunities for migrants. The relationship between GDP per capita and interprovincial migration is negative in all models. While people who are already in higher GDP per capita provinces do not want to move, provinces with higher GDP per capita tend to attract fewer migrants due to the high cost of living. We find similar results in other studies (Campaniello, 2014; Ghani et al., 2020; Karemera et al., 2000).

An increase in annual average income induces interprovincial migration to the destination provinces. It is statistically significant at the 1% level. If the annual average income increases by 1%, interprovincial migration rises by at least 2.5%. This finding supports Mincer (1978)'s thought, the view of the neoclassical economic model and Karemera et al. (2000). Sharing borders between provinces increases interprovincial migration within Canada and this is statistically significant at a 1% level across all SSIVs. Our results match with the literature (Campaniello, 2014; Ghani et al., 2020; Karemera et al., 2000).

Our findings reveal that provinces with bad winters may attract fewer migrants. The relationship between migration and weather conditions is negative and statistically significant at a 1% level for destination provinces. People also do not tend to move to provinces with more bad weather conditions if they are already in bad weather.

Table 7: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^1_{AGS\star AGSR}$	$SSIVT^2_{LAGS\star LAGSR}$	$SSIVT^3_{ADGS\star ADGSR}$	$SSIVT^4_{LADGS\star LADGSR}$
Independent Variables		**Estimator: PPML**		
Interprovincial Total Trade$_{ijt}$	1.535***	1.546***	1.526***	1.555***
	(0.379)	(0.379)	(0.378)	(0.379)
Distance$_{ij}$	-0.441***	-0.443***	-0.443***	-0.442***
	(0.023)	(0.023)	(0.023)	(0.024)
Participation rate$_{it}$	0.046	0.040	0.041	0.045
	(0.030)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.770***	-7.867***	-7.812***	-7.934***
	(1.387)	(1.396)	(1.395)	(1.394)
GDPC$_{it}$	-0.569***	-0.571***	-0.569***	-0.563***
	(0.193)	(0.193)	(0.193)	(0.194)
GDPC$_{jt}$	-0.158*	-0.157*	-0.155*	-0.157*
	(0.084)	(0.084)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.329	-0.325	-0.344	-0.415
	(0.499)	(0.499)	(0.500)	(0.496)
Average Yearly Income$_{jt}$	3.057***	3.041***	3.059***	3.089***
	(0.486)	(0.489)	(0.486)	(0.484)
Border$_{ij}$	0.280***	0.278***	0.277***	0.279***
	(0.044)	(0.044)	(0.044)	(0.279)
Weather$_{it}$	-0.240	-0.242	-0.227	-0.527
	(0.408)	(0.408)	(0.407)	(0.989)
Weather$_{jt}$	-1.648***	-1.647***	-1.641***	-1.642***
	(0.127)	(0.131)	(0.131)	(0.132)
Number of Observations	864	792	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	251.35	248.05	246.01	247.26
R Squared [FS]	0.8234	0.8414	0.8202	0.8210

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 8: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{17}_{AGS}$	$SSIVT^{18}_{LAGS}$	$SSIVT^{19}_{ADGS}$	$SSIVT^{20}_{LADGS}$
Independent Variables	**Estimator: PPML**			
Interprovincial Total Trade$_{ijt}$	1.556***	1.556***	1.556***	1.556***
	(0.379)	(0.379)	(0.379)	(0.379)
Distance$_{ij}$	-0.441***	-0.441***	-0.441***	-0.441***
	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.042	0.042	0.042	0.042
	(0.030)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.770***	-7.850***	-7.850***	-7.850***
	(1.387)	(1.391)	(1.391)	(1.394)
GDPC$_{it}$	-0.565***	-0.565***	-0.565***	-0.565***
	(0.193)	(0.193)	(0.193)	(0.193)
GDPC$_{jt}$	-0.164*	-0.164*	-0.164*	-0.164*
	(0.085)	(0.085)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.339	-0.339	-0.339	-0.339
	(0.500)	(0.500)	(0.500)	(0.500)
Average Yearly Income$_{jt}$	3.030***	3.030***	3.030***	3.030***
	(0.488)	(0.488)	(0.488)	(0.488)
Border$_{ij}$	0.281***	0.281***	0.281***	0.281***
	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	-0.263	-0.263	-0.227	-0.263
	(0.409)	(0.409)	(0.409)	(0.409)
Weather$_{jt}$	-1.648***	-1.647***	-1.648***	-1.648***
	(0.127)	(0.131)	(0.131)	(0.133)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	247.26	245.97	246.38	230.14
R Squared [FS]	0.8210	0.8202	0.8204	0.8247
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

Table 9: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{25}_{ASS\star ASSR}$	$SSIVT^{26}_{LASS\star LASSR}$	$SSIVT^{27}_{ADSS\star ADSSR}$	$SSIVT^{28}_{LADSS\star LADSSR}$
Independent Variables	**Estimator: PPML**			
Interprovincial Total Trade$_{ijt}$	1.514***	1.277***	1.526***	1.555***
	(0.389)	(0.377)	(0.378)	(0.393)
Distance$_{ij}$	-0.436***	-0.441***	-0.447***	-0.452***
	(0.023)	(0.023)	(0.023)	(0.024)
Participation rate$_{it}$	0.049	0.042	0.041	0.052
	(0.031)	(0.031)	(0.121)	(0.034)
Participation rate$_{jt}$	-7.746***	-7.847***	-7.747***	-6.815***
	(1.400)	(1.392)	(1.392)	(1.425)
GDPC$_{it}$	-485**	-0.566***	-0.472***	-632***
	(0.194)	(0.193)	(0.194)	(0.194)
GDPC$_{jt}$	-0.179**	-0.163**	-0.170**	-0.135
	(0.083)	(0.084)	(0.084)	(0.085)
Average Yearly Income$_{it}$	-0.400	-0.337	-0.487	-0.323
	(0.506)	(0.499)	(0.501)	(0.494)
Average Yearly Income$_{jt}$	3.265***	3.115***	3.059***	3.265***
	(0.481)	(0.487)	(0.496)	(0.494)
Border$_{ij}$	0.298***	0.281***	0.280***	0.272***
	(0.043)	(0.044)	(0.044)	(0.046)
Weather$_{it}$	-0.273	-0.271	-0.233	-0.028
	(0.418)	(0.408)	(0.407)	(0.422)
Weather$_{jt}$	-1.635***	-1.644***	-1.648***	-1.571***
	(0.130)	(0.131)	(0.133)	(0.137)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	344.30	324.91	246.49	233.26
R Squared [FS]	0.8646	0.8577	0.8205	0.8266
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*				

Table 10: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{65}_{ASS}$	$SSIVT^{66}_{LASS}$	$SSIVT^{67}_{ADSS}$	$SSIVT^{68}_{LADSS}$
Independent Variables	**Estimator: PPML**			
Interprovincial Total Trade$_{ijt}$	1.556***	1.556***	1.556***	1.556***
	(0.379)	(0.379)	(0.379)	(0.379)
Distance$_{ij}$	-0.441***	-0.441***	-0.440***	-0.440***
	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.042	0.042	0.042	0.042
	(0.030)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.850***	-7.850***	-7.850***	-7.850***
	(1.391)	(1.391)	(1.391)	(1.391)
GDPC$_{it}$	-0.565***	-0.565***	-0.565***	-0.565***
	(0.193)	(0.193)	(0.193)	(0.193)
GDPC$_{jt}$	-0.164*	-0.164*	-0.164*	-0.164*
	(0.085)	(0.085)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.339	-0.339	-0.339	-0.339
	(0.500)	(0.500)	(0.500)	(0.500)
Average Yearly Income$_{jt}$	3.030***	3.030***	3.030***	3.030***
	(0.488)	(0.488)	(0.488)	(0.488)
Border$_{ij}$	0.281***	0.281***	0.281***	0.281***
	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	-0.263	-0.263	-0.227	-0.263
	(0.409)	(0.409)	(0.409)	(0.409)
Weather$_{jt}$	-1.648***	-1.647***	-1.648***	-1.648***
	(0.313)	(0.131)	(0.131)	(0.131)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	246.26	232.25	248.07	230.14
R Squared [FS]	0.8204	0.8260	0.8214	0.8246

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 11: The Impact of Interprovincial Total Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{1}_{AGS\star AGSR}$	$SSIVT^{3}_{ADGS\star ADGSR}$	$SSIVT^{17}_{AGS}$	$SSIVT^{19}_{ADGS}$
	$SSIVT^{2}_{LAGS\star LAGSR}$	$SSIVT^{4}_{LADGS\star LADGSR}$	$SSIVT^{18}_{LAGS}$	$SSIVT^{20}_{LADGS}$
Independent Variables	**Estimator: PPML**			
Interprovincial Total Trade$_{ijt}$	1.436***	1.221***	1.556***	1.556***
	(0.388)	(0.394)	(0.379)	(0.379)
Distance$_{ij}$	-0.447***	-0.457***	-0.441***	-0.441***
	(0.025)	(0.024)	(0.023)	(0.024)
Participation rate$_{it}$	0.042	0.048	0.042	0.042
	(0.034)	(0.034)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.218***	-6.649***	-7.850***	-7.850***
	(1.412)	(1.434)	(1.391)	(1.391)
GDPC$_{it}$	-0.755***	-0.694***	-565***	-0.563***
	(0.185)	(0.194)	(0.193)	(0.193)
GDPC$_{jt}$	-0.146	-0.139	-0.164*	-0.164*
	(0.092)	(0.084)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.025	-0.158	-0.399	-0.339
	(0.490)	(0.501)	(0.500)	(0.500)
Average Yearly Income$_{jt}$	3.094***	3.165***	3.030***	3.030***
	(0.484)	(0.477)	(0.488)	(0.488)
Border$_{ij}$	0.266***	0.260***	0.281***	0.281***
	(0.045)	(0.045)	(0.044)	(0.044)
Weather$_{it}$	-0.133	-0.079	-0.263	-0.263
	(0.418)	(0.424)	(0.409)	(0.409)
Weather$_{jt}$	-1.580***	-1.564***	-1.648***	-1.648***
	(0.135)	(0.136)	(0.131)	(0.131)
Number of Observations	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	229.64	218.05	216.29	213.43
R Squared [FS]	0.8351	0.8278	0.8266	0.8247
Hansen's J Statistics [P Value]	0.1975	0.0510	0.2594	0.2594

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 12: The Impact of Interprovincial Total Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{25}_{ASS\star ASSR}$	$SSIVT^{27}_{ADSS\star ADSSR}$	$SSIVT^{65}_{ASS}$	$SSIVT^{67}_{ADSS}$
	$SSIVT^{26}_{LASS\star LASSR}$	$SSIVT^{28}_{LADSS\star LADSSR}$	$SSIVT^{66}_{LASS}$	$SSIVT^{68}_{LADSS}$
Independent Variables	**Estimator: PPML**			
Interprovincial Total Trade$_{ijt}$	1.265*** (0.397)	1.556*** (0.392)	1.556*** (0.379)	1.556*** (0.379)
Distance$_{ij}$	-0.439*** (0.024)	-0.454*** (0.024)	-0.440*** (0.023)	-0.440*** (0.024)
Participation rate$_{it}$	0.050 (0.033)	0.048 (0.034)	0.042 (0.031)	0.042 (0.031)
Participation rate$_{jt}$	-6.963*** (1.447)	-6.866*** (1.422)	-7.850*** (1.391)	-7.850*** (1.391)
GDPC$_{it}$	-0.629*** (0.188)	-0.584*** (0.200)	-565*** (0.193)	-0.563*** (0.193)
GDPC$_{jt}$	-0.154 (0.092)	-0.141 (0.092)	-0.164* (0.085)	-0.164* (0.085)
Average Yearly Income$_{it}$	-0.251 (0.507)	-0.353 (0.503)	-0.399 (0.500)	-0.339 (0.500)
Average Yearly Income$_{jt}$	3.359*** (0.471)	3.258*** (0.497)	3.030*** (0.488)	3.030*** (0.488)
Border$_{ij}$	0.289*** (0.044)	0.271*** (0.046)	0.281*** (0.044)	0.281*** (0.044)
Weather$_{it}$	-0.011 (0.429)	-0.002 (0.422)	-0.263 (0.409)	-0.263 (0.409)
Weather$_{jt}$	-1.554*** (0.133)	-1.579*** (0.137)	-1.648*** (0.131)	-1.648*** (0.131)
Number of Observations	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	335.54	218.17	216.61	214.78
R Squared [FS]	0.8809	0.8279	0.8266	0.8256
Hansen's J Statistics [P Value]	0.3601	0.0510	0.2594	0.2594

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 13: The Impact of Interprovincial Goods Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{1}_{AGS\star AGSR}$	$SSIVT^{2}_{LAGS\star LAGSR}$	$SSIVT^{3}_{ADGS\star ADGSR}$	$SSIVT^{4}_{LADGS\star LADGSR}$
Independent Variables	**Estimator: PPML**			
Interprovincial Goods Trade$_{ijt}$	1.140*** (0.305)	1.168*** (0.309)	1.157*** (0.307)	1.184*** (0.309)
Distance$_{ij}$	-0.443*** (0.024	-0.444*** (0.024)	-0.445*** (0.024)	-0.443*** (0.024)
Participation rate$_{it}$	0.055 (0.030)	0.047 (0.031)	0.049 (0.031)	0.053* (0.031)
Participation rate$_{jt}$	-7.696*** (1.398)	-7.828*** (1.411)	-7.808*** (1.411)	-7.929*** (1.411)
GDPC$_{it}$	-0.512*** (0.193)	-0.519*** (0.193)	-0.517*** (0.193)	-0.510*** (0.194)
GDPC$_{jt}$	-0.144*** (0.086)	-0.141*** (0.084)	-0.139*** (0.086)	-0.141*** (0.086)
Average Yearly Income$_{it}$	-0.440 (0.501)	-0.437 (0.031)	-0.459 (0.502)	-0.535 (0.496)
Average Yearly Income$_{jt}$	3.343*** (0.493)	3.319*** (0.496)	3.337*** (0.493)	3.374*** (0.491)
Border$_{ij}$	0.278*** (0.045)	0.275*** (0.044)	0.275*** (0.044)	0.277*** (0.045)
Weather$_{it}$	-0.300 (0.408)	-0.288 (0.306)	-0.292 (0.306)	-0.268 (0.308)
Weather$_{jt}$	-1.595*** (0.128)	-1.619*** (0.133)	-1.612*** (0.133)	-1.614*** (0.133)
Number of Observations	864	792	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	232.60	229.91	227.16	228.19
R Squared [FS]	0.8118	0.8100	0.8082	0.8089

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 14: The Impact of Interprovincial Goods Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{5}_{AGS\star DGSR^1}$	$SSIVT^{6}_{AGS\star DGSR^2}$	$SSIVT^{7}_{LAGS\star LDGSR^1}$	$SSIVT^{8}_{LAGS\star LDGSR^2}$
Independent Variables		**Estimator: PPML**		
Interprovincial Goods Trade$_{ijt}$	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)
Distance$_{ij}$	-0.442*** (0.024	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)
Participation rate$_{it}$	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)
Participation rate$_{jt}$	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)
GDPC$_{it}$	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)
GDPC$_{jt}$	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)
Average Yearly Income$_{it}$	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)
Average Yearly Income$_{jt}$	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)
Border$_{ij}$	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)
Weather$_{it}$	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)
Weather$_{jt}$	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	227.16	227.16	216.75	216.74
R Squared [FS]	0.8082	0.8082	0.8092	0.8158

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 15: The Impact of Interprovincial Goods Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{9}_{ADGS\star DGSR^1}$	$SSIVT^{10}_{ADGS\star DGSR^2}$	$SSIVT^{11}_{LADGS\star LDGSR^1}$	$SSIVT^{12}_{LADGS\star LDGSR^2}$
Independent Variables		**Estimator: PPML**		
Interprovincial Goods Trade$_{ijt}$	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)
Distance$_{ij}$	-0.442*** (0.024	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)
Participation rate$_{it}$	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)
Participation rate$_{jt}$	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)
GDPC$_{it}$	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)
GDPC$_{jt}$	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)
Average Yearly Income$_{it}$	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)
Average Yearly Income$_{jt}$	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)
Border$_{ij}$	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)
Weather$_{it}$	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)
Weather$_{jt}$	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	232.60	229.91	216.74	215.56
R Squared [FS]	0.8118	0.8100	0.8158	0.8089

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 16: The Impact of Interprovincial Goods Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{13}_{DGS^1 \star DGSR^1}$	$SSIVT^{14}_{DGS^2 \star DGSR^2}$	$SSIVT^{15}_{LDGS^1 \star LDGSR^1}$	$SSIVT^{16}_{LDGS^2 \star LDGSR^2}$
Independent Variables		**Estimator: PPML**		
Interprovincial Goods Trade$_{ijt}$	1.173*** (0.305)	1.139*** (0.306)	0.918*** (0.293)	0.907*** (0.292)
Distance$_{ij}$	-0.443*** (0.024	-0.446*** (0.024)	-0.448*** (0.025)	-0.451*** (0.025)
Participation rate$_{it}$	0.050 (0.031)	0.0478 (0.031)	0.052 (0.034)	0.056 (0.033)
Participation rate$_{jt}$	-7.696*** (1.398)	-6.695*** (1.411)	-7.808*** (1.410)	-6.741*** (1.422)
GDPC$_{it}$	-0.503*** (0.193)	-0.515*** (0.193)	-0.641*** (0.194)	-0.644*** (0.196)
GDPC$_{jt}$	-0.153*** (0.085)	-0.140*** (0.086)	-0.133*** (0.093)	-0.119 (0.093)
Average Yearly Income$_{it}$	-0.454 (0.502)	-0.460 (0.507)	-0.241 (0.504)	-0.340 (0.496)
Average Yearly Income$_{jt}$	3.314*** (0.496)	3.335*** (0.493)	3.401*** (0.484)	3.470*** (0.483)
Border$_{ij}$	0.280*** (0.045)	0.274*** (0.044)	0.271*** (0.046)	0.266*** (0.046)
Weather$_{it}$	-0.263 (0.308)	-0.307 (0.305)	-0.499 (0.300)	-0.524 (0.299)
Weather$_{jt}$	-1.620*** (0.132)	-1.608*** (0.133)	-1.557*** (0.136)	-1.544*** (0.137)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	228.19	227.45	227.45	218.08
R Squared [FS]	0.8159	0.8084	0.8048	0.8168

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 17: The Impact of Interprovincial Goods Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{17}_{AGS}$	$SSIVT^{18}_{LAGS}$	$SSIVT^{19}_{ADGS}$	$SSIVT^{20}_{LADGS}$
Independent Variables		**Estimator: PPML**		
Interprovincial Goods Trade$_{ijt}$	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)
Distance$_{ij}$	-0.442*** (0.024	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)
Participation rate$_{it}$	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)
Participation rate$_{jt}$	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)
GDPC$_{it}$	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)
GDPC$_{jt}$	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)
Average Yearly Income$_{it}$	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)
Average Yearly Income$_{jt}$	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)
Border$_{ij}$	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)
Weather$_{it}$	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)
Weather$_{jt}$	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	231.17	215.51	227.74	215.36
R Squared [FS]	0.8109	0.8150	0.8086	0.8149

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 18: The Impact of Interprovincial Goods Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{21}_{DGS^1}$	$SSIVT^{22}_{DGS^2}$	$SSIVT^{23}_{LDGS^1}$	$SSIVT^{24}_{LDGS^2}$
Independent Variables	**Estimator: PPML**			
Interprovincial Goods Trade$_{ijt}$	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)
Distance$_{ij}$	-0.442*** (0.024	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)
Participation rate$_{it}$	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)
Participation rate$_{jt}$	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)
GDPC$_{it}$	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)
GDPC$_{jt}$	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)
Average Yearly Income$_{it}$	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)
Average Yearly Income$_{jt}$	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)
Border$_{ij}$	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)
Weather$_{it}$	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)
Weather$_{jt}$	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	228.01	227.56	227.74	215.13
R Squared [FS]	0.8087	0.8084	0.8151	0.8147

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 19: The Impact of Interprovincial Total Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration						
Instruments	1-4	5-8	9-12	13-16	17-20	21-24
Independent Variables	**Estimator: PPML**					
Interprovincial Goods Trade$_{ijt}$	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)	1.184*** (0.309)
Distance$_{ij}$	-0.442*** (0.024)	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)	-0.442*** (0.024)	0.442*** (0.024)
Participation rate$_{it}$	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)	0.050 (0.031)
Participation rate$_{jt}$	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)	-7.848*** (1.409)
GDPC$_{it}$	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)	-0.510*** (0.193)
GDPC$_{jt}$	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)	-0.149*** (0.086)
Average Yearly Income$_{it}$	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)	-0.451 (0.501)
Average Yearly Income$_{jt}$	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)	3.313*** (0.496)
Border$_{ij}$	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)	0.279*** (0.045)
Weather$_{it}$	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)	-0.259 (0.308)
Weather$_{jt}$	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)	-1.620*** (0.133)
Number of Observations	792	792	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	191.19	178.64	177.62	181.02	179.02	177.22
R Squared [FS]	0.8285	0.8187	0.8266	0.8206	0.8190	0.8175
Hansen's J Statistics [P Value]	0.360	0.2211	0.2210	0.0887	0.2211	0.2250

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 20: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{25}_{ASS\star ASSR}$	$SSIVT^{26}_{LASS\star LASSR}$	$SSIVT^{27}_{ADSS\star ADSSR}$	$SSIVT^{28}_{LADSS\star LADSSR}$
Independent Variables	*Estimator: PPML*			
Interprovincial Services Trade$_{ijt}$	2.884*** (0.646)	2.661*** (0.644)	2.469*** (0.638)	2.546** (0.792)
Distance$_{ij}$	-0.436*** (0.024)	-0.440*** (0.024)	-0.446*** (0.023)	-0.451*** (0.025)
Participation rate$_{it}$	0.033 (0.032)	0.031 (0.031)	0.041 (0.032)	0.039 (0.035)
Participation rate$_{jt}$	-8.886*** (1.495)	-8.562*** (1.501)	-8.353*** (1.498)	-8.126*** (1.689)
GDPC$_{it}$	-0.657*** (0.209)	-0.707*** (0.205)	-0.611*** (0.207)	-0.760*** (0.212)
GDPC$_{jt}$	-0.188** (0.086)	-0.173** (0.086)	-0.181** (0.085)	-0.144 (0.095)
Average Yearly Income$_{it}$	-0.225 (0.519)	-0.204 (0.514)	-0.380 (0.513)	-0.207 (0.510)
Average Yearly Income$_{jt}$	2.614*** (0.528)	2.519*** (0.521)	2.673*** (0.531)	2.736*** (0.555)
Border$_{ij}$	0.294*** (0.044)	0.283*** (0.044)	0.283*** (0.044)	0.274*** (0.046)
Weather$_{it}$	1.973** (0.741)	1.684* (0.734)	1.478* (0.734)	1.529 (0.899)
Weather$_{jt}$	-1.690*** (0.137)	-1.688*** (0.136)	-1.688*** (0.137)	-1.619*** (0.143)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	346.49	341.79	251.05	235.66
R Squared [FS]	0.8653	0.8637	0.8232	0.8281

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 21: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{29}_{ASS\star DSSR^1}$	$SSIVT^{30}_{ASS\star DSSR^2}$	$SSIVT^{31}_{ASS\star DSSR^3}$	$SSIVT^{32}_{ASS\star DSSR^4}$	$SSIVT^{33}_{ASS\star DSSR^5}$	$SSIVT^{34}_{ASS\star DSSR^6}$
Independent Variables	*Estimator: PPML*					
Interprovincial Services Trade$_{ijt}$	2.618*** (0.642)	2.658*** (0.643)	2.637*** (0.644)	2.639*** (0.642)	2.651*** (0.645)	2.651*** (0.645)
Distance$_{ij}$	-0.440*** (0.023)	-0.441*** (0.024)	-0.440*** (0.023)	-0.440*** (0.024)	-0.440*** (0.023)	-0.440*** (0.023)
Participation rate$_{it}$	0.033 (0.031)	0.034 (0.031)	0.034 (0.031)	0.032 (0.031)	0.031 (0.031)	0.031 (0.031)
Participation rate$_{jt}$	-8.541*** (1.496)	-8.535*** (1.497)	-8.554*** (1.502)	-8.561*** (1.500)	-8.560*** (1.500)	-8.560*** (1.500)
GDPC$_{it}$	-0.703*** (0.205)	-0.676*** (0.205)	-0.683*** (0.204)	-0.701*** (0.205)	-0.704*** (0.206)	-0.704*** (0.206)
GDPC$_{jt}$	-0.174** (0.086)	-0.178** (0.086)	-0.178** (0.086)	-0.175** (0.086)	-0.174** (0.086)	-0.174** (0.086)
Average Yearly Income$_{it}$	-0.205 (0.512)	-0.226 (0.515)	-0.241 (0.511)	-0.209 (0.512)	-0.206 (0.512)	-0.206 (0.512)
Average Yearly Income$_{jt}$	2.528*** (0.524)	2.580*** (0.525)	2.558*** (0.522)	2.529*** (0.523)	2.528*** (0.524)	2.528*** (0.524)
Border$_{ij}$	0.283*** (0.044)	0.283*** (0.044)	0.283*** (0.044)	0.283*** (0.044)	0.283*** (0.044)	0.283*** (0.044)
Weather$_{it}$	-1.637** (0.739)	-1.690** (0.740)	-1.663** (0.742)	-1.659** (0.739)	-1.673** (0.742)	-1.673** (0.742)
Weather$_{jt}$	-1.687*** (0.136)	-1.690*** (0.136)	-1.687*** (0.136)	-1.686*** (0.135)	-1.687*** (0.136)	-1.687*** (0.136)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	249.92	251.77	249.71	249.92	251.28	251.06
R Squared [FS]	0.8225	0.8236	0.8224	0.8225	0.8233	0.8232

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 22: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{35}_{LASS\star LDSSR^1}$	$SSIVT^{36}_{LASS\star LDSSR^2}$	$SSIVT^{37}_{LASS\star LDSSR^3}$	$SSIVT^{38}_{LASS\star LDSSR^4}$	$SSIVT^{39}_{LASS\star LDSSR^5}$	$SSIVT^{40}_{LASS\star LDSSR^6}$
Independent Variables			**Estimator: PPML**			
Interprovincial Services Trade$_{ijt}$	2.619***	2.588***	2.633***	2.567***	2.650***	2.650***
	(0.796)	(0.795)	(0.793)	(0.794)	(0.645)	(0.645)
Distance$_{ij}$	-0.447***	-0.446***	-0.446***	-0.445***	-0.440***	-0.440***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)
Participation rate$_{it}$	0.031	0.030	0.031	0.032	0.031	0.031
	(0.035)	(0.035)	(0.035)	(0.035)	(0.031)	(0.031)
Participation rate$_{jt}$	-8.146***	-8.133***	-8.198***	-8.133***	-8.561***	-8.561***
	(1.695)	(1.696)	(1.702)	(1.696)	(1.500)	(1.500)
GDPC$_{it}$	-0.817***	-0.810***	-0.814***	-0.800***	-0.704***	-0.704***
	(0.209)	(0.208)	(0.209)	(0.207)	(0.206)	(0.206)
GDPC$_{jt}$	-0.143	-0.146	-0.146	-0.148	-0.174**	-0.174**
	(0.094)	(0.094)	(0.095)	(0.094)	(0.086)	(0.086)
Average Yearly Income$_{it}$	-0.077	-0.065	-0.076	-0.074	-0.206	-0.206
	(0.512)	(0.513)	(0.514)	(0.514)	(0.512)	(0.512)
Average Yearly Income$_{jt}$	2.605***	2.622***	2.597***	2.607***	2.528***	2.528***
	(0.549)	(0.546)	(0.546)	(0.545)	(0.524)	(0.524)
Border$_{ij}$	0.272***	0.273***	0.270***	0.273***	0.283***	0.283***
	(0.046)	(0.046)	(0.046)	(0.045)	(0.044)	(0.044)
Weather$_{it}$	-1.608	-1.577	-1.622	-1.551	-1.673**	-1.673**
	(0.950)	(0.904)	(0.903)	(0.903)	(0.742)	(0.742)
Weather$_{jt}$	-1.619***	-1.628***	-1.628***	-1.624***	-1.687***	-1.687***
	(0.143)	(0.143)	(0.143)	(0.143)	(0.136)	(0.136)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	232.98	231.49	231.49	232.14	231.24	231.20
R Squared [FS]	0.8265	0.8255	0.8255	0.8259	0.8254	0.8254

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 23: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{41}_{ADSS\star DSSR^1}$	$SSIVT^{42}_{ADSS\star DSSR^2}$	$SSIVT^{43}_{ADSS\star DSSR^3}$	$SSIVT^{44}_{ADSS\star DSSR^4}$	$SSIVT^{45}_{ADSS\star DSSR^5}$	$SSIVT^{46}_{ADSS\star DSSR^6}$
Independent Variables			**Estimator: PPML**			
Interprovincial Services Trade$_{ijt}$	2.533***	2.494***	2.674***	2.557***	2.647***	2.580***
	(0.792)	(0.790)	(0.794)	(0.793)	(0.795)	(0.794)
Distance$_{ij}$	-0.448***	-0.449***	-0.446***	-0.445***	-0.442***	-0.446***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.035	0.034	0.031	0.032	0.030	0.030
	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)
Participation rate$_{jt}$	-8.154***	-7.872***	-8.281***	-8.126***	-8.079***	-8.149***
	(1.687)	(1.682)	(1.715)	(1.696)	(1.686)	(1.695)
GDPC$_{it}$	-0.772***	-0.815***	-0.801***	-0.800***	-0.790***	-0.808***
	(0.208)	(0.208)	(0.209)	(0.206)	(0.211)	(0.209)
GDPC$_{jt}$	-0.150*	-0.142	-0.145	-0.150*	-0.159*	-0.135
	(0.094)	(0.094)	(0.095)	(0.094)	(0.093)	(0.094)
Average Yearly Income$_{it}$	-0.177	-0.023	-0.065	-0.070	-0.079	-0.090
	(0.504)	(0.514)	(0.518)	(0.514)	(0.518)	(0.514)
Average Yearly Income$_{jt}$	2.695***	2.633***	2.642***	2.613***	2.657***	2.656***
	(0.550)	(0.546)	(0.545)	(0.545)	(0.550)	(0.547)
Border$_{ij}$	0.275***	0.270***	0.268***	0.273***	0.286***	0.271***
	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.046)
Weather$_{it}$	-1.518*	-1.469	-1.670*	-1.542	-1.673*	-1.551*
	(0.899)	(0.897)	(0.903)	(0.901)	(0.902)	(0.902)
Weather$_{jt}$	-1.629***	-1.608***	-1.627***	-1.623***	-1.638***	-1.624***
	(0.143)	(0.141)	(0.145)	(0.143)	(0.142)	(0.143)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	252.06	251.50	250.53	252.05	249.73	253.519
R Squared [FS]	0.8238	0.8234	0.8265	0.8238	0.8244	0.8246

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 24: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{47}_{LADSS\star LDSSR^1}$	$SSIVT^{48}_{LADSS\star LDSSR^2}$	$SSIVT^{49}_{LADSS\star LDSSR^3}$	$SSIVT^{50}_{LADSS\star LDSSR^4}$	$SSIVT^{51}_{LADSS\star LDSSR^5}$	$SSIVT^{52}_{LADSS\star LDSSR^6}$
Independent Variables			*Estimator: PPML*			
Interprovincial Services Trade$_{ijt}$	2.533***	2.494***	2.674***	2.557***	2.647***	2.593***
	(0.792)	(0.790)	(0.794)	(0.793)	(0.795)	(0.795)
Distance$_{ij}$	-0.448***	-0.449***	-0.446***	-0.445***	-0.442***	-0.446***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.035	0.034	0.031	0.032	0.030	0.030
	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)
Participation rate$_{jt}$	-8.154***	-7.872***	-8.281***	-8.126***	-8.079***	-8.149***
	(1.687)	(1.682)	(1.715)	(1.696)	(1.686)	(1.695)
GDPC$_{it}$	-0.772***	-0.815***	-0.801***	-0.800***	-0.790***	-0.808***
	(0.208)	(0.208)	(0.209)	(0.206)	(0.211)	(0.209)
GDPC$_{jt}$	-0.150*	-0.142	-0.145	-0.150*	-0.159*	-0.135
	(0.094)	(0.094)	(0.095)	(0.094)	(0.093)	(0.094)
Average Yearly Income$_{it}$	-0.177	-0.023	-0.065	-0.070	-0.079	-0.090
	(0.504)	(0.514)	(0.518)	(0.514)	(0.518)	(0.514)
Average Yearly Income$_{jt}$	2.695***	2.633***	2.642***	2.613***	2.657***	2.656***
	(0.550)	(0.546)	(0.545)	(0.545)	(0.550)	(0.547)
Border$_{ij}$	0.275***	0.270***	0.268***	0.273***	0.286***	0.271***
	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.046)
Weather$_{it}$	-1.518*	-1.469	-1.670*	-1.542	-1.673*	-1.551*
	(0.899)	(0.897)	(0.903)	(0.901)	(0.902)	(0.902)
Weather$_{jt}$	-1.629***	-1.608***	-1.627***	-1.623***	-1.638***	-1.624***
	(0.143)	(0.141)	(0.145)	(0.143)	(0.142)	(0.143)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	236.85	231.40	233.73	234.96	231.35	239.23
R Squared [FS]	0.8288	0.8255	0.8269	0.8277	0.8254	0.8302

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 25: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{53}_{DSS^1\star DSSR^1}$	$SSIVT^{54}_{DSS^2\star DSSR^2}$	$SSIVT^{55}_{DSS^3\star DSSR^3}$	$SSIVT^{56}_{DSS^4\star DSSR^4}$	$SSIVT^{57}_{DSS^5\star DSSR^5}$	$SSIVT^{58}_{DSS^6\star DSSR^6}$
Independent Variables			**Estimator: PPML**			
Interprovincial Services Trade$_{ijt}$	2.506***	2.624***	2.691***	2.645***	2.757***	2.650***
	(0.638)	(0.643)	(0.644)	(0.643)	(0.645)	(0.644)
Distance$_{ij}$	-0.443***	-0.441***	-0.439***	-0.439***	-0.437***	-0.440***
	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.035	0.036	0.034	0.032	0.030	0.030
	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)	(0.031)
Participation rate$_{jt}$	-8.450***	-8.404***	-8.614***	-8.565***	-8.638***	-8.516***
	(1.495)	(1.492)	(1.507)	(1.499)	(1.486)	(1.497)
GDPC$_{it}$	-0.653***	-0.655***	-0.685***	-0.702***	-0.665***	-0.711***
	(0.205)	(0.207)	(0.205)	(0.205)	(0.212)	(0.205)
GDPC$_{jt}$	-0.178**	-0.181**	-0.177**	-0.175**	-0.187**	-0.167**
	(0.085)	(0.085)	(0.086)	(0.085)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.299	-0.248	-0.222	-0.205	-0.305	-0.221
	(0.511)	(0.516)	(0.515)	(0.512)	(0.515)	(0.512)
Average Yearly Income$_{jt}$	2.556***	2.645***	2.544***	2.527***	2.674***	2.521***
	(0.527)	(0.524)	(0.523)	(0.523)	(0.527)	(0.524)
Border$_{ij}$	0.283***	0.284***	0.281***	0.283***	0.295***	0.282***
	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)
Weather$_{it}$	-1.506**	-1.661**	-1.723**	-1.667**	-1.830**	-1.666**
	(0.734)	(0.739)	(0.741)	(0.739)	(0.740)	(0.741)
Weather$_{jt}$	-1.689***	-1.690***	-1.689***	-1.686***	-1.716***	-1.689***
	(0.135)	(0.136)	(0.137)	(0.135)	(0.135)	(0.135)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	233.42	231.57	233.06	235.284	231.44	244.89
R Squared [FS]	0.8267	0.8256	0.8265	0.827	0.8255	0.8335

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 26: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{59}_{LDSS^1 \star LDSSR^1}$	$SSIVT^{60}_{LDSS^2 \star LDSSR^2}$	$SSIVT^{61}_{LDSS^3 \star LDSSR^3}$	$SSIVT^{62}_{LDSS^4 \star LDSSR^4}$	$SSIVT^{63}_{LDSS^5 \star LDSSR^5}$	$SSIVT^{64}_{LDSS^6 \star LDSSR^6}$
Independent Variables			**Estimator: PPML**			
Interprovincial Services Trade$_{ijt}$	2.533***	2.494***	2.674***	2.557***	2.647***	2.580***
	(0.792)	(0.790)	(0.794)	(0.793)	(0.795)	(0.794)
Distance$_{ij}$	-0.448***	-0.449***	-0.446***	-0.445***	-0.442***	-0.446***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.035	0.034	0.031	0.032	0.030	0.030
	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)
Participation rate$_{jt}$	-8.154***	-7.872***	-8.281***	-8.126***	-8.079***	-8.149***
	(1.687)	(1.682)	(1.715)	(1.696)	(1.686)	(1.695)
GDPC$_{it}$	-0.772***	-0.815***	-0.801***	-0.800***	-0.790***	-0.808***
	(0.208)	(0.208)	(0.209)	(0.206)	(0.211)	(0.209)
GDPC$_{jt}$	-0.150*	-0.142	-0.145	-0.150*	-0.159*	-0.135
	(0.094)	(0.094)	(0.095)	(0.094)	(0.093)	(0.094)
Average Yearly Income$_{it}$	-0.177	-0.023	-0.065	-0.070	-0.079	-0.090
	(0.504)	(0.514)	(0.518)	(0.514)	(0.518)	(0.514)
Average Yearly Income$_{jt}$	2.695***	2.633***	2.642***	2.613***	2.657***	2.656***
	(0.550)	(0.546)	(0.545)	(0.545)	(0.550)	(0.547)
Border$_{ij}$	0.275***	0.270***	0.268***	0.273***	0.286***	0.271***
	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.046)
Weather$_{it}$	-1.518*	-1.469	-1.670*	-1.542	-1.673*	-1.551*
	(0.899)	(0.897)	(0.903)	(0.901)	(0.902)	(0.902)
Weather$_{jt}$	-1.629***	-1.608***	-1.627***	-1.623***	-1.638***	-1.624***
	(0.143)	(0.141)	(0.145)	(0.143)	(0.142)	(0.143)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	233.42	231.57	233.06	235.284	231.44	244.89
R Squared [FS]	0.8267	0.8256	0.8265	0.827	0.8255	0.8335

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 27: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	$SSIVT^{65}_{ASS}$	$SSIVT^{66}_{LASS}$	$SSIVT^{67}_{ADSS}$	$SSIVT^{68}_{LADSS}$
Independent Variables		**Estimator: PPML**		
Interprovincial Services Trade$_{ijt}$	2.651***	2.651***	2.651***	2.651***
	(0.645)	(0.645)	(0.645)	(0.645)
Distance$_{ij}$	-0.440***	-0.440***	-0.440***	-0.440***
	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.031	0.031	0.031	0.031
	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-8.561***	-8.561***	-8.561***	-8.561***
	(1.500)	(1.500)	(1.500)	(1.500)
GDPC$_{it}$	-0.704***	-0.704***	-0.704***	-0.704***
	(0.206)	(0.206)	(0.206)	(0.206)
GDPC$_{jt}$	-0.174**	-0.174**	-0.174**	-0.174**
	(0.086)	(0.086)	(0.086)	(0.086)
Average Yearly Income$_{it}$	-0.206	-0.206	-0.206	-0.206
	(0.512)	(0.512)	(0.512)	(0.512)
Average Yearly Income$_{jt}$	2.528***	2.528***	2.528***	2.528***
	(0.524)	(0.524)	(0.524)	(0.524)
Border$_{ij}$	0.283***	0.283***	0.283***	0.283***
	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	-1.673**	-1.673**	-1.673**	-1.673**
	(0.742)	(0.742)	(0.742)	(0.742)
Weather$_{jt}$	-1.687***	-1.687***	-1.687***	-1.687***
	(0.136)	(0.136)	(0.136)	(0.136)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	249.73	232.89	251.29	231.13
R Squared [FS]	0.8224	0.8264	0.8233	0.8253

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 28: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{69}_{DSS^1}$	$SSIVT^{70}_{DSS^2}$	$SSIVT^{71}_{DSS^3}$	$SSIVT^{72}_{DSS^4}$	$SSIVT^{73}_{DSS^5}$	$SSIVT^{74}_{DSS^6}$
Independent Variables	**Estimator: PPML**					
Interprovincial Services Trade$_{ijt}$	2.650***	2.650***	2.650***	2.650***	2.650***	2.650***
	(0.645)	(0.645)	(0.645)	(0.645)	(0.645)	(0.645)
Distance$_{ij}$	-0.440***	-0.440***	-0.440***	-0.440***	-0.440***	-0.440***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.031	0.031	0.031	0.031	0.031	0.031
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-8.561***	-8.561***	-8.561***	-8.561***	-8.561***	-8.561***
	(1.500)	(1.500)	(1.500)	(1.500)	(1.500)	(1.500)
GDPC$_{it}$	-0.704***	-0.704***	-0.704***	-0.704***	-0.704***	-0.704***
	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)
GDPC$_{jt}$	-0.174**	-0.174**	-0.174**	-0.174**	-0.174**	-0.174**
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Average Yearly Income$_{it}$	-0.206	-0.206	-0.206	-0.206	-0.206	-0.206
	(0.512)	(0.512)	(0.512)	(0.512)	(0.512)	(0.512)
Average Yearly Income$_{jt}$	2.528***	2.528***	2.528***	2.528***	2.528***	2.528***
	(0.524)	(0.524)	(0.524)	(0.524)	(0.524)	(0.524)
Border$_{ij}$	0.283***	0.283***	0.283***	0.283***	0.283***	0.283***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	-1.674*	-1.674*	-1.674*	-1.674*	-1.674*	-1.674*
	(0.742)	(0.742)	(0.742)	(0.742)	(0.742)	(0.742)
Weather$_{jt}$	-1.687***	-1.687***	-1.687***	-1.687***	-1.687***	-1.687***
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	251.86	249.78	249.76	250.50	249.72	249.70
R Squared [FS]	0.8224	0.8234	0.8229	0.8238	0.8244	0.8224

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 29: The Impact of Interprovincial Services Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration						
Instruments	$SSIVT^{75}_{LDSS^1}$	$SSIVT^{76}_{LDSS^2}$	$SSIVT^{77}_{LDSS^3}$	$SSIVT^{78}_{LDSS^4}$	$SSIVT^{79}_{LDSS^5}$	$SSIVT^{80}_{LDSS^6}$
Independent Variables	**Estimator: PPML**					
Interprovincial Total Trade$_{ijt}$	2.650***	2.650***	2.650***	2.650***	2.650***	2.650***
	(0.645)	(0.645)	(0.645)	(0.645)	(0.645)	(0.645)
Distance$_{ij}$	-0.440***	-0.440***	-0.440***	-0.440***	-0.440***	-0.440***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.031	0.031	0.031	0.031	0.031	0.031
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-8.561***	-8.561***	-8.561***	-8.561***	-8.561***	-8.561***
	(1.500)	(1.500)	(1.500)	(1.500)	(1.500)	(1.500)
GDPC$_{it}$	-0.704***	-0.704***	-0.704***	-0.704***	-0.704***	-0.704***
	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)
GDPC$_{jt}$	-0.174**	-0.174**	-0.174**	-0.174**	-0.174**	-0.174**
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Average Yearly Income$_{it}$	-0.206	-0.206	-0.206	-0.206	-0.206	-0.206
	(0.512)	(0.512)	(0.512)	(0.512)	(0.512)	(0.512)
Average Yearly Income$_{jt}$	2.528***	2.528***	2.528***	2.528***	2.528***	2.528***
	(0.524)	(0.524)	(0.524)	(0.524)	(0.524)	(0.524)
Border$_{ij}$	0.283***	0.283***	0.283***	0.283***	0.283***	0.283***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	-1.674*	-1.674*	-1.674*	-1.674*	-1.674*	-1.674*
	(0.742)	(0.742)	(0.742)	(0.742)	(0.742)	(0.742)
Weather$_{jt}$	-1.687***	-1.687***	-1.687***	-1.687***	-1.687***	-1.687***
	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	231.14	231.23	231.20	234.72	231.15	232.41
R Squared [FS]	0.8253	0.8254	0.8265	0.8254	0.8253	0.8261

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 30: The Impact of Interprovincial Services Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration					
Instruments	25-28	29-34	35-40	41-46	47-52
Independent Variables	**Estimator: PPML**				
Interprovincial Total Trade$_{ijt}$	2.828***	2.552***	2.657***	2.468***	2.654***
	(0.762)	(0.641)	(0.793)	(0.637)	(0.790)
Distance$_{ij}$	-0.443***	-0.441***	-0.447***	-0.443***	-0.448***
	(0.024)	(0.024)	(0.025)	(0.023)	(0.025)
Participation rate$_{it}$	0.047	0.039	0.032	0.044	0.036
	(0.035)	(0.032)	(0.035)	(0.032)	(0.035)
Participation rate$_{jt}$	-8.571***	-8.461***	-8.286***	-8.342***	-8.431***
	(1.681)	(1.505)	(1.697)	(1.501)	(1.693)
GDPC$_{it}$	-0.654***	-0.650***	-0.815***	-0.581***	-0.747***
	(0.203)	(0.202)	(0.207)	(0.207)	(0.212)
GDPC$_{jt}$	-0.170	-0.182**	-0.149	-0.190**	-0.145
	(0.095)	(0.086)	(0.095)	(0.084)	(0.094)
Average Yearly Income$_{it}$	-0.262	-0.247	-0.092	-0.459	-0.218
	(0.510)	(0.514)	(0.513)	(0.518)	(0.514)
Average Yearly Income$_{jt}$	2.828***	2.698***	2.564***	2.754***	2.768***
	(0.543)	(0.534)	(0.546)	(0.526)	(0.549)
Border$_{ij}$	0.287***	0.282***	0.271***	0.296***	0.278***
	(0.045)	(0.044)	(0.046)	(0.043)	(0.046)
Weather$_{it}$	-1.898*	-1.587*	-1.647*	-1.500*	-1.644*
	(0.870)	(0.734)	(0.903)	(0.732)	(0.898)
Weather$_{jt}$	-1.612***	-1.673***	-1.629***	-1.696***	-1.635***
	(0.145)	(0.136)	(0.143)	(0.135)	(0.145)
Number of Observations	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	294.74	187.45	173.66	187.76	177.32
R Squared [FS]	0.8817	0.8290	0.8320	0.8292	0.8349
Hansen's J Statistics [P Value]	0.2849	0.0723	0.2210	0.0887	0.2859
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*					

Table 31: The Impact of Interprovincial Services Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration					
Instruments	53-58	59-64	65-68	69-74	75-80
Independent Variables	*Estimator: PPML*				
Interprovincial Services Trade$_{ijt}$	2.6416***	2.6264***	2.6507***	2.6507***	2.6547***
	(0.632)	(0.779)	(0.645)	(0.645)	(0.790)
Distance$_{ij}$	-0.441***	-0.446***	-0.440***	-0.440***	-0.448***
	(0.023)	(0.024)	(0.023)	(0.023)	(0.025)
Participation rate$_{it}$	0.038	0.038	0.031	0.031	0.036
	(0.032)	(0.035)	(0.031)	(0.031)	(0.035)
Participation rate$_{jt}$	-8.511***	-8.086***	-8.560***	-8.560***	-8.431***
	(1.486)	(1.683)	(1.500)	(1.500)	(1.693)
GDPC$_{it}$	-0.595***	-0.763***	-0.703***	-0.703***	-0.747***
	(0.208)	(0.211)	(0.206)	(0.206)	(0.212)
GDPC$_{jt}$	-0.196**	-0.153	-0.174**	-0.174**	-0.145
	(0.083)	(0.093)	(0.086)	(0.086)	(0.094)
Average Yearly Income$_{it}$	-0.419	-0.134	-0.205	-0.205	-0.218
	(0.518)	(0.511)	(0.512)	(0.512)	(0.514)
Average Yearly Income$_{jt}$	2.764***	2.764***	2.528***	2.528***	2.768***
	(0.529)	(0.547)	(0.524)	(0.524)	(0.549)
Border$_{ij}$	0.299***	0.281***	0.282***	0.282***	0.278***
	(0.043)	(0.045)	(0.044)	(0.044)	(0.046)
Weather$_{it}$	-1.704**	-1.642*	-1.673*	-1.673*	-1.644*
	(0.725)	(0.887)	(0.742)	(0.742)	(0.898)
Weather$_{jt}$	-1.718***	-1.623***	-1.687***	-1.687***	-1.635***
	(0.136)	(0.143)	(0.135)	(0.135)	(0.145)
Number of Observations	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	189.96	179.34	189.19	182.98	169.87
R Squared [FS]	0.8309	0.8365	0.8370	0.8255	0.8389
Hansen's J Statistics [P Value]	0.1992	0.1581	0.3266	0.3267	0.3626
*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*					

2.5.4 The Impact of Interprovincial Migration on Trade

Tables 32 to 34 show the JI estimated results of the impact of interprovincial migration on trade, whereas Table 35 represents OI results.

The findings reveal that interprovincial migration significantly boosts interprovincial trade in aggregate and disaggregates across all versions of IV models. We find the causal relationships statistically significant at a 1% level. While interprovincial migration influences both goods and services trade, it impacts goods trade slightly more than services trade. A 1% increase in interprovincial migration will increase goods and services trade by at least 0.29% and 0.14%, respectively. The literature supports our findings (Wagner et al., 2002; Lewer & Van den Berg, 2009).

We find that our results are robust across all SSIVs in all versions of IV models. Our results demonstrate that all the derived instruments in this part of the study are very strong with significantly higher values of F-statistics (ranging from 163.37 to 187.30) and R-squared (ranging from 0.7188 to 0.7714). Notably, OI models with more than one instrument pass the Hansen J tests of the overidentifying restrictions. So, we claim that our instruments are valid.

The relationship between distance and trade at all levels is negative and statistically significant at a 1% level across all models. As distance represents trade costs and other impediments in the gravity model of trade, a larger distance between trading partners increases trade costs and barriers. This supports (Aziz et al., 2023; Dunlevy & Hutchinson, 1999; Gould, 1994; Lewer & Van den Berg, 2009; Wagner et al., 2002; Felbermayr et al., 2015).

An increase in the labor force participation rates in both origin and destination provinces increases trade overall. This relationship is statistically significant at a 1% level for aggregate trade and goods trade but positively associated with services trade. Moreover, GDP per capita and trade in aggregate and goods trade show a strong positive relationship across all versions of models. Our results resemble other empirical works (Aziz et al., 2023; Dunlevy & Hutchinson, 1999; Gould, 1994; Lewer & Van den Berg, 2009; Wagner et al., 2002; Felbermayr et al., 2015). However, the relationship between GDP per capita and services trade is negative. This highlights that larger provinces may be self-reliant on or fulfill their needs with international trade.

We find that higher income in destination provinces leads to higher trade in aggregate and disaggregate. While border sharing between provinces increases trade in aggregate and disaggregate substantially, bad weather conditions at both origin and destination provinces have a significant negative effect on trade at all levels.

Table 32: The Impact of Interprovincial Migration on Interprovincial Total Trade: JI Results

Dependent variable: Interprovincial Total Trade				
Instruments	$SSIVM^1_{AMS\star AMSR}$	$SSIVM^2_{LAMS\star LAMSR}$	$SSIVM^3_{AMS}$	$SSIVM^4_{LAMS}$
Independent Variables		**Estimator: PPML**		
Interprovincial Migration$_{ijt}$	0.532*** (0.142)	0.203*** (0.452)	0.203** (0.104)	0.303*** (0.083)
Distance$_{ij}$	-0.483*** (0.064)	-0.222*** (0.171)	-0.617*** (0.052)	-0.575*** (0.047)
Participation rate$_{it}$	-0.026 (0.026)	-0.061 (0.047)	-0.011 (0.024)	-0.016 (0.023)
Participation rate$_{jt}$	4.798*** (1.582)	8.315*** (2.902)	2.928** (1.500)	3.480** (1.441)
GDPC$_{it}$	0.198** (0.193)	0.517** (0.369)	0.046 (0.176)	0.092 (0.175)
GDPC$_{jt}$	0.157* (0.094)	0.316* (0.177)	0.069 (0.076)	0.096 (0.076)
Average Yearly Income$_{it}$	-0.544 (0.458)	-0.615 (0.639)	-0.531 (0.437)	-0.536 (0.437)
Average Yearly Income$_{jt}$	1.629** (0.778)	4.350** (1.729)	0.273 (0.624)	0.677 (0.549)
Border$_{ij}$	0.446** (0.071)	0.712*** (0.190)	0.320*** (0.062)	0.357*** (0.052)
Weather$_{it}$	-0.616** (0.212)	-0.148 (0.562)	-0.981** (0.172)	-0.868** (0.168)
Weather$_{jt}$	-0.725** (0.276)	-0.372 (0.737)	-1.284*** (0.201)	-1.114*** (0.178)
Number of Observations	864	864	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	171.70	163.37	187.30	215.69
R Squared [FS]	0.7293	0.7188	0.7461	0.7714

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 33: The Impact of Interprovincial Migration on Interprovincial Goods Trade: JI Results

Dependent variable: Interprovincial Goods Trade				
Instruments	$SSIVM^1_{AMS\star AMSR}$	$SSIVM^2_{LAMS\star LAMSR}$	$SSIVM^3_{AMS}$	$SSIVM^4_{LAMS}$
Independent Variables		**Estimator: PPML**		
Interprovincial Migration$_{ijt}$	0.838*** (0.240)	0.918*** (0.752)	0.360** (0.147)	0.286*** (0.118)
Distance$_{ij}$	-0.553*** (0.093)	-0.197 (0.233)	-0.734*** (0.066)	-0.760*** (0.062)
Participation rate$_{it}$	0.007 (0.038)	-0.038 (0.069)	0.027 (0.031)	0.031 (0.031)
Participation rate$_{jt}$	6.880*** (2.155)	12.564*** (4.559)	4.009** (1.858)	3.519** (1.808)
GDPC$_{it}$	0.924*** (0.307)	1.610** (0.711)	0.644*** (0.250)	0.580** (0.227)
GDPC$_{jt}$	0.241* (0.146)	0.502* (0.292)	0.110 (0.107)	0.084 (0.100)
Average Yearly Income$_{it}$	-0.332 (0.649)	-0.234 (0.997)	-0.316 (0.568)	-0.310 (0.563)
Average Yearly Income$_{jt}$	2.094* (1.101)	6.135** (2.689)	0.280 (0.750)	0.010 (0.668)
Border$_{ij}$	0.717*** (0.135)	1.250*** (0.394)	0.499*** (0.091)	0.460*** (0.070)
Weather$_{it}$	-0.241 (0.319)	-0.968 (0.889)	-0.782*** (0.232)	-0.860*** (0.220)
Weather$_{jt}$	-0.057 (0.443)	1.698 (1.202)	-0.874*** (0.278)	-1.004*** (0.234)
Number of Observations	864	864	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	171.70	163.37	187.30	215.69
R Squared [FS]	0.7293	0.7188	0.7461	0.7714

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 34: The Impact of Interprovincial Migration on Interprovincial Services Trade: JI Results

Dependent variable: Interprovincial Services Trade				
Instruments	$SSIVM^1_{AMS\star AMSR}$	$SSIVM^2_{LAMS\star LAMSR}$	$SSIVM^3_{AMS}$	$SSIVM^4_{LAMS}$
Independent Variables	**Estimator: PPML**			
Interprovincial Migration$_{ijt}$	0.308*** (0.106)	0.400** (0.157)	0.310** (0.194)	0.254*** (0.107)
Distance$_{ij}$	-0.425*** (0.052)	-0.528*** (0.115)	-0.510*** (0.049)	-0.450*** (0.040)
Participation rate$_{it}$	-0.040 (0.023)	-0.021 (0.027)	-0.029 (0.022)	-0.036 (0.023)
Participation rate$_{jt}$	3.094** (1.289)	1.814 (1.814)	2.000 (1.284)	2.823** (1.186)
GDPC$_{it}$	-0.273 (0.183)	-0.372 (0.208)	-0.351 (0.183)	-0.297 (0.180)
GDPC$_{jt}$	0.205** (0.081)	0.123 (0.096)	0.150** (0.074)	0.190** (0.076)
Average Yearly Income$_{it}$	0.882** (0.396)	0.706** (0.421)	0.883** (0.404)	0.880** (0.397)
Average Yearly Income$_{jt}$	0.974 (0.601)	0.290 (1.084)	0.197 (0.569)	0.790 (0.484)
Border$_{ij}$	0.235*** (0.051)	0.155 (0.095)	0.167*** (0.054)	0.219*** (0.046)
Weather$_{it}$	-1.028*** (0.187)	-1.309*** (0.319)	-1.253*** (0.166)	-1.096*** (0.164)
Weather$_{jt}$	-1.204*** (0.223)	-1.631*** (0.451)	-1.538*** (0.203)	-1.291*** (0.173)
Number of Observations	864	864	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	192.30	178.67	189.56	214.12
R Squared [FS]	0.8327	0.8243	0.8374	0.8462

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 35: The Impact of Interprovincial Migration on Interprovincial Trade: OI Results

Dependent Variables	**Total Trade**		**Goods Trade**		**Services Trade**	
Instruments	1–2	3–4	1–2	3–4	1–2	3–4
Independent Variables	**Estimator: PPML**					
Interprovincial Migration$_{ijt}$	0.227*** (0.113)	0.268*** (0.077)	0.299** (0.169)	0.294*** (0.106)	0.147*** (0.097)	0.222*** (0.067)
Distance$_{ij}$	-0.610*** (0.056)	-0.592*** (0.043)	-0.762*** (0.076)	-0.757*** (0.057)	-0.496*** (0.050)	-0.464*** (0.039)
Participation rate$_{it}$	-0.011 (0.023)	-0.017 (0.024)	0.028 (0.032)	0.031 (0.031)	-0.035 (0.025)	-0.032 (0.022)
Participation rate$_{jt}$	3.107** (1.524)	3.311** (1.426)	3.816** (1.908)	3.617** (1.790)	2.264 (1.284)	2.754** (1.173)
GDPC$_{it}$	0.049 (0.176)	0.082 (0.173)	0.556** (0.241)	0.579** (0.229)	-0.334 (0.184)	-0.316 (0.179)
GDPC$_{jt}$	0.082 (0.077)	0.089 (0.075)	0.106 (0.105)	0.087 (0.100)	0.147 (0.074)	0.184** (0.075)
Average Yearly Income$_{it}$	0.453 (0.438)	0.526 (0.439)	0.139 (0.559)	-0.317 (0.564)	0.754 (0.401)	0.871** (0.400)
Average Yearly Income$_{jt}$	-0.252 (0.690)	-0.583 (0.531)	-0.152 (0.879)	-0.030 (0.644)	-0.431 (0.614)	-0.752 (0.476)
Border$_{ij}$	0.348*** (0.062)	0.350*** (0.052)	0.508*** (0.097)	0.464*** (0.069)	0.189*** (0.051)	0.210*** (0.046)
Weather$_{it}$	-0.962*** (0.182)	-0.922*** (0.159)	-0.881*** (0.247)	-0.849*** (0.207)	-1.212*** (0.170)	-1.150*** (0.154)
Weather$_{jt}$	-1.232*** (0.224)	-1.176*** (0.166)	-0.912*** (0.324)	-0.987*** (0.215)	-1.513*** (0.206)	-1.329*** (0.169)
Number of Observations	864	864	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y	Y
F Statistics [FS]	157.44	224.13	157.44	224.13	157.44	224.13
R Squared [FS]	0.7297	0.7935	0.7297	0.7935	0.7297	0.7935
Hansen's J Statistics [P Value]	0.1201	0.4404	0.0501	0.0652	0.0560	0.1023

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

2.6 Policy Implications

Based on the results, this study identifies several areas for policy implications to address interprovincial trade and migration dynamics.

[a] Services Trade and Migration: Our findings suggest that services trade strongly impacts migration. If policymakers want to encourage migration, increasing openness to services trade could increase migration.

[b] Goods Trade and Migration: We find evidence that goods trade also influences migration. If policymakers want to increase migrants further, evaluating policies to reduce overall trade barriers may be beneficial.

Our results show that increasing to migration could also increase openness to trade. Further research should focus on the robustness of the relationship between trade and migration, especially for well-targeted policy interventions.

2.7 Conclusion

This study examines the bi-directional causality between interprovincial trade (in aggregate and disaggregate) and migration within Canada for the years 2007 to 2019. Our results reveal that both interprovincial trade and migration cause each other at a 1% significance level across just-identified and over-identified models.

We also find that services trade has a stronger effect on interprovincial migration than goods trade. While interprovincial migration significantly impacts trade (in aggregate and disaggregate), the effect is slightly higher on goods trade than services trade. Overall, the influence of interprovincial trade on migration has a substantial impact compared to the influence of interprovincial migration on trade.

To address the endogeneity problem between trade and migration, this study derives 80 SSIVs for interprovincial trade and 4 SSIVs for interprovincial migration. In addition to conventional SSIVs, we design our version of instruments to capture regional and sectoral heterogeneity with lag disaggregate shocks and shares. We further argue that our instruments eliminate any contemporaneous correlation between the instruments and the endogenous variable. Our empirical estimations are robust across all SSIVs. And all the instruments in this study produce very high values of F-statistic and R-squared at teh first-stage.

This paper contributes significantly by estimating the bi-direction causality between trade (in aggregate and disaggregate) and migration in one framework. Further, we recommend reducing trade barriers among provinces, especially services trade, if governments wish to facilitate interprovincial migration within Canada.

2.8 Robustness

To ensure the reliability and consistency of our estimations, this paper conducts a multi-step robustness check.

[a] We derive 80 SSIVs from both the goods and services sectors for interprovincial trade and 4 SSIVs for interprovincial migration. This study utilizes various combinations of aggregate and disaggregate shocks and shares (including lags) to develop all the instruments. We find similar positive and statistically significant results across all instruments.

[b] This paper estimates both just-identified and over-identified models to check the robustness of the results. And our findings produce consistent positive and significant causal effects.

[c] Lastly, we apply the Two-Stage Least Squares [TSLS] estimator as an alternative to the PPML estimator within the gravity model to check whether our results remain the same. First, we log linearize the gravity equation and estimate the models using the TSLS estimator. While examining the results for the casual effects of interprovincial trade on migration, we replace the endogenous variable, interprovincial trade, with exports and the instruments with aggregate goods and services share and aggregated goods and services shares. Once again, we found similar results [check, Table 1].

To check the sensitivity of our estimated results for the casual effects of interprovincial migration on trade, we also replace the dependent variable with the exports of goods and the instruments with migration shocks, both without and with lags. Yet again, we find consistent results [see, Table 2].

2.9 Future Research

In future, we plan to explore our research questions using any firm level data. Based on the firm-level evidence, we can develop more effective policies.

Furthermore, we can examine the relationship between interprovincial re-export of services and migration. This research can be helpful in framing evidence-based policies aiming at interprovincial trade and labor mobility within Canada.

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Chapter A

Appendix: Additional Results for Chapter 2

Table 1: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Instruments	**Aggregate Goods Share**	**Aggregate Services Share**	**Aggregated Goods Share**	**Aggregated Shares**
Independent Variables		**Estimator: 2SLS**		
Interprovincial Total Trade$_{ijt}$	0.120***	0.119***	0.105***	0.121***
	(0.049)	(0.048)	(0.048)	(0.048)
Distance$_{ij}$	-0.083***	-0.083***	-0.082***	-0.081***
	(0.004)	(0.003)	(0.003)	(0.004)
Participation rate$_{it}$	0.006	0.003	0.005	0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Participation rate$_{jt}$	-0.692***	-0.643***	-0.718***	-0.708***
	(0.289)	(0.293)	(0.291)	(0.290)
GDPC$_{it}$	-0.123***	-0.127***	-0.133***	-0.120***
	(0.029)	(0.030)	(0.029)	(0.029)
GDPC$_{jt}$	0.039***	0.045***	0.046***	0.048***
	(0.015)	(0.015)	(0.015)	(0.016)
Average Yearly Income$_{it}$	-0.070	-0.070	-0.084	-0.077
	(0.100)	(0.101)	(0.100)	(0.100)
Average Yearly Income$_{jt}$	0.444***	0.444***	0.404***	0.435***
	(0.108)	(0.109)	(0.106)	(0.106)
Border$_{ij}$	0.020***	0.029***	0.029***	0.027***
	(0.008)	(0.009)	(0.008)	(0.008)
Weather$_{it}$	-0.153***	-0.170***	-0.192***	-0.170***
	(0.068)	(0.069)	(0.068)	(0.068)
Weather$_{jt}$	-0.227***	-0.228***	-0.224***	-0.223***
	(0.028)	(0.028)	(0.028)	(0.028)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	275.67	368.79	219.49	346.55
R Squared [FS]	0.8364	0.8724	0.8028	0.8655
****P<.01, **P<.05, *P<.10*				

Table 2: The Impact of Interprovincial Migration on Interprovincial Total Trade: JI Results

Dependent variable: Interprovincial Goods Exports		
Instruments	**Migration Share**	**Lag Migration Share**
Independent Variables	**Estimator: 2SLS**	
Interprovincial Migration$_{ijt}$	0.028***	0.045***
	(0.005)	(0.008)
Distance$_{ij}$	0.015***	0.025***
	(0.003)	(0.005)
Participation rate$_{it}$	-0.001	0.002
	(0.001)	(0.002)
Participation rate$_{jt}$	0.263***	0.340***
	(0.0733)	(0.0943)
GDPC$_{it}$	0.013*	0.027**
	(0.007)	(0.010)
GDPC$_{jt}$	-0.002	-0.005
	(0.003)	(0.005)
Average Yearly Income$_{it}$	-0.003	0.006
	(0.022)	(0.030)
Average Yearly Income$_{jt}$	0.132***	0.200***
	(0.027)	(0.040)
Border$_{ij}$	0.009***	0.015***
	(0.002)	(0.004)
Weather$_{it}$	-0.070***	-0.033
	(0.011)	(0.019)
Weather$_{jt}$	-0.051***	-0.085***
	(0.012)	(0.018)
Number of Observations	864	864
Year Fixed Effects	Y	Y
Origin & Destination Fixed Effects	Y	Y
F Statistics [FS]	198.11	172.09
R Squared [FS]	0.7760	0.7786
****P<.01, **P<.05, *P<.10*		

Chapter 3

Endogeneity Between Trade & Migration: Insights from Shift-Share Instruments & Machine Learning

Abstract

This study explores the interplay between trade and migration within and across Canadian borders. Employing the Poisson Pseudo Maximum Likelihood (PPML) estimator in the gravity model for the years 2007 to 2019, this paper finds that interprovincial trade and international trade influence interprovincial and international migration in Canada. We find similar impacts for interprovincial and international exports on migration. Utilize the novel Shift-Share Instrumental Variable (SSIV) technique, we address the endogeneity problem between trade and migration and derive 16 SSIVs. The results indicate that all the instruments for trade are very strong and robust across all versions of IV models. We argue that our instruments - Modified SSIVs - improve the quality of instruments and are better than those of Conventional SSIVs. To eliminate any potential contemporaneous correlation between instruments and the endogenous variable, this research incorporates lag in both shocks and shares of SSIVs to predict the endogenous regressor solely based on past economic conditions. While showing new ways to derive instruments, we examine the predictive strength of all the SSIVs utilizing a machine learning technique, the Random Forests (RF) model. Machine learning findings reveal that the SSIVs and the shock instruments derived from exports have higher predictive strength than all other SSIVs. Results show that the impact of interprovincial trade on interprovincial migration is higher than the impact of international trade on international migration to Canada. However, the influences of international total trade and international total exports on international migration are similar. This paper suggests that the provinces keen on attracting migrants should minimize the trade barriers overall to encourage migrants interprovincially and internationally. Based on our empirical findings, we recommend that applied researchers should use lag in both aggregate shocks and share to improve the quality of SSIVs.

JEL Codes: C26, C36, F14, F22, F61, F68, R11 & P25.

Keywords: Interprovincial Trade, International Trade, Migration, SSIV, PPML & RF.

3.1 Introduction

The literature on trade and migration shows trade may impact migration (Akkoyunlu & Siliverstovs, 2009; Collins et al., 1999; Campaniello, 2014; Lopez & Schiff, 1998; Ghani et al., 2020). Since Canadian provinces engage in interprovincial trade and international trade, these trade dynamics may also influence interprovincial and international migration. To reveal the trade and migration dynamics within and outside Canada, we revisit the long-standing relationship between trade and migration with a novel focus on provincial dynamics.

Interprovincial trade and international trade may affect both interprovincial migration within Canada and international migration to Canada. For example, if Ontario trades with Manitoba, people may migrate interprovincially from Manitoba to Ontario. Alternatively, if Manitoba trades with North Dakota, international migration may happen from North Dakota to Manitoba. So, trading at provincial and international levels may influence migration and the level of influence may vary. The question is whether interprovincial trade impacts interprovincial migration and whether international trade influences international migration. If both affect migration, then which is more influential?

An increase in trade may induce both interprovincial and international migration. A boom in trade may boost exports. This increase in exports will create more employment opportunities (Biscourp & Kramarz, 2007; Coulombe, 2002). Failure to meet employers' demands by local labour markets would encourage migrants to obtain these opportunities and migrants may come from other provinces and countries. For example, people from Manitoba may come to Ontario and represent interprovincial migration whereas individuals moving from North Dakota to Manitoba show the context of international migration. Because an expansion in a province's trade may induce international migration. In addition to interprovincial migration, this study investigates whether international trade attracts international migration. While investigating the interplay between trade and migration, we further look into the impacts of interprovincial and international exports on interprovincial and international migration.

There is no current literature investigating whether the influence of interprovincial trade on interprovincial migration is higher than the effect of international trade on international migration to Canada. This paper provides new insight into the impact of international trade on international migration to Canada, along with the impact of interprovincial trade on interprovincial migration within Canada.

We address the following research questions: [1] Which part of the trade (interprovincial or international) impacts which part of the migration and by how much? To answer this question, we need to find answers to two more questions: [2] Does international trade influence international migration to Canada? and [3] Does interprovincial trade impact interprovincial migration within Canada? Once we have the answer to the first three questions, we can answer the question: [4] Is the influence of interprovincial trade on interprovincial migration higher than the effect of international trade on international migration?

To conduct this research, two panel datasets are built, one for interprovincial analysis and another for international analysis. We address the endogeneity problem of trade and migration by deriving 8 shift-share instrumental variables (SSIVs) for interprovincial trade and another 8 SSIVs for international trade, altogether 16 SSIVs. We estimate two types of IV models: just-identified (hereafter, JI) and over-identified (henceforth, OI) for robust estimations.

Firstly, we investigate how interprovincial trade impacts interprovincial migration in a panel structure for the years 2007 to 2019. We employ the PPML estimator in the gravity model for all Canadian provinces (except, Prince Edward Island) following an instrumental variable (IV) approach.

Secondly, we develop another panel dataset pairing all Canadian provinces (except, Prince Edward Island) with Canada's top nine trading partners to examine the impact of international trade on international migration. Using this dataset, we apply the PPML estimator and the IV approach to the gravity model for the years 2007 to 2019. China, Italy, Japan, Germany, the Netherlands, Switzerland, Mexico, the United Kingdom (UK) and the United States of America (USA) are Canada's top nine trading partners. Then, we test the empirical performance of the instruments employing JI and OI IV models.

Applying the Poisson Pseudo Maximum Likelihood (PPML, hereafter) estimator in the gravity model following the IV approach, we find that interprovincial trade impacts interprovincial migration. Similarly, using the other 8 instruments for international trade in JI and OI IV models, we show that international trade affects international migration to Canada. These relationships between trade and migration are statistically significant at a 1% level.

Utilizing the novel shift-share instrumental variable (SSIV) technique, this study addresses the endogeneity problem between interprovincial trade and migration with our designed SSIVs and conventional SSIVs. All SSIVs in this study produce very high values of the F-statistic and R-squared in the first stage (FS, hereafter) across both JI and OI models, satisfying the minimum and maximum thresholds for F-statistic values $F \geq 10$ (Stock & Yogo, 2002) and $F \geq 50$ (Keane & Neal, 2021).

This paper argues that the application of aggregate shock in SSIVs may risk the exclusion restriction of SSIVs as they affect the outcome variable indirectly. Therefore, our innovative approach deals with such a potential risk by incorporating lag in both shocks and shares of SSIVs to predict the endogenous regressor solely based on past economic conditions. This approach also eliminates any potential contemporaneous correlation between instruments and the endogenous variable. We suggest that applied researchers should use a lag aggregate shock and share in their studies.

Our first-stage estimations reveal that all the instruments for trade implemented in this study are very strong. Furthermore, our machine learning estimations show that the SSIVs derived from exports have higher predictive strength than the Conventional SSIVs. This study also finds that the SSIV derived from exports over total trade has better predictive power compared to the SSIV derived from exports over total exports . This result is consistent for all Modified SSIVs, and this finding supports the Bartik (1991) approach to forming instruments.

The results further reveal that the impact of interprovincial trade on interprovincial migration is higher than the impact of international trade on international migration to Canada. Moreover, the effect of interprovincial total trade on interprovincial migration is slightly strong than the impact of interprovincial total exports on migration. However, the influences of international total trade and international total exports on international migration are similar.

Our study makes several key contributions to the literature. It is the first study which compares the influence of interprovincial trade on interprovincial migration vs the impact of international trade on international migration for Canada's top 9 trading partners. We further develop and suggest new instruments - Modified SSIVs - in the literature to improve the quality of SSIVs. This study shows and estimates the predictive strength of 16 instruments using a machine learning technique. Finally, we recommend policies for provinces that are keen on attracting migrants interprovincially and internationally.

The remainder of the paper is arranged as follows: we present the literature review in Section 2, and Section 3 presents the methodology. We provide a data description in Section 4. The estimated results are discussed in Section 5. Then, we outline our policy considerations in Section 6. Section 7 concludes. In Section 8, we show robustness. Finally, Section 9 discusses future research.

3.2 Literature Review

Each province in Canada trades internationally and interprovincially and migration occurs both internationally and interprovincially. Coulombe (2002) shows that an increase in trade both internationally and interprovincially may create jobs. He studies the long-run impacts of interprovincial trade and international trade on Canadian provincial economies using a conditional convergence-growth model. He shows that both international trade and interprovincial trade generate employment and notes a higher long-run effect on per capita GDP from international trade compared to that of interprovincial trade. Biscourp & Kramarz (2007) also show that exports create jobs.

The neoclassical economic model states that people migrate for higher incomes or jobs. Karemera et al. (2000) investigate the impact of political, economic and demographic factors on the size and composition of migration flows to North America (Canada and USA) from 70 countries using a modified gravity model for the years 1976 to 1986. They show that two determinants of migration flow to Canada and the USA are the population of the origin countries and the income of the destination countries. A large share of immigrants come from the populated areas of Asia and Latin America. Migrants move with their family members to maximize family income (Mincer, 1978). Huinink et al. (2014) reveal that the impact of openness to migration on job search behaviour is positive. They also show that openness to migration increases job mobility rates independently.

The literature on trade and migration shows both sides of the relationship (complementary and substitutive). Modern trade theories and extensions support the complementary relationship between trade and migration, whereas traditional theories suggest this as substitutive.

The standard Heckscher-Ohlin model states that trade substitutes migration due to factor price equalization, whereas Markusen (2021); Wong (1983) demonstrate that trade complements migration under certain conditions such as specialized sectors. Empirical studies (Akkoyunlu & Siliverstovs, 2009; Collins et al., 1999; Lopez & Schiff, 1998) also conclude that the relationship between trade and migration is complementary.

Campaniello (2014) examines the causal relationship between bilateral exports and bilateral migration using a gravity model with OLS and 2SLS techniques for the years 1970 to 2000. She finds that exports and migration from the South to the North show a positive correlation indicating complementarity to one another. A study by Ghani et al. (2020) also investigates the causal link between bilateral trade flow and bilateral migration flow for 248 countries over the years 1990 to 2010. They employ the PPML estimator in the gravity model and instrument trade with World Trade Organization (WTO) affiliation and average tariff rates. Their study concludes that trade significantly affects migration.

The literature also provides evidence on trade substituting migration. Mundell (1957) applies the Heckscher-Ohlin model to show that trade and migration are substitutes allowing factor movement. An empirical paper (Bruder, 2004) examines the impact of trade on labour migration between Germany and Spain, Portugal, Greece, Italy, and Turkey. She finds that trade substitutes the foreign labour force.

The literature shows a possible link between trade and migration (either complementary or substitutive or causal), but there is no specific study, focusing on which part of trade impacts which part of the migration. This paper is the first one to conduct this study.

We also contribute by deriving SSIVs and employing these in JI and OI IV models to produce empirical evidence in the literature. We derive new instruments - Modified SSIVs - in the literature to improve the quality of SSIVs. In addition, we examine the strengths of the predictive powers of SSIVs using the RF model and provide evidence on which instruments have better predictability for trade in estimating the impact of trade on migration.

Lastly, we suggest policies on [a] interprovincial trade and interprovincial migration, [b] international trade and international migration, and [c] immigration policy and international migration to Canada.

3.3 Methodology

This section introduces the gravity model of trade and migration. Next, we discuss the endogeneity problem in the model and offer solutions to this problem. We show the derivation methods for developing shift-share instruments. We further derive 16 instruments and use those to establish the causal relationship between (interprovincial or international) trade and (interprovincial or international) migration in Canada.

We also explain the reasons for applying the PPML estimator in the gravity model following the IV approach. We further show how we apply the machine-learning technique - Random Forests model - to predict the strength of these instruments.

3.3.1 The Gravity Model in Trade and Migration

Since the gravity model describes the relationship between trade and migration, it is regularly used in the literature to evaluate their interplay (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020). Therefore, we also employ the gravity model to estimate the influence of (interprovincial or international) trade on (interprovincial or international) migration.

The origin of the gravity model goes back to Newton's universal law of gravitation*. While Tinbergen (1963) formally introduces the gravity model of international trade to describe the pattern of bilateral trade flows, Krugman & Obstfeld (2005) provide a simpler version of the gravity model shown in equation (3.1). Trade flow is proportional to the economic sizes of both regions and inversely proportional to the distance between the trading partners.

$$T_{ij} = A\frac{Y_i^{\alpha_1} Y_j^{\alpha_2}}{D_{ij}^{\alpha_3}} \tag{3.1}$$

Here, T_{ij} is the trade flow from origin i to destination j; A is a constant of proportionality and it captures factors affecting trade beyond economic size and distance. Y_i and Y_j are the economic sizes of regions i and j, and besides, these usually represent the Gross Domestic Product (GDP) or the Gross National Product (GNP) of each region. D_{ij} captures the distance between two regions i and j, which serves as a proxy for trade costs between trading partners. Also, it represents impediments to trade such as differences in religions, lack of trade agreements and other barriers. Note that α_1, α_2 and α_3 are the parameters.

Ravenstein (1885, 1889) first discuss the gravity-type properties of internal migration flow. Later, Zipf (1946) establishes the clear ground of the gravity model in migration with the famous paper discussing the intercity movement within the US.

*"Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between their centers".

A significant number of studies (Gallardo-Sejas et al., 2006; Helliwell, 1997; Ortega & Peri, 2013; Poot et al., 2016; Ramos & Suriñach, 2017; Skeldon, 2014) apply the gravity model of migration utilizing expression (3.2) Migration flow is proportional to the populations of both places of origin and destination. As distance represents migration costs, it has a negative relationship with the distance between origin and destination. An increase in distance increases the cost of migration.

$$M_{ij} = G\frac{P_i^{\gamma_1} P_j^{\gamma_2}}{D_{ij}^{\gamma_3}} \tag{3.2}$$

Here, M_{ij} is the migration flow from origin i to destination j. P_i and P_j denote the populations of provinces i and j. G is a constant of proportionality, reflecting factors influencing migration beyond population size and distance. Also, γ_1, γ_2 and γ_3 are the parameters.

In the next section, we address and solve the problem of endogeneity between trade and migration. Our study extends equation (3.2) and incorporates our variable of interest which is trade flow on the right-hand side and adds relevant controls to analyze the impact of trade on migration.

3.3.2 Trade and Migration: Endogeneity & IV Approach

While examining the relationship between trade and migration, the literature provides evidence of reverse causality between trade and migration. Campaniello (2014) and Ghani et al. (2020) show that trade causes migration whereas empirical works (Dunlevy & Hutchinson, 1999; Wagner et al., 2002; Gould, 1994; Wagner et al., 2002; Aziz et al., 2023; Steingress, 2018) show that migration impacts trade.

We further confirm the likelihood of the reverse causality between trade and migration utilizing the Granger (Non) Causality Test in this panel setup (Dumitrescu & Hurlin, 2012). Before testing for causation, we use the unit root test using Im et al. (2003) to check that the variables are stationary. Tables 5 and 6 provide evidence in favour of reverse causality between trade and migration.

Therefore, to investigate the causal effects of trade on migration, we need IVs for trade in this study. Campaniello (2014) uses two instrumental variables to show the causal impact of trade on migration: average trade tariffs and bilateral exchange rate volatility. Similarly, Ghani et al. (2020) instrument trade with WTO affiliation and average tariff rates to establish the causal impact of trade on migration. However, these instruments do not apply to our study.

Since this study considers how interprovincial trade influences interprovincial migration and how engaging in international trade with Canadian provinces attracts migrants to Canada, tariffs, exchange rates, nor WTO affiliation have any variation across provinces for any year. Therefore, average trade tariffs, bilateral exchange rate volatility, and WTO agreement do not qualify as instruments for this study.

We need to find appropriate IVs for trade which are relevant, exogenous to migration and consistent with the exclusion restriction. Our paper derives 16 IVs to solve the endogeneity problem: 8 instrumental variables for interprovincial trade and 8 instruments for international trade.

The following section shows the derivation of IVs using the SSIV technique, the framework and the estimator to estimate the impact of interprovincial trade on migration. We follow this same approach to analyze the impact of international trade on international migration to Canada.

3.3.3 Impact of Interprovincial Trade on Interprovincial Migration

We compile a panel dataset for all Canadian provinces for the years 2007 to 2019. We examine the impact of interprovincial trade on interprovincial migration by employing the gravity model framework with the PPML estimator.

In our study, interprovincial trade is endogenous, and we apply a two-stage approach to address the endogeneity of interprovincial trade. First, we discuss the mechanism to derive the SSIVs in the next section and then outline the estimation method for interprovincial trade. We do the same for international analysis.

3.3.4 Origin of Shift-Share Instruments

The origin of shift-share analysis goes back to Creamer (1943). While Dunn Jr (1960) gives it a modern accounting identity, Freeman (1980) uses the decomposition of nature and instruments of labour demand with the change in industry composition.

Timothy J Bartik (1991, 1993) provides a strong rationale for using shift-share instruments in economics. He reintroduces the idea of shift-share instruments by providing the logic of how the national growth rate component captures the shocks. And that is why these are called Bartik instruments. The key feature of the Bartik instrument or shift-share instrument is its decomposition approach, which generates exogenous variation and facilitates causal analysis. Later, Blanchard & Katz (1992) contributed significantly to this area.

They define their instrument as the local employment growth rate, which is constructed by the interacting local industry employment shares with the national industry growth rates. The employment share is plausibly exogenous, and the national industry growth rate represents a shock at the aggregate level and is also exogenous. Any shock at the national level is exogenous to the regional level and the regional share grows rapidly with that shock.

An SSIV captures the interaction between the shock of an industry using the national growth rate of that industry and the regional share of that industry. A shock at the country level is exogenous to the regional economy and the share of the regional economy responds to the shock from the country level. This is how the shift-share instrumental variable works as an instrument.

These features of this shift-share instrument are very appealing, and it is popular in the fields of economics (Acemoglu et al., 2016; Autor et al., 2013; Broxterman & Larson, 2020; Card, 2001, 2009; Goldsmith-Pinkham et al., 2020; Hummels et al., 2014; Peri, 2016; Xu, 2023), and particularly in labour economics (Card, 2001, 2009), and international trade (Hummels et al., 2014) for causal inference.

The growing number of works (Autor et al., 2013; Goldsmith-Pinkham et al., 2020; Broxterman & Larson, 2020) on this novel technique are opening the black box, revealing variations of this instrument. We develop our instruments following the works of Autor et al., 2013, Acemoglu et al. (2016), Goldsmith-Pinkham et al. (2020), and Broxterman & Larson (2020). Our study further constructs new instruments based on previous studies and suggests a new technique for estimating the causal impact of trade on migration, especially international trade.

3.3.5 Constructions of SSIVs for Interprovincial Trade

First, this study outlines the Conventional SSIV derivation method. Then, this section shows how we derive 8 types of shift-share instruments: [1] SSIV from the Goods Industry [2] SSIV from the Services Industry [3] "The Shock" from the Goods Industry [4] "The Shock" from the Services Industry [5] Modified SSIV from the Goods Industry [6] Modified SSIV from the Services Industry [7] "The Shock" from the Modified SSIV of the Goods Industry and [8] "The Shock" from Modified SSIV of the Services Industry.

Equation (3.3) shows the estimation method to construct shift-share instruments.

$$SSIV_{ijt}^{V} = N_t^k \times W_{ijt}^k \tag{3.3}$$

Here, $SSIV_{ijt}^{V}$ are the shift-share instruments for interprovincial trade and V is the index; N_t^k represents the shift of industry k at time t; W_{ijt}^k denotes the regional trade share of industry k in region j with trading partner i at time t. Notably, k is the number of industries. The sum of all shares must be 1, by expression $\sum_k W_{ijt}^k = 1$.

To create the SSIV, we first calculate the industry share using the equation (3.4). Then, we estimate the shift or the shock using the expression (3.5).

$$W_{ijt}^k = \frac{T_{ijt}^k}{T_{jt}} \tag{3.4}$$

T_{ijt}^k is the trade flow of industry k from origin i to destination j at time t; T_{jt} is the total trade of destination j at time t.

$$N_t^k = \left[\frac{T_t^k}{T_{t-1}^k}\right] - 1 \tag{3.5}$$

T_t^k is the country-level trade of industry k at time t; T_{t-1}^k is the country-level trade of industry k

at time $(t-1)$. Once we estimate the shifts and the share using equations (3.4) and (3.5), we can then calculate the SSIV.

Since we examine the impact of interprovincial trade on interprovincial migration and the effect of international trade on international migration, this study uses two different notations to clearly identify the instruments. Notably, SSIVP represents the shift-share instrumental variable for interprovincial trade, whereas SSIVI denotes the shift-share instrumental variable for international trade. The next section outlines how we derive instruments for interprovincial trade.

3.3.6 SSIVs Derived from Goods and Services Sectors

Table 1 represents the construction method of 8 instruments for interprovincial trade using goods and services sectors.

Table 1: SSIVs for Interprovincial Trade

Index	Instruments	Construction Method	Components
1–2	$SSIVP^1_{AGS\star AGSR}$; $SSIVP^2_{LAGS\star LAGSR}$	$N^G_{t-q}W^G_{t-r}$, , where $G=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate shocks and shares without & with lag
3–4	$SSIVP^3_{ASS\star ASSR}$; $SSIVP^4_{LASS\star LASSR}$	$N^S_{t-q}W^S_{t-r}$, , where $S=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Sum of disaggregate shocks and shares without & with lag
5–6	$SSIVP^5_{AGS}$; $SSIVP^6_{LAGS}$	N^G_{t-q} for $q=0,1$	Aggregate Goods Shocks only without & with lag
7 –8	$SSIVP^7_{ASS}$; $SSIVP^8_{LASS}$	N^S_{t-q} for $q=0,1$	Aggregate services shocks only without & with lag

Note: q and r denote the lag on the shock and share, respectively. While G represents aggregate goods industry, k indexes the 2 goods industries. The condition $q\neq 1$ for $r=0$ excludes lagged shocks with original shares $(N_{t-1}W_t)$. Also, $q\neq 0$ for $r=1$ excludes lagged shocks with original shares (N_tW_{t-1}).

Here: AGS and $AGSR$ refer to the aggregate goods shock and share, while $LAGS$ and $LAGSR$ represent their lagged counterparts. ASS ans $ASSR$ are aggregate services shock and share, whereas $LASS$ and $LASSR$ denote lag aggregate services shock and share.

[a] Using Aggregate Goods and Services Sectors

Using the expressions (3.3), (3.4) and (3.5), we derive $SSIVP^1_{AGS\star AGSR}$ from the aggregate goods sector. Following previous empirical studies Acemoglu et al. (2016); Algan et al. (2017); Borusyak et al. (2022); Jaeger et al. (2018), we derive another instrument, $SSIVP^2_{LAGS\star LAGSR}$, using the lagged shock and share.

Acemoglu et al. (2016) introduced lag in the share of this technique to address any concerns over the endogeneity of the share component, whereas Jaeger et al. (2018) suggested lagging the shock to isolate current effects from past effects. Therefore, $SSIVP^2_{LAGS\star LAGSR}$ relies only on past economic conditions. This lagging strategy improves the exogeneity of our instrument and tackles the possibility of contemporaneous shock effect.

Similarly, we derive another two instruments, $SSIVP^3_{ASS\star ASSR}$ and $SSIVP^4_{LASS\star LASSR}$, using aggregate services sector.

[b] Aggregate Goods and Services Shocks

This study derives another 4 instruments with the aggregate shocks using both with and without lags. We address the potential endogeneity of the "regional industry share by normalizing the shares following Goldsmith-Pinkham et al. (2020) and use the shocks as instruments for interprovincial trade.

Following this approach, this paper constructs $SSIVP^5_{AGS}$ using aggregate goods shocks and $SSIVP^6_{LAGS}$ using lagged aggregate shocks. Similarly, this study further develops $SSIVP^7_{ASS}$ using aggregate services shocks and $SSIVP^8_{LASS}$ using their lagged counterparts.

3.3.7 Exogeneity and Classification of SSIVs

To estimate the causal effect of interprovincial trade on migration, we construct our instruments using the mix of the trade share of regional industry and its national growth rate. We verify that this SSIV is exogenous to migration and is relevant to interprovincial trade.

We use this SSIV for the causal analysis of trade on migration and construct our instrument using the mix of the trade share of regional industry and its national growth rate. This SSIV is exogenous to migration and is relevant to interprovincial trade.

Let's break down the mechanism of the SSIVs in this context. The provincial trade share increases as the national growth rate increases. And trade influences migration only through SSIVs.

Regional trade share and the shock at the country level are exogenous to migration. Also, we develop the SSIVs with the combination of these two components (shift and share). Our further lagging strategy in SSIVs addresses any minor possibility of the endogeneity of the share components. As these lagged SSIVs solely depend on past economic events, this lagged decomposition nature eliminates the possibility of any endogeneity concerns in the share component of SSIVs.

Migration does not affect the SSIVs directly nor do the SSIVs affect migration. So, it also holds exclusion restrictions. Thus, the SSIVs satisfy all the criteria to qualify as instruments.

We introduce two types of instruments in this study: Conventional SSIVs and Modified SSIVs. We develop all Conventional SSIVs using original shocks and shares, whereas Modified SSIVs include lagged shocks and shares. We follow the same approach while estimating the causal effect of international trade on international migration.

Why our instruments are better?

Since we introduce lag in both shock and share, our version of instruments solely relies on past economic conditions. Our lagging approach isolates any contemporaneous correlation between the instruments and the endogenous variable. We further argue that aggregate shock may indirectly influence interprovincial migration and may weaken the exclusion restriction of an IV. In this case, adopting a lag shock solves the problem as Jaeger et al. (2018) recommended to use a lag shock to isolate past effect from present effect.

3.3.8 Empirical Strategy for Interprovincial Trade

This section explains our identification strategy to estimate the impact of interprovincial trade on interprovincial migration, where we employ 8 instruments from the goods and services sectors for interprovincial trade. We estimate the influence of interprovincial trade on migration in two ways: [a] the effect of interprovincial total trade on interprovincial migration and [b] the impact of interprovincial total exports on interprovincial migration. We apply such estimation methods to differentiate the impacts of overall trade and total exports. Also, this approach allows us to check the robustness of our estimations.

Moreover, this paper estimates both just-identified and over-identified IV models to ensure the robustness and reliability of our estimations. To estimate just-identified IV models, we instrument interprovincial trade by each of 8 SSIVs derived from goods and services sectors.

We further estimate the over-identified IV models by using all the SSIVs for interprovincial trade in several ways. The following combination shows how we set the instruments for over-identified IV models: [a] using Conventional SSIVs derived from the Goods and the Services sectors [b] instrumenting the shocks from these two sectors [c] utilizing Modified SSIVs from the Goods and the Services sectors [d] employing the lagged shocks and [e] including all the instruments.

Equation (3.6) shows the first stage of regression to establish the instruments for interprovincial trade. This paper instruments interprovincial trade between two regions by the SSIVs from the goods and services sectors and controls for the distance and border sharing between two provinces, the participation rate, the population sizes, Gross Domestic Products, annual average income, and weather conditions in both origin and destination provinces.

$$PT_{ijt}^{U^V} = \alpha_0 + \alpha_1 \, \mathrm{SSIVP}^V + \alpha_2 \, \mathrm{Controls}_{ij} + \alpha_3 \, \mathrm{Controls}_{it} + \alpha_4 \, \mathrm{Controls}_{jt} + \varepsilon_{ijt} \tag{3.6}$$

Here, $PT_{ijt}^{U^V}$ denotes the interprovincial trade flow from province i to province j at time t; U represent the form of trade. PT_{ijt}^{TG} and PT_{ijt}^{TE} are interprovincial total trade and interprovincial total exports †; SSIVP^V are the shift-share instrumental variables (SSIVs) derived from the goods and the services sectors for interprovincial trade.

$Controls_{ij}$ are D_{ij}^P and $Border_{ij}^P$. D_{ij}^P is the distance between two provinces, and $Border_{ij}^P$ represents a dummy variable if the two provinces share a border accordingly. We also include one addition control IMP_{ij}^P, which denotes the interprovincial imports flow from province i to province j at time t, for estimating the impact of interprovincial total exports on migration. $Controls_{it}$ are P_{it}^P. GDP_{it}^P, Inc_{it}^P, Par_{it}^P and WC_{it}^P. P_{it}^P is the size of the population of province i at time t; GDP_{it}^P is the GDP of province i at time t; Inc_{it}^P is the annual average income of province i at time t; Par_{it}^P is the labor participation rate of province i at time t; WC_{it} is the weather conditions of province i at time t in January and February.

$Controls_{jt}$ are P_{jt}^P, GDP_{jt}^P, Inc_{jt}^P, Par_{jt}^P and WC_{jt}^P. P_{jt}^P is the size of the population of province i at time t;$GDPC_{jt}^P$ is the GDP of province j at time t; Inc_{jt}^P is the annual average income at province j at time t; Par_{jt}^P is the labor participation rate at province j at time t; WC_{jt}^P is the weather conditions at province j at time t in January and February.

Using equation (3.7), this study estimates the impact of interprovincial trade on migration by incorporating all the control variables of the first-stage into this second-stage regression except interprovincial trade in equation (3.7). These variables instrument themselves in the second stage as shown in equation (3.7).

$$\begin{aligned} M_{ijt} = \exp\Big(&\beta_0 + \beta_1 \log\left(\hat{PT}_{ijt}^{U^V}\right) + \beta_2 \log \text{Controls}_{ij} + \beta_3 \log \text{Controls}_{it} \\ &+ \beta_4 \log \text{Controls}_{jt} + \tau_{it} + \tau_{jt} + \tau_t\Big) + \varepsilon_{ijt} \end{aligned} \tag{3.7}$$

Here, M_{ijt}^P is interprovincial migration flow from province i to province j; $\hat{PT}_{ijt}$ are the predicted provincial trade flows from province i to j; τ_{it}, τ_{jt} and τ_t are origin fixed effects, destination fixed effects, and year fixed effects, respectively.

We regress interprovincial migration flow between two provinces on the predicted provincial trade flows between two provinces, the distance between two provinces, the population sizes, the GDP, the participation rate, the weather conditions, and average annual income of both provinces and border sharing between two provinces. While estimating the impact of interprovincial total exports on migration, we add interprovincial imports flow between two provinces in the second-stage regressions.

†**Note**: TG and EG denote total trade and total exports.

3.3.9 Effect of International Trade on International Migration

To estimate the impact of international trade on international migration to Canada for the years 2000 to 2019, this paper applies the PPML estimator in the gravity model, following the IV approach.

We prepare a panel dataset for all Canadian provinces except Prince Edward Island and pair it with the top 9 trading partners (China, Italy, Japan, Germany, the Netherlands, Switzerland, Mexico, the UK, and the USA) of Canada.

3.3.10 Constructions of SSIVs for International Trade

While considering the share of this shift-share instrument, Bartik (1991) highlighted that he wanted to use the instrument to proxy the demand for a local area's exports (see, p.274) but later included all employment of all industries for its convenience. Broxterman & Larson (2020) further advance the thought from Bartik (1991) on the export share of employment and offer suggestions regarding the development of this instrument.

We develop our instruments for international trade based on the explanatory power of exports (Bartik, 1991, 1993; Broxterman & Larson, 2020). We also offer a new way to derive instruments and employ those instruments in estimating the impact of international trade on international migration to Canada.

This study shows two new ways to construct SSIVs in general using the goods sector using [i] exports over total exports and [ii] exports over total trade in both shift and share. Table 2 shows how we derive 8 instruments for international trade following these techniques.

Table 2: SSIVs for International Trade

Index	Instruments	Construction Method	Components
1–2	$SSIVI^1_{AGES\star AGESR}$; $SSIVI^2_{LAGES\star LAGESR}$	$NE^G_{t-q}WE^G_{t-r}$, , where $G=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate goods exports shocks and shares without & with lag
3–4	$SSIVI^3_{AGTES\star AGTESR}$; $SSIVI^4_{LAGTES\star LAGTESR}$	$NTE^G_{t-q}WTE^S_{t-r}$, , where $G=1$, $q=0,1$; $r=0,1$; $q\neq 1$ if $r=0$; $q\neq 0$ if $r=1$	Aggregate Total Exports of Goods shocks and shares without & with lag
5–6	$SSIVI^5_{AGES}$; $SSIVI^6_{LAGES}$	NE^G_{t-q} for $q=0,1$	Aggregate Goods Exports Shocks only without & with lag
7 –8	$SSIVI^7_{AGTES}$; $SSIVI^8_{LAGTES}$	NET^S_{t-q} for $q=0,1$	Aggregate Goods Total Exports shocks only without & with lag

Note: q and r denote the lag on the shock and share, respectively. While G represents aggregate goods industry, k indexes the 2 goods industries. The condition $q\neq 1$ for $r=0$ excludes lagged shocks with original shares ($N_{t-1}W_t$). Also, $q\neq 0$ for $r=1$ excludes lagged shocks with original shares (N_tW_{t-1}).

Here: $AGES$ and $AGESR$ refer to the aggregate goods exports shock and share, whereas $LAGS$ and $LAGSR$ represent their lagged counterparts. While $AGTES$ and $AGTESR$ are the aggregate goods shock and the aggregate goods exports share.

[a] Using Exports over Total Exports of Goods

Equation (3.8) shows the approach to estimating the shift-share instrumental variables for the exports over the total exports.

$$SSIV_{ijt}^{V} = NE_{t}^{k} \times WE_{ijt}^{k} \tag{3.8}$$

NE_t^k represents the aggregate shock of the exports of industry k at time t; WE_{ijt}^k denotes the regional share of export of industry k in region j with trading partner i at time t.

We use the expressions below to calculate the industry share and the shift.

$$WE_{ijt}^{k} = \frac{TE_{ijt}^{k}}{TE_{jt}}$$

TE_{ijt}^k is the export flow of industry k from origin i to destination j at time t; TE_{jt}^T is the total exports of destination j at time t.

$$NE_{t}^{k} = \left[\frac{TE_{t}^{k}}{TE_{t-1}^{k}}\right] - 1$$

TE_t^k is the country-level total exports of industry k at time t; TE_{t-1}^k is the country-level total export trade of industry k at the time $t-1$.

First, we conventionally derive $SSIVI_{AGES\star AGESR}^{1}$ using expression (3.8). Again, we assume that the export share may be endogenous. Then, following (Acemoglu et al., 2016; Jaeger et al., 2018; Algan et al., 2017; Borusyak et al., 2022), we introduce lag in both shock and share to create $SSIVI_{LAGES\star LAGESR}^{2}$ and name this lagged SSIV as "Modified SSIV". We predict the export flow of the current year using the previous year's export share and the last year's shift.

[b] Using Exports over Total Goods Trade

We offer another technique to derive SSIV using exports over total goods trade, as shown in expression (3.9).

$$SSIV_{ijt}^{V} = NT_{t}^{k} \times WT_{ijt}^{k} \tag{3.9}$$

NT_t^k represents the shift of the total trade of industry k at the time t; WT_{ijt}^k the regional share of exports over total trade of industry k in region j at the time $t-1$.

We use the expressions below to calculate the industry share and the shock.

$$WT_{ijt}^{k} = \frac{TE_{ijt}^{k}}{T_{jt}}$$

T_{jt} represents the total trade of destination j at time t.

$$NT_t^k = \left[\frac{T_t^k}{T_{t-1}^k}\right] - 1$$

T_t^k stands for the country-level total trade of industry k at time t; T_{t-1}^k refers to the country-level total trade of industry k at the time $t-1$.

Using expression (3.9), this paper derives $SSIVI^3_{AGTES\star AGTESR}$ conventionally. We create another "Modified SSIV", $SSIVI^4_{LAGTES\star LAGTESR}$, by lagging the share and the shift components to deal with the endogeneity concern.

[c] Aggregate Goods and Aggregate Goods Exports Shocks

Following Goldsmith-Pinkham et al. (2020), this study normalizes the shares of expressions (3.8) and (3.9) to get other instruments: $SSIVI^5_{AGES}$ and $SSIVI^7_{AGTES}$. Since any trade shocks at the country level are exogenous to migration and are positively related to the export flow, it qualifies as an instrument.

We further follow Jaeger et al. (2018) and derive another two instruments, $SSIVI^6_{LAGES}$ and $SSIVI^8_{LAGTES}$, by normalizing the shares of the Modified SSIVs.
The next section explains the empirical strategy using these SSIVs in the gravity model.

3.3.11 Empirical Strategy for International Trade

This study estimates the impact of international trade on international migration in two ways: [i] the effect of international total trade on international migration and [ii] the impact of international total exports on international migration.

We employ 8 instruments for international trade from the goods industry using the ratios of exports over total exports and exports over total trade in both shift and share. This research estimates just-identified IV models by instrumenting international trade with each of the SSIVs derived from the goods sector.

We also estimate over-identified models following several approaches: [a] utilizing the Conventional SSIVs, which we derive from the goods industry weighting exports over total exports and exports over total trade [b] instrumenting the shocks from these weighted ratios [c] utilizing Modified SSIVs weighting exports relative to total exports and exports relative to total trade [d] employing the lagged shocks based on the weights on these ratios and [e] incorporating all the instruments.

Equation (3.10) shows the first stage of regression to establish the instruments for interprovincial trade. This paper instruments interprovincial trade between two regions by the SSIVs from the goods and services sectors and controls for the distance and border sharing between two provinces, the participation rate, Gross Domestic Products (GDP) Per Capita, annual average income, and immigration policies in both origin and destination provinces.

$$IT_{ijt}^{U^V} = \gamma_0 + \gamma_1 \,\mathrm{SSIVT}^V + \gamma_2 \,\mathrm{Controls}_{ij} + \gamma_3 \,\mathrm{Controls}_{it} + \gamma_4 \,\mathrm{Controls}_{jt} + \varepsilon_{ijt} \tag{3.10}$$

Here, $IT_{ijt}^{U^V}$ denotes the international trade flow between two regions at time t; U represent the form of trade. IT_{ijt}^{TG} and IT_{ijt}^{EG} are international total trade and international total exports; SSIVT^V are the shift-share instrumental variables (SSIVs) derived from the goods sector for international trade.

$Controls_{ij}$ are D_{ij}^I and (IMP_{ij}^I, which we include only for estimating the impact of international total exports on international migration). D_{ij}^I is the distance between two regions, whereas IMP_{ij}^I denotes the international imports flow from country i to province j at time t.

$Controls_{it}$ are $GDPC_{it}^I$, Inc_{it}^I, Par_{it}^I and $Imm\ Policy_{it}^I$. $GDPC_{it}^I$ is the GDP Per Capita of country i at time t; Inc_{it}^I is the annual average income of country i at time t; and Par_{it}^I is the labor participation rate of country i at time t; $Imm\ Policy_{it}^I$ is the immigration policy at country i at time t. For example, we set 1 for strict immigration policy, and 0 for otherwise.

Moreover, $Controls_{jt}$ are $GDPC_{jt}^P$, Inc_{jt}^P, Par_{jt}^P [‡] and $Imm\ Policy_{jt}^I$ represents the immigration policy at province j at time t. This study sets 1 for strict immigration policy, and 0 for otherwise.

This paper estimates equation (3.11) to establish the causal effect of international trade on international migration. We incorporate all the control variables of the first-stage into this second-stage regression except interprovincial trade in equation as These variables instrument themselves in the second stage as shown in equation (3.11).

$$\begin{aligned} M_{ijt}^I = \exp\Big[&\delta_0 + \delta_1 \log\left(\hat{IT}_{ijt}^{U^V}\right) + \delta_2 \log \mathrm{Controls}_{ij} + \delta_3 \log \mathrm{Controls}_{it} \\ &+ \delta_4 \log \mathrm{Controls}_{jt} + \tau_{it} + \tau_{jt} + \tau_t\Big] + \varepsilon_{ijt} \end{aligned} \tag{3.11}$$

Here, M_{ijt}^I is international migration inflow from country i to province j; $\hat{IT}_{ijt}^{U^V}$ are the predicted international trade flows from country i to province j (and fixed effects.[§])

This study regresses the migration inflow between two regions by the predicted trade flow between two regions, the distance between two regions, the GDP Per Capita, the participation rate, the immigration policies, and average annual income of both origin and destination. While estimating the impact of international total exports on migration, we also control for international imports flow between two regions.

[‡]**Defined Variables:** $GDPC_{jt}^P$ is the GDP Per Capita of province j at time t; Inc_{jt}^P is the annual average income at province j at time t; Par_{jt}^P is the labor participation rate at province j at time t.

[§]τ_{it}, τ_{jt} and τ_t are origin fixed effects, destination fixed effects, and year fixed effects, respectively

3.3.12 Unobserved Heterogeneity, Fixed Effects & Estimator

We apply the PPML estimator in the gravity model and control unobserved heterogeneity using year-fixed effect, origin and destination-fixed effects. Moreover, this research uses the Hansen J test to check the over-identifying restrictions.

The PPML estimator has several advantages over other estimators. Conventionally, empirical studies log linearize the gravity equation and they estimate with the 2SLS estimator. However, Silva & Tenreyro (2006) show that log linearizing the gravity equation causes serious bias and suffers from heteroskedasticity. They also note that the 2SLS estimator fails to consider zero values and provides biased estimation. On the other hand, this PPML estimator efficiently handles zero and low observations of trade and migration. They recommend estimating the model in multiplicative form and using the Poisson Pseudo Maximum Likelihood (PPML) estimator to deal with the problem of heteroskedasticity.

Therefore, our study estimates the equations (3.7) and (3.11) in multiplicative form using the PPML estimator, rather than log-linearizing the equations.

This research also controls unobserved heterogeneity and multilateral resistance terms by introducing year-fixed effects, and origin and destination-fixed effects. Destination and origin fixed effects control the influencing factors of migration decisions that do not change over time, such as institutions, culture and attributes. These factors change slowly within a country (Ortega & Peri, 2012).

Following the work of Anderson & Van Wincoop (2003), the standard practice in the structural gravity model of trade is to account for multilateral resistance terms by incorporating individual dummies for each origin and destination. It is the same as taking fixed effects for origin and destination into the gravity model (Hummels, 1999).

Migration studies Ortega & Peri (2012, 2013) also popularize the multilateral resistance term, capturing the decisions to migrate to possible destinations. Therefore, it is important to control this multilateral resistance term. We control the multilateral resistance term by applying a PPML estimator in the gravity model with origin and destination fixed effects (Fally, 2015). His remarkable work sheds light on the missing link of whether these fixed effects capture the multilateral resistance terms. He shows that estimating the gravity equation with the PPML estimator with origin and destination fixed effects recovers the multilateral resistance indexes. Under reasonable assumptions, (Fally, 2015) shows that only the PPML estimator has the properties to satisfy these conditions. Santos Silva & Tenreyro (2022) revisit their estimator and support the findings from Fally (2015).

3.3.13 Predictive Strength of SSIVs & Machine Learning

To evaluate the strength of the instrumental variables, first we look at the first stage values of F-statistic and R-squared. In our analysis, while showing the impact of interprovincial trade on interprovincial migration, we have very high F-Statistics of more than 1600 in the case of all instruments. The literature (Bound et al., 1995; Stock & Yogo, 2002) suggests if the F-Statistics of the first stage is 10, the instruments are not weak. Therefore, our instruments for interprovincial trade are very strong. Moreover, the R-squared values of all the first-stage regressions are above 0.89, indicating higher predictability of the instruments (and the controls) for provincial trade.

Similarly, while showing the causal relationship between international trade and international migration, the values of F-statistic and R-squared in the first stage are higher than 600 and 0.69 respectively. These values indicate that our instruments for international trade are strong, and the instruments have very good explanatory power to predict international trade. Moreover, all the instruments in this study also satisfy a higher threshold of $F \geq 50$ (Keane & Neal, 2021).

While the conventional IV approach relies on linear first-stage regressions, this study explores the potential of machine learning technique - Random Forests - as alternative method for the first-stage regression diagnostics. To evaluate the predictive strength of all SSIVs, we apply the machine learning technique, the Random Forests Model, following the just-identified estimation approach. The next section explains the mechanism of the Random Forests model and outlines the approach to how we utilize it in our study.

3.3.14 Application of Random Forests Model & Predictive Strengths of SSIVs

Breiman (2001) introduces the RF model, a decision-tree-based ensemble machine-learning technique in the literature. This model captures complex and non-linear relationships and is well known for its high accuracy and efficiency with large datasets (Liaw et al., 2002). Therefore, this study employs the RF model in our study to capture the complex relationship of trade flow with the instruments. We intend to identify which instruments have superior power to explain trade. Expression 3.12 outlines the mechanism of the RF model.

$$\hat{Y} = \frac{1}{C} \sum_{i=1}^{C} T_i(X) \tag{3.12}$$

Where, $\hat{Y}$ is the predicted interprovincial trade flow, which we obtain by averaging the outcomes of C individual trees; $T_i(X)$ shows the prediction of the ith tree based on the instruments and the other control variables.

This RF model generates the predictions from multiple decision trees and sums up all these to increase the prediction accuracy. Then, it predicts the trade flow by taking the means of the outcomes of all individual trees.

We set the environment first to estimate the RF models for instruments of interprovincial and international trades. Since our datasets do not have any missing values, we split the datasets into 80% training and 20% testing subsets for validation (James, Witten, Hastie, Tibshirani, et al., 2013).

Furthermore, this study fine-tunes the key parameters such as learning rate, number of estimators, and subsample size using a grid search to optimize model performance (Probst et al., 2019).

This study assesses the performance of instruments based on variable importance scores and RMSE (Hyndman & Koehler, 2006; Strobl et al., 2007). We further test the model's ability to predict new data by the cross-validation technique. It evaluates how well it performs on an independent dataset. We employ $K - fold$ cross-validation and divide the entire dataset randomly by k subsets to validate the model (James, Witten, Hastie, Tibshirani, et al., 2013). Each iteration consists of one-fold as the testing set, and the remaining $(k - 1)$ as the training set. We repeat this process k times and take the average of the results from each fold to generate a single estimation.

The next section discusses the data sources from which we extract the variables.

3.4 Data Description

To investigate how interprovincial trade impacts interprovincial migration for all Canadian provinces, this research compiles the first-panel dataset using the following variables: interprovincial migration[¶], interprovincial trade flow, interprovincial total exports[‖], participation rate, annual yearly income, gross domestic product [GDP], and population from CANSIM for the years 2007 to 2019.

For the implementation of the gravity model, this panel data set includes distance. This study selects one major city of each Canadian province based on population density as a measure of the distance and we use the distance [**] between two provinces in the gravity model.

If a province shares a border with other provinces, this may increase the probability of migration. Therefore, it includes border as a dummy variable in the model, 1 for a province sharing a border with another province, and 0 otherwise. If a province experiences temperature below - 30° C in January and February for the years 2007 to 2019, our study treats that province as having the worst weather conditions as per Environment Canada (2020)'s monthly data. So, we set 1 for the worst weather conditions and 0 otherwise.

To evaluate whether international trade influences international migration for the years 2007 to 2019, it builds the second-panel dataset for all Canadian provinces (except Prince Edward Island) by selecting major trade partners: China, Italy, Japan, Germany, the Netherlands, Switzerland, Mexico, the UK, and the USA.

This panel dataset includes variables such as the population and GDP of selected trading partners from World Development Indicators [WDI], the participation rate, the average annual income.

[¶]Statistics Canada. *Table 17-10-0022-01 Estimates of interprovincial migrants by province or territory of origin and destination, annual* DOI: 10.25318/1710002201-eng.

[‖]Statistics Canada. *Table 12-10-0088-01: Interprovincial and international trade flows, basic prices, summary level (x 1,000,000).* DOI: 10.25318/1210008801-eng.

[**]https://www.distancefromto.net/

We measure the distance between a capital city of each province to a capital city of trading partners using the same source for provincial analysis.

Canadian variables are drawn from CANSIM: international total trade, international total exports, inflow of international migration to Canadian provinces from selected trading partners; population, participation rate, average annual income, and GDP of all provinces in Canada.

This study includes immigration policy in this part of the analysis. If a particular province offers an easily accessible program to obtain permanent residency, this study selects that province as an immigrant-friendly province. For example, people can gain permanent residence in Manitoba through the Provincial Nominee Program if a person works in the province for at least six months on a full-time basis. Therefore, this study sets the dummy variable immigration policy, 1 for Manitoba [††] and Saskatchewan (Saskatchewan Immigration Program) and 0 otherwise. We further set another immigration policy variable for our countries of interest, 1 for strict immigration policy and o otherwise. Following Solano & Huddleston (2020), we set 1 for countries such as China, Japan, Italy and Switzerland and 0 for other countries (including the USA, the UK, Mexico, Germany and the Netherlands).

3.5 Results

In this section, we discuss the summary statistics, heatmap analysis, and causality test results. Then we explain our main findings.

3.5.1 Descriptive Statistics

Since this paper includes two dimensions of analysis, this section introduces summary statistics in two parts: [a] interprovincial analysis, and [b] international analysis.

Table 3 shows the summary statistics for interprovincial analysis. The total number of observations is 1053. A province in Canada that trades interprovincially is, on average, $ 71,755.59 million. The minimum amount of interprovincial trade is $3,640 million and the maximum amount of interprovincial trade is $257,400 million. On average, 2,929.276 persons migrate to a province within Canada yearly. Each year, provincial averages range from a minimum of 78 persons who migrate interprovincially to a maximum of 29,304 persons.

Table 4 represents the summary statistics of international analysis. The total number of observations is 1053. Each province trades with the top trading partners, with an average of $974,3,955 million in trade, ranging from a minimum trade of $509.70 million to a maximum trade of $359,400,000 million. On average, 3940.764 people tend to migrate from these countries to Canada.

[††] https://immigratemanitoba.com/

Table 3: Summary Statistics of Interprovincial Analysis

Variables	Mean	Min	Max
Interprovincial Trade Flow (In Millions)	79,258.10	12,646.60	257,484
Interprovincial Migration Flow	2,929.276	78	29,304
GDP of Origin Province (In Millions)	193.78	28.8	752.39
Population (In Thousands)	3,864.476	509.055	14,544.70
Average Yearly Income (In Dollars)	46,089.74	37,600	61,900
Participation Rate	65.91	58.4	74.7
Distance (km.)	2,063.94	140.83	4,431.78
Total Number of Observations	936		

Table 4: Summary Statistics of International Analysis

Variables	Mean	Min	Max
International Trade Flow (In Millions)	974,395.5	509.70	359,400,000
Exports (In Millions)	4,860,825	171.8	197,000,000
Imports (In Millions)	4,975,058	0	166,000,000
International Migration (In Flow)	2,851.937	0	67,100
Participation Rate	4,243.49	48.142	40,854.55
GDP (In Millions)	4,700	477	21,400
Population (In Thousands)	239,546.90	7,551.12	1,407,745
Distance (km.)	6,297.759	564.81	10,778.4
Annual Income (In Dollars)	29,184.09	59.29858	70,650.76
Total Number of Observations	1,053		

3.5.2 Heatmap Analysis & Causality Test Results

Figure 1 and Figure 2 capture trade flow and migration flow between provinces within Canada for the years 2007 to 2019. Similarly, Figure 3 and Figure 4 display trade flow and migration in flow between provinces and the countries of interest over the years 2007 to 2019.

As we can see from Figure 1 and Figure 2, provinces engaging in more trade have more interprovincial migration. For example, Ontario trades the most among provinces and it has the highest number of interprovincial migrants.

While comparing Figure 3 and Figure 4, we find the provinces with higher trade with the countries of interest also have more incoming migrants. For example, provinces trade the most with China and the US and that's why we see a significant number of migrants coming from these countries.

Table 5 and Table 6 show the Granger non-causality test results for interprovincial and international analyses. Before assessing the reverse causality between trade and migration, Im et al. (2003) test results confirm that the variables are stationary. We find strong evidence in favour of reverse causality as we reject the null hypothesis at a 1% significant level. In both interprovincial and international analyses, trade does Granger-Cause migration.

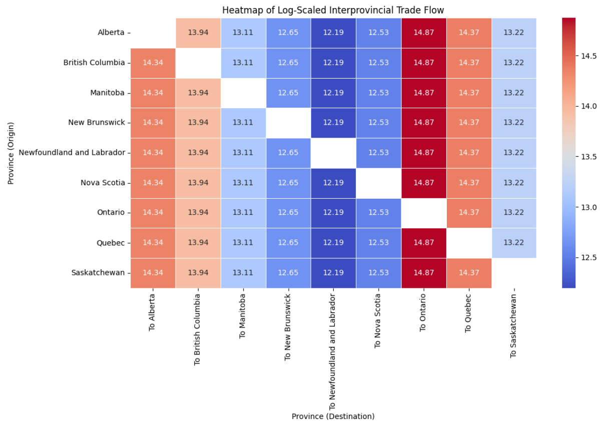

Figure 1: Heatmap of Log Interprovincial Trade Flow

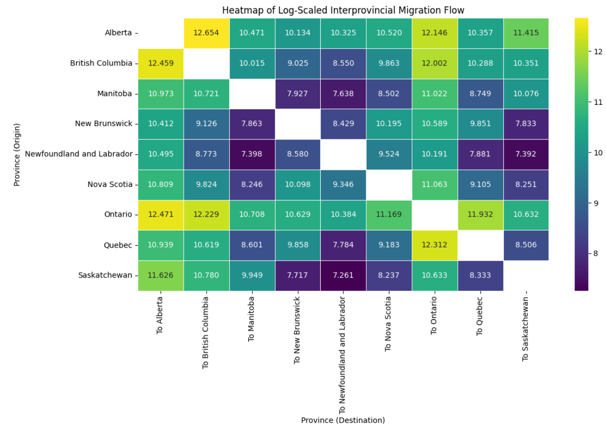

Figure 2: Heatmap of Log Migration Flow

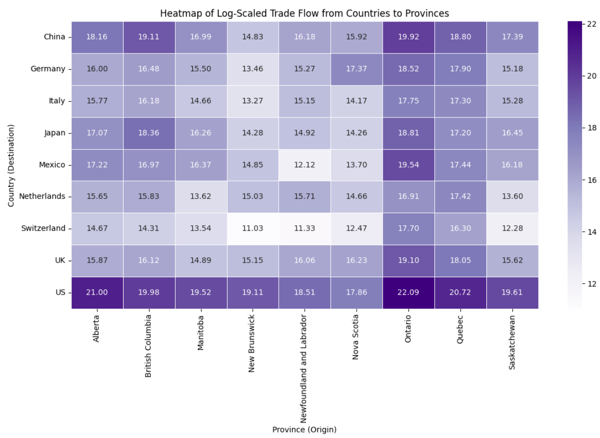

Figure 3: Heatmap of Log International Trade Flow

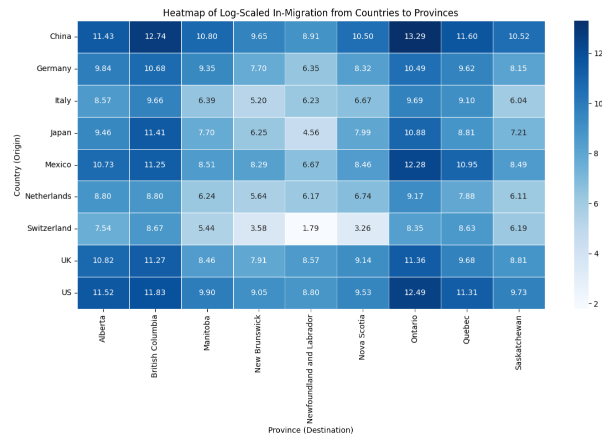

Figure 4: Heatmap of Log International Migration In Flow

Table 5: Granger Non-Causality Test Results for Interprovincial Analysis

Direction of Causality	P-Value
Interprovincial Trade → Interprovincial Migration	0.000
Interprovincial Migration → Interprovincial Trade	0.002

Table 6: Granger Non-Causality Test Results for International Analysis

Direction of Causality	P-Value
International Trade → International Migration	0.000
International Migration → International Trade	0.002

3.5.3 The Effect of Interprovincial Trade on Interprovincial Migration

Tables 7 and 8 show the JI IV estimations for the impact of interprovincial total trade on migration, whereas Tables 9 and 10 represent the JI IV estimations for the impact of interprovincial total exports on migration. Similarly, Tables 11 and 12 show the OI estimations for both, respectively.

Across all JI and OI IV models, we find that interprovincial total trade and total exports affect interprovincial migration positively and this relationship is statistically significant at a 1% level. This finding is consistent across all SSIVs. Other studies find similar results (Campaniello, 2014; Karemera et al., 2000; Akkoyunlu & Siliverstovs, 2009; Collins et al., 1999; Lopez & Schiff, 1998; Ghani et al., 2020).

The effect of interprovincial total trade is slightly strong than the impact of interprovincial total exports. We find our results are consistent across all OI IV models. While estimating the impact of interprovincial total exports on migration, we find a positive relationship between interprovincial migration and interprovincial total imports. All the SSIVs produce very high values of F-statistic and R-squared, satisfying the minimum [$F \geq 10$ (Bound et al., 1995; Stock & Yogo, 2002)] and maximum [$F \geq 50$ (Keane & Neal, 2021)] thresholds of F-statistic values to be a reliable instrument. Moreover, the results of Hansen J Statistics confirm that we cannot reject the null hypothesis of the over-identified models with the combinations of our instrument and conventional instruments. Therefore, we conclude that the over-identifying restrictions are valid.

We find similar results for the effect of interprovincial total trade on migration and the impact of interprovincial total export on migration. For instance, the relationship between interprovincial migration and distance is negative and statistically significant at a 1% level. It is also consistent across all the instruments and the IV models. Distance is the migration cost in the gravity model. Distance is the migration cost in the gravity model. A larger distance (or higher migration costs) between two provinces discourages migration and this is consistent with the existing literature (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020).

An increase in the number of people in the origin province increases interprovincial migration flow positively, whereas an increase in the population of the destination province decreases interprovincial migration flow. These are statistically significant across all SSIVs and IV models. This could be because more people are joining the labour force from the destination province. Therefore, a low inflow of migrants is evident and it may discourage outmigration. Campaniello (2014) show similar results.

If the participation rate of the labour force increases in the destination province, interprovincial migration decreases. More people from the destination province are interested in obtaining jobs within a province and this could discourage the outflow of migrants to the destination province. As the average annual income increases in each province, interprovincial migration also increases. This supports the view of the neoclassical economic model and the finding from Karemera et al. (2000).

Sharing borders between provinces may increase interprovincial migration within Canada and this is statistically significant across all SSIVs. Our results match with the literature (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020).

Migration and GDP of origin show a negative relationships and it is statistically significant at a 1% level. On the other-hand, the relationship between migration and GDP of destination is positive and statistically significant at a 1% level. These results are consistent with Campaniello (2014) and Ghani et al. (2020).

We use weather as one of our control variables for both origin and destination. The results show that migrants prefer to stay in the provinces which have better weather conditions in January and February. It is statistically significant at a 1% level across all SSIVs in JI and OI estimations.

Table 7: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^{1}_{AGS\star AGSR}$	$SSIVP^{2}_{LAGS\star LAGSR}$	$SSIVP^{3}_{ASS\star ASSR}$	$SSIVP^{4}_{LASS\star LASSR}$
		Estimator: PPML		
Interprovincial Total Trade$_{ijt}$	1.762***	1.762***	1.527***	1.658***
	(0.728)	(0.728)	(0.751)	(0.739)
Distance$_{ij}$	-0.465***	-0.465***	-0.465***	-0.465***
	(0.022)	(0.022)	(0.022)	(0.022)
Participation rate$_{it}$	0.032	0.032	0.046*	0.040
	(0.026)	(0.026)	(0.027)	(0.026)
Participation rate$_{jt}$	-4.740***	-4.740***	-4.629***	-5.089***
	(1.327)	(1.327)	(1.340)	(1.324)
GDP$_{it}$	-0.626	-0.626	-0.505	-0.572
	(0.406)	(0.406)	(0.402)	(0.404)
GDP$_{jt}$	3.084***	3.084***	3.399***	3.296**
	(1.095)	(1.095)	(1.154)	(1.124)
Population$_{it}$	1.795***	1.795***	1.766***	1.739**
	(0.348)	(0.348)	(0.334)	(0.337)
Population$_{jt}$	-7.652***	-7.652***	-7.767***	-7.649***
	(1.338)	(1.338)	(1.392)	(1.392)
Average Yearly Income$_{it}$	-0.071	-0.071	-0.097	-0.163
	(0.496)	(0.496)	(0.501)	(0.495)
Average Yearly Income$_{jt}$	0.209	0.209	0.396	0.368
	(0.714)	(0.714)	(0.744)	(0.743)
Border$_{ij}$	0.209***	0.209***	0.214***	0.208***
	(0.035)	(0.035)	(0.035)	(0.035)
Weather$_{it}$	-5.559***	-5.559***	-5.513***	-5.383***
	(1.124)	(1.124)	(1.160)	(1.165)
Weather$_{jt}$	-0.048	-0.048	-0.144	-0.063
	(0.520)	(0.520)	(0.525)	(0.524)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	5332.34	5505.03	5420.32	5350.27
R Squared [FS]	0.9713	0.9715	0.9714	0.9713

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 8: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^5_{AGS}$	$SSIVP^6_{LAGS}$	$SSIVP^7_{ASS}$	$SSIVP^8_{LASS}$
	Estimator: PPML			
Interprovincial Total Trade$_{ijt}$	1.880**	1.880**	1.880**	1.880**
	(0.712)	(0.712)	(0.712)	(0.712)
Distance$_{ij}$	-0.466***	-0.466***	-0.466***	-0.466***
	(0.022)	(0.022)	(0.022)	(0.022)
Participation rate$_{it}$	0.021	0.021	0.021	0.021
	(0.029)	(0.029)	(0.029)	(0.029)
Participation rate$_{jt}$	-3.354**	-3.354**	-3.354**	-3.354**
	(1.349)	(1.349)	(1.349)	(1.349)
GDP$_{it}$	-0.273	-0.273	-0.273	-0.273
	(0.484)	(0.484)	(0.484)	(0.484)
GDP$_{jt}$	2.827***	2.827***	2.827***	2.827***
	(1.131)	(1.131)	(1.131)	(1.131)
Population$_{it}$	1.855***	1.855***	1.855***	1.855***
	(0.378)	(0.378)	(0.378)	(0.378)
Population$_{jt}$	-8.653***	-8.653***	-8.653***	-8.653***
	(1.413)	(1.413)	(1.413)	(1.413)
Average Yearly Income$_{it}$	-0.091	-0.091	-0.091	-0.091
	(0.522)	(0.522)	(0.522)	(0.522)
Average Yearly Income$_{jt}$	0.119	0.119	0.119	0.119
	(0.732)	(0.732)	(0.732)	(0.732)
Border$_{ij}$	0.204***	0.204***	0.204***	0.204***
	(0.036)	(0.036)	(0.036)	(0.036)
Weather$_{it}$	-7.058***	-7.058***	-7.058***	-7.058***
	(1.301)	(1.301)	(1.301)	(1.301)
Weather$_{jt}$	-0.593	-0.593	-0.593	-0.593
	(0.625)	(0.625)	(0.625)	(0.625)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	5331.31	5736.41	5472.86	5855.35
R Squared [FS]	0.9713	0.9719	0.9715	0.9720

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 9: The Impact of Interprovincial Total Exports on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^1_{AGS\star AGSR}$	$SSIVP^2_{LAGS\star LAGSR}$	$SSIVP^3_{ASS\star ASSR}$	$SSIVP^4_{LASS\star LASSR}$
		Estimator: PPML		
Interprovincial Total Exports$_{ijt}$	1.241**	1.930**	1.048**	1.827**
	(0.523)	(0.702)	(0.532)	(0.716)
Distance$_{ij}$	-0.471***	-0.471***	-0.469***	-0.464***
	(0.023)	(0.024)	(0.023)	(0.024)
Participation rate$_{it}$	0.046	0.033	0.055*	0.044
	(0.031)	(0.036)	(0.032)	(0.037)
Participation rate$_{jt}$	-2.611*	-0.074	-3.425**	-0.502
	(1.575)	(2.185)	(1.576)	(2.171)
GDP$_{it}$	0.008	0.144	0.195	0.280
	(0.626)	(0.775)	(0.617)	(0.776)
GDP$_{jt}$	2.439***	2.519***	2.712**	2.230**
	(1.072)	(1.139)	(1.131)	(1.045)
Population$_{it}$	2.336***	2.477***	2.035**	2.400**
	(0.527)	(1.616)	(0.425)	(0.589)
Population$_{jt}$	-9.918***	-12.508***	-10.079***	-11.881***
	(1.505)	(1.892)	(1.559)	(1.898)
Average Yearly Income$_{it}$	-0.199	-0.730	-0.474	-0.354
	(0.738)	(0.656)	(0.576)	(0.651)
Average Yearly Income$_{jt}$	-0.291	-1.107	0.202	-0.216
	(0.849)	(0.848)	(0.888)	(0.259)
Border$_{ij}$	1.936***	-0.185	0.208***	0.185***
	(0.382)	(0.040)	(0.040)	(0.039)
Weather$_{it}$	-8.906***	-11.790***	-8.809***	-11.466***
	(1.380)	(1.380)	(1.408)	(1.284)
Weather$_{jt}$	-1.691*	-0.023	-1.554*	-2.153**
	(0.849)	(1.193)	(0.829)	(1.182)
Interprovincial Total Imports$_{ijt}$	0.814*	0.244	1.048**	0.262
	(0.462)	(0.636)	(0.468)	(0.639)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	1711.09	1566.84	1760.27	1613.56
R Squared [FS]	0.9775	0.9782	0.9703	0.9788

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 10: The Impact of Interprovincial Total Exports on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^{5}_{AGS}$	$SSIVP^{6}_{LAGS}$	$SSIVP^{7}_{ASS}$	$SSIVP^{8}_{LASS}$
	Estimator: PPML			
Interprovincial Total Exports$_{ijt}$	1.242**	1.241**	1.241**	1.242**
	(0.523)	(0.523)	(0.523)	(0.523)
Distance$_{ij}$	-0.471***	-0.471***	-0.471***	-0.471***
	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.046	0.046	0.046	0.046
	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-2.609*	-2.609*	-2.609*	-2.609*
	(1.576)	(1.576)	(1.576)	(1.576)
GDP$_{it}$	0.006	0.006	0.006	0.006
	(0.626)	(0.626)	(0.626)	(0.626)
GDP$_{jt}$	2.436***	2.435***	2.435***	2.435***
	(1.072)	(1.073)	(1.073)	(1.073)
Population$_{it}$	2.336***	2.335***	2.335***	2.335***
	(0.527)	(0.528)	(0.528)	(0.528)
Population$_{jt}$	-9.914***	-9.913***	-9.913***	-9.913***
	(1.505)	(1.506)	(1.506)	(1.506)
Average Yearly Income$_{it}$	-0.197	-0.197	-0.197	-0.197
	(0.738)	(0.738)	(0.738)	(0.738)
Average Yearly Income$_{jt}$	0.296***	0.296***	0.296***	0.296***
	(0.849)	(0.849)	(0.849)	(0.849)
Border$_{ij}$	1.936***	1.936***	1.936***	1.936***
	(0.382)	(0.382)	(0.382)	(0.382)
Weather$_{it}$	-8.905***	-8.905***	-8.905***	-8.905***
	(1.380)	(1.380)	(1.380)	(1.380)
Weather$_{jt}$	-1.689*	-1.689*	-1.689*	-1.689*
	(0.849)	(0.849)	(0.849)	(0.849)
Interprovincial Total Imports$_{ijt}$	0.812*	0.812*	0.812*	0.812*
	(0.462)	(0.462)	(0.462)	(0.462)
Number of Observations	864	864	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	1709.71	1564.49	1716.82	1567.49
R Squared [FS]	0.9775	0.9782	0.9775	0.9782

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 11: The Impact of Interprovincial Total Trade on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration					
Instruments	1 & 2	3 & 4	5 & 6	7 & 8	All
Independent Variables	**Estimator: PPML**				
Interprovincial Total Trade$_{ijt}$	1.885***	1.518***	1.880***	1.880***	1.476**
	(0.711)	(0.738)	(0.712)	(0.712)	(0.745)
Distance$_{ij}$	-0.467***	-0.465***	-0.466***	-0.466***	-0.469***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Participation rate$_{it}$	0.020	0.037	0.021	0.021	0.037
	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
Participation rate$_{jt}$	-3.364**	-4.073**	-3.354**	-3.354**	-4.219**
	(1.346)	(1.339)	(1.349)	(1.349)	(1.327)
GDP$_{it}$	-0.270	-0.049	-0.273	-0.273	-0.035
	(0.484)	(0.473)	(0.484)	(0.484)	(0.478)
GDP$_{jt}$	2.851***	3.376***	2.827**	2.827**	3.562**
	(1.129)	(1.232)	(1.131)	(1.131)	(1.234)
Population$_{it}$	1.850***	1.567***	1.855***	1.855***	1.512**
	(0.376)	(0.380)	(0.378)	(0.378)	(0.296)
Population$_{jt}$	-8.678***	-8.453***	-8.653***	-8.653***	-8.476***
	(1.401)	(1.518)	(1.413)	(1.413)	(1.500)
Average Yearly Income$_{it}$	-0.083	-0.438	-0.091	-0.091	-0.427
	(0.522)	(1.517)	(0.529)	(0.529)	(0.520)
Average Yearly Income$_{jt}$	0.097	0.312	0.119	0.119	0.216
	(0.727)	(0.797)	(0.732)	(0.732)	(0.787)
Border$_{ij}$	0.203***	0.219***	0.204***	0.204***	0.214***
	(0.036)	(0.037)	(0.036)	(0.036)	(0.036)
Weather$_{it}$	-7.053***	-6.457***	-7.059***	-7.059***	-6.295***
	(1.290)	(1.361)	(1.301)	(1.301)	(1.349)
Weather$_{jt}$	-0.589	-0.545	-0.594	-0.594	-0.495
	(0.623)	(0.625)	(0.626)	(0.626)	(0.637)
Number of Observations	792	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	5154.04	5083.23	5394.82	5649.92	4341.05
R Squared [FS]	0.9715	0.9714	0.9719	0.9723	0.9790
Hansen's J Statistics [P Value]	0.9896	0.0800	0.9112	0.9112	0.0514

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 12: The Impact of Interprovincial Total Exports on Interprovincial Migration: OI Results

Dependent variable: Interprovincial Migration					
Instruments	1 & 2	3 & 4	5 & 6	7 & 8	All
Independent Variables			**Estimator: PPML**		
Interprovincial Total Exports$_{ijt}$	1.931**	1.594**	1.242**	1.242**	1.636**
	(0.702)	(0.713)	(0.523)	(0.523)	(0.715)
Distance$_{ij}$	-0.474***	-0.461***	-0.471***	-0.471***	-0.467***
	(0.021)	(0.024)	(0.023)	(0.023)	(0.024)
Participation rate$_{it}$	0.031	0.049	0.046	0.046	0.046
	(0.036)	(0.037)	(0.031)	(0.031)	(0.037)
Participation rate$_{jt}$	-0.011	-1.464	-2.609*	-2.609*	-1.453
	(2.187)	(2.102)	(1.576)	(1.576)	(1.394)
GDP$_{it}$	0.121	0.333	0.006	0.006	0.229
	(0.777)	(0.766)	(0.626)	(0.626)	(0.768)
GDP$_{jt}$	2.514***	2.762**	2.436***	2.436***	2.553**
	(1.139)	(1.161)	(1.073)	(1.073)	(1.170)
Population$_{it}$	2.486***	2.186**	2.335***	2.335***	2.195**
	(0.624)	(0.507)	(0.528)	(0.528)	(0.527)
Population$_{jt}$	-12.603***	-11.889***	-9.913***	-9.913***	-12.095***
	(1.888)	(1.865)	(1.506)	(1.506)	(1.897)
Average Yearly Income$_{it}$	-0.315	-0.494	-0.197	-0.197	-0.616
	(0.657)	(0.651)	(0.738)	(0.738)	(0.648)
Average Yearly Income$_{jt}$	-0.140	0.082	0.296***	0.296***	0.066
	(0.825)	(0.837)	(0.849)	(0.849)	(0.841)
Border$_{ij}$	0.184***	0.199***	1.936***	1.936***	0.199***
	(0.040)	(0.039)	(0.382)	(0.382)	(0.039)
Weather$_{it}$	-11.896***	-10.889***	-8.905***	-8.905***	-11.309***
	(0.291)	(1.265)	(1.380)	(1.380)	(2.099)
Weather$_{jt}$	-1.995*	-1.949*	-1.689*	-1.689*	-1.792*
	(1.199)	(1.143)	(0.849)	(0.849)	(1.147)
Interprovincial Total Imports$_{ijt}$	0.273	0.482	0.812*	0.812*	0.571
	(0.635)	(0.636)	(0.462)	(0.462)	(0.637)
Number of Observations	792	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	1509.07	1569.10	1522.48	1519.70	1176.84
R Squared [FS]	0.9787	0.9795	0.8994	0.9789	0.9800
Hansen's J Statistics [P Value]	0.9667	0.0466	0.8482	0.8482	0.0522

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

3.5.4 The Impact of International Trade on International Migration

Tables 13 and 14 represent the JI IV estimations for the impact of international total trade on migration, whereas Tables 15 and 16 show the JI IV estimations for the impact of international total exports on migration. Similarly, Tables 17 and 18 show the OI estimations for both, respectively.

Provinces trading internationally attract international migration to Canada and this relationship is statistically significant at a 1% level across all SSIVs in JI and OI IV models. Empirical studies (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020) find a similar relationship between international trade and international migration. While estimating the impact of international total exports on migration, this paper finds a positive relationship between international migration and international total imports.The effects of international total trade and total exports are similar across all versions of IV models.

All instruments in this study meet the minimum [$F \geq 10$ (Bound et al., 1995; Stock & Yogo, 2002)] and maximum [$F \geq 50$ (Keane & Neal, 2021)] thresholds of F-statistic values to be a reliable instrument. The Conventional SSIVs which are weighted on the ratios of exports over total exports and exports over total trade perform better compared to Modified SSIVs in OI IV models. Moreover, OI IV model including all the instruments produces the same results compared to OI IV model using the Conventional SSIVs weighted on the ratios of exports over total exports and exports over total trade. The results indicate the explanatory power of exports by comparing the export shares with the overall trade. The empirical performance of the SSIVs from export share verifies Bartik (1991)'s and Broxterman & Larson (2020)'s words on considering export for superiority in the Bartik instruments.

The results of Hansen J Statistics indicate that we cannot reject the null hypothesis for all the over-identified IV models (see, Table 17). Therefore, over identifying restrictions are valid with the combinations of our instruments and conventional instruments.

We further discuss the results for other gravity controls for both analyses. Distance between two regions negatively impacts international migration. Surprisingly, the relationship is not statistically significant. The negative sign of the distance variable matches other empirical studies (Campaniello, 2014; Karemera et al., 2000; Ghani et al., 2020). All instruments produce similar findings for it.

The participation rate of the destination province inversely affects international migrants, and it is statistically significant at a 1% level. The coefficient of the participation rate is very high indicating a bigger impact on international migration to the origin country. On the other-hand, the participation rate of the origin country positively influences migrants and it is statistically significant at a 1% level. Moreover, a higher annual income in the destination province negatively affect international migration and this is statistically significant at a 1% level. The results are opposite to the neoclassical economic model and Karemera et al. (2000). This may be because many Canadian provinces with lower average annual income target international migrants through their provincial nominee program. Therefore, international migrants move to those low income provinces to secure permanent residency. On the contrary, provinces with high annual income have higher cost of living and this high cost of living may discourage migrants to move these high income provinces.

While looking at the results for the causal effect of international total trade on international migration, the GDP per Capita of the origin country and international migration show a positive relationship across all version of IV models. The GDP of the destination province negatively influences international migration to that province. Campaniello (2014) finds similar results. Our estimation for the impact of international total exports on international migration still holds for the positive relationship between GDP Per Capita and migration. However, we find a positive relationship between GDP Per Capita of destination and international migration. This finding matches Ghani et al. (2020).

A lenient immigration policy in origin encourages international migration to that place and this is statistically significant at a 1% level. We further observe negative relationship between migration and strict immigration policy at destination province. The results are the same across all the instruments in all IV models.

Table 13: The Impact of International Total Trade on International Migration: JI Results

Dependent variable: International Migration				
Independent Variables	$SSIVI^1_{AGES \star AGESR}$	$SSIVI^2_{LAGES \star LAGESR}$	$SSIVI^3_{AGTES \star AGTESR}$	$SSIVI^4_{LAGTES \star LAGTESR}$
		Estimator: PPML		
International Total Trade$_{ijt}$	0.461***	0.461***	0.460***	0.459***
	(0.038)	(0.038)	(0.038)	(0.038)
Distance$_{ij}$	-0.094*	-0.094*	-0.096*	-0.095*
	(0.055)	(0.055)	(0.055)	(0.055)
Participation Rate$_{it}$	8.837***	8.837***	8.890***	8.903***
	(3.345)	(3.345)	(3.321)	(3.350)
Participation Rate$_{jt}$	-1.057***	-1.057***	-1.102***	-1.060***
	(0.384)	(0.384)	(0.384)	(0.384)
GDPC$_{it}$	0.350	0.350	0.395	0.353
	(0.384)	(0.384)	(0.383)	(0.384)
GDPC$_{jt}$	-0.541	-0.541	-0.433	-0.532
	(1.654)	(1.654)	(1.647)	(1.653)
Average Annual Income$_{it}$	0.508	0.508	0.413	0.490
	(1.645)	(1.645)	(1.627)	(1.646)
Average Annual Income$_{jt}$	-1.143***	-1.143***	-1.189***	-1.146***
	(0.389)	(0.389)	(0.389)	(0.389)
Immigration Policy$_{it}$	0.555***	0.555***	0.563***	0.555***
	(0.086)	(0.086)	(0.086)	(0.086)
Immigration Policy$_{jt}$	-0.551***	-0.551***	-0.547***	-0.550***
	(0.153)	(0.153)	(0.153)	(0.153)
Number of Observations	1053	970	1053	970
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	662.800	660.350	661.050	658.820
R Squared [FS]	0.900	0.900	0.900	0.900

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 14: The Impact of International Total Trade on International Migration: JI Results

Dependent variable: International Migration				
Independent Variables	$SSIVI^{5}_{AGES}$	$SSIVI^{6}_{LAGES}$	$SSIVI^{7}_{AGTES}$	$SSIVI^{8}_{LAGTES}$
	Estimator: PPML			
International Total Trade$_{ijt}$	0.461***	0.461***	0.461***	0.461***
	(0.038)	(0.038)	(0.038)	(0.038)
Distance$_{ij}$	-0.094*	-0.094*	-0.094*	-0.094*
	(0.055)	(0.055)	(0.055)	(0.055)
Participation Rate$_{it}$	8.717***	8.717***	8.717***	8.717***
	(3.301)	(3.301)	(3.301)	(3.301)
Participation Rate$_{jt}$	-1.095***	-1.095***	-1.095***	-1.095***
	(0.383)	(0.383)	(0.383)	(0.383)
GDPC$_{it}$	0.387	0.387	0.387	0.387
	(0.383)	(0.383)	(0.383)	(0.383)
GDPC$_{jt}$	-0.486	-0.486	-0.486	-0.486
	(1.646)	(1.646)	(1.646)	(1.646)
Average Annual Income$_{it}$	0.487	0.487	0.487	0.487
	(1.626)	(1.626)	(1.626)	(1.626)
Average Annual Income$_{jt}$	-1.182***	-1.182***	-1.182***	-1.182***
	(0.388)	(0.388)	(0.388)	(0.388)
Immigration Policy$_{it}$	0.558***	0.558***	0.558***	0.558***
	(0.086)	(0.086)	(0.086)	(0.086)
Immigration Policy$_{jt}$	-0.546***	-0.546***	-0.546***	-0.546***
	(0.153)	(0.153)	(0.153)	(0.153)
Number of Observations	1053	970	1053	970
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	654.61	654.78	590.83	591.02
R Squared [FS]	0.8990	0.8990	0.8977	0.8978

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 15: The Impact of International Total Exports on International Migration: JI Results

Dependent variable: International Migration				
Independent Variables	$SSIVI^1_{AGES\star AGESR}$	$SSIVI^2_{LAGES\star LAGESR}$	$SSIVI^3_{AGTES\star AGTESR}$	$SSIVI^4_{LAGTES\star LAGTESR}$
		Estimator: PPML		
International Total Exports$_{ijt}$	0.482***	0.478***	0.483***	0.481***
	(0.060)	(0.060)	(0.060)	(0.060)
Distance$_{ij}$	-0.026	-0.022	-0.027	-0.022
	(0.056)	(0.056)	(0.056)	(0.056)
Participation Rate$_{it}$	4.906**	5.057**	5.007**	5.047**
	(2.927)	(2.945)	(2.930)	(2.935)
Participation Rate$_{jt}$	-0.912**	-0.831**	-0.916**	-0.842**
	(0.406)	(0.404)	(0.406)	(0.404)
GDPC$_{it}$	0.283	0.201	0.288	0.214
	(0.410)	(0.408)	(0.410)	(0.408)
GDPC$_{jt}$	1.508	1.268	1.539	1.290
	(1.725)	(1.742)	(1.723)	(1.738)
Average Annual Income$_{it}$	0.301	0.447	0.258	0.435
	(1.539)	(1.570)	(1.537)	(1.566)
Average Annual Income$_{jt}$	-0.971**	-0.889**	-0.975**	-0.900**
	(0.413)	(0.410)	(0.413)	(0.411)
Immigration Policy$_{it}$	0.659***	0.649***	0.659***	0.650***
	(0.098)	(0.098)	(0.098)	(0.098)
Immigration Policy$_{jt}$	-0.305*	-0.313*	-0.307*	-0.310*
	(0.163)	(0.164)	(0.163)	(0.164)
Total Imports$_{ijt}$	0.014	0.016	0.013	0.015
	(0.040)	(0.040)	(0.040)	(0.041)
Number of Observations	1053	970	1053	970
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	376.77	168.72	168.92	168.08
R Squared [FS]	0.9808	0.6964	0.6967	0.8996

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 16: The Impact of International Total Exports on International Migration: JI Results

Dependent variable: International Migration				
Independent Variables	$SSIVI^{5}_{AGES}$	$SSIVI^{6}_{LAGES}$	$SSIVI^{7}_{AGTES}$	$SSIVI^{8}_{LAGTES}$
	Estimator: PPML			
International Total Exports$_{ijt}$	0.482***	0.478***	0.483***	0.481***
	(0.060)	(0.060)	(0.060)	(0.060)
Distance$_{ij}$	-0.026	-0.022	-0.027	-0.022
	(0.056)	(0.056)	(0.056)	(0.056)
Participation Rate$_{it}$	4.906**	5.057**	5.007**	5.047**
	(2.927)	(2.945)	(2.930)	(2.935)
Participation Rate$_{jt}$	-0.912**	-0.831**	-0.916**	-0.842**
	(0.406)	(0.404)	(0.406)	(0.404)
GDPC$_{it}$	0.283	0.201	0.288	0.214
	(0.410)	(0.408)	(0.410)	(0.408)
GDPC$_{jt}$	1.508	1.268	1.539	1.290
	(1.725)	(1.742)	(1.723)	(1.738)
Average Annual Income$_{it}$	0.301	0.447	0.258	0.435
	(1.539)	(1.570)	(1.537)	(1.566)
Average Annual Income$_{jt}$	-0.971**	-0.889**	-0.975**	-0.900**
	(0.413)	(0.410)	(0.413)	(0.411)
Immigration Policy$_{it}$	0.659***	0.649***	0.659***	0.650***
	(0.098)	(0.098)	(0.098)	(0.098)
Immigration Policy$_{jt}$	-0.305*	-0.313*	-0.307*	-0.310*
	(0.163)	(0.164)	(0.163)	(0.164)
Total Imports$_{ijt}$	0.014	0.016	0.013	0.015
	(0.040)	(0.040)	(0.040)	(0.041)
Number of Observations	1053	970	1053	970
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	167.02	167.17	150.93	150.97
R Squared [FS]	0.6943	0.6945	0.6916	0.6916

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 17: The Impact of International Total Trade on International Migration: OI Results

Dependent variable: International Migration					
Instruments	1 & 3	2 & 4	5 & 7	6 & 8	All
Independent Variables	**Estimator: PPML**				
International Total Trade$_{ijt}$	0.461***	0.461***	0.460***	0.459***	0.462***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Distance$_{ij}$	-0.094*	-0.094*	-0.096*	-0.095*	-0.093*
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Participation Rate$_{it}$	8.837***	8.837***	8.890***	8.903***	8.850***
	(3.345)	(3.345)	(3.321)	(3.350)	(3.330)
Participation Rate$_{jt}$	-1.057***	-1.057***	-1.102***	-1.060***	-1.055***
	(0.384)	(0.384)	(0.384)	(0.384)	(0.384)
GDPC$_{it}$	0.350	0.350	0.395	0.353	0.348
	(0.384)	(0.384)	(0.383)	(0.384)	(0.384)
GDPC$_{jt}$	-0.541	-0.541	-0.433	-0.532	-0.540
	(1.654)	(1.654)	(1.647)	(1.653)	(1.654)
Average Annual Income$_{it}$	0.508	0.508	0.413	0.490	0.505
	(1.645)	(1.645)	(1.627)	(1.646)	(1.645)
Average Annual Income$_{jt}$	-1.143***	-1.143***	-1.189***	-1.146***	-1.140***
	(0.389)	(0.389)	(0.389)	(0.389)	(0.389)
Immigration Policy$_{it}$	0.555***	0.555***	0.563***	0.555***	0.560***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Immigration Policy$_{jt}$	-0.551***	-0.551***	-0.547***	-0.550***	-0.552***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
Number of Observations	792	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	618.96	617.27	654.61	549.84	420.12
R Squared [FS]	0.9007	0.9005	0.8990	0.8980	0.9018
Hansen's J Statistics [P Value]	0.0491	0.3138	0.1844	0.1844	0.0803

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 18: The Impact of International Total Exports on International Migration: OI Results

Dependent variable: International Migration					
Instruments	1 & 2	3 & 4	5 & 6	7 & 8	All
Independent Variables			**Estimator: PPML**		
International Total Exports$_{ijt}$	0.458***	0.457***	0.461***	0.461***	0.467***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Distance$_{ij}$	-0.094*	-0.098*	-0.094*	-0.093*	-0.087*
	(0.055)	(0.055)	(0.055)	(0.055)	(0.052)
Participation Rate$_{it}$	9.000***	9.177***	8.717***	8.717***	8.595***
	(3.382)	(3.397)	(3.301)	(3.301)	(3.169)
Participation Rate$_{jt}$	-1.059***	-1.061***	-1.094***	-1.094***	-1.146***
	(0.385)	(0.384)	(0.383)	(0.383)	(0.387)
GDPC$_{it}$	0.352	0.354	0.387	0.387	0.437
	(0.385)	(0.384)	(0.382)	(0.382)	(0.387)
GDPC$_{jt}$	-0.520	-0.472	-0.486	-0.486	-0.581
	(1.656)	(1.654)	(1.646)	(1.646)	(1.670)
Average Annual Income$_{it}$	0.464	0.389	0.487	0.487	0.575
	(1.650)	(1.652)	(1.626)	(1.626)	(1.594)
Average Annual Income$_{jt}$	-1.146***	-1.149***	-1.182***	-1.182***	-1.236***
	(0.390)	(0.390)	(0.388)	(0.388)	(0.393)
Immigration Policy$_{it}$	0.561***	0.561***	0.558***	0.558***	0.568***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Immigration Policy$_{jt}$	-0.551***	-0.551***	-0.546***	-0.546***	-0.548***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
Number of Observations	792	792	792	792	792
Year Fixed Effects	Y	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y	Y
F Statistics [FS]	623.48	617.27	609.62	550.65	403.99
R Squared [FS]	0.901	0.901	0.8994	0.8982	0.9020
Hansen's J Statistics [P Value]	0.2840	0.3036	0.1844	0.1844	0.0803

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

3.5.5 Random Forests & Predictive Strength of SSIVs

Tables 19, 20, 21 and 22 show the results from RF Models for all SSIVs and the results from the first-stage of the instruments. Among all the SSIVs, the usual instruments for interprovincial and international trade have higher values of F-Statistic. Moreover, Modified SSIVs have similar values of F-Statistic.

All the shift instruments for interprovincial trade have almost similar and high values of F-Statistic. Additionally, the shift instruments without and with lags for international trade have similar values of F-Statistics.

Looking at the results from the RF models, we identify the most featured SSIVs to explain trade. In all cases, we can see low values of RMSE, which indicates that the models have good explanatory power. The Conventional SSIVs for interprovincial trade have slightly better predictive strength compared to the lagged SSIVs. The usual shifts and the lagged shifts for interprovincial trade have the same predictive strength.

While comparing the explanatory powers of exports over total trade and exports over total exports, we observe that SSIVs with exports over total trade exhibits higher predictive strength compared to SSIVs with exports over total exports. This difference is evident across all instruments derived from exports over total trade and exports over total exports.

All these SSIVs are very strong instruments for trade. From the results, we can conclude that the instruments derived from exports have higher predictive strength rather than the Conventional SSIVs. Our results provide empirical evidence of the thoughts of Bartik (1991) (see page. 274) and Broxterman & Larson (2020). We find evidence that considering the share of exports over total trade gives more strength to the instrument rather than exports over total exports. This is what Bartik (1991) thought while forming his instruments and Broxterman & Larson (2020) highlight this in their study again.

Table 19: Results from RF & FS OLS - Impact of Interprovincial Total Trade on Migration

	Random Forests		First Stage (OLS)	
Instruments	Predictive Strength	RMSE	F-Statistics	R-Squared
$SSIVP^1_{AGS\star AGSR}$	0.001	3.956	5332.34	0.971
$SSIVP^2_{LAGS\star LAGSR}$	0.001	4.093	5505.03	0.972
$SSIVP^3_{ASS\star ASSR}$	0.0002	1.333	5420.32	0.971
$SSIVP^4_{LASS\star LASSR}$	0.001	2.103	5350.27	0.971
$SSIVP^5_{AGS}$	0.0002	1.497	5331.31	0.971
$SSIVP^6_{LAGS}$	0.001	4.063	5736.41	0.972
$SSIVP^7_{ASS}$	0.00007	1.803	5472.86	0.972
$SSIVP^8_{LASS}$	0.001	1.869	5855.35	0.972

Table 20: Results from RF & FS OLS - Impact of Interprovincial Total Exports on Migration

	Random Forests		First Stage (OLS)	
Instruments	Predictive Strength	RMSE	F-Statistics	R-Squared
$SSIVP^1_{AGS\star AGSR}$	0.001	3.956	1711.09	0.978
$SSIVP^2_{LAGS\star LAGSR}$	0.001	4.093	1566.84	0.978
$SSIVP^3_{ASS\star ASSR}$	0.0002	1.333	1760.27	0.978
$SSIVP^4_{LASS\star LASSR}$	0.001	2.103	1613.56	0.970
$SSIVP^5_{AGS}$	0.0002	1.497	1709.71	0.978
$SSIVP^6_{LAGS}$	0.001	4.063	1546.49	0.978
$SSIVP^7_{ASS}$	0.0001	1.803	1716.82	0.978
$SSIVP^8_{LASS}$	0.001	1.869	1567.49	0.978

Table 21: Results from RF & FS OLS - Impact of International Total Trade on Migration

	Random Forests		First Stage (OLS)	
Instruments	Predictive Strength	RMSE	F-Statistics	R-Squared
$SSIVI^1_{AGES\star AGESR}$	0.090	3.956	662.80	0.900
$SSIVI^2_{LAGES\star LAGESR}$	0.047	4.093	680.35	0.900
$SSIVI^3_{AGTES\star AGTESR}$	0.052	1.333	661.05	0.900
$SSIVI^4_{LAGTES\star LAGTESR}$	0.025	2.103	658.82	0.900
$SSIVI^5_{AGES}$	0.004	1.497	654.61	0.899
$SSIVI^6_{LAGES}$	0.003	4.063	654.78	0.899
$SSIVI^7_{AGTES}$	0.004	1.803	590.83	0.898
$SSIVI^8_{LAGTES}$	0.004	1.869	591.02	0.898

Table 22: Results from RF & FS OLS - Impact of International Total Exports on Migration

	Random Forests		First Stage (OLS)	
Instruments	Predictive Strength	RMSE	F-Statistics	R-Squared
$SSIVI^1_{AGES\star AGESR}$	0.090	3.956	376.77	0.981
$SSIVI^2_{LAGES\star LAGESR}$	0.047	4.093	168.72	0.696
$SSIVI^3_{AGTES\star AGTESR}$	0.052	1.333	168.92	0.697
$SSIVI^4_{LAGTES\star LAGTESR}$	0.025	2.103	168.08	0.900
$SSIVI^5_{AGES}$	0.004	1.497	167.02	0.694
$SSIVI^6_{LAGES}$	0.004	4.063	167.17	0.695
$SSIVI^7_{AGTES}$	0.003	1.803	150.93	0.692
$SSIVI^8_{LAGTES}$	0.004	1.869	150.97	0.692

3.6 Policy Considerations

The results of this study highlight several potential areas for Canadian provinces which are keen on attracting migrants.

[a] Provincial Trade and Provincial Migration: The paper shows that provinces can attract migrants through trade both provincially and internationally. Notably, provincial migration is higher than international migration. Provinces aiming to encourage migration may explore ways to reduce interprovincial trade barriers.

[b] International Trade and International Migration: Our findings indicate that openness to international trade, especially with the top 9 trading countries, may attract international migrants to Canada.

[c] International Migration and Immigration Policy: This study finds that a lenient immigration policy encourages international migration to the Canadian Provinces.

In sum, our findings suggest that both interprovincial and international trade could facilitate interprovincial and international migration. However, further research is necessary to strengthen evidence-based effective policies.

3.7 Conclusion

This study investigates which part of the trade impacts which part of the migration and by how much across Canadian provinces. It finds that interprovincial trade has more influence on migration compared to international trade using the PPML estimator in the gravity model.

We solve the endogeneity problem of trade and migration by deriving 16 SSIVs both for interprovincial trade and international trade. We find that interprovincial trade influences interprovincial migration and it is statistically significant at a 1% level. The results are consistent across all instruments across all IV models. It follows the same process for international trade and finds that international trade affects international migration to Canada. The relationship between trade and migration is statistically significant at a 1% level in both JI and OI IV models.

Our results indicate that the effect of interprovincial total trade of migration is slightly more influential than the impact of interprovincial total exports. On the other-hand, we find similar effects of international total trade and international total exports on international migration to Canada.

Our First-stage estimations show that all the instruments in this study are very strong as these produce very high values of F-statistic and R-squared. In addition, machine learning estimations indicate that the instruments derived from exports have higher predictive strength rather than the Conventional SSIVs.

This study produces new evidence in the literature for the Canadian context and this is the first study which compares the influence of interprovincial trade on interprovincial migration vs the impact of international trade on international migration for the top 9 trading partners.

While deriving 16 instruments and providing empirical evidence in JI and OI IV models, this study introduces new instruments - Modified SSIVs - in the literature. This study further contributes by testing the predictive strength of those instruments using a machine learning technique, the RF Model.

3.8 Robustness

We ensure the reliability and consistency of our estimations with a multi-step robustness checks. Firstly, this paper replaces four variables such as GDPs and population sizes of both origin and destination with their two GDP per capita for interprovincial analysis in both the first-stage and the second-stage regressions. We find similar positive and statistically significant results (check our results, Tables 1, 2, 3 and 4)

Our approach to examining the performance of all SSIVs employing JI and OI IV models proves that all the results in this study are robust. For example, we use different instruments such as lag shocks and Modified SSIVs to establish the causal relationship between trade and migration. Our results are robust across all instruments in all IV models.

We further apply the Two-Stage Least Squares [2SLS] estimator as an alternative to the PPML estimator within the gravity model to check whether our results remain the same. First, we log linearize the gravity equation and estimate the models using the 2SLS estimator. While examining the results for the casual effects of interprovincial total trade on migration, we found similar results with 2SLS estimator (check, Table 5).

Lastly, this study considers the top 9 trading partners of Canada and China as one of these for international analysis. There could be speculation that the presence of China is the reason for this causal effect of international trade on international migration to Canada. Therefore, we drop China from the dataset to check its robustness. We still get the same positive and significant results for international analysis (check, Table 6). Thus, we can claim that our results are robust.

3.9 Future Research

While our research demonstrates a positive and significant effect of trade on migration, our future research will focus on industry specific studies based on our findings. For example, we will investigate whether provinces with a greater concentration of the fastest growing industries (such as technology) demand for skilled labor and consequently attract skilled migrants.

Furthermore, a firm-level study can examine how trade expansions across various industries influence labor mobility within and across provinces. Also, our future work will leverage big data sources to capture trade and migration dynamics in real-time.

Using platforms such as Linkedin, Twitter or Indeed, researchers can reveal emerging trends in job posting volumes, skill demand, and workforce mobility more quickly than traditional surveys and administrative datasets. We plan to employ Machine Learning techniques to track job applications based on geographical locations and enhance the precision of policy responses.

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Chapter A

Appendix: Additional Results for Chapter 3

Table 1: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^1_{AGS\star AGSR}$	$SSIVP^2_{LAGS\star LAGSR}$	$SSIVP^3_{ASS\star ASSR}$	$SSIVP^4_{LASS\star LASSR}$
		Estimator: PPML		
Interprovincial Total Trade$_{ijt}$	1.535***	1.546***	1.514***	1.559***
	(0.379)	(0.379)	(0.389)	(0.377)
Distance$_{ij}$	-0.441***	-0.443***	-0.437***	-0.440***
	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.046	0.041	0.049	0.042
	(0.030)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.770***	-7.867***	-7.746***	-7.847***
	(1.387)	(1.394)	(1.400)	(1.392)
GDPC$_{it}$	-0.569***	-0.571***	-0.486***	-0.566***
	(0.193)	(0.193)	(0.194)	(0.193)
GDPC$_{jt}$	-0.158*	-0.157*	-0.179**	-0.163*
	(0.084)	(0.084)	(0.083)	(0.084)
Average Yearly Income$_{it}$	-0.329	-0.325	-0.399	-0.337
	(0.499)	(0.499)	(0.506)	(0.499)
Average Yearly Income$_{jt}$	3.057***	3.041***	3.264***	3.027***
	(0.486)	(0.489)	(0.481)	(0.487)
Border$_{ij}$	0.280***	0.278***	0.298***	0.281***
	(0.044)	(0.044)	(0.043)	(0.043)
Weather$_{it}$	0.240	0.242	0.273	0.266
	(0.408)	(0.408)	(0.418)	(0.408)
Weather$_{jt}$	-1.628***	-1.647***	-1.635***	-1.648***
	(0.127)	(0.131)	(0.129)	(0.131)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	251.35	248.05	334.30	324.91
R Squared [FS]	0.8234	0.8214	0.8646	0.8577

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 2: The Impact of Interprovincial Total Trade on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^5_{AGS}$	$SSIVP^6_{LAGS}$	$SSIVP^7_{ASS}$	$SSIVP^8_{LASS}$
	Estimator: PPML			
Interprovincial Total Trade$_{ijt}$	1.556***	1.556***	1.556***	1.556***
	(0.379)	(0.379)	(0.379)	(0.379)
Distance$_{ij}$	-0.440***	-0.440***	-0.440***	-0.440***
	(0.023)	(0.023)	(0.023)	(0.023)
Participation rate$_{it}$	0.042	0.042	0.042	0.042
	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.850***	-7.850***	-7.850***	-7.850***
	(1.391)	(1.391)	(1.391)	(1.391)
GDPC$_{it}$	-0.565***	-0.565***	-0.565***	-0.565***
	(0.193)	(0.193)	(0.193)	(0.193)
GDPC$_{jt}$	-0.163*	-0.163*	-0.163*	-0.163*
	(0.084)	(0.084)	(0.084)	(0.084)
Average Yearly Income$_{it}$	-0.339	-0.339	-0.339	-0.339
	(0.499)	(0.499)	(0.499)	(0.499)
Average Yearly Income$_{jt}$	3.030***	3.030***	3.030***	3.030***
	(0.488)	(0.488)	(0.488)	(0.488)
Border$_{ij}$	0.281***	0.281***	0.281***	0.281***
	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	0.263	0.263	0.263	0.263
	(0.409)	(0.409)	(0.409)	(0.409)
Weather$_{jt}$	-1.648***	-1.648***	-1.648***	-1.648***
	(0.131)	(0.131)	(0.131)	(0.131)
Number of Observations	864	792	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	248.74	245.97	246.26	232.25
R Squared [FS]	0.8218	0.8202	0.8204	0.8260

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 3: The Impact of Interprovincial Total Exports on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^1_{AGS\star AGSR}$	$SSIVP^2_{LAGS\star LAGSR}$	$SSIVP^3_{ASS\star ASSR}$	$SSIVP^4_{LASS\star LASSR}$
		Estimator: PPML		
Interprovincial Total Exports$_{ijt}$	0.811**	0.775**	0.834**	0.833**
	(0.441)	(0.431)	(0.432)	(0.432)
Distance$_{ij}$	-0.442***	-0.438***	-0.440***	-0.440***
	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.040	0.052*	0.041	0.041
	(0.030)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.572***	-7.450***	-7.544***	-7.544***
	(1.307)	(1.343)	(1.300)	(1.300)
GDPC$_{it}$	-0.559***	-0.476***	-0.553***	-0.553***
	(0.194)	(0.193)	(0.193)	(0.193)
GDPC$_{jt}$	-0.158*	-0.178**	-0.165*	-0.165*
	(0.084)	(0.083)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.327	-0.443	-0.341	-0.341
	(0.491)	(0.502)	(0.490)	(0.490)
Average Yearly Income$_{jt}$	3.168***	3.282***	3.167***	3.167***
	(0.534)	(0.522)	(0.532)	(0.532)
Border$_{ij}$	0.278***	0.296***	0.281***	0.281***
	(0.044)	(0.043)	(0.044)	(0.044)
Weather$_{it}$	0.219	0.035	0.251	0.251
	(0.415)	(0.408)	(0.414)	(0.414)
Weather$_{jt}$	-1.647***	-1.632***	-1.649***	-1.649***
	(0.132)	(0.130)	(0.131)	(0.131)
Interprovincial Total Imports$_{ijt}$	0.637*	0.756**	0.626*	0.626*
	(0.363)	(0.367)	(0.354)	(0.354)
Number of Observations	864	792	864	792
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	1599.89	1604.46	1633.43	1602.33
R Squared [FS]	0.9697	0.8698	0.9703	0.9697

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 4: The Impact of Interprovincial Total Exports on Interprovincial Migration: JI Results

Dependent variable: Interprovincial Migration				
Independent Variables	$SSIVP^{5}_{AGS}$	$SSIVP^{6}_{LAGS}$	$SSIVP^{7}_{ASS}$	$SSIVP^{8}_{LASS}$
	Estimator: PPML			
Interprovincial Total Exports$_{ijt}$	0.829***	0.631**	0.828**	0.828**
	(0.442)	(0.365)	(0.443)	(0.442)
Distance$_{ij}$	-0.440***	-0.440***	-0.440***	-0.440***
	(0.024)	(0.024)	(0.024)	(0.024)
Participation rate$_{it}$	0.042	0.041	0.042	0.042
	(0.031)	(0.031)	(0.031)	(0.031)
Participation rate$_{jt}$	-7.554***	-7.554***	-7.554***	-7.554***
	(1.309)	(1.309)	(1.309)	(1.309)
GDPC$_{it}$	-0.552***	-0.553***	-0.552***	-0.552***
	(0.194)	(0.193)	(0.194)	(0.194)
GDPC$_{jt}$	-0.164*	-0.165*	-0.164*	-0.164*
	(0.085)	(0.085)	(0.085)	(0.085)
Average Yearly Income$_{it}$	-0.341	-0.341	-0.341	-0.341
	(0.491)	(0.490)	(0.491)	(0.491)
Average Yearly Income$_{jt}$	3.166***	3.166***	3.165***	3.165***
	(0.533)	(0.533)	(0.533)	(0.533)
Border$_{ij}$	0.281***	0.281***	0.281***	0.281***
	(0.044)	(0.044)	(0.044)	(0.044)
Weather$_{it}$	0.249	0.249	0.249	0.249
	(0.417)	(0.417)	(0.417)	(0.417)
Weather$_{jt}$	-1.649***	-1.649***	-1.649***	-1.649***
	(0.131)	(0.131)	(0.131)	(0.131)
Interprovincial Total Imports$_{ijt}$	0.631*	0.631*	0.631*	0.631*
	(0.364)	(0.364)	(0.364)	(0.364)
Number of Observations	864	792	864	864
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	1262.58	1155.34	1262.58	1262.58
R Squared [FS]	0.9688	0.96971	0.9695	0.9688

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Table 5: The Impact of International Total Trade on International Migration: JI Results

Dependent variable: International Migration (log)

Independent Variables	$SSIVI^1_{AGES \star AGESR}$	$SSIVI^2_{LAGES \star LAGESR}$	$SSIVI^3_{AGTES \star AGTESR}$	$SSIVI^4_{LAGTES \star LAGTESR}$
		Estimator: 2SLS		
International Total Trade$_{ijt}$	0.061***	0.061***	0.061***	0.061***
	(0.005)	(0.005)	(0.005)	(0.005)
Distance$_{ij}$	-0.063***	-0.062***	-0.063***	-0.062***
	(0.011)	(0.011)	(0.011)	(0.011)
Participation Rate$_{it}$	0.061	0.077	0.061	0.079
	(0.478)	(0.478)	(0.478)	(0.478)
Participation Rate$_{jt}$	-0.012	-0.009	-0.012	-0.009
	(0.067)	(0.067)	(0.067)	(0.067)
GDPC$_{it}$	-0.118*	-0.120*	-0.117*	-0.120*
	(0.068)	(0.068)	(0.068)	(0.068)
GDPC$_{jt}$	-0.351	-0.350	-0.349	-0.350
	(0.275)	(0.275)	(0.275)	(0.275)
Average Annual Income$_{it}$	0.525**	0.528**	0.523**	0.527**
	(0.216)	(0.216)	(0.216)	(0.216)
Average Annual Income$_{jt}$	-0.045	-0.042	-0.045	-0.042
	(0.068)	(0.068)	(0.068)	(0.068)
Immigration Policy$_{it}$	0.157***	0.156***	0.157***	0.156***
	(0.016)	(0.016)	(0.016)	(0.016)
Immigration Policy$_{jt}$	-0.202***	-0.200***	-0.202***	-0.200***
	(0.035)	(0.034)	(0.035)	(0.034)
Number of Observations	1053	972	1053	972
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	662.800	660.350	661.050	658.820
R Squared [FS]	0.900	0.900	0.900	0.900

*Note: ***P<.01, **P<.05, *P<.10*

Results Excluding China

Table 6: The Impact of International Total Trade on International Migration: JI Results

Dependent variable: International Migration				
Independent Variables	$SSIVI^1_{AGES*AGESR}$	$SSIVI^2_{LAGES*LAGESR}$	$SSIVI^3_{AGTES*AGTESR}$	$SSIVI^4_{LAGTES*LAGTESR}$
	Estimator: PPML			
International Total Trade$_{ijt}$	0.389***	0.389***	0.389***	0.389***
	(0.024)	(0.024)	(0.024)	(0.024)
Distance$_{ij}$	-0.157***	-0.158***	-0.158***	-0.158***
	(0.032)	(0.032)	(0.032)	(0.032)
Participation Rate$_{it}$	4.671**	4.657**	4.662**	4.653**
	(1.878)	(1.878)	(1.879)	(1.879)
Participation Rate$_{jt}$	1.100***	1.107***	1.101***	1.105***
	(0.333)	(0.334)	(0.333)	(0.334)
GDPC$_{it}$	-2.140***	-2.145***	-2.140***	-2.143***
	(0.343)	(0.344)	(0.342)	(0.344)
GDPC$_{jt}$	0.729	0.718	0.726	0.715
	(1.213)	(1.212)	(1.213)	(1.211)
Average Annual Income$_{it}$	1.377	1.392	1.380	1.393
	(0.923)	(0.923)	(0.923)	(0.923)
Average Annual Income$_{jt}$	-0.950**	-0.956**	-0.950**	-0.955**
	(0.336)	(0.337)	(0.336)	(0.337)
Immigration Policy$_{it}$	1.075***	1.076***	1.075***	1.076***
	(0.079)	(0.079)	(0.079)	(0.079)
Immigration Policy$_{jt}$	-0.951***	-0.952***	-0.952***	-0.952***
	(0.157)	(0.157)	(0.157)	(0.157)
Number of Observations	934	934	934	934
Year Fixed Effects	Y	Y	Y	Y
Origin & Destination Fixed Effects	Y	Y	Y	Y
F Statistics [FS]	687.01	684.94	686.07	684.08
R Squared [FS]	0.907	0.906	0.907	0.906

*Note: Values in parentheses are robust standard errors; ***P<.01, **P<.05, *P<.10*

Conclusion

This dissertation contributes significantly to the literature on trade, migration and regional economics methodologically and empirically. Chapter 1 introduces an SSIV Search Method with 58 SSIVs and demonstrates that SSIVs with lagged disaggregate shocks and shares outperform literature-suggested SSIVs in empirical validity, predictive accuracy, and bias reduction. It further produces new empirical evidence on the causal effect of services trade on goods trade, complementing the firm-level findings.

Chapter 2 presents the first comprehensive analysis of trade (in aggregate and disaggregate) and migration in one framework. It employs 80 SSIVs for interprovincial trade and 4 SSIVs for interprovincial migration. While the findings reveal the substantial impact of trade on migration, they provide new insights into the literature by identifying the strong influence of services trade on migration.

Chapter 3 compares the influence of interprovincial trade on interprovincial migration vs the impact of international trade on international migration. It introduces new instruments for robust estimations. These results indicate that interprovincial trade substantially attracts migrants than international trade.

This dissertation provides a practical prescription with three empirical examples for applied researchers to address endogeneity in provincial and similar regional settings. The key findings indicate that an increase in services trade leads to a substantial increase in goods trade, demonstrating interconnection between trade sectors. Additionally, reducing overall trade barriers, especially services trade, can facilitate migration faster across Canadian provinces. Our results further show that provinces can increase migration through trading interprovincially and internationally. Provinces aiming to attract more international migration should strengthen trade relationships with key trading partners. This research underscores the critical role of trade liberalization as one of the tools to increase labour mobility and economic integration.

By unmasking the complex interplay between trade and migration at the Canadian provincial level, this dissertation lays a strong foundation for robust estimation to support evidence-based effective policies.