

Determinants of Internal Migration in Thailand: Evidence from Mobile Phone Data

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This study uses high-frequency, geographically detailed mobile phone location data to estimate origin–destination migration flows—information that is not available in official statistics—enabling a high-resolution analysis of internal migration in Thailand and its sectoral drivers. A gravity-type model incorporating push and pull factors, together with a dynamic fixed-effects panel regression, is employed. The findings confirm that the migration–urbanization nexus persists and continues to shape Thailand’s structural transformation. Differences in earning opportunities are crucial, particularly in attracting workers from the agriculture sector to the manufacturing sector. The analysis also highlights the role of agriculture as a shelter sector, accommodating in-migration during the coronavirus disease pandemic. The reversal of migration patterns during the pandemic was driven by sharp declines in earning opportunities in the service and manufacturing sectors

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rather than by incentives originating from agriculture. Beyond income factors, digital technology plays an important role in attracting in-migration, except in manufacturing, where a potential labor replacement effect of technology is observed.

Keywords: internal migration, mobile phone data, Thailand

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I. Introduction

Internal migration is widely recognized as the key mechanism driving industrialization and structural transformation—the process through which an economy changes its sectoral composition—in developing countries (Hasan and Molato 2019, Sen 2019, Gibson 2024). This process is generally associated with the creation of better-paid employment opportunities relative to subsistence agriculture, enhanced productivity and economic growth, and improved social mobility. Although the undesirable impacts of internal migration—particularly economic divergence and disparities linked to internal labor mobility—have been widely discussed, and numerous policy initiatives have been implemented in developing countries to limit internal movements and narrow economic disparities, evidence suggests that internal migration remains substantial across most developing economies (Lucas 2016, Hasan and Molato 2019). Given the scale and persistence of these flows, a deeper understanding of their determinants is crucial for effective socioeconomic planning, including industrial policy, infrastructure development, and public service provision.

The key objective of this paper is to analyze the determinants of interprovincial internal migration using Thailand as an in-depth case study. Specifically, it investigates how relative earning opportunities across the agriculture, manufacturing, and service sectors, alongside provincial-level worker characteristics and the country's rapid digital transformation, shaped migration decision during 2019–2021. A gravity-type model incorporating push and pull factors and a dynamic panel regression model with fixed effects are employed for the analysis.

The novelty of this study lies in three main aspects. First, this study contributes to the migration and structural transformation literature by jointly examining how sectoral earning differentials, worker characteristics, and digital technology shape internal migration decisions. While existing literature on structural transformation and sectoral employment shifts is substantial (McMillan, Rodrik, and Verduzco-Gallo 2014; Haraguchi, Cheng, and Smeets 2017; Anderson and Ponnusamy 2019; Hasan

and Molato 2019; Sen 2019; Pritadrajati et al. 2024), relatively few studies integrate these three dimensions to explain migration behavior. In the Thai context, research has focused predominantly on migration outcomes (e.g., education, cognitive development among school-age children, and health) rather than its determinants. The few studies that analyzed determinants tend to emphasize worker characteristics and absolute individual returns, while overlooking three critical aspects: (i) relative returns across sectors, (ii) the potentially different impacts of shocks to sectoral opportunities, and (iii) the role of digital technology in reducing frictions (Thongluang 1990; Junge, Revilla Diez, and Schätzl 2015; Phujampa and Ayuwat 2025).

Second, this study provides an in-depth empirical case study of Thailand to show how internal migration responds to changing economic opportunities and digital connectivity in a middle-income economy undergoing structural transformation. Thailand presents a suitable case study as internal migration continues to play a significant role in its structural transformation. Although the share of internal migrants in the total population has declined slightly over the past decade, attributing to government efforts to decentralize economic growth, as well as declining birth rates, internal migration remained pronounced during the coronavirus disease (COVID-19) period and has gradually increased in the postpandemic phase. In addition, approximately 70% of all migrants are engaged in employment, primarily in the manufacturing and service sectors, while the remaining migrants are involved in other activities such as education and health-related migration.¹ Given the substantial share of migrants participating in employment even during the COVID-19 period, examining the interplay of economic incentives and digital technology provide insights for policies aimed at advancing socioeconomic development in Thailand, with potential lessons for other countries at similar developmental stages.

Third, this study employs a novel data source to overcome key limitations in traditional migration research. While internal migration is typically analyzed using censuses or surveys—which are hampered by infrequent sampling, limited coverage, and response biases—this work utilizes high-frequency global positioning system (GPS) data from mobile phones, which have received much more attention as an alternative data source in recent decades (see, for example, Gibson and McKenzie 2007, Gibson et al. 2021, Fenz et al. 2024), to estimate the origin–destination patterns. This approach is particularly advantageous during crises like the COVID-19 pandemic when traditional data collection was disrupted. GPS-derived digital trace data provide

¹Over 30% of these workers are involved in remittance activities, which play a significant role in driving economic transformation and development (National Statistical Office of Thailand 2025).

continuous, unbiased records of movement, allowing for precise, real-time analysis of migration flows at flexible temporal and spatial resolutions.²

The rest of this paper is organized as follows. Section II reviews the literature to lay the groundwork for the empirical analysis. Section III presents the patterns of internal migration derived from the GPS data. Section IV outlines the empirical model, variable definitions, and data sources. Section V discusses the results. Finally, section VI concludes with policy implications and recommendations.

II. Literature Survey

Understanding internal migration flows is crucial for improving a country's socioeconomic development. This section reviews the existing literature across two interconnected areas to lay the groundwork for the empirical analysis: (i) determinants of internal migration, and (ii) data sources for migration analysis.

A. Determinants of Internal Migration

A substantial body of literature examines structural transformation and its close relationship with internal migration (McMillan, Rodrik, and Verduzco-Gallo 2014; Haraguchi, Cheng, and Smeets 2017; Anderson and Ponnusamy 2019; Hasan and Molato 2019; Sen 2019; Pritadrajati et al. 2024). These studies examine structural transformation from various lenses, including shifts in production, employment, product diversification and complexity, urbanization, and wage dynamics (Asian Development Bank [ADB] 2013, Hasan and Molato 2019). Sen (2019) synthesizes three core stylized facts directly involving internal migration: (i) the declining share of agricultural employment, (ii) the concave trajectory of manufacturing employment, and (iii) the rise of the service sector. These patterns inherently drive population movements across sectors and locations.

Conventional theory attributes these movements to productivity and income differentials across sectors. However, Rodrik (2016) and Sen (2019) document a

²Digital trace data can be revealed through other sources such as geo-located social media data such as Facebook, Twitter, Skype, or LinkedIn; repeated logins to the same website or email address; online search data; and bibliometric data (see, for example, Fiorio et al. 2017, Chi et al. 2020, Martin et al. 2020). However, concerns over reliability, scope, and detail regarding the location of this digital trace data seem to be more problematic than that of mobile phones (Tjaden 2021). Regarding digital trace data through mobile phones, GPS devices can record travel time and the coordinates of locations every second. As traditional calls become less frequent with the shift to app-based communication, the use of satellite-based GPS has become more accurate in revealing mobile-related activities than call detail records.

contrasting pattern in many underdeveloped economies, where workers move from agriculture into nonbusiness services despite comparable productivity. This suggests that productivity growth and income effects alone may be insufficient to explain internal migration and structural change in underdeveloped countries, indicating other factors likely play a more significant role.

A growing body of research—from both developed and developing countries—examines the determinants of internal migration beyond sectoral productivity by incorporating nonpecuniary factors such as public goods, infrastructure, social networks, and place attachment (Williams and Jobes 1990; Johnson and Rasker 1995; Percy, Hawkins, and Maier 1995; Gustafson 2001; Howell-Moroney 2008; Hotchkiss and Rupasingha 2021). For example, studies from the Republic of Korea and the United States show that perceptions of local public goods—such as education, public services, amenities, and health care—are critical determinants of residential choice even when economic opportunities are limited (Howe and Huskey 2022, Choi 2024).

Social capital and regional development also play significant roles. Research in the United States indicates that individuals are reluctant to move to areas that lack social capital, which is often linked to better public services and economic growth (Hotchkiss and Rupasingha 2021). In the Thai context, studies highlight how return migration responds to regional improvements beyond economic aspects, especially social and institutional environments (Junge, Revilla Diez, and Schätzl 2015). Phujampa and Ayuwat (2025) reveal that individual characteristics such as age; gender; and, particularly, education shape youth migration.

B. Data Sources for Migration Analysis: From Surveys to Digital Traces

Most empirical studies on internal migration, including those on Thailand, have relied on traditional survey-based sources such as censuses and labor force surveys. While valuable, these data face well-documented limitations: infrequent sampling, limited coverage, and response biases. These limitations become particularly pronounced during crisis periods, such as the COVID-19 pandemic, when survey disruption leads to data gaps.

These data constraints matter for development research because they hinder the ability to track labor reallocation during structural transformation and to understand how workers respond to economic shocks. Recent research has focused on alternative data sources (e.g., Gibson and McKenzie 2007, Gibson et al. 2021, Fenz et al. 2024), including GPS data from mobile phone systems, offering an opportunity to address these gaps. Such data have been widely used to track population movements, estimate

migration flows, and analyze dynamic population densities (Blumenstock 2012, Wesolowski et al. 2013, Ruktanonchai et al. 2016, Wesolowski et al. 2017, Lai et al. 2019). By providing high-frequency, geographically detailed observations of population movements, such data enable researchers to examine migration dynamics at temporal and spatial resolution that is not possible with traditional surveys.

Application spans diverse contexts. Ruktanonchai et al. (2016) demonstrate that mobile phone data can predict short-term movement patterns relevant to malaria transmission in Haiti, validating findings against census records. Wesolowski et al. (2017) quantify seasonal mobility variations in Kenya, Namibia, and Pakistan, showing holiday-related travel significantly alters movement patterns and influences infectious disease spread. Lai et al. (2019) further show that mobile phone data can precisely predict migration flows in Namibia, matching census-derived statistics using linear models based on call detail records and gravity-type spatial interaction models. Meanwhile, gravity-type models have been applied extensively to estimate flows based on populations and distance (Garcia et al. 2015; Wesolowski et al. 2015; Ruktanonchai et al. 2016; Vobruba, Körner, and Breitenecker 2016).

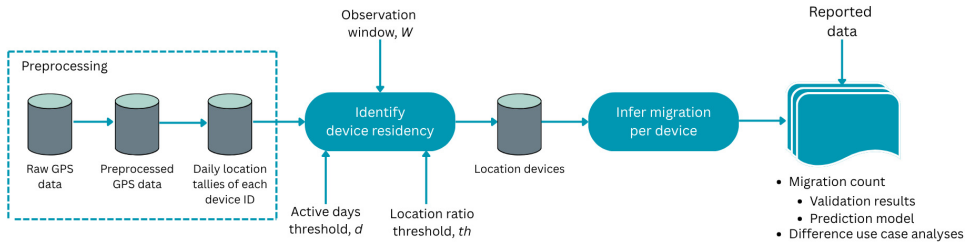
However, mobile phone data are not without limitations. They reveal time and location but lack individual attributes such as identity, travel mode, purpose, and group composition. Thus, this study combines mobile phone data with conventional surveys to provide a more comprehensive analysis of migration patterns.

Overall, the existing empirical literature confirms that migration is a multidimensional decision, while there is limited evidence on the determinants of internal migration in Thailand. The existing studies on Thailand have focused primarily on individual characteristics and absolute returns, largely overlooking two critical contemporary drivers: relative earning differentials across sectors and the enabling or disruptive role of digital technology. To date, no empirical study has employed mobile phone GPS data, which can capture migration patterns during crisis or pandemic periods more accurately than traditional survey-based data sources.

III. GPS Mobile Phone Data and Internal Migration in Thailand

This study utilizes mobile GPS location data from January 2019 to June 2021, comprising approximately 35 million unique devices, to analyze the determinants of internal migration in Thailand. The longitudinal nature of these data allows for the examination of both common migration drivers and the exogenous shock of the COVID-19 pandemic. To isolate domestic migration, devices with a lifespan of less than 60 days, which is a strong indicator of tourist activity, were filtered out.

Figure 1. Pipeline for Estimating Migration Count



GPS = global positioning system, ID = identification.

Notes: Internal migration estimates were derived from mobile GPS data. After deduplication and timestamp standardization, a device's province of residence was assigned as the location recording more than 60% of nighttime pings within a 6-month observation window. A change in this residence between consecutive months was classified as an internal migration event.

Source: Authors' illustration.

The remaining data were preprocessed by removing all duplicate records (i.e., those with the same device identification, location, and timestamp). The complete migration estimation pipeline is summarized in Figure 1.

Following the precedent of prior studies (e.g., Wesolowski et al. 2017, Lai et al. 2019), a device's provincial residence was defined as the location accounting for more than 60% of its nighttime pings over a 6-month observation window. A change in this inferred residence between two consecutive periods was classified as an internal migration event.

To capture pandemic-related dynamics, mobile GPS data was divided into four subperiods to coincide with COVID-19 waves and their corresponding lockdowns in Thailand (Table 1).³ Migration flows for each phase were identified by comparing residences between consecutive time subperiods. For instance, a residence change between subperiods I and II identifies a migrant during the pre-COVID-19 baseline; a change between subperiods II and III captures migration during the first wave and the

³There were four waves of COVID-19 contagion in Thailand: (i) 15 March–30 April 2020, (ii) 15 December 2020–15 March 2021, (iii) April–December 2021, and (iv) January 2022 onward. By the end of September 2022, COVID-19 had been removed from the list of dangerous communicable diseases. The most severe subperiod was the third, which began around mid-April 2021 and lasted for 9 months. Like other countries, Thailand imposed border control measures together with social distancing measures to suppress the virus' spread. The first nationwide lockdown was in April 2020 to combat the first wave (15 March–30 April 2020). The full-scale national lockdown, together with curfews and stay-home policies, were introduced. For the second wave, a partial lockdown at its epicenter (Samut Sakhon province) was introduced. For the third wave, the government was slow to impose a nationwide lockdown, and the full-scale lockdown was imposed on June 2021. For more information, see Kohpaiboon, Jongwanich, and Boonyarat (2025).

Table 1. Subperiods for Internal Migration Analysis

Subperiods	Months	Reflection of Internal Movements Between the Two Subperiods
I	Jan 2019–Jun 2019	A comparison of data between January–June 2019 and July–December 2019 reflects the usual pattern of internal movements.
	Jul 2019–Dec 2019	
II	Jan 2020–Jun 2020	A comparison of data between January–June 2020 and July–December 2019 reflects internal migration during the first wave of COVID-19 spread and the first lockdown period.
	Jul 2020–Dec 2020	
III	Jan 2021–Jun 2021	A comparison of data between January–June 2021 and July–December 2020 reflects internal migration during the second and third waves and lockdown periods.
	Jul 2021–Dec 2021	

COVID-19 = coronavirus disease.

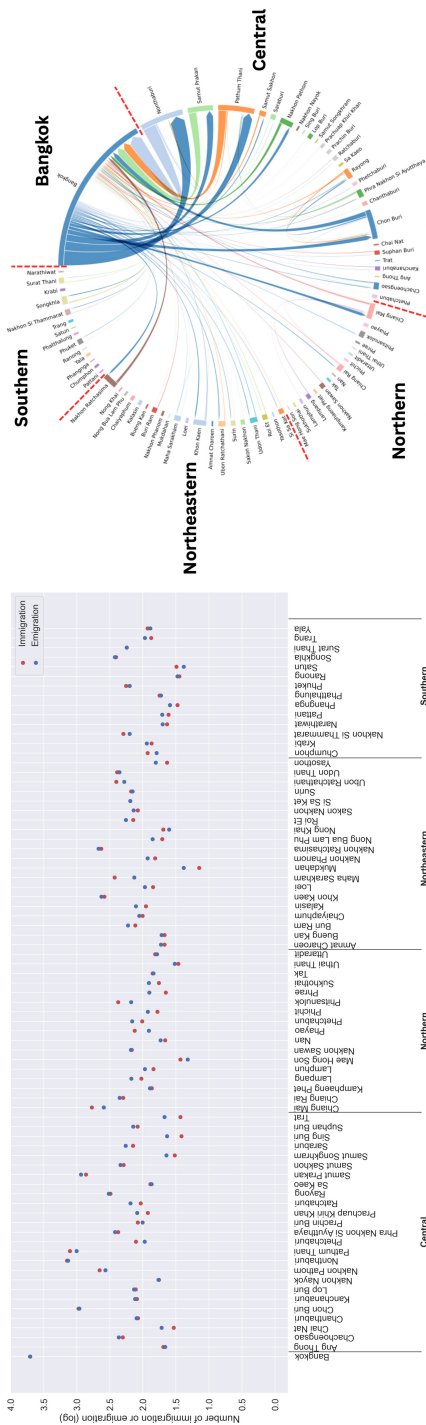
Source: Authors' compilation.

national lockdown. Validation of GPS data against official survey data is included in Appendix 1.

Using GPS data from the four subperiods, Figure 2 illustrates pre-COVID-19 internal migration patterns. Labor mobility was dominated by Bangkok, which attracted migrants from all regions, while the central region—particularly provinces with established manufacturing hubs such as Chonburi, Nakhon Pathom, Pathum Thani, and Prachinburi—served as a major destination for Bangkok out-migrants. In the northeast, migration was concentrated in Khon Kaen and Nakhon Ratchasima, with net emigration elsewhere except in higher-income provinces (Maha Sarakham, Ubon Ratchathani, Udon Thani, and Nong Khai). In the north, Chiang Mai and Phitsanulok emerged as net in-migration hubs, while most other provinces experienced net emigration. The south recorded net emigration overall, except in Phuket, Nakhon Si Thammarat, Songkhla, and Surat Thani.

During the first COVID-19 wave and national lockdown, mobility declined sharply, with tracked devices falling by nearly 70% relative to the pre-COVID-19 period. Significant net emigration occurred in Bangkok and other previously high in-migration provinces including Chiang Mai, Chonburi, Nakhon Pathom, Pathum Thani, Maha Sarakham, Ubon Ratchathani, Udon Thani, and Phuket (Figures 3[a] and 4[a]). After the first lockdown eased, net immigration resumed in Bangkok and major

Figure 2. Thailand's Internal Migration Before COVID-19

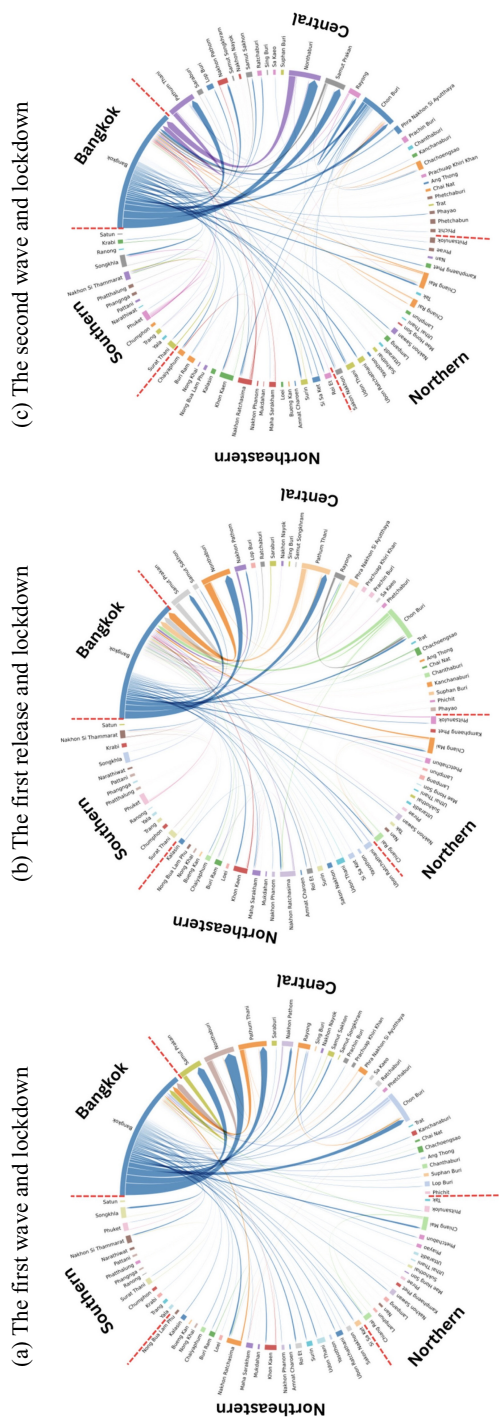


COVID-19 = coronavirus disease, GPS = global positioning system.

Notes: The scatter plot (left) shows provincial-level immigration and emigration counts (log scale); the vertical gap between points for each province indicates the net migration flow. The chord diagram (right) visualizes origin–destination flows between provinces, where ribbon thickness corresponds to the relative volume of migrants.

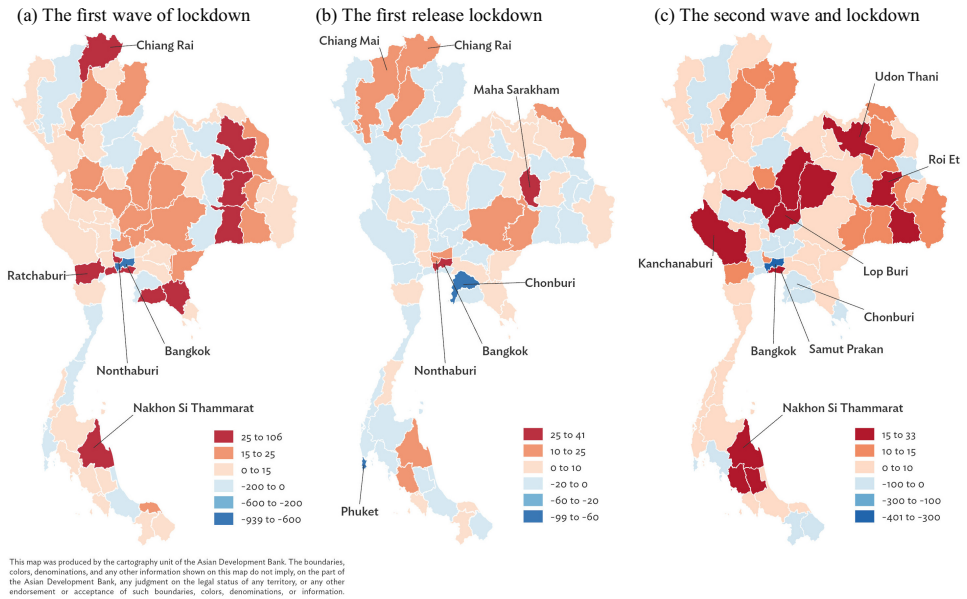
Source: Authors' illustration from Thai mobile GPS location data.

Figure 3. Thailand's Bilateral Migration Chart, July 2019–June 2021



GPS = global positioning system.
Note: See Table 1 concerning the coronavirus disease (COVID-19) subperiods and national lockdown periods.
Source: Authors' compilation from Thai mobile GPS location data.

Figure 4. Thailand's Net Migration, July 2019–June 2021



GPS = global positioning system.

Notes: See Table 1 concerning the coronavirus disease (COVID-19) subperiods and national lockdown periods. The blue-shaded provinces show net emigration, while the red-shaded provinces display net immigration.

Source: Authors' compilation from Thai mobile GPS location data.

provinces, although overall mobility remained well below prepandemic levels (Figures 3[b] and 4[b]). During the second lockdown, a similar but less pronounced pattern of net emigration reemerged in Bangkok and major provinces (Figures 3[c] and 4[c]). Within-region migration became more prominent, particularly in the central and southern regions, possibly reflecting more nuanced impacts of income and urbanization in determining migration decisions.

IV. Empirical Model

The empirical model is motivated by its ability to capture both the determinants of internal migration suggested by previous studies—primarily individual characteristics and absolute returns (section II)—and three critical contemporary drivers that have been largely overlooked in the literature: (i) relative returns across sectors, (ii) the potentially differential impacts of shocks on sectoral opportunities, and (iii) the role of digital technology in reducing frictions.

To capture these determinants, the modified gravity model is employed by including possible push and pull factors from both the origin (i) and destination (j) provinces. The original gravity model (Zipf 1946) for determining internal migration is shown in equation (1)—that is, the flow of migration between provinces (i) and (j) is proportional to the product of their total populations and inversely proportional to the distance between them:

$$MIG_{i,j,t} = \frac{Pop_{i,t}^{\beta_1} Pop_{j,t}^{\beta_2}}{Dist_{i,j,t}^{\beta_3}}, \quad (1)$$

where $MIG_{i,j,t}$ is the internal migration from province i to j at time t , $Pop_{i,t}$ is the population density of province i at time t , $Pop_{j,t}$ is the population density of province j at time t , and $Dist_{i,j,t}$ is the distance between provinces i and j at time t .

A. The Model's Core Determinants

The possible push (i) and pull (j) variables are included in equation (1) to achieve the contributions of this paper and obtain more accurate estimates, as suggested by previous studies and given data availability. The push (i) and pull (j) factors include real gross domestic product (GDP) per capita ($RGDP$) from both the origin (i) and destination (j) provinces, divided into agriculture ($Agdp$), manufacturing ($Mgdp$), and services ($Sgdp$); educational level (Edu); average age of population (Age); gender ($Gender$); and inflation ($Infla$).

Based on previous literature (Lucas 2016), earning opportunities are an important driver for internal migration. Provinces dominated by manufacturing and services tend to attract more migrants due to higher returns and rapid sectoral transformation. However, these patterns may vary by development strategy, sectoral technology adoption, and technological advancements in agriculture that could potentially draw workers back from industry and services.

Education also plays a key role. Returns to education, which are typically higher in urban areas, increase the propensity to migrate toward locations offering greater rewards for skills (De Brauw and Rozelle 2008; De Vreyer, Gubert, and Roubaud 2009; Lucas 2016). Worker characteristics and the general environment of both the origin and destination provinces further shape migration decisions (Lucas 2016). Accordingly, we include average age, gender composition, and inflation in the analysis.

Incorporating these factors, we modify the gravity equation model presented in equation (1) to include these variables, as presented in equation (2). In equation (3),

GDP per worker, $RGDP$, is disaggregated by sector—agriculture ($Agdp$), manufacturing ($Mgdp$), and services ($Sgdp$)—to capture sector-specific earnings

$$\begin{aligned} \ln MIG_{i,j,t} = & \beta_0 + \beta_1 Pop_{i,t} + \beta_2 Pop_{j,t} + \beta_3 Dist_{i,j,t} + \beta_4 RGDP_{i,t} \\ & + \beta_5 RGDP_{j,t} + \beta_6 Edu_{i,t} + \beta_7 Edu_{j,t} + \beta_8 Age_{i,t} + \beta_9 Age_{j,t} \\ & + \beta_{10} Gender_{i,t} + \beta_{11} Gender_{j,t} + \beta_{12} Infla_{i,t} + \beta_{13} Infla_{j,t} \\ & + v_i + v_j + v_t + \varepsilon_{i,j,t} \quad \text{and} \end{aligned} \quad (2)$$

$$\begin{aligned} \ln MIG_{i,j,t} = & \beta_0 + \beta_1 Pop_{i,t} + \beta_2 Pop_{j,t} + \beta_3 Dist_{i,j,t} + \beta_4 Agdp_{i,t} + \beta_5 Agdp_{j,t} \\ & + \beta_6 Mgdp_{i,t} + \beta_7 Mgdp_{j,t} + \beta_8 Sgdp_{i,t} + \beta_9 Sgdp_{j,t} + \beta_{10} Edu_{i,t} \\ & + \beta_{11} Edu_{j,t} + \beta_{12} Age_{i,t} + \beta_{13} Age_{j,t} + \beta_{14} Gender_{i,t} + \beta_{15} Gender_{j,t} \\ & + \beta_{16} Infla_{i,t} + \beta_{17} Infla_{j,t} + v_i + v_j + v_t + \varepsilon_{i,j,t}, \end{aligned} \quad (3)$$

where i , j , and t denote the origin province, destination province, and period, respectively; v_i and v_j are unobserved province-specific effects; v_t is time-specific effects; and $\varepsilon_{i,j,t}$ is the error term.

B. Relative Income and Sectoral Differentials

Since the relative, not the absolute, earning opportunities between provinces may be a crucial factor driving migration, the relative income (proxied by $RRgdp$) between provinces (i) and (j) is used as an alternative variable in equation (4), replacing the absolute income variable as shown in equations (2) and (3), which is included separately for push and pull factors in the model. In addition to income, other explanatory variables—including education ($EEdu$), age ($AAge$), gender ($GGender$), and inflation ($IInfla$)—are also included in the model as relative terms:

$$\begin{aligned} \ln MIG_{i,j,t} = & \beta_0 + \beta_1 Pop_{i,t} + \beta_2 Pop_{j,t} + \beta_3 Dist_{i,j,t} + \beta_4 RRgdp_{i,j,t} \\ & + \beta_5 EEdu_{i,j,t} + \beta_6 AAge_{i,j,t} + \beta_7 GGender_{i,j,t} + \beta_8 IInfla_{i,j,t} \\ & + v_i + v_j + v_t + \varepsilon_{i,j,t}, \end{aligned} \quad (4)$$

where $RRgdp_{i,j,t}$ is the real GDP per capita of province (i) relative to that of province (j) at time t ; $EEdu_{i,j,t}$ is the education level of province (i) relative to that of province (j) at time t ; $AAge_{i,j,t}$ is the average age of province (i) relative to that of province (j) at time t ; $GGender_{i,j,t}$ is the average male participation of province (i) relative to that of province (j) at time t .

With real GDP disaggregated into three sectors, relative sectoral GDP per worker between provinces is included in the model. Recognizing that workers substitute across sectors to some extent, nine relative income terms are specified: three capturing within-sector differentials (agriculture $AAgdp_{i,j,t}$, manufacturing $MMgdp_{i,j,t}$, and

services ($SSgdp_{i,j,t}$) and six capturing across-sector differentials. The latter group includes (i) agricultural income in province i relative to the manufacturing income in province j ($AMgdp_{i,j,t}$) and its reverse ($MAGdp_{i,j,t}$), (ii) agricultural income relative to service income ($ASgdp_{i,j,t}$ and $SAGdp_{i,j,t}$), and (iii) manufacturing income relative to service income ($MSgdp_{i,j,t}$ and $SMgdp_{i,j,t}$). These variables are included in the model with careful attention to potential multicollinearity.

C. The Role of Digital Technology

Digital technology, through internet access, improved substantially during the COVID-19 pandemic (Jongwanich 2023). According to Lall, Timmins, and Yu (2009); Ackah and Medvedev (2010); and Fafchamps and Shilpi (2013), infrastructure plays a crucial role in determining in- and out-migration, as improved facilities and infrastructure permit production expansion, discouraging out-migration and encouraging in-migration. However, as mentioned in Lucas (2016), the relationship between amenities and infrastructure improvement and internal migration is not obvious, with some forms of improved local amenities, such as improved rural transport, exacerbating net out-migration. Further, the impact of digital technology, especially through internet access, on internal migration remains unexplored. The technology could provide more opportunities for local workers to expand their business and enhance their existing production and service capacity, discouraging out-migration. By contrast, as in the case of improved rural transportation, internet access may help enhance workers' ability to access new job opportunities outside their provinces, therefore stimulating in-migration in some provinces. To investigate these competing possibilities, this study includes internet access (*internet*) both as an additional explanatory factor and as a mediating factor interacting with income ($RGDP_{i,t} \times internet_{i,t}$), as shown in equation (5):

$$\begin{aligned} \ln MIG_{i,j,t} = & \beta_0 + \beta_1 Pop_{i,t} + \beta_2 Pop_{j,t} + \beta_3 Dist_{i,j,t} + \beta_4 RGDP_{i,t} \\ & + \beta_5 RGDP_{i,t} \times internet_{i,t} + \beta_6 RGDP_{j,t} + \beta_7 RGDP_{j,t} \times internet_{j,t} \\ & + \beta_8 Edu_{i,t} + \beta_9 Edu_{j,t} + \beta_{10} Age_{i,t} + \beta_{11} Age_{j,t} + \beta_{12} Gender_{i,t} \\ & + \beta_{13} Gender_{j,t} + \beta_{14} Infla_{i,t} + \beta_{15} Infla_{j,t} + \beta_{16} internet_{i,t} \\ & + \beta_{17} internet_{j,t} + v_i + \varepsilon_{i,t} \quad \text{and} \end{aligned} \quad (5)$$

$$\begin{aligned} \ln MIG_{i,j,t} = & \beta_0 + \beta_1 Pop_{i,t} + \beta_2 Pop_{j,t} + \beta_3 Dist_{i,j,t} + \beta_4 RRgdp_{i,j,t} \\ & + \beta_5 RRgdp_{i,j,t} \times iinternet_{i,j,t} + \beta_6 EEdu_{i,j,t} + \beta_7 AAage_{i,j,t} \\ & + \beta_8 GGender_{i,j,t} + \beta_9 IInfla_{i,j,t} + \beta_{10} iinternet_{i,j,t} + v_i + \varepsilon_{i,t}. \end{aligned} \quad (6)$$

The internet access variable enters equations (5) and (6) as a mediating factor for all three types of sectoral GDP, with careful consideration of potential multicollinearity among them. In addition to the time dummy variables included in the base model, slope dummy variables referring to the interaction between the time dummy variables and other key independent variables, especially GDP per capita, are also introduced to investigate whether the importance of income in influencing people's movement changes between subperiods. In addition to using real GDP to represent earning opportunities, many establishments in key sectors per worker—including manufacturing factories (*Fac*), hotels and restaurants (*Hotel*), wholesales and retails (*Wholes*), and real estate (*Realest*)—are employed as alternatives for such earning opportunities. Variable measurements and data sources are summarized in Table A2.1 in the Appendix; descriptive statistics and the correlation matrix are presented in Tables A2.2 and A2.3 in the Appendix, respectively.

D. Estimation Technique

The estimation technique for equations (2)–(6) is the dynamic panel model with fixed effects (Blundell and Bond 1998; Blundell, Bond, and Windmeijer 2001). Blundell and Bond (1998) proposed a system estimation in which first differences are estimated together with levels, instead of estimating only equations in first differences and using lagged levels as instruments. The instruments for the regression in differences are lagged levels, as proposed by Arellano and Bond (1991), while the instruments for the regression in levels are lagged first differences of the variable. The appropriateness of the latter assumes that the first differences are uncorrelated with the error term and unobservable heterogeneity.

The system generalized method of moments (GMM) regression addresses shortcomings that tend to arise from the Arellano and Bond (1991) difference estimator, which has been found to have poor finite sample properties when the lagged levels of the series are only weakly correlated with subsequent first differences. This is the case when the explanatory variables have large autoregressive parameters, as in this study. Blundell and Bond (1998) clearly showed that weak instruments could cause large finite-sample biases when using the first-differenced GMM method.⁴

⁴To check the robustness of our results, an Arellano and Bond (1991) panel system GMM is also applied. For independent variables, their lags are included in the analysis; to a certain extent, these could help to redress the endogeneity problem mentioned in Pesaran, Shin, and Smith (2001). The model applied in the study is based on a sound analytical framework and the Sargan test for overidentifying restrictions. The Arellano–Bond test for autocorrelation in the differenced errors are tested in the panel GMM and reported in the estimation results (Levendis 2025).

V. Results

This section presents the empirical findings on the determinants of internal migration in Thailand. The results are organized to parallel the model structured outline in section IV, moving from the core determinants to sectoral earning differentials and the role of digital technology.

A. Core Determinants

Table 2 reports the findings without considering the role of internet access. The influence of income on internal migration is unclear when real GDP per capita is considered, likely due to varying responses to earning incentives across sectors (column A). However, when total income is divided among the three sectors, income incentives in the manufacturing sector more effectively explain internal migration. That is, the lower the manufacturing income per capita in the original province (i), the more that out-migration is observed; the higher the income per capita in the destination province (j), the more immigration is encouraged. This is reflected by the negative coefficient associated with $Mgdp_i$ and the positive coefficient corresponding to $Mgdp_j$ (column B). The importance of earning opportunities in attracting people's movement to the manufacturing sector highlights the dominance of this sector in driving economic transformation in Thailand. Income in the agriculture and service sectors tends to influence internal migration in only one direction: as a pull factor in the former and a push factor in the latter. The insignificance of these income variables may reflect the greater importance of relative earning opportunities, particularly in comparison with the manufacturing sector, rather than absolute income levels.

B. Relative Earning Opportunities

When the relative earning opportunities are considered, the results resemble those where the absolute income is used as an explanatory variable—that is, income (per worker) in manufacturing is effective in determining internal migration, especially compared with other sectors. The earning gaps between the agriculture and manufacturing ($AMgdp_{i,j}$) sectors, as well as between the service and manufacturing ($SMgdp_{i,j}$) sectors, matter significantly in influencing internal migration (Table 3, columns B and C). The significantly negative coefficient corresponding to $AMgdp_{i,j}$ implies that when manufacturing income per worker in the destination province j increases, widening the income gap between the agriculture and manufacturing sectors, in-migration to province j is encouraged (Table 3, column B). A similar result,

Table 2. Empirical Results—Push and Pull Factors

Column A	Coefficient	Robust Std. Err.	Column B	Coefficient	Robust Std. Err.	Column C	Coefficient	Robust Std. Err.	Column D	Coefficient	Robust Std. Err.
$MIG_{i,j,t-1}$	0.275	0.016***	$MIG_{i,j,t-1}$	0.277	0.016***	$MIG_{i,j,t-1}$	0.228	0.015***	$MIG_{i,j,t-1}$	0.289	0.017***
$RGDP_{i,t}$	-0.346	0.231									
$RGDP_{i,t-1}$	0.539	0.185***									
$RGDP_{j,t}$	-0.603	0.219***									
$RGDP_{j,t-1}$	0.587	0.164***									
			$Agdp_{i,t}$	-0.099	0.092	$Agdp_{i,t}$			$Agdp_{i,t}$	-0.099	0.090
			$Agdp_{i,t-1}$	0.041	0.068	$Agdp_{i,t-1}$			$Agdp_{i,t-1}$	0.040	0.067
			$Agdp_{j,t}$	0.211	0.091**	$Agdp_{i,t} \times dummy2$			$Agdp_{j,t}$	—	—
			$Agdp_{j,t-1}$	-0.132	0.067**	$Agdp_{i,t-1} \times dummy2$			$Agdp_{j,t-1}$	-0.296	0.155*
			$Mgdp_{i,t}$	0.251	0.204	$Agdp_{i,t} \times dummy3$			$Agdp_{j,t} \times dummy2$	0.622	0.267**
			$Mgdp_{i,t-1}$	-0.291	0.115**	$Agdp_{i,t-1} \times dummy3$			$Agdp_{j,t-1} \times dummy2$	0.066	0.177
			$Mgdp_{j,t}$	0.378	0.204*	$Agdp_{i,t} \times dummy4$			$Agdp_{j,t} \times dummy3$	0.501	0.148***
			$Mgdp_{j,t-1}$	-0.115	0.116	$Agdp_{i,t-1} \times dummy4$			$Agdp_{j,t-1} \times dummy3$	-0.039	0.294
			$Sgdp_{i,t}$	-0.813	0.356**	$Agdp_{j,t}$			$Agdp_{j,t} \times dummy4$	0.697	0.143***
			$Sgdp_{i,t-1}$	0.705	0.241***	$Agdp_{j,t-1}$			$Agdp_{j,t-1} \times dummy4$	—	—
			$Sgdp_{j,t}$	-0.273	0.317	$Mgdp_{i,t}$			$Mgdp_{i,t}$	0.260	0.204
			$Sgdp_{j,t-1}$	0.085	0.200	$Mgdp_{i,t-1}$			$Mgdp_{i,t-1}$	-0.295	0.115**
						$Mgdp_{j,t}$			$Mgdp_{j,t}$	-0.085	0.219
						$Mgdp_{j,t-1}$			$Mgdp_{j,t-1}$	0.279	0.124**
						$Sgdp_{i,t}$			$Sgdp_{i,t}$	-0.801	0.353**
						$Sgdp_{i,t-1}$			$Sgdp_{i,t-1}$	0.709	0.239***

Continued.

Table 2. Continued.

Column A	Coefficient	Robust Std. Err.	Column B	Coefficient	Robust Std. Err.	Column C	Coefficient	Robust Std. Err.	Column D	Coefficient	Robust Std. Err.
$Pop_{i,t}$	-8.347	4.449*				$Sgdp_{j,t}$	-0.249	0.305	$Sgdp_{j,t}$	0.339	0.321
$Pop_{i,t-1}$	5.314	3.516	$Pop_{i,t}$	-11.634	4.366***	$Sgdp_{j,t-1}$	0.065	0.195	$Sgdp_{j,t-1}$	-0.429	0.190**
$Pop_{j,t}$	14.384	4.231***	$Pop_{i,t-1}$	8.498	3.509***	$Pop_{i,t}$	-10.930	4.145***	$Pop_{i,t}$	-11.441	4.321***
$Pop_{j,t-1}$	-12.342	3.312***	$Pop_{j,t}$	11.030	4.137***	$Pop_{j,t}$	11.834	3.369***	$Pop_{i,t-1}$	8.477	3.454**
$Infla_{i,t}$	1.647	0.796**	$Pop_{j,t-1}$	-9.694	3.283***	$Pop_{j,t}$	10.046	4.006**	$Pop_{j,t}$	-2.374	3.971
$Infla_{i,t-1}$	0.368	0.780	$Infla_{i,t}$	1.248	0.844	$Pop_{j,t-1}$	-9.302	3.188***	$Pop_{j,t-1}$	2.432	3.17
$Infla_{i,t}$	2.683	0.806***	$Infla_{i,t-1}$	0.532	0.835	$Infla_{i,t}$	0.918	0.89	$Infla_{i,t}$	1.215	0.835
$Infla_{i,t-1}$	-0.454	0.896	$Infla_{j,t}$	2.470	0.869***	$Infla_{i,t-1}$	0.603	0.834	$Infla_{i,t-1}$	0.570	0.833
$Edu_{i,t}$	-0.071	0.074	$Infla_{i,t-1}$	-0.074	0.976	$Infla_{j,t}$	2.488	0.836***	$Infla_{j,t}$	3.987	0.948***
$Edu_{i,t-1}$	0.039	0.04	$Edu_{i,t}$	-0.088	0.075	$Infla_{j,t-1}$	0.061	0.954	$Infla_{j,t-1}$	-1.805	0.986*
$Edu_{j,t}$	-0.002	0.076	$Edu_{i,t-1}$	0.047	0.041	$Edu_{i,t}$	-0.031	0.071	$Edu_{i,t}$	-0.087	0.073
$Edu_{j,t-1}$	-0.055	0.043	$Edu_{j,t}$	-0.023	0.078	$Edu_{i,t-1}$	0.070	0.040*	$Edu_{i,t-1}$	0.044	0.039
$Gender_{i,t}$	0.004	0.084	$Edu_{j,t-1}$	-0.037	0.047	$Edu_{j,t}$	-0.031	0.076	$Edu_{j,t}$	0.098	0.079
$Gender_{i,t-1}$	0.032	0.044	$Gender_{i,t}$	0.024	0.084	$Edu_{j,t-1}$	-0.036	0.046	$Edu_{j,t-1}$	-0.070	0.048
$Gender_{j,t}$	0.032	0.095	$Gender_{i,t-1}$	0.014	0.043	$Gender_{i,t}$	0.035	0.082	$Gender_{i,t}$	0.033	0.083
$Gender_{j,t-1}$	0.106	0.052***	$Gender_{j,t}$	0.048	0.096	$Gender_{i,t-1}$	0.058	0.044	$Gender_{i,t-1}$	0.010	0.042
$Age_{i,t}$	0.045	0.046	$Gender_{j,t-1}$	0.098	0.053*	$Gender_{j,t}$	0.047	0.092	$Gender_{j,t}$	-0.023	0.098
$Age_{i,t-1}$	0.008	0.006	$Age_{i,t}$	0.036	0.047	$Gender_{j,t-1}$	0.100	0.052**	$Gender_{j,t-1}$	0.143	0.055**
			$Age_{i,t-1}$	0.009	0.006	$Age_{i,t}$	0.059	0.047	$Age_{i,t}$	0.037	0.046
						$Age_{i,t-1}$	-0.011	0.006*	$Age_{i,t-1}$	0.007	0.006

Continued.

Table 2. *Continued.*

Column A	Coefficient	Robust Std. Err.	Column B	Coefficient	Robust Std. Err.	Column C	Coefficient	Robust Std. Err.	Column D	Coefficient	Robust Std. Err.	Robust Std. Err.
$Age_{i,t}$	0.094	0.043**	$Age_{i,t}$	0.110	0.044**	$Age_{i,t}$	0.106	0.043**	$Age_{i,t}$	0.064	0.045	
$Age_{i,t-1}$	-0.031	0.011**	$Age_{i,t-1}$	-0.032	0.012**	$Age_{i,t-1}$	-0.030	0.011**	$Age_{i,t-1}$	-0.027	0.012**	
$cons$	-8.764	29.918	$cons$	4.248	30.103	$cons$	-37.851	29.145	$cons$	18.580	30.132	
Wald chi2(29)	1,147.46		Wald chi2(37)	1,155.14		Wald chi2(41)	1,204.75		Wald chi2(41)	1,252.42		
Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		
AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00		
AR(2) p -value	0.57		AR(2) p -value	0.53		AR(2) p -value	0.53		AR(2) p -value	0.54		
Sargan p -value	0.28		Sargan p -value	0.38		Sargan p -value	0.36		Sargan p -value	0.38		

Column E	Coefficient	Robust Std. Err.	Column F	Coefficient	Robust Std. Err.	Column G	Coefficient	Robust Std. Err.	Column H	Coefficient	Robust Std. Err.	Robust Std. Err.
$MIG_{i,t-1}$	0.276	0.016***	$MIG_{i,t-1}$	0.278	0.016***	$MIG_{i,t-1}$	0.275	0.015***	$MIG_{i,t-1}$	0.277	0.016***	
$Agdp_{i,t}$	-0.059	0.095	$Agdp_{i,t}$	-0.099	0.092	$Agdp_{i,t}$	-0.200	0.092**	$Agdp_{i,t}$	-0.099	0.092	
$Agdp_{i,t-1}$	0.008	0.069	$Agdp_{i,t-1}$	0.041	0.068	$Agdp_{i,t-1}$	-0.046	0.069	$Agdp_{i,t-1}$	0.041	0.068	
$Agdp_{j,t}$	0.210	0.090**	$Agdp_{j,t}$	0.302	0.095***	$Agdp_{j,t}$	0.165	0.089*	$Agdp_{j,t}$	0.194	0.096**	
$Agdp_{i,t-1}$	-0.132	0.067**	$Agdp_{i,t-1}$	-0.157	0.069***	$Agdp_{i,t-1}$	-0.142	0.064**	$Agdp_{i,t-1}$	-0.055	0.074	
$Mgdp_{i,t}$	-5.291	4.688	$Mgdp_{i,t}$	0.251	0.204	$Mgdp_{i,t}$	0.067	0.210	$Mgdp_{i,t}$	0.251	0.204	
$Mgdp_{i,t-1}$	2.589	2.467	$Mgdp_{i,t-1}$	-0.291	0.115**	$Mgdp_{i,t-1}$	-0.339	0.119***	$Mgdp_{i,t-1}$	-0.291	0.115	
$Mgdp_{i,t} \times dummy_{year2}$	—	—	$Mgdp_{i,t}$	-0.057	4.854	$Mgdp_{i,t}$	0.269	0.202	$Mgdp_{i,t}$	0.501	0.218**	
$Mgdp_{i,t-1} \times dummy_{year2}$	-3.030	2.478	$Mgdp_{i,t-1}$	0.070	2.552	$Mgdp_{i,t-1}$	-0.096	0.114	$Mgdp_{i,t-1}$	-0.174	0.122	
$Mgdp_{i,t} \times dummy_{year3}$	3.030	2.479	$Mgdp_{i,t} \times dummy_{year2}$	—	—	$Sgdp_{i,t}$	-0.212	0.551	$Sgdp_{i,t}$	-0.812	0.356**	

Continued.

Table 2. *Continued.*

Column E	Coefficient	Robust Std. Err.	Column F	Coefficient	Robust Std. Err.	Column G	Coefficient	Robust Std. Err.	Column H	Coefficient	Robust Std. Err.
$Mgd p_{i,t-1} \times dummy3$	-5.361	4.709	$Mgd p_{i,t-1} \times dummy2$	-0.555	2.557	$Sgd p_{i,t-1}$	6.685	4.071	$Sgd p_{i,t-1}$	0.705	0.241***
$Mgd p_{i,t} \times dummy4$	5.342	4.710	$Mgd p_{i,t} \times dummy3$	0.579	2.557	$Sgd p_{i,t} \times dummy2$	-11.818	7.884	$Sgd p_{i,t}$	-1.943	0.563***
$Mgd p_{i,t-1} \times dummy4$	—	—	$Mgd p_{i,t-1} \times dummy3$	0.135	4.857	$Sgd p_{i,t-1} \times dummy2$	-5.801	4.069	$Sgd p_{i,t-1}$	-2.926	3.919
$Mgd p_{i,t}$	0.377	0.204*	$Mgd p_{i,t} \times dummy4$	-0.166	4.858	$Sgd p_{i,t} \times dummy3$	-5.997	3.836	$Sgd p_{i,t} \times dummy2$	7.633	7.591
$Mgd p_{i,t-1}$	-0.115	0.116	$Mgd p_{i,t-1} \times dummy4$	—	—	$Sgd p_{i,t-1} \times dummy3$	-11.860	7.883	$Sgd p_{i,t-1} \times dummy2$	2.987	3.92
$Sgd p_{i,t}$	-0.836	0.361**	$Sgd p_{i,t}$	-0.812	0.356**	$Sgd p_{i,t} \times dummy4$	—	—	$Sgd p_{i,t} \times dummy3$	4.639	3.696
$Sgd p_{i,t-1}$	0.730	0.244***	$Sgd p_{i,t-1}$	0.705	0.241***	$Sgd p_{i,t-1} \times dummy4$	—	—	$Sgd p_{i,t-1} \times dummy3$	7.609	7.590
$Sgd p_{i,t}$	-0.272	0.317	$Sgd p_{i,t}$	-0.365	0.331	$Sgd p_{i,t}$	-0.319	0.315	$Sgd p_{i,t} \times dummy4$	—	—
$Sgd p_{i,t-1}$	0.084	0.200	$Sgd p_{i,t-1}$	0.175	0.209	$Sgd p_{i,t-1}$	0.126	0.196	$Sgd p_{i,t-1} \times dummy4$	—	—
$Pop_{i,t}$	-11.737	4.403***	$Pop_{i,t}$	-11.626	4.366***	$Pop_{i,t}$	-7.468	3.386**	$Pop_{i,t}$	-11.627	4.364***
$Pop_{i,t-1}$	8.753	3.522**	$Pop_{i,t-1}$	8.500	3.508**	$Pop_{i,t-1}$	8.008	3.371**	$Pop_{i,t-1}$	8.490	3.508**
$Pop_{i,t}$	11.000	4.135***	$Pop_{i,t}$	10.166	4.202**	$Pop_{i,t}$	4.412	2.997	$Pop_{i,t}$	10.016	4.234**
$Pop_{i,t-1}$	-9.682	3.283***	$Pop_{i,t-1}$	-8.635	3.326***	$Pop_{i,t-1}$	-4.315	2.901	$Pop_{i,t-1}$	-8.945	3.427***
$Infla_{i,t}$	1.494	0.852*	$Infla_{i,t}$	1.247	0.842	$Infla_{i,t}$	-1.326	0.811	$Infla_{i,t}$	1.248	0.845
$Infla_{i,t-1}$	0.648	0.845	$Infla_{i,t-1}$	0.533	0.834	$Infla_{i,t-1}$	2.606	0.763***	$Infla_{i,t-1}$	0.532	0.834
$Infla_{i,t}$	2.471	0.867***	$Infla_{i,t}$	2.926	0.871***	$Infla_{i,t}$	0.642	0.811	$Infla_{i,t}$	2.963	0.872***
$Infla_{i,t-1}$	-0.068	0.975	$Infla_{i,t-1}$	-0.364	0.985	$Infla_{i,t-1}$	0.378	0.886	$Infla_{i,t-1}$	-0.648	0.967
$Edu_{i,t}$	-0.100	0.075	$Edu_{i,t}$	-0.088	0.074	$Edu_{i,t}$	-0.076	0.075	$Edu_{i,t}$	-0.088	0.075
$Edu_{i,t-1}$	0.053	0.041	$Edu_{i,t-1}$	0.047	0.041	$Edu_{i,t-1}$	0.032	0.042	$Edu_{i,t-1}$	0.046	0.041
$Edu_{i,t}$	-0.024	0.078	$Edu_{i,t}$	0.004	0.08	$Edu_{i,t}$	0.001	0.078	$Edu_{i,t}$	-0.100	0.081
$Edu_{i,t-1}$	-0.037	0.047	$Edu_{i,t-1}$	-0.037	0.048	$Edu_{i,t-1}$	-0.052	0.046	$Edu_{i,t-1}$	0.026	0.049
$Gender_{i,t}$	-0.002	0.084	$Gender_{i,t}$	0.025	0.085	$Gender_{i,t}$	0.051	0.085	$Gender_{i,t}$	0.024	0.084
$Gender_{i,t-1}$	0.021	0.044	$Gender_{i,t-1}$	0.014	0.043	$Gender_{i,t-1}$	0.007	0.045	$Gender_{i,t-1}$	0.013	0.043
$Gender_{i,t}$	0.048	0.096	$Gender_{i,t}$	0.042	0.096	$Gender_{i,t}$	0.078	0.095	$Gender_{i,t}$	0.028	0.099

Continued.

Table 2. *Continued.*

Column E	Coefficient	Robust Std. Err.	Column F	Coefficient	Robust Std. Err.	Column G	Coefficient	Robust Std. Err.	Column H	Coefficient	Robust Std. Err.
$Gender_{j,t-1}$	0.097	0.053*	$Gender_{j,t-1}$	0.112	0.054**	$Gender_{j,t-1}$	0.081	0.052	$Gender_{j,t-1}$	0.123	0.055**
$Age_{i,t}$	0.048	0.047	$Age_{i,t}$	0.036	0.047	$Age_{i,t}$	0.038	0.047	$Age_{i,t}$	0.036	0.047
$Age_{i,t-1}$	0.008	0.006	$Age_{i,t-1}$	0.009	0.006	$Age_{i,t-1}$	0.010	0.007	$Age_{i,t-1}$	0.009	0.006
$Age_{j,t}$	0.110	0.044**	$Age_{j,t}$	0.101	0.044**	$Age_{j,t}$	0.098	0.044**	$Age_{j,t}$	0.119	0.045**
$Age_{j,t-1}$	-0.032	0.012***	$Age_{j,t-1}$	-0.034	0.012***	$Age_{j,t-1}$	-0.027	0.012**	$Age_{j,t-1}$	-0.036	0.012***
<i>_cons</i>	2.665	30.168	<i>_cons</i>	0.561	30.409	<i>_cons</i>	-13.488	10.422	<i>_cons</i>	5.272	30.297
Wald chi2(41)	1,147.47		Wald chi2(41)	1,163.74		Wald chi2(41)	1,087.57		Wald chi2(41)	1,155.07	
Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00	
AR(1) <i>p</i> -value	0.00		AR(1) <i>p</i> -value	0.00		AR(1) <i>p</i> -value	0.00		AR(1) <i>p</i> -value	0.00	
AR(2) <i>p</i> -value	0.53		AR(2) <i>p</i> -value	0.53		AR(2) <i>p</i> -value	0.51		AR(2) <i>p</i> -value	0.52	
Sargan <i>p</i> -value	0.42		Sargan <i>p</i> -value	0.38		Sargan <i>p</i> -value	0.42		Sargan <i>p</i> -value	0.43	

COVID-19 = coronavirus disease, Std. Err. = standard error.

Notes: All variables are in logarithmic form. The subscript (*i*) represents the original province, and the subscript (*j*) refers to the destination province. ***, **, * and * represent 1%, 5%, and 10% significance levels, respectively. The sample comprises 17,556 observations across 5,852 groups. The Arellano–Bond test for serial correlation and the Sargan test are applied to all reported equations for autocorrelation overidentifying restrictions. *dumyear2* represents the periods during the first wave of COVID-19 and first lockdown; *dumyear3* represents the released lockdown periods; *dumyear4* refers to the second and the third lockdown periods.

Source: Authors' calculations.

with marginal significance, is observed when the income gap between services and manufacturing ($SMgdp_{i,j}$) is considered (Table 3, column C). The concentration of migration flows into Bangkok and the central provinces—observed both before the pandemic and after lockdown measures were lifted (Figures 2 and 3[b])—is consistent with the strong pull effects of manufacturing income and, to a lesser extent, services income (Tables 2 and 3).

By contrast, when relative income in the agriculture sector increases in the destination province (j), regardless of sectoral income in the original province (i), this higher income does not encourage in-migration to province j (Table 3, columns B and C). This may reflect a lagging development strategy and outdated technologies in the agriculture sector that prevent workers from being drawn back from the industry or service sectors. In the case of the service sector, an increase in service income in the destination province (j) relative to manufacturing income in the original province (i) encourages in-migration to province j with a lag effect. However, the net impact of such an income increase is negligible. The insignificant impact is also evident when the gap between agricultural income in the original province (i) and service income in the destination province (j) is considered.

The negligible impact of agriculture and service income may be due to the inclusion of the COVID-19 and national lockdown periods in the samples. The time dummy variables, interacting with sectoral income, are introduced to investigate such issues, both in terms of absolute and relative income. Most of the results resemble those without interaction terms, except for a few cases. These include a case of absolute agriculture income where, during the crisis periods, the agriculture sector tends to act as a shelter accommodating in-migration. The negative and significant coefficients of the time dummy variables correspond to agricultural income in the original province (i), with the still positive coefficient revealed during the normal period—as in the case of not having an interaction term—confirming the effectiveness of agricultural income incentives in maintaining workers in the original province (i) during the crisis period (Table 3, column F). This result aligns with previous empirical studies showing that agriculture and rural areas tend to serve as a buffer or fallback during major economic shocks (see, for example, Smith et al. 2002, Huang et al. 2011). Smith et al. (2002), employing Indonesian labor force data and the Indonesia Family Life Survey, show that during the 1997/98 Asian financial crisis, employment in the agriculture sector expanded by 20%, led by gains among women. Meanwhile, all other sectors—especially manufacturing, construction, and retail—experienced dramatic job losses. Huang et al. (2011), using the 2008 China National Rural Survey covering 58 randomly selected villages in six rural provinces in the People's Republic

Table 3. Empirical Results—Relative Importance of Push and Pull Factors

Column A	Coefficient	Robust Std. Err.	Column B	Coefficient	Robust Std. Err.	Column C	Coefficient	Robust Std. Err.	Column D	Coefficient	Robust Std. Err.	Column E	Coefficient	Robust Std. Err.
$MG_{i,t-1}$	0.233	0.019***	$MG_{i,t-1}$	0.231	0.019***	$MG_{i,t-1}$	0.232	0.019***	$MG_{i,t-1}$	0.232	0.019***	$MG_{i,t-1}$	0.239	0.020***
$AGdp_{i,t}$	-0.058	0.359	$AGdp_{i,t}$	-0.526	0.122***	$ASgdp_{i,t}$	-0.078	0.2	$AGdp_{i,t}$	-0.078	0.2	$AGdp_{i,t}$	-0.603	0.126***
$AGdp_{i,t-1}$	0.621	0.329*	$AGdp_{i,t-1}$	0.237	0.079***	$ASgdp_{i,t-1}$	-0.092	0.144	$AGdp_{i,t-1}$	-0.092	0.144	$AGdp_{i,t-1}$	0.183	0.081***
$MMgdp_{i,t}$	-0.122	0.104	$MSgdp_{i,t}$	0.253	0.122**	$MGdp_{i,t}$	0.326	0.130**	$MSgdp_{i,t}$	0.326	0.130**	$MSgdp_{i,t}$	0.566	0.124***
$MMgdp_{i,t-1}$	0.037	0.065	$MSgdp_{i,t-1}$	-0.225	0.078***	$MGdp_{i,t-1}$	-0.100	0.082	$MSgdp_{i,t-1}$	-0.100	0.082	$MSgdp_{i,t-1}$	-0.400	0.081***
$SSgdp_{i,t}$	-0.053	0.173	$Sgdp_{i,t}$	-0.131	0.214	$SMgdp_{i,t}$	-0.364	0.124***	$Sgdp_{i,t}$	-0.364	0.124***	$Sgdp_{i,t}$	-0.952	0.318***
$SSgdp_{i,t-1}$	0.135	0.13	$Sgdp_{i,t-1}$	0.544	0.163***	$SMgdp_{i,t-1}$	0.354	0.082***	$Sgdp_{i,t-1}$	0.354	0.082***	$Sgdp_{i,t-1}$	1.665	0.782**
									$Sgdp_{i,t} \times dummy2$	-1.185	1.458	$AGdp_{i,t} \times dummy2$	-0.909	0.758
									$Sgdp_{i,t-1} \times dummy2$	-0.467	0.801	$AGdp_{i,t-1} \times dummy3$	0.956	0.76
									$Sgdp_{i,t} \times dummy3$	-0.619	0.721	$AGdp_{i,t} \times dummy3$	-1.406	1.426
									$Sgdp_{i,t-1} \times dummy3$	-1.271	1.456	$AGdp_{i,t-1} \times dummy4$	1.369	1.428
									$Sgdp_{i,t} \times dummy4$	—	—	$AGdp_{i,t} \times dummy4$	—	—
									$Sgdp_{i,t-1} \times dummy4$	—	—	$AGdp_{i,t-1} \times dummy4$	-0.262	0.131**
$Pop_{i,t}$	-10.224	4.156**	$Pop_{i,t}$	-10.455	4.169**	$Pop_{i,t}$	-11.944	4.191***	$Pop_{i,t}$	-11.944	4.191***	$Pop_{i,t}$	0.343	0.083***
$Pop_{i,t-1}$	5.420	3.383	$Pop_{i,t-1}$	7.328	3.407**	$Pop_{i,t-1}$	7.423	3.404**	$Pop_{i,t-1}$	7.423	3.404**	$Pop_{i,t-1}$	-3.843	4.158
$Pop_{i,t}$	12.531	4.071***	$Pop_{i,t}$	12.348	4.092***	$Pop_{i,t}$	13.481	4.125***	$Pop_{i,t}$	13.481	4.125***	$Pop_{i,t}$	0.388	3.403
$Pop_{i,t-1}$	-10.332	3.132***	$Pop_{i,t-1}$	-9.393	3.119***	$Pop_{i,t-1}$	-9.993	3.156***	$Pop_{i,t-1}$	-9.993	3.156***	$Pop_{i,t-1}$	4.554	3.95
$Infl_{i,t}$	-0.208	0.528	$Infl_{i,t}$	-0.537	0.4947	$Infl_{i,t}$	-0.011	0.498	$Infl_{i,t}$	-0.011	0.498	$Infl_{i,t}$	-2.378	3.081
$Infl_{i,t-1}$	-0.584	0.801	$Infl_{i,t-1}$	-0.526	0.766	$Infl_{i,t-1}$	0.037	0.772	$Infl_{i,t-1}$	0.037	0.772	$Infl_{i,t-1}$	-1.040	0.498**
$Edu_{i,t}$	-0.010	0.02	$Edu_{i,t}$	-0.012	0.02	$Edu_{i,t}$	-0.022	0.020	$Edu_{i,t}$	-0.022	0.020	$Edu_{i,t}$	0.654	0.772
$Edu_{i,t-1}$	0.017	0.013	$Edu_{i,t-1}$	0.015	0.0134	$Edu_{i,t-1}$	0.022	0.013	$Edu_{i,t-1}$	0.022	0.013	$Edu_{i,t-1}$	-0.018	0.02
$GGender_{i,t}$	-0.010	0.039	$GGender_{i,t}$	0.002	0.038	$GGender_{i,t}$	-0.026	0.038	$GGender_{i,t}$	-0.026	0.038	$GGender_{i,t}$	0.000	0.013
$GGender_{i,t-1}$	-0.007	0.019	$GGender_{i,t-1}$	-0.014	0.019	$GGender_{i,t-1}$	-0.005	0.019	$GGender_{i,t-1}$	-0.005	0.019	$GGender_{i,t-1}$	0.059	0.038
$GGender_{i,t}$	-0.042	0.071	$GGender_{i,t}$	-0.012	0.071	$GGender_{i,t}$	-0.014	0.071	$GGender_{i,t}$	-0.014	0.071	$GGender_{i,t}$	-0.016	0.019
$GGender_{i,t-1}$	0.072	0.026	$GGender_{i,t-1}$	0.065	0.025**	$GGender_{i,t-1}$	0.057	0.025**	$GGender_{i,t-1}$	0.057	0.025**	$GGender_{i,t-1}$	-0.025	0.07
$\_cons$	34.930	33.442	$\_cons$	3.863	34.354	$\_cons$	14.747	34.419	$\_cons$	17.173	34.331	$\_cons$	0.072	0.043
Wald chi2(23)	647.37		Wald chi2(23)	650.88		Wald chi2(23)	641.74		Wald chi2(27)	719.16		Wald chi2(27)	0.041	0.026
Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	21.596	34.201
AR(1) p-value	0.00		AR(1) p-value	0.00		AR(1) p-value	0.00		AR(1) p-value	0.00		AR(1) p-value	668.7	
AR(2) p-value	0.36		AR(2) p-value	0.31		AR(2) p-value	0.35		AR(2) p-value	0.37		AR(2) p-value	0.00	
Sargan p-value	0.39		Sargan p-value	0.33		Sargan p-value	0.34		Sargan p-value	0.34		Sargan p-value	0.35	

Table 3. *Continued.*

Column F	Coefficient	Robust Std. Err.	Column G	Coefficient	Robust Std. Err.	Column H	Coefficient	Robust Std. Err.	Column I	Coefficient	Robust Std. Err.
$MG_{i,t-1}$	0.217	0.019***	$MG_{i,t-1}$	0.236	0.020***	$MG_{i,t-1}$	0.230	0.019***	$MG_{i,t-1}$	0.193	0.019***
$AMgdpt_{i,t}$	-4.503	1.243***	$ASgdpt_{i,t}$	0.011	0.219	$AMgdpt_{i,t}$	-0.539	0.123***	$ASgdpt_{i,t}$	0.984	0.321***
$AMgdpt_{i,t-1}$	2.363	0.666***	$ASgdpt_{i,t-1}$	-0.121	0.156	$AMgdpt_{i,t-1}$	0.201	0.079**	$ASgdpt_{i,t-1}$	2.465	0.773***
$AMgdpt_{i,t} \times dummy2$	—	—	$AMgdpt_{i,t}$	0.259	0.132**	$MSgdpt_{i,t}$	0.262	0.180	$ASgdpt_{i,t} \times dummy2$	-5.968	1.390***
$AMgdpt_{i,t-1} \times dummy2$	-2.053	0.666***	$AMgdpt_{i,t-1}$	-0.081	0.083	$MSgdpt_{i,t-1}$	1.363	0.945	$ASgdpt_{i,t-1} \times dummy2$	-2.766	0.778***
$AMgdpt_{i,t} \times dummy3$	2.078	0.667***	$SMgdpt_{i,t}$	-2.035	1.571	$MSgdpt_{i,t} \times dummy2$	-2.927	1.757	$ASgdpt_{i,t} \times dummy3$	-3.055	0.669***
$AMgdpt_{i,t-1} \times dummy3$	-4.451	1.254***	$SMgdpt_{i,t-1}$	1.193	0.849	$MSgdpt_{i,t-1} \times dummy2$	-1.583	0.946*	$ASgdpt_{i,t-1} \times dummy3$	-5.745	1.386***
$AMgdpt_{i,t} \times dummy4$	4.531	1.254***	$SMgdpt_{i,t} \times dummy2$	-0.740	0.842	$MSgdpt_{i,t} \times dummy3$	-1.373	0.829	$ASgdpt_{i,t} \times dummy3$	—	—
$AMgdpt_{i,t-1} \times dummy4$	—	—	$SMgdpt_{i,t-1} \times dummy2$	—	—	$MSgdpt_{i,t-1} \times dummy3$	-2.961	1.756*	$ASgdpt_{i,t-1} \times dummy3$	—	—
$AMgdpt_{i,t}$	-0.036	0.127	$SMgdpt_{i,t} \times dummy3$	0.706	0.842	$MSgdpt_{i,t} \times dummy4$	—	—	$AMgdpt_{i,t}$	0.402	0.129***
$MSgdpt_{i,t-1}$	-0.215	0.078***	$SMgdpt_{i,t-1} \times dummy3$	-2.262	1.600	$MSgdpt_{i,t-1} \times dummy4$	—	—	$MSgdpt_{i,t-1}$	-0.154	0.081*
$ASgdpt_{i,t}$	-0.026	0.221	$SMgdpt_{i,t} \times dummy4$	2.267	1.6	$MSgdpt_{i,t}$	0.009	0.226	$SMgdpt_{i,t}$	-0.368	0.123***
$ASgdpt_{i,t-1}$	0.497	0.161***	$SMgdpt_{i,t-1} \times dummy4$	—	—	$ASgdpt_{i,t}$	0.514	0.167***	$SMgdpt_{i,t-1}$	0.464	0.085***
$Pop_{i,t}$	-10.944	4.100***	$Pop_{i,t}$	-12.740	4.206***	$Pop_{i,t}$	-10.321	4.190**	$Pop_{i,t}$	-11.530	4.036***
$Pop_{i,t-1}$	8.517	3.363**	$Pop_{i,t-1}$	8.127	3.430**	$Pop_{i,t-1}$	7.060	3.412**	$Pop_{i,t-1}$	9.231	3.309***
$Pop_{i,t}$	11.277	4.131***	$Pop_{i,t}$	13.514	4.191***	$Pop_{i,t}$	12.946	4.096***	$Pop_{i,t}$	10.384	4.036***
$Pop_{i,t-1}$	-9.639	3.105***	$Pop_{i,t-1}$	-9.795	3.167***	$Pop_{i,t-1}$	-9.504	3.143***	$Pop_{i,t-1}$	-10.457	3.108***
$Infla_{i,t}$	-0.695	0.487	$Infla_{i,t}$	-0.140	0.4971	$Infla_{i,t}$	-0.505	0.496	$Infla_{i,t}$	-0.247	0.481
$Infla_{i,t-1}$	-0.936	0.763	$Infla_{i,t-1}$	-0.003	0.777	$Infla_{i,t-1}$	-0.484	0.767	$Infla_{i,t-1}$	-0.036	0.754
$Edu_{i,t}$	-0.008	0.02	$Edu_{i,t}$	-0.017	0.020	$Edu_{i,t}$	-0.009	0.020	$Edu_{i,t}$	-0.003	0.019
$Edu_{i,t-1}$	0.011	0.013	$Edu_{i,t-1}$	0.013	0.013	$Edu_{i,t-1}$	0.016	0.013	$Edu_{i,t-1}$	0.015	0.013
$GGender_{i,t}$	0.015	0.038	$GGender_{i,t}$	-0.018	0.038	$GGender_{i,t}$	0.002	0.039	$GGender_{i,t}$	0.015	0.037
$GGender_{i,t-1}$	-0.007	0.019	$GGender_{i,t-1}$	-0.011	0.019	$GGender_{i,t-1}$	-0.013	0.019	$GGender_{i,t-1}$	-0.024	0.019

Continued.

Table 3. *Continued.*

Column F	Coefficient	Robust Std. Err.	Column G	Coefficient	Robust Std. Err.	Column H	Coefficient	Robust Std. Err.	Column I	Coefficient	Robust Std. Err.
$GGender_{i,j,t}$	0.009	0.071	$GGender_{i,j,t}$	-0.023	0.072	$GGender_{i,j,t}$	-0.004	0.072	$GGender_{i,j,t}$	-0.085	0.069
$GGender_{i,j,t-1}$	0.052	0.025**	$GGender_{i,j,t-1}$	0.071	0.026***	$GGender_{i,j,t-1}$	0.061	0.026**	$GGender_{i,j,t-1}$	0.045	0.025*
$\_cons$	16.448	34.228	$\_cons$	12.903	34.351	$\_cons$	-0.820	34.060	$\_cons$	37.460	33.894
Wald chi2(27)	674.5		Wald chi2(27)	633.67		Wald chi2(27)	654.2		Wald chi2(27)	801.57	
Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00	
AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00	
AR(2) p -value	0.32		AR(2) p -value	0.35		AR(2) p -value	0.36		AR(2) p -value	0.37	
Sargan p -value	0.36		Sargan p -value	0.36		Sargan p -value	0.36		Sargan p -value	0.35	

COVID-19 = coronavirus disease, Std. Err. = standard error.

Notes: All variables are in logarithmic form. The subscript (i) represents the original province, and the subscript (j) refers to the destination province. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The sample comprises 14,896 observations across 5,852 groups. The Arellano-Bond test for serial correlation and the Sargan test are applied to all reported equations for autocorrelation overidentifying restrictions. *dumyear2* represents the periods during the first wave of COVID-19 and first lockdown; *dumyear3* represents the released lockdown periods; *dumyear4* refers to the second and the third lockdown periods.

Source: Authors' calculations.

of China, show that the global financial crisis caused a noticeable increase in off-farm layoffs. However, roughly half of those laid off were subsequently reemployed, confirming the role of rural areas in cushioning external shocks.

In another case, when relative income is considered, the slope dummy is not statistically significant when the agriculture sector is treated as the destination province (j). This implies that the smaller magnitude of income reduction in agriculture compared to manufacturing and services during the COVID-19 pandemic does not encourage in-migration to province j (Table 3, columns D and E). By contrast, when the service and manufacturing sectors are treated as the destination province (j), the slope dummy variables are statistically significant and negative. This reflects that the greater magnitude of income reduction in these two sectors during the COVID-19 pandemic results in falling in-migration to province j (Table 3, columns F and I). In other words, changes in agricultural returns tend to have less power in affecting workers' movements than those in the manufacturing and service sectors. The reverse migration observed in Bangkok and the central provinces during the pandemic (Figures 3[a], 3[c], 4[a], and 4[c]) is consistent with the strong push effect created by the relative decline in both the manufacturing and service sectors rather than the higher income observed in the agriculture sector (Table 3).

Regarding service income, when the slope dummy variables are included in the case where absolute service income is considered, the slope dummy variables are insignificant in all scenarios (Table 2, columns G and H). However, the coefficient of service income at the destination province (j) for the base case (normal periods) turns out to be negative and significant, implying its inability to attract workers and likely stimulating return migration during the COVID-19 and lockdown periods (Table 2, column H). This result confirms the importance of changes in service income during the COVID-19 pandemic in causing return migration, as discussed earlier. For relative earnings, the significance of the slope dummy when the service sector is treated as the destination province (j) is revealed only in the case where its return is compared with agricultural income, as mentioned above (Table 3, column I). However, it is only mildly significant when compared with manufacturing income (Table 3, column E). This mild significance could be due to the fact that income in both sectors reduced noticeably during the pandemic, causing a negligible change in relative returns.

When income is replaced by the number of establishments in various key subsectors—including manufacturing factories, hotels and restaurants, real estate, and wholesale and retail businesses—the lack of statistical significance is clearly observed for manufacturing factories and is evident on both sides (i.e., push and pull factors) (Table 4, column A). This confirms the importance of income incentives in explaining

people's movement related to the manufacturing sector, instead of the number of established factories. By contrast, the number of service establishments plays a role in either pushing or pulling migration, suggesting that a cluster of these services tends to be significant in drawing migration (Table 4, column A). A faster turnover and shorter periods for upskilling and reskilling in these service subsectors could make a service cluster more relevant for the working prospects of migrants. In addition, this finding implies, to some extent, that social capital plays a more crucial role in determining internal migration than the manufacturing sector.

C. The Role of Digital Technology

Regarding the role of internet access (*internet*), regardless of whether it is considered in absolute terms (i.e., separating push [*i*] and pull [*j*] factors) or in relative terms, improvements in internet access in the destination province (*j*) and a larger gap of this variable between the two provinces tend to encourage in-migration to the destination province (*j*) (Table 4, columns B and C). Interestingly, when the interaction terms between internet access and relative sectoral income are considered, it appears that progress in internet usage in the destination province (*j*) relative to the original province (*i*) helps reduce in-migration to province *j* when manufacturing income corresponds to the destination province (*j*) and agricultural income corresponds to the original province (*i*). This is reflected in the positive coefficient associated with $AMgdp_{ij} \times internet\_diff_{ij}$ (Table 4, column D), causing the negative value of coefficient associated with $AMgdp_{i,j}$ to become smaller, which to some extent signals (i) the substitutive effect of digital technology on labor in the manufacturing sector, or (ii) that labor markets clear more quickly as information flows about jobs are more efficient within-destination. Jongwanich, Kohpaiboon and Obashi (2022), using labor force survey data and various forms of technology, also reveal that workers in certain manufacturing industries are adversely affected by technological growth.

By contrast, progress in internet access in the destination province (*j*) relative to the original province (*i*) helps encourage more migration to province *j* when service and agricultural incomes increase, reflected by the negative coefficients of their interaction value with the internet (i.e., $MSgdp_{ij} \times internet\_diff_{ij}$, $Sagdp_{ij} \times internet\_diff_{ij}$, and $MAgdp_{ij} \times internet\_diff_{ij}$). This demonstrates the complementary role of technology and labor in these two sectors. Jongwanich, Kohpaiboon, and Obashi (2022) also highlight the complementary roles of technology and labor in these sectors. Digital technologies, such as using the internet for e-commerce, have a significant positive impact on the labor market and labor reallocation.

Table 4. *Continued.*

Column A	Coefficient	Robust Std. Err.	Column B	Coefficient	Robust Std. Err.	Column C	Coefficient	Robust Std. Err.	Column D	Coefficient	Robust Std. Err.	Column E	Coefficient	Robust Std. Err.
$\Delta cons$	-17.285	28.947	$\Delta cons$	0.680	30.25	$\Delta cons$	2.030	34.337	$\Delta cons$	3.427	34.628	$\Delta cons$	15.820	34.534
Number of obs.	17,556		Number of obs.	17,556		Number of obs.	14,896		Number of obs.	14,896		Number of obs.	14,896	
Number of groups	5,852		Number of groups	5,852		Number of groups	5,852		Number of groups	5,852		Number of groups	5,852	
Wald chi2(41)	1,223.05		Wald chi2(41)	1,153.14		Wald chi2(25)	648.32		Wald chi2(25)	673.96		Wald chi2(25)	663.38	
Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00		Prob > chi2	0.00	
AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00		AR(1) p -value	0.00	
AR(2) p -value	0.44		AR(2) p -value	0.42		AR(2) p -value	0.36		AR(2) p -value	0.35		AR(2) p -value	0.34	
Sargan p -value	0.37		Sargan p -value	0.35		Sargan p -value	0.38		Sargan p -value	0.39		Sargan p -value	0.35	

Std. Err. = standard error.

Notes: All variables are in logarithmic form. The subscript (i) represents the original province, and the subscript (j) refers to the destination province. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The Arellano–Bond test for serial correlation and the Sargan test are applied to all reported equations for autocorrelation overidentifying restrictions.

Source: Authors' calculations.

For other control variables in all scenarios, the significant impact of population, particularly in the destination province (j), implies that migration remains concentrated in large cities with high population density. This suggests that the migration–urbanization nexus continues in the country despite various initiatives aimed at reducing regional disparities, particularly in terms of education and infrastructure development. The positive and significant coefficient for inflation in the destination province (j) further supports this finding. Significance is also observed for gender and age, with a higher proportion of males and a larger working-age population in the destination province (j) tending to encourage in-migration. The insignificance of education, both in absolute and relative terms, may be due to the fact that almost 70% of all migrants are driven by employment opportunities, while the remaining migrants are pursuing other activities such as education and health. Given the small proportion of such migrants, the significance of this variable is not observed in the study.

VI. Conclusions and Policy Implications

This study utilizes GPS-based mobile phone data to analyze internal migration in Thailand from January 2019 to June 2021. It emphasizes key factors influencing internal migration at the provincial level, particularly sectoral earning opportunities, digital technology, and worker characteristics. A modified gravity-type model incorporating push and pull factors is employed, using a fixed-effects panel regression estimated by the GMM.

A. Conclusions

Our findings can be summarized in four points. First, consistent with much of the literature on structural transformation in developing countries, which shows that emigration from the agriculture sector to the industry and service sectors leads to a decline in agricultural employment, our GPS-based mobile phone data show that manufacturing income is the primary driver of internal migration in Thailand. When income is considered in aggregate, its influence on migration is unclear. However, disaggregating income by sector reveals that lower manufacturing income per capita in origin provinces increases out-migration, while higher manufacturing income in destination provinces encourages in-migration. This finding underscores the dominance of the manufacturing sector in driving Thailand’s economic transformation.

The quantitative findings clearly show that relative earning opportunities are crucial in attracting workers, though their importance varies across sectors. Differences

in earning opportunities play a key role in drawing workers from the agriculture sector into manufacturing. However, no significant income effect is found within the agriculture sector itself, which may reflect a lagging development strategy and outdated technologies that limit its capacity to retain workers or attract them back from industry or services. In contrast, earning opportunities in the service sector, relative to those in manufacturing and agriculture, help explain in-migration, although the effect is only mildly significant.

Second, factors beyond income also play an important role in influencing people's movements in Thailand. Our results show that the number of service establishments significantly affects migration, functioning as either push or pull factors depending on the context. By contrast, no significant effect is observed for the number of manufacturing establishments. This contrast confirms that income incentives, rather than the mere presence of factories, drive migration related to the manufacturing sector. In the service sector, however, the clustering of establishments itself attracts migrants, potentially reflecting the importance of social capital, as well as faster turnover and shorter training periods, in making service sector jobs more accessible.

Worker characteristics such as age and gender, along with destination province conditions including population density and inflation, further shape internal migration patterns. The significance of these destination-related factors provides evidence that the migration–urbanization nexus persists in Thailand despite various initiatives aimed at reducing regional disparities.

Third, digital technology plays a crucial role in encouraging in-migration to destination provinces. However, its mediating effect on relative earning opportunities varies across sectors. Internet access amplifies the role of earning opportunities in attracting migrants to the service and agriculture sectors, reflecting a complementary relationship between technology and labor in these sectors. In contrast, no such amplifying effect is observed in manufacturing, which may indicate the prevalence of labor-displacing technologies or faster labor market clearing facilitated by technology, thereby limiting in-migration. Consistent with this interpretation, Jongwanich, Kohpaiboon, and Obashi (2022) find a replacement effect of technology on labor in manufacturing, while a complementary relationship between technology and labor is evident in other sectors, particularly services.

Finally, the COVID-19 pandemic triggered a reversal of migration patterns, with movements from the manufacturing and service sectors toward agriculture, alongside out-migration from Bangkok and major provinces. This indicates that the agriculture sector functioned as a crisis shelter, absorbing in-migration during economic disruption. This result echoes previous findings that agriculture and rural

areas often act as a buffer during economic shocks (e.g., Smith et al. 2002, Huang et al. 2011). These reversed migration flows were driven primarily by sharp declines in earning opportunities in the manufacturing and service sectors, rather than by improved incentives in agriculture. In addition, within-regional migration became more pronounced, particularly in the southern and central regions of Thailand, reflecting more nuanced income effects in shaping migration decisions during the crisis period.

B. Policy Implications for Thailand and Beyond

There are three policy inferences that can be drawn from this study that may be beneficial to Thailand and other developing countries at a comparable stage of economic development. First, while the agriculture sector usually plays a limited role in industrial transformation and inevitably contributes less to employment generation and economic growth, preventing its decline often requires increasing policy support and budgetary allocations over time (see, for example, Anderson and Ponnusamy 2019). However, in Thailand, this sector remains crucial as a backward linkage to the agro-food industry, with the country continuing to hold comparative advantages in several subsectors such as fresh and processed fruits, fresh and processed crustaceans, and related food industries. It also accommodates in-migration and helped smooth the transition toward economic recovery during the recent COVID-19 pandemic. Thus, continued efforts to support and enhance productivity and development in the agriculture sector are warranted. Nevertheless, such support should be strategically designed to use government resources efficiently by aligning policies with the country's comparative advantages and deploying more advanced digital technologies to improve efficiency across entire supply chains. Our study shows that digital technology continues to play a complementary role with labor in this sector. These efforts could help retain workers in agriculture and potentially draw them back from the industry or service sectors.

In addition, while tariff and nontariff protections, both technical and nontechnical, remain relatively high in the agriculture and food sectors compared with others, gradually liberalizing tariffs and nontechnical measures such as quotas should be seriously considered to enhance productivity in the medium to long term. At the same time, technical measures, including sanitary and phytosanitary measures, should be introduced and enforced strictly for food safety and to prevent substandard products. They should also not be abused or misused for protectionist purposes.

Second, our study confirms that relative earning opportunities are crucial determinants of internal migration, particularly in the manufacturing and service sectors. As Thailand's capital city and major provinces continue to dominate in-migration, efforts to enhance relative earning opportunities and promote greater regional parity through supply-side adjustments, while leveraging each region's comparative advantages, are likely to yield more desirable outcomes. While determinants beyond earning opportunities vary across sectors, intersectoral planning focused on supply-side improvements at the local level is essential to ensure effective efforts to reduce regional disparities.

The Government of Thailand has initiated the Economic Corridors Development program, comprising four economic corridors, to support regional development.⁵ The initiative is accompanied by investments in infrastructure, human resource and entrepreneurship development, research and development, innovation, and financial support mechanisms. However, concerns remain over the unclear provincial coverage of each corridor and the lack of clarity in integrating manufacturing and service promotion strategies, both of which should be addressed to enhance policy effectiveness.⁶

Third, since digital technology is important both in its own right and as a mediating factor linking earning opportunities to internal migration, promoting the development of both hard and soft digital infrastructure across provinces is crucial for fostering greater regional equality. Although various indicators suggest that Thailand's digital infrastructure—such as mobile cellular networks, fixed and mobile broadband, and 4G and 5G coverage—has improved over the past decade (see, for example, Jongwanich 2023), gaps remain. Compared with other Asian countries—including the

⁵These four corridors include the (i) Northern Economic Corridor: Chaing Mai, Chiang Rai, Lampang, and Lamphong, or the so-called "Creative Lanna"; (ii) Central–Western Economic Corridor: Phra Nakhon Si Ayutthaya, Nakhon Pathom, Suphan Buri, and Kanchanaburi; (iii) Northeastern Economic Corridor: Nakhon Ratchasima, Khon Kaen, Udon Thani, and Nong Khai; and (iv) Southern Economic Corridor: Chumphon, Ranong, Surat Thani, and Nakhon Sri Thammarat.

⁶For example, some of the selected provinces have relatively fewer economic activities and lower in-migration compared to neighboring provinces. For example, Suphan Buri and Kanchanaburi in the Central–Western Economic Corridor experience lower migration and have lower GDP per capita than other provinces in Thailand's western region. Additionally, some provinces where migration has been notable, such as Songkhla in the south, have not been included in the Southern Economic Corridor. To promote human resource and entrepreneur development, as well as research and development and innovation, collaboration between governments, the private sector, and universities is crucial. Songkhla, with its strong private university collaboration potential, is well-positioned for such efforts. In addition to provincial coverage, the goal of creating both manufacturing and service hubs within one framework for the National Economic Corridor may constrain its success as the nature of these two sectors differs significantly, including their incentives for attracting workers as revealed in the study. Infrastructure development to foster a creative economic ecosystem in Chiang Rai or to build tourism attractions in Kanchanaburi may not align with efforts to establish an electronics hub in Lampoon or an agro-food center in Nakhon Pathom.

People's Republic of China, Malaysia, Singapore, and Viet Nam—Thailand continues to lag in several respects, particularly in terms of access, affordability, and information and communication technology (ICT) skills among the population.⁷

Regarding the digital technology–labor nexus, our study indicates a potential replacement effect of digital technology on labor, particularly in the manufacturing sector. This highlights the importance of accelerating efforts to upskill and reskill existing workers in the labor market. Collaboration with private firms and universities is essential for effectively managing information, particularly on job creation and destruction across firms and industries, and for reducing labor market frictions. The government should act as a facilitator by providing strong incentives to accelerate upskilling and reskilling in the sector, thereby minimizing the adverse impacts of technology-driven job replacement and displacement.

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⁷For example, only 69% of households in rural areas have home internet access, while in urban areas, home internet access reaches 81%. In terms of ICT skills, only 1% of the Thai population would be classified as having advanced ICT skills, while around 20% have basic ICT skills.

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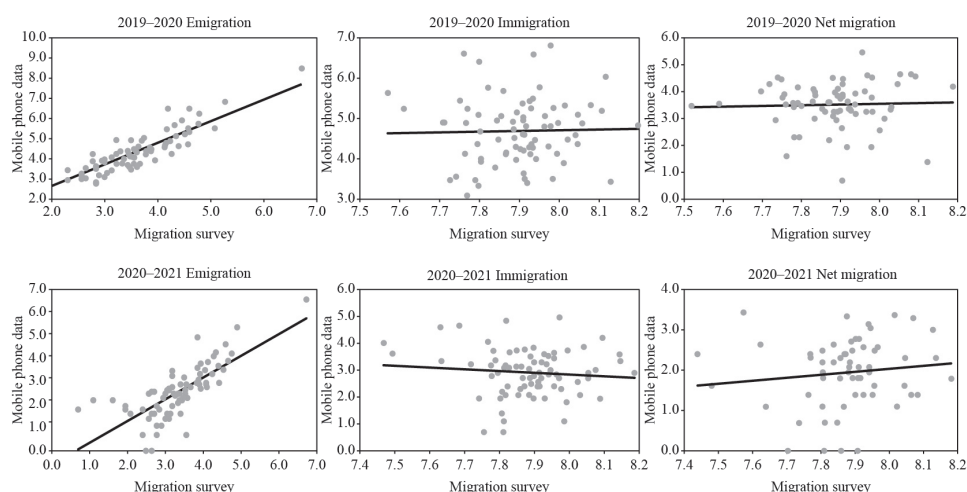
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Appendix 1. Correlations Between Thai Mobile Phone GPS Location Data, the Internal Migration Survey, and Other Key Variables During 2019–2021

To assess validity, the derived estimates from the global positioning system (GPS) were compared with official migration survey data from Thailand’s National Statistical Office.⁸ Provincial-level correlations between the two data sources are positive for emigration, immigration, and net migration; however, a strong positive correlation is observed only for emigration (Figure A1). Weaker correlations for immigration and net migration likely reflect survey undercounts during the pandemic, when data collection was challenging. The stronger correlation for emigration may stem from highly concentrated outflows from Bangkok during the crisis, which are easier to track than more dispersed immigration destinations.

Figure A1. Correlations Between Thai Mobile Phone GPS Location Data and the Internal Migration Survey, 2019–2021



Notes: Number of people (movements) from both data sources are in logarithmic form. With limited data from the Thai mobile phone global positioning system (GPS) location source in 2021, the migration flows of mobile phone users during 2020–2021 is conducted from September 2020 to June 2021.

Source: Authors’ compilation from Thai mobile GPS location data and the internal migration survey.

⁸Since the internal migration survey is conducted every year during September–October, to match as closely as possible the time frame used in the official survey, the residence of each user revealed by the mobile GPS location data is redefined for each year (i.e., September 2019–September 2020 and September 2020–September 2021) instead of every 6 months as in a case where patterns and determinants of internal migration before and during the coronavirus disease are analyzed. However, with limited data, for the second year, the time frame is shortened to be between September 2020 and June 2021.

Appendix 2. Supplementary Tables

Table A2.1. Variable Measurements and Data Sources

Variable	Variable Measurement	Data Source	Variable	Variable Measurement	Data Source
$MIG_{i,j,t}$	Number of people movements between original place (i) and destination place (j) at time t	GPS mobile phone data	$Edu_{i,t}$	Educational level of province i at time t : proportion of workers who obtain secondary degree and higher and proportion of male workers to total workers at provincial level	Labour Force Survey, National Statistical Office (NSO)
$Pop_{i,t}$	The population density of province i at time t	Labour Force Survey, NSO	$Edu_{j,t}$	Educational level of province j at time t	Labour Force Survey, NSO
$Pop_{j,t}$	The population density of province j at time t	Labour Force Survey, NSO	$EEdu_{i,j,t}$	The relative educational level between province i and province j at time t	Labour Force Survey, NSO
$RGDP_{i,t}$	Real GDP per capita of province i at time t	National Economic and Social Development Board (NESDB)	$Age_{i,t}$	Average age of population in province i at time t	Labour Force Survey, NSO
$RGDP_{j,t}$	Real GDP per capita of province j at time t	NESDB	$Age_{j,t}$	Average age of population in province j at time t	Labour Force Survey, NSO
$Agdp_{i,t}$	Real agriculture income per capita of province i at time t	NESDB	$AAge_{i,j,t}$	The relative age between province i and province j at time t	Labour Force Survey, NSO
$Agdp_{j,t}$	Real agriculture income per capita of province j at time t	NESDB	$Gender_{i,t}$	Gender: proportion of male workers to total workers at province i at time t	Labour Force Survey, NSO

Continued.

Table A2.1. *Continued.*

Variable	Variable Measurement	Data Source	Variable	Variable Measurement	Data Source
$Mgdp_{i,t}$	Real manufacturing income per capita of province i at time t	NESDB	$Gender_{i,t}$	Gender: proportion of male workers to total workers at province j at time t	Labour Force Survey, NSO
$Mgdp_{j,t}$	Real manufacturing income per capita of province j at time t	NESDB	$GGender_{i,j,t}$	The average male participation of province i , relative to that of province j at time t	Labour Force Survey, NSO
$Sgdp_{i,t}$	Real service income per capita of province i at time t	NESDB	$Infla_{i,t}$	Inflation of province i at time t	Ministry of Commerce
$Sgdp_{j,t}$	Real service income per capita of province j at time t	NESDB	$Infla_{j,t}$	Inflation of province j at time t	Ministry of Commerce
$RRgdp_{i,j,t}$	The relative real income per capita between province i and province j at time t	NESDB	$IIinfla_{i,j,t}$	The relative inflation between province i and j at time t	Ministry of Commerce
$AAgdp_{i,j,t}$	The relative real agriculture income per capita between province i and province j at time t	NESDB	$Fac_{i,t}$	Number of establishments in manufacturing factories of province i at time t	Business and Service Trade survey, NSO
$MMgdp_{i,j,t}$	The relative real manufacturing income per capita between province i and province j at time t	NESDB	$Fac_{j,t}$	Number of establishments in manufacturing factories of province j at time t	Business and Service Trade survey, NSO
$SSgdp_{i,j,t}$	The relative real service income per capita between province i and province j at time t	NESDB	$Hotel_{i,t}$	Number of establishments in hotels and restaurants of province i at time t	Business and Service Trade survey, NSO

Continued.

Table A2.1. *Continued.*

Variable	Variable Measurement	Data Source	Variable	Variable Measurement	Data Source
$AMgdp_{i,j,t}$	The agricultural income of province i , relative to the manufacturing income of province j at time t	NESDB	$Hotel_{j,t}$	Number of establishments in hotels and restaurants of province j at time t	Business and Service Trade survey, NSO
$MAGdp_{i,j,t}$	The manufacturing income of province i , relative to the agriculture income of province j at time t	NESDB	$Wholes_{i,t}$	Number of establishments in wholesales of province i at time t	Business and Service Trade survey, NSO
$ASgdp_{i,j,t}$	The agriculture income of province i , relative to the service income of province j at time t	NESDB	$Wholes_{j,t}$	Number of establishments in wholesales of province j at time t	Business and Service Trade survey, NSO
$SAGdp_{i,j,t}$	The service income of province i , relative to the agriculture income of province j at time t	NESDB	$Realest_{i,t}$	Number of establishments in real estate of province i at time t	Business and Service Trade survey, NSO
$MSgdp_{i,j,t}$	The manufacturing income of province i , relative to the service income of province j at time t	NESDB	$Realest_{j,t}$	Number of establishments in real estate of province j at time t	Business and Service Trade survey, NSO
$SMgdp_{i,j,t}$	The service income of province i , relative to the manufacturing income of province j at time t	NESDB	$internet_{j,t}$	Internet access of province j at time t	ICT survey, NSO
$internet_{i,t}$	Internet access of province i at time t	ICT survey, NSO	$iiinternet_{i,j,t}$	Relative Internet access between province i and j at time t	ICT survey, NSO

GDP = gross domestic product, GPS = global positioning system, ICT = information and communication technology.

Source: Authors' compilation.

Table A2.2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
<i>MIG</i>	23,408	0.29	0.64	0.00	6.88
<i>RGDP</i>	23,408	11.25	0.84	10.19	13.47
<i>Agdp</i>	23,408	9.20	0.79	5.37	10.76
<i>Mgdp</i>	23,408	9.30	1.46	6.85	13.16
<i>Sgdp</i>	23,408	10.64	0.68	9.87	13.35
<i>Pop</i>	23,408	13.45	0.64	12.16	15.55
<i>Edu</i>	23,408	0.18	0.11	0.00	0.63
<i>Gender</i>	23,408	0.39	0.11	0.00	0.69
<i>Age</i>	23,408	3.39	0.52	0.00	4.15
<i>Infla</i>	23,408	4.60	0.01	4.56	4.62
<i>Fac</i>	23,408	1.35	0.50	0.00	2.95
<i>Hotel</i>	23,408	1.34	0.60	0.07	2.64
<i>Realest</i>	23,408	0.40	0.27	0.00	1.48
<i>Wholes</i>	23,408	2.47	0.80	0.39	4.09
<i>internet</i>	23,408	0.35	0.09	0.08	0.64

Note: Since the analysis is at the provincial level, the summarized information between provinces i and j is symmetric.

Source: Authors' compilation.

Table A2.3. Correlation Matrix

	$MIG_{i,t}$	$RGDP_{i,t}$	$RGDP_{j,t}$	$AgDP_{i,t}$	$AgDP_{j,t}$	$MgDP_{i,t}$	$MgDP_{j,t}$	$SpDP_{i,t}$	$SpDP_{j,t}$	$Pop_{i,t}$	$Pop_{j,t}$	$Fac_{i,t}$	$Fac_{j,t}$	$Hotel_{i,t}$	$Hotel_{j,t}$	$RealEst_{i,t}$	$RealEst_{j,t}$	$Wholes_{i,t}$	$Wholes_{j,t}$	$Infl_{i,t}$	$Infl_{j,t}$	$Edu_{i,t}$	$Edu_{j,t}$	$Gender_{i,t}$	$Gender_{j,t}$	$Age_{i,t}$	$Age_{j,t}$	$internet_{i,t}$	$internet_{j,t}$			
$MIG_{i,t}$	1.000																															
$RGDP_{i,t}$	0.261	1.000																														
$RGDP_{j,t}$	0.213	-0.013	1.000																													
$AgDP_{i,t}$	-0.371	-0.703	0.009	1.000																												
$AgDP_{j,t}$	-0.309	0.009	-0.703	-0.013	1.000																											
$MgDP_{i,t}$	0.069	0.439	-0.005	-0.324	0.004	1.000																										
$MgDP_{j,t}$	0.063	-0.005	0.439	0.004	-0.324	-0.013	1.000																									
$SpDP_{i,t}$	-0.014	-0.616	0.009	0.512	-0.007	-0.474	0.007	1.000																								
$SpDP_{j,t}$	-0.006	0.009	-0.616	-0.007	0.512	0.007	-0.474	-0.012	1.000																							
$Pop_{i,t}$	0.326	0.091	-0.001	-0.355	0.005	0.122	-0.002	0.152	-0.002	1.000																						
$Pop_{j,t}$	0.302	-0.001	0.091	0.005	-0.355	-0.002	0.122	-0.002	0.152	-0.013	1.000																					
$Fac_{i,t}$	-0.155	-0.435	0.008	0.529	-0.007	0.009	0.003	0.348	0.000	-0.032	0.001	1.000																				
$Fac_{j,t}$	-0.115	-0.008	-0.435	-0.007	0.529	0.003	0.009	0.000	0.348	0.001	-0.032	0.002	1.000																			
$Hotel_{i,t}$	-0.334	-0.684	0.006	0.765	-0.010	-0.482	0.001	0.620	-0.018	-0.445	0.005	0.362	-0.035	1.000																		
$Hotel_{j,t}$	-0.299	0.006	-0.684	-0.010	0.765	0.001	-0.482	-0.018	0.620	0.005	-0.445	-0.035	0.362	0.050	1.000																	
$RealEst_{i,t}$	-0.204	-0.378	-0.003	0.318	-0.004	-0.242	-0.009	0.434	-0.027	-0.085	-0.001	0.128	-0.067	0.606	0.129	1.000																
$RealEst_{j,t}$	-0.185	-0.003	-0.378	-0.004	0.318	-0.009	-0.242	-0.027	0.434	-0.001	-0.085	-0.067	0.128	0.129	0.606	0.283	1.000															
$Wholes_{i,t}$	-0.327	-0.666	0.001	0.651	-0.009	-0.379	-0.008	0.601	-0.030	-0.188	0.001	0.353	-0.072	0.833	0.131	0.729	0.297	1.000														
$Wholes_{j,t}$	-0.289	0.001	-0.666	-0.009	0.651	-0.008	-0.379	-0.030	0.601	0.001	-0.188	-0.072	0.353	0.131	0.833	0.297	0.729	0.297	1.000													
$Infl_{i,t}$	0.012	-0.116	0.008	0.097	0.002	0.080	0.010	0.155	0.009	-0.051	0.002	0.113	0.028	0.072	-0.036	0.138	-0.079	0.053	-0.106	1.000												
$Infl_{j,t}$	0.023	0.008	-0.116	0.002	0.097	0.010	0.080	0.009	0.155	0.002	-0.051	0.028	0.113	-0.036	0.072	0.138	-0.106	0.053	0.300	1.000												
$Edu_{i,t}$	0.012	-0.003	-0.003	-0.038	0.000	-0.171	-0.003	-0.001	-0.007	0.059	-0.001	-0.057	-0.020	0.008	0.042	0.120	0.090	0.124	0.099	-0.120	-0.067	1.000										
$Edu_{j,t}$	-0.152	-0.002	-0.158	-0.003	0.204	-0.003	-0.308	-0.011	0.660	0.003	-0.304	-0.030	-0.101	0.058	0.351	0.132	0.196	0.139	0.316	-0.080	-0.124	0.047	1.000									
$Gender_{i,t}$	0.025	0.025	-0.001	-0.028	0.000	0.125	-0.003	-0.023	-0.002	0.138	-0.002	-0.061	-0.003	-0.129	0.013	-0.021	0.024	-0.007	0.029	0.020	-0.020	-0.035	0.015	1.000								
$Gender_{j,t}$	0.045	-0.003	0.130	0.002	-0.146	-0.003	0.106	-0.002	-0.085	-0.001	0.073	-0.007	-0.131	0.020	-0.052	0.041	0.015	0.047	-0.043	-0.030	-0.037	0.018	0.084	0.008	1.000							
$Age_{i,t}$	0.006	0.070	-0.006	-0.091	0.000	0.007	-0.008	-0.027	-0.012	0.168	-0.003	-0.092	-0.033	-0.075	0.074	0.132	0.157	0.120	0.173	-0.100	-0.109	0.253	0.084	0.439	0.031	1.000						
$Age_{j,t}$	-0.013	-0.005	0.146	0.001	-0.108	-0.006	0.144	-0.005	-0.143	0.000	-0.035	-0.018	-0.112	0.043	-0.074	0.091	-0.005	0.101	-0.027	-0.060	-0.056	0.037	0.178	0.014	0.381	0.066	1.000					
$internet_{i,t}$	0.081	0.596	-0.009	-0.403	0.006	0.292	-0.005	-0.621	0.005	-0.038	0.000	-0.386	-0.007	-0.394	0.034	-0.270	0.065	-0.422	0.065	-0.030	0.030	0.067	0.021	0.077	0.003	0.065	0.012	1.000				
$internet_{j,t}$	0.060	-0.009	0.596	0.006	-0.403	-0.005	0.292	0.005	-0.621	0.000	-0.038	-0.007	-0.386	0.034	-0.394	0.065	-0.270	0.065	-0.422	0.030	-0.031	0.011	0.010	0.002	0.201	0.021	0.071	0.007	1.000			

Source: Authors' compilation.

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