Migration decisions and persistent earnings differentials: Evidence from Thailand

Ashish Shenoy*
UC Davis Department of Agricultural and Resource Economics

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Abstract

I estimate the perceived cost of internal migration and associated labor supply elasticity in Thailand using the revealed-preference location decisions of workers. I develop a multiperiod model of the location decision where observed earnings are an imperfect proxy for the net present value of a migration. I use global commodity prices to construct instruments that identify permanent and transitory components of local earnings. Reduced-form evidence suggests that workers are sensitive to the share of the permanent component in an earnings innovation. Given this, I estimate a structural model of migration to recover cost parameters, exploiting variation in net present value induced by the instruments. Over a range of discount rates, I estimate the average cost of migration to an individual to lie between 0.3 and 1.1 times annual earnings. Fixed costs of moving (which include both financial and psychic costs) account for 60 percent of this, with the remaining 40 percent varying by distance. Furthermore, variation in idiosyncratic preferences is more than double the spatial variation in earnings. Using the parameter estimates of the model, I find that migration contributes 8.6 percentage points to local labor supply elasticity, split almost evenly between workers entering a province and fewer locals exiting. The model suggests that 20% of long-term earnings differentials over space can be attributed to perceived moving costs.

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1 Introduction

Migration is a key component of labor supply, affecting welfare at the household level and productivity at the aggregate level. Wage signals theoretically help allocate workers within and across markets to smooth out spatial and temporal variation and to direct labor to its most productive use. The market mechanism makes working most attractive when and where it generates the highest return. The aggregate effects of efficient labor allocation are potentially very large.

Migration can also smooth local variation in earnings. As workers relocate in response to changing labor market conditions, the resulting shifts in labor supply theoretically lower the gap between wages in disparate markets. Thus the option to migrate may act as an insurance mechanism, both to households that relocate and to others in the same labor market or insurance network.

Despite the high potential economic gains to migration, wages remain highly dispersed both across and within countries. In Thailand in the 1980's and 90's, the standard deviation of income across provinces was around half of the median province earnings. The presence of such large gaps raises the question of why migration does not appear to effectively reallocate workers over space and bring earnings in line across the nation. To address this, I investigate the spatial elasticity of labor supply by computing the perceived cost of relocation.

In this paper I estimate the cost of migration within Thailand using revealed preferences of workers' location decisions. The key challenge in calculating a cost lies in determining the net present value of a change in earnings. Since migration is an action with benefits realized over time, information about future expectations is crucial in assigning dollar values to actions. To investigate expectations over the future, I construct a set of shocks to local markets based on global commodity prices. I then exploit variation in the permanence of each commodity price to back out perceived migration costs from the revealed preference migration decisions of workers.

I first provide reduced-form evidence that workers are responsive to changes in earnings and migrate more in response to shocks of greater permanence. I embed this finding in a model of migration choice based on earnings, expected future labor market conditions, and the cost of relocation. The model explicitly incorporates the various durations of shocks to compute net present value. Estimation based on revealed preference suggests that the perceived cost of migration ranges from 0.3–1.1 times average annual earnings, around 60 percent of which is a fixed cost; the remainder of the cost varies with distance. Results also indicate that individual tastes play a greater role than earnings in workers' location decisions.

I then use parameter estimates to compute the local labor supply elasticity generated by migration alone. Parameter values suggest that migration contributes 8.6 percentage points to local labor supply elasticity. In response to a one percent change in local earnings, the size of the labor force increases by an average of 0.086 percentage points due to migration. This response is split almost evenly between outsiders moving into a province and locals (not) moving out. A back-of-the-envelope calculation suggests that over the long term, migration costs explain between 18 and 22 percent of the spatial variation in earnings. Were labor perfectly mobile, local earnings would exactly offset differences in local amenity values. The estimated variation in local amenities is roughly 80 percent as large as the observed variation in earnings, with the remained attributed to imperfect mobility.

In addition to these substantive contributions, this paper makes a methodological contribution by incorporating the data sampling process into the structural model. I use one of the few data sets that contains detailed migration data at an annual frequency. However, migration rates are measured with noise and individual-level sampling probabilities are endogenously based on outcomes. Both problems are common to survey data. Measurement error appears when a survey is small relative to the presence or variance in outcomes of interest, which is true of the Thai Labor Force Survey relative to the total number of migrants. Furthermore, sampling is stratified at the province level. Therefore a worker's probability of being sampled is dependent on her location choice. In general, endogenous sampling may arise when agents with rare outcomes are oversampled to gather more information.

Structural estimation addresses these issues by incorporating information about data sampling. Since the sampling method is well-documented, I am able to explicitly model the data generation process on top of the underlying discrete choice setup to recover consistent parameter estimates. I apply maximum likelihood treating the aggregate observed number of migrants as a random draw from a multinomial distribution with the (unobserved) true share of migrants as the probability parameter. I further impose the constraint that migration probabilities must be consistent with known province populations, which are a linear combination of aggregate location choices. These two adjustments to the standard estimation procedure overcome the problem of noise in observed aggregate shares and endogenous choice-based sampling at the micro level. Without them I would significantly overestimate the cost of migration.

Section 2 reviews the existing literature relating to migration and spatial wage differentials. In Section 3 I describe the available data and provide some descriptive facts about the sample of study. Section 4 introduces the basic choice model motivating the investigation. In Section 5 I present reduced-form evidence that migrants are sensitive to the duration of wage gaps. Next, in Section 6 I outline the maximum likelihood estimation procedure and report results in Section 7.

2 Related Literature

At a macro level, migration can be seen as an allocation mechanism that matches workers to locations with high labor productivity. Across countries, earnings disparities may be attributed in large part to differences in local TFP (Klein and Ventura, 2007, 2009). Such a view postulates that significant gains in global production could be achieved simply by moving workers from low-TFP regions to high-TFP regions. Clemens (2011) estimates that the potential gains worldwide from free worker relocation are on the order of trillions of dollars. Clemens and other authors suggest that restrictive government policy represents the largest barrier to realizing this potential.

However, political regulation is not the only barrier to worker migration. Other costs of moving may prevent many workers from relocating to more productive areas. Two recent papers (Morten and Oliveira, 2014; Bryan and Morten, 2015) investigate migration rates within countries with low political barriers and predict the potential economic gains from lowering relocation costs. The former suggests that a 50% decrease in road distance between regions in Brazil can increase welfare by 10–20%. The latter estimates that 20% of Indonesian GDP growth from 1976–2012 can be attributed to lowering of migration costs, and that 4% of the GDP gap between Indonesia and the US is explained by differences in cost of migration between the two countries.

The research presented here contributes to investigation along these lines by estimating the actual magnitude of migration costs. The cost of moving is greater than just transportation: it includes both financial and psychic penalties as well as potential loss of services from local social networks and other relocation difficulties. Thus, the total cost may be significantly higher than any calculation based on transportation alone. My results suggest that the perceived cost to migrate is on the order of a year's earnings, composed mostly of a fixed relocation cost that has little to do with travel distance. This is likely much higher than the cost of transportation, and thus internal policy to facilitate labor relocation may be better served by focusing on nontransportation barriers to migration.

Migration may also facilitate growth by alleviating financial constraints to entrepreneurship. Stark (1991) presents a model of limited credit in which migration is one part of a household decision. One or two family members will work away from the home for a period of years, and the household will use the extra earnings to finance investments that would otherwise be inaccessible. The distribution of Thai workers is consistent with this dynamic: the majority of migrants are employed at existing firms while over half of non-migrant households run self-owned or family-owned businesses. In the long run, Rapoport (2002) shows that migration can sustain equitable growth. An economy that would otherwise be stuck in an equilibrium with high inequality and low entrepreneurship can grow out of this trap if the option to self-finance through migration is broadly accessible.

Much research focuses on the additional role of migration as a tool to smooth variation over space. The motivation for this effect draws from the canonical model of spatial equilibrium introduced by Rosen (1979) and Roback (1982). The model, summarized in the handbook chapter by Moretti (2011), views a nation as a set of discrete labor markets in which workers locate. Shocks to one market affect wages and rents locally, but also may spill over to other markets via labor supply/housing demand as workers reallocate geographically. A straightforward result of this setup is that the extent to which shocks are spread geographically depends crucially on the mobility of workers, which mediates the labor supply response.

Empirical evidence suggests that households use migration as a smoothing mechanism over the short term. Most directly, households facing negative shocks send members to outside labor markets, and the remittances received supplement lost income. Yang (2004) finds Bangkok to be a major destination of short-term migrants in Thailand, with remittances closing up to half the income gap. Further research documents local spillovers from short-term migration. Morten (2013) presents a model of local risk sharing with limited commitment and the option to migrate. In rural India, the option to migrate appears to substitute for local risk-sharing networks by offering another channel through which to smooth shocks. Jayachandran (2006) reports that migration also stabilizes local wages through local labor supply. She finds wages in villages in India that have lower migration costs tend to respond less to local rainfall shocks, indicating that even those who do not migrate benefit from the options of others to migrate.

However, this short-term smoothing may not be sustained over the medium and long term. Following trade reforms in the 1990s in Brazil, Dix-Carneiro and Kovak (2015) find that local wage changes induced by the reforms persist and potentially increase over the next twenty years. Most of the response to changes in the terms-of-trade of locally produced goods comes from changes in labor force participation and movement between the formal and informal sector; there is little migration and little cross-region equalization. My investigation seeks to explain the extent to which the cost to semi-permanent moves may contribute to the lack of smoothing.

Commensurate with the observed levels of income smoothing in the short versus long term, policy that targets income stabilization or redistribution through migration may be significantly more expensive if it focuses on more permanent moves. Bryan et al. (2014) find that even a small financial incentive can induce households into temporary migration during the lean season, and that this behavior persists several years after the incentive is removed. In contrast, I find the cost of a permanent move to be considerably larger, meaning a substantial investment would be required to generate such migration on a large scale.

Any revealed preference investigation of costs requires first that agents respond to price signals. Past research finds this to be true in many settings. In the US, Blanchard and Katz (1992) document that most of the adjustment following a local shock takes place in the labor market; firms are much more limited in their ability to relocate geographically. A similar pattern of appears among OECD countries (Mayda, 2010), and McKenzie et al. (2014) find a positive response to destination earnings in international migration flows from the Philippines. The authors find that even though national labor shocks do not affect migrant earnings due to minimum wage regulations, migrant flows are sensitive to economic conditions in destination countries due to changes in labor demand.

I extend this line of investigation by using the variation in response to shocks of different duration to back out the cost of moving. Prior research uses commodity shocks as a source of identifying variation for earnings across a range of fields (e.g. Kline, 2008; Stock and Watson, 2012;

Young, 2014). An innovation of my research is to exploit differences in duration between different commodity prices to identify the net present value of earnings in addition to the current level. Any household decision that has earnings and utility implications over multiple periods is likely sensitive to expectations about the future. For instance, Paxson (1992) documents that the relationship between income and household savings and consumption varies with whether components of income are permanent or transitory, and Topel (1986) postulates this dynamic response in an equilibrium model of US state wages. I confirm that Thai workers respond differently to different components of a wage shock and then use the variation in instruments to estimate structural cost parameters.

Parameters to be estimated are conceptually similar to trade-based literature on occupational switching costs. Artuç et al. (2010) compute the cost of changing occupations in the U.S. to be on the order of 6 times annual earnings even when staying in the same location. Dix-Carneiro (2014) argues that some portion of this high cost might be due to sectoral comparative advantage among workers. Accounting for selection, he estimates that the cost of changing occupations in Brazil is 1.4–2.3 times annual earnings. Selection is less of an issue for counterfactual wages in my setting because (a) the labor force is largely uneducated and employed in highly substitutable occupations, and (b) most locations offer employment opportunities in a range of sectors. I find a range of relocation costs slightly below these numbers.

This paper more generally relates to a growing literature on the effects of trade on local labor markets (see Harrison et al., 2011). As countries become increasingly open to trade, access to international markets brings many benefits while imposing large costs on some sectors of the economy. This variation in costs and benefits is experienced both across sectors and across locations. As with any economic policy, the extent to which the gains from trade are shared within the economy depends on the labor market's ability to appropriately reallocate. Understanding how workers make such decisions will better enable policymakers to forecast the distribution of winner and losers after a change in trade policy. By identifying a portion of labor productivity shocks using commodity prices, this paper assesses the potential impact of changes in effective trade conditions on local wages and migration.

The results I present are most closely related to research on migration in the US by Kennan and Walker (2011). The authors use agents' migration history as a proxy for knowledge of past markets, and estimate migration costs based on the willingness to try an unknown market after observing a bad draw in a known market. They find moving costs in the U.S. to be around $300,000 in 2010 USD. I arrive at a comparable figure in a different setting using a different empirical strategy. In this paper, I rely on the predicted future evolution of known wage shocks to estimate the discounted net present value of a migration. Relative to per capita national earnings, my estimate of moving costs in Thailand are of a comparable magnitude.

3 Setting

I study migration among the 73 provinces in Thailand from 1985 to 2000. Research covers a period of rapid economic transformation in the country. GDP over these years grew at a rate of six percent per year, averaging eight percent excluding the years of the financial crisis. In per capita terms, incomes increased by five percent annually. Growth was accompanied by significant structural transformation. At the start of the period, over 60 percent of the labor force was employed in agriculture; by 2000 this number had fallen to 40 percent. Most of these workers moved into manufacturing, construction, and services, which each grew by 50 percent relative to baseline over fifteen years. In this context I investigate migration costs and local labor supply elasticities.

3.1 Data

Data primarily comes from the Thai labor force survey (LFS), an annually repeated cross-sectional survey that collected migration data from the years 1985 to 2000. Each survey covers a representative sample of households stratified by province and land type (rural or urban). Households exclude boarding houses, shelters, dormitories, and military facilities. Hence, temporary seasonal migration is less likely to be observed in the data. Housing facilities established at work locations such as factories or construction sites are included. Most years consist of two rounds of surveys: one in the first quarter and one in the third. I deseason both earnings and migration rates as discussed in Appendix C.

The LFS contains information on demographics, labor market outcomes, and migration history for each individual currently residing in a survey household. Demographic information includes individuals' age, sex, and highest education completed. Respondents also report their current labor market status including employment, earnings, hours worked, industry, and occupation. Importantly, individuals are asked about their location and labor market history. Respondents report how long they have lived in their current location (up to nine years) and where they resided previously if they moved within the previous five years. Employed respondents also report their employment status, including industry and occupation, from the previous year.

The structure of the LFS makes it well-suited to research on migration and labor markets. It is a large, nationally representative survey that elicits both source and destination information at an annual frequency. I use the questions on migration to construct a pseudo-panel of annual flows between each pair of provinces in Thailand, and the scope of the survey covers the entire nation. Moreover, the annual frequency permits analysis that exploits year-to-year variation in earnings and migration, which I use for estimation. The Thai LFS is one of the few data sources to include all of these features.

Survey households were selected in two stages: first, a random sample of census blocks was selected based on a population-weighted lottery within each survey stratum. Next, surveyors performed a complete enumeration of households within survey blocks, and then surveyed a random sample of households from the block. The survey covers roughly 0.15% of the population from in each round 1985–1993, with two rounds per year except in two instances, and doubles to around 0.3% of the population per round thereafter, with two rounds per year from 1994–2000.

The sampling procedure generates two challenges that I address in structural estimation. First, the sample size is small relative to the number of migrants in the population. The size of the survey induces measurement error in the observed flow or workers between any two provinces, including observations of 0 migration along many channels. Structural estimation using observed flows as proxies for actual flows will be inconsistent due to the nonlinear transformation of noisy data (Gandhi et al., 2013). Furthermore, stratification at the province level creates endogenous sampling. Individuals' sampling frequency is determined by their location, i.e. the outcome of their migration decision. Ideal data would comprise a random sample of the population prior to migration; choice-based sampling can generate inconsistency in parameter estimates (Cosslett, 1981). I address both issues by explicitly modeling the sampling process in estimation.

A drawback of the LFS is that it omits several variables of interest. In particular, respondents are not asked about their province of birth or duration of residence in prior locations. Location history likely influences workers' preferences over future destinations. Relatedly, migration questions only ask about the most recent move; multiple migrations and time between moves are unobserved for any individual. Finally, the survey only covers current residents in sample households. Therefore the LFS contains no information with regards to split households or extended family. Without data on these factors, I cannot explore heterogeneity along these dimensions.

This paper restricts analysis to men between the ages of 16 and 60, excluding those who are out of the labor force for disability, age, or education reasons. Roughly one quarter of the total number of respondents meet these criteria. In the first four years of the survey my sample includes roughly 18,000 respondents per round in 73 provinces. From 1989–1993 this number is roughly 25,000, and from 1994 onward the sample size increases to around 44,000 respondents per round.

Women are excluded due to confounding factors in both reported earnings and migration. In the selected age range, almost 20 percent of respondents claim to be out of the labor force for household duties (compared to only 0.1% of men). This choice is an endogenous decision, and no earnings or productivity data is available for home labor. To properly estimate labor market earnings and more directly isolate migration in response to labor market opportunities, I restrict analysis to working-age men.

3.2 Descriptive Facts

Migration in Thailand comprises on average 5 percent of the working age population of men and remains steady at that level over the entire period of study. Summary statistics for demographic characteristics of migrants and the full sample are presented in Table 1. In general, migrants tend to be younger than the general population. They work slightly longer hours and earn less, in part due to lower employment rates. Otherwise, they look very similar demographically to the general population. In particular, the period of study is characterized by universally low levels of education. Only a quarter of the population has completed primary education and only ten percent has completed secondary education; these rates are almost identical for both migrants and non-migrants.

Relative to the rest of the population, migrants are much less likely to be employed in agriculture and tend to concentrate in the manufacturing and construction sectors. Among non-migrants just over half the population works in agriculture; this number drops to 40 percent among those who have migrated within the last year, many of whom are likely to be seasonal workers. Among those who migrated between 1 and 8 years ago, only 30 percent work in agriculture. Figure 1 plots the full distribution of industries by migration status. As shown in Figure 2, 30–40 percent of migration within the country involves Bangkok, whose population is an order of magnitude greater than that of any other province. The remainder takes place between other provinces.

On average, gross migration between two provinces is roughly five times the net flow. This number suggests there is an average direction to most migrant flows, but it is not large. Consistent with other studies of population flows, migration from one province to another is a significant predictor of the size of the reverse flow. However, the predictive value is small in this setting with an R-squared of only 0.08.

Preferences over destination seem to matter: migrants travel only 85 percent as far as they would had they selected a destination at random (either uniformly or weighted by destination population), and the average earnings at their destination of choice is on average 7 percent higher than that of a random province.

Aggregating over individual decisions, a province's average earnings level is a significant predictor of its population growth. Figure 3 charts province average wages in 1985 in the left panel and population growth rates from 1985–2000 in the right panel, and Figure 4 presents the same data as a scatter plot of population growth versus log average earnings. Regression confirms that a log point increase in average earnings in 1985 is correlated with a 19 percent rise in population over the period of study.

Despite the flow of population to destinations with higher earnings, spatial variation in income remains large and persistent. Over the course of the sample, the standard deviation of province average earnings falls from around 60 percent of the mean to around 45 percent of the mean. By 2000, there still remain significant gaps in province earnings across space. Figure 5 presents a histogram of earnings by province in 2000. Furthermore, these gaps persist over time. A province's earnings level in 1985 predicts its average income in 2000 with an R-squared of 0.73. Motivated by large, persistent earnings variation, I investigate the perceived costs of migration and the implied spatial labor supply elasticity.

4 Empirical Model

To understand the migration process, I use a theoretical framework based on a standard model of location choice. The model consists of a set of forward-looking agents who each make a location decision in each period. Agents have preferences over expected earnings, unobserved province-specific amenities, migration costs, and idiosyncratic tastes. Estimation of the model aims to uncover the cost of migration and a parameter describing agents' attitudes toward the future.

Crucially, agents are forward-looking and therefore place value on the net present value of current and future earnings rather than simply considering observed current earnings. In the data, expected future earnings are unobservable and therefore not available for estimation. To circumvent this problem, I decompose the province wage process into components with known and unknown future properties, and then use the component with known permanence for estimation.

I use shocks to global commodity price series to generate variation with known permanence. Following the household finance literature, I model each series as the combination of a stochasic process and random walk (e.g. Blundell and Preston, 1998; Blundell et al., 2008). Although the permanence of any individual shock is still unobservable under this decomposition, the expected permanence of the shock is readily computed from the relative size of the variance of each component.

Given a set of country-wide shocks to prices, I construct province-level shocks using a Bartik-style calculation of industry intensity. For a given shock in a given province, the expected effect of the shock on that province is computed as the sum of each industry's sensitivity to the shock multiplied by the industry intensity within that province. Cross-sectional variation in industry composition by province interacted with time-series variation in shocks creates a set of instruments for current earnings that vary at the province-year level. These instruments are associated with varying levels of expected permanence based on the underlying price series and are plausibly exogenous to individual migration decisions.

Plugging these instruments back into the value function allows the expected earnings term to be divided into a component with known permanence and a component with unknown permanence. The former can then be to estimate parameters in the choice model.

4.1 Location Choice

Formally, let the economy be characterized by a continuum of workers indexed by n distributed across J provinces. At each time t, each worker has an initial location i and must choose a destination location j. The worker then supplies one unit of labor inelastically to the labor market at j and earns the local wage. The timing is such that in each period workers observe the prevailing wage everywhere, form expectations about the future, make a location decision, and then earn income for the period.

Let worker preferences be given by

$$V_{nijt} = \mathbb{E}[Y_{jt}] + A_j - c_{ijt} + \epsilon_{nijt} \tag{1}$$

where Y_{jt} is the net present value of earnings at the destination, A_j is an unobserved province-specific amenity, c_{ijt} is the cost of moving, and ϵ_{nijt} is an individual preference shock.[1] Further, parameterize the cost of migration as the sum of two components

$$c_{ijt} = \mathbf{1}\{i \neq j\}(C + \eta d_{ij}) \tag{2}$$

where C is a fixed cost for any migration and η is a cost based on the distance between two provinces d_{ij}. Finally, let the expected value of earnings be given by

$$\mathbb{E}[Y_{ijt}] = w_{jt} + \sum_{\tau=1}^{T} \delta^{\tau} \mathbb{E}_t[w_{jt+\tau}] \tag{3}$$

which is simply the current earnings level plus the discounted value of expected future earnings.

The key parameters are the fixed cost of migration C, variable (distance-based) cost of moving η, and a forward-lookingness parameter that encompasses the discount rate δ and horizon T. The main identification challenge stems from the fact that expected future earnings are unobserved. Discount-rate parameters are are necessary to translate an observed wage into its expected net present value. This valuation provides a scale with which to translate migration costs into dollar terms. The next sections present a strategy to recover expected future earnings.

4.2 Observed Components of Earnings

To deal with the challenge of unobserved expectations about the future, I construct a set of instruments for province wages using global commodity price series. For each series, it is possible to compute the expected permanence of a given shock. Thus any change in a province's earnings level driven by a shock to that series has the same expected permanence. In this way province wages can be written as the sum of components with known permanence and a residual component with unknown permanence. This strategy also overcomes standard endogeneity concerns, which I discuss in more depth below.

Instruments are generated at the province-year level by interacting commodity prices with province sensitivity to the price. This construction follows a Bartik-style procedure taking a weighted average over the province industry composition (see Bartik, 1991). I first calculate the wage response to a shock by industry at the national level, and then define the province-level re-

[1] Note at this time the subscript i is superfluous; I include it for consistency in notation when aggregating to province-level flows later.

sponse to be the weighted average of industry responses using industry shares in a base period. Then, the instrument value for a province-year observation is the commodity price shock for the year times the province-level response.

First, I compute industry sensitivity to each commodity series using a time-series regression at the national level. For each commodity k, I regress earnings for all workers in industry ℓ on the price

$$w_{nt} = \omega^{k,\ell}\tilde{p}_t^k + \varepsilon_{nt}$$

independently for each industry at the 2-digit industry level. For the price shock $\tilde{p}$ I use deviation from a linear trend to isolate the unexpected component of of the series.

Second, I derive each province's sensitivity to a commodity as the weighted sum of industry sensitivities, weighted by the labor force composition. Formally, the sensitivity of province j to commodity k, given 2-digit industries indexed by ℓ, is $\sum_\ell \omega^{k,\ell}s_{j0}^\ell$. In this expression, s_{j0}^ℓ is the share of the labor force of province j employed in industry ℓ in the base year, which in my data is 1985.

Third, I compute a province-year instrument value for each commodity by interacting the cross-sectional variation in province sensitivities with time-series variation in price shocks. Formally,

$$z_{jt}^k = \tilde{p}_t^k \sum_{ell} \omega^{k,\ell} s_{j0}^\ell \tag{4}$$

Since the time-series variation in instrument value stems only from variation in the commodity price, the instrument has the same permanence characteristics as the underlying price series.

Finally, given a set of local instruments for price, I can decompose province earnings into a component with known (or estimable) permanence characteristics and an unknown residual. Formally, let province earnings be defined by

$$w_{jt} = \sum_k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j + \mu_{jt} \tag{5}$$

where $\bar{w}_j$ is the province average earnings, κ^k is the province earnings response to the instrument z_{jt}^k, and $\tilde{z}$ denotes a deviation from the mean. Note that $\bar{w}_j$ subsumes the mean instrument value so that only deviations are necessary for identification. The first terms in this expression represent components with defined permanence characteristics, and the final term μ_{jt} is a residual with unobserved permanence.

Generating a province-level shock as the sum of local industry-level shocks is motivated by an underlying model of integrated local labor markets. The key assumption is that local labor markets can be characterized by a single local wage. Therefore, a shock to an industry drives up the wage in that industry, drawing in workers from other local industries until the local wage equilibrates at a new, higher level. I formally model this dynamic in Appendix A.

This identification strategy also overcomes the standard threat of endogeneity. Unobserved taste shocks ϵ_{nijt} may be correlated with earnings w_{jt}. Most directly, increased labor supply leads to movement along the labor demand curve: as agents enter a province, the growing size of the labor force may drive down wage levels. Other time-varying preference shocks may also be correlated with local labor market conditions.

Bartik-style instruments based on commodity shocks employ two sources of variation that are plausibly orthagonal to individual preferences and therefore plausibly exogenous. The first source of variation comes from time-series changes in global commodity prices. Since Thailand is small relative to the global economy, it is unlikely that prices are driven by domestic labor market conditions. Even if the nation were large enough to move commodity prices as a whole, no single province is likely to have a significant effect.

The second source of variation comes from cross-sectional differences in industry composition. This cross-sectional variation is drawn from a reference period of 1985, preceding any analysis, and therefore is unlikely to have been influenced by subsequent taste shocks. Furthermore, all fixed province characteristics correlated with industry composition will be absorbed by the amenity term A_j. Combining these these two sources of variation, each of which is plausibly exogenous, generates a set of valid instruments for local earnings; the only remaining correlation between w and ϵ must operate through μ.

4.3 Shock Permanence

To characterize the observable permanence of the earnings process, it only remains to estimate the permanence of commodity price series. To do so I model each series as the sum of a random walk and a stochastic component, following methodology commonly used in literature on household income. Under the assumption of normality, the expected permanence of an observed shock is determined by the relative variance of each component.

Formally, define each price series, suppressing the k indices, as

$$\begin{aligned} p_t &= R_t + s_t \\ R_t &= R_{t-1} + r_t \end{aligned} \tag{6}$$

where r_t and s_t are normally distributed shocks drawn from stationary distributions that are independent from each other and across time. Under the assumption of normality we can define a permanence parameter ρ to be

$$\mathbb{E}_t[p_{t+\tau}|p_t] = \frac{\sigma_r^2}{\sigma_r^2 + \sigma_s^2} p_t \equiv \rho p_t$$

where σ^2 denotes variance. This expression follows readily from treating p_t and $p_{t+\tau}$ as joint normal variables. I discuss estimation of these values in the next section.

Since the time-series properties of the instruments are inherited from the underlying commodity price series, expected future earnings are easily written in terms of instruments and their permanence. Following (5),

$$\begin{aligned} w_{jt} &= \sum_k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j + \mu_{jt} \\ \implies \mathbb{E}_t[w_{jt+\tau}] &= \sum_k \rho^k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j + \mathbb{E}_t[\mu_{jt+\tau}] \end{aligned}$$

In this expression, every term is observable except for the expected future value of the residual component of earnings μ. This expression can then be plugged into (3) so that the value function (1) has observable future components.

Importantly, the observed instrument values generate variation in expected future income that is not collinear with the present shock. In other words, two observed wage shocks of identical size may have different observed expected future earnings if they are generated by commodities of differing permanence. This variation is crucial in identifying preferences over the future, which is necessary to understand the scale of the other parameters in the model.

An additional advantage of modeling series permanence in this way is that the net present value of an instrument shock is multiplicatively separable into the expected future value, based on ρ^k, and a term representing the discount rate $\sum_{\tau=1}^{T} \delta^\tau$. This is because the permanent component of each series enters as a random walk so that

$$\begin{aligned} &\mathbb{E}_t[\tilde{p}_{t+\tau}^k] = \mathbb{E}_t[\tilde{p}_{t+\tau'}^k] \quad \forall \tau, \tau' > 0 \\ \implies &\sum_{\tau=1}^{T} \delta^\tau \mathbb{E}_t[w_{jt+\tau}] = (\sum_k \rho^k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j) \sum_{\tau=1}^{T} \delta^\tau + \sum_{\tau=1}^{T} \delta^\tau \mathbb{E}_t[\mu_{jt+\tau}] \end{aligned}$$

That is, all future periods have the same expected price level, which means that all future periods have the same predictable component of earnings. Because of this separability, the forward-lookingness term $\sum_{\tau=1}^{T} \delta^\tau$ can be collpased into a single parameter and is not dependent on the choice of T or δ. Similarly, estimation is not sensitive to alternate functional forms such as β-δ or hyperbolic discounting.

4.4 Embedded Assumptions

The model abstracts from individual heterogeneity, labor market segmentation, and some dynamics. Each of these is discussed in Appendix A. Selection or market segmentation may matter if worker income varies by industry or workers have location-specific skills. In this case, province average earnings would not represent appropriate counterfactual earnings for potential migrants. This discrepancy would make agents appear to be less responsive to earnings, which would load onto estimated migration costs. These factors are likely not so important due to the uniformly low education level of the labor force, the prevalence of non-salaried jobs, and the fact that migrants tend to match non-migrants on all characteristics except for age. The economy seems to be characterized by a low-skill, largely substitutable labor force that is mobile across industries.

Risk does not enter the value function because it is unobservable in the data and would not be cleanly identified even if it could be measured. I would ideally need a province-year varying measure of the average difference between expected and actual earnings. However, with cross-sectional data on earnings the closest observable measure of earnings risk within a labor market is the variance of the earnings distribution. Unfortunately this value conflates both idiosyncratic risk and variance in individual fixed characteristics. Even panel data would not overcome the problem. While a panel could help purge the individual variation from the observed income variance, it would at best allow me to construct a province-level measure of risk over time. Since analysis relies on variation at the province-year level, this would not generate sufficient variation for estimation. Furthermore, even with an ideal measure of risk, identification would still be a challenge. All commodity-based instruments for earnings affect the average earnings level. Any extrapolation to other moments of the earnings distribution would be identified entirely by functional form alone. Reassuringly, I use earnings variance as a proxy for risk and I show that it likely has little impact on estimates of the value of earnings in Appendix A.

Finally, to limit the computational complexity of the problem, I make two simplifying assumptions about expectations over the future to move from the fully recursive dynamic optimization to the valuation presented above. A recursive formulation would require a state variable that consists of current location, current earnings in each province, current instrument values, expected permanence for each instrument, and expected residual permanence. The size of the state space leads to an optimization problem that is computationally infeasible to solve. To simplify, I first assume that agents collapse the perceived return to all future migrations to a single value so that each migration decision is considered independently. I then fix expectations about the future by constraining the way agents update their beliefs over anticipated wages. These two assumptions are each discussed in detail in the appendix.

5 Reduced Form Evidence

Instruments with varying permanence can help identify parameters of the choice model above, but identification relies on workers being sensitive to instrument permanence. Sensitivity requires two things: first, workers must indeed be forward-looking and have preferences over expected future earnings. Second, workers must be sophisticated enough respond differentially to different instruments. Note that this second condition does not require each agent to fully understand the times series properties of each commodity price and its transmission to local earnings. Instead, there are many mechanisms that may cause agents to respond appropriately to income variation with differing permanence. For instance, it would be sufficient if local labor markets sent signals about the permanence of shocks or if agents associated greater permanence with areas more sensitive to instruments of greater permanence.

In this section I construct shocks with differing levels of permanence based on global commodity prices and then present reduced-form evidence that workers are sensitive to the expected future component of these shocks. I first select instruments based on Thai manufacturing imports and estimate their permanence characteristics. I focus on earning shocks driven by crude oil, cotton, and wood prices. The former two series have a very high degree of permanence, while sawn wood has a larger transitory component. All three are significant predictors of local earnings.

Next, I present two-stage least squares regression results of the effect of local earnings on migration. Since a more permanent commodity price corresponds to a higher net present value of earnings given an observed earnings level, the model predicts that two-stage least squares using a more permanent instrument for earnings will estimate a larger migration response. The results confirm that the migration response to earnings shocks induced by crude oil and cotton prices is larger than the response to earnings driven by wood prices. The reduced form results are consistent with individuals forming accurate beliefs about future earnings and justify the revealed preference estimation in the next section.

5.1 Commodity-Based Instruments

Instruments for local earnings are derived from prices of major Thai manufacturing imports. In particular I consider crude oil, cotton, and wood. Oil and petroleum products are significant inputs in the manufacturing industry and in 1995 represented 6.5% of national imports. I use the average spot price of Dated Brent, West Texas Intermediate, and Dubai Fateh price series for analysis. Cotton also represents a large input in the manufacturing sector during the period of study, comprising 1.1% of imports in 1995 while clothing and textile products made up roughly 6.5% of exports. Cotton prices are derived from the A Index, CIF at Liverpool. Finally, in 1995 wood and lumber represented around 2% of Thai imports, while furniture and other wood products comprised a comparable fraction of exports in addition to the other sectors that use lumber. For the price of wood, I use the Japanese import price for Malaysian meranti. All prices are computed as deviations from a linear trend as before. Instrument selection is discussed in Appendix B.

I first verify that each commodity instrument does indeed induce variation in provincial earnings. Doing so is equivalent to running a first-stage regression for a two-stage least squares specification using the Bartik-style constructed variable as an instrument for earnings. The regression follows almost directly from (5): for a given price instrument, suppressing the k subscript, I run

$$w_{jt} = \kappa \tilde{z}_{jt} + \gamma_j + \gamma_t + \mu_{jt} \tag{7}$$

where each observation is a province-year, κ is the effect of a commodity price shock on local earnings, γ_j is a province fixed effect, and γ_t is a year fixed effect.

Table 2 presents results from the first-stage regression of earnings on each commodity instrument. Regression verifies that each instrument has a significant impact on earnings which persists even after controlling for the other instruments. Since all three represent manufacturing inputs, it is natural that an increase in the price corresponds to a decrease in local earnings in those provinces most sensitive to the commodity price.

For each series I next compute the expected permanence of a price shock. Recall that each series is modeled as the sum of a permanent and transitory component given in (6). The relative size of the variance of these components governs the permanence of each series. Variance can be estimated in the data using first differences of the price series. Note that

$$\Delta p_t = r_t + \Delta s_t$$

This expression generates the two moment conditions

$$\begin{aligned} \text{var}(\Delta p_t) &= \sigma_r^2 + 2\sigma_s^2 \\ \text{cov}(\Delta p_t, \Delta p_{t-1}) &= -\sigma^2 s \end{aligned} \tag{8}$$

For each commodity, (8) identifies the expected relative contribution of permanent and temporary shocks to a change in the international price. Any observed price shock induced by a series can be thought to have permanent and temporary components in these ratios.

Table 3 presents the long-run permanence characteristics of the three commodity price series through the end of the period of study. Crude oil prices appear to be the most permanent: over 98 percent of a shock to the price of oil is expected to persist into the future. Cotton prices have a similarly high degree of permanence, with 91.5 percent of the variation being generated by the random walk component. In contrast, the price of wood appears to have a significant transitory component. Permanent and transitory shocks contribute to wood prices to an equal degree, meaning that roughly half of a shock to the price is expected to dissipate by the following year.

Given the variation in permanence, each instrument corresponds to a different net present value of earnings conditional on an observed earnings level. For an observed shock to earnings, the full discounted value of the shock is largest in absolute terms when the shock is driven by the price of crude oil and smallest when the shock is driven by the price of wood. If agents are forward-looking, theory predicts that the migration response to shocks identified by these series will be proportionately sized.

5.2 Regression Results

To determine whether agents respond to expected future labor market conditions, I run regressions of the form

$$m_{ijt} = \lambda^w w_{jt} + \lambda^d d_{ij} + \lambda^x w_{jt} \times d_{ij} + \gamma_j + \gamma_{it} + \varepsilon_{ijt} \tag{9}$$

where the unit of observation is a source-destination-time cell with source province i, destination province j, and year t. w_{jt} is the log residual wage at the destination in year t, d_{ij} is the distance between the two provinces, and γs represent fixed effects. Note that with source-year fixed effects, using the destination wage as a regressor is identical to using the earnigns gap between source and destination. Distance is included because of the role it plays in explaining migration empirically, and the interaction term allows for a more flexible relationship between migration and earnings.

I consider three different outcomes related to migration: the number of agents from province i surveyed in province j, the percent of the $t-1$ population of province i that is surveyed in province j at time t, and a dummy for the presence of any observed migrants from i to j. The three outcomes are discussed in detail in Appendix C. Percent migration is an unbiased estimate of the migration response to an earnings gap, from which elasticity can be calculated. However, given the sampling, the estimate is highly skewed right with a median well below the mean. The other two outcomes are nonlinear transformations of the migration response that are increasing in migration but also include other factors. In practice they are more precisely estimated but difficult to interpret. For the two-stage least squares estimates I present results for migration counts and the migration dummy. Outcomes and earnings are both seasonally adjusted, as discussed in the appendix.

Ordinary least squares results for (9) are presented in Table 4. An increase in earnings in a given destination is consistent with an increase in migration to that destination using all three measures. Overall, a one log point increase in wages at a given destination correlates to 0.05 percent more of the population moving to that destination. This change corresponds to 88 more migrants surveyed there on average, and a 19 percent greater chance of observing any migrant from a given source at the destination. As expected, distance has a negative effect on the likelihood of migration after summing the main effect and the interaction term.

OLS estimation suffers from two problems analogous to the discussion in Section 4, both solved with instrumental variables. First is the traditional issue of endogeneity. Migration will affect local wages through the labor supply channel as long as demand is not perfectly elastic. Furthermore, any time-varying local characteristics correlated with both migration and earnings are omitted variables biasing estimation. For the same reasons discussed before, Bartik-style commodity instruments are plausibly exogenous to these factors because they interact external time-series variation with predetermined cross-sectional variation.

Second, the OLS lacks a scale. With any degree of forward-lookingness, an observed earnings level or gap is a poor proxy for the level or difference in net present value. Two provinces with the same current earnings may have very different valuations if their expected earnings trajectory differs greatly. In contrast, the two-stage least squares estimate isolates the portion of the variation in the endogenous variable, in this case local earnings, generated by the instrument. Since I use instruments with known permanence, this means isolating components of the earnings process with known expected future value.

Differences in the permanence of each instruments generate a prediction about the relative magnitudes of coefficients estimated with each instrument. Specifically, if agents are forward-looking and have rational expectations, then the estimate coefficient on earnings in (9) should be larger for estimates using instruments of greater permanence. This is because the estimated coefficient can be expressed as the migration response to total discounted earnings multiplied by the permanence of the instrument.

To see this decomposition, consider a simple model with constant treatment effects. In what follows, treat all variables as residuals after controlling for distance and fixed effects. Let the relationship between earnings, migration, and an instrument with permanence ρ^z be given by

$$\begin{aligned} m_{ijt} &= \Lambda \mathbb{E}[Y_{jt}] + \varepsilon_{ijt} \\ w_{jt} &= \kappa z_{jt} + \mu_{jt} \\ \implies \mathbb{E}[w_{jt}] &= \left(1 + \sum_{\tau} \delta^{\tau} \rho^{z}\right) \kappa z_{jt} + \left(1 + \sum_{\tau} \delta^{\tau} \rho^{\mu}\right) \mu_{jt} \end{aligned}$$

for discount rate δ and some unknown residual permanence ρ^μ. Then the two-stage least squares estimate of the analog of (9) is

$$\begin{aligned} \hat{\lambda}^{2SLS} &= (z'w)^{-1}(z'm) \\ &= (z'(z\kappa + \mu))^{-1} \left(z' \left(\left(1 + \sum_{\tau} \delta^{\tau} \rho^{z}\right) z_{jt} \kappa \Lambda + \left(1 + \sum_{\tau} \delta^{\tau} \rho^{\mu}\right) \mu_{jt} \Lambda + \varepsilon \right)\right) \\ &\to (1 + \delta \rho^z) \Lambda \end{aligned}$$

where the final equality holds because z is orthogonal to μ by construction and to ε by assumption. From this final expression it is clear the estimated coefficient is increasing in instrument permanence.

This exercise is merely suggestive due to heterogeneity in the elasticity Λ. With heterogeneous treatment effects, the 2SLS parameter estimate is a weighted average of underlying elasticities weighted by the strength of the first stage. In the model, Λ is a function of both the preference for earnings and the distribution of idiosyncratic tastes. For instance, with an extreme value distribution, the elasticity increases in migration probabilities[2] as well as preferences. Therefore if instruments differentially affect locations or years with higher migration, this will also induce variation in the 2SLS estimate. Since migration rates are observed with high noise, I cannot explicitly test for this issue. For the same reason, the ratio of reduced form coefficients cannot directly be interpreted. However, higher coefficient estimates for more permanent instruments are consistent with agents having accurate expectations about the future.

The main two-stage least squares results are presented in Table 5. All point estimates are positive; higher earnings in a province increases the likelihood that migrants are observed in that province. Estimates suggest that a log point increase in average earnings in a province induced by the more permanent oil or cotton prices increase the likelihood that migrants are observed along channels to that province by 47 percentage points. In contrast, a log point increase in earnings driven by wood prices only raises this likelihood by 17 percentage points. The coefficient on earnings in response to changes in the price of wood is just over one third the coefficient in response to a change in the price of crude oil. An overidentification test confirms that the coefficients are significantly different: Hansen's J statistic for a joint regression with all three instruments rejects instrument equality at the 2% level.

Moreover, these estimates are equal to or greater than the OLS. This may either be caused by endogeneity in the OLS or by the fact that all instruments have a relatively large permanent component, and therefore identify variation with a higher net present value than the average observed wage differential.

Two-stage least squares results taking the number of observed migrants as an outcome are broadly consistent with this pattern. Results are presented in Table 6. The coefficient on earnings is consistently larger than the OLS, and it is larger when estimated using the more permanent instruments than when estimated using the more temporary instrument. However, there is much more noise in this specification. Standard errors are large enough to allow almost any relationship between the three coefficients. Results using percent migration follow a similar ordering, but noise in the estimate and the median bias make them even more difficult to interpret. The results are provided in Appendix C.

The reduced form results indicate that agents respond differently to wage variation induced by shocks of different permanence when making migration decisions. This implies both that workers

[2] For low levels of migration.

are forward-looking when considering whether to migrate and that they are sufficiently informed about the expected nature of variation generated by global commodity price fluctuation. Even though the point estimates are averages over transformations of the underlying choice model and therefore difficult to interpret, these two facts are crucial to establishing the validity of structural estimation. Having confirmed that the instruments I construct generate sufficient variation, I can use the revealed preference decisions of workers in response to shocks to estimate the cost of moving.

6 Structural Estimation

In this section I outline a strategy to estimate parameters of the choice model introduced in Section 4 based on revealed-preference migration decisions. The main parameters to be estimated are the fixed and variable costs of migration and the variance in idiosyncratic tastes. Estimation will also recover province amenity values net of average earnings. Throughout this section I maintain an assumption of rational expectations with regards to the wage and labor market effects of shocks.

Identification comes from the number of observed migrants traveling between provinces. In particular, moving costs are identified by the number of migrants and geographic distribution of migration destinations. All results are scaled by the relative weight placed on earnings to translate parameters into dollar terms.

To estimate the model, I first rewrite the value function in (1) to isolate the parameters that can be identified. To do so, I break the expected earnings term into observable and unobservable components, with the observable components governed by interpretable parameters. I also address endogeneity in the taste parameter using using a control function approach similar to that of Rivers and Vuong (1988). These two steps allow the (1) to be restated as a function of values that can be observed or consistently estimated from the data.

The rewritten value function contains an unobserved taste term purged of correlation with all other variables. I next make a distributional assumption on this term to aggregate individual preferences into migration probabilities. This step follows the standard discrete choice methodology that assumes an extreme value distribution to compute logit choice probabilities conditional on the underlying specification of the value function (e.g. Train, 2009).

Finally, I explicitly model the data sampling strategy and aggregate population numbers given choice probabilities to generate a likelihood function. This final step overcomes potential inconsistency in estimation due to data sampling. The data suffer from two weaknesses. The small sample size means that actual migration flows are badly measured and often missed entirely. Any strategy that matches aggregate moments without accounting for measurement error will be inconsistently estimated. Furthermore, stratification at the province level means that sampling is endogenous with respect to any migration source. My estimation procedure directly addresses these two threats to validity.

6.1 Identified Parameters

Recall from Section 4 that the value of migration is given by expected earnings, migration costs, location-specific amenities, and an individual taste shock. Using instruments for earnings, I express expected earnings as a function of current earnings, instruments, and an unobserved expected future residual. Similarly, I model the taste shock as the sum of an independent idiosyncratic shock and an endogenous residual. In both cases, the residual is a linear function of the error term in the first stage regression of earnings on instruments. Since this error term is consistently estimated in the fist-stage regression, fitted errors can be used in structural estimation. This allows the value function to be rewritten as a function of current earnings, expected future instrument values, migration costs, a province-specific average value, an estimated endogenous residual, and an exogenous taste shock.

Formally, the value to individual n moving from province i to province j at time t is given by (1)

$$V_{nijt} = \mathbb{E}[Y_{jt}] + A_j - c_{ijt} + \epsilon_{nijt}$$

as a function of earnings, amenities at the destination, moving costs, and an idiosyncratic preference. Further recall that costs and earnings are parameterized by (2) and (3) as

$$c_{ijt} = \mathbf{1}\{i \neq j\}(C + \eta d_{ij})$$
$$\mathbb{E}[Y_{ijt}] = w_{jt} + \sum_{\tau=1}^{T} \delta^\tau \mathbb{E}_t[w_{jt+\tau}]$$

where costs are divided into fixed and distance-based costs, and earnings are a net present value sum of current earnings and expected future earnings. Plugging these into the value function yields value as a function of current earnings, expected future earnings, amenities, fixed and variable moving costs, and a taste shock.

Further recall that period earnings can be expressed from (5) as a function of instruments and a residual

$$w_{jt} = \sum_k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j + \mu_{jt}$$
$$\implies \mathbb{E}_t[w_{jt+\tau}] = \sum_k \rho^k \kappa^k \tilde{z}_{jt}^k + \bar{w}_j + \mathbb{E}_t[\mu_{jt+\tau}]$$

where the second line characterizes expected future earnings as a function of instruments, their permanence, and an unobserved residual.

Here I make two assumptions about the relationship between residual earnings μ, expected future residual earnings, and unobserved tastes ϵ. First, for tractability, I place a restriction on the form of the unobserved future earnings residual. Let the expectation

$$\mathbb{E}_t[\mu_{jt+\tau}] = \rho^{\mu,\tau}\mu_t$$

be a linear function of the current earnings residual. This assumption admits many functional forms including the stochastic/random walk form of the instruments or a stationary AR1 process. It allows for multiplicative separability between μ_{jt} and any combination of discounting and decay in the future so that the term can continue to enter linearly into the value function.

The second assumption deals with endogeneity in tastes. Individual preferences are likely correlated with earnings, primarily through the local labor market; hence the need for instruments. Under the assumption of instrument exogeneity, the taste term can be expressed as the sum of an endogenous and exogenous component. Let the endogenous component of the taste shock also be a linear function of the earnings residual so that

$$\epsilon_{nijt} = \phi\mu_{jt} + e_{nijt}$$

where e_{nijt} is i.i.d. and uncorrelated with all other variables. This assumption follows the method presented by Rivers and Vuong (1988) for instrumental variables in nonlinear probit. Substantively, it rules out endogeneity of moving costs or amenities. The linear functional form is again for tractability so that μ_{jt} continues to be linear in the value function.

Substituting everything into (**??**) and grouping like terms yields the value function

$$\begin{aligned} V_{nijt} &\equiv \bar{V}_{ijt} + e_{nijt} \\ \bar{V}_{ijt} &= w_{jt} + \beta \sum_k \kappa^k \rho^k z^k_{jt} + \xi_j - \mathbf{1}\{i \neq j\}\left(C + \eta d_{ij}\right) + \varphi\mu_{jt} \end{aligned} \tag{10}$$

in terms of current earnings, instruments and their permanence, province fixed effects, fixed and variable moving costs, and the residual component of current earnings. A full derivation of this expression can be found in Appendix E. Earnings w_{jt}, instruments z^k_{jt}, and distance d_{ij} are observed in the data. The permanence of each instrument ρ^k is computed from the time series of commodity prices. The only remaining unobserved input terms are κ^k and μ_{jt}. This coefficient and residual are consistently estimated in the first stage, and therefore the expression can be estimated by substituting $\hat{\kappa}^k$ and $\hat{\mu}_{jt}$ from a first-stage regression.

Key parameters of interest in (10) are C, η, and σ_e. Note that the coefficient on current earnings w_{jt} is normalized to 1 so that earnings naturally serve as the numeraire. C represents a fixed cost of migration and η a distance-based cost, both in terms of dollars. With the scale set by earnings, I also estimate the variance in e, the unobserved taste shock. This variance describes the importance of earnings relative to other unobserved factors in the migration decision.

In (10), β characterizes the weight placed on expected future earnings. In the model it is specified as $\sum_\tau \delta^\tau$ for a discount rate δ and time horizon τ. However, as discussed previously, this term can embody other specifications of discounting because every future period has the same expected shock value in a random walk process. I estimate the model over a range of possible discount rates; potential identification of the discount rate is discussed below.

Additional parameters to be estimated are $\{\xi_j\}$ and φ. The set of $\{\xi_j\}$ fixed effects incorporate both province-level amenities and province average earnings and instrument values; this term is difficult to interpret by itself but allows for consistent estimation of the parameters of interest. To fix the location, $\xi_{Bangkok}$ is set to 0. φ encompasses both the endogeneity in earnings as well as expectations over the unexplained component of earnings. Due to both components being specified as linear functions of the first stage residual, this term is again difficult to cleanly interpret.

6.2 Estimation of Parameters

To estimate the identified parameters, I use maximum likelihood given the observed explanatory variables, the observed number of migrants, and known province population sizes. I first make a distributional assumption on the error term to map choice values as a function of data and parameters into aggregate migration flows. I then model the sampling procedure to compute the likelihood of seeing the observed number of migrants given the computed aggregate flows, imposing the restriction the restriction that flows must be consistent with the evolution of each province's population over time. This second step overcomes potential inconsistencies due to sparse and endogenous sampling. Estimation can roughly be described as choosing parameters to maximize the probability of migration along channels where the largest number of migrants are observed, subject to the sampling.

Let the exogenous portion of individual taste shocks, e_{nijt}, be drawn i.i.d. from a type one extreme value distribution. If individuals in each period choose a destination j according to maximize expected utility, i.e.

$$j(n) \in \arg\max_{1\leq j'\leq J} V_{nijt} = w_{j't} + \beta \sum_k \rho^k z^k_{j't} + \xi_j - \mathbf{1}\{i \neq j'\}\left(C + \eta d_{ij'}\right) + \varphi\mu_{j't} + e_{nij't}$$

aggregate migration flows will take a familiar logistic form. For a given source i in year t, the portion of the population that relocates to a destination j will be

$$m_{ijt} = \frac{\exp(\bar{V}_{ijt})}{\sum_{j'} \exp(\bar{V}_{ij't})} \tag{11}$$

where $\bar{V}$ includes expected earnings, local amenities, and a migration cost as long as $j \neq i$.

Actual migration rates m_{ijt} are noisily measured in the data due to small sample size, an issue common to much survey data. Even though the observed rates are unbiased estimates of true migration rates, estimation that relies on matching moments to the observed rates will be biased. Bias derives from the fact that structural estimation takes nonlinear transformations of observed moments. In general non-linear transformations do not preserve the mean of a distribution, and therefore unbiased noise in the moment translates to bias in parameter estimates. This problem is discussed in detail by Gandhi et al. (2013). The authors present a strategy to estimate bounds on the true parameter values. In my setting I have more information about the data generating process and therefore am able to explicitly incorporate it into estimation.

Within a province, the likelihood of observing a migrant can be computed given migration flows, population sizes, and the survey size. Let the population of province j in year t be denoted by N_{jt}, and let the number of people sampled in the province be denoted by s_{jt}. The probability that a random citizen came from province i in the previous year is $m_{ijt} * N_{it-1}/N_{jt}$. The numerator reflects the total number of people from i living in j at time t, which is the population of i multiplied by the probability of moving, and the denominator is the total population of j. A similar calculation can be made for every possible source.

When s_{jt} people are surveyed, the number from each possible source province can be considered to be a draw from a multinomial distribution with probabilities as given above, summing to 1. The quantity of migrants from each source i observed in j at time t is distributed according to

$$\{Q_{ijt}\} \sim \mathcal{M}\left[s_{jt}, \left\{m_{ijt}\frac{N_{it-1}}{N_{jt}}\right\}\right]$$

where $\mathcal{M}$ denotes a multinomial distribution.

The likelihood of a given observation, conditional on choice probabilities m_{ijt}, is given by

$$\mathcal{L}\left[Q_{ijt}|m_{ijt}\right] = \prod_{jt}\left[\frac{s_{jt}!}{\prod_i Q_{ijt}!}\prod_i\left(m_{ijt}\frac{N_{it-1}}{N_{jt}}\right)^{Q_{ijt}}\right]$$

where m_{ijt} is computed from data and parameters according to (11). The model is estimated by maximizing this likelihood subject to two the constraints that all probabilities must sum to 1:

$$\sum_{j'} m_{ij't} = 1; \qquad \sum_{i'} \frac{m_{i'jt}N_{i't-1}}{N_j t} = 1$$

The former dictates that in a source i at time t, the portion of the population going to each possible destination j' must sum to 1. It is met by construction in the logistic specification of choice probabilities. The latter condition dictates that in a given destination j at time t, the probabilities of surveying an individual from each possible source i' must sum to 1. This is not necessarily met and is imposed as a constraint on maximization.

The two constraints together have a natural interpretation as a law of motion for population. Combining them yields

$$N_{jt} = N_{jt-1} - \sum_{i' \neq j} m_{ji't} N_{jt-1} + \sum_{i' \neq j} m_{i'jt} N_{i't-1} \forall j, t$$

That is, the population of province j at time t equals the population at time $t-1$ minus the number of out-migrants plus the number of in-migrants.

This formulation circumvents the problem of endogenous sampling as well. The ideal data for discrete choice estimation comprises a random sample of agents from each market. In this case, a market is defined as a source province i in a year t. However, agents are sampled in their destination province and the LFS is stratified by province; since the destination province of an agent dictates their sampling probability, sampling is endogenous to location choice. Cosslett (1981) discusses the identification challenges posed by endogenous sampling and proposes solutions based on the use of aggregate choice shares. Even though I cannot observe aggregate choice shares within any single market, my solution is conceptually similar because the law of motion is a linear combination of aggregate shares.

After using the constraints to substitute for the portion of nonmigrants m_{jjt} in each province and year, the log likelihood simplifies to

$$\log \mathcal{L}[\cdot] = \mathbb{C} + \sum_{j, i \neq j, t} Q_{ijt} \log(m_{ijt}) + \sum_{j,t} Q_{jjt} \log \left(N_{jt} - \sum_{i \neq j} m_{ijt} N_{it-1} \right) \tag{12}$$

with a constant $\mathbb{C}$. Note that the observed number of migrants Q_{ijt} multiplies the log of the computed choice probability m_{ijt}. Maximization essentially consists of choosing parameters to maximize the choice probability m for the channels with the highest number of observed migrants Q, with a penalty paid for a high migration rate when many non-migrants are surveyed (Q_{jjt}). Since the number of observed workers relative to the population varies by province, it implicitly provides a weighting for each migration channel.

To implement estimation I proceed in two steps: First, I estimate ρ^k and run the first-stage regression to estimate $\hat{\kappa}^k$ and construct $\hat{\mu}_{jt}$. The second step is to maximize (12) over the parameter space given the observed number of migrants surveyed Q_{ijt}, earnings w_{jt}, distances d_{ij}, instruments z_{jt}, population sizes N_{jt}, and first-stage residuals $\hat{\mu}_{jt}$. Migration probabilities m_{ijt} are computed as an intermediate value but not essential to optimization.

6.3 Identification

Identification of the model comes from migration decisions in response to earnings shocks. In each period, I take the geographic distribution of population as given and identify off of changes in location. This approach has the advantage that persistent wage dispersion need not be explained by variation in amenity values alone. In spatial models identified by equilibrium outcomes, any geographic disparities must be exactly compensated by preference variation. In contrast, my estimation allows for the alternate explanation that high migration costs prevent the existing population from arbitraging spatial variation. I discuss the identifying variation and nonparametric identification of the main components in detail in Appendix E.

6.3.1 Identification of Migration Costs and Amenities

The cost of migration is identified by the number and geographic distribution of people who move. The total number of migrants corresponds to how high an unobserved preference shock must be before a worker decides to move; low levels of migration indicate that only people with a very high preference for another province are willing to move. This situation arises when, absent a taste shock, the value of the home province is much higher than *all* other provinces, i.e. moving costs are high. If this dynamic occurs uniformly across the country, then fixed migration costs can be said to limit general mobility. In contrast, if observed migration is highly concentrated in nearby locations, then distance-based costs likely limit migration to far destinations while the fixed cost is low enough to allow nearby travel.

One challenge to my approach lies in the interpretation of migration costs and location-specific preferences. These components present three separate identification concerns. First, there may be common, economy-wide preferences for certain provinces. These preferences are identified net of province average earnings as the parameter ξ_j. The identifying variation for this parameter comes form net migration flows. If two provinces have the same level of NPV earnings, then the difference in amenities between them governs the net flow of workers. Since preferences are invariant to linear utility transformations, ξ_j is only identified in relative terms. For estimation I fix the value for Bangkok to be 0.

Second, there may be individual heterogeneity in tastes for provinces. I impose the assumption that taste shocks e_{nijt} are independent across both location and time for a given individual. However workers may have persistent, heterogeneous preferences over destinations. If heterogeneity is such that workers have a persistent preference for their current location, for instance due to established local social networks, then it may be interpreted as a migration cost. When a worker considers migrating, she faces a cost that includes the loss of this home benefit in net present value terms. My model abstracts from the alternate possibility that workers have fixed, heterogeneous preferences over possible destinations for tractability.

Third, agents' utility may be endogenous to their location choice. In this sense I estimate a perceived cost of migration, which determines elasticities but may be misleading in welfare calculations. To the extent that ex post utility differs from ex ante expected utility, for instance due to adaptation, ambiguity aversion, or learning, the welfare effects of migration cannot be computed by simply subtracting the gains from the costs. Estimation based on revealed preference can only uncover perceived costs because all observed decisions are, by definition, made under ex ante beliefs.

6.3.2 Identification of the Value of Earnings

Sensitivity to earnings in general are similarly identified by the migration response to earnings shocks. A large migration flow between two provinces when the earnings gap between them is high would indicate a high value of earnings, while little migration regardless of the earnings gap would indicate low sensitivity to earnings. Note that migration costs and sensitivity to earnings are only defined relative to each other; high sensitivity to earnings corresponds to a low cost of migration. However, since earnings have a readily interpretable scale in terms of dollars, both figures can be rescaled to this value.

Earnings overall are a combination of present and expected future earnings. The value of the future relative to the present is in principle identified by the variation in instrument permanence. For a given observed earnings shock, the future value differs based on whether it is generated by instruments with high or low permanence. If migration varies significantly with expected shock permanence, conditional on the level of current earnings, then agents can be said to place high value on the future relative to the present. In contrast, if agents are unresponsive to the permanence of the underlying drivers of current wages, then they likely place little value on the future.

In practice there is insufficient power to identify this parameter. Recall from Section 5 that the relative value of the future can be expressed by a ratio of elasticities subject to averaging over heterogeneous treatment effects. Heterogeneity stems primarily from variation in migration rates, which are unobserved. These latent values are implicitly used in maximum likelihood estimation, and any noise in their construction will hinder estimation. Separately identifying the value of the future relative to the present requires that the variation in the explanatory variables be large relative to the noise in constructed latent migration rates.

Estimation of the model as presented reveals that the data lack sufficient variation between the current size of a shock and its expected future value. Over 100 iterations with random starting values, the migration cost parameters and the coefficient on the first stage error μ are consistently estimated. However, province fixed values and the relative values of current and future earnings, which are necessary to scale other parameters into dollar terms, are very sensitive to initial conditions. Figure 6 demonstrates why: the figure depicts a trace of the inverse log likelihood over the coefficients on current and future earnings for a fixed value of all other parameters. The likelihood is fairly flat over a large range of parameters; allowing optimization over the other parameters exacerbates the problem with more degrees of freedom. In effect, optimization jointly estimates latent migration rates (as a function of all parameters) and the relative value of the future. However, observed migration rates are noisy enough relative to the variation in earnings shocks to be consistent with a wide range of values. Identification of discount rates is a common problem in many studies of dynamic choice (see Frederick et al., 2002; Magnac and Thesmar, 2002).

Note that this issue is less damaging in the reduced form. Two-stage least squares does not require any stance, explicit or implicit, on latent migration rates. Estimation returns a parameter that averages over the unobserved components and the sampling error, weighting observations by their sensitivity to the instrument. As long as the sampling error is sufficiently low and instrument sensitivity is sufficiently uncorrelated with baseline migration, estimation will preserve the ordering of coefficients. The challenge arises in computing structural parameters, which implicitly requires a full characterization of unobserved variables and sampling error.

To address this problem, I fix the valuation of the future to be a function of discounting and the likelihood of re-migration. Although individual re-migration is unobserved, the aggregate rate can be inferred from the year-to-year decline in migrants. The number of people who report having migrated between 1 and 2 years before the survey is slightly higher than 80 percent of the number who report having migrated less than a year ago. An almost identical ratio is present for 2–3 years relative to 1–2 years and for 3–4 years relative to 2–3 years.[3] This consistent decay suggests that after migrating once, an agent has just under a 20 percent chance of migrating again every year.

With no discounting except for the likelihood of another migration, the net present value of expected future earnings approaches 5.3 times the value of current earnings as time horizon over which decisions are made approaches infinity. This value represents a likely upper bound on the valuation of the future; it seems implausible that agents would value future earnings above their likelihood of actually achieving those earnings. Obviously as agents discount the future their valuation of it decreases.

In the next section I present results for three different discount rates: 0.97, 0.95, and 0.90. These values correspond to future valuations of 4.7, 4.4, and 3.7, respectively. Likelihood maximization with a constraint on the valuation of the future relative to the present is extremely stable and insensitive to initial conditions.

7 Results

Results suggest that perceived migration costs are on the order of an average years' earnings. The majority of this value comes as a fixed cost for any relocation. These costs generate an average elasticity of migration along a channel between two provinces of 1.1 percent. At the labor market level, migration contributes 8.6 percentage points to local labor supply elasticity. That is, a 1 percent increase in earnings at a destination causes the labor force to grow by 0.086 percent due to migration, split almost evenly between more workers moving in and fewer workers moving out.

[3] There is a significant dip at 4–5 years followed by an uptick at 5–6 years and another significant dip at 6–7 years. The uptick is mathematically impossible and suggests that respondents start rounding around 5 years out.

7.1 Cost of Migration

Maximum likelihood estimation provides a range of values for the cost of migration. Across different rates of discounting, I find the average cost of a possible migration to be between 0.3 and 1.1 times average annual earnings. The average cost of an observed migration is only slightly smaller, due to the fact that the majority of the cost comes from a fixed cost of any relocation and idiosyncratic preferences play a large role. These results suggest that any policy based on relocation is potentially very expensive.

Results are presented in Table 7. Estimates are scaled so that the coefficient on log earnings is 1. Every other coefficient can be interpreted in terms of this value. The cost of migration represents a utility penalty to the value function, translated into dollars by exponentiation. For comparison, average annual earnings in Thailand for this period are $2,225 in 2015 USD.

Estimates suggest that migration costs are high relative to earnings. The average cost of a potential move ranges from $664 to $2,488 depending on the specification of discount rate. Relative to average earnings, the cost of a potential move is 0.3 to 1.1 times as large. This figure represents the cost of taking a random individual from the population and relocating her to another random province. At the extreme of no discounting, the upper bound for this cost is 2.5 times annual earnings. All cost parameters rescaled into dollar terms are presented in Table 8.

The bottom two rows of Table 8 show the importance of accounting for expected permanence in calculating migration costs. If all earnings shocks are assumed to be perfectly transitory, migration cost and and taste parameters are estimated to be between a fourth and a fifth as large. With a log earnings specification, this translates to an extremely small moving cost of $5 on average. Similarly, if all earnings shocks are assumed to be fully permanent, estimated parameters would be around 20 percent larger, roughly quadrupling the cost estimates. In this case fully transitory estimate is much worse because I exploit variation in migration in response to instruments that are largely permanent.

Observed migrations are predictably less expensive than possible migrations because agents select when and where to migrate. However, they are still quite costly relative to annual earnings. The average cross-province move observed in the data costs between $573 and $2,097, still on the order of a year's earnings. The range of realized costs spans from 0.26 to 0.93 times the level of average earnings. The upper bound for this value, with no discounting, is 2.1 times annual earnings.

Observed moves are only slightly less expensive than the cost of any potential move for two reasons. First, a high portion of migration costs are fixed for any move. The fixed cost of migrating comprises 60 percent of the total utility penalty of a move. Workers must pay this portion for any possible migration; the remaining distance-based cost accounts for only 40 percent of the cost of moving on average. Therefore, selection over destination can mitigate moving costs by only so much.

Second, the estimates suggest that individual taste shocks play a significant role in location decisions. The standard deviation of individual tastes in utility terms ranges from 0.81 to 0.97. This is over twice as large in utility terms as the variation in log earnings, which has a standard deviation of 0.34. The relative amount of variation in these two values provides another explanation for why spatial variation is large and persistent. Although workers are responsive to earnings, other preferences play a much larger role in their choice of where to locate.

7.2 Model Selection

The model fits the data considerably better than random chance. The likelihood ratio index, defined as $1 - \log \mathcal{L}(\hat{\theta})/\log \mathcal{L}(0)$, compares the model to one in which all parameter values are 0. The minimum value occurs when 0 is the maximum likelihood parameter estimate, in which case the index is 1. The maximum approaches 1 as the predictive power of the model improves; at the limit the model exactly predicts the data meaning the likelihood is 1 making the log likelihood 0. The likelihood ratio index for the model is 0.99996. Note that this does not indicate the model almost perfectly predicts the data, only that the model does a considerably better job than random chance.

The model is also selected over alternatives that constrain shocks to be perfectly permanent or temporary. The log likelihood under model assumptions is 18 greater than the log likelihood with the restriction that all shocks are viewed as perfectly transitory, $\rho = 0$. This is equivalent to an assumption of pure mypoia. The log likelihood is 432 greater than with the restriction that all shocks are seen as purely permanent, $\rho = 1$. The likelihood ratio test statistic to compare these, $-2(\log \mathcal{L}(\hat{\theta}^R) - \log \mathcal{L}(\hat{\theta}))$, is distributed as a ξ^2 with degrees of freedom equal to the number of restrictions, in this case 3 for the number of instruments with a permanence parameter. This test rejects equivalence of the parameters at the 1% level in both cases.

Table 9 demonstrates the importance of accounting for both the duration of earnings and the sampling procedure. The first column of the table presents the main parameter estimates over the range of discount rates. The next two columns present estimates under the assumption that earnings innovations are fully transitory and fully permanent. These two assumptions bracket the possible valuations that may be inferred from an observed income level or shock. The parameter estimates vary significantly, ranging from 20% and 120% of the main estimate. The size of this range, translated into dollar terms above, highlights the role expected future earnings play in computing costs. Without insight into net present value, it is difficult to assign even an order of magnitude to migration costs.

The final two columns of Table 9 present results using estimation procedures that fail to account for measurement error and endogenous sampling. Column 4 presents estimates from estimation using method-of-moments treating the observed migration rates as precise measures of the truth. Point estimates on costs are extremely high, well over double the the truth. This overestimate derives from the fact that many migration flows are observed to be 0. Estimation that matches predicted migration to observed migration considers each of these zero flows to be true and thereby underestimates the level of migration in the economy, attributing the lack of migration to high costs relative to potential earnings. In contrast, my estimator recognizes that observed zeros are random draws from a discrete distribution and allows for greater actual population flows.

The fifth column of Table 9 presents results from multinomial logit estimation that ignores endogenous sampling. I construct this estimate by computing logit choice probabilities according to (11) and maximizing the likelihood of each observed choice weighted by sampling probability. The estimates differ drastically from all other specifications: migration costs are extremely high, distance-based costs dwarf fixed costs, and there is much less variation in idiosyncratic tastes. The bias stems from the fact that migrants moving from large provinces to small ones are most likely to be surveyed, even after adjusting for sampling frequency. Inferring migration rates from the survey alone without constraining estimates to be consistent with population growth skews the results.

7.3 Labor Supply Elasticity

I use the estimated parameter values to compute the contribution of migrants to local labor supply elasticity. As discussed above, this figure is badly measured in the reduced form due to the noise in measured migration. True migration rates can be viewed as an unobserved latent variable that governs data generation. I construct these latent variables using observed data and estimated parameters to calculate elasticities. All results in this section use the middle discount rate of 0.95.

The elasticity of migration between any two provinces can be computed analytically given the parametric assumption on e_{nijt}. For migration along any province-province channel, the migration elasticity is defined as $\partial m_{ijt}/\partial w_{jt} * w_{jt}/m_{ijt}$. Since utility is specified in terms of log wages, this expression can be rewritten as

$$\mathbb{E}\left[\frac{\partial m_{ijt}}{\partial \log w_{jt}} \times \frac{1}{m_{ijt}}\right] = \mathbb{E}\left[\sigma_e^{-1} m_{ijt}(1 - m_{ijt}) \times \frac{1}{m_{ijt}}\right]$$

Estimates suggest that the average elasticity of migration along any province-province channel is roughly 1.1 percent. On average, a one percent increase in the earnings at a destination j induces 0.0006 percent of the population from a province i to move to j. Although this is a very small number, the average flow between two provinces in a given year is comparably small. On average, 0.055 percent of the population of a province i relocates to a given province j in any year. Thus, a one percent increase in earnings at a destination raises migration to that destination on average by 1.1 percent.

Aggregating across provinces by population, migration induces a local labor supply elasticity of 0.086. That is, a one percent increase in earnings raises the size of the local labor force by 0.086 percentage points due to migration. Of this, just over half is explained by migrants entering a province. Variation in inmigration induces a local labor supply elasticity of 4.5 percentage points. The remaining 4.1 percentage points consists of current residents deciding (not) to relocate in response to local conditions.

7.4 Long-Term Differentials

A back-of-the-envelope calculation suggests that migration costs account for around 20% of the spatial variation in earnings over the long term. In the model, equilibrium earnings are set so that for any two provinces, the marginal migrant is indifferent to moving. If there were no migration costs, earnings would be determined by province-specific amenities and local labor demand. Variation beyond this level can be attributed to moving costs.

I first back out estimates of local amenity values from the province-specific term ξ_j in (10). In estimation, ξ_j is the sum of local amenities A_j and province average earnings $\bar{w}_j$ in net present value terms. The latter is estimated consistently in the first stage regression (7) as γ_j and can therefore be partialled out. Since current earnings are included in the value function in full, the NPV value of earnings excludes the present. Amenities are similarly estimated in present-value terms and must be adjusted accordingly. Formally,

$$\xi_j = \frac{\beta}{1-\beta}\bar{w}_j + \frac{1}{1-\beta}\alpha_j$$

for a discount factor β, average earnings level $\bar{w}_j$, and a single-year amenity value α_j.

Lacking a reliable estimate of local labor demand, I use the counterfactual approximation that earnings would exactly offset amenities in the absence of moving costs. This assumption corresponds to the simplest formulation of the Rosen/Roback spatial equilibrium model in which all workers are identical. Without individual-specific preferences, the marginal mover will only be indifferent between locations when the wage plus amenity at each possible destination is exactly equal. This benchmark represents the counterfactual earnings variation when labor is perfectly mobile.

The actual spatial distribution of earnings is determined by both the distribution of amenities and the distribution of population. Earnings will offset amenities to some extent, but there may be excess variation. Since workers are imperfectly mobile, local labor supply is determined in part by the initial distribution of population. Although some workers relocate in response to value differences across provinces, others do not move due to relocation costs. Therefore any earnings variation in excess of the variation in amenities can be attributed to migration frictions.

Earnings and amenities are indeed negatively correlated. If the initial population distribution were independent of local amenity values due to historical accident, then we would expect the correlation between earnings and amenities to be exactly -1. In the data I estimate the correlation to be -1.15, significant at the 1 percent level. Although the negative correlation is in part mechanical due to the way the amenity estimate is constructed, the magnitude of the coefficient suggests that estimation is capturing the true local amenity value.

Local earnings show variation in excess of the variation in local amenities. The standard deviation of amenity values estimated by the model is 0.201. This value represents the expected standard deviation in earnings across provinces when labor is perfectly mobile. However, in the data, the standard deviation in log earnings ranges from 0.256 in 1985 to 0.245 in 2000. Thus, local amenities explain only 78.5–82.1 percent of the spatial earnings variation. The remainder is caused by labor imperfectly adjusting to local conditions.

8 Conclusion

In this paper I estimate the cost of migration and migration-related supply elasticity in Thailand. Estimation relies on the revealed preference location decisions of workers over the years 1985–2000. I first provide reduced-form evidence that workers migrate more in response to shocks of greater permanence. To do so I construct a set of shocks based on global commodity prices to identify permanent and transitory components of the earnings process, exploiting variation in the permanence of the price series. The increase in likelihood of observing a migrant in response to a shock to a permanent series is almost three times as high as that in response to a shock to a temporary series.

I next estimate a structural model of location choice to back out cost parameters. Estimation uses maximum likelihood to overcome problems of measurement error and endogenous sampling in the data. Results indicate that a migration costs 0.3–1.1 times average annual earnings, and 60 percent of that cost is a fixed penalty that is insensitive to distance. Furthermore, the variance in individual tastes is greater than the variance in earnings around the country, suggesting that earnings only represent a small portion of the factors workers consider when deciding where to live.

Together, these two facts combine to produce a low migration component in local labor supply elasticity. Migration in response to an earnings shock causes labor supply to fluctuate by only 8.6 percent of the proportional size of the shock. This response is split almost evenly between residents from elsewhere in the country moving into a province and locals moving out. The low elasticity provides an explanation for high, persistent dispersion of wages around the country.

These numbers suggest that labor markets may be slow to respond to spatial disparities. High migration costs combined with idiosyncratic preferences generate low spatial earnings elasticities. Furthermore, since fixed costs appear to be the predominant barrier to migration, it appears that transportation infrastructure or subsidies are not sufficient to significantly alleviate spatial differences. Instead, it would take significant investment to induce greater spatial mobility.

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A Model Simplifications

A.1 Derivation of Bartik-Style Instruments

Bartik-style instruments rely on the local labor market assumption of a single local wage rate to translate local industry shocks into local market-wide shocks. Instruments are constructed by interacting exogenous, generally national-level shocks to industries with local industry intensities. Motivation for this form can be derived in a specific-factor trade model, followingJones (1975) and Kovak (2013). In what follows, I suppress province and time subscripts jt and move the industry index ℓ from a superscript to a subscript for simplicity in notation.

Consider a local economy comprising L sectors indexed by ℓ. Each sector has a fixed, sector-specific input M_ℓ, and sectors share a common local labor market with total labor force N. M_ℓ can be thought of as either a long-term capital investment or a local factor, such as land fertility, that makes labor relatively more productive in a given sector. Wages w and returns to capital r_ℓ are determined locally, and the locality takes all output prices P_ℓ from the world market.

Assume that each sector is perfectly competitive and has a production function characterized by a constant returns to scale technology. Sector profits are given by

$$\Pi_\ell = P_\ell A_\ell F(N_\ell, M_\ell) - WN_\ell - R_\ell M_\ell \equiv E_\ell F_\ell(N_\ell, M_\ell) - WN_\ell - R_\ell M_\ell$$

where E represents the combination of output price and a multiplicative sector productivity. In this setting, A can be interpreted as either technology or the international price of traded inputs for which the local sector acts as a price taker facing an elastic international market. Shocks to output prices, technology, and input prices all have have comparable in this model.

I explore what happens in response to a proportional shock to E, either through output prices, technology, or input prices. For ease of exposition, let $\ddot{x} = dx/x$ be the proportional response of a variable to a proportional change in E. Further, call $Y_\ell = F_\ell(N, M)$ the effective production and define n_ℓ and m_ℓ to be the cost-minimizing factor requirements to produce a single effective unit of output. In addition, let θ_ℓ be the cost share of the fixed factor such that $r_\ell M_\ell = \theta_\ell E_\ell Y_\ell$. Finally, define $s_\ell = N_\ell/N$ to be the share of local labor involved in industry ℓ.

First, note that the zero-profit condition implies

$$m_\ell R_\ell + n_\ell W = E_\ell, \quad \forall \ell$$

Proportionally differentiating yields

$$\ddot{E}_\ell = \theta_\ell \ddot{R}_\ell + (1 - \theta_\ell)\ddot{W}, \quad \forall \ell \tag{13}$$

which follows because

$$\theta_\ell \ddot{m}_\ell + (1 - \theta_\ell)\ddot{n}_\ell = 0, \quad \forall \ell$$

from the envelope condition of the unit cost minimization problem. Intuitively, this condition suggests that a price or technology shock affects the labor and capital markets in proportion to their share of cost in each sector.

Furthermore, market clearing in a locality requires

$$m_\ell Y_\ell = M_\ell, \quad \forall \ell$$
$$\sum_\ell n_\ell Y_\ell = N$$

differentiating gives

$$\ddot{m}_\ell + \ddot{Y}_\ell = 0, \quad \forall \ell$$

because to total endowment M_ℓ is fixed. Similarly,

$$\ddot{N} = \sum_\ell s_\ell(\ddot{n}_\ell + \ddot{Y}_\ell) = \sum_\ell s_\ell(\ddot{n}_\ell - \ddot{m}_\ell)$$

due to proportional differentiation of the labor market-clearing condition. By the definition of elasticity of substitution,

$$(\ddot{n}_\ell - \ddot{m}_\ell) = \sigma_\ell(\ddot{R}_\ell - \ddot{W})$$

so that substituting yields

$$\ddot{N} = \sum_\ell s_\ell \sigma_\ell(\ddot{R}_\ell - \ddot{W}) \tag{14}$$

This final equality describes how the local labor market will change in response to a shock. The magnitude of this change is governed by the relative change shocks to factor prices in each sector multiplied by the elasticity of substitution in that sector, weighted by the size of that sector in the labor force.

The zero-profit conditions (13) and market-clearing conditions (14) provide a system of $\ell + 1$ equations that pin down the responses of the ℓ rates of return to sector-specific capital and the local wage following a price or productivity shock. Solving this system for the local wage yields

$$\ddot{W} = \sum_\ell S_\ell \ddot{E}_\ell - \frac{\ddot{N}}{\sum_\ell s_\ell \frac{\sigma_\ell}{\theta_\ell}}$$
$$S_\ell = \frac{s_\ell \frac{\sigma_\ell}{\theta_\ell}}{\sum_{\ell'} s_{\ell'} \frac{\sigma_{\ell'}}{\theta_{\ell'}}}$$

That is, the change in wage is the weighted sum of the shock to each sector's labor demand curve plus a term reflecting the impact of a movement along the labor demand curve due to a change in labor supply.

To construct a valid instrument for wage, I drop the second term representing the endogenous response of labor supply to a change in labor demand. Thus, the predicted wage shock is a weighted sum of the wage effects of labor demand shocks in each sector. The common approach, which I follow, makes the further simplification that σ_ℓ/θ_ℓ is constant across industries so that industry weights ζ_ℓ collapse to industry labor shares s_ℓ. A sufficient condition for this assumption is that production takes a Cobb-Douglas form with constant factor weights across sectors within a region.

Finally, sectoral productivity shocks $\ddot{E}_t$ are predicted by the sensitivity of a sector to a commodity price shock $\ddot{P}_t^k$, which I compute from regression. Even though each location in the model shares a common wage rate, a rise in the earnings of sector ℓ relative to all other sectors nationally corresponds to a rise in the average earnings in regions where sector ℓ is prominent relative to those where other sectors are prominent. As long as any location-specific shocks outside of the specific-factors framework are uncorrelated with the national shock, this systematic difference in earnings growth must be attributed to a positive shock to sector ℓ relative to other sectors; otherwise, wages in regions where a different sector was prominent would have seen a comparable or greater earnings increase. Therefore a time-series regression of sector earnings on commodity prices identifies sectoral sensitivity.

A.2 Risk and Individual Variation

The model abstracts from other individual heterogeneity in earnings. Beyond selection, heterogeneity may stem from either individual characteristics or earnings risk. The model easily incorporates individual characteristics as long as they are portable across locations since they do not affect the location decision. Risk is more difficult to include if it varies across time and space because it is neither well-measured nor identified. However, I provide some evidence that it is a second order concern in relation to average earnings.

Individual characteristics may take the form of a constant earnings premium or discount for an individual at any location. The underlying assumption is that individuals have a fixed, portable set of labor market skills that are broadly applicable anywhere. This type of heterogeneity has no impact on the choice model because it acts as a level shift to earnings or utility in any location. Adding a fixed term to each possible location option will not affect optimization in any way.

While fixed heterogeneity does not affect the decision model, average earnings may be mismeasured if the composition of the labor force varies significantly across provinces. To deal with this concern, I perform all analysis after first residualizing earnings for age and education premia. In each year, I estimate the average national labor market premium or discount for each age and education bin. I then take province average earnings after controlling for the premium. Results using raw earnings rather than residuals are broadly similar but noisier. The main specification using a dummy for migration is presented in Table 10

Earnings may also vary by person due to risk in the labor market. Not all workers are able to find a job at all times. Unfortunately, this is difficult to address empirically due to both measurement and identification. Labor market risk is not readily characterized with repeated cross-sectional data. It is impossible to determine whether an individual with low earnings is facing an unlucky year or is a persistent low earner. Panel data can facilitate estimation of province average risk, but it is still insufficient to generate a measure of risk that varies at the province-year level with the rest of the analysis. Risk that is constant over time or across geography will be captured by fixed effects so that only that province-time varying component matters. Furthermore, were a measure with such variation possible, it still suffers from potential endogeneity and would need to be identified with exogenous instruments.

Empirically, the effect of risk on migration appears to be small relative to earnings. As a proxy for market risk, I take the income variance within a given province-year cell. Incorporating this measure into the regression in (9) shows that risk is likely unimportant in two ways. First, the point estimates on earnings variance are small relative to the coefficients on level. Across all three outcomes, coefficients are around an order of magnitude small for variance. Since variable mean is also one sixth of the mean earnings level, this is suggestive that risk plays a much smaller role than earnings. Second, the point estimates on the effect of earnings levels are largely unchanged when variance inters the regression. To the extent that market risk enters migration considerations it seems to have little effect on the decision with respect to earnings. These two facts suggest that estimation of the model without explicitly incorporating risk will still be consistent.

A.3 Dynamics

The model provides a simplified version of a dynamic location choice problem. A fully dynamic model would incorporate the likelihood of future migration as a function of parameters. This means optimizing over both labor market conditions at a destination and the potential for subsequent moves from that destination. Estimating this model is infeasible due to the high dimensionality of the choice problem and the fact that migration probabilities are not precisely observed in the data. The simplification I use corresponds to collapsing the value of future migration to a constant and holding fixed expected future earnings.

The fully dynamic model can be written recursively, suppressing individual subscripts, as

$$V(j|i;W) = U(i,j;W) + \nu\mathbb{E}[\max_{j'} V(j'|j;W')]$$

for an individual with discount rate ν living in province i considering moving to province j facing a national earnings profile W. The period utility is defined similarly to the value function in the choice model

$$U(j|i;W) = w_j + \alpha_j - c_{ij} + \upsilon_j$$

as a function of period earnings, destination amenities, a moving cost, and unobserved tastes . The expected future component can be rewritten as the sum of migration probabilities multiplied

$$\mathbb{E}[\max_{j'} V(j'|j;W)] = \sum_{j'} \pi_{j'}\mathbb{E}[V(j'|j;W')|V(j'|j;W') \geq V(j''|j;W')]$$

This formulation presents two challenges in estimation. First, earnings W evolve independently for all 73 provinces. Furthermore, estimation relies on decomposing earnings into observed and unobserved components with known permanence for observed components. Therefore the state variable consists of a $73 \times 3 + 1$-dimensional Markov process representing observed wage, permanence, and unobserved wage at each location as well as the individual's current province. Second, empirical choice probabilities from province to province are badly measured in the data. Much of the estimation procedure focuses on recovering parameters even though aggregate choice shares are only observed with error.

To bring down the dimensionality and avoid choice probabilities entering the value function, I collapse the value of future migrations to a constant F. This valuation can be explained by either bounded rationality or a migration strategy where the next destination is fixed, say a home province. Future expectations reduce to

$$\mathbb{E}[\max_{j'} V(j'|j;W)] = \pi\mathbb{E}[V(j|j;W')|V(j|j;W') \geq V(j|j';W')] + (1-\pi)F$$

where the probability of staying after a migration can be observed by the decline in people surveyed who report having moved τ years ago. Since $(1-\pi)F$ enters every value function symmetrically, it can be dropped from the formulation.

I next make the simplification that agents do not update their expectation of future earnings with their future migration choice. In reality, not moving should be an indication of higher earnings at the home location; a significantly negative shock would induce outmigration. That is

$$F \leq w'_j + \alpha_j - \epsilon'_j + \nu \mathbb{E}[\max_{\tilde{j}} V(\tilde{j}|j; W'')]$$
$$\implies \mathbb{E}[w'_j] < \mathbb{E}[w'_j | V(j|j; W') \geq V(j|j'; W')]$$

I simplify to assume that agents only update their beliefs on υ' rather than updating the full stochastic vector (W', υ'). One motivation is that, with the previous simplification, updating is sensitive to the level of the future migration value F. Moving the updating to the unobserved taste shock, which has no ex ante level or scale, eliminates this sensitivity.

These two simplifications together allow the value function to be rewritten as an infinite or finite sum

$$\begin{aligned} V(j|i; W) &= w_{j0} + \sum_{\tau=1} \nu^\tau \pi^\tau \mathbb{E}[w_{j\tau}] + \sum_{\tau=0} \nu^\tau \pi^\tau \alpha_j - c_{ij} + \sum_{\tau=0} \nu^\tau \pi^\tau \upsilon_{j\tau} \\ &\equiv w_{j0} + \sum_{\tau=1} \delta^\tau \mathbb{E}[w_{j\tau}] + A_j - c_{ij} + \epsilon_{j0} \end{aligned}$$

which I estimate. Note that this will be a lower bound on utility. With a single strategic location decision and random remigration, this is what a worker would earn. Workers with the opportunity to migrate again would only do so if the choice netted higher utility.

B Instrument Selection

I select instruments based on 1995 Thai imports as reported by the Observatory of Economic Complexity.[4] I consider all commodities that make up at least one percent of imports. In addition to the three series presented this list includes iron, aluminum, and copper. Iron accounted for 4.5% of imports in 1995, while the latter two metals made up just over 1% each. For iron I use the Chinese import price for iron ore fines at Tianjin port; for the other two metals I use the London Metals Exchange CIF spot price. I also use a composite metals price index consisting of aluminum, copper, iron ore, lead, nickel, tin, and zinc complied by the World Bank.

Unfortunately, these instruments have no predictive power for local earnings. Table 12 reports first-stage estimates from (7) for these four price series. No series is a significant predictor of local earnings, nor are all four jointly significant. Due to the lack of a first stage, I drop these instruments from analysis.

Inclusion of these instruments does not significantly change any estimates. Table 13 reports reduced form and maximum likelihood estimates with extra instruments included. The top panel contains coefficients from the manual two-stage least squares version of (9) taking the migration dummy as the outcome. I rescale each instrument series by multiplying by the first stage coefficient, and then regress the outcome on the rescaled coefficients. The second panel in the table reports maximum likelihood parameters. In neither case does the

[4] http://atlas.media.mit.edu/en/visualize/tree_map/hs92/import/tha/all/show/1995/

inclusion of insignificant instruments qualitatively affect the outcome.

C Outcome Measures

Estimation suffers from high noise due to the sparseness of the survey. To isolate individual local markets as much as possible, I define a labor market to be a province, of which there are 73 in the country. However, this means that the number of people surveyed is small relative to the number of migrants and total possible migration channels. As a result, many migration flows are missed and coded as 0, which causes difficulty in estimation.

In the data, there are no observed migrants from a given source to destination in the vast majority of cases. In only 16 percent of source-destination-year cells is any migration present in the survey. The majority of zeros observed in the data are likely not generated by an underlying truth of no migration, but are more likely caused by the fact that the survey is sparse relative to the number of migrants. This conjecture is supported by the fact that the number of cells with any observed migration is around 10 percent per year in the earlier years with smaller surveys (and only 5 percent in the two years with only one survey round), and climbs to over 30 percent in the later, significantly larger surveys. At the same time, the 95^{th} and 99^{th} percentiles of migration share remain stable over time; only lower percentiles get filled in as the survey size increases. Taken together, these two facts suggest that many small migration flows are missed entirely. To avoid bias from the number of 0s, I run the reduced form with three alternate specifications.

C.1 Migration Percent

I first consider the percent of the population of i that relocates to j at time t. Were this measured accurately, it would be the ideal outcome to use as a measure of elasticity. However, the sparseness of the survey means it is

The percent migration measure is formally constructed as

$$m_{ijt} = \frac{\sum_{j(n)=j} P_n^{-1} \mathbf{1}[i(n) = i]}{N_i}$$

where n indexes individuals surveyed; $i(n)$ and $j(n)$ are the individuals' previous and current provinces, respectively; P_n is the sampling probability; and N_i is the total population size of province i. For simplicity, I assume stable province sizes and drop time subscripts. For a given observation, the indicator function is simply a Bernoulli random variable that takes value 1 with probability $m^*_{ijt} N_i / N_j$ for the true migration rate m^*_{ijt}.

Taking expectations under the assumption that sampling frequency is independent of the probability of being a migrant,

$$\mathbb{E}[m_{ijt}] = \frac{\sum_{j(n)=j} P_n^{-1} \frac{m^*_{ijt} N_i}{N_j}}{N_i} = \frac{m^*_{ijt}}{N_j} \sum_{j(n)=j} P_n^{-1} = m^*_{ijt}$$

The variance of this measure is

$$\text{Var}[m_{ijt}] = (N_i)^{-2} \sum_{j(n)=j} P_n^{-2} \frac{m^*_{ijt} N_i}{N_j} \left(1 - \frac{m^*_{ijt} N_i}{N_j}\right) = m^*_{ijt} \left(\frac{N_j}{N_i} - m^*_{ijt}\right) \sum_{j(n)=j} (P_n)^{-2}$$

For small values of m^* this variance is increasing in m^*, the population of the destination province, and the variance of survey probabilities. It is decreasing in the population of the source province and the size of the survey. Taking these two expressions together, we can rewrite $m_{ijt} = m^*_{ijt} + \zeta_{ijt}$ for some mean-0 ζ that is independent across observations but not identically distributed.

Using the relationship given by (9), the OLS estimator becomes

$$\hat{\beta} = (X'X)^{-1}X'm = \beta + (X'X)^{-1}X'(\varepsilon + \zeta)$$

with a comparable derivation for 2SLS. This final expression reveals two facts about this regression, also true after instrumenting. First, the sampling method introduces heteroskedasticity, even when ε is homoskedastic, because the variance of ζ depends on sampling and the parameters.

Second, and more worrisome, estimation of β is generally not median unbiased. Although $\hat{\beta} = \beta$ in expectation, the error term ζ is a recentered sum of Bernoulli variables; in the extreme base of constant sampling probabilities it is Binomial. As the sample gets large relative to m^*, it converges to a normal distribution. However, with small samples, in particular when $\frac{m^*_{ijt} N_i}{N_j} < 1$, the majority of the probability mass is on an observation of 0 migrants and the median lies below the mean. Thus the majority of estimates $\hat{\beta}$ will be below the true value of β.

The median bias is apparent in the IV regression: coefficients follow roughly the same ordering as with the other two outcomes, but estimation is noisier and several point estimates are actually below 0. Results are presented in Table 14.

C.2 Migrant Counts

This measure is what is most directly observed in the data, and what is used for maximum likelihood estimation. It is the same as above without dividing by the source province population. It is therefore increasing in the migration rate, but also sensitive to province population sizes. In all regressions using it, I control for the source and destination population size. Formally, it is constructed as

$$Q_{ijt} = \sum_{j(n)=j} P_n^{-1} \mathbf{1}[i(n) = i]$$

C.3 Migration Dummy

To address the problem of sparseness and zeros, I consider an alternate parameterization replacing the dependent variable with a dummy for whether any migration is observed from province i to j in year t. Since zero observed flow likely does not indicate truly zero flow, but rather is probably an artifact of the survey size, observing any worker who moved from i to j is an indication that the flow of migrants was likely high; the flow was large enough that at least one migrant appeared in a random population sample.

This measure generates significant variation across the full range of data. 70 percent of migration channels have any migrants over the period, and only two percent of channels have a migrant in every period. Furthermore, every source and destination has observed migration with at least 25 percent of other provinces, and only Bangkok has more than 2 destinations where migration is always seen. In no province does more than 15 percent of possible sources always show migration. Since the likelihood of seeing a migrant is increasing in the number of migrants, this variation provides information on the migration rate.

Formally, let the outcome $\hat{m}_{ijt} = \mathbf{1}\{m_{ijt} > 0\}$. In expectation,

$$\mathbb{E}[\hat{m}_{ijt}] = \mathbb{P}[m_{ijt} > 0] = 1 - \left(1 - \frac{m^*_{ijt} N_i}{N_j}\right)^{s_j}$$

This outcome is increasing in m^*_{ijt} and the fraction of a population that migrated from a specific source, and therefore is informative about the effect of parameters on migration. However, it is also increasing in the population of the source province, and decreasing in the destination population. For any instrumental variables specification to satisfy the exclusion restriction, it is necessary that the instrument be uncorrelated with these factors. To address this concern, all IV specifications are based on instruments that are determined at a national or international level and therefore not related to an individual province's characteristics.[5]

D Seasonality

Seasonality affects both migration and earnings in the data. Among migrants, there are significantly more migrants who have lived in a location for less than one year in the third-quarter rounds of survey than in the first quarter. This pattern corresponds with the agricultural season in most of the country, during which time many people temporarily stay with relatives in rural areas to help with farm labor. The average ratio of migrants observed in the third quarter relative to the first quarter is strongly correlated with the fraction of a province engaged in agriculture, supporting this pattern. No such seasonality is observed among migrants who have lived in the province for one year or more, suggesting that the swell in migrants in the third quarter is largely temporary seasonal work.

I address seasonality in migration by adjusting migration rates based on the destination and quarter of survey. For each province, I compute the ratio of zero-year migrants to one-year migrants from the previous year in each quarter. I treat the ratio in the first quarter as the true ratio, and and excess or deficit in the third quarter relative to the first to represent seasonal migration. I thus deflate the observed migration flows to a given destination in the third quarter this ratio of ratios. Annual migration is computed as the average of adjusted first-quarter-equivalent migration in each included round of the survey for a given year.

The seasonal pattern in the labor market also generates cyclicality in earnings. Earnings are are around two percent higher during the third quarter across all sectors of the labor force. However, this pattern masks different underlying mechanisms by industry. In the lower human capital sectors of agriculture, construction, and retail trade, the wage increase persists even after controlling for years of education. This suggests that higher demand relative to supply boosts wages across the board for these sectors during the thick part of the labor cycle. However, in higher human capital sectors such as manufacturing, utilities, and the public sector, the seasonal pattern in earnings disappears after controlling for education. These sectors shrink as a

[5] With variable population provinces, m^*_{ijt} actually appears in both the numerator and denominator of the expression. For small values of m, $\mathbb{E}[\hat{m}_{ijt}]$ is still increasing in m. It is also necessary that any instrument is uncorrelated with population growth of population that is not explained by migration, e.g. fertility, but this condition is more difficult to test since migration is imperfectly measured and province-level fertility is not readily observed in the data.

portion of the labor force during the thick season; these two facts together suggest that seasonality is driven by selection: in the third quarter the lower end of the earnings distribution switches sectors to meet seasonal demand.

Given the varying drivers of seasonality by sector, I deseason earnings by regressing earnings on a dummy for third quarter, year dummies, and dummies for age and education bin separately for each sector. I then partial out the seasonal component for all analysis. Earnings are also Winsorized at the 99th percentile.

I consider labor market returns in terms of total earnings rather than the hourly wage rate because a significant portion of the population draws income from either family agriculture or self-owned businesses for which hours worked is not well defined. Furthermore, hours are only reported for a single week of work; imputing wage rates from this data would lead to significant measurement error in hours. In contrast, income is computed over a full month and reported in significantly more detail, making it a more accurate measure of labor market returns.

E Identification of the Model

E.1 Identified Parameters in the Value Function

Agents optimize according to

$$j^* \in \arg\max_j \mathbb{E}[Y_{jt}] + A_j - c_{ij} + \epsilon_{nijt}$$

where

$$\begin{aligned} \mathbb{E}[Y_{jt}] &= w_{jt} + \sum_\tau \delta^\tau \mathbb{E}[w_{jt+\tau}] \\ w_{jt} &= \sum_k \kappa^k \tilde{z}^k_{jt} + \bar{w}_j + \mu_{jt} \\ \mathbb{E}[z^k_{jt+\tau} | z^k_{jt}] &= \rho^k z^k_{jt} \\ c_{ij} &= \mathbf{1}\{i \neq j\}(C + \eta d_{ijt}) \end{aligned}$$

a bar represents a time-average and where tilde represents a deviation from the average. I add the two simplifying assumptions

$$\begin{aligned} \mathbb{E}[\mu_{jt+\tau} | \mu_{jt}] &= \rho^{\mu,\tau} \mu_{jt} \\ \epsilon_{nijt} &= \phi \mu_{jt} + e_{nijt} \end{aligned}$$

Plugging everything into the value function and grouping like terms gives

$$\begin{aligned}
V_{nijt} &= w_{jt} + \sum_\tau \delta^\tau \sum_k \kappa^k \tilde{z}^k_{jt} + \sum_\tau \delta^\tau w_j + \sum_\tau \delta^\tau \rho^{\mu,\tau}\mu_{jt} + A_j + \mathbf{1}\{i \neq j\}(C + \eta d_{ijt}) + \phi\mu_{jt} + e_{nijt} \\
&= w_{jt} + \sum_\tau \delta^\tau \sum_k \kappa^k z^k_{jt} + \mathbf{1}\{i \neq j\}(C + \eta d_{ijt}) \\
&\quad + \left[A_j + \sum_\tau \delta^\tau \bar{w}_j + \sum_\tau \delta^\tau \sum_k (1-\rho^k)\kappa^k \bar{z}^k_j\right] + \left[\sum_\tau \delta^\tau \rho^{\mu,\tau} + \phi\right]\mu_{jt} + e_{nijt} \\
&\equiv w_{jt} + \beta \sum_k \rho^k z^k_{jt} + \xi_j - \mathbf{1}\{i \neq j\}\left(C + \eta d_{ij}\right) + \varphi\mu_{jt} + e_{nijt}
\end{aligned}$$

E.2 Nonparametric Identification of Logit Parameters

Although I estimate parameters under functional form assumptions on the cost of migration and the value of expected earnings, it is worth noting that both moving costs and province-year values are nonparametrically identified by migration rates subject to the distributional assumption for tastes. Estimation treats the underlying migration rate as a latent, unobserved variable and maximizing the likelihood of the observed number of migrants conditional on this value.

Given true migration rates and the parametric assumption on tastes, note that

$$\frac{m_{ijt}}{m_{iit}} = \frac{\exp[\bar{V}_{ijt}]}{\exp[\bar{V}_{iit}]} = \frac{\exp[u_{jt} + \xi_j - c_{ijt}]}{\exp[u_{it} + \xi_i]} \tag{15}$$

$$= \exp[u_{jt} + \xi_j - u_{it} - \xi_i - c_{ijt}] \tag{16}$$

where u_{jt} is curent value of a location determined by current and expected future earnings, xi_j is a fixed amenity (net of average earnings), and c_{ijt} is the perceived migration cost. We can symmetrically write

$$\frac{m_{jit}}{m_{jjt}} = \exp[u_{it} + \xi_i - u_{jt} - \xi_j - c_{jit}]$$

Subtracting one from the other, under the assumption of symmetric travel costs $c_{ijt} = c_{jit}$ gives

$$\log\left[\frac{m_{jit}}{m_{jjt}} \times \frac{m_{iit}}{m_{ijt}}\right] = -2c_{ijt}$$

The model fits these estimated costs in all periods and times to a linear function of distance and a constant; the number and distribution of migrants determine the slope and intercept of this function.

Province-time values are identified by taking time-differences of (15). In what follows I assume c_{ij} is constant over time for simplicity of notation; since this value is identified in every period the derivation is almost identical with more terms if moving costs are time-varying. Differencing time gives

$$\log\left[\frac{m_{ijt}}{m_{iit}} \times \frac{m_{iit'}}{m_{ijt'}}\right] = (u_{jt} - u_{it}) - (u_{jt'} - u_{it'})$$

In a two-period model, with J total provinces there are $J \times 2$ parameters to be identified: utilities for each province at each time. Taking differences of (15) generates $J \times (J-1)$ total expressions, one for migration between each pair of provinces in each direction. As long s $J \geq 3$, the number of expressions exceeds the number of parameters in a system of linear expressions and thus the model is overidentified. To estimate I parameterize these values as a linear combination of current earnings, the predictable component of expected future earnings, and the earnings residual.

Finally, with c_{ijt}, u_{it}, and u_{jt} identified for all province pairs in all times, (15) gives the relative amenity values between two provinces. Since the choice model is invariant to a symmetric level shift in amenities across all provinces ξ_j is only identified in relative terms. For estimation I normalize the amenity value of Bangkok to be 0.

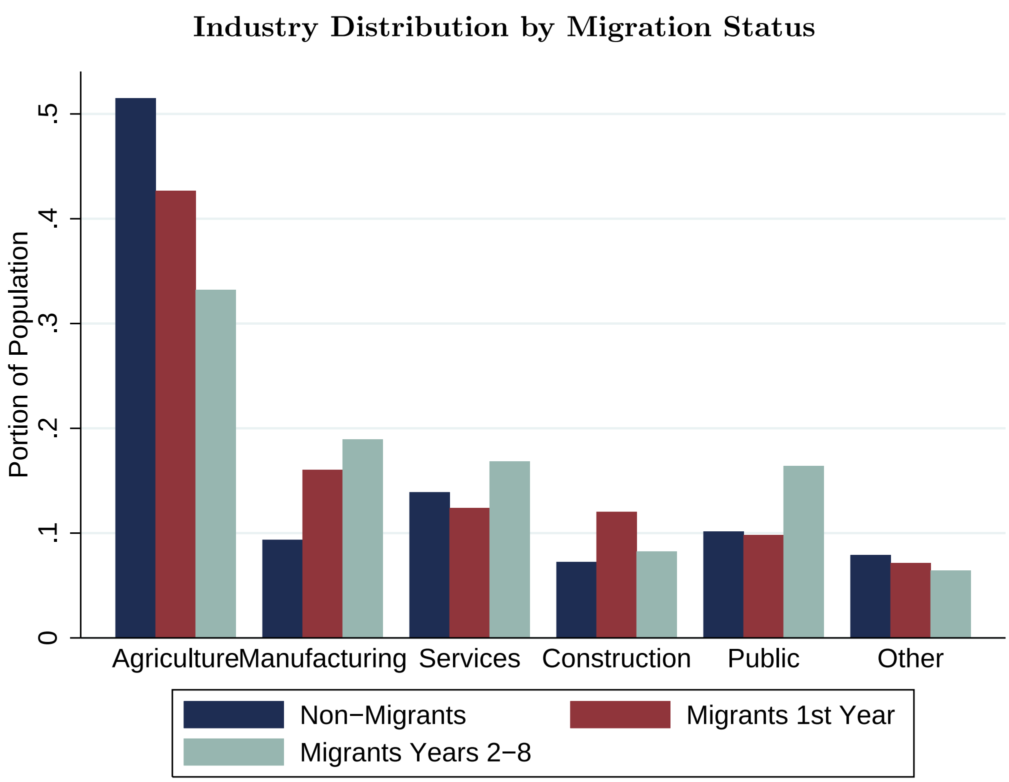


Figure 1: Industry of occupation by migration status, weighted by inverse sampling frequency.

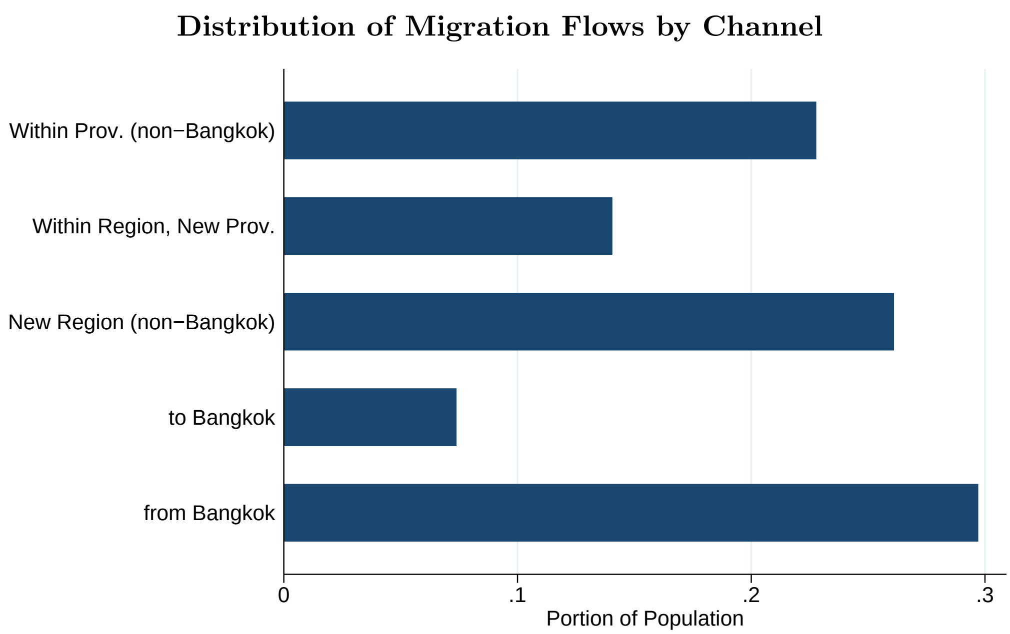
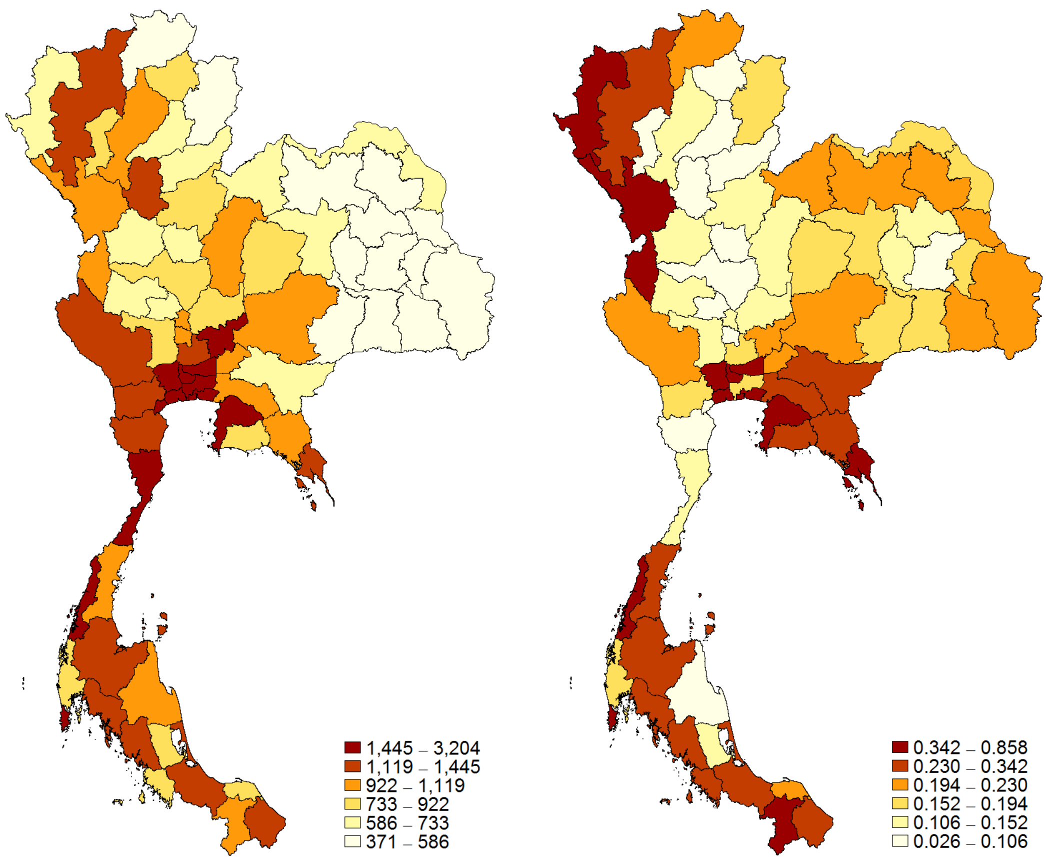


Figure 2: Destinations for migrants in the LFS data weighted by inverse sampling frequency.

1985 Earnings Distribution and 1985–2000 Population Growth



(a) Average Earnings in 1985 (2015 USD)

(b) Population Growth 1985–2000

Figure 3: Average province earnings in 1985 (2015 USD) and population growth between 1985 and 2000.

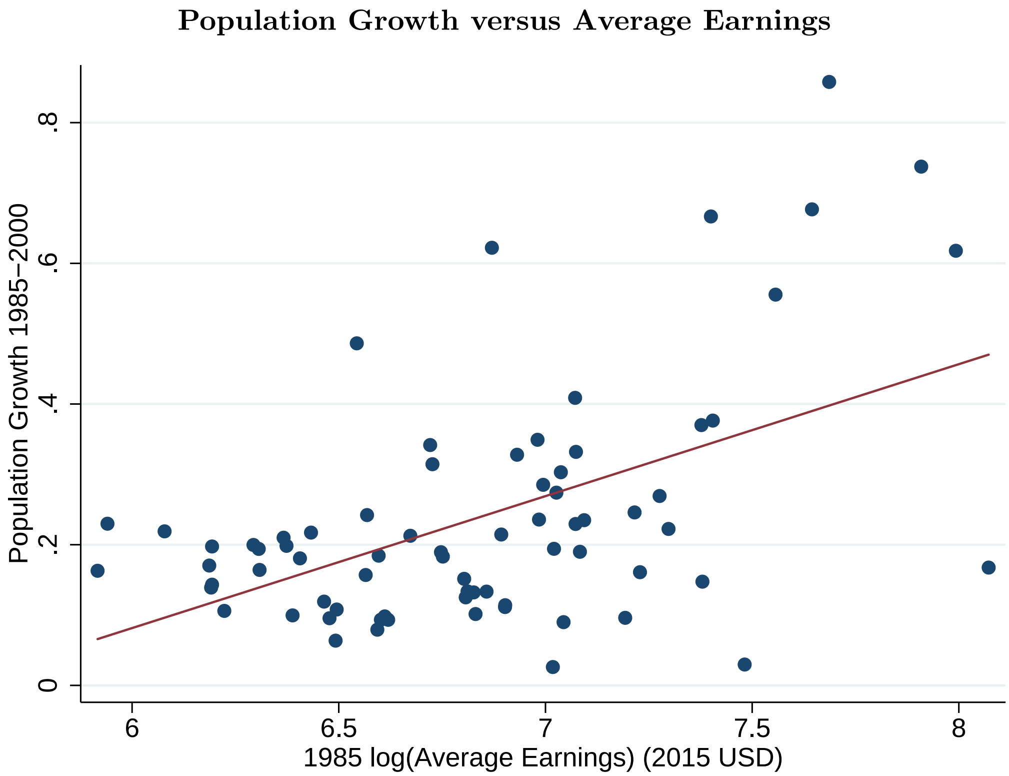


Figure 4: Scatter plot of population growth from 1985–2000 versus log average earnings in 1985 by province. The slope of the regression line is 18.8 and significant at the 1% level.

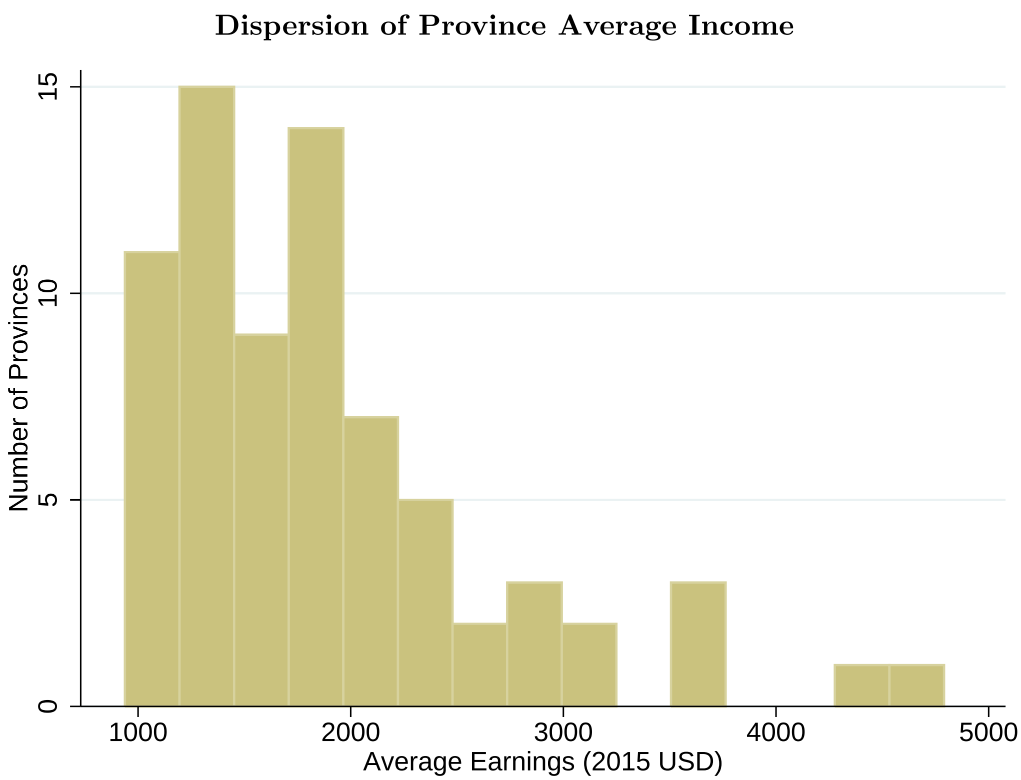


Figure 5: Province-level histogram of average earnings in 2000 (2015 USD/year). The standard deviation across provinces is 46.7 percent of earnings in the median province.

Trace of the Inverse Likelihood Function

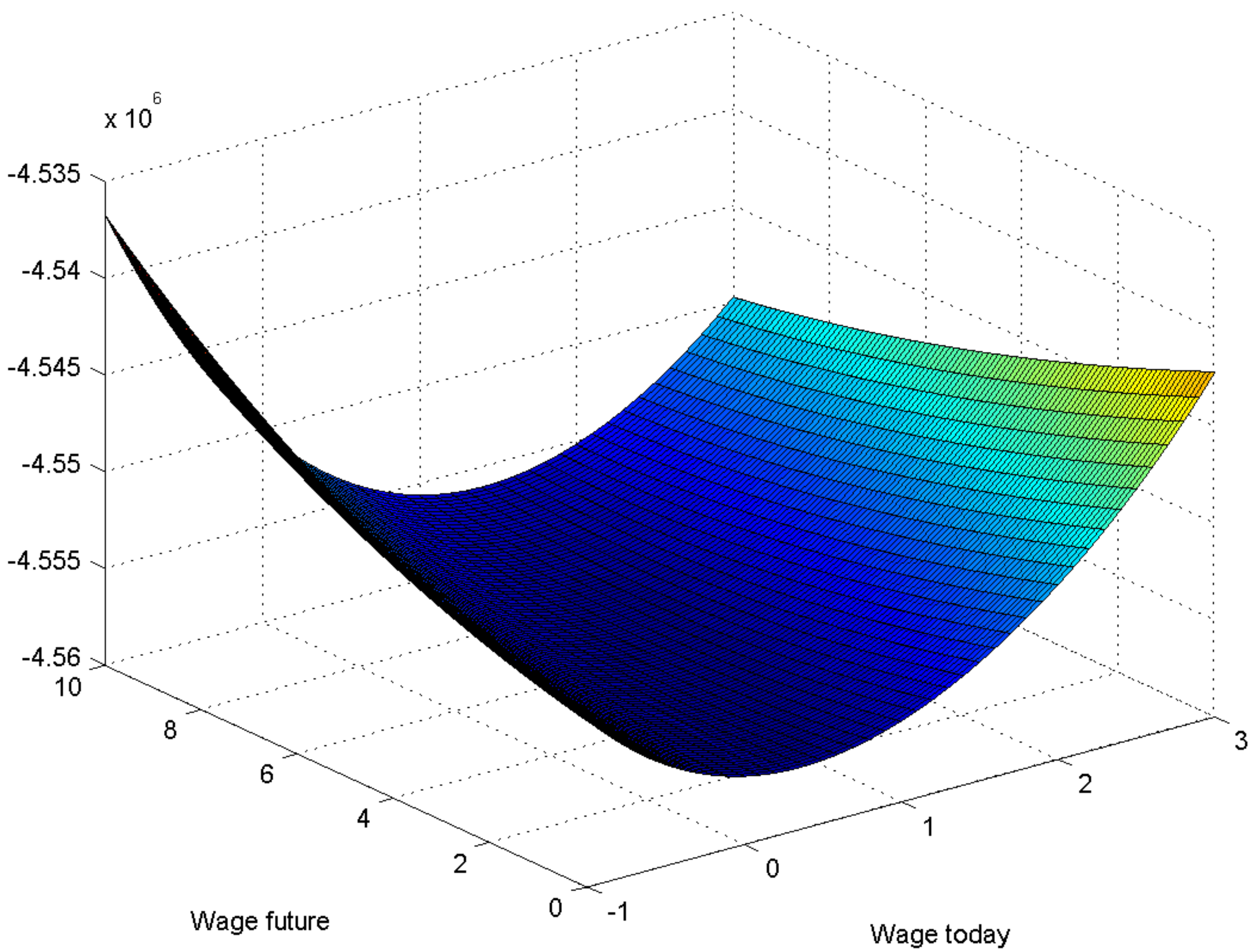


Figure 6: A trace of the inverse log likelihood over the coefficients on current and future earnings for fixed values of the other parameters. The trace is flat over a large range of values.

Summary Statistics

	All	Migrants
Age	35.0	29.14
	(12.0)	(9.66)
Household size	5.0	4.5
	(2.0)	(2.8)
Employment	0.94	0.90
	(0.23)	(0.31)
Earnings	1,738	1,537
	(2,628)	(2,209)
Hours (cond. on work)	52.7	54.4
	(13.9)	(13.5)
At least primary education	0.24	0.26
	(0.43)	(0.44)
At least secondary education	0.11	0.09
	(0.31)	(0.29)
N	993,227	54,776

Table 1: Averages weighted by inverse sampling frequency. Standard deviations in parentheses.

Earnings Responsiveness to Commodity Shocks				
Crude Oil	-0.155***			-0.0996***
	(0.0378)			(0.0346)
Cotton		-0.340***		-0.168*
		(0.0774)		(0.0887)
Wood			-0.222***	-0.133***
			(0.0502)	(0.0457)
Fixed Effects:				
Province	X	X	X	X
Year	X	X	X	X
R Squared	0.934	0.933	0.934	0.935
Observations	1095	1095	1095	1095
Partial F	16.72	19.31	19.51	15.10

Table 2: First-stage regression of province earnings on province exposure to commodity price shocks. Robust standard errors clustered by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Permanence of Various Commodities

	Crude Oil	Cotton	Wood
Fraction Permanent	0.983	0.915	0.512
	(0.21)	(0.24)	(0.39)
var(Perm.)	0.36	0.45	0.02
var(Temp.)	0.03	0.08	0.02

Table 3: The long-run permanence of various commodity series, running from 1960 through 2000. Data from the World Bank's databank. Bootstrapped standard errors in parentheses.

OLS Regressions of Migration on Destination Earnings

	Percent		Number		Dummy	
log(Dest. Income)	0.0258	0.0462**	126.9***	88.12	8.175***	19.12***
	(0.0165)	(0.0193)	(42.95)	(59.62)	(2.443)	(2.824)
Distance	-0.0172***	0.0350	-22.43***	-122.1	-4.955***	23.21***
	(0.00204)	(0.0382)	(3.988)	(121.7)	(0.186)	(3.716)
Income×Distance		-0.00687		13.12		-3.707***
		(0.00504)		(16.23)		(0.491)
Dest. Population			5.978***	6.050***	-0.130	-0.150
			(1.251)	(1.261)	(0.152)	(0.155)
Source Population			19.17***	19.58***	0.409***	0.368***
			(3.462)	(3.497)	(0.0141)	(0.0179)
Fixed Effects:						
Destination	X	X	X	X	X	X
Source×Year	X	X	X	X	X	X
R-Squared	0.095	0.095	0.256	0.256	0.222	0.225
Observations	78840	78840	78840	78840	78840	78840

Table 4: OLS results of the share of migrants moving from i to j, the number of migrants from i observed in j, and a dummy for any observed migration regressed on the log average earnings at j. Robust standard errors clustered by destination province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Commodity Instruments: Migration Dummy

	Crude Oil	Cotton	Wood	Combined
Dest. Income	47.25***	46.90**	17.49	31.71**
	(14.14)	(21.77)	(15.97)	(13.10)
Distance	35.26***	38.51***	28.47***	31.50***
	(5.302)	(7.775)	(5.169)	(4.754)
Income×Distance	-5.294***	-5.721***	-4.399***	-4.799***
	(0.700)	(1.028)	(0.684)	(0.629)
Fixed Effects:				
Destination	X	X	X	X
Source×Year	X	X	X	X
Population Controls	X	X	X	X
R Squared	0.222	0.222	0.225	0.225
Observations	78840	78840	78840	78840

Table 5: IV regressions of a dummy for any observed migration on earnings at destination. Robust standard errors clustered by destination province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Commodity Instruments: Number of Migrants

	Crude Oil	Cotton	Wood	Combined
Dest. Income	378.7**	544.2	337.4	383.6*
	(187.0)	(337.3)	(279.1)	(210.2)
Distance	-82.81	-84.35	-65.15	-75.42
	(100.3)	(78.12)	(74.79)	(74.81)
Income×Distance	8.835	9.038	6.510	7.862
	(13.32)	(10.31)	(9.948)	(9.973)
Fixed Effects:				
Destination	X	X	X	X
Source×Year	X	X	X	X
Population Controls	X	X	X	X
R Squared	0.258	0.257	0.258	0.258
Observations	78840	78840	78840	78840

Table 6: IV regressions of migrants from a source observed in a destination on earnings at destination. Robust standard errors clustered by destination province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

ML Estimated Parameters

Fixed Parameters			
Discount Rate (δ)	0.97	0.95	0.9
Remigration Rate	0.19	0.19	0.19
Time Horizon (T)	∞	∞	∞
Estimated Coefficients (Log earnings)			
Fixed Cost	-4.55	-4.29	-3.78
	[-5.90, -3.51]	[-5.57, -3.30]	[-4.91, -2.90]
log(Distance)	-0.57	-0.54	-0.47
	[-0.73, -0.45]	[-0.69, -0.42]	[-0.61, -0.37]
St. Dev. Tastes	0.97	0.92	0.81
	[0.76, 1.26]	[0.71, 1.18]	[0.63, 1.04]

Table 7: Estimated structural parameters for a range of discount parameters. All values are in terms of log earnings. Bootstrapped 95% confidence intervals in square braces. The likelihood ratio index for all specifications, relative to a model in which all parameters are 0, is 0.99996

ML Estimated Migration Costs

Fixed Parameters			
Discount Rate (δ)	0.97	0.95	0.9
Remigration Rate	0.19	0.19	0.19
Time Horizon (T)	∞	∞	∞
Average Moving Cost (2015 USD)			
Possible	2,488	1,594	664
To Bangkok	2,119	1,025	581
Actual	2,079	1,346	573
Including in-province	1,584	1,156	436
Estimated Average Cost under Alternate Assumptions			
Purely transitory wage	5.4	5.4	5.4
Purely permanent wage	12,097	6,930	2,323

Table 8: Estimated migration costs for a range of discount parameters. Average earnings over the period are $2,225. The average cost of a possible migration ranges from 0.3–1.1 times annual earnings; the average cost of an observed migration ranges from 0.26–0.93 times annual earnings. The bottom panel reports estimated costs if all shocks are assumed to be perfectly transitory or perfectly permanent.

Parameter Estimates under Alternate Specifications

	Model	Shock Duration		Alternate Method	
	Estimate	Transitory	Permanent	GMM	Logit
Discount Rate = 0.90					
Fixed Cost	-3.78	-0.95	-4.51	-9.16	-2.76
	[-4.91, -2.90]				
log(Distance)	-0.47	-0.12	0.56	-0.96	-23.3
	[-0.61, -0.37]				
St. Dev. Tastes	0.81	0.21	0.96	1.87	0.27
	[0.63, 1.04]				
Discount Rate = 0.95					
Fixed Cost	-4.29	-0.95	-5.14	-10.38	-2.95
	[-5.57, -3.30]				
log(Distance)	-0.54	-0.12	-0.64	-1.09	-25.0
	[-0.69, -0.42]				
St. Dev. Tastes	0.92	0.21	1.10	2.12	0.29
	[0.71, 1.18]				
Discount Rate = 0.97					
Fixed Cost	-4.55	-0.95	-5.47	-11.00	-3.05
	[-5.90, -3.51]				
log(Distance)	-0.57	-0.12	-0.68	-1.15	-25.9
	[-0.73, -0.45]				
St. Dev. Tastes	0.97	0.21	1.17	2.24	0.30
	[0.76, 1.26]				

Table 9: Estimated parameters with alternate specifications. Columns 2 and 3 assume observed earnings are fully transitory and fully permanent, respectively. Column 4 contains parameter estimates obtained using GMM to match predicted migration to observed migration ignoring measurement error. Column 5 contains parameter estimates obtained using multinomial logit ignoring endogenous sampling.

Robustness: Unresidualized Earnings

	Crude Oil	Cotton	Wood	Combined
Dest. Income	47.25***	46.90**	17.49	31.71**
	(14.14)	(21.77)	(15.97)	(13.10)
Distance	35.26***	38.51***	28.47***	31.50***
	(5.302)	(7.775)	(5.169)	(4.754)
Income×Distance	-5.294***	-5.721***	-4.399***	-4.799***
	(0.700)	(1.028)	(0.684)	(0.629)
Fixed Effects:				
Destination	X	X	X	X
Source×Year	X	X	X	X
Population Controls	X	X	X	X
R Squared	0.222	0.222	0.225	0.225
Observations	78840	78840	78840	78840

Table 10: IV regressions of a dummy for any observed migration on earnings at destination without removing age and education effects. Results are qualitatively similar to the specification with residualized earnings. Robust standard errors clustered by destination province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

OLS Regressions Including Income Variance

	Percent		Number		Dummy	
log(Dest. Income)	0.0462**	0.0466**	88.12	90.38	19.12***	19.18***
	(0.0193)	(0.0191)	(59.62)	(58.92)	(2.824)	(2.795)
Income Variance		0.00506		27.27**		0.752*
		(0.00412)		(13.49)		(0.434)
Distance	0.0350	0.0344	-122.1	-125.4	23.21***	23.12***
	(0.0382)	(0.0384)	(121.7)	(122.7)	(3.716)	(3.748)
Income×Distance	-0.00687	-0.00679	13.12	13.55	-3.707***	-3.695***
	(0.00504)	(0.00507)	(16.23)	(16.36)	(0.491)	(0.495)
Dest. Population			6.050***	6.109***	-0.150	-0.148
			(1.261)	(1.325)	(0.155)	(0.158)
Source Population			62.04	63.17	-2.153	-2.124
			(62.0)	(45.1)	(7.1)	(4.6)
Fixed Effects:						
Destination	X	X	X	X	X	X
Source×Year	X	X	X	X	X	X
R-Squared	0.095	0.095	0.256	0.257	0.225	0.225
Observations	78840	78840	78840	78840	78840	78840

Table 11: OLS results of the share of migrants moving from i to j, the number of migrants from i observed in j, and a dummy for any observed migration regressed on the log average earnings at j. Robust standard errors clustered by destination province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Earnings Responsiveness to Commodity Shocks

Iron Ore	0.00565				0.685
	(0.942)				(0.799)
Aluminum		0.00676			-0.642
		(0.299)			(0.727)
Copper			0.287		0.315
			(0.396)		(0.452)
Metals Index				0.0814	0.350
				(0.195)	(0.525)
Fixed Effects:					
Province	X	X	X	X	X
Year	X	X	X	X	X
R Squared	0.932	0.932	0.932	0.932	0.932
Observations	1095	1095	1095	1095	1095
Partial F	0.000	0.001	0.526	0.175	0.505

Table 12: First-stage regression of province earnings on province exposure to commodity price shocks. Robust standard errors clustered by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Estimates with Extra Instruments Included

Reduced Form Estimates			
Crude Oil	57.56***	56.13***	56.90***
	(19.07)	(18.12)	(18.87)
Cotton	57.23*	94.77**	87.04**
	(29.84)	(47.57)	(37.88)
Wood	-131.8**	-302.1***	-137.0**
	(55.90)	(99.86)	(53.94)
Distance	-4.955***	-4.955***	-4.955***
	(0.186)	(0.186)	(0.186)
Fixed Effects:			
Province	X	X	X
Year	X	X	X
Population Controls	X	X	X
R Squared	0.222	0.222	0.222
Observations	78840	78840	78840
Maximum Likelihood Estimates			
Fixed Cost	-4.29	-4.58	-3.97
	[-5.57, -3.30]		
log(Distance)	-0.54	-0.57	-0.48
	[-0.69, -0.42]		
St. Dev. Tastes	0.97	0.98	0.81
	[0.71, 1.18]		
Included Instruments:			
Iron Ore		X	
Aluminum		X	
Copper		X	
Metals Index			X

Table 13: Reduced form and maximum likelihood estimates with other instruments included. The top panel reports regression results from manual two-stage least squares of a dummy for any migration regressed on commodity prices rescaled so that the first stage regression produces a coefficient of 1. Robust standard errors clustered by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The second panel reports maximum likelihood estimates with the assumption of a 0.95 discount rate. Adding insignificant instruments does not significantly change any results.

Commodity Instruments: Migration Percent

	Crude Oil	Cotton	Wood	Combined
Dest. Income	-0.0899	0.0383	-0.116	-0.0880
	(0.0813)	(0.0725)	(0.109)	(0.0759)
Distance	0.0165	-0.0111	0.00485	0.00729
	(0.0304)	(0.0382)	(0.0280)	(0.0257)
Income×Distance	-0.00378	-0.000144	-0.00225	-0.00257
	(0.00402)	(0.00504)	(0.00366)	(0.00338)
Fixed Effects:				
Destination	X	X	X	X
Source×Year	X	X	X	X
R Squared	0.105	0.107	0.104	0.105
Observations	78840	78840	78840	78840

Table 14: IV regressions of the portion of a source province that migrates to a destination on earnings at destination. Robust standard errors clustered by destination province in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$