A model of dynamic flows: Explaining Turkey’s inter-provincial migration*

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October 30, 2022

Abstract

The flow of resources across nodes over time (e.g. migration, financial transfers, peer-to-peer interactions) is a common phenomenon in sociology. Standard statistical methods are inadequate to model such interdependent flows. We propose a hierarchical Dirichlet-multinomial regression model and a Bayesian estimation method. We apply the model to analyse 25,632,876 migration instances that take place between Turkey’s 81 provinces from 2009 to 2018. We then discuss the methodological and substantive implications of our results. Methodologically, we demonstrate the predictive superiority of our model compared to its most common alternative in migration research, namely the gravity model. We also discuss our model in the context of other approaches, mostly developed in the social networks literature. Substantively, we find that population, economic prosperity, the spatial and political distance between the origin and destination, the strength of the AKP (Justice and Development Party) in a province and the network characteristics of the provinces are important predictors of migration, while the proportion of ethnic minority Kurds in a province has no positive association with in- and out-migration.

Keywords: Hierarchical Bayesian modelling; Dirichlet-multinomial regression; Markov chain Monte Carlo; Migration; Turkey

1 Introduction

Flows of items such as people, resources, and information across a finite number of units such as places, institutions, and individuals over time constitute a very common type of data in sociology and the wider social sciences. While migration is one of the most frequent types of such flows, other examples include financial transfers between institutions or individuals, passengers through transportation systems, mobility tables, and the number of times participants trust

*The authors contributed equally to the manuscript. We thank Zsofia Boda and Burak Sönmez for their comments on earlier drafts. An anonymised replication package with the data and the code that produce the results are available at <https://github.com/SocNetMigration/MigNet-MATLAB-code.git>.

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or donate to others during an experiment. Due to the highly interdependent nature of such situations, certain modelling problems arise (e.g. destinations ‘compete’ over a fixed amount of flow) which are not straightforward to address with standard statistical models (Block et al., 2022).

Here we first aim to contribute methodologically to the analysis of such dynamic flows. We frame our model within a migration context. Indeed we developed our model with a motivation to analyse real-world migration data. Nevertheless, our model can be applied to other situations that similarly involve dynamic discrete flows across a finite number of units. One of the most widely used methods of analysing migration flows is the so-called *gravity model* (Barthélemy, 2011; Karemera et al., 2000; Expert et al., 2011). In this model, the (logarithm) of the number of people migrating from i to j is modelled as a function of the characteristics of i and j , and the distance between i and j . A problem with this approach is that when a person migrates from i to j , they mechanistically cannot migrate to another destination k . Likewise, the characteristics of k may affect migration from i to j , too. For example, k can be a competitor of j in receiving migration from i . This dependence in migration probabilities across destinations is ignored in the gravity model, while it is taken into account in our model.

In this study, we propose a Dirichlet-multinomial model, which is an extension of a class of econometric discrete choice models (Guimaraes and Lindrooth, 2007; Alamá-Sabater et al., 2017). Our model differs from those existing choice models in the treatment of non-migration. The existing models base their estimates *conditional* on migration taking place. We believe that any inference about the causes of migration would be problematic if one ignores those who choose to not move. This is because in that case, observations for which the causes of migration might have been present but did not generate migration, i.e., non-migration counts, are omitted. In other words, ignoring non-migration results in ‘selection on the dependent variable’. In our model, the probabilities of migration to the available destinations as well as the probability of not migrating are directly modelled as functions of the covariates. We further extend our model with random intercepts for provinces to account for the longitudinal nature of migration flows. We fit our model within the Bayesian framework via a Markov chain Monte Carlo (MCMC) algorithm.

There is a long array of models that are developed mostly in the social networks literature which can also be applied to dynamic flows. These include Stochastic Actor Oriented Models (Snijders, 1996, 2001), Dynamic Network Actor and other similar Relational Event Models (Stadtfeld and Block, 2017; Stadtfeld et al., 2017b; Block et al., 2019), Exponential Random Graph Models (Lusher et al., 2013) and its various extensions and forms (Westveld and Hoff, 2011; Desmarais and Cranmer, 2012; Almquist and Butts, 2014; Krivitsky and Handcock, 2014; Krivitsky and Butts, 2017; Block et al., 2022), Latent Space and Latent Factor Models (Hoff et al., 2002; Minhas et al., 2019). Some of these models are theoretically flexible and very general but may be difficult to adapt to the specific case; others are computationally demanding. The application of some will require significant programming. Nevertheless, those models offer a powerful way of dealing with relational data. We believe that our approach provides a rela-

tively straightforward and natural way to deal with dynamic flows, at the same time offering computational simplicity while taking into account key features of the data. We discuss similarities and differences between our model and those network models in Section 2.2. We believe that we contribute to the methodological literature by enriching the methodological arsenal for dealing with dynamic flows.

We also aim to contribute substantially to the migration literature. Various determinants of voluntary migration have been identified in this literature (Boyle et al., 1998). These include characteristics of the origin and the destination such as economic prospects (Borjas, 1999; Levy, 2010), immigration legislation (Palmer and Pytlikova, 2015); and characteristics of the origin-destination pair such as linguistic, cultural and physical distance (Levy, 2010; Windzio, 2018; Expert et al., 2011) between the origin and the destination. Migration can be *international* as well as *intra-national*. Yet, the migration literature is based mostly on international migration and hence the dynamics of internal migration, particularly in non-Western countries are understudied (Kuhn, 2015; Bell and Muhidin, 2009). The focus on international migration is understandable, for it seems highly consequential in shaping public opinion and politics (Chan et al., 2020; Gimpel and Schuknecht, 2001). The scarcity of research on internal migration, however, is surprising. Internal migration may not be as economically advantageous for the migrant or topical as international migration is. However, it is far less costly and risky. Consequently, compared to international migration, much larger shares of populations are affected by internal migration, particularly in non-Western countries (Kuhn, 2015). For example, according to the official statistics, in 2018 a total of 323,918 people emigrated abroad from Turkey, our study context, whereas in the same year 3,057,606, nearly ten times more, moved from one Turkish province to another. Internal migration is thus a strong determinant of local population structures, and it is important to understand its drivers.

We contribute to the migration literature by addressing this gap. Using a unique dataset compiled from the administrative, registry, and survey data, we analyse the dynamics of more than 25 million migration instances between the 81 provinces of Turkey from 2009 to 2018. Almost all empirical work on internal migration in Turkey, however scarce, was conducted with data spanning until 2000 (Gedik, 1997; Filiztekin and Gökhan, 2008; Yazgi et al., 2014). The more recent work is descriptive and focuses on larger inter-regional migration (Akin and Dökmeci, 2015). Turkey has gone through a large economic, demographic, and political transformation in the meantime (Aksoy and Billari, 2018), which has affected migration too (Çoban, 2013). It is thus unknown if these earlier insights into Turkey’s internal migration apply to more recent migration patterns. Internal migration in Turkey is relevant for Europe too. Turkey’s ascension to the European Union (EU) has stalled. One of the fears as to the expansion of the EU is large-scale immigration (Strasser, 2008). Understanding the determinants of inter-province migration in Turkey will help predict the extent of potential migration from Turkey to Europe and its likely destinations within the EU, should Turkey ever be part of the EU (Filiztekin and Gökhan, 2008).

Overall, by providing novel insights into the internal migration of Turkey and a conve-

nient model of migration flows, our study contributes to the literature both substantively and methodologically.

2 A model of migration flows

We now describe our model in a migration context. Note, however, that our model can be applied to many other settings with minimal adjustment, e.g. provinces below can be replaced by individuals or institutions, and migration can be replaced by the number of financial transfers or interactions. In fact, in many of those alternative settings, one could directly proceed with modelling the $H_t(i, j)$'s below. The migration case needs a slight adjustment, as we will describe now, for the stock of people who could migrate but did not is dynamic due to changes in births and deaths.

Assume that we have $n > 1$ provinces, and $T > 1$ consecutive years, and that for each year we have data on the population of and migration between the provinces. Specifically, we observe

$$P_t(i) = \text{the population of province } i \text{ at the beginning of year } t$$

for all $i = 1, \dots, n$ and $t = 1, \dots, T$; and

$$H_t(i, j) = \text{the number of people who migrated from province } i \text{ to province } j \text{ in year } t$$

for all $1 \leq i, j \leq n$ pairs with $i \neq j$, respectively. Let us define

$$E_{t,t+1}(i) := P_{t+1}(i) - \left[P_t(i) - \sum_{j \neq i} H_t(i, j) + \sum_{j \neq i} H_t(j, i) \right], \quad i = 1, \dots, n,$$

which is the net change in population for province i after taking into account the inter-province migration during year t . The net change captures births, deaths, and people who are registered in the system for the first time for any other reason. Taking the net change into account, we define the *adjusted population* of province i for year t as

$$X_t(i) := P_t(i) + E_{t,t+1}(i) = P_{t+1}(i) + \sum_{j \neq i} H_t(i, j) - \sum_{j \neq i} H_t(j, i), \quad i = 1, \dots, n.$$

We consider this adjusted population to find the number of people who did *not* migrate from province i during year t as

$$H_t(i, i) = X_{t+1}(i) - \sum_{j \neq i} H_t(i, j), \quad i = 1, \dots, n.$$

Therefore, given the assumptions, we can summarise the relation between the quantities $H_t(i, j)$ s

and $X_t(i)$ s as

$$X_t(i) = \sum_{j=1}^n H_t(i, j), \quad i = 1, \dots, n. \quad (1)$$

As a prelude to our proposed model, let us assume for now the existence of a probability of migrating from province i to province j in year t , denoted by $\rho_t(i, j)$, and that $\rho_t(i, j)$ is same for all citizens in province i . This yields a multinomial distribution for $(H_t(i, 1), \dots, H_t(i, n))$ for each t and i , specified as

$$(H_t(i, 1), \dots, H_t(i, n)) \sim \text{Multinomial}(X_t(i); \rho_t(i, 1), \dots, \rho_t(i, n)).$$

A multinomial regression can be constructed by modelling $\rho_t(i, j)$ as a function of the factors about provinces i and j individually, as well as the factors about the relation between i and j . Generically, we assume that there are $d_u \geq 1$ and $d_v \geq 1$ factors that affect the likelihood of migrating from and to a province, respectively. Those factors can vary across the years and provinces, hence are denoted by $u_t(i) \in \mathbb{R}^{d_u}$ and $v_t(i) \in \mathbb{R}^{d_v}$, respectively. Note that some factors can both push and pull migration (e.g. (un)employment) and hence appear both as $u_t(i)$ and $v_t(i)$. Furthermore, for each (i, j) pair we also have $d_z \geq 1$ factors of sort $z_t(i, j) \in \mathbb{R}^{d_z}$ defined as edge-level factors that may affect migration from i to j . Those factors altogether determine the probability $\rho_t(i, j)$ of migrating from i to j in year t as

$$\rho_t(i, j) = \frac{\exp\{\theta_0 + \theta_1 \cdot u_t(i) + \theta_2 \cdot v_t(j) + \theta_3 \cdot z_t(i, j)\}}{1 + \sum_{j' \neq i} \exp\{\theta_0 + \theta_1 \cdot u_t(i) + \theta_2 \cdot v_t(j') + \theta_3 \cdot z_t(i, j')\}}.$$

Here, $(\theta_0, \theta_1, \theta_2, \theta_3)$ is the vector of model parameters. The components $\theta_1 \in \mathbb{R}^{d_u}$, $\theta_2 \in \mathbb{R}^{d_v}$, and $\theta_3 \in \mathbb{R}^{d_z}$ correspond to the sending ($\rightarrow$), the receiving ($\leftarrow$), and the joint (edge-level) factors ($\leftrightarrow$), respectively. The scalar component $\theta_0 \in \mathbb{R}$ is the ‘base’ parameter, which solely determines the probability of migration at all when all factors are zero. Finally, exponentiation is used to ensure that we have positive terms. The resulting model is an instance of the multinomial logistic regression model (Theil, 1969).

A limitation of the above expression may be the deterministic relation between the factors and the migration probability $\rho_t(i, j)$. We would like to allow for variability in those probabilities, such that even under the same factor values the probabilities $\rho_t(i, j)$ s may differ across province-year pairs, for example, due to unsystematic residual factors that our model may fail to cover (Nelson, 1984). This can be done by modelling the probabilities using a Dirichlet distribution for each of those province-year pairs. Specifically, we let $\rho_t(i, j)$ s be random variables themselves, with $(\rho_t(i, 1), \dots, \rho_t(i, n))$ having a Dirichlet distribution independently for each t and i , that is,

$$(\rho_t(i, 1), \dots, \rho_t(i, n)) \sim \text{Dirichlet}(\alpha_t(i, 1), \dots, \alpha_t(i, n)).$$

This time, it is the parameters of the Dirichlet distribution that we model via regression.

Specifically,

$$\alpha_t(i, j) = \begin{cases} \exp\{\theta_0 + \theta_1 \cdot u_t(i) + \theta_2 \cdot v_t(j) + \theta_3 \cdot z_t(i, j) + \theta_4\} & i \neq j \\ \exp\{\theta_4\} & i = j. \end{cases} \quad (2)$$

The resulting model is a Dirichlet-multinomial regression. Observing the expected probabilities

$$E(\rho_t(i, j)) = \frac{\alpha_t(i, j)}{\sum_{j'=1}^n \alpha_t(i, j')},$$

we note that, in this model, the vector $(\theta_0, \theta_1, \theta_2, \theta_3)$ lends itself to a similar interpretation as in the multinomial logistic regression model introduced earlier. The extra scalar parameter $\theta_4 \in \mathbb{R}$ is present in each $\alpha_t(i, j)$, hence does not affect the expected probabilities. The parameter θ_4 instead captures the variances of the probabilities – the larger θ_4 , the smaller the variances.

According to our Dirichlet-multinomial regression, people’s decisions *within a province* are dependent even when conditioned on the covariates. This is because, given the covariates, the same *random* migration probability vector applies to all individuals in the same province, introducing a positive correlation among their choices. The strength of this correlation decreases as θ_4 increases. This makes our model rather flexible and may be considered another positive feature, as it captures the possibility that individuals living in the same province may be influenced by each other in deciding to migrate or not migrate. Furthermore, we can gauge the amount of within-province interpersonal influence by estimating θ_4 using the data.

Due to its flexibility, we proceed with the Dirichlet-multinomial regression model described above. Note that, from an inference perspective, the Dirichlet-multinomial specification does not introduce additional complications compared with the multinomial logistic specification. As it is well known, after integrating out $\rho_t(i, j)$ s, $H_t(i, j)$ s follow a Dirichlet-multinomial distribution,

$$(H_t(i, 1), \dots, H_t(i, n)) \sim \text{Dirichlet-multinomial}(X_t(i); \alpha_t(i, 1), \dots, \alpha_t(i, n)),$$

which can easily be computed.

Our data are multilevel, that is, migration from i to j for all i and j are observed over the $T > 1$ years. Accordingly, we expand the specification in (2) to address this multilevel structure by assuming that the base parameter θ_0 is a random variable defined at the province level (i.e. a ‘random intercept’). More specifically, we modify equation (2) as

$$\alpha_t(i, j) = \begin{cases} \exp\{\theta_0(i) + \theta_1 u_t(i) + \theta_2 v_t(j) + \theta_3 z_t(i, j) + \theta_4\} & i \neq j \\ \exp\{\theta_4\} & i = j. \end{cases} \quad (3)$$

Next, by our aim of Bayesian inference, we build up the prior distributions for the model parameters introduced so far. The parameters $\theta_1, \theta_2, \theta_3$, and θ_4 are assumed *a priori* independent and have priors $\theta_i \sim \eta_i, i = 1, \dots, 4$. Further, independently from $\theta_1, \theta_2, \theta_3$, and θ_4 , the base parameter $\theta_0(i)$ for each $i = 1, \dots, n$ are also assumed independent with a common normal

distribution

$$\theta_0(i) \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu_0, \sigma_0^2), \quad i = 1, \dots, n. \quad (4)$$

The parameters μ_0 and σ_0^2 are themselves treated as random variables, that are independent with $\mu_0 \sim \mathcal{N}(\mu_h, \sigma_h^2)$ and $\sigma_0^2 \sim \mathcal{IG}(a_h, b_h)$, where the latter is the inverse-Gamma distribution with shape and scale parameters a_h and b_h , respectively. We assume that the hyperparameters μ_h , σ_h^2 , a_h , and b_h are known.

The full parameter vector of the resulting hierarchical model is the $(1 + 1 + n + d_u + d_v + d_z + 1) \times 1$ vector

$$\boldsymbol{\theta} = (\mu_0, \sigma_0^2, \theta_0(1), \dots, \theta_0(n), \theta_1, \theta_2, \theta_3, \theta_4).$$

This completes the description of our model of migration in a closed system. We refer to our model whose Dirichlet-multinomial parameters are given by (3) as a *hierarchical specification*, for it models the base parameter $\theta_0(i)$ as random across provinces.

Note that one could expand the model above by making $\theta_0(i)$, the base parameter, a polynomial function of time, of order $d_b \geq 0$. In that case, the base parameter could be expressed as

$$\theta_0(i) = \sum_{k=0}^{d_b} \theta_{0,k}(i) t^k,$$

where the polynomial coefficients for province i would be modelled as random with

$$\boldsymbol{\vartheta}_i := (\theta_{0,0}(i), \dots, \theta_{0,d_b}(i)) \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu_0, \Sigma_0), \quad i = 1, \dots, n,$$

and μ_0 , Σ_0 would be multivariate random variables with suitable priors, such as $\mu_0 \sim \mathcal{N}(\mu_h, \Sigma_h)$ and $\Sigma_0 \sim \mathcal{W}^{-1}(\nu_h, \Psi_h)$, the inverse-Wishart distribution with ν_h degrees of freedom and the scale matrix Ψ_h . With $d_b = 1$, for example, we would have a model with ‘random slopes’ of time.

In our implementations, we will not present results with this polynomial specification. Our results below will be restricted to the ‘random intercept’ specification where the base parameters are random across provinces as in (4). This is mainly because province log populations, which are included in the model as predictors, are increasing almost as a linear function of time, rendering the estimation of a separate time slope unnecessary and numerically difficult. We did fit specifications with linear as well as quadratic random time slopes which did not make noticeable differences in our models, apart from creating convergence problems. That being said, the polynomial specification for the base parameter may be useful in other applications; hence we will describe our inference method below by considering the polynomial specification.

2.1 Inference

Before presenting the study context and data, we describe our inference method. To quantify the uncertainties in the estimation of $\boldsymbol{\theta}$ conveniently, we aim for Bayesian inference of $\boldsymbol{\theta}$ given

the data

$$\mathcal{D} = \{H_t(i, j); \quad i, j \in \{1, \dots, n\}, t \in \{1, \dots, T\}\}.$$

Note that the (adjusted) province populations $\{X_t(i) : t = 1, \dots, T; i = 1, \dots, n\}$ are implicitly contained in $\mathcal{D}$ also, thanks to the relation given in (1). More specifically, we aim to find the posterior distribution for the hierarchical model

$$p(\boldsymbol{\theta}|\mathcal{D}) \propto p(\boldsymbol{\theta})p(\mathcal{D}|\boldsymbol{\theta}).$$

Here, $\boldsymbol{\theta} = (\mu_0, \Sigma_0, \vartheta_1, \dots, \vartheta_n, \theta_1, \theta_2, \theta_3, \theta_4)$ is the parameter vector with the hierarchical specification for the polynomial coefficients of the province-dependent base parameters; $p(\boldsymbol{\theta})$ is the probability density of the prior distribution given by

$$p(\boldsymbol{\theta}) = \left[\prod_{j=1}^4 \eta_j(\theta_j) \right] \left[\prod_{i=1}^n \mathcal{N}(\vartheta_i; \mu_0, \Sigma_0) \right] \mathcal{N}(\mu_0; \mu_h, \Sigma_h) \mathcal{W}^{-1}(\Sigma_0; \nu_h, \Psi_h);$$

and $p(\mathcal{D}|\boldsymbol{\theta})$ is the likelihood given by a product of Tn Dirichlet-multinomial probabilities as

$$p(\mathcal{D}|\boldsymbol{\theta}) = \prod_{t=1}^T \prod_{i=1}^n p(H_t(i, :) | \alpha_t^{\boldsymbol{\theta}}(i, :)), \quad (5)$$

where the superscript $\boldsymbol{\theta}$ over $\alpha_t^{\boldsymbol{\theta}}(i, :)$ is used from now on to indicate the dependency on $\boldsymbol{\theta}$ explicitly and $p(H_t(i, :) | \alpha_t^{\boldsymbol{\theta}}(i, :))$ is the Dirichlet-multinomial probability

$$p(H_t(i, :) | \alpha_t^{\boldsymbol{\theta}}(i, :)) = \frac{X_t(i)! \Gamma\left(\sum_{j=1}^n \alpha_t^{\boldsymbol{\theta}}(i, j)\right)}{\Gamma\left(X_t(i) + \sum_{j=1}^n \alpha_t^{\boldsymbol{\theta}}(i, j)\right)} \prod_{j=1}^n \frac{\Gamma(H_t(i, j) + \alpha_t^{\boldsymbol{\theta}}(i, j))}{H_t(i, j)! \Gamma(\alpha_t^{\boldsymbol{\theta}}(i, j))}$$

where $\Gamma(\cdot)$ is the gamma function.

As the posterior distribution is analytically intractable, we develop a Metropolis-Hastings-within-Gibbs (MHwG) algorithm (see e.g. Tierney (1994)) to sample from the posterior distribution. In MHwG, the parameter vector $\boldsymbol{\theta}$ is divided suitably into disjoint blocks of components, and those blocks are updated in turn by either a Gibbs move (if sampling from the full conditional distribution of the block is possible) or a Metropolis-Hastings move (otherwise). We describe this process in detail in Algorithm 1, where the aforementioned blocks are taken as

$$\{\theta_1\}; \{\theta_2\}; \{\theta_3\}; \{\theta_4\}; \{\vartheta_1, \dots, \vartheta_n\}; \{\mu_0\}; \{\Sigma_0\}.$$

We note some important remarks on the computational complexity of Algorithm 1. While updating each of $\{\theta_1\}; \{\theta_2\}; \{\theta_3\}; \{\theta_4\}$, a product of nT Dirichlet-multinomial distributions, each with n categories, is computed in the numerator and the denominator of the acceptance ratio. Given the rest of the components, the variables $\vartheta_1, \dots, \vartheta_n$ are conditionally independent, therefore they can be updated in parallel, each requiring the computation of T Dirichlet-multinomial

distributions, each with n categories, in the numerator and the denominator of the acceptance ratio. Finally, the blocks $\{\mu_0\}$ and $\{\Sigma_0\}$ can be updated in turn with Gibbs moves since their full conditional distributions have closed forms, thanks to conjugacy.

Algorithm 1: MHwG for Dirichlet-multinomial model with the hierarchical specification for its province-dependent base parameters

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1 Start with  $\theta^{(0)}$ .
2 for  $k = 1, 2, \dots$  do
3   Set  $\theta = \theta^{(k-1)}$ .
4   for  $j = 1, 2, 3$  do
5     Propose  $\theta'_j \sim q_j(\theta'_j | \theta_j)$ 
6     Construct the proposed parameter vector  $\theta'$  by replacing  $\theta_j$  by  $\theta'_j$  in  $\theta$ .
7     Update  $\theta_j$  as  $\theta'_j$  with acceptance probability
        
$$\min \left\{ 1, \frac{q_j(\theta_j | \theta'_j) \eta_j(\theta'_j) \prod_{t=1}^T \prod_{i=1}^n p(H_t(i, :) | \alpha_t^{\theta'}(i, :))}{q(\theta'_j | \theta_j) \eta_j(\theta_j) \prod_{t=1}^T \prod_{i=1}^n p(H_t(i, :) | \alpha_t^{\theta}(i, :))} \right\};$$

        otherwise, keep  $\theta_j$  as before.
8   for  $i = 1, \dots, n$  do
9     Propose  $\vartheta'_i \sim q_0(\vartheta'_i | \vartheta_i)$ .
10    Construct  $\theta'$  by replacing  $\vartheta_i$  by  $\vartheta'_i$  in  $\theta$ .
11    Update  $\vartheta_i$  as  $\vartheta'_i$  with acceptance probability
        
$$\min \left\{ 1, \frac{q_0(\vartheta_i | \vartheta'_i) \mathcal{N}(\vartheta'_i; \mu_0, \Sigma_0) \prod_{t=1}^T p(H_t(i, :) | \alpha_t^{\theta'}(i, :))}{q_0(\vartheta'_i | \vartheta_i) \mathcal{N}(\vartheta_i; \mu_0, \Sigma_0) \prod_{t=1}^T p(H_t(i, :) | \alpha_t^{\theta}(i, :))} \right\};$$

        otherwise, keep  $\vartheta_i$  as before.
12   Sample  $\mu_0 \sim \mathcal{N}(\mu_{\text{post}}, \Sigma_{\text{post}})$  where  $\Sigma_{\text{post}} = (\Sigma_h^{-1} + n\Sigma_0^{-1})^{-1}$  and
         $\mu_{\text{post}} = \Sigma_{\text{post}}(\Sigma_h^{-1}\mu_h + \Sigma_0^{-1}\sum_{i=1}^n \vartheta_i)$ .
13   Sample  $\Sigma_0 \sim \mathcal{W}^{-1}(\nu_h + n, \Psi_h + \sum_{i=1}^n (\vartheta_i - \mu_0)(\vartheta_i - \mu_0)^T)$ 
14   
$$\theta^{(k)} = (\mu_0, \Sigma_0, \vartheta_1, \dots, \vartheta_n, \theta_1, \theta_2, \theta_3, \theta_4),$$

   the vector of current samples.

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2.2 Related methodology

Our model's closest relative is the one proposed by [Guimaraes and Lindrooth \(2007\)](#). [Guimaraes and Lindrooth \(2007\)](#) develop a Dirichlet-multinomial regression as an extension of the multinomial logistic regression within a discrete choice random utility framework. They use this to model counts from different groups to multiple destinations (e.g. hospital choice of different groups of patients) whereby for each group multinomial probabilities for the destinations are modelled independently with a Dirichlet distribution.

This Dirichlet-multinomial regression model is used by [Alam-Sabater et al. \(2017\)](#) to explain immigration to different parts of Spain from various regions outside of Spain. Our model and the model of [Alam-Sabater et al. \(2017\)](#) have critical differences. Firstly, [Alam-Sabater](#)

et al. (2017) aim to explain how much migration a certain factor ‘pulls’, hence only focus on factors of the receiving regions, (corresponding to our $v_t(j)$ s, or the $\leftarrow$ factors). Whereas, in this study, we consider migration on a matrix of provinces. Consequently, our model includes factors in sending ($\rightarrow$) and receiving ($\leftarrow$) nodes as well as edge-level covariates ($\leftrightarrow$). A second crucial difference between our model and the model in both Guimaraes and Lindrooth (2007) and Alamá-Sabater et al. (2017) is that our model accounts for people who have *not* migrated, while the latter two omit ‘self-edges’. Alamá-Sabater et al. (2017) model the flows of immigration to different provinces in Spain, conditional on immigration taking place. Likewise, Guimaraes and Lindrooth (2007) omit those who do not decide to migrate at all. We believe that an omission of self-edges and no-choice cases would create a serious issue in our setting, for in that case the analysis would be restricted to the cases for which a positive outcome is observed.

A further difference between our model and those in Guimaraes and Lindrooth (2007) and Alamá-Sabater et al. (2017) is that our model is hierarchical, allowing a random intercept. Finally, while Guimaraes and Lindrooth (2007) and Alamá-Sabater et al. (2017) implement maximum likelihood estimation, we use Bayesian inference to quantify the uncertainties in our estimates effectively.

The most common model that is used to analyse migration is the co-called gravity model (Karemera et al., 2000; Barthélemy, 2011; Expert et al., 2011; Poot et al., 2016). In this model, the logarithm of the number of people moved from i to j at time T is simply regressed on the features of i and j such as population and some measure of the distance between i and j . The estimation is straightforward, for it can be performed within the standard maximum likelihood framework that is used for regression modelling. The disadvantages are as follows. Firstly, the model does not incorporate systemic effects, for example, origin populations constrain the total size of out-migration which is not directly incorporated in the model (Poot et al., 2016). In addition, destinations compete for migration, for if an individual migrates to j , they simultaneously cannot migrate to k . Naturally, then the properties of k should also affect the decision to migrate to j which are typically ignored in the gravity model. Furthermore, non-migration (zero cell counts) is mostly omitted in this model, conditioning the estimates on migration having taken place and creating a selection on the dependent variable, just as in the models of Guimaraes and Lindrooth (2007) and Alamá-Sabater et al. (2017) discussed above. Nevertheless, this is a very popular model of migration, hence we will compare the predictive power of our model with that of the gravity model below.

The literature on social networks, too, offers a long list of statistical models that can be applied to flows. A canonical model is the Exponential Random Graph Model (ERGM) (Lusher et al., 2013) which takes the entire data as a network of nodes (e.g. provinces) and edges (e.g. migration flows). In ERGMs the whole network is modelled as a function of node, edge, and network-level covariates. ERGM enjoys greater generality than our model; because, using it, one can naturally include various local or global network statistics as explanatory variables and incorporate complex contemporaneous dependencies in the data (i.e. network dependencies in a

cross-sectional measurement). The standard ERGM deals with binary edges and cross-sectional settings, so it cannot be directly applied to our problem. ERGM, however, has been extended to deal with longitudinal data (Krivitsky and Handcock, 2014) and with count or weighted edges and multi-layered networks (Block et al., 2022; Krivitsky et al., 2020; Krivitsky and Handcock, 2014; Krivitsky, 2012; Desmarais and Cranmer, 2012).

While an ERGM type of model would be very flexible and general, it can be challenging to perform inference in ERGMs (Almquist and Butts, 2013, 2014), particularly for various generalisations of it. The major challenge may be having to sample the whole network (typically several times) at every iteration, which can only be done approximately, for example by using Gibbs sampling, unless the network is very small—note that we also use a Gibbs sampler, but in our case inference is much simpler as we will elaborate shortly. Consequently, while ERGM is generalised to deal with longitudinal data and weighted edges, most applications are constrained to either longitudinal binary networks, cross-sectional networks with weighted edges, or relatively small networks. We have tried to implement an ERGM for count edges (Krivitsky, 2012; Krivitsky et al., 2021) to our data. Unfortunately, it failed to converge even for a single year of our migration data, let alone the 10 years our data spans. In a recent example, Block et al. (2022) develop a weighted ERGM for mobility networks, but the application is restricted to cross-sectional observations. Another issue that needs to be tackled in an ERGM-type model is that the total flow of out-migration is bounded by the population of the origin, and this constraint may be difficult to implement in an ERGM. In our model, these ‘row-sums’ are naturally handled through the Dirichlet-multinomial distribution.

Another class of models that are developed in the social networks literature that have some similarities with our model comprise the Stochastic Actor-Oriented Model (SAOM) (Snijders, 2001), the Dynamic Network Actor Model (DyNAM) (Stadtfeld and Block, 2017), the Relational Event Model (REM) (Butts, 2008) and other similar models (Almquist and Butts, 2014). These models are designed to analyse longitudinal dynamic binary network data, though extensions for count data exist (Stadtfeld et al., 2017a). In the actor-based SAOM and DyNAM, two processes are modelled separately: the timing of an event (e.g. a tie to be formed), and the target of the event (e.g. whom a person sends a tie) which is modelled with a multinomial specification. In the tie-based REM, the timing and the position of an event (e.g. which two nodes are connected) are modelled simultaneously. In our model the exact timing of migration is unknown, apart from it taking place during a given year. Moreover, many migration flows take place during a given year. To apply the dynamic network models discussed here, however, one needs to be able to calculate the conditional distribution of the migration data of a year given the state of variables in the previous year. This is not available in our case, since we do not know the times of individual migration events and integrating them out is analytically intractable. One can only approximate those conditionals, making this class of models inconvenient for us to apply in our case.

There is a final class of models, developed again mainly in the social networks literature. These include latent space (Hoff et al., 2002; Hoff and Ward, 2004) and latent factor models

(Minhas et al., 2019). Most recently, and perhaps most relevantly, Minhas et al. (2019) describe a latent factor model in which cell outcomes in a matrix (e.g. migration flows in our case) are modelled as a function of the sender and proposer characteristics plus a latent factor matrix. The elements of this matrix are the sender and receiver latent factors multiplied by a sender-receiver pair parameter. This latent multiplicative factor capture higher-order dependence structures which are not explained by the observed covariates included in the model. Minhas et al. (2019) then propose a Bayesian estimation procedure which assumes certain prior distributions for the parameters, including the elements of the latent factor matrix. This class of models is very flexible too. Applications, however, are often restricted to binary data, though an extension to the multinomial and count data is possible. In addition, diagonals are often not modelled explicitly (see, e.g. Minhas et al. (2019) and it is not straightforward to constrain the row-sums which are bounded in our data by the province populations.

Overall, we argue that the methodology and the modelling approach of these relational and network models are too general for our problem. In contrast, our specific model is directly related to the migration (and other similar) flows and can be derived from a small number of assumptions (such as Multinomial probabilities and independence of the actors in different provinces). For example, staying within the notation in our manuscript, the SAOM in Snijders (1996) takes (H_t, Z_t) as the state and assumes that this is a Markov process. H_t corresponds to the relation matrix in SAOM, and Z_t the exogenous variables. However, in our model (H_t, Z_t) is not a Markov process, in that H_t depends on the cumulative effect of the previous $H_{1:t-1}$'s, since those sum up to the populations. In this sense, our model is similar to the model discussed by Hanneke et al. (2010) which condition the current network on the earlier network realisations. Consequently, the parameters of our model can be inferred with a fairly standard MCMC algorithm, see Algorithm 1. This convenience is due to the assumption in our model that out-migration in two *different* provinces are independent, *conditional* on covariates which include factors related to migration in the previous year (however, recall that our model addresses the dependency of migration decisions among people who live in the same province). This assumption is plausible in the migration context: when a person in province i is deciding to migrate to a certain province j (or not to migrate at all) at time point t , this decision is likely independent of another person's decision in province $k \neq i$ at *the same time-point*, provided that we take key relevant factors into account. Note that in our model a person's decision in province i *can* depend on another person's decision in province j that was made in the previous year, for we include factors that are functions of past migration as predictors of future migration. For example, if we think that a person in province i is more likely to migrate to province j if others from other provinces also migrate to j , we can include this dynamic in the model explicitly as we will do below by adding a *popularity* measure of a province. Hence, we can ameliorate possible misfits due to the conditional independence assumption by including relevant covariates in the model.

Nevertheless, we believe that those models developed in the social networks literature reviewed above are rich, very general, flexible; and in principle can be applied to the type of

data we have here. A systematic comparison of all possible alternative modelling approaches, however, is beyond the scope of the current study.

3 Determinants of migration

We now move on to the substantive discussion of the expected drivers of migration and describe the Turkish context to which our data belongs.

Migration is a complex phenomenon with multiple causes, hence there is no single theory for it. A non-exhaustive list of the determinants of voluntary migration can be grouped into economic, demographic, geographical, cultural, and social network factors (Boyle et al., 1998). In classical economic theory, income maximisation relative to the costs of moving is a key driver of migration (Borjas et al., 1992). Economic prospects, such as a high per capita income, employment opportunities, or wages thus should pull migrants. Conversely, poor economic prospects should push migration.

Migration flows are also shaped by population. The larger the population of the origin and the destination, the larger will be the flow between the two (Barthélemy, 2011; Levy, 2010). This prediction is due to the empirical regularity that flows correlate positively with stocks in either direction (Poot et al., 2016). A large population means that there is more capacity to send and receive migrants.

While the increasing population may increase migration flows, the spatial distance between the origin and the destination constrains it. Next to the gravity model, spatial network models, too, show that distance affects ties between individuals, see, e.g. Butts et al. (2012). The effect of spatial distance operates via various channels (Schwartz, 1973). First, it directly increases the cost of moving, a key factor in the economic model of migration too. Second, it hinders maintaining contact with friends and family in the origin, hence imposing also a ‘psychological’ cost on migration. Third, the larger the spatial distance, the lower the information flow between the origin and the destination. A lower information flow means that it is more difficult to hear about available opportunities at the destination. The combined effects of population and spatial distance on migration is sometimes referred to as the ‘gravity law’ whereby the ‘mass’ (i.e. population) of the origin and the destination relative to the spatial distance between the two determines flows (Barthélemy, 2011; Levy, 2010).

The ‘gravity law’ focuses exclusively on spatial distance but it is known that cultural or linguistic distances constrain migration too. The similarity between the origin and the destination concerning language and religion, for example, improves the labour market integration of migrants (Van Tubergen et al., 2004; Windzio, 2018). Furthermore, cultural similarity facilitates migration due to homophily (McPherson et al., 2001), and by reducing discrimination and acculturation costs for migrants (Van Tubergen et al., 2004).

Finally, social networks are highly consequential for migration (Massey and España, 1987). This is true for the social network of the individual migrant (Massey and España, 1987) as well as macro-level network features of the origin and the destination (Windzio, 2018; Levy, 2010). Knowing people who migrated previously reduces the cost of migration for the prospective

migrant. The social network in the destination can introduce the prospective migrant to possible employers, suggest places to live, offer information on vacancies, and provide social support which reduces the psychological costs of migration (Massey and España, 1987). These effects make migration self-perpetuating: the more migration there is from i to j , the more migration is expected to take place from i to j in the future (Massey, 1990).

One would expect the reverse to be true as well: the more migration there is from i to j , the more migration is expected to take place from j to i too. In other words, one expects a *reciprocity* effect. This is firstly due to return migration (Borjas and Bratsberg, 1996; Danchev and Porter, 2018). But once a link is established between i and j through large-scale migration, natives in j will be introduced to the opportunities and the networks in i as well. This may facilitate migration from j to i even among the natives of j .

Betweenness centrality (Freeman, 1977) and in-degree assortativity (Newman, 2002) are other network characteristics that are expected to affect migration. The betweenness centrality of a node in a network indicates how many (weighted) shortest paths pass through the node. A high level of betweenness centrality of an area implies that the area acts as a migration hub. This also means that there is high diversity, for people from different origins come to the area and likewise go to different destinations. This may offer new economic opportunities that attract further migration. Indeed, Damelang and Haas (2012) show using an instrumental variable design that in Germany cultural diversity enhances the labour market success of immigrants.

Finally, if two provinces i and j have attracted migration from similar other provinces, as measured by in-degree assortativity, one expects more migration to take place between j and k too. This is because in that case both j and k will include networks of people from similar origins. This will, in turn, facilitate information flow and reduce the costs of migration between j and k .

The aforementioned factors are expected to affect migration generically, international as well as intra-national. Below we discuss what we know about internal migration in Turkey.

3.1 Internal migration in Turkey

Historically, Turkey has sent a large number of emigrants to Europe. Most research has thus focused on Turkish immigrants' integration into Europe. Since the 1980s, however, emigration from Turkey to Europe has decreased (İçduygu and Sert, 2009). Far larger shares of the population migrate internally. Our data show that annually around 2.5 million people migrate between the 81 provinces of Turkey. Annual emigration abroad, on the other hand, is around 250 thousand.

Work on the determinants of internal migration in Turkey is scarce (Koramaz and Dökmeci, 2017b). Most of the existing research is carried out by urban planners whose main focus is on spatial issues (Filiztekin and Gökhan, 2008). Also, almost all existing studies analyse data up to the year 2000, i.e. the last year a population census was conducted. Studies that make use of more recent migration data are mainly descriptive; for example, Akin and Dökmeci (2015) classify the 12 regions of Turkey based on inter-regional migration patterns.

[Gedik \(1997\)](#) shows that starting from the 1980s the vast majority of migration in Turkey takes place from city to city as opposed to rural to urban. This pattern is also confirmed by [Evcil et al. \(2006\)](#). As expected, economic factors such as per capita Gross Domestic Product (GDP), wages, industrial workforce, and unemployment rates are found to be important determinants of migration ([Filiztekin and Gökhan, 2008](#); [Gezici and Keskin, 2005](#)). [Evcil et al. \(2006\)](#) argue that GDP differentials are one of the most important drivers of internal migration.

In line with the ‘gravity law’, populations in the origin and destination are found to be positively associated with migration flows ([Filiztekin and Gökhan, 2008](#); [Gezici and Keskin, 2005](#)). The findings on the second component of the gravity law, namely spatial distance, are equivocal. [Gedik \(1997\)](#) argues that beyond the immediate neighbouring cities, the effect of spatial distance on migration is minimal. [Koramaz and Dökmeci \(2017a\)](#), however, report that after peaking at a distance of 200-400 kilometres, migration decreases rapidly as spatial distance increases. [Koramaz and Dökmeci \(2017a\)](#) also report that in provinces in the East, most of which have large shares of Kurds, the effect of spatial distance is less pronounced.

Earlier studies also indicate the importance of social networks. [Gedik \(1997\)](#) shows that previous migrants who are friends or relatives from the same area are as effective forces as economic factors in facilitating migration. [Filiztekin and Gökhan \(2008\)](#) use the stock of earlier migration between i and j as an indicator of a network effect and register a strong effect of this earlier stock on future migration. To our knowledge, no study looks at further social network characteristics of Turkey’s provinces, such as betweenness centrality, reciprocity, and assortativity.

Other important social forces may affect internal migration in Turkey. The first is politics. [Aksoy and Billari \(2018\)](#) and [Aksoy and Gambetta \(2021\)](#) show that provinces and districts that are ruled by Erdoğan’s AKP (Justice and Development Party) are more efficient in providing local services and social assistance than those controlled by the opposition. This can potentially lead to ‘welfare migration’ from opposition to AKP municipalities. [Aksoy and Billari \(2018\)](#) do not find evidence for such welfare migration, but migration is not their focus and hence their analysis is rather descriptive. Political polarization is also rife in Turkey. A recent poll shows that a vast majority of participants (78%) do not “approve of their daughter marrying a supporter” of a party other than their own ([Erdoğan and Semerci, 2017](#)). We are not aware of any previous work that systematically focuses on the effect of politics and political distance on migration in Turkey. Yet, we expect Turkey’s political divides to play an important role in migration decisions.

A further potentially important factor is ethnicity. There are sizeable Kurdish populations living in the large cities of Turkey. This is due to both economic as well as forced migration. Violent conflicts in the 1990s resulted in the forced displacement of Kurds ([Ergin, 2014](#)). Kurds tend to have higher levels of unemployment, poverty, and fertility ([Koc et al., 2008](#)) which are factors that traditionally push people to migrate. Due to historical and political reasons, data on ethnicity in Turkey are scarce, so much so that no population census since 1965 includes a question on ethnicity ([Koc et al., 2008](#)). Hence, it is unknown if Kurdish migration is particularly

high, once economic factors and population are accounted for. In this study, we will provide the first comprehensive test.

4 Data and descriptive results

4.1 Data and variables

We compile a new dataset for this study as described below. All variables are at the province level and there are 81 provinces. All variables are obtained from the Turkish Statistical Institute (TurkStat), except the proportion of Kurds in a province, which is estimated from two representative surveys.

4.1.1 Dependent variable: migration counts

The number of individuals who moved from one province to another in a given year is available from TurkStat from 2009. These data come from Turkey’s *Address Based Population Registration System* (ABPRS) which replaced the census in 2007. By law, each Turkish citizen is required to be registered at a single primary address. Any change in one’s primary address is required to be updated in ABPRS within 20 working days, online or in-person. Not complying results in penalties. There are other incentives to keep the primary address up-to-date, for example, school access is determined by residence and any official communication takes place via the registered address. Migration that is not yet registered in the system is not captured by these data. Hence, our dependent variable should be interpreted as ‘official’ internal migration.

We also calculate the number of people who did not migrate. We do so by subtracting net migration (out- minus in-migration) from the population of a province in a year. We also apply a correction by adjusting for the number of births, deaths, or those who register for the first time in the province in a given year (see section 2 above and the part leading up to equation (1) there).

This gives us an 81×81 matrix for each year from 2009 to 2018, with off-diagonals indicating the number of people migrating between provinces, and the diagonals indicating those who stay.

4.1.2 Explanatory variables

We predict migration with the following explanatory variables. In our model, all dynamic (i.e. time-varying) explanatory variables are lagged by one year.

As indicators of economic prospects, we obtain annual provincial *GDP* per capita and the *unemployment rate*. Unemployment rates are only available at the Nuts-2 level which comprises 26 large regions.

As the elements of the ‘gravity law’, we use annual *population* in and the *spatial distance* between provinces. Spatial distance is measured as the driving distance in kilometres between province centres.

To measure the ‘*political distance*’ between provinces, we calculate the absolute difference in vote shares of the political parties in the 2004, 2009, and 2014 mayoral elections. Political distance is a dynamic variable.

We calculate the following network characteristics using the (one-year lagged) migration matrix. The self-perpetuating nature of migration is captured by the number of people migrated from i to j in the *previous year* and by total in-migration in j , i.e. *popularity* (or equivalently weighted in-degree). *Reciprocity* for migration from i to j is calculated as the number of migrants from j to i in the previous year. *Betweenness centrality* of a province is calculated as the normalised number of geodesics (shortest paths) going through a province in the migration network. In-degree assortativity is operationalised as the correlation between the migration in-flows of i and j . The higher this correlation between two provinces, the more similar the provinces are in terms of the origin and flows of incoming migrants, so this variable can be interpreted as in-flow *similarity* too.

We also obtain the proportion of municipalities in a province that is controlled by the *AKP* after the 2004, 2009, and 2014 elections as a dynamic variable. This variable has a $[0\ 1]$ range corresponding to the provinces in which *AKP* controls none and all of the municipalities in a province in a given year.

Finally, we estimate the percentage of *Kurds* in a province as a dynamic variable. There is no official data on ethnicity, so we use Turkey’s Demographic and Health Survey 2008 and 2013 waves (Koc et al., 2008). Both surveys are representative and sample women of reproductive age (15 to 49) (Hacettepe University Institute of Population Studies, 2013). The survey includes a question about the respondent’s mother tongue using which we identify if someone is Kurdish. We use the 2008 and 2013 waves to estimate the proportion of Kurds in a province in and before those years.

To facilitate estimation and interpretation, we normalise all explanatory variables, except time, to the $[-1\ 1]$ range, by centring around the mean and dividing by the maximum of the absolute of the centred values, hence one of the $-1, 1$ boundaries is attained. Finally, we worked with the factors regarding *popularity*, *population*, *previous year*, and *reciprocity* in the log domain.

4.2 Descriptive results for migration

Figure 1 shows out- and in-migration in the 81 provinces of Turkey. The figure shows the absolute level of migration, migration as the percentage of the number of inhabitants at the start of the year, and the 2018-2009 difference in the latter. The figure shows that large provinces, such as İstanbul, Ankara, İzmir, Adana, and Antalya have high levels of out- and in-migration (see Figure 2 for province names). This is in line with gravity law. There is almost a perfect correlation between out- and in-migration levels across provinces.

Migration as a percentage of the number of inhabitants, however, shows a different pattern. Proportional to their populations, large provinces (e.g. İstanbul, Ankara, İzmir, Adana, and Antalya) have relatively low migration. Smaller provinces in the centre-east, such as Gümüşhane

and Tunceli have the highest migration per capita. The difference between absolute and relative migration will become important when we present our model estimates below.

The changes displayed in Figure 1 (bottom panels) show that, on average, the change in out-migration per capita is rather stable. However, it is slightly negative in some places and slightly positive in others, the largest change is in Gümüşhane.

Figure 1 shows only the origins and destinations of migration. Figure 2 shows absolute migration flows. In Figure 2 we omit small flows for clarity. These small flows will be part of the analyses in Section 5. Figure 2 shows that İzmir, Antalya, Tekirdağ, Ordu, Tokat, and Ankara are popular destinations, especially for those from İstanbul. There are also local clusters, such as Şanlıurfa, Konya, Gaziantep, Adana and Mersin that attract and send migrants.

Figure 1: Absolute, per 100, and change in per 100 between 2018 and 2009 in out- and in-migration per province.

Figure 2: Migration flows between provinces.

Finally, Figure 3 shows the bi-variate correlations for the one-way (i.e. variables defined for a province–‘node’ characteristics) and two-way factors (i.e. variables defined for a pair of provinces–‘edge’ characteristics). As expected, many predictors are correlated. Below we will analyse how these factors are associated with migration flows, our dependent variable, after describing our model of migration in detail.

Figure 3: Sample correlation matrix for the one-way and two-way factors

5 Results

In this section, we provide the results of our implementation of our methodology using the migration data described in Section 4. The experiments were performed in MATLAB, version R2021b. All data and the code that produce the results below are available (anonymised for peer-review) at <https://github.com/SocNetMigration/MigNet-MATLAB-code.git>.

Table 1: Means, standard deviations, and 90% credible intervals for the marginal posterior distributions of the parameters of the Dirichlet-multinomial model with the hierarchical specification.

Parameter	mean	std	90% Cred. Int.	Parameter	mean	std	90% Cred. Int.
GDP $\rightarrow$	0.0088	0.0155	(-0.0175 0.0335)	GDP $\leftarrow$	0.2698	0.0060	(0.2601 0.2796)
Unemp. $\rightarrow$	0.0406	0.0079	(0.0279 0.0533)	Unemp. $\leftarrow$	-0.0286	0.0055	(-0.0372 -0.0192)
AKP $\rightarrow$	-0.0742	0.0044	(-0.0816 -0.0671)	AKP $\leftarrow$	-0.0124	0.0028	(-0.0167 -0.0078)
Popularity $\rightarrow$	0.5691	0.0237	(0.5310 0.6078)	Popularity $\leftarrow$	-0.1511	0.0164	(-0.2064 -0.1538)
Population $\rightarrow$	0.2935	0.1187	(0.0899 0.4920)	Population $\leftarrow$	0.1419	0.0141	(0.1177 0.1642)
Between. $\rightarrow$	0.3358	0.0334	(0.2876 0.3892)	Between. $\leftarrow$	0.1408	0.0199	(0.1083 0.1727)
Kurd $\rightarrow$	-0.0642	0.0090	(-0.0785 -0.0487)	Kurd $\leftarrow$	-0.0305	0.0039	(-0.0370 -0.0240)
Polit. dist. $\leftrightarrow$	-0.0376	0.0040	(-0.0441 -0.0310)	base mean	-8.4527	0.1286	(-8.6645 -8.2419)
Spat. dist. $\leftrightarrow$	-0.0213	0.0037	(-0.0275 -0.0152)	base var.	1.3366	0.2274	(1.0079 1.7467)
Prev. year $\leftrightarrow$	3.2927	0.0153	(3.2675 3.3177)	Scale	10.5472	0.0064	(10.5368 10.5576)
Reciprocity $\leftrightarrow$	1.9850	0.0140	(1.9616 2.0079)				
In-flow sim. $\leftrightarrow$	0.0982	0.0040	(0.0916 0.1048)				

5.1 Model estimates

We implemented the sampling method in Algorithm 1 to estimate θ . We use non-informative priors for θ described in Appendix A. Algorithm 1 is run for 5×10^5 iterations, and the posterior distributions are estimated based on the draws obtained during the last 80% of the iterations (following a burn-in). Convergence is confirmed by visual inspection of the history of the draws from the chain.

Figure 4: Box plots of marginal posterior distributions of factor coefficients in the hierarchical (random intercepts across provinces) Dirichlet-multinomial model described. See Table 1 for the posterior distributions of the intercepts.

Figure 4 shows the box plots for the estimated marginal posterior distributions of the coefficients for our predictors of migration. Table 1 displays the means, standard deviations, and 90% credible intervals of those parameters, and additionally of the random intercept and the ‘scale’ parameter of the Dirichlet-multinomial model (see (2) and (3)). Furthermore, the correlation structure in the posterior distribution for $\theta_1, \theta_2, \theta_3$ is shown in Figure 5. Appendix B.1 includes the histograms of the posterior distributions of the parameters.

The correlation structure in the posterior in Figure 5 is in line with the correlation matrix of the predictors given in Figure 3. A comparison of these two figures shows the typical trend that a positive correlation between two predictors yields a negative correlation between their coefficients in the posterior, and vice versa, as expected. This justifies the general cautionary

Figure 5: Posterior correlation matrix

rule that applies to almost all multivariate models that the effects of correlated predictors should not be considered in isolation from each other.

The results are also mostly in line with theory. Unemployment (→) in the sender province is positively associated with out-migration and unemployment (←) in the target has a negative association with in-migration. While GDP (→) in the sending province does not seem to have a strong association with out-migration, GDP (←) in the target is strongly and positively associated with in-migration.

Regarding the elements of the ‘gravity law’, a large population (→) is associated with a higher probability of out-migration—the posterior mean of its coefficient is 0.29. Population (←) in the target also has a very strong positive association with in-migration. We also find a negative association between spatial distance (↔) and migration. These results are in line with the ‘gravity law’.

We also find a negative association between provincial political distance (↔) and migration. Interestingly, the size of the coefficient for political distance is slightly higher than that for spatial distance.

As expected, network characteristics are strongly associated with migration. Migration from i to j in the previous year (↔) is a very strong predictor of current migration. Its coefficient is the largest of all. Interestingly, the popularity (←) of a province (total in-migration) in a given year is associated negatively with in-migration the next year, net of all other factors controlled in the model.

We also find strong reciprocity (↔): the larger the migration from j to i in a given year, the larger the migration from i to j the next year. Betweenness centrality of a province in a given year also makes a province attractive the next year (←). Likewise, betweenness centrality (→)

of the origin is associated strongly and positively with out-migration. Hence, central provinces seem to act as hubs, attracting and initiating further migration. In-flow similarity ($\leftrightarrow$), which captures in-degree assortativity, is associated positively with migration too.

Interestingly, we find that the strength of the AKP in a province is negatively associated with both out-migration ($\rightarrow$) and in-migration ($\leftarrow$), although its coefficient is small in both cases. This shows that migration both out of and into AKP-dominated regions is low. Together with the strong negative coefficient for political distance, this finding further indicates the negative association of political divides with migration.

Finally, the proportion of Kurds in a province is associated negatively with both out- ($\rightarrow$) and in-migration ($\leftarrow$). Although its coefficients are low in the absolute sense, negative values refute the common belief that migration is a Kurdish phenomenon.

The coefficients for $\leftarrow$ and $\leftrightarrow$ factors can be interpreted in terms of relative probabilities of attracting migration from a given province. For example, suppose that the maximum observed GDP value is normalised to 1 (recall that all factors are centred around the mean and normalised to the $[-1, 1]$ range). Then the mean of the posterior of the coefficient for “GDP $\leftarrow$ ” suggests that, from a given province, the probability of migration to a province with the highest GDP per capita is 31% higher ($\exp(0.27) = 1.31$) than the probability of migration to an average province *ceteris paribus*. Likewise, the probability of migration to the spatially farthest province is 2% lower ($\exp(-0.02) = 0.98$) than that to an average province (provided that the maximum spatial distance has been normalised to 1). The coefficients for $\rightarrow$ factors can be interpreted in terms of the relative probability of migration to any province versus not migration. For example, one unit increase in unemployment (e.g. the change from average to maximum observed value) in province i is associated with a 4% ($\exp(0.04) = 1.04$) increase in relative migration probability from i , *ceteris paribus*.

Table 1 also shows the mean and the variance of the intercept which is random across provinces. They show that there is considerable variability in the levels of out-migration probabilities across provinces, the largest in Bayburt and the smallest in Istanbul. Figure 6 shows the posterior distribution of the intercepts per province, estimated with our hierarchical specification. These provincial variations somewhat match the descriptive statistics given in Figure 1, although they are not equal because these intercepts are obtained after controlling for the predictors of migration.

Figure 6: Box plots of the marginal posterior distributions of random intercepts for provinces in the hierarchical specification of the Dirichlet-multinomial model.

Additional estimation results: Some scholars argue that controlling for the lagged dependent variable accounts for path dependency or autocorrelation of residuals in panel regressions, though it may also bias downwards the coefficients for other explanatory variables (Keele and Kelly, 2006). This potential issue has been shown to apply to temporal ERGMs, too (Block et al., 2018). To address this potential issue, we fitted our models after excluding variables that are calculated from past migrations. These variables are popularity, betweenness, previous year, reciprocity, and in-flow similarity. The results after excluding these variables are given in Appendix B.2.

These additional results show that including the measures based on migration in the previous year in the model generally does not suppress the coefficients of the other variables. In fact, for some variables, the estimated coefficients are somewhat smaller after excluding the lagged measures (e.g. AKP $\leftarrow$). Coefficients do increase, in absolute value, for some variables (e.g. GDP $\rightarrow$, Kurd $\leftarrow$) after excluding lagged variables. But because of a lack of general suppression of coefficients due to including in the model measures based on lagged values of migration, we conclude that the above issue is not particularly problematic in our case. Note that one expects differences in the coefficients of variables that are estimated before and after the inclusion of lagged migration variables due to the conditional nature of the Dirichlet-multinomial regression, which we observe too. Additionally, as shown in Table 3 in Appendix B.3, the exclusion of lagged measures reduces the predictive performance substantially, further suggesting the need for including them in the model.

5.2 Comparison with the gravity model in terms of predictive power

The gravity model assumes a linear regression for the non-diagonal log-migration counts. Although the essential factors of the gravity model are population and distance, one could easily include other one-way and two-way factors in the model. Therefore, for fairness in comparison, we constructed a gravity model that includes all the factors considered in our model. This corresponds to the following relation for $i, j \in \{1, \dots, n\}$; $i \neq j$, and $t \in \{1, \dots, T\}$,

$$\log H_t(i, j) = \theta_0(i) + \theta_1 \cdot u_t(i) + \theta_2 \cdot v_t(j) + \theta_3 \cdot z_t(i, j) + e_t(i, j),$$

where the sum on the right-hand side serves as the base parameter as before, $e_t(i, j)$ are uncorrelated deviation terms, assumed to have zero mean and common variance, and $u_t(i)$, $v_t(j)$, and $z_t(i, j)$ are as defined before. (Wherever $H_t(i, j) = 0$, we substituted it with a 1 to avoid $\log 0$.) We fitted this model by calculating the best linear unbiased estimator for the parameter vector $(\theta_0(1), \dots, \theta_0(n), \theta_1, \theta_2, \theta_3)$ (which corresponds to the least squares solution), which is also the maximum likelihood estimator if $e_t(i, j)$'s are normal.

We compared the gravity model and the Dirichlet-Multinomial model in terms of their out-of-sample prediction performances with the following process. Recall that the total data consists of 10 consecutive years between 2009 and 2018. For every single year, we excluded its migration data and used the rest of the years for training the model. The training results are then used to predict the migrations in the excluded year. For the Dirichlet-multinomial model,

Table 2: Prediction errors for the Dirichlet-Multinomial model and the gravity model for different specifications of the outcome (log counts or counts, diagonals excluded or included), different types of error (squared or absolute error), and different summary statistics for the error (mean or median).

Predicted value	Error type	Statistic	Dirichlet-Multinomial	Gravity
log counts diagonals excluded	squared	mean	0.1273	0.1895
		median	0.0358	0.0692
	absolute	mean	0.2563	0.3305
		median	0.1891	0.2630
log counts all	squared	mean	0.1258	0.1872
		median	0.0346	0.0670
	absolute	mean	0.2532	0.3265
		median	0.1861	0.2588
counts diagonals excluded	squared	mean ($\times 10^6$)	0.0928	0.1868
		median	314.1539	499.8232
	absolute	mean	69.3741	109.7198
		median	17.7244	22.3567
counts all	squared	mean ($\times 10^6$)	1.0842	1.8186
		median	326.9823	521.3947
	absolute	mean	108.6471	178.7883
		median	18.0827	22.8341

we ran Algorithm 1 to obtain samples from the posterior distribution of θ given the training data, and we predicted the migration counts in the test year by the Monte Carlo estimation of their expectations with respect to their posterior predictive probability distribution. For the gravity model, the maximum likelihood estimates for the parameter vector, obtained from the training data, were substituted for calculating the expectation of $\log H_t(i, j)$ for the test year t . Moreover, for the gravity model, for a test year t , the non-migration counts, i.e., $H_t(i, i)$, $i = 1, \dots, n$ are predicted by $P_t(i) - \sum_{j=1, j \neq i}^n \hat{H}_t(i, j)$, where $\hat{H}_t(i, j)$ is the predicted value for $H_t(i, j)$. The prediction results for the ten test years are then aggregated to calculate overall error statistics.

Table 2 shows several overall error statistics for the Dirichlet-Multinomial and the gravity models. We calculate separate error statistics for different specifications of the outcome variable: plain counts or log counts and excluding diagonals (this is because in a typical gravity model self-edges are excluded) or including the diagonals, too. In addition, we calculate two types of error, namely squared error $[(\text{predicted} - \text{observed})^2]$ and absolute error $[\text{abs}(\text{predicted} - \text{observed})]$. Finally, we look at both the mean and median errors over the 10 years of test data.

The results show that the Dirichlet-Multinomial model has a superior performance over the gravity model in predicting both the log-migration counts and the plain migration counts. Prediction errors for the Dirichlet-Multinomial are consistently lower than that for the gravity model. Moreover, the superiority is present in terms of both the mean and the median of the squared error, as well as both the mean and the median of the absolute error. Finally,

the Dirichlet-Multinomial model prevails both when we include and exclude the diagonal (non-migration) values in the predicted outcome. Also note in Table 2 that the average absolute error of our hierarchical model for all counts including non-migration is only 108.6 which corresponds to less than 0.05% of the standard deviation of migration counts. This shows that our model predicts migration flows reasonably well.

As a visual illustration of prediction errors, Figure 7 shows the true vs predicted plain migration counts for both our hierarchical Dirichlet-Multinomial model and the gravity model (the non-migration counts, i.e. diagonals, are excluded for better visibility). The figure confirms the better performance of the Dirichlet-Multinomial model compared with the gravity model since the $(true, predicted)$ points for the gravity model are visibly more scattered.

Figure 7: True versus predicted plain migration counts for the Dirichlet-multinomial model with the hierarchical specification and the gravity model.

Comparison with simpler variants: We compared the predictive performance of our method with that of two simpler variants of our Dirichlet-Multinomial model. Those variants are a non-hierarchical specification with a single common base parameter instead of random province bases, and the variant that excludes variables based on the previous year’s migration flows. We present the results in Table 3 in Appendix B.3. The results suggest that random province-specific base parameters improve the performance, and hence those random effects do not lead to over-fitting. Additionally, the exclusion of lagged measures hampers predictive performance substantially, pointing to the need of including them in the model as we do.

6 Discussion and conclusions

In this study, we propose a Dirichlet-multinomial model and a Bayesian inference method to analyse the interdependent flows. We apply the developed methodology to analyse the dynamic migration flows of the 81 provinces of Turkey from 2009 to 2018. Our study offers methodological and substantive contributions to the literature.

On the methodological front, our Dirichlet-multinomial model alleviates several shortcomings of the popular models applied to migration flows. The advantages of our model are as

follows. *First*, it naturally captures systemic effects. That is, our model incorporates the effects of the characteristics of destinations where migration did not take place on migration that happened to a particular place. *Second*, in our model, non-migration is accounted for. The alternative of ignoring non-migration and conditioning the results on migration having taken place, which is a common practice in the literature, results in the so-called selection on the dependent variable. *Third*, our model adheres to the natural boundary of migration and the mechanistic relationship between migration and non-migration. That is, out-migration and in-migration change the populations of the origin and the destination, and the total number of out-migration cannot exceed the population of the origin in a given time period. Our model naturally incorporates these phenomena. *Fourth*, our model lends itself to an estimation method that is computationally much simpler than many of its alternatives. The computational simplicity, in fact, allows us to expand our model with a hierarchical specification that captures variations in the baseline of and potentially also longitudinal changes in migration probabilities.

To demonstrate those advantages, we carried out an out-of-sample prediction comparison of our model vis-a-vis the *gravity model*, one of the most common models used in the migration literature. The gravity model ignores systemic effects, and it typically ignores non-migration as well as the mechanistic relationship between populations, non-migration, and migration flows. We showed that our model consistently outperforms the gravity model in predicting migration flows.

Note that while we framed our model within a migration setting, and indeed we developed it to understand migration flows and their determinants, the model is more general. It can be applied to any other setting that involves discrete dynamic flows between a finite number of origins and destinations.

We should note that there are several models developed in the social networks literature, that are very general and flexible and, in principle, can also be applied to dynamic flows with some adjustments. These include Exponential Random Graph Models and their various extensions for count data or longitudinal data; relational event models, dynamic network actor models, stochastic actor-oriented models, and latent space and latent factor models. We discussed those models in detail and compared them with ours. While they are indeed very powerful and flexible, we argued that they may be too general for our problem at hand. Our method provides a straightforward approach to model dynamic flows while offering computational simplicity and at the same time taking into account key features of and dependencies in the data.

The computational simplicity of our model rests on the assumption that migrations from different origins at a given time point are independent, *conditional* on the covariates which can include those that are based on previous migration flows. We believe that this assumption is not unrealistic in our longitudinal context. When an individual is deciding to migrate or not in a given time-point, they may not consider or indeed be aware of the migration decisions of others outside their provinces at the same time point. Moreover, dependencies among migration probabilities that may violate this assumption can be explained away, to a certain degree, by including in the model the predictors that are the likely causes of that dependence. For example,

if one expects a ‘herding’ dynamic for migration (i.e. people in different provinces imitating each other in migrating to a specific destination) this factor can be added to the model, by adding a destination *popularity* factor based on previous migration flows into the destination, as we do in our analysis. In other words, because we have longitudinal data, we can condition current flows on earlier flows, which makes the conditional independence assumption more plausible.

We also note that our model allows further extensions. One particular direction is the following. In our hierarchical specification, we include random intercepts for out-migration (i.e. for sending provinces). One can include such random effects for the receiving provinces, too. This would result in a *cross-classified* model (Snijders and Bosker, 2011, Chapter 13). In fact, we have fitted this cross-classified version. The parameter estimates as well as the predictive performance of our model hardly changed. At the same time, however, the receiver random effects increased the computational complexity of the model substantially. This is because, in a cross-classified model, each of the n random intercepts of the receiving provinces would affect the Dirichlet-multinomial probabilities for all provinces. Thus, the acceptance probability in the estimation which is needed to accept or reject a proposed update for each of those parameters would require the computation of the whole product in (5). Note that this is in stark contrast with the update of the intercept of the sending provinces, for which we calculate a single Dirichlet-multinomial probability for each t in the numerator and the denominator of the acceptance ratio, see Algorithm 1. Because receiver random effects were inconsequential to our results and the predictive performance of our model, we decided to proceed without the receiver random effects. Nevertheless, they could be incorporated should the researcher sees a need to do so.

Overall, we contribute to the literature methodologically by providing a viable alternative for analysing migration and other types of flows.

Our study also offers substantive contributions to the migration literature. Far greater shares of populations are affected by internal migration than by international migration. Most past research, however, focuses on the latter. Using a new dataset and a model, we analyse inter-provincial migration in Turkey. Our results largely confirm the existing theories of migration: economic prospects, population, spatial distance, and network characteristics shape the flow of internal migration in Turkey. We also offer several novel findings.

Firstly, we register that political distance between provinces (measured using electoral results) is negatively associated with migration flows. This negative association is even stronger than that between spatial distance and migration. Moreover, we find that the strength of the AKP (Justice and Development Party) in a province is negatively associated with out- and in-migration. These findings together imply that political divisions in the country contribute to the sorting of province populations as well. This association between politics and migration, in turn, may accelerate further the political polarisation between the provinces of Turkey which is already rife.

We also provide, to our knowledge, the first systematic test of whether the proportion of Kurds in a province is associated with migration. Kurds are affected by higher levels of

unemployment and poverty and have higher fertility. These factors are traditionally associated with migration. Indeed there has been large-scale Kurdish migration to western parts of Turkey. Our analysis, however, shows that conditional on the factors we include in our model, the share of Kurds in a province has a small negative association with migration. Hence, internal migration in Turkey is not a ‘Kurdish phenomenon’.

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A Prior and proposal distributions

In the hierarchical specification, θ_1 , θ_2 , θ_3 , and θ_4 are assigned flat priors ($\eta_i(\theta_i) \propto 1$), while for the hyperparameters of the mean and covariance of the prior distribution of ϑ_i 's we set $\mu_h = 0$ and $\sigma_h^2 = 100$, $\nu_h = 1$ and $\Psi_h = 1$. We use a Metropolis-Hastings update for $\theta_1, \theta_2, \theta_3$. The proposal distributions are set as $q_j(\theta'_j|\theta_j) = \mathcal{N}(\theta'_j; \theta_j, 0.025^2 \times C_j^{-1})$, where

- C_1 is the sample covariance matrix calculated from $\{u_t(i) : i = 1, \dots, n; t = 1, \dots, T\}$,
- C_2 is the sample covariance matrix calculated from $\{v_t(i) : i = 1, \dots, n; t = 1, \dots, T\}$,
- C_3 is the sample covariance matrix calculated from $\{z_t(i, j) : i, j = 1, \dots, n; t = 1, \dots, T\}$,

We use a random walk Metropolis-Hastings to update θ_4 and ϑ_i s also, with $q_0(\theta'_4|\theta_4) = \mathcal{N}(\theta'_4; \theta_4, 10^{-4})$ and $q_0(\vartheta'_i|\vartheta_i) = \mathcal{N}(\vartheta'_i; \vartheta_i, 10^{-4})$.

B Additional numerical results

B.1 Histogram of the parameters of the hierarchical Dirichlet-Multinomial model

Figure 8 shows the histograms for θ_1 , θ_2 , θ_3 , and θ_4 (the ‘scale’ parameter) obtained from 5×10^5 samples for the hierarchical Dirichlet-multinomial model. Figure 9 shows the same for μ_0 and Σ_0 , the mean and variance parameters for the province-specific intercepts.

Figure 8: Histograms for θ_1 , θ_2 , and θ_3 for the hierarchical Dirichlet-multinomial model.

B.2 Excluding explanatory variables based on past migration

Figure 10 shows the box plots of marginal posterior distributions of factor coefficients in the hierarchical Dirichlet-multinomial model, after excluding variables that are based on lagged

Figure 9: Left: Histograms for (μ_0, Σ_0) , the mean and variance parameters for the province-specific intercepts, and θ_{sc} , the ‘scale’ parameter, for the hierarchical Dirichlet-multinomial model.

values of migration. These coefficients do not show a general suppression effect for those reported in the paper which are adjusted for lagged measures. Figure 11 shows the posterior correlations of these parameters. Figure 12 shows the posterior distributions of the intercepts per province. Figure 13 (left) shows the histograms for θ_1 , θ_2 , and θ_3 . Figure 14 shows the histograms for (μ_0, Σ_0) (left) and θ_4 , the ‘scale’ parameter (right).

Figure 10: Box plots of marginal posterior distributions in the hierarchical Dirichlet-multinomial model described, after excluding variables that are based on lagged values of migration.

B.3 Predictive performance of the variants of the Dirichlet-multinomial model

Table 3 shows the prediction results for the hierarchical Dirichlet-multinomial model and its simpler variants. Those simpler variants are a non-hierarchical specification with a single common base parameter instead of random province bases, and a specification that excludes variables based on the previous year’s migration flows. Comparing the errors in the first and the second columns with the last, we can see that not regressing on the past data considerably reduces the predictive performance. Also, comparing the errors in the first and the third columns, we can see that the random province-specific base parameters improve the performance. The latter observation suggests that the inclusion of province-specific base parameters does not lead to overfitting, hence capturing a genuine aspect of the true phenomenon.

Figure 11: The posterior correlation matrix of factor coefficients in the hierarchical Dirichlet-multinomial model, after excluding variables that are based on lagged values of migration.

Figure 12: Box plots of the marginal posterior distributions of random intercepts for provinces in the hierarchical Dirichlet-multinomial model, after excluding variables that are based on lagged values of migration.

Figure 13: Histograms for θ_1 , θ_2 , and θ_3 obtained from 5×10^5 samples for the hierarchical Dirichlet-multinomial model, after excluding variables that are based on lagged values of migration.

Figure 14: Histograms for (μ_0, Σ_0) (left) and θ_4 (right) for the hierarchical Dirichlet-multinomial model, after excluding variables.

Table 3: Predictive performance of the hierarchical Dirichlet-multinomial model and its simpler variants

Predicted value	Error type	Statistic	DM-hier	DM common θ_0	DM-hier wo past
log counts non-diag	squared	mean	0.1301	0.1327	0.8566
		median	0.0371	0.0372	0.5185
	absolute	mean	0.2596	0.2619	0.7757
		median	0.1925	0.1928	0.7200
log counts all	squared	mean	0.1285	0.1311	0.8460
		median	0.0359	0.0360	0.5063
	absolute	mean	0.2564	0.2587	0.7662
		median	0.1895	0.1898	0.7116
counts non-diag	squared	mean ($\times 10^6$)	0.0943	0.1096	0.7395
		median	319.9717	334.0139	7018.9
	absolute	mean	71.0278	71.4449	257.5537
		median	17.8878	18.2760	83.7789
counts all	squared	mean ($\times 10^6$)	1.0788	1.8661	3.0924
		median	333.2062	347.8265	7286.0
	absolute	mean	113.4352	115.8654	327.6714
		median	18.2539	18.6501	85.3583