The University of Queensland
Australia

An evaluation of internal migration forecasting models

Charles Siriban, Aude Bernard and Tom Wilson

NZ Population Conference 2023, 29-30 August, 2023

Introduction

- **Migration is an important component of demographic change at both the national and sub-national levels**
  - But main source of error in population projections

- **Compared to forecasting other drivers of demographic change, slower methodological advance for migration**
  - Common approaches: qualitative scenarios or most recent historical data

- **No systematic attempt to evaluate the relative strengths and weaknesses of existing migration forecasting approaches**
  - Out-of-sample forecast performance evaluation is rare
  - Limited comparison of a wide range of models

Our work

Identifies broad families of migration forecasting models

- **Demographic adjustment methods** (Feeney 1973; Plane 1982; Plane 1993; Vandresse 2016; Dion 2017)
  - Use adjustment factors to allow OD flows to vary with projected regional population at destination area

- **Time-series extrapolation methods (with and without explanatory variables)** (Frees 1992; Disney et al 2015; Schrier and McRae 2000; Raymer, Abel and Rogers 2012; Bernard et al 2020; Fantazzini 2021)
  - Assume a continuation of past migration trends while accounting or not for the broader social, economic and demographic contexts

- **Gravity-types of models** (Stillwell 1986; Raymer, Bonaguidi, and Valentini 2006; Raymer, Bai, and Smith 2020; Kim and Cohen 2010; Cameron 2018)
  - Spatial interaction and econometric gravity models
  - Quantify push and pull factors underpinning bilateral flows

Our work

Identifies broad families of migration forecasting models

- **Bayesian models** (Bijak and Wiśniowski 2010; Disney et al. 2015; Azose and Raftery 2015; Wiśniowski, Bijak, and Shang 2014; Zhang and Bryant 2020)
  - Allows researchers to forecast using different sources of information

- **Machine learning** (Grossman et al 2022; Nair et al 2020; Carammia, Iacus and Wilkin 2022)
  - Data-driven approaches that focus on developing algorithms that yield good out-of-sample predictions

Our work

Evaluates their out-of-sample forecast performance using Australian data

- **Inter-GCCSA migration flows and rates:** Regional Internal Migration Estimates, ABS
  - FY 2006/07 to 2021/22
  - Includes all 15 GCCSA's $\Rightarrow$ 210 origin-destination GCCSA pairs
- **National**
  - GDP
  - Unemployment
- **State**
  - Gross state product
  - Mining capital expenditure
  - Public sector employment
- **GCCSA**
  - Unemployment rate
  - Total number of dwelling units approved
  - Residential housing prices

An evaluation of internal migration forecasting models

Methods: models tested

1. **Random walk with drift (ARIMA (0,1,0)):** $M_{ij,t} = \alpha + M_{ij,t-1} + u_t$
2. **Unconstrained autoregressive model of order 1 (ARIMA(1,0,0)):** $M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t$
3. **ARMA(1,1) model (ARIMA(1,0,1))**: $M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t + \theta u_{t-1}$
4. **Autoregressive model of order 1 applied on first-difference (ARIMA(1,1,0))**

   $\Delta M_{ij,t} = \rho_0 + \rho_1 \Delta M_{ij,t-1} + u_t$, where $\Delta M_{ij,t} = M_{ij,t} - M_{ij,t-1}$
5. **Autoregressive model of order 1 applied on de-trended series (ARIMA(1,0,0) + trend)**

   $\ddot{M}_{ij,t} = \rho_0 + \rho_1 \ddot{M}_{ij,t-1} + u_t$, where $\ddot{M}_{ij,t} = M_{ij,t} - (a_0 + a_1 t)$
6. **GCCSA-pair specific ARIMA:** use Akaike or Bayesian information criterion (AIC/BIC) to determine the number of lags

An evaluation of internal migration forecasting models

Methods: forecasting horizon

Cases	Training period	Out of sample period
Training and out of sample periods are pre-COVID	2006/07 to 2014/15 (9 years)	2015/16 to 2018/19 (4 years)
Training period is pre-COVID; Out-of-sample period includes COVID	2006/07 to 2018/19 (13 years)	2019/20 to 2021/22 (3 years)

Evaluation of internal migration forecasting models

Methods: forecast performance measures

- Focus on out-of-sample forecast performance
- Forecast performance measure
  - Absolute percentage error-based measures: $\left|\frac{F_t - A_t}{A_t}\right|$ where F is forecast and A is actual
    - Median Absolute Percentage Error (MedAPE)
- Evaluate forecast performance for specific origin-destination GCCSAs

Results

- Similar performance of extrapolation methods without explanatory variables
  - Similar results for flows and rates
- No evidence that extrapolation methods perform worse in forecasting COVID-era OD flows
- Similar results when using an alternative measure of out-of-sample forecast performance Weighted Mean Absolute Percentage Error
- No evidence that more parsimonious ARIMA models (Frees 1992) unambiguously perform worse
- Extrapolation methods with controls do not perform better than those without

Next steps

- Investigate to what extent the inclusion of explanatory variables improve forecast performance
  - Big issue: need to forecast the explanatory variables
  - Explore different methods to forecast the explanatory variables
  - Test other families of models

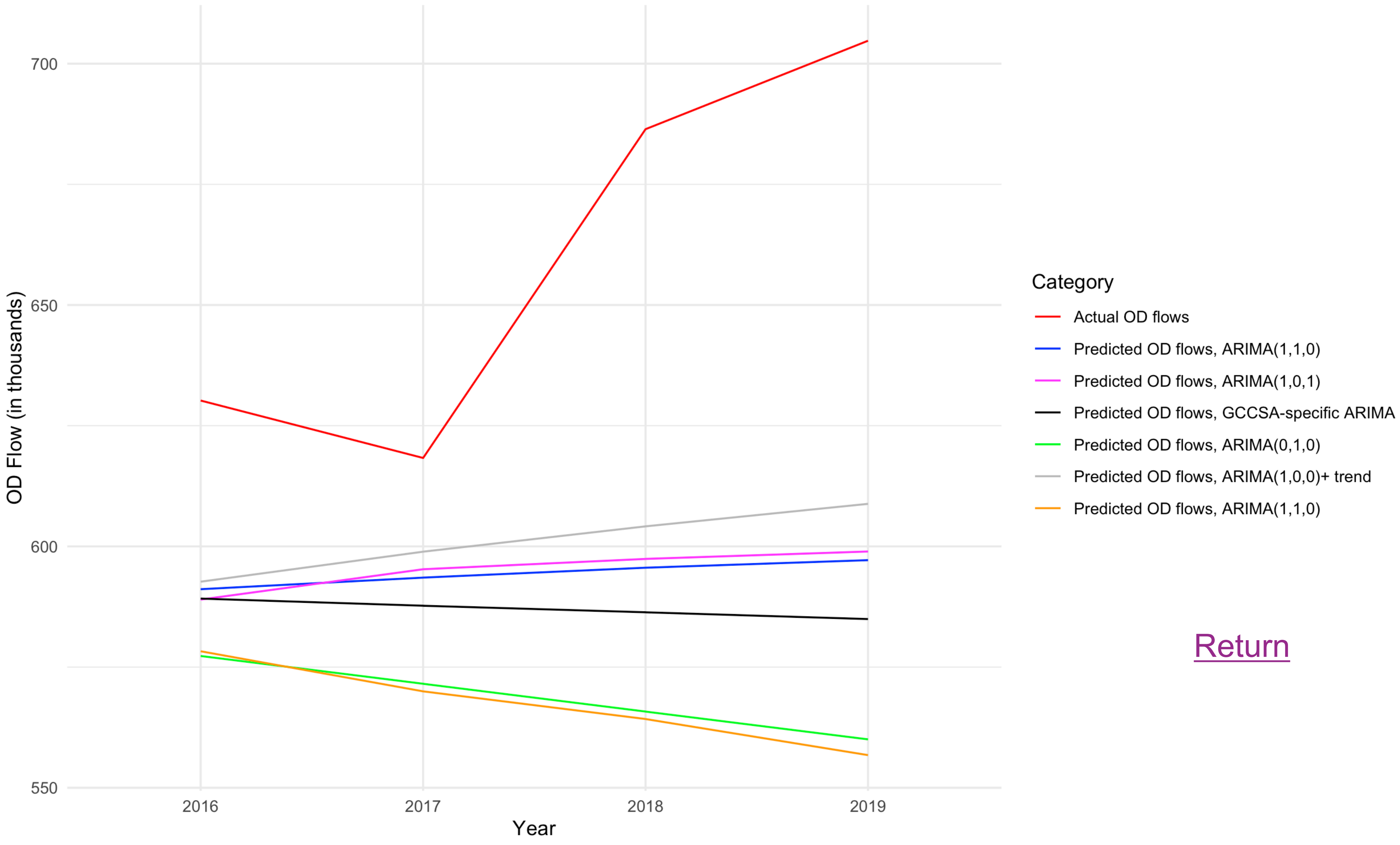
ARIMA models: forecast performance (flows)

Median APE: Training and forecast periods are both pre-COVID

Methods	Year 1	Year 2	Year 3	Year 4
ARIMA (0,1,0)	9.86%	20.95%	19.47%	22.63%
ARIMA (1,0,0)	9.11%	15.44%	16.68%	17.88%
ARIMA (1,1,0)	10.02%	16.70%	20.07%	23.04%
ARIMA (1,0,1)	9.97%	16.73%	17.29%	18.61%
ARIMA (1,0,0)+ trend	8.66%	16.53%	18.77%	16.71%
GCCSA-pair specific ARIMA	9.76%	16.12%	17.03%	19.00%

Return

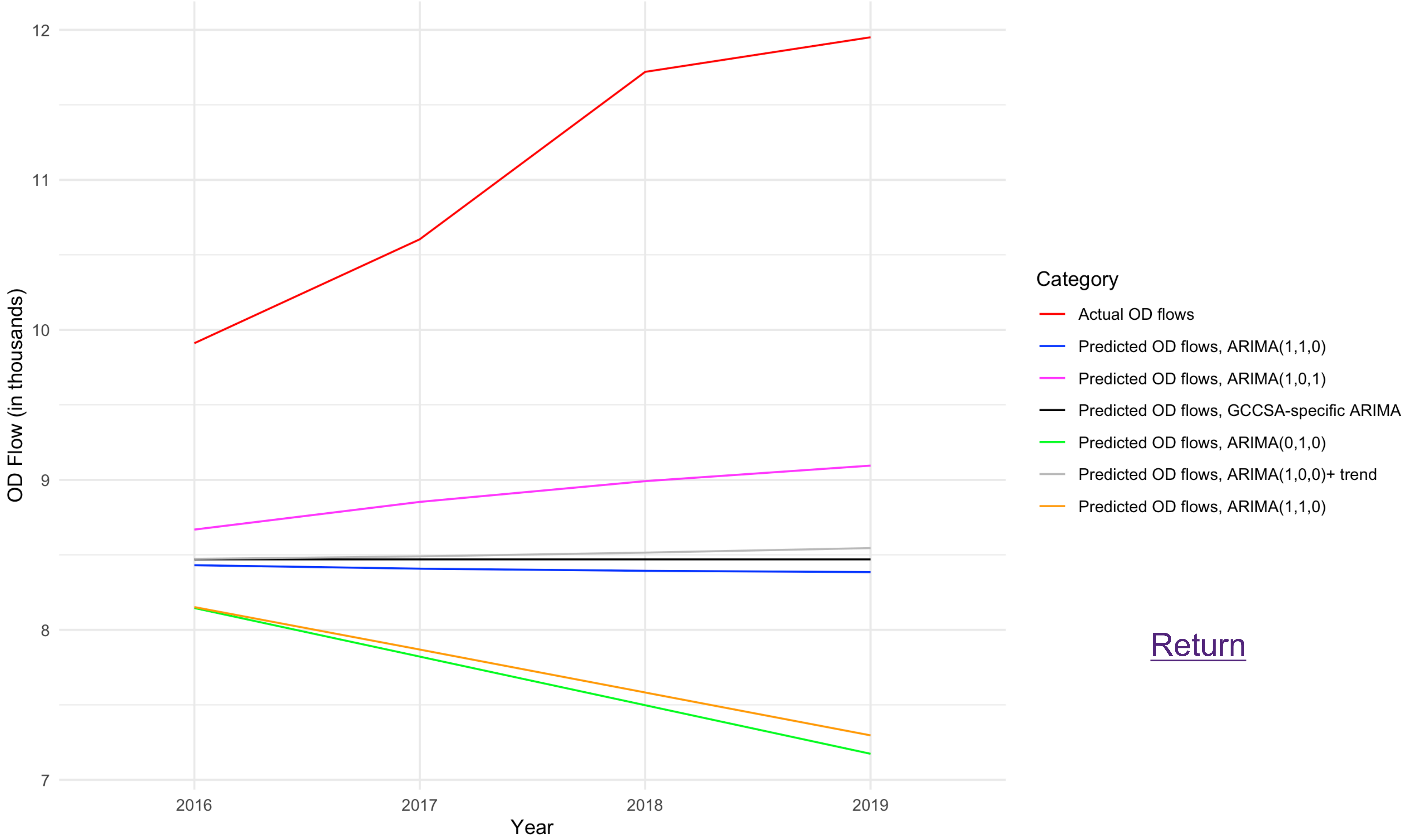
Actual and Predicted Total Migration Flows, 2016 to 2019



THE UNIVERSITY OF QUEENSLAND AUSTRALIA

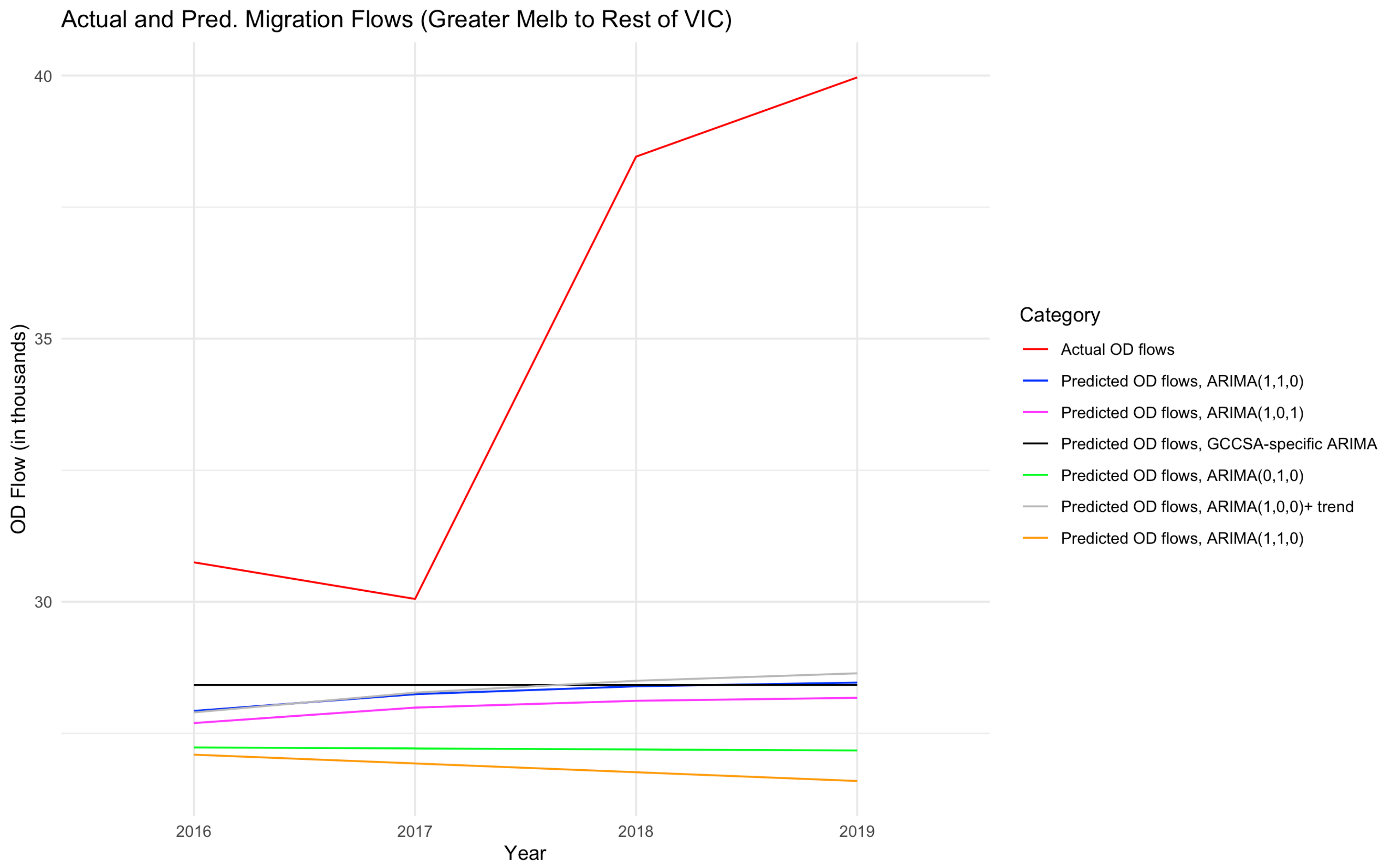
Return

Actual and Predicted Total Migration Flows (Greater Sydney to Greater Brisbane), 2016 to 2019



THE UNIVERSITY OF QUEENSLAND AUSTRALIA

Return


Actual and Pred. Migration Flows (Greater Melb to Rest of VIC)
OD Flow (in thousands)
40
35
30
2016
2017
2018
2019
Year
Category
Actual OD flows
Predicted OD flows, ARIMA(1,1,0)
Predicted OD flows, ARIMA(1,0,1)
Predicted OD flows, GCCSA-specific ARIMA
Predicted OD flows, ARIMA(0,1,0)
Predicted OD flows, ARIMA(1,0,0)+ trend
Predicted OD flows, ARIMA(1,1,0)

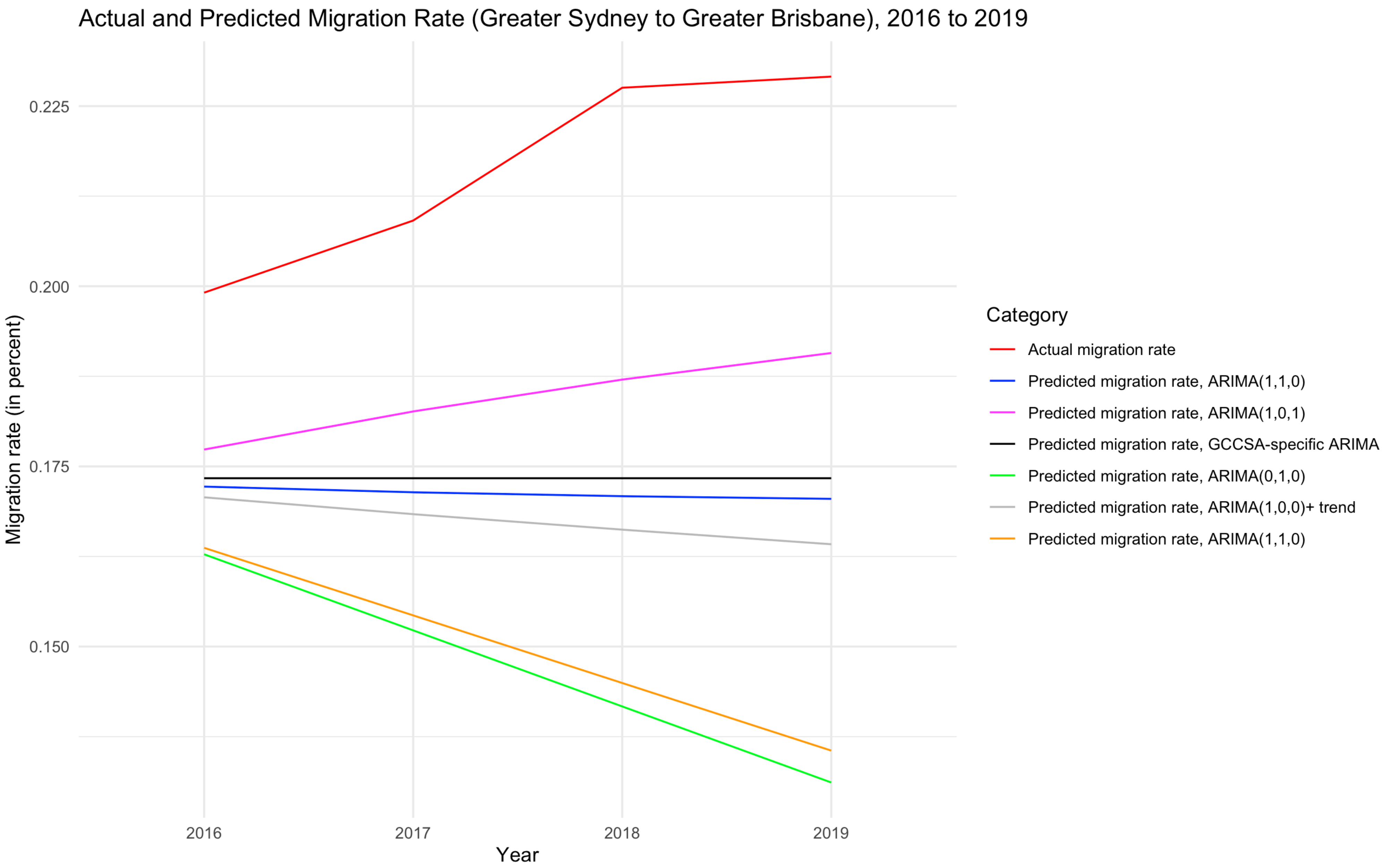
Return

ARIMA models: forecast performance (rates)

Median APE: Training and forecast periods are both pre-COVID

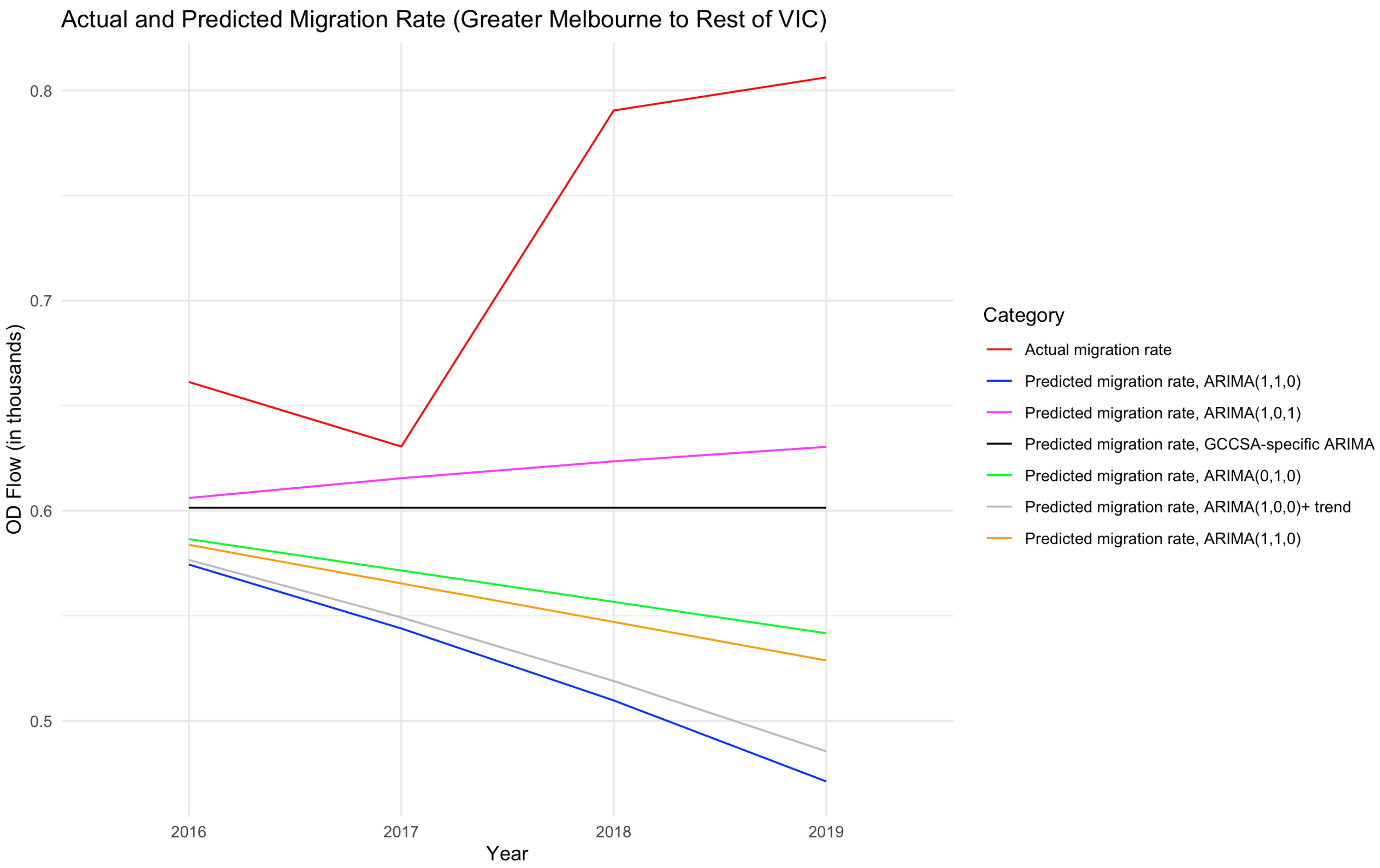
Methods	Year 1	Year 2	Year 3	Year 4
ARIMA (0,1,0)	10.20%	17.82%	20.79%	24.77%
ARIMA (1,0,0)	8.20%	15.26%	16.76%	16.33%
ARIMA (1,1,0)	10.32%	16.86%	22.04%	24.71%
ARIMA (1,0,1)	8.73%	14.85%	15.37%	13.39%
ARIMA (1,0,0)+ trend	10.61%	16.32%	19.66%	20.61%
GCCSA-pair specific ARIMA	9.45%	15.17%	16.78%	17.12%

Return



THE UNIVERSITY OF QUEENSLAND AUSTRALIA

[Return](#)



THE UNIVERSITY OF QUEENSLAND AUSTRALIA

Return

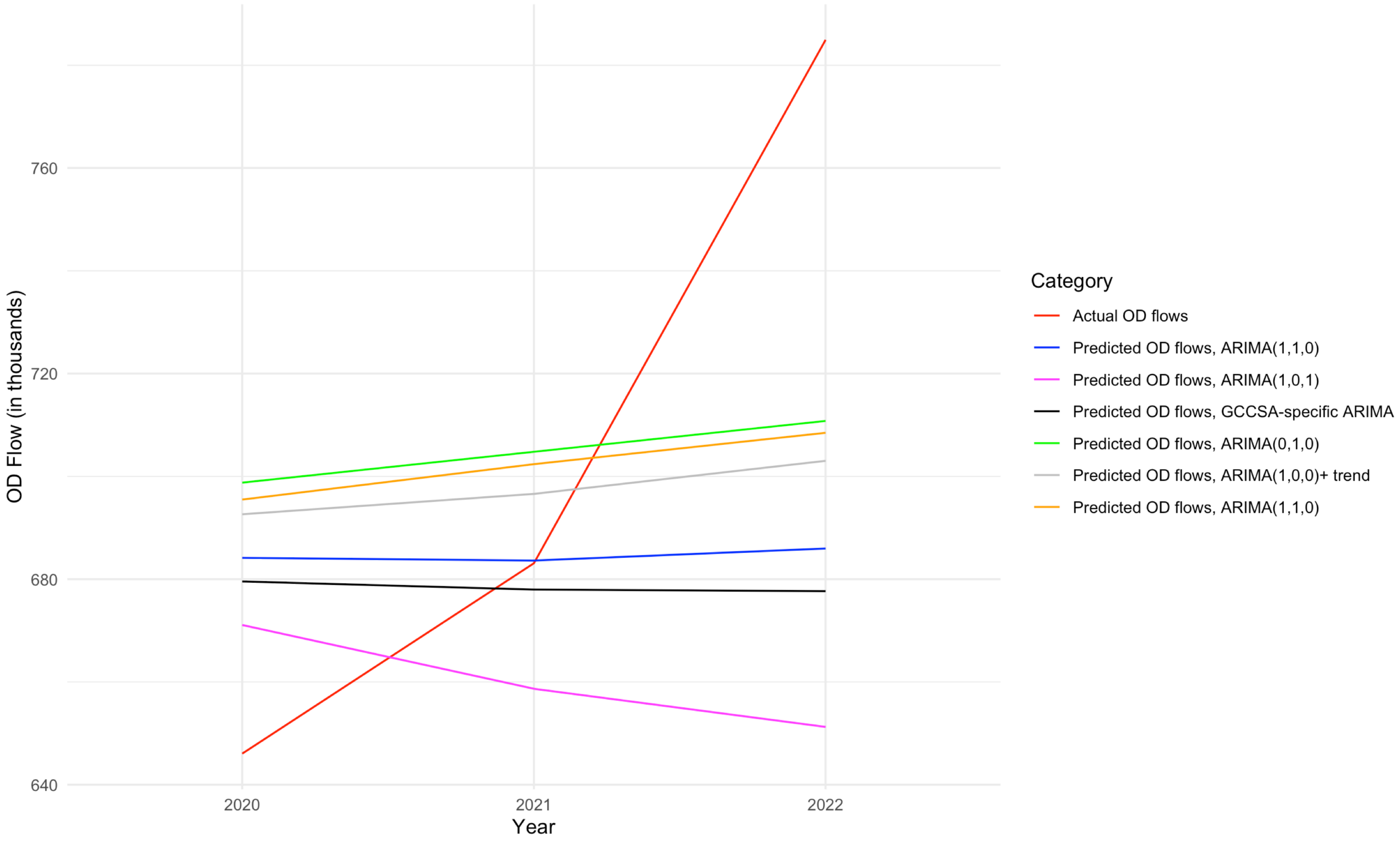
ARIMA models: forecast performance (flows)

Median APE: Training period is pre-COVID; forecast period is during COVID

Methods	Year 1	Year 2	Year 3
ARIMA (0,1,0)	10.29%	15.96%	16.60%
ARIMA (1,0,0)	9.28%	12.40%	18.64%
ARIMA (1,1,0)	10.21%	15.34%	16.77%
ARIMA (1,0,1)	10.16%	11.63%	18.93%
ARIMA (1,0,0)+ trend	12.22%	17.49%	15.63%
GCCSA-pair specific ARIMA	9.38%	13.84%	19.43%

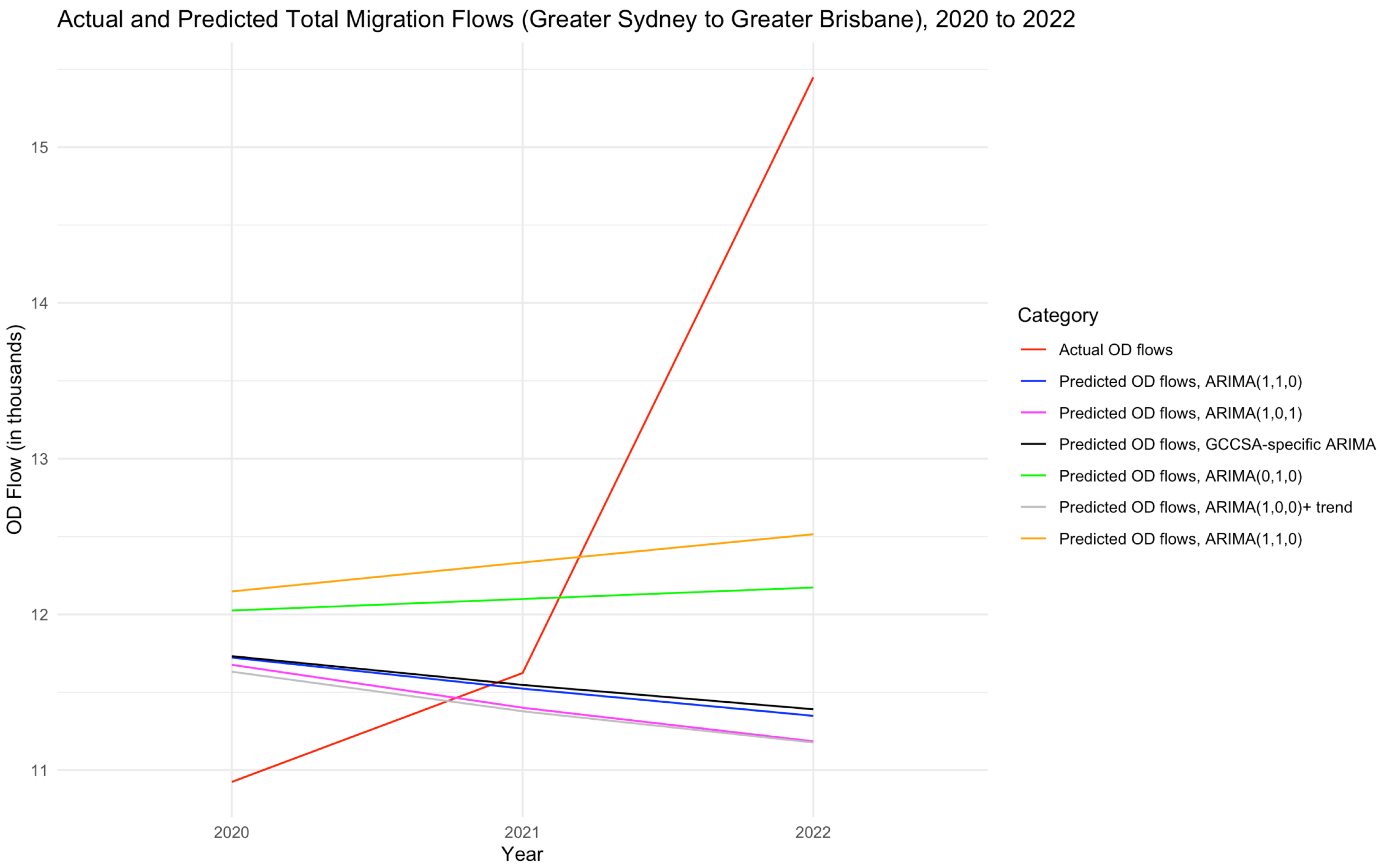
Return

Actual and Predicted Total Migration Flows, 2020 to 2022



The University of Queensland Australia

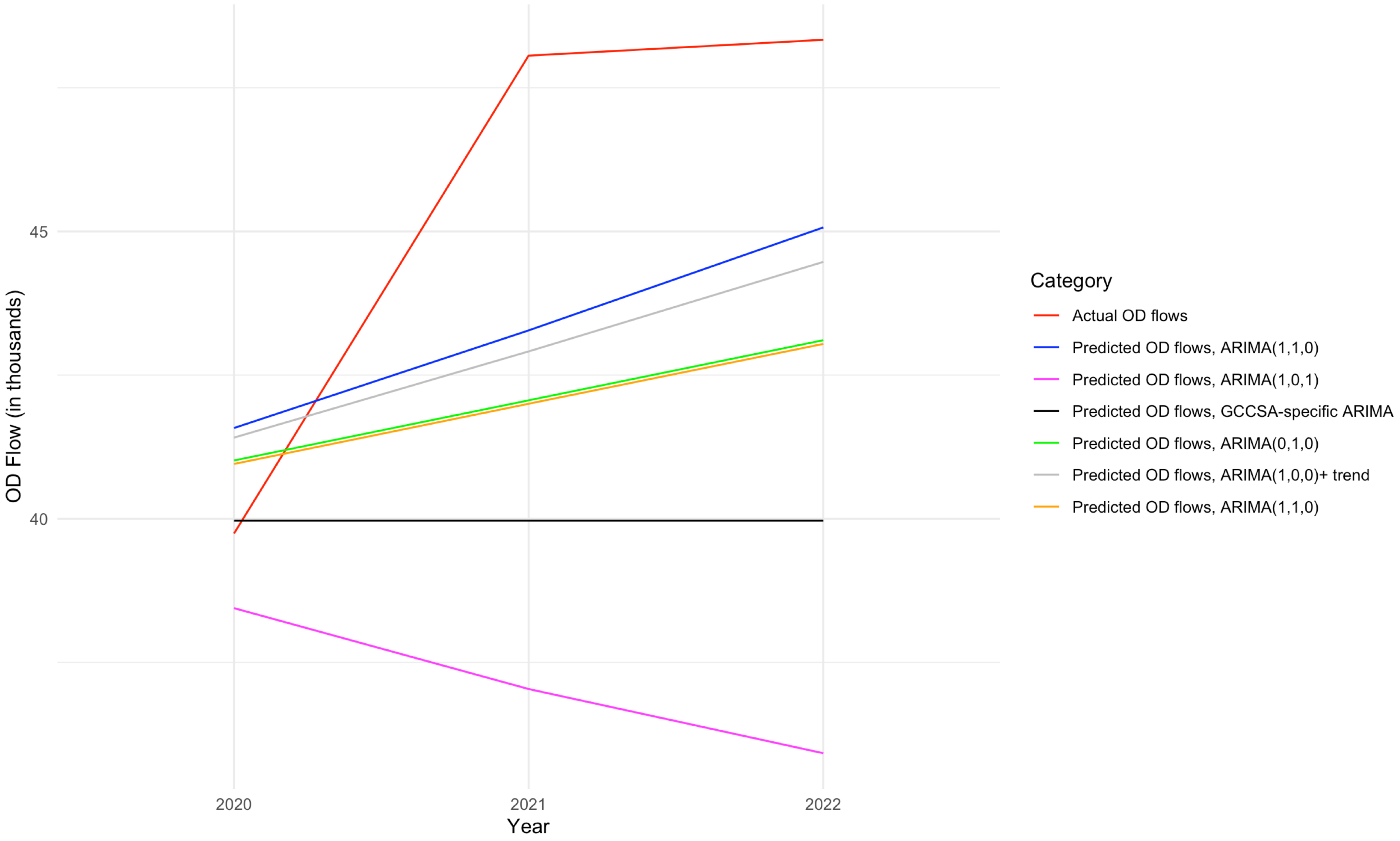
Return



Actual and Predicted Total Migration Flows (Greater Sydney to Greater Brisbane), 2020 to 2022
OD Flow (in thousands)
15
14
13
12
11
2020
2021
2022
Year
Category
Actual OD flows
Predicted OD flows, ARIMA(1,1,0)
Predicted OD flows, ARIMA(1,0,1)
Predicted OD flows, GCCSA-specific ARIMA
Predicted OD flows, ARIMA(0,1,0)
Predicted OD flows, ARIMA(1,0,0)+ trend
Predicted OD flows, ARIMA(1,1,0)

Return

Actual and Predicted Total Migration Flows (Greater Melbourne to Greater VIC), 2020 to 2022



THE UNIVERSITY OF QUEENSLAND AUSTRALIA

Return

ARIMA models: forecast performance (WMAPE)

Weighted Mean APE: Training and forecast periods are both pre-COVID

Methods	Year 1	Year 2	Year 3	Year 4
ARIMA (0,1,0)	9.44%	12.62%	20.24%	21.90%
ARIMA (1,0,0)	8.58%	12.77%	17.80%	18.00%
ARIMA (1,1,0)	9.37%	12.58%	20.17%	22.12%
ARIMA (1,0,1)	8.95%	14.24%	17.82%	17.94%
ARIMA (1,0,0)+ trend	8.51%	12.90%	17.99%	18.03%
GCCSA-pair specific ARIMA	9.32%	12.77%	18.93%	19.55%

Return

ARIMA models: forecast performance (WMAPE)

Weighted Mean APE: Training period is pre-COVID; forecast period is during COVID

Methods	Year 1	Year 2	Year 3
ARIMA (0,1,0)	9.25%	12.67%	14.82%
ARIMA (1,0,0)	8.14%	12.12%	17.34%
ARIMA (1,1,0)	8.75%	12.59%	14.85%
ARIMA (1,0,1)	6.82%	12.41%	19.67%
ARIMA (1,0,0)+ trend	8.75%	12.85%	16.86%
GCCSA-pair specific ARIMA	7.96%	12.51%	17.79%

Return

Parsimonious models

Examine the model performance based on the following assumptions:

Consider an ARIMA (1,0,0) model

- Coefficients are the same for all observations:

$$M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t$$

- Coefficients are the same for OD pairs with the same origin GCCSA:

$$M_{ij,t} = \rho_{0,\boldsymbol{i}} + \rho_{1,\boldsymbol{i}} M_{ij,t-1} + u_{\boldsymbol{i},t}$$

- Coefficients are the same for OD pairs with the same destination GCCSA:

$$M_{ij,t} = \rho_{0,\boldsymbol{j}} + \rho_{1,\boldsymbol{j}} M_{ij,t-1} + u_{\boldsymbol{j},t}$$

- Coefficients are OD pair-specific

$$M_{ij,t} = \rho_{0,\boldsymbol{i},\boldsymbol{j}} + \rho_{1,\boldsymbol{i},\boldsymbol{j}} M_{ij,t-1} + u_{\boldsymbol{i},\boldsymbol{j},t}$$

ARIMA models: forecast performance

Median APE: Training and forecast periods are both pre-COVID [Forecast for Year 1]

Same coefficient	$ARIMA\ (0,1,0)$	$ARIMA\ (1,0,0)$	$ARIMA\ (1,1,0)$	$ARIMA\ (1,0,0) + trend$
All	11.37%	8.67%	11.30%	8.90%
By origin GCCSA	11.15%	9.29%	10.64%	8.84%
By destination GCCSA	11.17%	9.05%	11.01%	8.99%
By OD GCCSA	9.86%	9.11%	10.02%	8.66%

Return

ARIMA models: forecast performance

Weighted Mean APE: Training and forecast periods are both pre-COVID [Forecast for Year 1]

Same coefficient	$ARIMA\ (0,1,0)$	$ARIMA\ (1,0,0)$	$ARIMA\ (1,1,0)$	$ARIMA\ (1,0,0) + trend$
All	9.17%	9.37%	9.19%	9.34%
By origin GCCSA	9.30%	9.53%	9.39%	9.48%
By destination GCCSA	9.13%	9.35%	9.19%	9.30%
By OD GCCSA	9.44%	8.58%	9.37%	8.51%

Return

ARIMA models: forecast performance

Median APE: Training period is pre-COVID; forecast period is during COVID

Same coefficient	$ARIMA\ (0,1,0)$	$ARIMA\ (1,0,0)$	$ARIMA\ (1,1,0)$	$ARIMA\ (1,0,0) + trend$
All	12.97%	10.47%	13.64%	10.18%
By origin GCCSA	11.65%	11.03%	12.29%	11.38%
By destination GCCSA	11.41%	11.49%	10.63%	11.81%
By OD GCCSA	10.29%	9.28%	10.21%	12.22%

Return

ARIMA models: forecast performance

Weighted Mean APE: Training period is pre-COVID; forecast period is during COVID

Same coefficient	$ARIMA\ (0,1,0)$	$ARIMA\ (1,0,0)$	$ARIMA\ (1,1,0)$	$ARIMA\ (1,0,0) + trend$
All	9.09%	9.22%	8.50%	9.15%
By origin GCCSA	9.09%	9.35%	8.45%	9.38%
By destination GCCSA	9.33%	9.53%	8.53%	9.54%
By OD GCCSA	9.25%	8.14%	8.75%	8.75%

Return

Extrapolation methods with controls

ARDL models: perfect foresight

We estimate the following model:

$$M_{ij,t} = \rho_{0,\boldsymbol{i}} + \rho_{1,\boldsymbol{i}} M_{ij,t-1} + \boldsymbol{\beta X} + u_{\boldsymbol{i},t}$$

where

- $\boldsymbol{X}$: controls of interest: (i) GCCSA-level unemployment at origin and destination; (ii) real gross state product per capita at origin and destination
- Three variations
  - Only include GCCSA-level unemployment at origin and destination
  - Only include real gross state product per capita at origin and destination
  - Include all controls

ARDL models, perfect foresight: forecast performance (flows)

Median APE: Training and forecast periods are both pre-COVID

Controls included	Year 1	Year 2	Year 3	Year 4
GCCSA-level unemployment	9.94%	18.17%	18.00%	19.92%
Real gross state product per capita	9.87%	17.21%	20.47%	22.14%
Both controls	10.73%	18.61%	22.99%	23.11%
ARIMA (1,0,0)	9.11%	15.44%	16.68%	17.88%

Return

ARDL models, perfect foresight: forecast performance (flows)

Median APE: Training and forecast periods are both pre-COVID

Controls included	Year 1	Year 2	Year 3	Year 4
GCCSA-level unemployment (lagged)	12.01%	18.65%	21.39%	19.55%
Real gross state product per capita (lagged)	9.47%	16.29%	20.63%	24.20%
Both controls (lagged)	13.01%	22.41%	26.72%	25.53%
ARIMA (1,0,0)	9.11%	15.44%	16.68%	17.88%

Return

Appendix

Methods: models to be tested

Models	Variations
Time series extrapolation without explanatory variables	6 variations of ARIMA models
Time series extrapolation with explanatory variables	4 approaches to forecast explanatory variables
Spatial interaction models	4 methods to extrapolate multiplicative components
Bayesian approach	10 variations
Machine learning approach	Light gradient boosting algorithm (LGBM)

Return

Variations of ARIMA models

- Random walk with drift (ARIMA (0,1,0)): $M_{ij,t} = \alpha + M_{ij,t-1} + u_t$
- Unconstrained autoregressive model of order 1 (ARIMA(1,0,0)): $M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t$
- ARMA(1,1) model (ARIMA(1,0,1)): $M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t + \theta u_{t-1}$
- Autoregressive model of order 1 applied on first-difference (ARIMA(1,1,0))
  - $\Delta M_{ij,t} = \rho_0 + \rho_1 \Delta M_{ij,t-1} + u_t$, where $\Delta M_{ij,t} = M_{ij,t} - M_{ij,t-1}$
- Autoregressive model of order 1 applied on de-trended series (ARIMA(1,0,0) + trend)
  - $\ddot{M}_{ij,t} = \rho_0 + \rho_1 \ddot{M}_{ij,t-1} + u_t$, where $\ddot{M}_{ij,t} = M_{ij,t} - (a_0 + a_1 t)$
- GCCSA-pair specific ARIMA: use Akaike or Bayesian information criterion (AIC/BIC) to determine the number of lags

Return

Forecasting explanatory variables: Cases considered

- Perfect foresight: use actual values
- Utilize external forecast, e.g. RBA
- Forecast using ARIMA
- Use Vector Autoregressive Model of order 1 (VAR(1))

Return

Extrapolation of multiplicative components

Spatial interaction models

- **Each origin-destination GCCSA flow is expressed as:** $M_{ij} = T \times O_i \times D_j \times OD_{ij}$
  - T: total no. of internal migrants (total effects)
  - O_i, D_j: main effects associated with origin and destination GCCSA's
  - OD_{ij}: origin-destination interaction effect

- **Which multiplicative component to extrapolate?**
  - Case 1: total, main, and interaction effects
  - Case 2: total and main effects
  - Case 3: total effect only
  - Case 4: use most recent values of OD flows

Return

Next steps

- Evaluate the performance of ARIMA models using interstate migration data
  - Have longer time series to train the models
  - Capture the early 1990s recession in the training model

- Use other error measures
  - Mean Absolute Scaled Error (MASE)
  - Percent of observed values that fall within 80 and 95 percent confidence intervals

An evaluation of internal migration forecasting models

Timeline

	JUNE		JULY					AUGUST				SEPTEMBER			
Tasks	19	26	3	10	17	24	31	7	14	21	28	4	11	18	25
1. Forecasting results and analysis															
1.1. Extrapolation w/o explanatory variables															
1.2. Extrapolation w/ explanatory variables															
1.3. Spatial interaction															
1.4. Bayesian															
1.5. Machine learning															
2. Conference presentation															
2.1. NZ Pop Conference															
2.2. IGU symposium (Greece)															
3. First draft writing and release															

- Two more papers
  - Forecast into the future beyond 2023
  - Scenario analysis paper, with more explanatory variables

Forecast models tested	Model equation
Random walk with drift (ARIMA (0,1,0))	$M_{ij,t} = \alpha + M_{ij,t-1} + u_t$
Autoregressive model of order 1 (ARIMA(1,0,0))	$M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t$
ARMA(1,1) model (ARIMA(1,0,1))	$M_{ij,t} = \rho_0 + \rho_1 M_{ij,t-1} + u_t + \theta u_{t-1}$
Autoregressive model applied on first-difference (ARIMA(1,1,0))	$\Delta M_{ij,t} = \rho_0 + \rho_1 \Delta M_{ij,t-1} + u_t$, where $\Delta M_{ij,t} = M_{ij,t} - M_{ij,t-1}$
Autoregressive model applied on de-trended series (ARIMA(1,0,0) + trend)	$\ddot{M}_{ij,t} = \rho_0 + \rho_1 \ddot{M}_{ij,t-1} + u_t$ where $\ddot{M}_{ij,t} = M_{ij,t} - (a_0 + a_1 t)$
GCCSA-pair specific ARIMA	Akaike or Bayesian information criterion (AIC/BIC) to determine the number of lags

An evaluation of internal migration forecasting models

Methods: forecasting horizon

Cases	Training period	Out of sample period
Training and out of sample periods are pre-COVID	2006/07 to 2014/15 (9 years)	2015/16 to 2018/19 (4 years)
Training period is pre-COVID; Out-of-sample period includes COVID	2006/07 to 2018/19 (13 years)	2019/20 to 2021/22 (3 years)