# Economic Growth and Migration

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# 1 Introduction

Migration and economic growth are two variables that are clearly supposed to be interlinked. On one hand, most of the literature agrees on the positive impact of migration on GDP-growth as migration allows people with different skills and new perspectives to participate in the economy, which is confirmed by empirical studies (Boubtane, Dumont, & Rault, 2016; Bove & Elia, 2017). On the other hand, standard microeconomic theory predicts that a flourishing economy attracts foreign workers by means of incentives in the form of higher wages and better working conditions, as labour is scarce in a boom phase. Thus, one would also expect a mechanism leading to a positive causality from economic growth to immigration, which might even be stronger than vice versa, as those incentives start to work immediately whereas immigrant workers possibly only start to get productive over-proportionally with some delay.

The purpose of this project is to gather empirical evidence on this presumed link between GDP growth and immigration by first examining time series on both variables individually in order to get some deeper insight in the structure of this kind of data and consequently fitting a vector autoregressive model to them. Probably due to rather poor data, I do not find any statistically significant relation, although the results that I do obtain are, albeit insignificant, qualitatively as expected.

# 2 Data

I use Austrian data on both variables. The data on economic growth, measured in GDP-growth, which I retrieved from the World Bank's data bank, covers the years 1961-2017, which corresponds to 56 observations. My measure for migration is the net migration rate, i.e. $\frac{immigration_t - emigration_t}{inhabitants_t} \times 1,000$. I have also thought about using net migration in absolute numbers, but then decided against doing so, as I consider including the development of the Austrian population a helpful proxy for the growth of the populations of potential countries of origin. I.e., by using the net migration rate, I implicitly control for the fact that populations generally grew over the period of interest, which would also lead to more migration (in absolute numbers), thus taking out some of the time dependence in the data. Nevertheless, trying out both variables showed that the results hardly change anyway. Also, I could have considered only immigration, but as the above arguments are equally (or rather: vice versa) valid for emigration, net migration seemed the most reasonable measure to me. The data on net migration rate ranges from 1960-2017 and is retrieved from Eurostat, the European Union's statistical office.

# 3 Separate Analysis

## 3.1 GDP-Growth

Figure 1: GDP-growth: time line

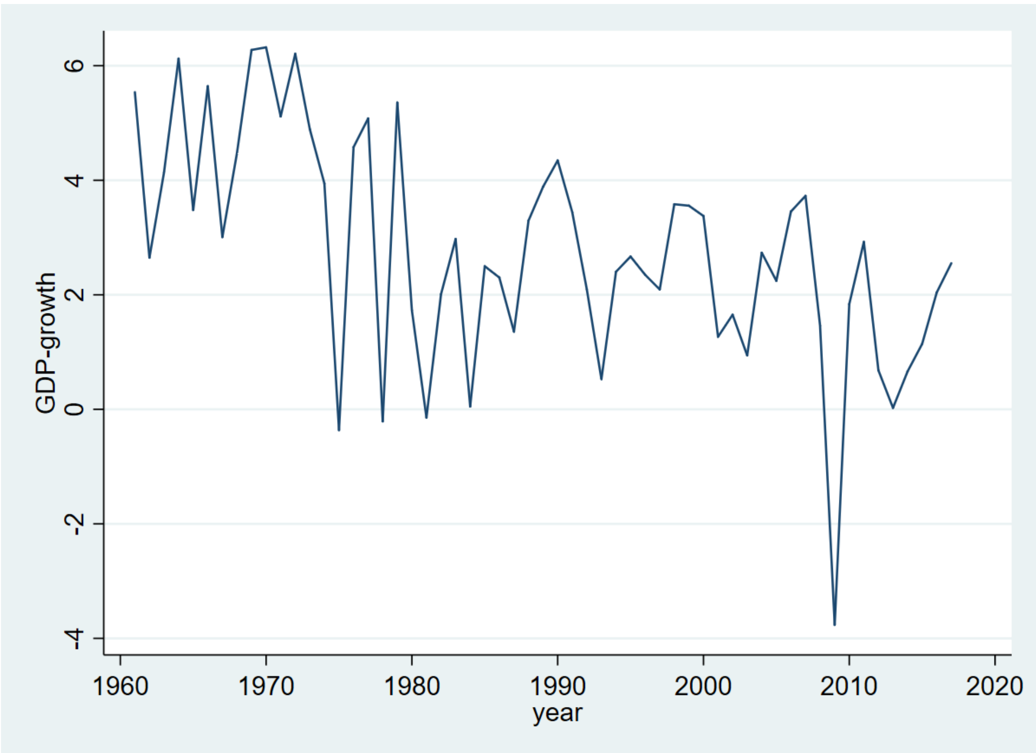
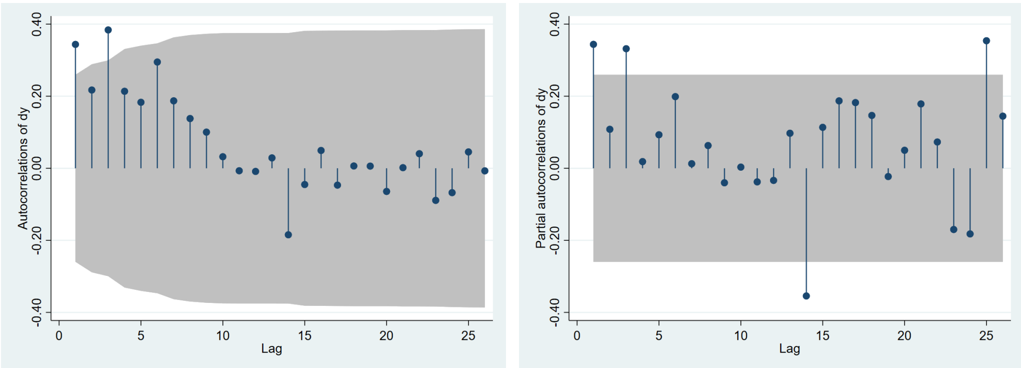


Figure 2: GDP-Growth:

(a) ACF (b) PACF




The time series for GDP-growth is rather volatile, with a noticeable negative peak around the years 2008/2009, indicating the Great Recession (see Figure 1). In addition, there seems to be a slight downwards trend, which makes sense given that GDP growth is always relative to the level of GDP, which again increases steadily almost throughout the whole period.

The ACF shows a (rather noisy) geometric decline, which indicates an AR process. Similarly, the PACF does not fall to zero sharply as well, so there might be some MA elements as well on a first glance, although there seems to be a lot of noise (see Figure 2). However, AIC and BIC both suggest an ARMA(1,1) process, resulting in equation 1 (standard errors in paranthesis):

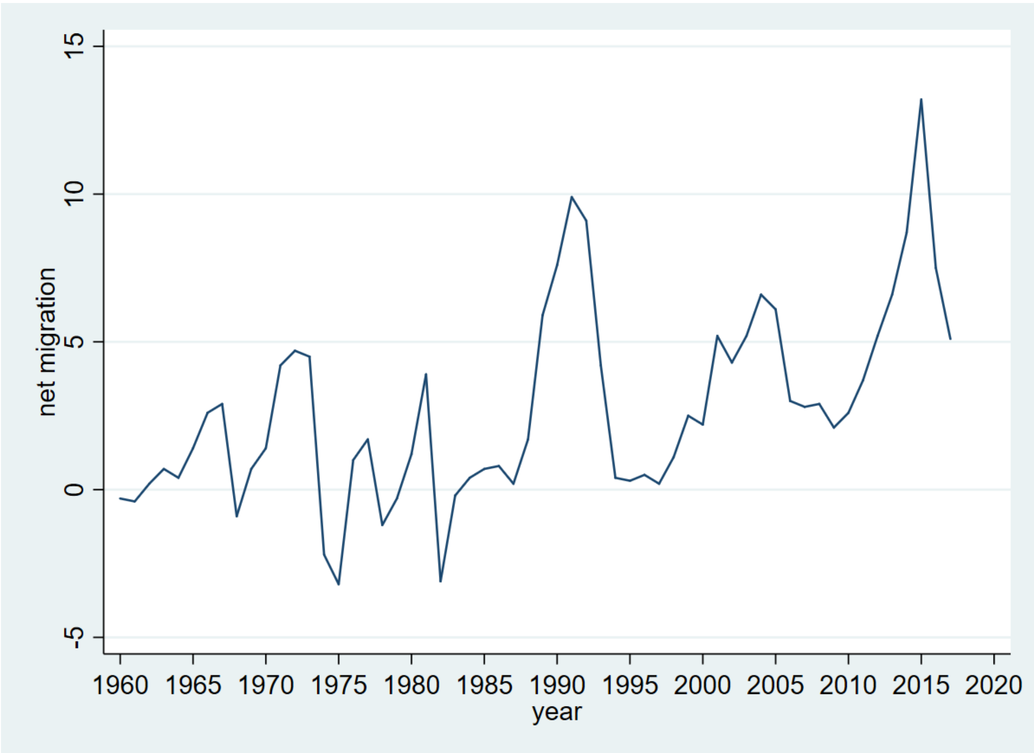
$$\underset{(.954)}{dy_t = 2.851} + \underset{(.086)}{.930 dy_{t-1}} - \underset{(.192)}{.735 \varepsilon_{t-1}} + \varepsilon_t \tag{1}$$

Interestingly, things seem not to be so clear, as with the default optimization technique Stata does not find a global maximum of the log likelihood function when fitting the regression. Indeed AIC and the BIC start to fall again when lag orders increase, although higher lags do not make any sense anyway with so few observations, so I can ignore this fact.

The null-hypothesis that the series follows a random walk is rejected by the DF test at every common significance level, allowing for a time trend, i.e. the process has no unit root and is therefore stable.

### 3.2 Net migration rate

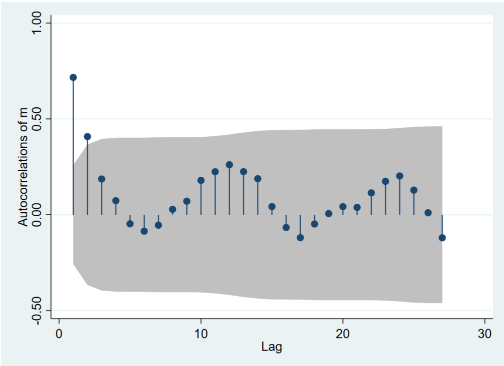
Figure 3: Net Migration Rate: time line



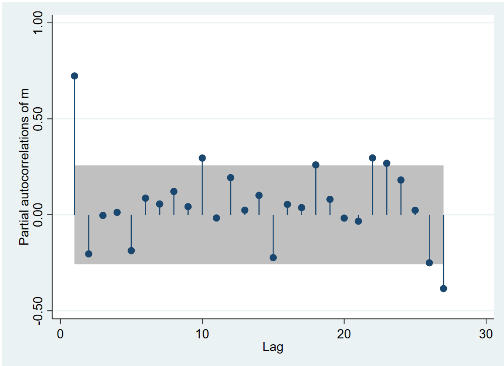

As expected, Figure 3 shows a steady net immigration to Austria except for only very few years. One can also clearly see two peaks in the early 90's and in 2015, caused by the Yugoslav Wars and the Refugee Crisis. The ACF shows the classical geometric decay of an AR process, whereas the PACF falls sharply after the first observation (see Figure 4. AIC and BIC suggest an AR(2) and an AR(1) process, respectively. The Portmanteau test shows, that even for the AR(1) specification, residuals are not significantly different from white noise at any common significance level (i.e. no structure left in the residuals), so I would definitely favour the AR(1), especially when the PACF is so clear, resulting in equation 2 (standard errors in paranthesis):

Figure 4: Net Migration Rate:

(a) ACF




(b) PACF




$$m_t = \underset{(1.235)}{2.702} + \underset{(.093)}{.721} m_{t-1} + \varepsilon_t \tag{2}$$

The Dickey-Fuller-test with trend again rejects, thus I conclude that the process is asymptotically stationary.

# 4 Joint Analysis

To do the joint analysis and fit an autoregressive model, I first de-trend the data, as otherwise, I would probably observe a spurious regression. I obtain the cyclical components of both variables by applying the Hodrick-Prescott filter, with sensitivity parameter set to 100, as I use yearly data. The advantage of this technique as opposed to simply including a trend in the model, is that this way I can not only abstract from a linear time trend, but from any trend, irrespective of its functional form.

Table 1: Results: Vector Autogegression Model

| | m | m | m | dy | dy | dy |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L.m | 0.452*** | 0.598*** | 0.529*** | -0.0171 | 0.0618 | 0.0557 |
| | (0.119) | (0.134) | (0.137) | (0.0885) | (0.0979) | (0.0979) |
| L2.m | | -0.315* | -0.291 | | -0.0579 | -0.0644 |
| | | (0.130) | (0.157) | | (0.0944) | (0.112) |
| L3.m | | | -0.103 | | | 0.121 |
| | | | (0.174) | | | (0.124) |
| L4.m | | | -0.113 | | | -0.165 |
| | | | (0.146) | | | (0.104) |
| L.dy | 0.250 | 0.204 | 0.251 | -0.0945 | -0.134 | -0.147 |
| | (0.181) | (0.178) | (0.187) | (0.134) | (0.130) | (0.134) |
| L2.dy | | 0.0440 | 0.136 | | -0.320* | -0.412** |
| | | (0.179) | (0.194) | | (0.131) | (0.138) |
| L3.dy | | | 0.208 | | | -0.0941 |
| | | | (0.191) | | | (0.136) |
| L4.dy | | | 0.294 | | | -0.269* |
| | | | (0.188) | | | (0.134) |
| _cons | -0.0108 | 0.00374 | 0.0128 | -0.0204 | -0.000805 | -0.0263 |
| | (0.270) | (0.261) | (0.260) | (0.200) | (0.190) | (0.186) |
| $N$ | 56 | 55 | 53 | 56 | 55 | 53 |

$S$tandard errors in parentheses.

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The different criteria provided by Stata suggest lag-orders 1, 2 or 4. Tables 1 shows the regression results. We see that the coefficients for the first lag are fairly robust to adding more lags, and additional lags are not significant, so I choose lag order 1, as BIC suggests. Applying these estimates results in the following model:

$$\begin{bmatrix} dy_t \\ m_t \end{bmatrix} = \begin{bmatrix} -.020 \\ -.011 \end{bmatrix} + \begin{bmatrix} -.095 & -.017 \\ .250 & .452 \end{bmatrix} \begin{bmatrix} dy_{t-1} \\ m_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{dy,t} \\ \varepsilon_{m,t} \end{bmatrix} \tag{3}$$

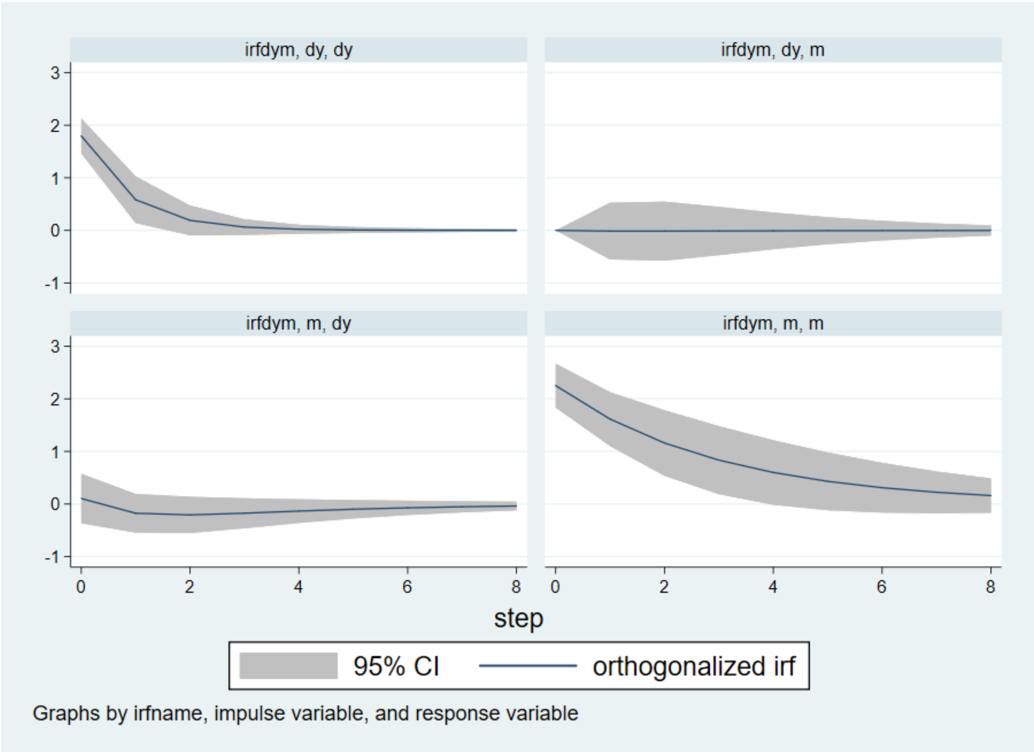
Where $dy$ is the de-trended growth of GDP and $m$ the de-trended net migration rate. A LM test on autocorrelation in the residuals cannot reject the null hypothesis (that there is no autocorrelation), i.e. the model seems to be correctly specified. A test for Granger causality cannot reject the null hypothesis that any of the variables causes the other one. Considering the insignificant coefficients in the vector auto regression, this is what I would already have suspected. The interpretation is that the variables are not helpful in predicting each other given that one may use the lags of the variable of interest itself as well.

Figure 5 provides a graph of the orthogonalised impulse response functions, which show that the effects are economically and statistically (confidence intervals) insignificant.

# 5 Conclusion and Outlook

Analysing time series on the growth of GDP and the net migration rate in Austria yields that GDP growth can be well described by an ARMA(1,1) process, whereas the net migration rate seems to follow an AR(1) process, which is also supported by a very beautiful and clear PACF. However, trying to explain a relation between the two variables by estimating a vector autoregression is not so successful; coefficients are only significant for each of the variables' own lag, and there is no Granger causality. This can have several reasons, e.g. that a prosperous economic situation in a country is only one of many factors that contributes to being attractive to immigrants. This is

Figure 5: Impulse Response Function




especially true for the two most prominent peaks in net migration rate, both of which were not caused by classical labour migration. Also, the growth of GDP could be the wrong measure - being one of the richest countries in the world in terms of absolute GDP per capita, the annual growth rate of Austria's economy might not be as relevant. Secondly, a sample size of only 56 observations is rather small, although not unusual in the context of time series analysis. Using panel data might yield more reliable results due to a higher number of observations, eg. one could try to use data on within-EU migration and economic growth in EU-countries.

# References

Boubtane, E., Dumont, J.-C., & Rault, C. (2016). Immigration and economic growth in the oecd countries 1986–2006. *Oxford Economic Papers*, *68*(2), 340–360.

Bove, V., & Elia, L. (2017). Migration, diversity, and economic growth. *World Development*, *89*, 227–239.