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An empirical study on the macroeconomic effects of immigration

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Abstract

In this paper, we study the macroeconomic effects of an immigration shock in Sweden, using a Structural Autoregressive (SVAR) model with sign restrictions. We find that labor immigration increases output, participation and immigration, leave real wages unaffected and lowers unemployment (even among native workers). We also compare our results for Sweden to the same analysis done by Furlanetto and Robstad (2019) for Norway. The results are generally similar, suggesting that labor immigration to Norway and Sweden leads to some of the same macroeconomic responses. However, we find that the immigration shock is more persistent in Norway. Also, unemployment reacts differently to an immigration shock in Norway, as it is less cyclical and volatile than in Sweden.

Acknowledgements

We want to express our sincere gratitude to our supervisor Tommy Sveen for excellent guidance and advice given along the way. Also, we would like to thank our co-supervisor Francesco Furlanetto for invaluable inspiration and help. We would also like to thank our family and friends for their support.

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1. Introduction

In the last few decades, we have seen a significant increase in terms of migration across borders in Europe. Immigration has gone from a marginal phenomenon to the main driver of population growth. In 1960, the share of immigrants in Sweden was 4 %. In 2018, this number was significantly higher, with 19,1% (Statistics Sweden, 2019). This makes Sweden one of the countries with the highest share of foreign-born in Europe.

Work was the most important reason for immigration until the start of 1970. Sweden got out of World War II with an intact industry, ready to produce for a Europe under reconstruction. Sweden therefore had a high demand for labor, which south Europeans covered a large part of. Also, a lot of Finnish people were unemployed at the time and traveled to Sweden for work (Pettersen & Østby, 2013).

The Nordic countries have been a part of the open European labor market since 1994 through the EU/EEA agreement. However, the immigration to Scandinavia was heavily boosted by the opening of the national borders through the EU-enlargement in 2004, which created a larger flow of people coming from Eastern European countries. Also, there was a change in national politics regarding labor immigration, refugees and family reunion from countries outside the EU as well. This led to an increased immigration flow that has lasted for the last 40 years (Pettersen & Østby, 2013).

After the EU-enlargement, immigration from Poland and the Baltic states dominated in Scandinavia. Besides, family reunion and refugees still counted for a considerable part of the immigration flow. After the year 2000, immigration to Denmark has been quite stable, while immigration to Sweden and Norway has more than doubled. In 2015, Sweden had three times as much immigrants as its neighbor countries, where Sweden had 1,43, Norway had 0,55 and Denmark had 0,44 million people, respectively. Even though this difference is mostly due to non-labor immigration, this is a sign of Sweden’s willingness to accept immigration in general (Pettersen & Østby, 2013).

Sweden is currently the highest ranked country on the Mipex index, an index of how countries promote the integration of immigrants into their countries. The index tells us something about the countries willingness to accept immigrants into the labor market and the rights the immigrants are entitled to in the respective country. Some of the indicators that Sweden scores highest on is labor market mobility, anti-discrimination and permanent-residence. The country ranked number two on the Mipex index is Portugal, while New Zealand is ranked number three. Finland and Norway share fourth place. With Denmark on the thirteenth place of a total of 38 countries, all the Scandinavian countries are represented in the upper part of the list (Mipex, 2015).

Our study is based on Furlanetto and Robstads (2019) empirical paper where they study the macroeconomic effects of immigration to Norway. We adopt their model and methodology, with a few moderations on the sign restrictions, to the Swedish labor market. We use a Structural Autoregressive (SVAR) model where immigration is a fully endogenous variable. Immigration reacts to exogenous immigration shocks in addition to a business cycle shock, a wage bargaining shock, a labor force participation shock and a residual shock (to complete the system).

Our data set ranges from the second quarter of 2005 to the fourth quarter of 2018.[1] This interval captures the period after the EU-enlargement, and we observe a significant share of labor immigrants in Sweden. In our study, we focus on labor immigration, as other immigrants (i.e., asylum seekers and refugees) would intervene with our identification assumption which states that we need immigrants to enter rapidly into the labor market. Therefore, our immigration data includes immigrants from North America and Europe. It is important to emphasize that our study is not valid for any other type of immigration, like for example refugees or asylum seekers.

[1] We thank Mårten Löf, a researcher in Riksbanken, for providing us with Swedish labor market data.

At the end of our paper, we make a comparison between Furlanetto and Robstad`s (2019) results for Norway to our results for Sweden. Norway and Sweden are similar countries in many ways and give us a natural comparable environment to study immigration patterns. This leads us to our research question: *The macroeconomic effects of immigration to Sweden, with a comparison to Norway*.

The rest of the paper is structured as follows: In section 2, we present a literature review on the thesis topic. In section 3, we present our methodology, our model set-up and describe our data. In section 4, we present our results and discuss their implications. In section 5, we compare Norway and Sweden. Finally, in section 6, we conclude. In the appendix, we include tables and figures that are not included in the text.

2. Literature review

While there are several studies on the effects of immigration in the microeconomic literature, there seems to be less research on it in the macroeconomic literature. However, a few studies have been done using a VAR methodology to estimate the effects of immigration. In this section, we give a brief overview of some existing literature on the thesis topic.

We are basing our thesis on the academic paper of Francesco Furlanetto and Ørjan Robstad (2019) «Immigration and the macroeconomy: Some new empirical evidence». In that paper, the authors use a SVAR model to estimate the effect of labor immigration on some key macroeconomic variables in Norway. The paper was feasible as Norway is one of the few countries with quarterly net immigration data. Furlanetto and Robstad use a SVAR scheme where immigration is a fully endogenous variable. It reacts to exogenous shocks to immigration as well as the variables GDP, real wage, domestic labor force participation and unemployment. Using a limited number of sign restrictions they disentangle immigration shocks from other structural disturbances, namely a business cycle shock, a wage bargaining shock, a domestic labor supply shock and a residual shock. They identify the wage bargaining shock as a shock that lowers the real wage and reduce the participation rate.

To disentangle the domestic labor supply shock, they use a restriction on the ratio of immigrants over participants that is naturally procyclical in response to an expansionary domestic labor supply shock. They define the business cycle shock as a shock that moves output and real wages in the same direction to capture the shocks that do not originate in the labor market. The results in their baseline model suggest that a positive immigration shock has a small negative effect on real wage on impact, a positive effect on GDP and participation as well as a negative effect on unemployment, even among natives.

There are also other macroeconomic studies done on the effect of immigration in the past literature. McDonald (2013) and Armstrong and McDonald (2016) use data from New Zealand to study the effect of immigration on house prices, using a VAR model. They find that an immigration shock has a strong positive effect on house prices and construction activity, thus boosting aggregate demand. They also extend their model to include an immigration shock that reflects Australian unemployment. They find that higher net immigration due to higher unemployment in Australia leads to higher New Zealand unemployment, but higher net immigration for other reasons reduces unemployment in New Zealand. Boubtane, Coulibaly and D`Albis (2015) study the effects of immigration in France using a VAR model. They find that there is a complementarity between immigrating workers and native-born workers. Kiguchi and Mountford (2013) do a VAR study on the macroeconomics of immigration in the US. They use an unexpected rise in the working population as the immigration series. They find that immigration shocks are not associated with rises in non-residential investment or short-run reductions in average wages. This is also confirmative that immigrant labor does not substitute native labor, but is rather complementary. Morley (2005) use the Autoregressive Distributed Lag (ARDL) approach to cointegration and error correction models (ECM) to find if there were any causality between economic growth (per capita) and immigration. What they find is that there is no causality from immigration to GDP growth per capita, but a causality from GDP growth per capita to immigration. The countries included in the study are Australia, Canada and the USA.

3. Methodology

The econometric theory in this section is based on Bjørnland and Thorsrud (2015) and Furlanetto and Robstad (2019), if otherwise is not explicitly cited.

3.1 Vector Autoregressive (VAR) Model

Vector Autoregressive (VAR) models are extensively used in macroeconomics, for purposes such as forecasting and modeling expectations in theoretical macroeconomic models. The VAR model is a multivariate extension of the univariate AR model, and let us do estimations with several variables at the same time. The model builds on simple time series concepts, but let us perform advanced analysis and computations.

The properties of a time series y at time t can be expressed by a $(K \times 1)$ vector of random variables:

$$y_t = (y_{1,t}, \dots y_{K,t})' \qquad (1)$$

Therefore, a VAR model of order p can be written as:

$$y_t = \mu + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t, \qquad (2)$$

where A is a $(K \times K)$ coefficient matrix, μ denotes a $(K \times 1)$ vector of intercept terms, and e_t is a $(K \times 1)$ dimension vector of error terms which we assume are white noise, with the following properties:

$$E[e_t] = 0 \qquad (3)$$

$$E[e_t, e_s'] = \begin{cases} \Sigma_e \, for \; t = s \\ 0 \; otherwise \end{cases} \qquad (4)$$

This is the reduced form representation of the VAR model. The white noise has mean zero and a constant variance equal to the variance-covariance matrix Σ_e when $t = s$ and zero otherwise.

3.2 Structural Vector Autoregressive (SVAR) Model

Sims (1980) developed the VAR model further, to a so-called structural vector autoregressive (SVAR) model. With this model, one can identify the structural shocks from the reduced form VAR so that they match their theoretical counterparts. When you want to use the SVAR model, you need to decide on what variables you want to include, the number of lags, the type of deterministic components and a way to treat the non-stationary components. When this is done, you assess the results through impulse response functions and variance decompositions. An advantage with the SVAR model, in contrast to other large-scale macroeconomic models, is that the results are easy to interpret and are conveniently available once the model is computed.

In our study, we want to transform the standard reduced-form VAR representation into a SVAR model. In order to map the economically meaningful structural shocks from the reduced form estimated shocks, we need to impose restrictions on the estimated variance-covariance matrix. We assume that the reduced form residuals e_t can be written as a linear combination of structural innovations ε_t.

$$e_t = D\varepsilon_t \qquad (5)$$

with $\varepsilon_t \sim N(0, I)$, where I is an $(N \times N)$ identity matrix and where D is a non-singular parameter matrix. The variance-covariance matrix therefore has the structure $\Sigma = DD'$. Now, we want to identify D from the symmetric matrix Σ. We obtain this by imposing a number of sign restrictions, where the restrictions are summarized in table 2 below. We restrict the shocks with the variables GDP, real wage, participation rate, the share of immigrants in participation and the unemployment rate.

3.3 Model specifications

Our model specifications are similar to those of Furlanetto and Robstad (2019). The model is specified using Bayesian methods, due to the large number of variables that we are going to estimate. The Bayesian method also has another advantage; the approach can be used regardless of the presence of non-stationarity. Therefore, we estimate the model with the variables in levels.

Furthermore, in order to keep the information in the likelihood dominant, we specify diffuse priors. These priors lead us to a Normal-Wishart posterior with mean and variance parameters corresponding to the OLS estimates.

The number of lags to include in the model is an important decision. Including too many or too few lags may lead to a mis specified model with inadequate, inefficient and biased estimates. To decide on the lag length, one can use a statistical information criterion, like AIC or BIC, or one can use economic theory. In our case, we have used a lag length of five lags. This is the standard practice when using quarterly data series, and therefore find support in econometric theory. However, our results are also confirmed using four lags, which are an adequate number of lags for the residuals to behave like white noise.

3.4 Sign restrictions

Our identification strategy will be based on imposing a limited number of sign restrictions on the macroeconomic variables in order to disentangle immigration shocks from other business cycle fluctuation sources. The sign restriction methodology is used to seek identification by restricting the shape of the impulse response functions so that, e.g. when real wages go up, domestic labor supply goes down, meaning that they have a negative relationship. The methodology has been developed by Faust (1998), Canova and Nicoló (2002) and Uhling (2005), among others. Using sign restriction for identification has both advantages and disadvantages compared to other identification approaches. One clear advantage is that the restrictions are ready to use just from economic theory. However, a disadvantage is that sign restrictions does not necessarily imply a unique identification as there may be many impulse responses that satisfy the specific sign restriction imposed. In our case, we use the sign restriction approach due to its ability to disentangle the exogenous and the endogenous component of immigration in a system that takes into account feedback effects between different variables. An alternative solution to the identification problem would be the Cholesky decomposition, which is the most popular method.

We continue with the relationship that we assumed above, where $e_t = D\varepsilon_t$. The number of possible D matrices will be infinite, and we can refer to each D as a "draw". There are several ways to find the D matrix. To explain the basic idea, we follow Canova and Nicoló (2002). Construct $D(\omega)$, where $\omega \in (0, \pi]$. $D(\omega)$, are called the Givens rotation matrices. An example of such a matrix for $K = 2$ is:

$$D(\omega) = \begin{bmatrix} \cos\omega & -\sin\omega \\ \sin\omega & \cos\omega \end{bmatrix} \qquad (6)$$

Varying ω, we can trace out all possible structural MA representations that could have generated the date we are examining. Hence, identification requires restrictions on ω. The use of sign restrictions requires that we produce a series of responses, but keep only those that satisfy the theoretical restrictions imposed. This will restrict ω to be in a certain subset of $(0, \pi]$.

We started our analysis by using the same restrictions as Furlanetto and Robstad (2019), see table 1. However, with these restrictions, the residual shock has greater importance than desired for a residual shock. The results can be seen in table 12 through 16 in the appendix. We therefore developed alternative restrictions. The alternative restrictions can be seen in table 2. It turns out that participation is less cyclical and volatile in Sweden than in Norway, and that unemployment is more volatile in Sweden. We therefore leave participation unrestricted in the business cycle shock and instead restrict unemployment to have a negative relationship to output. This also led to a change in the sign restrictions for the residual shock, in order to complete the system. The results can be seen in figure 1 through 5. Now, the residual shock accounts for less of the variability in the variables, while we the business cycle shock can explain much more of the variability in unemployment, which gives a more correct view of the Swedish economy.

We only change the restrictions for two of the shocks, and the remaining shocks are unaffected by the change. The impulse response functions for these shocks look exactly like before. For the rest of the analysis, we use the results from the alternative restrictions.

	Business Cycle	Wage Barg.	Dom. Labor Supply	Immigration	Residual shock
GDP	$+$	$+$	$+$	$+$	$+$
Real Wages	$+$	$-$	$-$	$-$	$+$
Participation Rate	$+$	$-$	$+$	$+$	$-$
Immigrants/ Participants	NA	NA	$-$	$+$	NA
Unemployment Rate	NA	NA	NA	NA	NA

Table 1. Sign restrictions as used by Furlanetto and Robstad (2019).

	Business Cycle	Wage Barg.	Dom. Labor Supply	Immigration	Residual shock
GDP	$+$	$+$	$+$	$+$	$+$
Real Wages	$+$	$-$	$-$	$-$	$+$
Participation Rate	NA	$-$	$+$	$+$	NA
Immigrants / Participants	NA	NA	$-$	$+$	NA
Unemployment Rate	$-$	NA	NA	NA	$+$

Table 2. Alternative sign restriction, which we use for the rest of the analysis.

The restrictions are imposed only on impact after the recommendation of Canova and Paustian (2011). The procedure behind the specific restrictions is more closely described in Rubio-Ramirez, Waggoner and Zha (2010). All restrictions find theoretical support in a New Keynesian model based on Foroni, Furlanetto and Lepetit (2018) that is extended to include immigration shocks modeled as in Kiguchi and Mountford (2017), Lozej (2018) and Weiske (2017).

The restrictions let us identify five shocks. The first shock is a business cycle shock. This shock moves output and real wages in the same direction, and output and unemployment in the opposite direction. The business cycle shock is supposed to capture different types of demand shocks, such as a monetary policy shock or a government expenditure shock, as well as foreign shocks and also technology shocks (even though the effect of technology on participation can be both positive and negative, cf. (Christiano, Eichenbaum & Trabandt, 2015)).

The three next shocks have its origin in the labor market. The wage bargaining shock moves output and real wages in different directions, as well as output and participation in different directions. These assumptions find theoretical support in several papers, e.g. Foroni et al. (2018) and Galí, Smets and Wouters (2011). The increased wage will make firms reduce their activity level, and it will make people outside the workforce want to participate. Sweden, like Norway, has a centralized wage negotiation system, which makes it a fascinating country for wage bargaining investigation.

The domestic labor supply shock is defined as a shock that moves output and real wages in the opposite direction, output and participation in the same direction and output and the immigration rate in the opposite direction. In practice, it would mean that a flow of natives would be ready to take on a job. This will lead to higher economic activity and therefore increase output and participation. However, the wage level will decrease as a larger workforce is now available, and it is an employer's market. Besides, it will also make less space for labor immigrants. Lastly, the immigration shock moves output and real wages in the opposite direction, and output, participation and the immigration rate in the same direction. In other words, an immigration flow would, by following our assumption's, lower real wages, but increase output and participation.

Finally, there is a fifth shock to capture the residual dynamics in the system. The shock moves output, real wages and unemployment in the same direction. This shock is included to match the number of variables with the number of shocks in order to complete the identification system.

3.5 Data description

A VAR model is a useful tool when we want to estimate the effect of several variables at the same time. However, we cannot include an unlimited number of variables, because the VAR-model easily becomes heavily parameterized and it is troublesome if we end up with too many parameters to estimate relative to observations in the data. We therefore have to pick our variables carefully and wisely. In our model, we have included data on GDP, the real wage, the participation rate, the immigration rate and the unemployment rate for Sweden. These five macroeconomic variables give us a good indication of how the macroeconomy in Sweden reacts to an immigration shock - and can tell us something about the horizon for which this shock lasts. The data that we use is quarterly data from the second quarter in 2005 to the fourth quarter in 2018 (2005:Q2-2018:Q4). This gives us a total of 55 quarters or about 13 years. The series is somewhat shorter than ideal when working with labor market shocks, but we were not able to obtain a longer quarterly series of immigration in Sweden. The whole sample period is after the EU-enlargement in 2004, which gives us a good picture of the immigration effects in the aftermath of including Eastern European countries in the EU. Also, the data if relatively "new", which gives us an up-to-date analysis. All the data is collected from Statistics Sweden and Riksbanken.

The data on Swedish GDP is collected as GDP in the expenditure approach in current prices of SEK in millions. The data on real wages is the quarterly real wage for the total Swedish economy. The participation rate is collected as a total percentage of people aged 15-74 who are in the labor force. The immigration rate is the labor force participants born in North America and Europe in percent of the total population aged 15-74. Finally, the unemployment rate is collected as a total percentage of people aged 15-74 who are unemployed. All variables appear in logs, except unemployment that appears in percent of the workforce. All the data is seasonally adjusted.

4. Results

In this section, we will present our results. We will analyze the impulse response functions and the median forecast error variance decomposition in order to understand the drivers of the variables. All variables are expressed in percentage except for unemployment, which is expressed in percentage points.

4.1 A business cycle shock

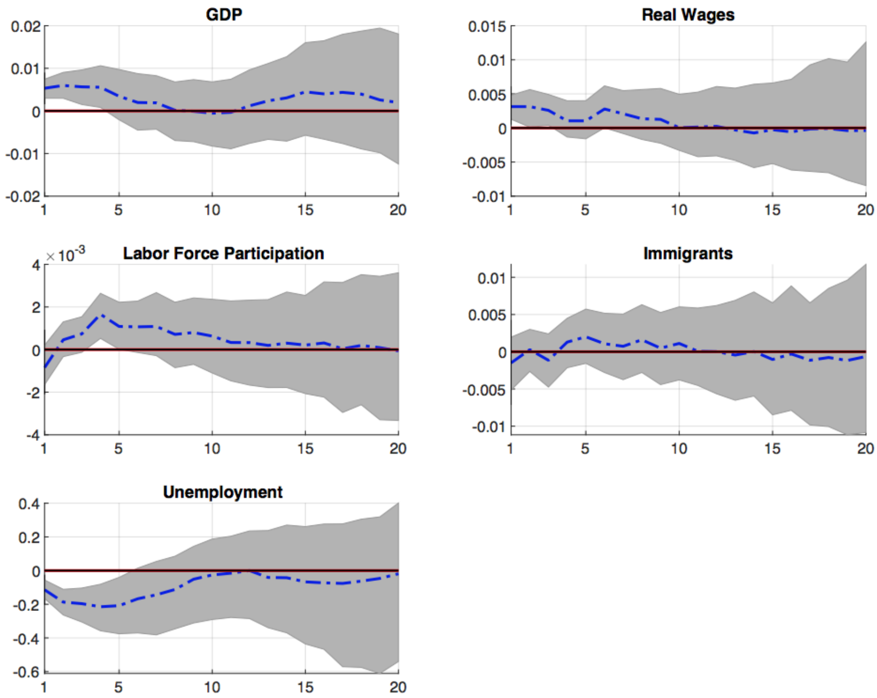

Figure 3. Impulse response to a one-standard-deviation business cycle shock. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

An expansionary business cycle shock has a small positive effect on real wages, labor force participation. Unemployment stays below baseline for a few quarters; we see a significant negative effect. This is expected and in line with economic theory. There is no significant effect on immigration, which implies that immigration reacts little to the state of the economy. These results are interesting, as we would expect an increase in immigration with a positive business cycle shock. This could be due to an increase in labor force participation amongst natives, which will reduce the demand for immigrant workers. The flexible natives will take on the jobs that initially would attract immigrants.

4.2 A wage bargaining shock

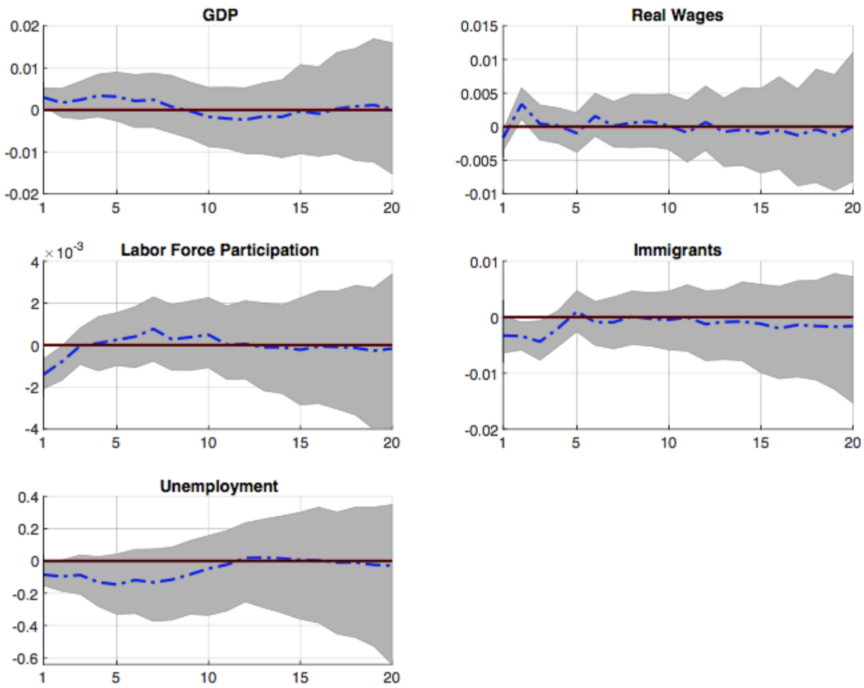

Figure 4. Impulse response to a one-standard-deviation wage bargaining shock. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

A wage bargaining shock seems to have negative effect on immigration for a small period. The maximum effect is seen after a few quarters, likely because immigrants need time to adjust. The decrease in immigration could both be due to a less attractive market for immigrants, but also to a lower demand for immigrant workers in Sweden.

Our results indicate that what we see is likely not a wage bargaining shock, but rather a technology shock. The results we see are in line with the effects of a temporary increase in productivity. Gali (1999) find that a technology shock that increases productivity will lead to a temporary decrease in demand for human labor. There are two effects on the real wage; a lowered demand for labor and an increase in productivity. This will first lead to a decrease in the real wage, before it increases. As the demand for labor decreases, this will also affect the demand for immigrant labor, which would be the reason why we see a decrease in immigration.

4.3 A domestic labor supply shock

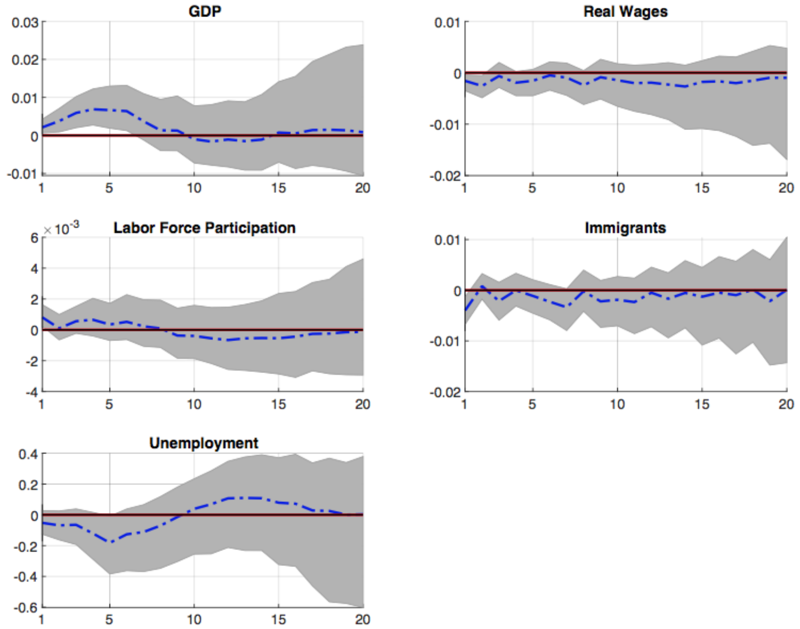

Figure 2. Impulse response functions to a one-standard-deviation domestic labor supply shock. The dashed-dotted line represents the posterior median at each horizon, and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

An expansionary domestic labor supply shock has persistent effects on output, which increase on impact and return to baseline after a few quarters. We see a small decrease in immigration on impact, but it quickly returns to baseline. This is logical as when more natives contribute to the labor force; there will be less room for immigrants. When labor force participation is low amongst natives, for example due to more people taking higher education, there are bigger opportunities for immigrants in the labor market. There is also a small reaction in real wages, but this is, however, barely significant.

The response in unemployment is somewhat puzzling. Usually, when someone decides to take a job, they need to register as a job seeker first. Therefore, an increase in unemployment would seem natural. However, the effect on labor force participation dies out almost immediately, reflecting an absorbing effect in the Swedish economy.

4.4 An immigration shock

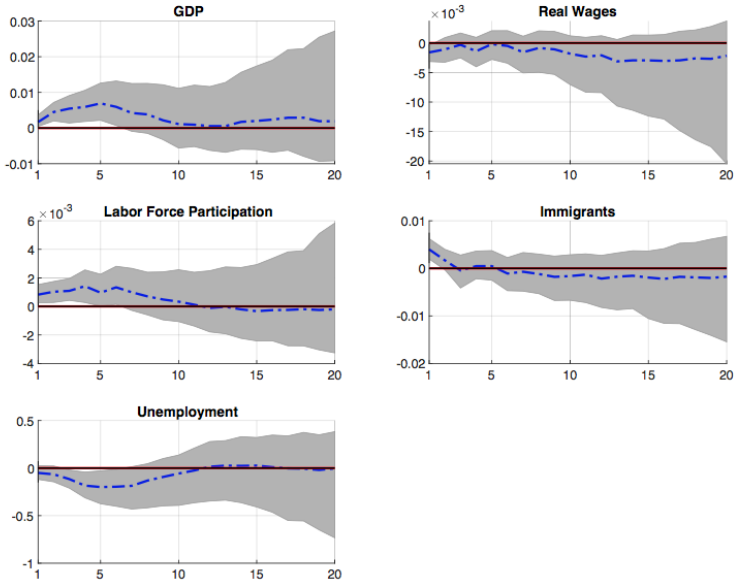

Figure 1. Impulse response functions to a one-standard-deviation immigration shock. The dashed-dotted line represents the posterior median at each horizon, and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

An expansionary immigration shock has persistent effects on GDP, the participation rate and unemployment. There is, however, no persistent effect on real wages. Output and participation increase on impact and stay above baseline for a few quarters. Because we are studying labor immigration, this is a natural result and is consistent with our restrictions. Immigrants come to Sweden to work, which in turn increase participation and output. Further, we see an unexpected decrease in unemployment. However, the same results are found by Armstrong and McDonalds (2016) and Boubtane et al. (2015). One explanation for this may be that immigrants come to Sweden already with a job offer and enter the labor market as employed. Another explanation may be that the immigrants are complementary to the native workers. The immigrants can release native workers from their jobs, letting natives take on other kinds of jobs, or cover a lack of employees in a particular occupational group at the time. If we take it a step further, we could explain the fact that the unemployment rate decreases with a delay, because the higher economic activity created leads to increased hiring. Employers experience an improvement in their business and need to hire more people. This explanation is supported by the fact that unemployment also goes down when we only consider native workers, jf. figure 11. New fellow countrymen require more supermarkets, more houses etc., creating more jobs.

4.5 The median forecast error variance decomposition

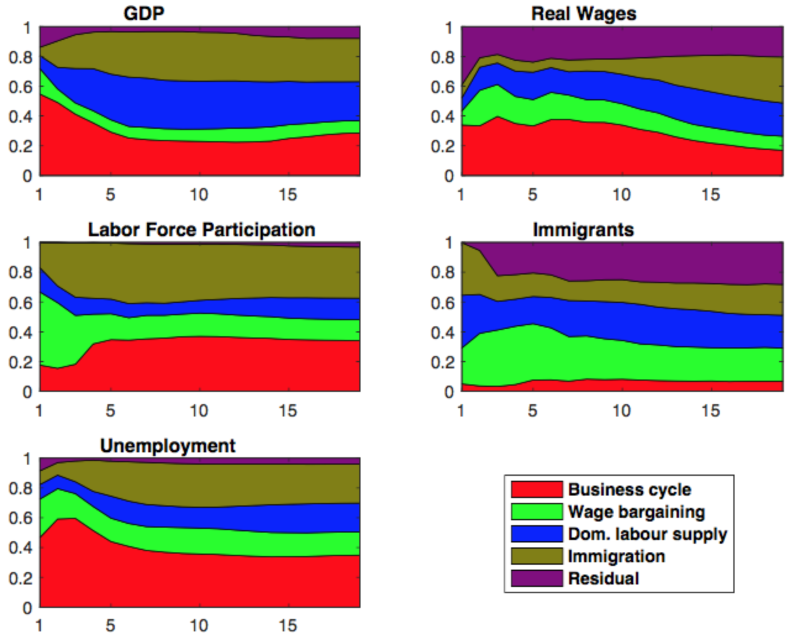

Figure 5. Median forecast error variance decomposition at each horizon in the model.

In figure 5, we see the variance decomposition across different horizons as derived from our model. When we look at the variance decomposition for immigration, we see how the wage bargaining shock plays an essential role in the immigration rate. Not surprisingly does the domestic labor supply shock account for much of the variation in immigration. The business cycle shock, however, has little effect, which tells us that the general state of the economy is somehow irrelevant for immigration. The residual shock can explain the last part of the drivers of immigration. This shock moves output, real wages and unemployment in the same direction. This can, with our assumptions, be interpreted as a productivity or technology shock where e.g. a robot replaces a human.

Seen from a different perspective, we see that in our model, the immigration shock accounts for a big part of the variation in both GDP, the participation and unemployment. This tells us that immigration influences the Swedish economy. We see that the immigration shock accounts for about ⅓ of the variation in the participation rate, where the response is a boost in participation given an expansionary immigration shock.

5. Norway and Sweden

Norway and Sweden are similar countries in many ways - the culture, the demographics, the laws and the environment, to mention some. Both countries have a strong wage negotiation system and a powerful social democratic welfare state. With so many similar political and social commonalities between the countries, we are getting as close to a natural experiment as possible (Pettersen & Østby, 2013). Some key factors that make Sweden and Norway comparable are the strong ALMP`s, policies that make it easier to stay out of unemployment (Ho & Shirono, 2015).

However, there are also some differences between the two countries. While Sweden has by far the largest share of immigrants among the northern countries, Norway has the highest share of labor immigration (Pettersen & Østby, 2013). The difference is clearly seen in the aftermath of the EU enlargement. While immigration from EU countries is more stable in Sweden, we see a boom in Norway after 2005 (Ho & Shirono, 2015). Nevertheless, the wage level has traditionally been higher in Norway than in Sweden. Norway is also a popular country for young, Swedish workers. In 2013 there were more than 55 000 swedes employed in Norway (Langberg, 2015).

To investigate the similarities and differences of the macroeconomic response of an immigration shock in Norway and Sweden, we compare the impulse response functions and the median forecast error variance decomposition from our SVAR model. This will help us detect possible differences and similarities. This analysis is useful in order to understand immigration patterns and the connection to the macroeconomic variables for the two countries. It is important to state that Furlanetto and Robstad (2019) has used a data set with more observations than us. Their data set has 98 quarters, from 1990Q1 - 2014Q2, while our data set has 55 quarters from 2005Q2 - 2018Q4. This makes the impulse response functions for Norway appear smoother and slimmer, due to more data points to estimate from.

5.1 A business cycle shock

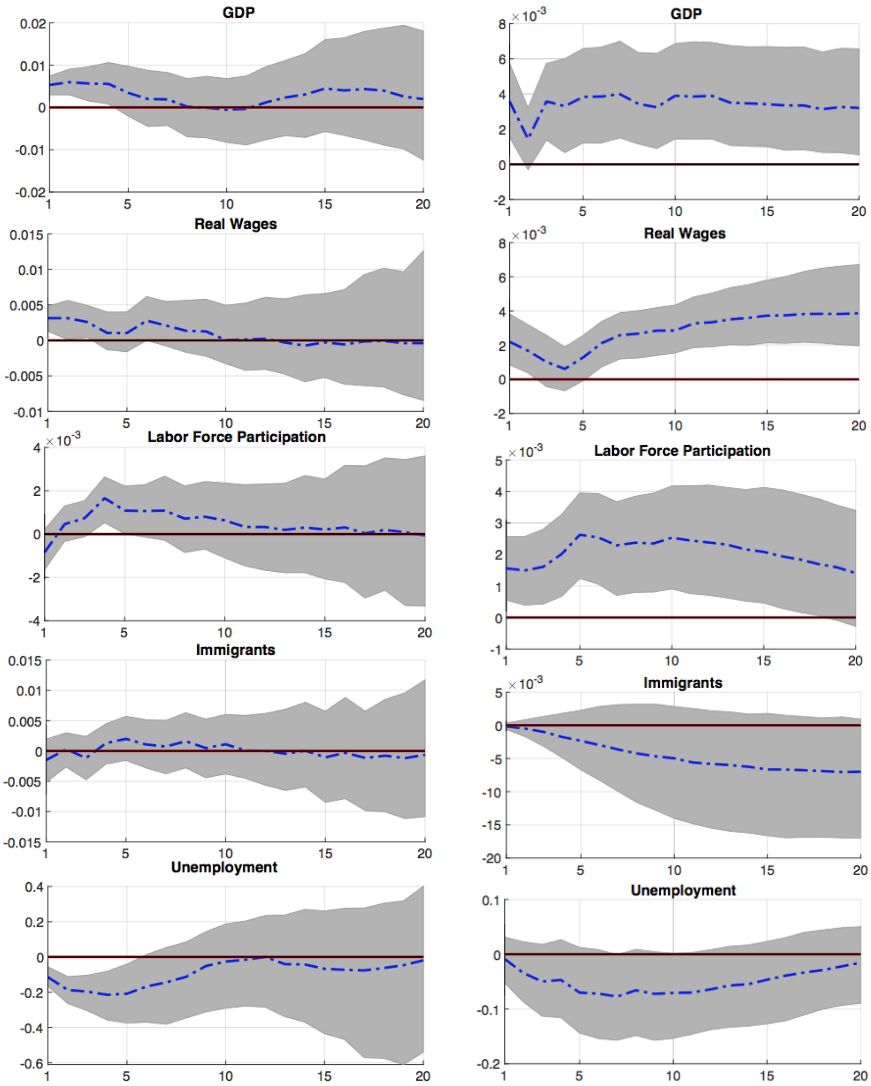

Figure 7. Impulse response functions to a one-standard-deviation business cycle shock. The dashed-dotted line represents the posterior median at each horizon, and the shaded area indicates the 68th posterior probability region of the estimated impulse responses. Sweden on the left-hand-side and Norway on the right.

For the business cycle shock, we observe quite different results in the two countries. The first thing to notice is that the Norwegian business cycle shock causes significant persistent effects on both output, real wages and participation, while there is no significant effect on immigration and unemployment. Immigration in Sweden is also unaffected by the business cycle shock, which tells us that immigration is not particularly affected by the state of the economy in any of the countries. GDP increase on impact in both countries, but the shock is less persistent in Sweden. This may witness that the Swedish economy is more absorbent of the state of the business, whereas Norway is more responsive to changes in the business cycle.

Furthermore, there is only a small response in Swedish real wage, which dies out almost immediately. Real wages in Norway, on the other hand, increases and stays above baseline for more than 20 quarters. Again, we observe that the Norwegian economy is more responsive to changes in the business cycle, this time in terms of wages. This may witness that when economic times are good, there is a higher increase in wages in Norway than in Sweden, reflecting that employers are more dynamic in Norway. Stronger unions that make wages more cyclical could be a factor.

The same pattern can also be observed in the participation rate. Sweden has a minimal increase in the participation rate, while we see a more persistent response in Norway. The boom of people who suddenly want to work lasts longer in Norway, reflecting the other variables such as the persistence of the shock itself and the increased wage level, all contributing to higher overall economic activity.

While unemployment in Norway has no significant change, unemployment in Sweden decrease on impact and stays below baseline for a few quarters. This is a natural effect, as firms need to hire more staff in order to keep the output level increased. The result for Norway can be explained by the fact that participation increases a lot, and therefore the unemployment effect is neutralized when employment increases. Another explanation may be, as we briefly mentioned before, that the increase in participation was from people that were not registered as unemployed in the first place.

5.2 A wage bargaining shock

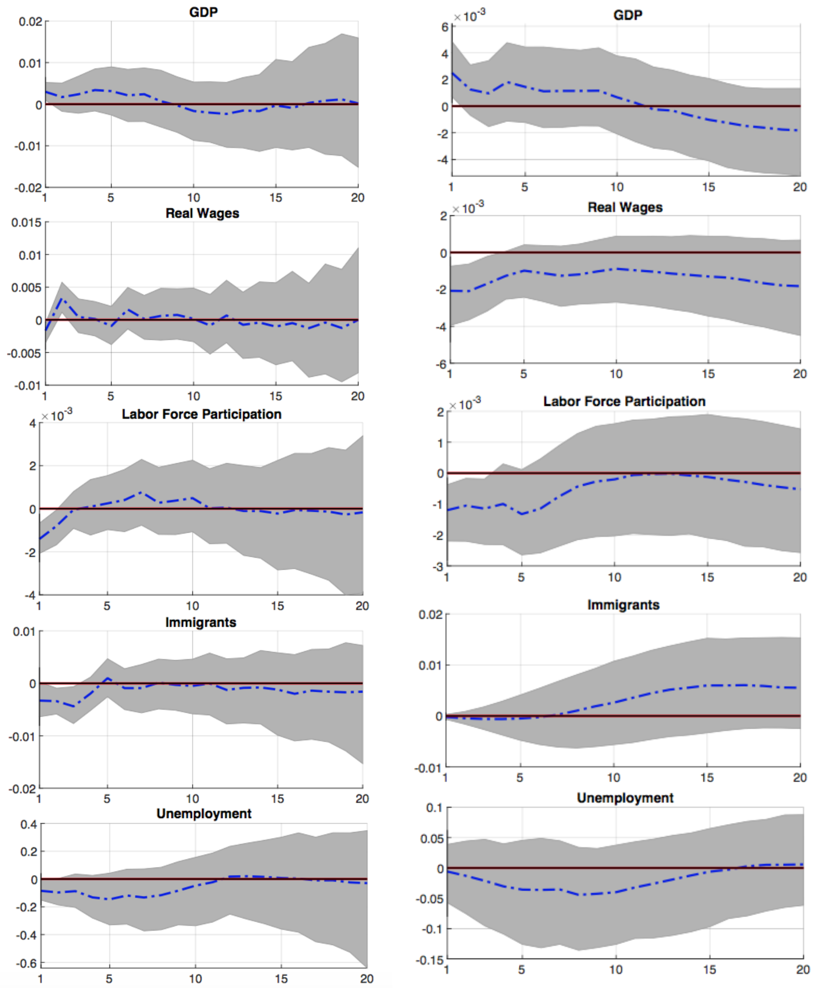

Figure 7. Impulse response functions to a one-standard-deviation wage bargaining shock. The dashed-dotted line represents the posterior median at each horizon, and the shaded area indicates the 68th posterior probability region of the estimated impulse responses. Sweden on the left-hand-side and Norway on the right.

When we compare the results of a wage bargaining shock in Sweden and Norway, they are naturally different, as we are not observing the same shock. While we see a fully identified wage bargaining shock in Norway, we likely have a technology shock in Sweden, as explained in section 4.2. GDP, labor force participation and unemployment seem to behave quite equally in both countries. The effect on wages in purely negative in Norway, while it is first negative before it becomes positive in Sweden. While the results are different, both countries have effects that are in line with excepted outcomes of the respective shocks. A wage bargaining shock has no effect on immigration in Norway, which tells us that immigration is not affected by the changes in wages for natives. This could also be the case for Sweden, as Norway and Sweden have similar wage negotiation systems, but we cannot draw any conclusion based on our results.

5.3 A domestic labor supply shock

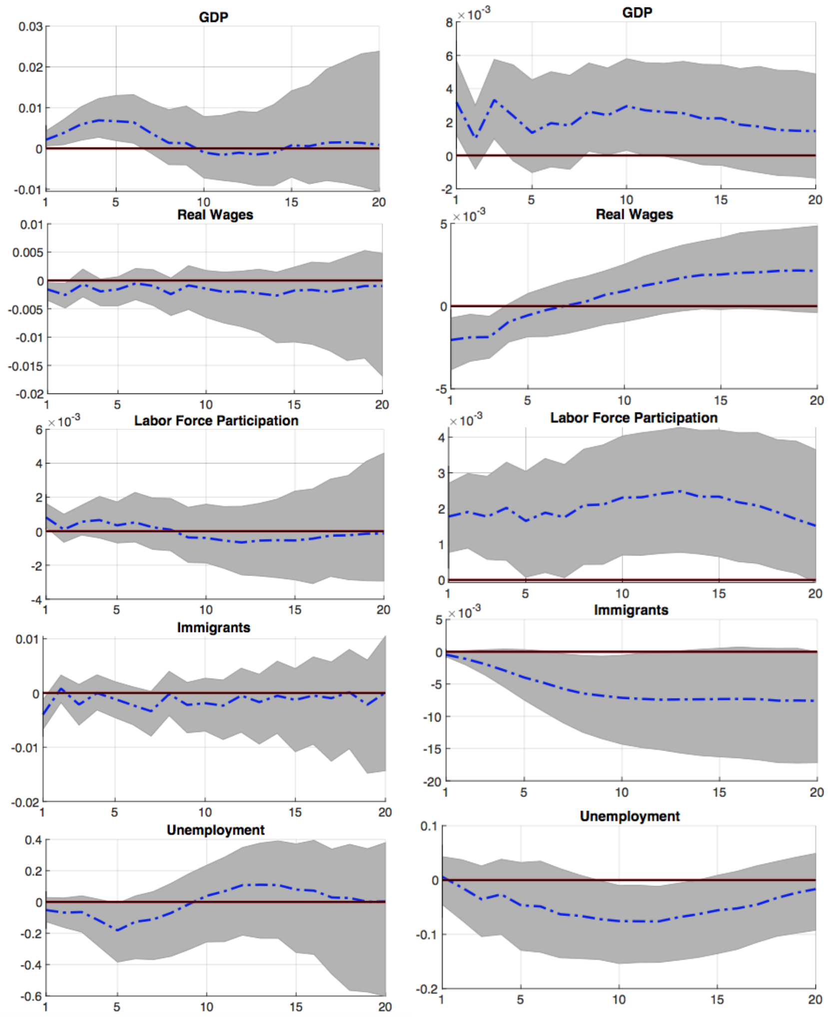

Figure 7. Impulse response functions to a one-standard-deviation domestic labor supply shock. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses. Sweden on the left-hand-side and Norway on the right.

Next, we compare the impulse response functions to a one-standard-deviation domestic labor supply shock in the two countries. Also, here, the movements are generally similar. However, the response of a domestic labor supply shock on output is somewhat more prominent in Sweden. For Norway, real wages decline on impact before returning to baseline after a few quarters. For Sweden, there is no significant change in real wages. This tells us that a boom in participation leads to a lower wage level in Norway the first year after the boom, but the same thing cannot be observed for Sweden. In both countries, there is almost no significant effect on immigration from a domestic labor supply shock. There is a small decrease in Norway after a few quarters and a small, but significant, decrease on impact in Sweden.

For Norway, we observe a delayed decline in unemployment lasting for about a year. As we discussed earlier, one would usually expect an increase in unemployment after a participation boom, since the participants usually would need to register as unemployed first. However, since Furlanetto and Robstad (2019) used unemployment statistics from NAV, the participants would not be recognized as unemployed on their rate. For Sweden, on the other hand, there is no significant response, suggesting an unchanged unemployment rate in response to a boom in participation.

5.4 An immigration shock

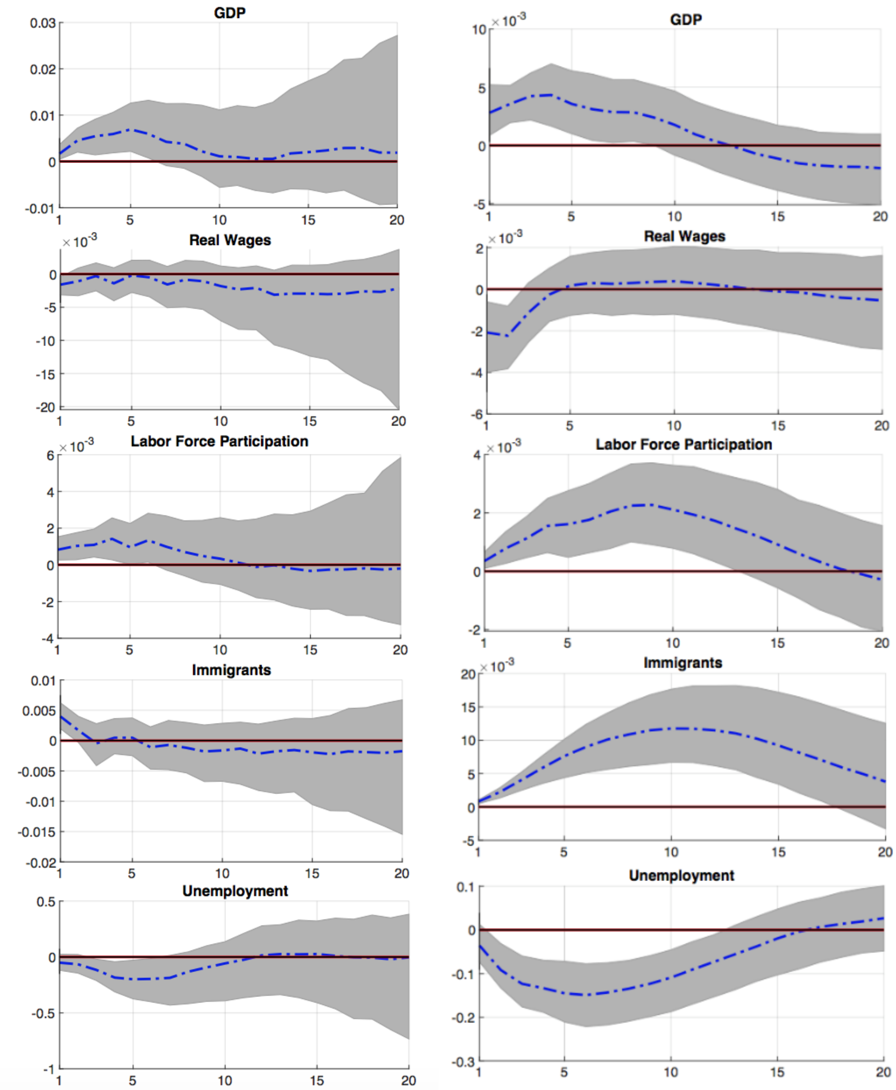

Figure 6. Impulse response functions to a one-standard-deviation immigration shock. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses. Sweden to the left-hand-side and Norway on the right.

We compare the impulse response functions of a one-standard-deviation immigration shock in Sweden and Norway. As a first observation, we can see that the impulse response curves move in the same direction in both countries, implying quite similar responses, as one would expect.

For both countries, GDP increases on impact, before the effect dies out within 3 years. The increase on impact seems to be pretty similar in both countries but lasts longer in Norway. This effect is in line with economic theory. In other words, a flow of labor immigrants will increase output in the respective country.

For Norway, there is a small decrease in the real wage. For Sweden, however, there is no significant change in the real wage. This could be explained by the traditionally higher wages in Norway, and that immigrants might be offered a lower wage.

The participation rate has quite a different shape in the two countries. While the participation rate in Sweden only has a small increase and quickly returns to baseline, the participation rate in Norway has a more persistent effect. This witness, as we have already mentioned, that participation in Norway is more volatile and may react strongly to an event, like for example an immigration shock. The participation rate in Sweden is more stable and do not react as much.

Also, for immigration, we observe quite different effects in the two countries. In Sweden, there is an increase on impact, before it shortly after returns to baseline, and the effect dies out. For Norway, however, the function starts in baseline and gradually increases, reaching its top point after about 3 years, before it declines back to baseline. The effects of an immigration shock on immigration itself therefore has greater importance in Norway. The hump-shaped response in immigration may be due to family reunifications, registration delays or network effects (i.e. immigrants from the same countries tend to follow each other). The same continued flow is not observed for Sweden, following our results. This is a bit puzzling, as one would expect to see some of the same effects for Sweden, for there is no reason to believe that families do not reunite in Sweden.

Finally, for the unemployment rate, we can observe quite similar effects. We see that there is a significant decline on impact in Norway, while the effect in Sweden is delayed. Either way, an immigration flow will reduce unemployment in the respective country, according to our results.

5.5 The median forecast error variance decomposition

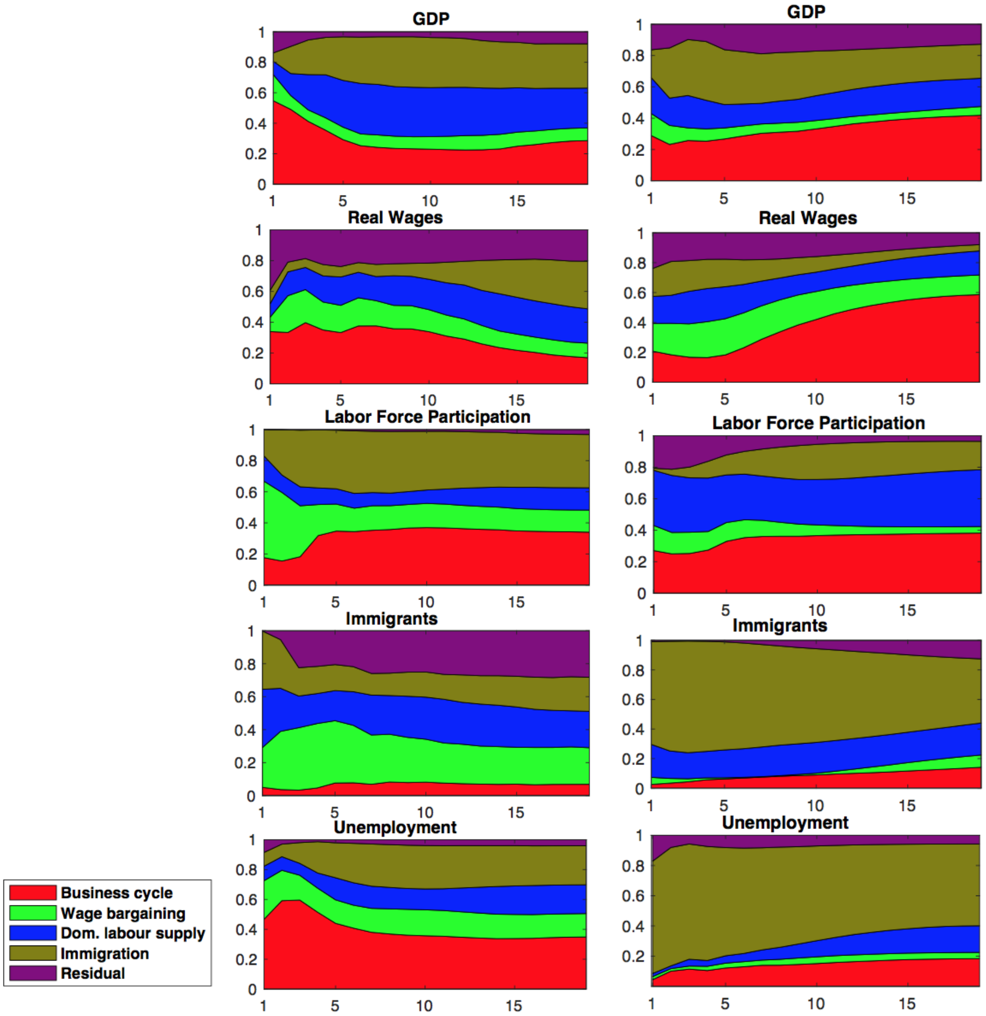

Figure 10. Median forecast error variance decomposition at each horizon in the model. Sweden on the left-hand-side and Norway on the right.

Finally, we compare the median forecast error variance decomposition. This is where our result differs the most from the Norwegian results and the reason why we chose to make changes in the identification strategy. We see how the residual shock gains more importance in Sweden, which causes for some explanation.

For both countries, we can see that GDP is driven quite equally by all variables. However, the business cycle seems to be a more significant driver of Norwegian GDP, whereas the three labor market shocks seem to account for most of the variation in Swedish GDP.

The same observation can, to some extent, also explain the variation in real wages. The business cycles seem to play a more prominent role for real wages than GDP in the long run. The residual shock also seems to gain some more importance in Sweden.

As for the labor force participation, a great part of both countries' variation can be explained by the business cycle shock. The rest of the variation for Sweden is mainly explained by the immigration shock, whereas the domestic labor supply counts for most of the rest of the variation in Norwegian participation.

The next observation is quite interesting as the immigration to Norway is mainly driven by its own shock and immigration to Sweden is mainly driven by the three labor market shocks and the residual shock. The results may indicate that immigrants are less dependent on each other in Sweden than in Norway. In Norway, we see how immigrants tend to follow each other and bring their whole family (family reunification), while this might not be the case for Sweden.

Finally, the fluctuations in unemployment in Norway can be almost entirely explained by the immigration flow. Only a small part can be explained by the business cycle and the domestic labor supply. For Sweden, on the other hand, the unemployment fluctuations can be explained by the business cycle and the three labor market shocks.

6. Conclusion

In this paper, we have used a Structural Vector Autoregressive (SVAR) Model to try to disentangle the drivers of immigration and the impact of immigration shocks on a set of macroeconomic variables in the Swedish economy. With this paper, we wish to contribute with an aggregate analysis on business cycle fluctuations and implications for macroeconomic policies in response to an exogenous immigration shock. We find that an expansionary immigration shock increase output and participation, lower unemployment (even among native workers) and do not affect real wages. Moreover, a domestic labor supply shock has a positive effect on output, but puzzling enough, no significant effect on the unemployment rate. A positive business cycle shock has no significant effect on immigration, implying that immigration reacts little to the state of the Swedish economy. Furthermore, we find that a positive wage bargaining shock has a negative effect on immigration. Finally, through the variance decomposition, we find that immigration can be explained by equal parts of the immigration shock itself, wage bargaining, labor force participation and the residual component. The business cycle, on the other hand, does not seem to impact immigration considerably. When we look at it the other way, we find that the immigration shock accounts for a considerable part of the variation in both GDP, the participation rate and the unemployment rate. Real wages, however, is not noteworthily impacted by immigration.

We conclude our analysis on Sweden with a comparison to Norway, based on the results in Furlanetto and Robstad (2019). We find that the effects of immigration are quite similar in the two countries. However, to point out some differences, we find that the immigration shock is more persistent in Norway, whereas it dies out almost immediately in Sweden. Furthermore, in response to the immigration shock, the unemployment rate in Norway declines on impact while the unemployment in Sweden declines with a delay. Finally, we find that the Norwegian business cycle shock itself is much more persistent than the Swedish business cycle shock, and also creates larger effects in real wages and participation than in Sweden. Swedish unemployment decrease (as one would expect), while Norwegian unemployment is, somewhat puzzling, unaffected by the positive business cycle shock.

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Appendix

AAKI	Labour force
AALI	Unemployed
ASY	Employed
AUAI	Outside the labour force
ABF	Population
ins	Born in Sweden
uts	Born outside of Sweden
AF	Born in Africa
EN	Born in Europe
NM	Born in North America
AS	Born in Asia
OV	Other
SM	South America

	AAKI1574INS	AAKI1574UTS	AALI1574INS	AALI1574UTS	ABF1574INS	ABF1574UTS	AALIEN	AALINM
2005Q2	4085,18667	625,47	285,146667	85,94	5686,696667	968,443333	35,5	1,5
2005Q3	4080,29	629,0266667	273,75	91,6866667	5696,68	972,343333	34,2	2,3
2005Q4	4103,06667	631,65	272,213333	88,7033333	5707,046667	976,316667	33,7	2,1
2006Q1	4096,52	640,5566667	266,65	88,3333333	5716,526667	984,786667	37,7	2,5
2006Q2	4105,86333	645,7066667	259,486667	87,58	5725,15	998,716667	39	2,1
2006Q3	4129,94	652,02	247,96	80,9	5731,75	1010,33333	31,7	1,7
2006Q4	4128,26667	661,37	230,983333	82,7833333	5740,436667	1018,22667	34,2	0,9
2007Q1	4152,91667	664,3033333	227,806667	80,81	5748,24	1027,20667	32,7	0,8
2007Q2	4146,17333	674,22	215,06	77,3566667	5756,416667	1037,22	32	1,9
2007Q3	4164,23667	687,4833333	209,146667	80,98	5763,236667	1049,07667	32,3	2
2007Q4	4171,65	697,1633333	211,133333	83,9466667	5769,713333	1059,43667	31,7	1,1
2008Q1	4175,25	705,7833333	203,393333	83,0966667	5777,94	1073,31	34,8	0,9
2008Q2	4181,56667	719,9533333	208,923333	85,0666667	5786,693333	1082,80333	38,2	1,9
2008Q3	4177,20333	720,3366667	215,996667	86,2433333	5794,793333	1092,23667	31,1	1,5
2008Q4	4176,1	733,4633333	237,063333	91,7933333	5801,556667	1106,73333	33,6	2
2009Q1	4162,82667	742,3666667	261,976667	102,646667	5807,906667	1118,04	39,2	2,4
2009Q2	4169,4	747,1666667	296,166667	115,503333	5815,603333	1129,41	44,9	2
2009Q3	4134,05667	755,06	306,98	114,9	5822,703333	1142,45	42,7	2,4
2009Q4	4150,53	765,9666667	311,996667	120,2	5828,88	1155,80667	41,2	3,5
2010Q1	4154,45333	769,98	318,53	121,183333	5834,723333	1165,5	47,3	2,5
2010Q2	4167,23	776,2966667	306,006667	127,053333	5838,456667	1175,52333	48	1,5
2010Q3	4166,13333	789,0933333	293,62	128,743333	5842,6	1184,48	43,4	1,8
2010Q4	4167,72	795,8433333	271,873333	130,506667	5846,473333	1197,22667	45,9	2,7
2011Q1	4182,99	817,67	259,776667	133,83	5848,99	1207,26	48,9	1,8
2011Q2	4193,62	821,1266667	256,36	134,15	5849,366667	1218,72	48,1	2
2011Q3	4184,39333	829,6333333	250,67	133,17	5850,963333	1229,05333	45	2,4
2011Q4	4194,83667	838,01	259,98	131,036667	5853,36	1235,54333	43,4	2,1
2012Q1	4189,73333	838,7866667	257,443333	130,97	5855,273333	1243,98333	46,7	2
2012Q2	4200,16333	852,7033333	266,476667	130,3	5856,82	1252,84667	44,8	2,1
2012Q3	4208,63667	858,17	271,716667	138,86	5857,996667	1262,65667	44,5	2,6
2012Q4	4209,84667	872,4366667	271,076667	143,73	5856,946667	1272	47,8	2,9
2013Q1	4211,63667	880,5033333	269,783333	142,153333	5856,67	1282,9	51	2,3

2013Q2	4210,05333	894,6366667	270,73	138,816667	5856,156667	1294,45333	45,2	2,7
2013Q3	4219,16	898,1333333	260,89	147,72	5855,7	1305,99333	45,3	2,1
2013Q4	4232,87	909,57	258,51	151,293333	5855,8	1316,32667	46,7	3,1
2014Q1	4224,16	920,8866667	264,04	151,06	5853,853333	1330,52333	50,3	2,8
2014Q2	4229,8	939,95	254,703333	157,083333	5853,346667	1345,36333	52,5	2,3
2014Q3	4248,72667	962,0233333	254,943333	153,93	5853,376667	1359,36333	41,5	2,8
2014Q4	4233,66	968,9066667	256,37	150,586667	5851,236667	1374,51	39,4	2,5
2015Q1	4229,85333	985,0166667	243,203333	160,963333	5849,73	1386,37333	46,8	2,4
2015Q2	4223,39667	992,8233333	235,693333	163,673333	5849,223333	1400,36667	46,8	1,9
2015Q3	4230,62333	993,5766667	219,996667	151,803333	5847,676667	1416,33667	35,2	2,7
2015Q4	4224,26	1017,183333	209,516667	160,656667	5848,47	1430,98667	37,5	1,1
2016Q1	4231,02	1025,223333	212,776667	163,166667	5848,766667	1445,75	40,6	1,8
2016Q2	4238,75667	1036,543333	202,856667	159,69	5848,913333	1462,25	36,1	3,2
2016Q3	4202,6	1060,046667	194,736667	166,133333	5847,543333	1482,74667	37,5	2,2
2016Q4	4225,53	1084,513333	197,503333	167,446667	5845,563333	1507,88667	34,4	1,5
2017Q1	4234,69	1115,516667	189,51	170,58	5844,136667	1533,64	39,4	2,6
2017Q2	4236,53333	1132,706667	189,873333	169,173333	5840,433333	1554,81	37,7	2,8
2017Q3	4249,26333	1147,433333	187,283333	174,76	5838,28	1572,61	36,8	2,3
2017Q4	4251,26333	1149,236667	177,53	175,013333	5834,996667	1591,78	38,1	2,2
2018Q1	4258,29333	1161,496667	162,423333	174,57	5831,19	1609,87	36,4	2,6
2018Q2	4251,77333	1186,616667	155,336667	184,656667	5826,75	1627,24667	33,4	2,9
2018Q3	4264,89	1206,636667	168,79	186,846667	5822,353333	1645,01	35	3,1
2018Q4	4273,16	1220,956667	153,653333	186,443333	5819,716667	1659,78333	34,8	2,9

Table 3. Swedish labor market data on natives and immigrants provided to us by researcher in Riksbanken Mårten Löf.

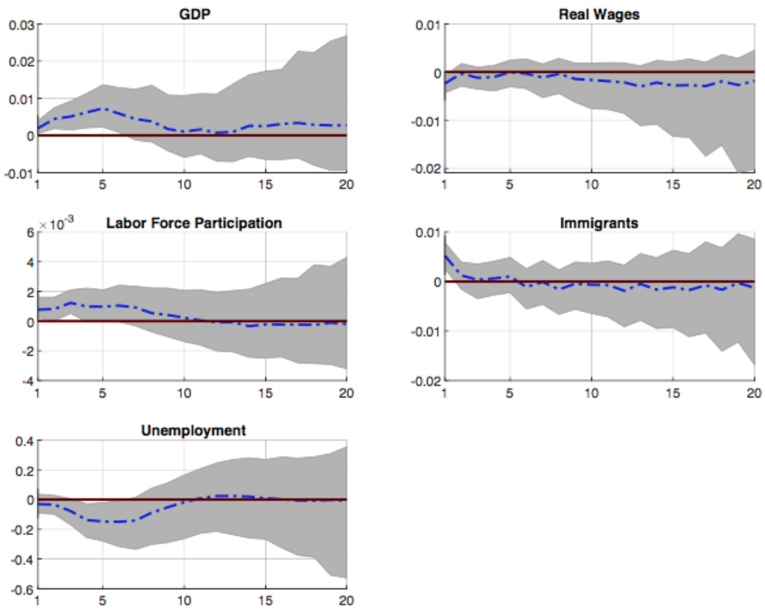

Figure 11. Impulse response functions to an one-standard-deviation immigration shock with only native unemployment.

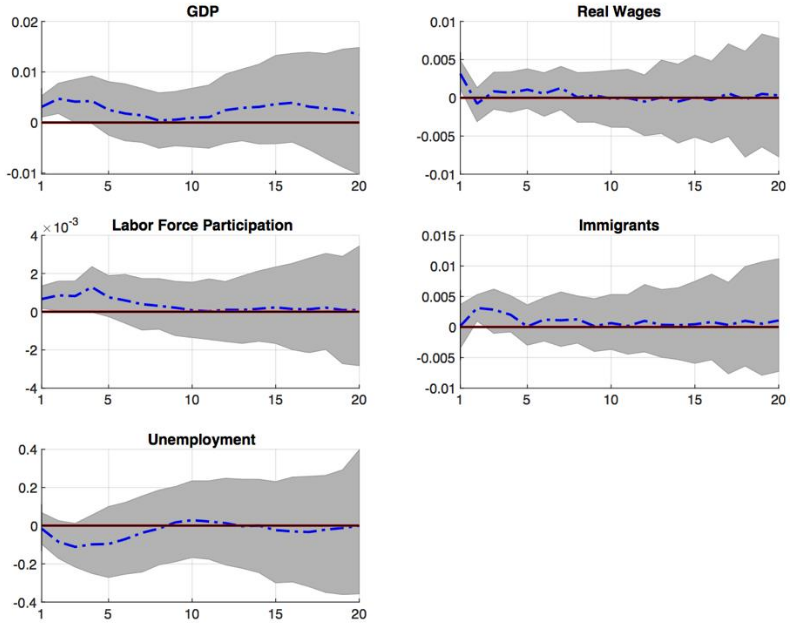

Figure 12. Impulse response functions to a one-standard-deviation business cycle shock with the original sign restrictions. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

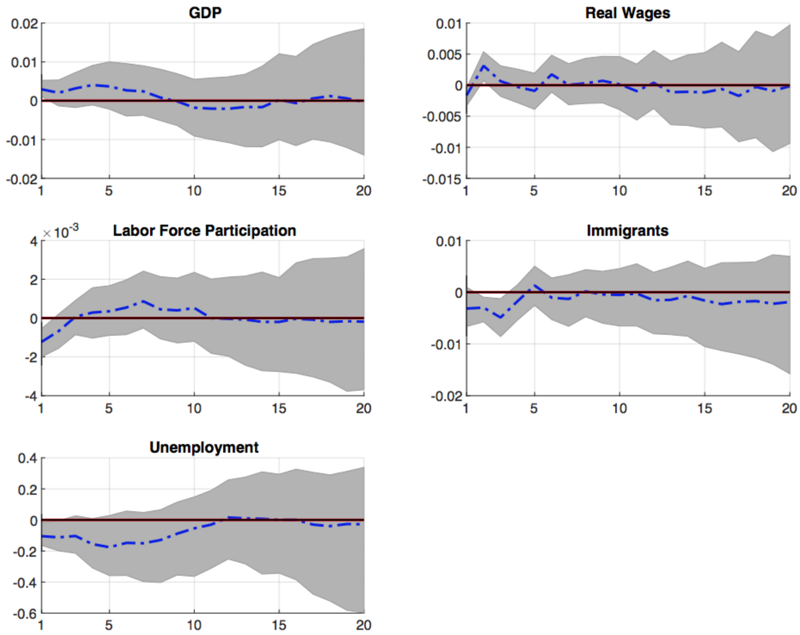

Figure 13. Impulse response functions to a one-standard-deviation wage bargaining shock with the original sign restrictions. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

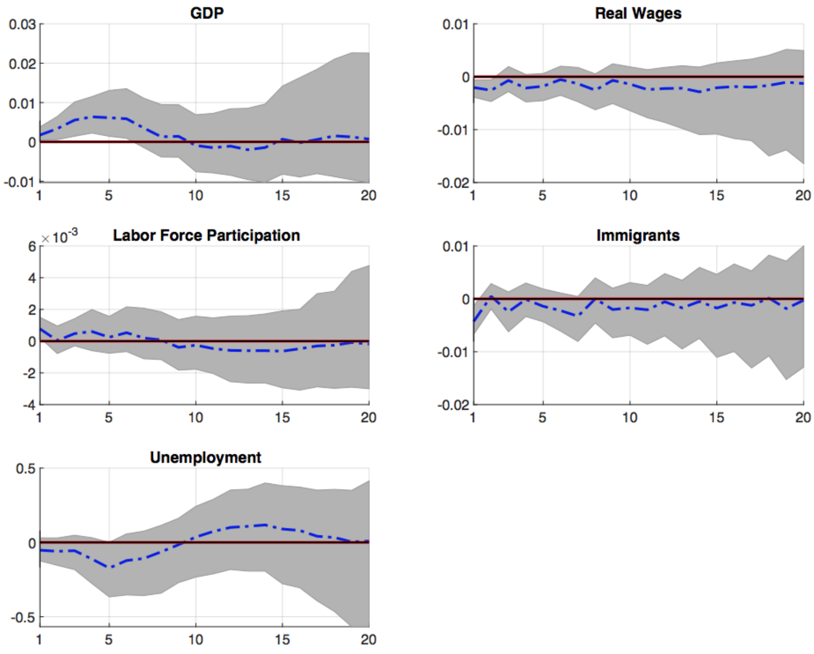

Figure 14. Impulse response functions to a one-standard-deviation domestic labor supply shock with the original sign restrictions. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

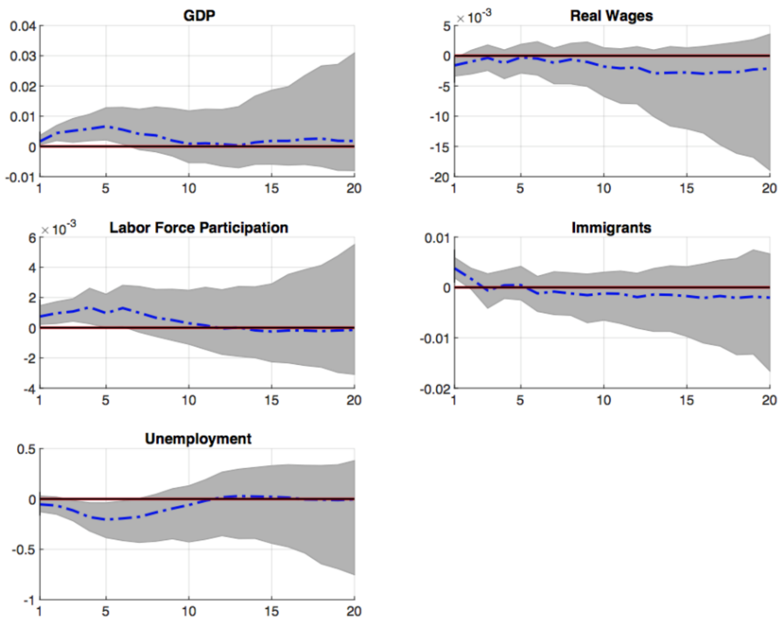

Figure 15. Impulse response functions to a one-standard-deviation immigration shock with the original sign restrictions. The dashed-dotted line represents the posterior median at each horizon and the shaded area indicates the 68th posterior probability region of the estimated impulse responses.

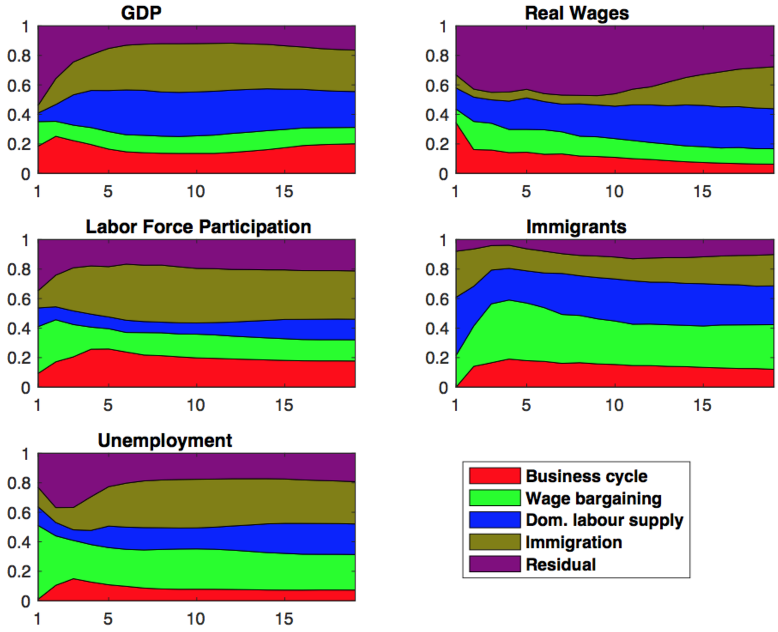

Figure 16. Median forecast error variance decomposition at each horizon in the model, with the original sign restrictions.

```
% Baseline model of Furlanetto Robstad 2016 Based on constant Coefficient Version of Foroni, Furlanetto and Lepetit (2014) % The code is using paralell programing on matlab 2014.
clear all
clc
%bol.sample=1;
bol.sign=0;    % 1: IY restricted or not (TO BE CHANGED FOR FFL)
bol.unrestricted=0;
addpath('procs');
%load database_mei
database=xlsread('data_baseline1');
data=database(:,1:5);%    %Ordering: GDP  REAL WAGES PARTICIPATION IMMIGRANT RATE UNEMPLOYMENT RATE
%% VAR-Analysis with sign restricions
p=5; %number of lags
xt=data;
T=size(xt,1);
N= size(xt,2);
y =xt;
sel=2;
maxd    = 2980;
b_sel=1001:sel:maxd;
drawfin=size(b_sel,2);
%clus = parcluster('HFC_R2014a_Big');
%pp = parpool(clus,22);
% Starting draws
parforw=1:maxd+1  %
%w
[Phi_all_f_1,b, Q,nx,ut,bfo] = VARmin(y,p,1,[0 0]);
b_a(:,:,w)      = b;
Q_a(:,:,w)      = Q;
PhiVAR_a(:,:,:,w) = Phi_all_f_1;
ut_a(:,:,w)     = ut;
bfo_a(:,:,w)    = bfo;
end
b_a = b_a(:,:,b_sel);
Q_a = Q_a(:,:,b_sel);
PhiVAR_a = PhiVAR_a(:,:,:,b_sel);
```

```
ut_a       = ut_a(:,:,b_sel);
bfo_a      = bfo_a(:,:,b_sel);
save results_baselineb_aQ_aPhiVAR_aNmaxdxtdrawfinut_abfo_a
load results_baselineb_aQ_aPhiVAR_aNmaxdxtdrawfinut_abfo_a
%FR_identification %% tatt bort
%delete(gcp);
%   Calculates impulse responses
%clc;clear;
tic
s = RandStream('mrg32k3a');
RandStream.setGlobalStream(s);
%%  General settings
K          = N;
draws      = drawfin; %
numbercore=2;  %
process_draws = draws/numbercore; %Furlanetto_robstad
horizon     = 20; % number of steps for impulse responses
alpha       = 1;
HK          = 1; % number of restricted periods after shock
candd       = zeros(K,K,horizon,alpha);
response    = struct('f',zeros(K,K, horizon,draws*alpha),'unique',zeros(K,K, horizon),'ratio_alpha',0);
vardec      = struct('unique',zeros(K,K, horizon-1));
response      =     struct('f',zeros(K,K,     horizon,draws*alpha),'median',zeros(K,K,     horizon),'mean',zeros(K,K,
horizon),'unique',zeros(K,K, horizon),'ratio_alpha',0);
vardec      =    struct('f',zeros(K,K,    horizon-1,draws*alpha),'median',zeros(K,K,    horizon-1),'mean',zeros(K,K,
horizon-1),'unique',zeros(K,K, horizon-1));
w_text      = 'resp.m';
ratio_alpha=0;
ratio_alpha_Tot = 0;
parfors=1:numbercore %
  initialvalue=(s-1)*process_draws+1;
  finalvalue=s*process_draws;
  forw = initialvalue:finalvalue
     disp(w)
     %

     A1          = chol(Q_a(:,:,w))';

     impres_alpha=NaN(N,N,horizon,alpha);
     index_alpha=zeros(1,alpha);
     HT_inverse=NaN(N,N,alpha);
     A2=PhiVAR_a(:,:,:,w);

     forix= 1:alpha
        WW = mvnrnd(zeros(N), eye(N));
            [Qr Rr] = qr_frs(WW);
          HT = Qr;
        bqrloop       = A1*HT;
            HT_inverse(:,:,ix)=-Qr;
              bqr = reshape( bqrloop,N,N);
             candd = impulsdtrf( A2,(bqr),horizon);

        % Ordering variables: Ordering: GDP, Real wage, Labor participation,
        % immigration, unemployment
             % Ordering shocks: Business cycle, Wage bargaining, Dom Labor
        % supply, immigration, residual

       if  (min(candd(1,1,1:HK)) > 0) && ...
              (min(candd(2,1,1:HK)) > 0) && ...
              (max(candd(5,1,1:HK)) < 0) && ...
              (min(candd(1,2,1:HK)) > 0) && ...
              (max(candd(2,2,1:HK)) < 0) && ...
              (max(candd(3,2,1:HK)) < 0) && ...
              (min(candd(1,3,1:HK)) > 0) && ...
              (max(candd(2,3,1:HK)) < 0) && ...
```

```
        (min(candd(3,3,1:HK)) > 0) && ...
        (max(candd(4,3,1:HK) - candd(3,3,1:HK)) < 0) && ...
        (min(candd(1,4,1:HK)) > 0) && ...
        (max(candd(2,4,1:HK)) < 0) && ...
        (min(candd(3,4,1:HK)) > 0) && ...
        (min(candd(4,4,1:HK) - candd(3,4,1:HK)) > 0) && ...
        (min(candd(1,5,1:HK)) > 0) && ...
        (min(candd(2,5,1:HK)) > 0) && ...
        (min(candd(5,5,1:HK)) > 0)

      impres_alpha(:,:,:,ix)= candd;
      index_alpha(1,ix)=2;
      ratio_alpha=ratio_alpha+1;


     elseif(max(candd(1,1,1:HK)) < 0) && ...
        (max(candd(2,1,1:HK)) < 0) && ...
        (min(candd(5,1,1:HK)) > 0) && ...
        (max(candd(1,2,1:HK)) < 0) && ...
        (min(candd(2,2,1:HK)) > 0) && ...
        (min(candd(3,2,1:HK)) > 0) && ...
        (max(candd(1,3,1:HK)) < 0) && ...
        (min(candd(2,3,1:HK)) > 0) && ...
        (max(candd(3,3,1:HK)) < 0) && ...
        (min(candd(4,3,1:HK) - candd(3,3,1:HK)) > 0) && ...
        (max(candd(1,4,1:HK)) < 0) && ...
        (min(candd(2,4,1:HK)) > 0) && ...
        (max(candd(3,4,1:HK)) < 0) && ...
       (max(candd(4,4,1:HK) - candd(3,4,1:HK)) < 0) && ...
       (max(candd(1,5,1:HK)) < 0) && ...
       (max(candd(2,5,1:HK)) < 0) && ...
       (max(candd(5,5,1:HK)) < 0)

      index_alpha(1,ix)=1;

    end
   ratio_alpha_Tot=ratio_alpha_Tot+1;
end

ifmax(index_alpha)==1
   correction=find(index_alpha==1);
   forix=1:size(correction,2)
      HT=reshape(HT_inverse(:,:,correction(ix)),N,N);
      bqr =A1*HT;

      candd = impulsdtrf( PhiVAR_a(:,:,:,w),(bqr),horizon);
      impres_alpha(:,:,:,correction(ix))= candd;
      ratio_alpha=ratio_alpha+1;
   end
elseifmax(index_alpha)==0
   forix=1:alpha
      impres_alpha_check=NaN(N,N,horizon);
      while(isnan(impres_alpha_check)==ones(size(impres_alpha_check)))
        WW = mvnrnd(zeros(N), eye(N));

        [Qr Rr] = qr_frs(WW);

        HT = Qr;
        bqr =A1*HT;

       candd = impulsdtrf( PhiVAR_a(:,:,:,w),(bqr),horizon);

        if(min(candd(1,1,1:HK)) > 0) && ...
       (min(candd(2,1,1:HK)) > 0) && ...
       (max(candd(5,1,1:HK)) < 0) && ...
```

```
                (min(candd(1,2,1:HK)) > 0) && ...
                (max(candd(2,2,1:HK)) < 0) && ...
                (max(candd(3,2,1:HK)) < 0) && ...
                (min(candd(1,3,1:HK)) > 0) && ...
                (max(candd(2,3,1:HK)) < 0) && ...
                (min(candd(3,3,1:HK)) > 0) && ...
                (max(candd(4,3,1:HK) - candd(3,3,1:HK)) < 0) && ...
                 (min(candd(1,4,1:HK)) > 0) && ...
                (max(candd(2,4,1:HK)) < 0) && ...
                (min(candd(3,4,1:HK)) > 0) && ...
                (min(candd(4,4,1:HK) - candd(3,4,1:HK)) > 0) && ...
                 (min(candd(1,5,1:HK)) > 0) && ...
                (min(candd(2,5,1:HK)) > 0) && ...
                (min(candd(5,5,1:HK)) > 0)


                  impres_alpha_check= candd;
                   ratio_alpha=ratio_alpha+1;

                 elseif(max(candd(1,1,1:HK)) < 0) && ...
                (max(candd(2,1,1:HK)) < 0) && ...
                (min(candd(5,1,1:HK)) > 0) && ...
                (max(candd(1,2,1:HK)) < 0) && ...
                (min(candd(2,2,1:HK)) > 0) && ...
                (min(candd(3,2,1:HK)) > 0) && ...
                (max(candd(1,3,1:HK)) < 0) && ...
                (min(candd(2,3,1:HK)) > 0) && ...
                (max(candd(3,3,1:HK)) < 0) && ...
                (min(candd(4,3,1:HK) - candd(3,3,1:HK)) > 0) && ...
                 (max(candd(1,4,1:HK)) < 0) && ...
                (min(candd(2,4,1:HK)) > 0) && ...
                (max(candd(3,4,1:HK)) < 0) && ...
                (max(candd(4,4,1:HK) - candd(3,4,1:HK)) < 0) && ...
                 (max(candd(1,5,1:HK)) < 0) && ...
                (max(candd(2,5,1:HK)) < 0) && ...
                (max(candd(5,5,1:HK)) < 0)

                   HT = -Qr;
                   bqr =A1*HT;

                   candd = impulsdtrf( PhiVAR_a(:,:,:,w),(bqr),horizon);
                  impres_alpha_check= candd;
                  ratio_alpha=ratio_alpha+1;
                 end
                ratio_alpha_Tot=ratio_alpha_Tot+1;
                impres_alpha(:,:,:,ix)=impres_alpha_check;
                 %              if ratio_alpha_Tot==5606
                 %                disp('ciao');
                 %              end
              end
           end
        end

        savefile = sprintf('Temp1/Impres_%d',w);
       parsave(savefile,impres_alpha);
    end
end
forsim=1:draws
   filename = sprintf('Temp1/Impres_%d.mat',sim);
  response.f(:,:,:,(sim-1)*alpha+1:sim*alpha)=importdata(filename);
end
delete(gcp)
response.ratio_alpha=ratio_alpha/ratio_alpha_Tot;
% % Calculate statistics
distance_med=zeros(K,K, horizon,draws*alpha);
```

```
forShock=1:K
  forReac=1:K
     fori=1:horizon
        resp_05(Reac,Shock,i)   = prctile(response.f(Reac,Shock,i,:), 5);
        resp_16(Reac,Shock,i)   = prctile(response.f(Reac,Shock,i,:),16);
        resp_50(Reac,Shock,i)   = prctile(response.f(Reac,Shock,i,:),50);
        resp_84(Reac,Shock,i)   = prctile(response.f(Reac,Shock,i,:),84);
         resp_95(Reac,Shock,i)   = prctile(response.f(Reac,Shock,i,:),95);
%
         resp_mean(Reac,Shock,i) =   mean(squeeze(response.f(Reac,Shock,i,:)));
        distance_med(Reac,Shock,i,:)=((squeeze(response.f(Reac,Shock,i,:))-
ones(draws*alpha,1)*resp_mean(Reac,Shock,i))/nanstd(squeeze(response.f(Reac,Shock,i,:)))).^2;
     end% for i
  end% for Reac
end% for Shock
forShock=1:K
 forReac=1:K
     fori=1:horizon-1
%
         vd_05(Reac,Shock,i)   = prctile(vardec.f(Reac,Shock,i,:),5);
         vd_16(Reac,Shock,i)   = prctile(vardec.f(Reac,Shock,i,:),16);
         vd_50(Reac,Shock,i)   = prctile(vardec.f(Reac,Shock,i,:),50);
         vd_84(Reac,Shock,i)   = prctile(vardec.f(Reac,Shock,i,:),84);
         vd_95(Reac,Shock,i)   = prctile(vardec.f(Reac,Shock,i,:),95);
     end% for i
  end% for Reac
end% for Shock
%
% %% unique solution
vardec.median=vardec_sr_new(resp_50);
% save impres response
%% plot impulse responses
FR_plot
toc
% remoteparfor - support for parallel_function.
% Copyright 2013-2018 The MathWorks, Inc.
classdefremoteparfor < handle
 properties(GetAccess = private, SetAccess = immutable)
     Session
     ParforController
     IntervalCompleteQueue
 end
 properties(Access = private)
     NormalCompletion = false;
 end
 properties(SetAccess = immutable)
     % Used by parallel_function
     NumWorkers
 end
 properties
     % Set by parallel_function
     CaughtError
 end
 methods(Static)
     function[OK, pool] = tryRemoteParfor()
     % This is a static method of distcomp.remoteparfor that indicates if it is
     % OK to try constructing a distcomp.remoteparfor object. This will stop
     % obvious errors being thrown.
        [OK, pool] = pctTryCreatePoolIfNecessary();
     end
     functionoldVal = maxBacklog(newVal)
     % 'Backlog' refers to how many intervals the ParforController will send to the
     % workers without requiring a result.
     %
     % See the discussion in 'numIntervalsFactor' for how this factor
```

```
% interacts with that value.
   persistentMAX_BACKLOG
   ifisempty(MAX_BACKLOG)
      MAX_BACKLOG = 2;
   end
   oldVal = MAX_BACKLOG;
   ifnargin > 0
      MAX_BACKLOG = newVal;
   end
end
functionoldVal = numIntervalsFactor(newVal)
% numIntervalsFactor allows control over the total number of intervals that will
% get created. The relationship is not linear, and is determined by the
% implementation of divide_biharmonic. Here are some approximate numbers
% of intervals per worker for different values of the factor:
% factor : approx intervals / worker
%    0.5 : 3.6
%    1 : 4.5
%    2 : 5.5
%    3 : 6.5
%    4 : 7.5
%    5 : 8.5
%    6 : 9.4
%
% Note that when tuning PARFOR performance, there is an interaction
% between the number of intervals and the maxBacklog. If the number of
% intervals is relatively small, and backlog is high, then towards the
% end of execution, poor load-balancing might be seen. Contrariwise, if
% the allowed backlog is low and the number of intervals is high, then
% the client must deal with a higher number of messages, without
% necessarily being able to overlap this with the worker execution.
%
% The default parameters chosen here attempt to balance the backlog
% against the number of intervals produced across a range of parfor
% loops.
   persistentFACTOR
   ifisempty(FACTOR)
      FACTOR = 2; % roughly 5.5 intervals per worker
   end
   oldVal = FACTOR;
   ifnargin > 0
      FACTOR = newVal;
   end
end
functionoldVal = initialDispatchFactor(newVal)
% parallel_function.m uses getInitialDispatchSize() to choose how many intervals
% to hand off in the first round of dispatch. That method scales the
% number of workers by this factor to choose the initial dispatch
% size. The default is to allow parallel_function to dispatch all
% intervals up-front. This allows distcomp.remoteparfor to receive all
% the intervals as soon as possible and then send them to the workers.
%
% This factor is provided to allow an approximation of the old behaviour
% to be achieved; however, it is not anticipated that there is any
% appreciable benefit to changing this value.
   persistentFACTOR
   ifisempty(FACTOR)
      FACTOR = Inf;
   end
   oldVal = FACTOR;
   ifnargin > 0
      FACTOR = newVal;
   end
end
functionoldVal = smallInitDataBufferSize(newVal)
```

```
      % If the ParforController tells us to prefer small buffers when sending the
      % initialization data, this is our value of 'small'.
        persistentBUFFER_SIZE
        ifisempty(BUFFER_SIZE)
          % Use 10MB buffers as 'small' buffers.
          BUFFER_SIZE = 10 * 1024 * 1024;
        end
        oldVal = BUFFER_SIZE;
        ifnargin > 0
          BUFFER_SIZE = newVal;
        end
      end
    end
    methods
      functionobj = remoteparfor(pool, maxLabsToAcquire, varargin)
        ifisempty(pool) || ~pool.Connected
          errorMessageInput = iGetParpoolLinkForError();
          error(message('parallel:lang:parfor:NoSession', errorMessageInput));
        end
        feval('_pct_parforLog');
        session = pool.hGetSession();
        % If anything goes wrong during construction of this interface then we
        % need to clean up the parfor controller, otherwise all subsequent
        % parfor statements will revert to running locally.
        cleanupControllerBeforeAquiringLabs = parallel.internal.general.DisarmableOncleanup(...
          @() session.releaseCurrentParforController());
        try
          % Make a new parfor controller - this might throw a
          % SessionDestroyedException
          p = parallel.internal.getJavaFutureInterruptibly(...
            session.createParforController());
        catcherr
          [~, exceptionType] = isJavaException(err);
          if~isempty(regexp(exceptionType, 'SessionDestroyedException', 'once'))
            errorMessageInput = iGetParpoolLinkForError();
            error(message('parallel:lang:parfor:NoRunningSession', errorMessageInput));
          else
            rethrow(err);
          end
        end

        % Now we have a parforcontroller we can use that to clean up
        % once the acquireWorkers method has been called on it.
        interruptControllerOnError = parallel.internal.general.DisarmableOncleanup(...
          @() p.interrupt());
        serializedInitData = [];
        try
          obj.Session = session;
          obj.ParforController = p;
          % Get the IntervalReturnQueue
          obj.IntervalCompleteQueue = p.getIntervalCompleteQueue;
          % Try to acquire some workers
          maxLabsToAcquire = cast(maxLabsToAcquire, 'like', zeros('int32'));
          obj.NumWorkers = p.acquireWorkers(maxLabsToAcquire, ...
                              int32(distcomp.remoteparfor.maxBacklog()));
          % Labs aquired, therefore disable the first oncleanup
          cleanupControllerBeforeAquiringLabs.disarm();
          % Serialize the initialization data and store it locally
          spmdlang.BaseRemote.saveLoadCount( 'clear');

          ifp.preferSmallInitDataBuffers
            initDataBufSize = distcomp.remoteparfor.smallInitDataBufferSize();
          else
            % Here, '0' means unlimited.
            initDataBufSize = 0;
```

```
      end
      serializedInitData = parallel.internal.pool.serialize(varargin, initDataBufSize);
      % Error if we're about to broadcast Composites to the labs
      ifspmdlang.BaseRemote.saveLoadCount( 'get') ~= 0
        error(message('parallel:lang:parfor:IllegalComposite'));
      end
      p.beginLoop(serializedInitData);
      % We've handed the serialized data to the java layer, never
      % free it from here, assume java layer will do that.
      serializedInitData = []; %#ok<NASGU> should never see this value in the 'catch' block...
    catcherr
      % If we catch an error then we need to free the data we were going to
      % send to the remote labs.
      if~isempty( serializedInitData )
        arrayfun( @free, serializedInitData );
      end
      rethrow(err);
    end
  interruptControllerOnError.disarm();
end
functionOK = addFinalInterval(obj, tag, varargin)
    data = parallel.internal.pool.serialize(varargin);
    OK = obj.ParforController.addFinalInterval(tag, data);
end
functionOK = addInterval(obj, tag, varargin)
    data = parallel.internal.pool.serialize(varargin);
    OK = obj.ParforController.addInterval(tag, data);
end
functioncomplete(obj)
% We get into this function both during normal parfor execution as well as when
% the user code throws an error.  In both cases, this is our one and only chance
% to flush partial lines that may be pending in the command window output.
    % Indicate normal completion to stop the workers from being
    % interrupted.
  dctSchedulerMessage(4, 'remoteparfor.complete() called.');
  obj.NormalCompletion = true;
  obj.awaitCompletionDisplayingOutput();
end
function[tags,  results] = getCompleteIntervals(obj, numIntervals)
    q = obj.IntervalCompleteQueue;
    tags = ones(numIntervals, 1);
    results = cell(numIntervals, 1);
    fori = 1:numIntervals
      r = [];
      whileisempty(r)
        r = q.poll(1, java.util.concurrent.TimeUnit.SECONDS);
        obj.displayOutput();
        % Only test to see if the session is failing if we didn't get a
        % results from the queue
        ifisempty(r) && ~obj.Session.isSessionRunning
          errorMessageInput = iGetParpoolLinkForError();
          error(message('parallel:lang:parfor:SessionShutDown', errorMessageInput));
        end
      end
      % Check to see if the interval result has an error
      ifr.hasError
        % Java code has already interrupted the remote execution of the parfor
        % body and halted the receipt of further IO.  Before throwing an error,
        % we perform the normal cleanup activities.
        obj.complete();
        throw(iIntervalErrorDispatch(r));
      else
        tags(i) = r.getTag;
        data = r.getResult;
        results{i} = parallel.internal.pool.deserialize(data(2));
```

```
            end
        end
    end
    functiondelete(obj)
    % was pObjectBeingDestroyed
        ifobj.NormalCompletion || isempty(obj.ParforController)
            % No need to interrupt nor drain output
            return;
        end
        % Interrupt the remote execution and display all the command window output that
        % we receive.
        % Send a Ctrl+C to remote end.
        ifobj.CaughtError
            obj.ParforController.interruptOnError;
        else
            % Do note if the controller is in state 'complete' interrupt does
            % nothing so it is safe to call after the controller is complete.
            obj.ParforController.interrupt;
        end
        obj.awaitCompletionDisplayingOutput();
    end
    functionfcn = getDivisionFcn(~)
        fcn = divide_biharmonic(@(N, W) W);
    end
    functionsz = getInitialDispatchSize(~, k, W)
    % How many intervals parallel_function will hand to us in the first round.
    % Defaults to 'all' because the default value of
    % initialDispatchFactor is Inf.
        sz = iClamp(distcomp.remoteparfor.initialDispatchFactor() * W, ...
                1, k);
    end
  end
  methods(Access = private)
    functiondisplayOutput(obj)
        iDisplayStringArray(obj.ParforController.getDrainableOutput().drainOutput());
    end
    functionawaitCompletionDisplayingOutput(obj)
    % Make sure we wait for the parfor to complete and continue displaying command
    % window output whilst we are doing so.
        millis = java.util.concurrent.TimeUnit.MILLISECONDS;
        output = obj.ParforController.getDrainableOutput();
        ifisempty(output)
            % Can get here if no labs were acquired before the
            % ParforController was deleted. If this is the case there
            % is obviously no ouput to drain.
            return;
        end
        while~obj.ParforController.awaitCompleted(100, millis) ...
                && obj.Session.isSessionRunning
            dctSchedulerMessage(5, 'remoteparfor.awaitCompletionDisplayingOutput() still thinks not
completed');
            iDisplayStringArray(output.drainOutput());
        end
        iDisplayStringArray(output.drainAllOutput());
    end
  end
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% iDisplayStringArray - display a java.lang.String[] in the command window.
functioniDisplayStringArray(msgs)
  % Tiny performance improvement for the common case where 'msgs' is empty - avoid
  % conversion of empty array etc.
  if~isempty(msgs)
    cellfun(@(msg) disp(char(msg)), cell(msgs));
  end
```

```
end
functionerrorMessageInput = iGetParpoolLinkForError()
iffeature('hotlinks')
  errorMessageInput = '<a href="matlab: help parpool">parpool</a>';
else
  errorMessageInput = 'parpool';
end
end
functionval = iClamp(inVal, minBound, maxBound)
val = min(max(inVal, minBound), maxBound);
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Divide the range into a "biharmonic" series. This starts with a
% harmonically-increasing portion. The initial intervals are smaller to allow
% the client to send them more quickly to get the workers started more quickly
% at the start of the loop. The middle intervals saturate at the maxChunk size,
% and then decay to a small value. The end intervals are small to allow for
% better worker utilisation at the end of loop execution.
functiond = divide_biharmonic(f)
  functionoutput = div(base, limit, W)
     N = limit - base;
     W = f(N, W);
     N3 = floor(N/3);
     idx = 0;
     scaleFactor = distcomp.remoteparfor.numIntervalsFactor();
     minChunk = ceil(max(1, ceil(N/(scaleFactor * 10 * W))));
     maxChunk = floor(max(1, ceil(N/(scaleFactor * W))));
     output = zeros('like', base);
     curr = 0;
     whilecurr < N3
        idx = 1 + idx;
        chunk = ceil(4 * curr / W);
        curr = curr + iClamp(chunk, minChunk, maxChunk);
        output(idx) = curr;
     end
     % Use a smaller minimum chunk size towards the end of the loop. By this point in
     % the loop execution, hopefully all the workers are busy, and we can
     % better tolerate a smaller chunk size.
     minChunk = ceil(minChunk / 2);
      whilecurr < N
        idx = 1 + idx;
        chunk = ceil((N - curr) / W);
        curr = curr + iClamp(chunk, minChunk, maxChunk);
        output(idx) = curr;
     end
     output(idx) = N;
     output = base + output;
  end
  d = @div;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Return an appropriate error from a failing interval result.
functionerr = iIntervalErrorDispatch(r)
  intervalError = r.getError;
  ifr.isWorkerAbortedError
     err = MException(message('parallel:lang:pool:WorkerAborted'));
  elseifischar(intervalError)
     err = MException(message('parallel:lang:pool:UnexpectedParforFailure', ...
                      intervalError));
  else
     [isMvmErr, mvmErr] =...
       parallel.internal.general.transformIfMvmException(intervalError);
     ifisMvmErr
        origErr = mvmErr;
        % intervalError must have been a Java Exception - log it.
```

```
      parallel.internal.general.logJavaException(...
          0, 'Failed to get result from PARFOR.', intervalError);
    else
      origErr = parallel.internal.pool.deserialize(intervalError);
    end
    clientStackToIgnore = 'parallel_function';
    % Create a new exception that stitches together the client and worker stack.
    err = ParallelException.hBuildRemoteParallelException(...
      origErr, clientStackToIgnore);
  end
end
```

Table 4. The code for our model, provided to us by researchers in Norges Bank Francesco Furlanetto and Ørjan Robstad.