How do shocks to consumption growth affect the Austrian labor market in the short-term?

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Preface and Acknowledgements

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Statutory Declaration

I herewith declare that I have composed the present thesis myself and without the use of any other than the cited sources and aids. Sentences or parts of sentences quoted literally are marked as such; other references with regard to the statement and scope are indicated by full details of the publications concerned. The thesis in the same or similar form has not been submitted to any examination body and has not been published. This thesis was not yet, even in part, used in another examination or as a course performance.

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Abstract

The recent pandemic caused by COVID-19 played an enormous role in the consumption behavior of the Austrian population. In the past two years, the economy experienced downturns and booming markets in different areas of the labor market. Therefore, this paper focuses on how consumer spending growth in Austria affects the labor market in the short-term. Several models are constructed using a vector autoregression (VAR) approach to examine the impact of positive shocks to consumption expenditure growth on various Austrian labor market variables and the change in real gross domestic product. The analysis indicates that shocks within the system positively impact variables like the growth rate of unfilled job vacancies. The results further suggest that variations in employment rates for females between 25 and 54 years old as well as 15 to 64 years old are positively affected. Likewise, employment growth rates for 15 to 24 years old males seem to be affected too. A labor sector-specific study implies a positive impact on the change in the services sector after a shock to consumer spending growth. The remaining sectors do not provide any clear and significant image of how they are influenced by a shock to private consumer spending. Additionally, this thesis finds that consumption expenditure change has considerable explanatory power for many variables in the subsequent periods after the shock occurred. For example, for the growth of unfilled job vacancies the explanatory effect reaches 49.5%, and for the change in the unemployment rate consumer spending growth accounts for 80% at its peak.

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1 Introduction

The recent economic downturns caused by the COVID-19 pandemic globally disturbed people's consumption behavior and affected the labor markets all around the world. A study by the Austrian National Bank shows that the COVID-19 crisis affected the Austrian labor market much heavier than the Great Recession of 2009 (Ragacs et al., 2021). Even though the short-time work scheme of the Austrian government prevented colossal damage to the labor market, many participants in the labor market suffered from the crisis. More precisely, they documented that the tourism industry was hit the hardest, with an enormous impact on its sector-specific unemployment rate. Moreover, young Austrian workers and foreign employees suffered more from higher unemployment due to the pandemic than people from tertiary education. The pandemic influenced the unemployment rate and employment all over the country.

Thus, this paper aims to identify whether consumption is indeed one of the main drivers in the Austrian labor market. This study estimates the short-term impact of shocks in personal consumer spending growth on diverse labor market variables and the growth in the real gross domestic product (GDP). Since the labor market consists of several aggregates, this thesis uses various main labor market variables like the unemployment rate, age-gender-specific and sector-specific labor market variables to trace out shocks to personal consumption expenditure.

On top of that, examining this topic is highly relevant from a policy perspective. More detailed information about the key drivers of changes in the labor market helps the government to prevent further damage in downturns. On the one hand, governments could take precautionary actions. On the other hand, better information allows for better preparation in case of negative shocks to private consumption. Hence, the implementation of policy decisions could stimulate consumption and stabilize the labor market.

Using three different models in this work, it is expected that positive shocks in consumption expenditure growth positively impact variables like the growth in unfilled job vacancies or the employment rate changes in various age groups for females and males but negatively influence the overall unemployment rate variation. Furthermore, there may be some positive impacts on sector-specific growth rates. There exists literature that examines the evolution of the unemployment rate using a structural VAR approach (Maidorn, 2003). However, this paper contributes to former studies with a more detailed view on the Austrian labor market.

The main research question can be formulated as follows: How do shocks to consumption expenditure impact the Austrian labor market and GDP in the short-run?

Additionally, this paper aims to answer multiple subquestions to structure the work and receive a clearer insight into the effect in the short-term.

1. Do shocks to private consumption expenditure growth reflect themselves in the job vacancy stock?

2. Do variations of the unemployment rate immediately respond to shocks in the changes in consumer spending?

3. How do shocks to private consumption expenditure growth change the growth pattern to GDP?

4. What is the impact of a consumer spending growth shock on different age groups in the labor market?

5. How are specific labor sectors influenced by shocks of changes in consumer spending?

Using a VAR approach, this work establishes three different models to investigate the impact of shocks in personal consumption expenditure on labor market variables and real GDP in the short-run.

Therefore, chapter 2 summarizes former literature regarding consumption and the labor market. The empirical section (chapter 3) examines the requirements of the variables and explains the methodology. Thus, it is also mentioned why certain decisions on the specification and the empirical framework have been made. In addition, it includes a graphical and a preliminary analysis of the data to show the properties between the variables. Next, chapter 4 presents the vector autoregressive analysis, which implies diverse tests for the validity of the models. In section 5, the impulse response functions and the error forecast variance decompositions of the various models are displayed and described, and the results are discussed. Subsequently, robustness checks with the inclusion of consumer sentiment as a new primary variable to strengthen the findings are conducted (see section 6). Moreover, the section 7 points out the potential limitations of this thesis. Finally, chapter 8 comprises concluding remarks regarding the analysis and the research questions.

2 Literature Review

A vast body of literature supports the influential role of consumption in driving a country's economy (e.g. Juhro, 2015; Pardede and Zahro, 2017). For instance, Narayan et al. (2008) use a structural vector autoregressive model to show that shocks to electricity consumption positively impact the real GDP in the short-run. Moreover, Iyke and Ho (2019) find that lower consumption causes not only a decrease in production but also a decline in the demand for inputs, which negatively affects income and increases the unemployment rate. Maidorn (2003) documents the importance of demand shocks for the Austrian labor market. In the structural VAR approach, the impulse response analysis demonstrates that the unemployment rate decreases and employment increases in the first two years after a shock. The effect on the unemployment rate declines after two years but remains higher for employment.

Leamer (2007) considers various demand components of GDP growth to show that residential investment delivers by far the best early warning indicator of oncoming recessions. More precisely, he finds that a decline in the contribution of residential investment to GDP growth is a good indication of a future downturn. Furthermore, Aastveity et al. (2017) examines the importance of personal consumption expenditure for economic declines. The authors use in-sample and out-of-sample tests for 12 Organization for Economic Cooperation and Development (OECD) countries to show that residential investment is helpful in forecasting recessions. Their results remain stable if they include typical economic indicators such as the term spread, stock prices, consumer confidence surveys, and oil prices. In general, demand and private consumption expenditure are highly related to consumer confidence in the literature.

Recent literature has already proved, that during the period of the pandemic, the behavior of consumers changed significantly (Abosedra et al., 2021), implying that they have changed their consumption behavior due to the uncertainty caused by the pandemic. Their analysis in the United States before and during the COVID-19 period gave evidence for the persistence of a consumer confidence shock's impact on consumer spending for almost one year. They also included the unemployment rate in their VAR model but did not find any statistically significant effect. Additionally, they could not analyze a model with subperiods, including the unemployment rate, because of insufficient data points.

Matsusaka and Sbordone (1995) worked with a VAR model to indicate that consumption expenditure does Granger cause gross national product (GNP). In general, they examine linkages between consumer sentiment and economic fluctuations by controlling for economic fundamentals. Their variance decomposition results show that consumer sentiment contributes between 13 and 26 percent of the information to GNP. The relationship between consumer sentiment and consumption will be used in section 6 of this thesis for robustness checks to underline the importance of personal consumption expenditure growth for the Austrian labor market.

3 Methodology and Data

The following section describes the methodology and the preliminary data analysis. First, the decision on the specification is made. Second, the empirical framework is defined. The final paragraphs elaborate further on the data and its characteristics.

3.1 Decision on the specification

To estimate a VAR model, it is required that all variables are stationary. If all variables within the system are integrated of order zero I(0), the variables can be considered stationary in their original format. If the variable is not integrated of order zero, one can obtain stationary integrated of order one variables I(1) by first differencing. The order of integration depends on how often the process of differencing is required to receive stationary variables. However, suppose the variables are not I(0). In that case, it is possible to use variables integrated of order one I(1) and either estimate a vector error correction model (VECM) in case of cointegration between the variables when looking at the short-term and long-term relationship or simply estimate a VAR in first differences for short-term analysis.

In the existing body of literature, several studies examine which model is the best to deal with variables that are not I(0). Overall it can be said that there is no clear consensus about the best option. Hoffman and Rasche (1996) argue that the advantage of vector error correction models occurs in longer time horizons. At the same time, VAR in levels or VAR in first differences provides good forecasting for the short-run and can even outperform VECM in some cases. These findings are likewise supported by Clements and Hendry (1995), who additionally find that the advantage of VECM is lower in small samples. Another paper from Ashley and Verbrugge (2009) concludes that VAR in first differences is an appropriate method as long as cointegration is no issue. A cointegrating equation in a system implies a long-run relationship which is essential to consider if effects in the short-run and the long-run are analyzed. Regardless, there is considerably more literature on this topic. However, since this thesis focuses on the development in the short-term and the subsequent data analysis (see 3.6) reveals that the variables in most cases are not I(0), a VAR model in first differences is used to estimate the impulse response functions and variance decompositions.

3.2 Empirical framework

In this study, three different models are used. Model 1, the baseline analysis, includes the growth rates of consumption expenditure, unfilled job vacancies, unemployment rate, and real GDP. Model 2 uses the first differences of consumption expenditure, the age-gender-specific employment rates, and real GDP. Finally, Model 3 consists of consumer spending, sector-specific variables, and real GDP variations.

In 1980, Sims introduced the VAR model as a solution to allow for a multivariate framework where one variable is defined by both its own past values and the lags of the other variables within the system. The multivariate model, which is only an extension of the univariate vector autoregression, allows shocks in one variable to impact other variables within the model. In general, using this model has some benefits. First, no a priori restrictions are placed on the structural relationship between the different variables in the model. Second, no a priori distinctions between the endogenous and exogenous variables ought to be recognized. Third, the variables used in the system are treated equally.

The following section of this paper elaborates on the methodology for the analysis. A vector autoregressive model is used to analyze the short-term effect of shocks to consumer spending growth on the change of the various labor market variables and the variation in real GDP. After estimating the VAR models, the impulse response functions and their variance decomposition are considered as the key features of tracing out any effect of a shock on consumption growth. Thereby this work follows the empirical framework of Bachmann and Sims (2012) and Khan et al. (2019, p. 11). Just like in their papers, the baseline equation is:

$$A_0 Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + \varepsilon_t. \tag{3.1}$$

Y_t is a $k \times 1$ vector that will contain different variables depending on the model of the analysis. In other words, for the baseline estimation Y_t includes all the variables of model 1 (growth rates of consumption expenditure, unfilled job vacancies, unemployment rate, and real GDP). In Model 2, Y_t consists of the growth rates of consumption expenditure, the female age groups and real GDP in the first estimation and consumption expenditure, the male age groups, and real GDP in the second regression. The final part (model 3) investigates the impact of a shock in consumer spending variation on the growth rates of the employment sectors. Implying that Y_t is a vector of the changes in consumption expenditure, the sector-related variables, and real GDP.

A_j is a $k \times k$ matrix that will include the autoregressive coefficients, p denotes the number of lags, and j provides the information about the order of the lag. Moreover, ε_t is a $k \times 1$ vector that specifies structural shocks, which are defined as being mutually uncorrelated, and A_0 is the $k \times k$ lower triangular matrix for which most of the recent literature declares in the first row all elements except (1,1) being zero (e.g. Sims, 1980; Blanchard and Perotti, 2002). The reduced form of the model will look like the following equation:

$$Y_t = \sum_{j=1}^{p} A_0^{-1} A_j Y_{t-j} + u_t, \tag{3.2}$$

where $u_t = \ A_0^{-1}\varepsilon_t$ denotes the reduced form shocks (in the baseline case the structural shocks in the growth rates of consumer spending, job vacancies, unemployment rate and real GDP) and ε_t is the vector of all structural shocks which is a zero mean white noise process. Implying that the covariance matrix is $E(\varepsilon_t \varepsilon_t') \equiv \Omega_\varepsilon = I_k$, such that the reduced form shocks covariance matrix is $E(u_t u_t'\ ) \equiv \Omega_u = A_0^{-1} A_0^{-1\prime}$. Additionally, to recover the structural VAR, restrictions on A_0 need to be imposed. The matrix where all $a_{1,1}, a_{2,2}, a_{3,3}, a_{4,4}$ can assumed to be 1 because each of them describe the dynamics between the variables itself, looks like the expression below:

$$A_0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{2,1} & 1 & 0 & 0 \\ a_{3,1} & a_{3,2} & 1 & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & 1 \end{pmatrix}_{k \times k.} \tag{3.3}$$

Similar to Khan et al. (2019) the concept of Cholesky decomposition of the variance-covariance matrix of reduced form shocks, Ω_u, is applied to implement the identification assumption. For the baseline case, it is assumed that the order of the variables will be the growth in consumption expenditure, job vacancies, the unemployment rate, and real GDP. Remember the assumption of all elements except (1,1) being zero. Economically, this implies that the changes in job vacancies, unemployment rate, and real GDP react contemporaneously to shocks in the variation of consumption expenditure. On the other hand, the latter variable does not respond contemporaneously to shocks of the remaining variables in the system.

Once all restrictions have been imposed, and the lower triangular Matrix A_0 has been identified, it is possible to express everything in a companion matrix as a VAR(1) such that

$$Z_t = \Lambda Z_{t-1} + U_t \tag{3.4}$$

$$Z_t = \begin{bmatrix} Y_t \\ Y_{t-1} \\ \cdot \\ \cdot \\ Y_{t-p+1} \end{bmatrix}_{kp\times 1} \qquad \Lambda = \begin{bmatrix} A_0^{-1}A_1 & A_0^{-1}A_2 & \cdots & \cdots & A_0^{-1}A_p \\ I & 0 & 0 & \cdots & 0 \\ 0 & I & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & \cdots & I & 0 \end{bmatrix}_{kp\times kp}$$

and

$$U_t = \begin{bmatrix} u_t \\ u_{t-1} \\ \cdot \\ \cdot \\ u_{t-p+1} \end{bmatrix}_{kp\times 1.}$$

Considering $A_0^{-1}(q)$ as the q^{th} column of A_0^{-1}, the resulting impulse response of a variable i to a structural shock of q at the time horizon $h = 1, ..., H$ is:

$$\Phi_{i,q,h} = e_i \Lambda^{h-1} A_0^{-1}(q), \tag{3.5}$$

where e_i is a selection row vector of dimension $1 \times k$, with a one in the i^{th} place and zeros elsewhere.

3.3 Data

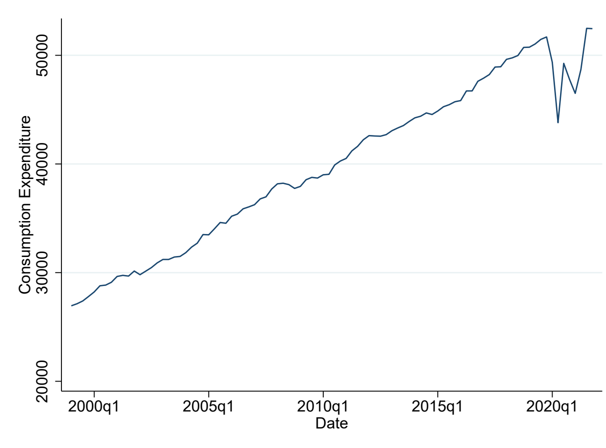
For this analysis, quarterly data from the first quarter of 1999 to the fourth quarter of 2021 is used. The primary variable used in the different VAR analyses is real consumption expenditure which is seasonally adjusted private final consumer spending in euros (Organization for Economic Co-operation and Development, 2022c). To make the interpretation more convenient later on, it is transformed into millions of euros. Furthermore, this data, originally from the OECD, is obtained from the FRED database of the Federal Reserve Bank of St. Louis. Real gross domestic product is another variable in the model that was also retrieved from the FRED database (Eurostat, 2022). The Bank of St. Louis obtained the data from Eurostat, and they provide it on their website seasonally adjusted and in the following unit: "Millions of Chained 2010 Euros".

Any labor market variables for the different analyses are obtained from the OECD database (OECD.Stat, 2022). The total unemployment rate and the total stock of job vacancies are both seasonally adjusted. Next, several employment variables of different age groups and various economic activities exist. The study will contain four age groups 15 to 24, 25 to 54, 55 to 64, and a comprehensive one with 15 to 64 years old people. These groups are then separated further into two subgroups containing values for males and females. Besides, these employment rates are seasonally adjusted. Lastly, the study also analyzes the impact on particular sectors in the economy. These are the types of economic activity consisting of the sectors of agriculture, construction, industry (excluding construction), manufacturing, and services. This data is measured in units of thousands of persons employed and is seasonally adjusted.

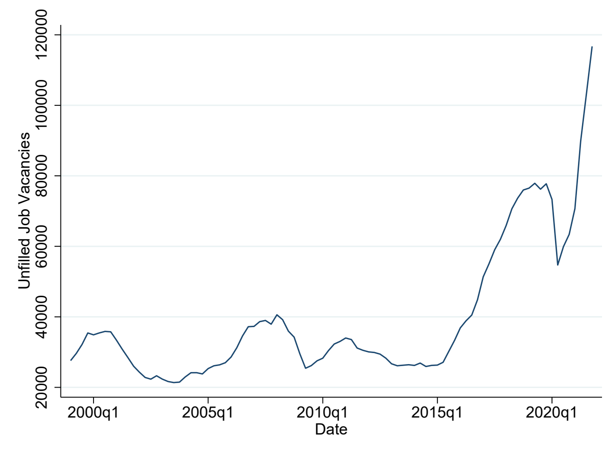
3.4 Graphical trends

The following section includes graphical trends of the original variables of the dataset. Implying that no transformation has been done yet. The main variable, consumption expenditure in Austria (see figure 1a), exhibits a steady growth with minor dents (e.g. in 2009). However, a considerable decline can be observed for the second quarter and the start of the COVID-19 pandemic. For a few quarters, private consumption expenditure was at a lower level reaching its pre-crisis level again in the third quarter of 2021. Figure 1b shows the time trend for total unfilled job vacancies from 1998 to 2021. Between 1998 and the mid of 2016, the number of total unfilled vacancies oscillated in an interval from 2000 to 4000. Starting in 2016, the number of unfilled vacancies experienced a sharp increase until the pandemic began. An enormous decline in the first three quarters of 2020 was followed by a skyrocketing growth for the subsequent periods .

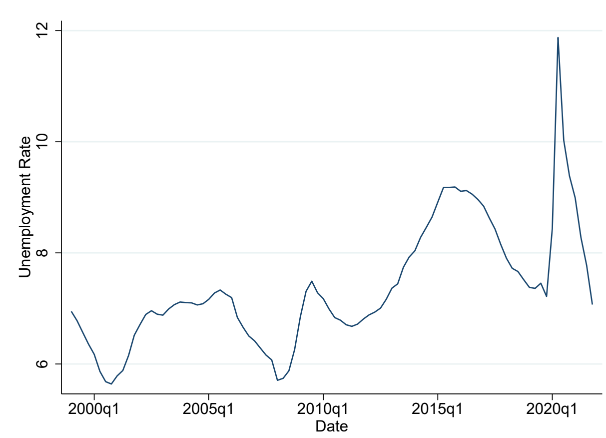
Figure 1



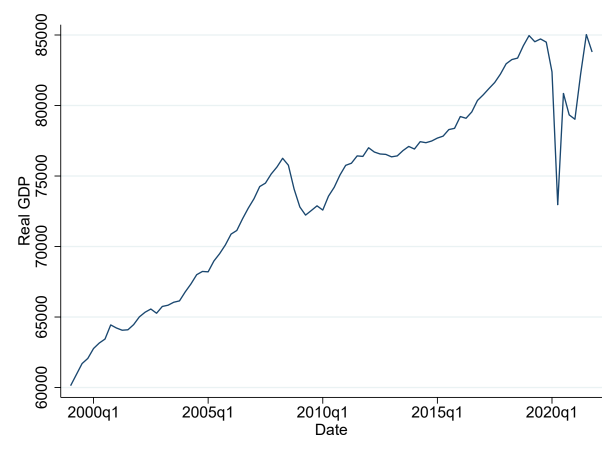
(a) Trend: Consumption expenditure



(b) Trend: Unfilled Job Vacancies



(c) Trend: Unemployment Rate



(d) Trend: Real GDP

Note. Graphical trends for PCE, JOV, UNR and GDP of the original dataset. The variables are not in logarithmic form or first differences.

Although the unemployment rate fluctuated a lot, it revealed an overall rise until 2015, which was then followed by five years of decrease until 2020. The shocks of the pandemic generated a sharp increase which immediately went down when the economy started to boom again (see figure 1c). Real GDP indicates a very similar pattern to consumer spending. In recent years it was almost steadily growing until the first significant drop occurred in 2008 and 2009 due to the financial crisis. However, the most substantial decline occurred in times of the COVID-19 crisis (see figure 1d).

Next, the remaining graphical trends for the variables which are used in their transformed state in model 2 and model 3 are displayed. Figure 2a comprises any time trends of the female age groups. The highest growth can be observed for 55 to 64 years old females. Generally, except for the youngest group, the female employment rates increased over the recent decades. This might be due to higher support for women in the labor market or (financial) programs that encouraged men to stay at home and women to work in their children's early years (Baierl and Kapella, 2014; von Alemann et al., 2017; Wernhart and Halbauer, 2018). However, it might also be due to a rise in the willingness of firms to raise their women's percentage rate (Wernhart and Halbauer, 2018). On the other hand, for males (see figure 2b), only the oldest group exhibits an increasing time trend. The remaining ones fluctuated over the past years or decreased marginally. The rise in the most senior group might be because of the development in the job market. Due to modern technological developments, the number of vacancies unrelated to corporal work has increased (Piva and Vivarelli, 2018). Also, the government raised the age threshold for pensions in Austria during these periods.

Figure 2

(a) Trends: Employment rates females

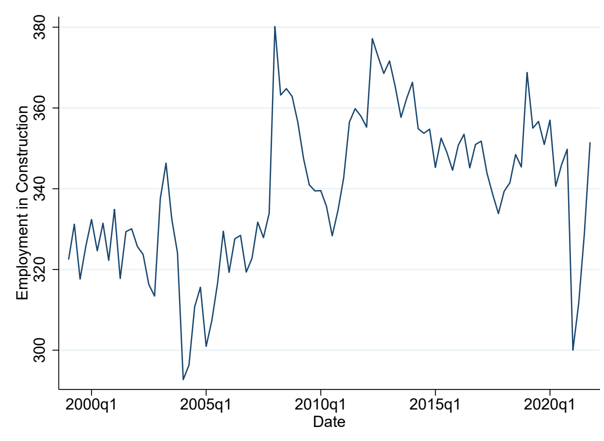
(b) Trends: Employment rates males

Note. Graphical trends for the employment rates in the diverse age groups of the original dataset for females and males: Variables are not in logarithmic form or first differences. Their transformed variables are utilized in model 2.

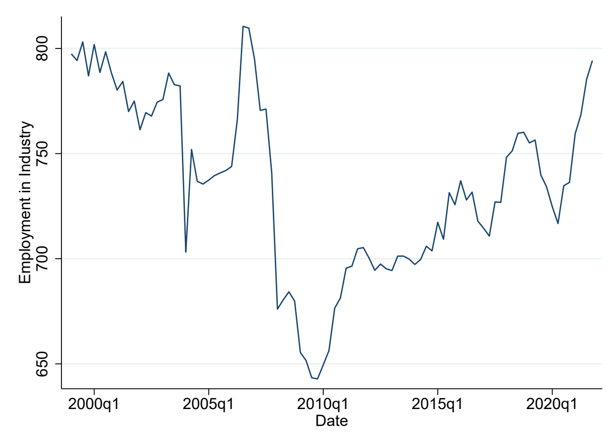
The last five plots describe the time pattern for the different sector-related variables. The agricultural sector (see figure 3a) faced an overall decline whereas the services sector (see figure 3e) increased. The industry and the manufacturing sectors fluctuated considerably; however, during the financial crisis, they experienced a massive decrease in people employed (see figures 3c and 3d). Moreover, in any of the five cases (also figure 3b) the pandemic forced the number of employed people to drop dramatically.

Figure 3

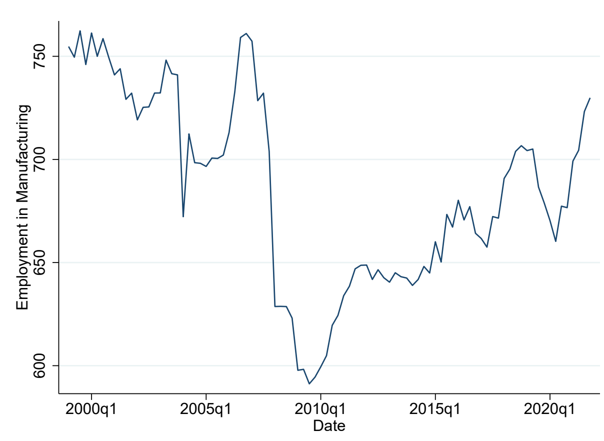
(a) Trends: Agriculture sector



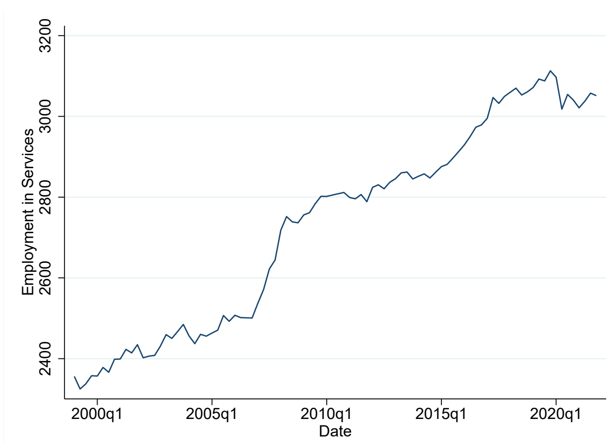
(b) Trends: Construction sector



(c) Trends: Industry sector



(d) Trends: Manufacturing sector



(e) Trends: Services sector

Note. Graphical trends for employment in the various labor market sectors in thousands of persons. The variables are not in logarithmic form or first differences. The transformed variables are used for the analysis in model 3.

3.5 Preliminary analysis of the data

At the beginning of this section, all variables are summarized and displayed in table 1. The descriptive statistics include the variables in their original format. Due to the reason that the data on employment variables is limited, the analysis contains a total of 92 observations of each variable. Generally, the summary statistics indicate high variation in terms of mean, standard deviation, minimum values, and maximum values. For example, the maximum amount of 52481.55 Million euros was consumed and the highest value of real GDP in Austria (85029.7 Million euros) was added in the third quarter of 2021. Interestingly, the peak in the unemployment rate was reached in the second quarter of 2020, indicating the negative impact of the COVID-19 crisis and the subsequent downturn in the economy.

Table 1

Summary statistics: Model 1					
	Obs	Mean	Std. dev.	Min	Max
PCE	92	39752.32	7465.803	26947.07	52481.55
UNR	92	7.362105	1.100127	5.64065	11.87533
JOV	92	39367.04	19741.8	21362.63	116721.2
GDP	92	73921.26	6763.95	60131	85029.7
Summary statistics: Additional variables of model 2 and model 3					
ER15_24fe	92	48.82441	1.729207	44.54662	53.09296
ER15_24ma	92	55.56869	2.07344	51.31137	61.91139
ER25_54fe	92	78.19422	2.757406	72.51309	82.70589
ER25_54ma	92	88.4052	1.617861	85.20086	91.59692
ER55_64fe	92	31.33147	10.39742	14.47137	49.74011
ER55_64ma	92	49.59827	8.79645	35.64954	64.44351
ER15_64fe	92	64.65429	3.25376	59.35184	69.31562
ER15_64ma	92	76.06909	1.145047	73.16494	78.29602
EmAgriculture	92	196.6324	22.00915	154.6909	235.8961
EmConstruction	92	339.5899	18.96862	292.7312	380.1525
EmIndustry	92	735.2065	42.65044	642.8474	810.5507
EmManufacturing	92	685.4734	47.02722	591.214	762.3513

EmServices	92	2731.586	249.8879	2324.924	3112.859

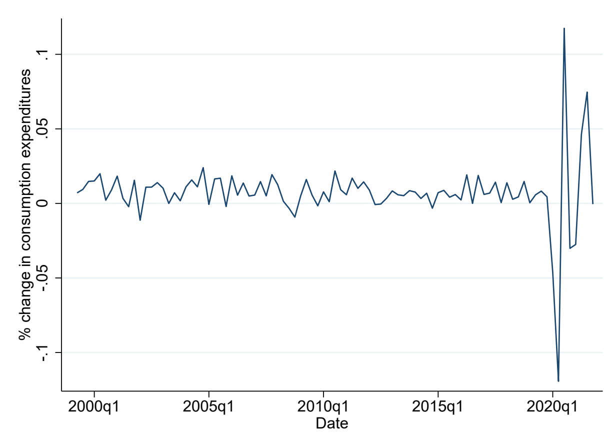
Note. All variables are displayed in their original state, meaning that there has not yet been done any logarithmic transformation or first differencing. Consumption expenditure (PCE) and Real gross domestic product (GDP) are in millions of euros, and the variable for unfilled job vacancies (JOV) is the total stock in numbers. UNR is the variable for the unemployment rate. The remaining variables are the age-group gender-specific employment rate variables, and the employment variables for the different branches, which are in the unit of total numbers in thousands of persons. For example, ER15_24fe stands for the employment rate of 15 to 24 years old females, and EmAgriculture is the employment variable of the agriculture sector.

3.6 Stationarity and correlation matrices

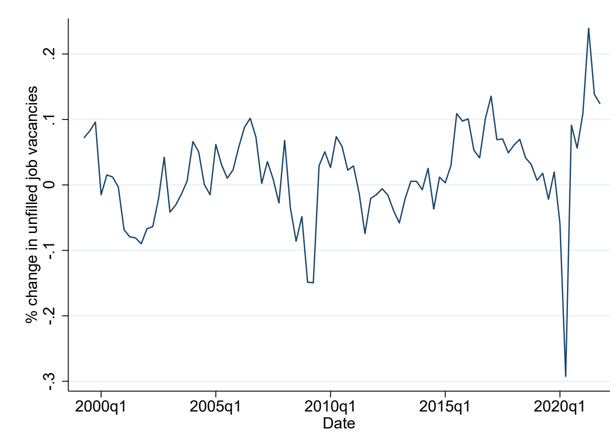
Time series variables are assumed to be stationary if their statistical properties, such as mean, variance, and covariances for each lag, are all constant over time. Granger and Newbold (1974), argue that performing a regression, although the residual series is strongly autocorrelated, results in misspecified equations. Consequently, the interpretation of the coefficients will be meaningless. In general, most time series data exhibits non-stationarity over the time horizon. Therefore, it is necessary to use stationary variables because executing an analysis with a non-stationary time series implies serious problems like the risk of running a spurious regression (Brooks, 2014).

In the first step, augmented Dickey-Fuller tests (ADF) are applied to see which variables are I(0), I(1), or even integrated of a higher order (Dickey and Fuller, 1979). This test is an extended version of the standard Dickey-Fuller test that recognizes autocorrelation over a higher lag length than one. Similar to the lag length selection result (see 4.1), five lags are used to run the ADF test. A rejection of the null hypothesis of containing a unit root allows the conclusion that the time series is stationary; hence it can be employed in the regression model. The initial tests for the variables in levels and the logarithmic form indicated that no variable was stationary in the baseline model, meaning I(0). Hereafter, the first differences of all variables were computed, and the augmented Dickey-Fuller tests were repeated. The results denoted stationarity for all first difference variables irrespective of the model. Preliminary analyses showed that some combinations of the variables show cointegration while others do not. Since this analysis comprises different models with diverse variable combinations, and as already mentioned, the interest lies only in the short-term, it was determined not to use the VEC model and stick to VAR in the first differences. This paper uses the concept of the Phillips–Perron test to strengthen the findings of the ADF tests. The tables with the augmented Dickey-Fuller and Phillips–Perron test results are depicted in the appendix (see A). The following graphs show the first differenced variables of model 1 (see figure 4). The plots for model 2 and model 3 are displayed in appendix B.

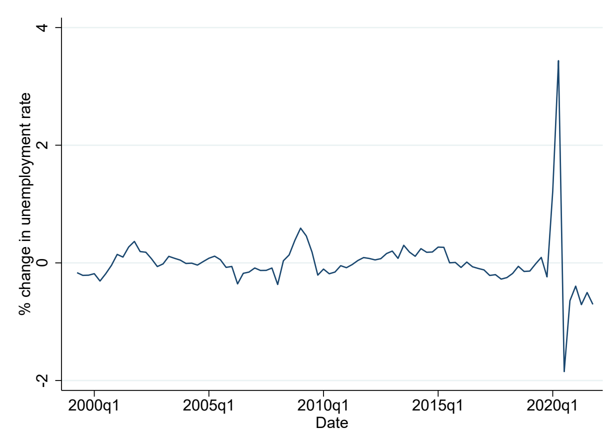
Figure 4



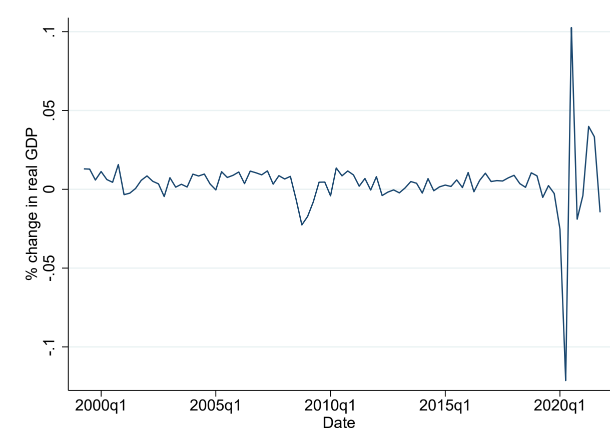
(a) Model 1: I(1) PCE variable



(b) Model 1: I(1) JOV variable



(c) Model 1: I(1) UNR variable



(d) Model 1: I(1) GDP variable

Note. These are the first differenced variables of the baseline model. Moreover, PCE, JOV, and GDP are in logarithmic form to interpret all variables of model 1 as percentage changes.

The ensuing tables exhibit the correlations between the pairs of variables for all three analyses. The first table illustrates the baseline analysis values, including consumption expenditure, job vacancies, the unemployment rate, and real GDP (see table 2). Some variables were changed into logarithmic values to make their interpretation more convenient. Important to remember is that the analysis in Stata showed that growth rates (variables in first differences) have to be used (see part 3.6). According to the results, the growth in consumption expenditure positively correlates with the change in job vacancies and the first difference in real GDP, implying that if the economy is booming, more jobs are available, and the GDP growth increases. However, there is a negative co-movement with the change in the unemployment rate. Higher consumption very likely boosts the economy; hence, the negative correlation with the unemployment rate makes sense economically (Bean and Pissarides, 1993). Furthermore, the change in the job vacancies is negatively associated with the variation in the unemployment rate and positively correlated with the growth in real GDP. If the unemployment rate decreases, the number of unfilled job vacancies should decrease as well. Lastly, the change in the unemployment rate is negatively correlated with the movements in real GDP. Worth mentioning is that all variables are significant at the 5% level.

Table 2

Correlation matrix of percentage growth rates: Model 1

	PCE	JOV	UNR	GDP
PCE	1			
JOV	0.4636 0.0000***	1		
UNR	-0.7667 0.0000***	-0.7175 0.0000***	1	
GDP	0.8958 0.000***	0.5768 0.0000***	-0.8508 0.0000***	1

Note. * denotes 10% significance level, ** stands for 5% significance level, and *** indicates significance at the 1% level. PCE is the first difference logarithm of private consumption expenditure, UNR is the first difference variable of the unemployment rate, JOV indicates the first difference logarithm of job vacancies, and GDP denotes the first difference of the logarithmic variable of real GDP.

The next table presents the correlations of the variables included in model 2 (see table 3). Model 2 estimates the effect of consumption expenditure on various age groups of employment rates for females and males. The top half of the table shows the correlations for female groups, while the bottom half exhibits males' values. The second column is most important for the analysis, which provides the correlation values between the change in consumption expenditure and all the other variables. In the second column, all correlation values are statistically significant, except for the employment rate growth of 55 to 64 years old males. Generally, consumer spending growth has a positive co-movement with the variations in employment rates and the first difference in GDP. A flourishing economy positively impacts the labor market and increases the changes in employment rates. Once again, consumption expenditure and real GDP were transformed into logarithmic form before the first differences were computed.

Table 3

Correlation matrix of percentage growth rates: Model 2						
	PCE	ER15_24m	ER25_54m	ER55_64m	ER15_64m	GDP
PCE	1					
ER15_24m	0.2914 0.0051***	1				
ER25_54m	0.5183 0.0000***	0.3360 0.0011***	1			
ER55_64m	0.1678 0.1119	-0.0992 0.3497	0.2489 0.0174**	1		
ER15_64m	0.4569 0.0000***	0.5287 0.0000***	0.8334 0.0000***	0.5346 0.0000***	1	
LogGDP	0.8958 0.0000***	0.3587 0.0005***	0.5727 0.0000***	0.1517 0.1510	0.4973 0.0000***	1
	PCE	ER15_24f	ER25_54fe	ER55_64f	ER15_64f	GDP
PCE	1					
ER15_24f	0.2700 0.0096***	1				
ER25_54f	0.7706 0.0000***	0.1847 0.0796*	1			
ER55_64f	0.2202 0.0360**	-0.0318 0.7647	0.3468 0.0008***	1		
ER15_64f	0.6647* 0.0000	0.4966* 0.0000	0.8441* 0.0000	0.4553* 0.0000	1	
GDP	0.8958 0.0000***	0.3253 0.0017***	0.7603 0.0000***	0.1744 0.0982*	0.6861 0.0000***	1

Note. PCE is the first difference logarithm of private consumption expenditure. ER15_24f, ER25_54f, ER55_64f, ER15_64f are the first difference variables of the female employment rates of the age groups, ER15_24m, ER25_54m, ER55_64m, and ER15_64m stand for the male first difference employment rates. Finally, GDP denotes the first difference of the logarithmic variable of real GDP.

The final table displays the correlations between the change in consumption expenditure, the growth rates in the employment sectors, and the growth in GDP (see table 4). All variables were converted into a logarithmic form before the first differences were calculated. As in the table above, the second column is the one of interest. It exhibits the correlation values between the growth in consumer spending and the other variables. For any variable, the co-movement with the change in consumption expenditure is positive, and for the construction sector, the service sector, and GDP, the values are statistically significant at the 5% level.

Table 4

Correlation matrix of percentage growth rates: Model 3

	PCE	Agri	Cons	Indu	Manu	Serv	GDP
PCE	1						
Agri	0.0242 0.8202	1					
Cons	0.2547 0.0148**	0.0158 0.8821	1				
Indu	0.1155 0.2756	0.3384 0.0010***	-0.0698 0.5110	1			
Manu	0.1295 0.2211	0.3669 0.0003***	-0.1282 0.2257	0.9755 0.0000***	1		
Serv	0.4441 0.0000***	0.0116 0.9128	0.1814 0.0853*	-0.1905 0.0705*	-0.1949 0.0642*	1	
GDP	0.8958 0.0000***	0.0181 0.8649	0.1776 0.0921*	0.1457 0.1683	0.1662 0.1153	0.4197 0.0000***	1

Note. Again, PCE denotes the first difference logarithm of private consumption expenditure. Agri, Cons, Indu, Manu, and Serv are the logarithmic first difference variables of the agriculture, construction, industry, manufacturing, and services sectors. GDP once more implies the first difference of the logarithmic variable of real GDP.

4 VAR analysis

The upcoming paragraphs imply any essential econometric steps for executing an accurate VAR analysis. The first part deals with the correct lag length selection. Next, several diagnostic tests are conducted to guarantee the validity of the analysis, the models, and the study.

4.1 Lag length selection

One of the most crucial things in a VAR analysis is determining the appropriate number of lags. Thereby various selection criteria help to select the correct lag length. However, since these criteria can deliver different outcomes, it is essential to consider economic theory in order to make a valid and robust decision. Ivanov and Kilian (2005) compare the most commonly applied lag length selection criteria and conclude that Hannan-Quinn Criterion (HQC) produces the best results in quarterly data, with the exception of smaller sample sizes (observations < 120), for which the Schwarz Information Criterion (SIC) appears to be the most accurate. Even though the number of observations in all three models is below 120, it is vital to consider the subsequent diagnostic tests to decide on the correct lag length. Choosing a number of lags makes no sense when the model exhibits autocorrelation at the selected lag order. The analysis in Stata delivers different results. The SIC indicates using one lag in the baseline model, but succeeding diagnostic tests imply autocorrelation when choosing only one lag. Note that the p-values of the autocorrelation test are not the same when a VAR with one lag is estimated (see table 8). In the case of a VAR estimation with one lag, the Lagrange multiplier test for autocorrelation produces a p-value of 0.02138. However, HQC recommends using a number of five lags which is approved by no autocorrelation at the selected lag order. In model 2 and model 3, Stata suggests using zero lags. This is non-sensical in the view of the target of this thesis. On the one hand, if the lag length is too small, the model will be misspecified. On the other hand, if the lag length is too large, degrees of freedom will be wasted. Consequently, with consideration of economic theory (e.g. Ivanov and Kilian, 2005), it leads to the decision to use five lags for all models. Ivanov and Kilian (2005) used level and first difference variables in their study. Table 6 in the appendix displays the results of the lag order selection criteria. Since the recommended number of lags for models 2 and 3 are non-sensical, the tables will not be presented in this work.

4.2 Diagnostic tests

To ensure that the model makes sense, various diagnostic tests need to be performed. After the decisions regarding the specification and the lag length criteria have been made and the stability of the VAR is confirmed, a Granger causality test for all models is conducted to show the relationship between the variables. Finally, the autocorrelation test helps to notice whether the selected lag length order is appropriate.

4.2.1 VAR Stability Condition

The test for stability condition checks if all inverse roots of the characteristic autoregressive polynomial lie inside the unit circle, implying that they have a modulus less than one. A stable VAR model entails stationarity. Therefore, the stability condition is known in the literature as the "stationarity condition". Additionally, the stability of the VAR model is an essential feature for the validity of the model. If a model is not stable, the various diagnostic tests executed in the VAR model and the impulse standard errors may be invalid. Nonetheless, the tests in model 1, model 2, and model 3 exhibited that all the eigenvalues lie inside the unit circle. Accordingly, the VAR models satisfy the stability condition and allow us to continue with further diagnostic tests.

4.2.2 Granger causality Wald test

The Granger causality test is a widely used concept to examine a causal relationship between variables in a time series study (Freeman, 1983; Thornton and Batten, 1985). The idea behind this is to look at whether a variable X is useful to predict another variable Y, if so then X does Granger cause Y. However, the causal relationship can occur in a unilateral but also a bilateral direction. Moreover, it is also possible that a combination of variables within a system can Granger cause another variable. Table 5 shows the results of the Granger causality test for the baseline analysis.

Table 5

Granger causality Wald test: Model 1			
Equation	Excluded	test statistic	p-value

PCE	JOV	6.9798	0.222
PCE	UNR	24.627	0.000***
PCE	GDP	23.894	0.000***
PCE	ALL	62.111	0.000***
JOV	PCE	16.595	0.005***
JOV	UNR	22.3	0.000***
JOV	GDP	13.551	0.019**
JOV	ALL	66.52	0.000***
UNR	PCE	10.315	0.067*
UNR	JOV	9.3123	0.097*
UNR	GDP	21.338	0.001***
UNR	ALL	44.394	0.000***
GDP	PCE	5.5291	0.355
GDP	JOV	6.5451	0.257
GDP	UNR	19.146	0.002***
GDP	ALL	34.521	0.003***

Note. The variables are in the same format as they will be used in the VAR estimation. This means that PCE, JOV, and GDP are already the first differences in their logarithmic variable and UNR is the first difference in its level variable. ALL denotes a combination of all remaining variables within the system. The tables for model 2 and 3 can be seen in the appendix A.

The test implies that all variables together impact the left-hand-side variable in each combination. Furthermore, UNR and GDP Granger cause PCE on their own (in the bivariate system). The same pattern can be observed for PCE, UNR, and GDP when looking at the relationship to JOV, for UNR on GDP, and GDP on UNR. Overall, there is a causal relationship between these variables in model 1. Thus, it is reasonable to investigate the impact of a shock in the growth in consumption expenditure on the other variables. The tables of model 2 and model 3 are displayed in appendix A. However, the results suggest a causal relationship between some bivariate systems and almost all multivariate systems in both cases. The knowledge of predictive power between the variables helps to continue with the test for autocorrelation at the lag-selection.

4.2.3 Test for Autocorrelation

According to the method developed by Johansen (1995), a Lagrange multiplier (LM) test for autocorrelation in the residuals of the VAR models was implemented in the next step of this analysis. The null hypothesis in this test implies no autocorrelation at the selected lag order. Therefore, a p-value more significant than 0.05 indicates that the null hypothesis can not be rejected, and the chosen number of lags is appropriate. The results for all three models are exhibited in the appendix table 11.

Although the target of not rejecting the null hypothesis could be reached with a lower number of lags in all models, it is crucial to mention that the selected number of lags needs to be confirmed by a stable VAR model. Thus, the resulting selection of five lags in the models is a combined decision of the lag-selection criteria (see 4.1), the test for autocorrelation, and the test for stability in the model, which can be found at the beginning of this section (see 4.2.1). Several tests with different lag lengths were conducted during the whole analysis in Stata. In the end, the selection of five lags delivered the best fit acknowledging the theory and econometrics. From a theoretical perspective, choosing zero or one lag is not sensical since it is crucial to allow even further past values to have an impact on the system.

5 Results

The results of the diverse models will be explained in the first part. The second part deals with the impulse response functions, which exhibit the reaction of a variable to a one standard deviation shock of another variable. Finally, the section is rounded off by the concept of variance decomposition, which indicates the error made by forecasting a variable over time due to a specific shock.

5.1 Estimation results of the VAR models

The estimations of the diverse VAR specifications are displayed in table 6. The coefficients resulting from the VAR model can be treated as causal in the short-term. Since this paper tries to determine the impact of a shock in consumption spending growth on other variables in the system within the short-term, only the coefficients for the variable of interest (PCE) are presented. These coefficients do not yet provide a clear picture of the possible impact if a shock to consumer spending growth arises. Nevertheless, they show that lagged consumption expenditure has a statistically significant impact on the other variables. The bold values show in which lags PCE had a significant positive or negative effect at the 1%, 5%, or 10% significance level. For instance, when looking at the 5% level in the baseline model, consumption expenditure growth has a significant impact on the variation in job vacancies in the first lag and on the change in the unemployment rate in the first and second lag ceteris paribus. In the first lag, model 2 for females exhibits a significant positive impact for the second age group. Whereas in model 2 for males, the consumption growth is only statistically significant for the first group in the third and fifth lag (negative influence) and GDP in the first lag (positive effect). In model 3, PCE hurts the growth in the agriculture sector in the third lag and harms the change in the construction sector in the fourth and fifth lag. Finally, the variation in consumption expenditure positively affects the growth in the manufacturing sector in the fourth lag and in the services sector in the first lag. Important to mention is that the variable format is again in the first differences, and additionally, PCE, GDP, and all the sector-specific variables are in logarithmic form.

Table 6

Impact of PCE growth on other variables within the system					
	Lags				
	1	2	3	4	5
JOV	**2.98**	1.26	**-1.69**	-0.83	**1.95**
	0.003***	0.208	**0.092***	0.408	**0.051***
UNR	**-2.05**	0.13	**2.01**	0.53	-1.34
	0.040**	0.899	**0.045****	0.598	0.180
GDP	1.57	0.80	-0.84	-0.88	0.98
	0.118	0.421	0.398	0.377	0.328
ER15_24f	**1.64**	-0.96	0.56	**2.02**	-0.87
	0.100*	0.335	0.573	**0.043***	0.386
ER25_54f	**2.25**	-1.23	-1.15	-0.92	-0.04
	0.025**	0.219	0.250	0.356	0.970
ER55_64fe	0.56	0.44	1.10	0.52	-1.10
	0.573	0.657	0.271	0.603	0.270
ER15_64fe	**2.72**	-0.82	-0.15	-0.11	-0.61
	0.007*	0.412	0.878	0.912	0.540
GDP	**2.19**	0.04	-0.35	-0.98	0.68
	0.029*	0.967	0.728	0.327	0.498

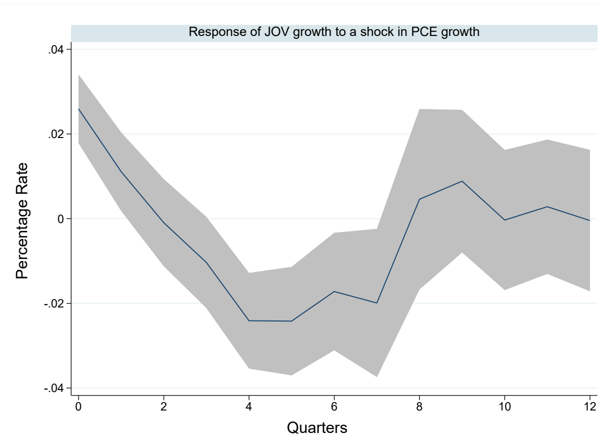
ER15_24m	**1.90**	-1.77	**-2.21**	-1.54	**-2.98**
	0.058*	0.077*	**0.027****	0.123	**0.003*****
ER25_54m	0.69	-1.20	-1.04	0.15	-0.37
	0.490	0.229	0.297	0.878	0.712
ER55_64m	1.14	-0.18	-0.05	-0.82	-1.54
	0.255	0.856	0.960	0.414	0.124
ER15_64m	1.52	-0.86	-1.13	-0.56	-1.59
	0.128	0.388	0.258	0.578	0.112
GDP	**2.00**	-1.15	-1.58	-1.03	0.20
	0.046**	0.252	0.115	0.301	0.838
Agri	0.65	0.34	**2.89**	0.40	0.59
	0.518	0.737	**0.004*****	0.689	0.555
Cons	0.57	-0.07	0.05	**-2.13**	**-2.48**
	0.572	0.942	0.956	**0.033****	**0.013****
Indu	-1.33	-0.66	-0.46	1.56	0.11
	0.183	0.511	0.649	0.119	0.916
Manu	-1.35	-0.44	0.19	**2.09**	0.56
	0.178	0.657	0.849	**0.036****	0.574
Serv	**2.63**	-0.45	-0.21	-1.24	-1.04
	0.008***	0.651	0.835	0.216	0.296
GDP	**1.80**	-0.80	-0.37	0.77	0.48
	0.071*	0.424	0.710	0.441	0.628

Note. Only the estimates for the impact of PCE on the other variables are displayed. The table is split into four parts. The top is for model 1, the two central parts are for model 2 of the females and males, and the bottom displays the coefficients for model 3.

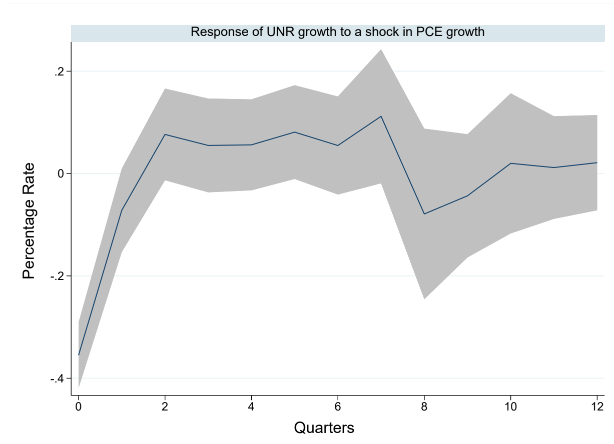
5.2 Impulse response functions

The subsequent section delivers the graphical results for the impulse response functions (IRF) to a positive one standard deviation shock of personal consumption expenditure growth (PCE) for all three models. Additionally, the results will be interpreted and compared with theoretical macroeconomic expectations. First, the plots for the responses of the variables in the baseline model are illustrated in figure 5. Beginning with graph 5a which indicates the response of the change in the unfilled job vacancies to a shock in the variation of consumer spending. Initially, a positive one standard deviation shock in PCE growth positively influences the change in job vacancies. After that, it gradually declines, exhibiting a negative impact from the second to the eighth quarter. From the eighth quarter onwards, it fluctuates around zero, implying that the shock dies out. It is important to remember that the VAR model in first differences can only deliver good results in the short-run, signifying that the initial shocks are especially interesting for this work.

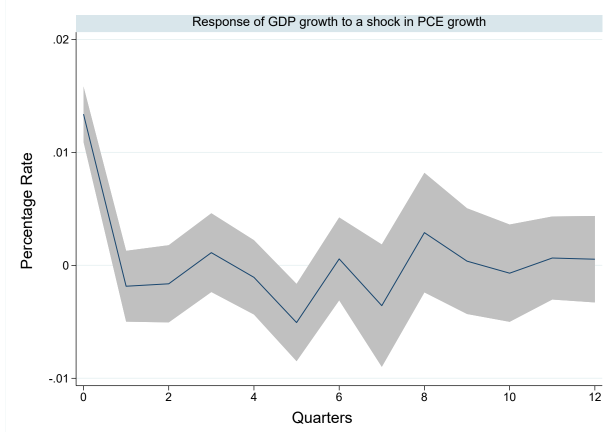
Figure 5



(a) IRF Model 1: JOV on PCE



(b) IRF Model 1: UNR on PCE



(c) IRF Model 1: GDP on PCE

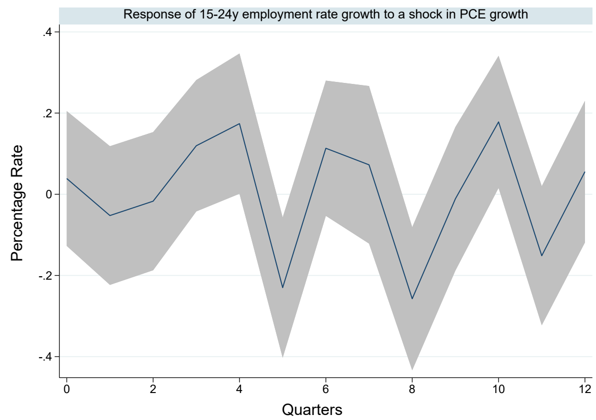
Note. Impulse response functions of model 1 for a one standard deviation shock to personal consumption expenditure. Variables are used in their logarithmic and first difference transformation.

Next, the unemployment rate growth response to a positive shock in PCE growth is displayed in plot 5b. The immediate reaction of UNR change is negative, meaning that the unemployment rate growth is reduced. This observation is in line with macroeconomic theory (Bean and Pissarides, 1993). An increase in consumption expenditure growth should decrease unemployment rate growth due to higher demand in the labor market. From the second quarter onwards, the shock dies out and oscillates around zero. Finally, a positive one standard deviation shock in consumption expenditure variation has an immediate positive impact on the growth in real GDP (see figure 5c). In the ongoing periods, the shock decreases the change in real GDP, and the effect declines to around zero.

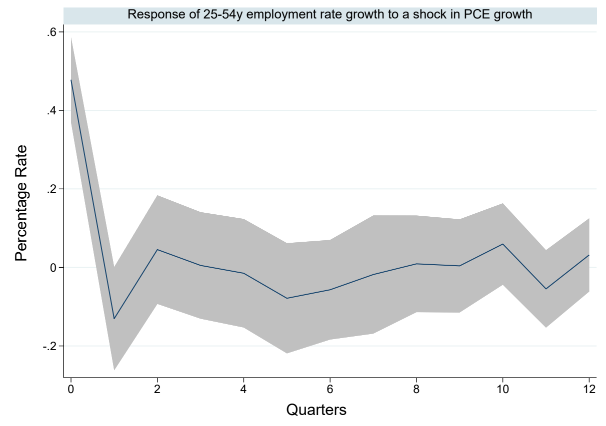
Model 2 investigates the impact of a shock in consumer spending growth on various employment rates of different age groups for females and males. Figure 6 presents the graphs for the female employment rates. Apart from figure 6a which exhibits an unclear picture of economic reasoning, all age groups result in the same pattern. A one standard deviation shock to the variation in PCE initially increases the employment rate growth in the groups of 25 to 54 years old, 55 to 64 years old, and 15 to 64 years old females. The shock steadily declines and dies out between the first and the second quarter. This outcome makes sense in terms of macroeconomic theory, implying that if consumption growth suddenly increases, the economy is positively affected, which also spills over to the labor market, concretely to female employment rates (Bean and Pissarides, 1993). For the group of 25 to 54 years old females, the graph depicts the largest response. In numbers, this age group comprises the highest amount of employees, which is likely one of the main reasons why the effect is the most significant. It is difficult to explain why the youngest age group exhibits high fluctuations.

Important to consider is that young female employees are underrepresented in apprenticeships (Dornmayr and Nowak, 2020). Many young women choose secondary or tertiary education. If young employees are still in their apprenticeship, a positive shock to consumption does not necessarily respond to the growth rates of young females immediately. Often, it takes time for companies to adapt their contingent of apprenticeships to the economic situation. On the other hand, in case of a negative shock, one might not expect the youngest group to be affected the heaviest since apprenticeships are of low costs for employers and protected by the government's support.

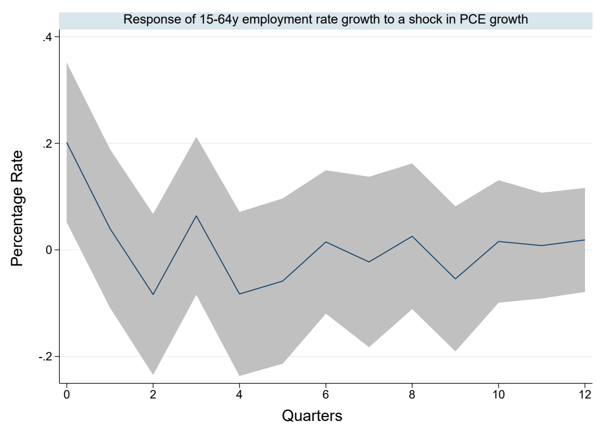
Figure 6



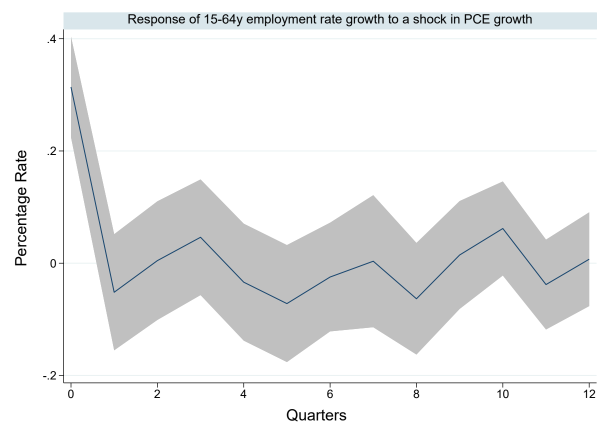
(a) IRF Model 2: Females 15-24y



(b) IRF Model 2: Females 25-54y



(c) IRF Model 2: Females 55-64y

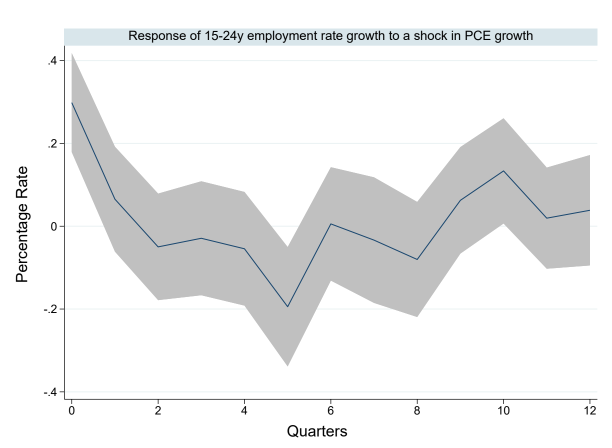


(d) IRF Model 2: Females 15-64y

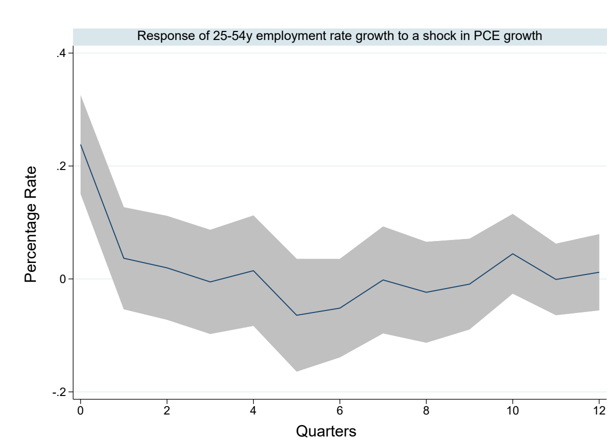
Note. Impulse response functions of model 2 for a one standard deviation shock to personal consumption expenditure. Variables are used in the first difference transformation. Additionally, PCE and GDP are utilized in the logarithmic format. The IRF for GDP is very similar to the baseline case; therefore, it can be seen in the appendix B.

The second part of model 2 focuses on the impulse response function for the male employment rates (see figure 7). In any of the four cases, a positive one standard deviation shock to consumption expenditure positively affects the change in the employment rates in the early stage. Although for the 55 to 64 years old males, the picture is slightly less transparent. Same as in the analysis with the data for females, the results are in line with current economic theories (e.g. Bean and Pissarides, 1993). The authors argue that lower saving propensity increases the market for consumption goods and results in higher employment. In the case of this analysis, when a positive shock boosts the growth in consumer spending, it positively influences the labor market. Hence, the employment rate growth in the various male age groups is amplified. After the immediate positive impact, the percentage rates decline. However, in all four groups, the effect of the shock begins to disappear between the first and the second quarter, and fluctuates around zero for the subsequent periods. On the contrary to the female case, the youngest male group exhibits an initial positive effect. The same holds for the second age group. These two groups represent the majority of the male working force; thus, it makes sense that they respond most significantly. The fluctuations in the highest age group might be because firms prefer to employ younger workers. Therefore, older workers do not benefit from a positive shock to consumption like the two younger age groups.

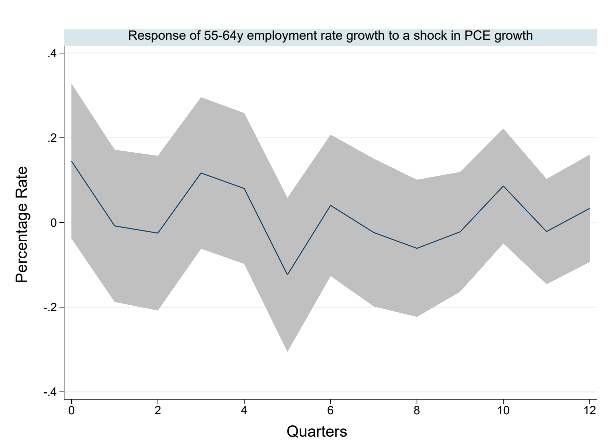
Figure 7



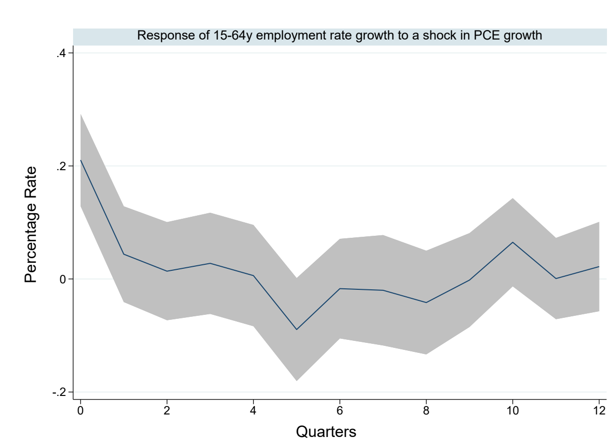
(a) IRF Model 2: Males 15-24y



(b) IRF Model 2: Males 25-54y



(c) IRF Model 2: Males 55-64y

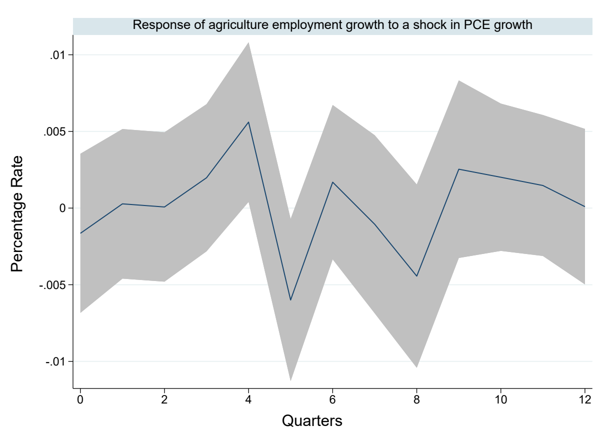


(d) IRF Model 2: Males 15-64y

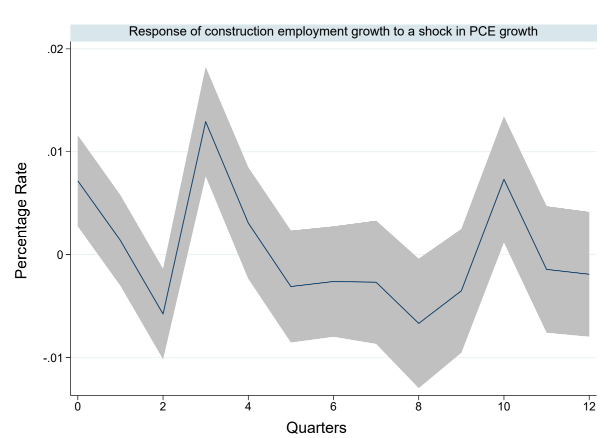
Note. Impulse response functions of model 2 for a one standard deviation shock to personal consumption expenditure. Variables are used in the first difference transformation. Additionally, PCE and GDP are utilized in the logarithmic format. The IRF for GDP is very similar to the baseline case; therefore, it can be seen in appendix B.

The final part of the analysis in this section deals with the impulse response functions of the diverse labor market sectors (see figure 8). Graphs 8a and 8b are extremely volatile over the entire time horizon. For both sectors, it is almost impossible to draw any meaningful conclusion due to the fluctuating responses to a positive shock in consumer spending growth. The effect on the change in employment in the construction sector might be positive, but this idea is remarkably vague and cannot be backed by a solid analytical result. Nevertheless, there are more interesting results in the remaining four cases. Starting with the industry sector (see figure 8c) and the manufacturing sector (see figure 8d), it seems that a one standard deviation shock to PCE does not significantly impact the employment growth in these sectors. The high oscillation in the graphs does not indicate any positive or negative impact in these branches. On the other hand, it is possible to see an initial effect in the service sector and for real GDP in model 3. A shock to the variation in consumer spending positively influences the service sector for around one quarter and then swings around zero for the remaining periods (see figure 8e). Similar to the baseline model and model 2, a shock to PCE growth positively impacts the change in real GDP in the short-run (see figure 8f). The responses for real GDP in model 2 can be seen in appendix B of this work.

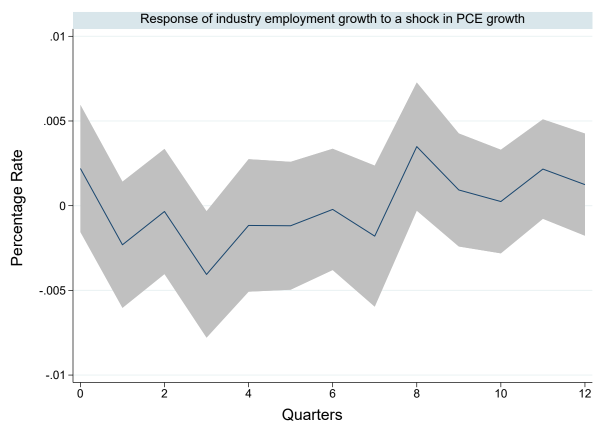
Figure 8



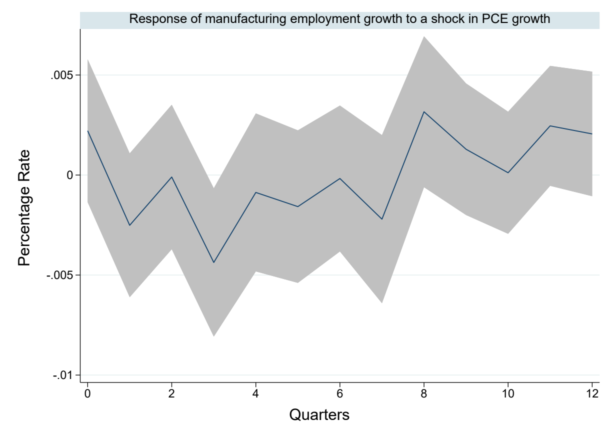
(a) IRF Model 3: Agricultural sector



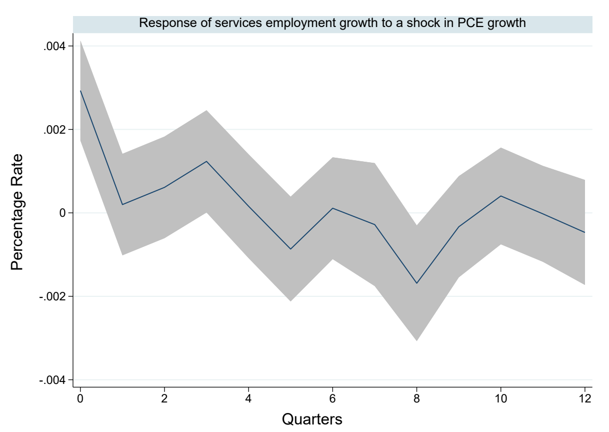
(b) IRF Model 3: Construction sector



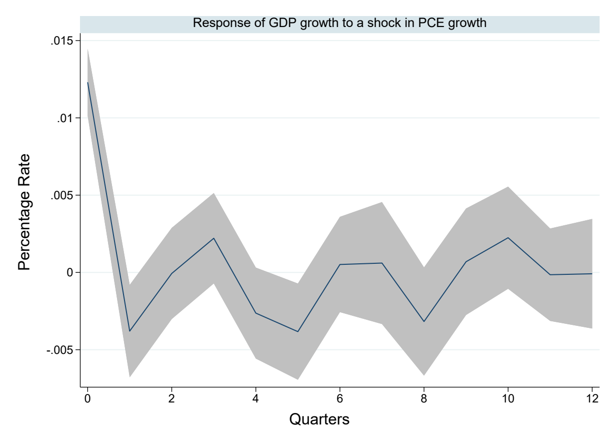
(c) IRF Model 3: Industry sector



(d) IRF Model 3: Manufacturing sector



(e) IRF Model 3: Services sector



(f) IRF Model 3: GDP

Note. Impulse response functions of model 3 for a one standard deviation shock to personal consumption expenditure. Variables are used in their logarithmic and first difference transformation.

5.3 Discussion of Results

As demonstrated in the former paragraphs, a shock to consumption expenditure growth may initially impact the change in the other variables within the system. The impulse response functions of the baseline model are in line with economic expectations; however, a comparison with the preliminary tests in this analysis, for instance, the Granger causality test or the correlation matrix, confirms that the impact on the unfilled job vacancies variation and unemployment rate growth is significant. The Granger causality test strengthened the IRF graphs by significance at the 5% and the 10% level, respectively. Moreover, the correlation matrix is significant at the 1% level for any variables of the baseline model. Therefore, it is sensical to conclude that sudden shocks to consumer spending variation influence growth rates in the Austrian labor market.

A more detailed analysis of employment rates in diverse age groups for females and males provides interesting results for some but not for all variables in the study. Thus, the graphical representation of the impulse response functions 6b and 6d mirror the observation of Granger causality at the 5% significance level. Additionally, the correlation matrix supports the notion of massive reliance on a PCE growth shock in the first few quarters. In numbers, these are the most prominent groups of the working population. Hence, they are influenced the most by a shock to consumption growth. Interestingly, the changes in male employment rates seem to be most substantially affected in the group of 15 to 24 years old people. Only in this group, the pattern of the impulse response is reinforced by the Granger causality test and a significant correlation. Just because there is no significant result for the Granger causality test does not mean that the impulse response functions do not make sense. On the contrary, it is possible to use them for argumentation. Nonetheless, this paper tries to support the results with as many statistical and economic tools as possible. The finding that a positive one standard deviation shock to personal consumption expenditure growth positively impacts the growth in various age-gender-specific employment rates is, in general, helpful because it is under the expectations.

The sectoral comparison in model 3 delivers ambiguous results. On the one hand, figure 8e indicates a positive impact of one standard deviation shock to consumer spending growth on the growth in the services sector. This can be confirmed since PCE growth does Granger cause the change in the sector, and the correlation matrix demonstrates high significance. On the other hand, for the remaining sectors, neither the impulse response graphs nor the Granger causality tests provide evidence for any meaningful statistical or economic conclusion. Notwithstanding the sections above, it is doubtful that only the service sector would be affected in the face of a consumption growth shock. Hence, it is essential to be particularly cautious about the results of the third model. Furthermore, sectoral impacts depend on a country's economy and its reliance on the various sectors. For instance, a relatively stark country in the manufacturing sector would expect heavier effects in this sector if a shock to consumption expenditure growth emerges.

Especially if one is thinking about the COVID-19 pandemic, the relevance of shocks to economic variables is undeniable. More than two years of economic downturns and booms showed that shocks could occur in diverse manners. Of course, consumption is also influenced by other variables like consumer confidence. If consumers anticipate that something will change in the future, they may act quickly and change their purchasing habits. This can lead to shocks in consumption expenditure. For example, at the beginning of the recent crisis, people started to buy more of specific goods like toilet paper, disinfectants, or oil. As a result, the skyrocketing demand for certain goods could not be equalized by a steady or lower supply, which caused empty supermarket shelves, et cetera. Similar things happened to specific materials used in the construction industry. Moreover, lockdowns all over the globe affected the production in the middle- to long-term. Consequently, prices started to increase, which in turn affected consumption and the labor market.

5.4 Forecast error variance decomposition

The variance error decomposition of forecast errors exhibits the error made by forecasting a variable over time due to a specific shock. The concept of variance decompositions is applied to see how much of the variability in the variable is explained by its own shocks versus the shocks in the other variables of the system. Therefore, it is possible to indicate which variables have short-term and long-term impacts on the other variables in the system with this approach. Once again, this thesis focuses on the short-term effects.

Furthermore, Lütkepohl (2005) stresses the connection between the forecast error variance decomposition and Granger causality. In a bivariate case where one variable does not Granger cause the other variable, it is still possible that the variance decomposition results are non-zero. Note that the concept of Granger causality and forecast variance decomposition is quite different. The concept of Granger causality shows the relationship between two variables or two subsets of variables, whereas forecast error variance decomposition focuses on instantaneous causality. While the result of the Granger causality test is unique, the variance decomposition depends on how A_0 is defined.

Thus Lütkepohl (2005, p. 66) argues that "the interpretation of a forecast error variance decomposition is subject to similar criticisms as the interpretation of impulse responses". Moreover, it underlies the same critical points as in the concept of Granger causality. The various components of forecast error variance decomposition may vary if the number of variables changes. Additionally, the decompositions could be biased by measurement errors, seasonal adjustment, and the use of aggregates (Lütkepohl, 2005).

The baseline model indicates that around 37% of the variability in the growth of total unfilled job vacancies is explained by a shock to consumption expenditure growth in the first quarter (see table 7). This percentage rate increases to around 48.5%-49.5% from the seventh quarter onward. For the change in the unemployment rate, the impact of a shock on PCE growth is even more severe. Initially, consumer spending growth accounts for 80%. The higher the period after the shock, the lower is the explanatory effect of PCE growth, and the higher it is for the growth rates in JOV and real GDP. A similar result is observed for the variability of real GDP growth itself. While the change in private consumption expenditure has an explanatory power of more than 81% in the first quarter, this rate declines to below

60% in the 12^{th} period.

The values of the variance decomposition reinforce the pattern of the impulse response function in model 2 for females. The variability in the groups of 25 to 54 years old females and the 16 to 64 years old females depends strongly on the shock in PCE variation. On the contrary, the groups of 15 to 24 years old and 55 to 64 years old people have the highest explanatory power due to themselves. A shock to consumer spending growth explains approximately 22% of the variability in the employment rate changes for 15 to 24 years old people. However, for 25 to 54 years old and 15 to 64 years old people, the values reach 60% and 43%. For 55 to 64 years old female employment rate, the impact of a PCE shock is meager compared to the other variables. In the male case, the values are between 18% and 29%, except for the oldest group, where the effect is low again. In Model 3, consumer spending growth has a relevant explanatory power of circa 30% and 25% for the construction and service sectors, respectively.

Table 7

Forecast error variance decomposition: Model 1					
Forecast error in the the growth of	Forecast horizon (in quarters)	Proportions of forecast error variance h periods ahead accounted for by innovations in			
		ϵ_P	ϵ_J	ϵ_U	ϵ_G
PCE	1	1	0	0	0
	4	70.48	3.48	16.94	9.1
	8	64.4	3.92	19.55	12.13
	12	60.93	4.49	19.48	15.10
JOV	1	37.18	62.82	0	0
	4	31.86	48.64	14.40	5.1
	8	49.62	26.41	20.49	3.48
	12	48.48	25.84	20.52	5.16
UNR	1	81.37	12.44	6.19	0
	4	64.65	16.55	7.59	11.21
	8	62.65	19.31	7.17	10.87
	12	59.78	19.87	7.71	12.64

GDP	1	80.14	2.75	3.94	13.17
	4	57.34	4.61	12.89	25.16
	8	55.75	5.68	16.18	22.39
	12	52.24	6.32	16.54	24.9

Note. Forecast error variance decomposition of model 1. The variables PCE, JOV, UNR and GDP are in first differences and except for UNR in logarithmic format. The variables ϵ_P, ϵ_J, ϵ_U and ϵ_G denote the percentage proportions for PCE, JOV, UNR and GDP. The tables for models 2 and 3 are displayed in appendix A.

6 Robustness Checks

An empirical analysis by Khan et al. (2019) investigates the role of consumer sentiment in household investment dynamics. They "explore the role of consumer's beliefs or attitudes as potential drivers of the household investment dynamics over the business cycle"(p. 5), and especially the first part of their analysis is from an empirical point of view somehow comparable to the examinations of this work, even though this paper does not focus on consumer confidence but consumption expenditure as the main variable. They use a vector autoregressive (VAR) approach with four variables (ICE, household investment, hours worked, and output) to show how the latter three variables respond to a confidence shock. ICE is their measure for consumer sentiment, and household investment includes residential investment plus consumer durables. Their paper stresses that household investment, hours worked and output increase after the shock and are statistically significant. Accordingly, in their study, the variance decomposition indicates that ICE shocks are responsible for 46, 38, and 74 percent of the forecast error variance of these three variables. In the literature, there exists a lot more evidence that consumption is heavily impacted by consumer confidence (e.g. Friedman, 1957; Acemoglu and Scott, 1994; Carroll et al., 1994; Bram and Ludvigson, 1998).

Thus, to strengthen the findings of the various models in this work, this section extends the models by including a consumer sentiment index in the analysis. Now, the first variable in the system, consumer sentiment, is obtained from the FRED database of the Federal Reserve Bank of ST. Louis (Organization for Economic Co-operation and Development, 2022a). It is a consumer opinion survey based on the OECD confidence indicator for Austria. The index is based on questions and answers about consumers' anticipated financial situation, their confidence about the general economic situation, unemployment, and capability of savings.

This gives one an impression of the future evolution of the households' consumption and saving. If the index lies above 100, consumers have an optimistic view of the future and are willing to consume more in the subsequent four quarters. On the contrary, values below 100 indicate a pessimistic attitude which is correlated with a higher tendency to save more and spend less on consumption (Organization for Economic Co-operation and Development, 2022b).

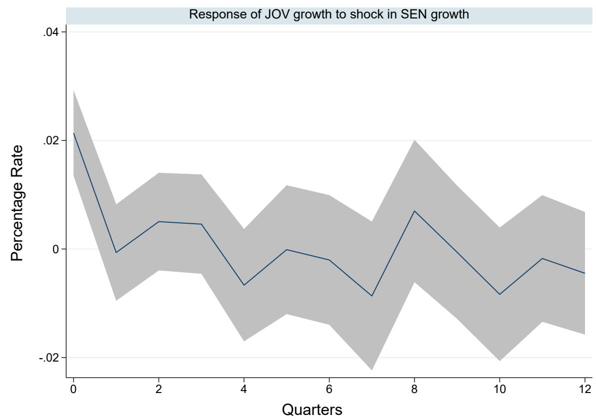
The graphs in the figure 9 show that the impulse response function's time patterns remain stable even if the growth of consumer sentiment is included in the baseline model. For the changes in unfilled stock vacancies and real GDP, it is still possible to observe a positive impact for a one standard deviation shock to growth in PCE. However, PCE does Granger cause JOV on its own but not GDP anymore. Moreover, a positive shock to PCE growth decreases the variation in the UNR in the short-run. A significant Granger causality test also confirms this. For consumer sentiment, Granger causality is exclusively found in the case of unfilled job vacancies. The correlation matrix exhibits significant values for all variables. In the model, the appropriate lag length remains at five lags; diagnostic tests indicate no autocorrelation at the selected lag length, and the model is stable.

The robustness checks for the gender-specific age groups provide evidence that if the growth of consumer confidence is included in the study, the model itself and the analysis' results remain stable. For females, the groups of 25-54 and 15-64 deliver not only a clear positive immediate effect caused by a shock to consumption expenditure growth in the IRFs but also a significant result in the Granger causality test. Additionally, the variables imply a significant positive correlation with the growth of consumer spending.

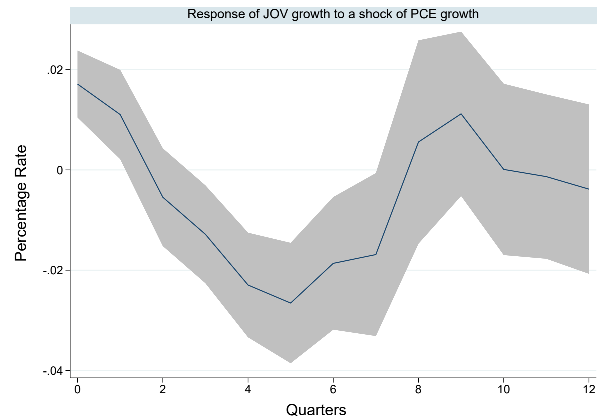
Similar to the model without consumer sentiment, the changes in male employment rates are most significantly affected in the group of 15 to 24 years old people. Even though all impulse response functions initially illustrate a positive effect, the Granger causality test only supports the graphical results in this group. On top of that, the analysis exhibits a significant correlation between this group and the consumption expenditure growth.

Lastly, the robustness check was executed for the model with various labor sectors. Once more, the analysis reinforces the model's findings without consumer confidence growth. The impulse response of the service sector to a shock in consumer spending growth is again positive, and the Granger causality test exhibits a significant result at the 10% level (almost 5%). Furthermore, the correlation matrix indicates that consumption expenditure growth and growth in the service sector employees are significantly positively comoving if sentiment change is included.

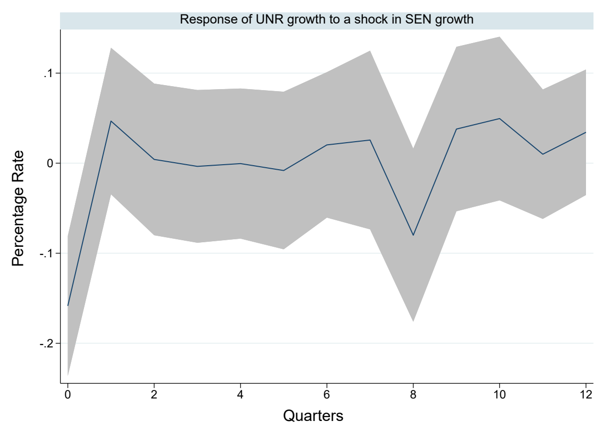
Figure 9



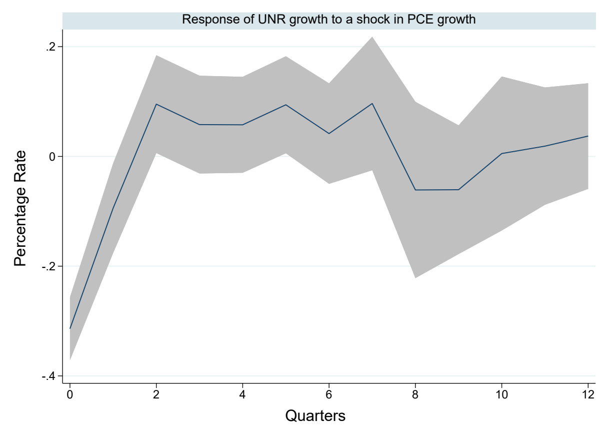
(a) IRF Model 4: JOV on SEN



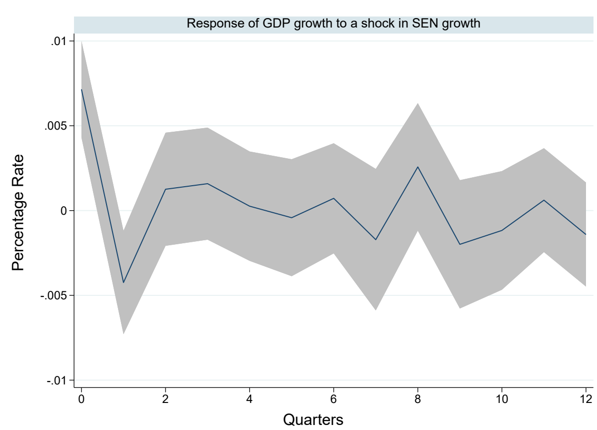
(b) IRF Model 4: JOV on PCE



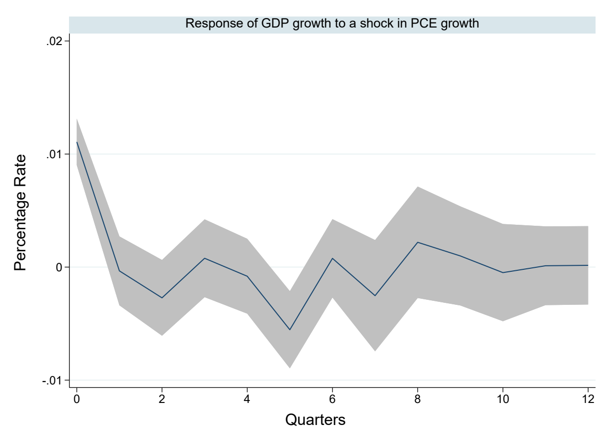
(c) IRF Model 4: UNR on SEN



(d) IRF Model 4: UNR on PCE



(e) IRF Model 4: GDP on SEN



(f) IRF Model 4: GDP on PCE

Note. Impulse response functions of model 4 (robustness checks) for a one standard deviation shock to consumer sentiment and personal consumption expenditure. Variables are used in their logarithmic and first difference transformation.

Overall the results of the variance decompositions do not change significantly when consumer confidence is included. The Granger causality test results, the correlation matrices and the results of the variance decompositions for the analysis with consumer sentiment will not be included in this thesis. The same applies to the impulse response functions of model 2 and model 3.

Since Stata also recommended using one lag for the analysis, it was tried to estimate the results by selecting one lag. However, even though the results exhibited the same picture in the short-term, they cannot be used in the robustness checks because a further investigation of the models showed autocorrelation at the selected lag order.

7 Limitations

Even though many findings of this paper are economically sensical, it is essential to mention that this analysis has several potential drawbacks. First, this analysis only uses quarterly data from the first quarter of 1999 to the fourth quarter of 2021. A larger dataset in terms of observation length or even monthly data would help make the analysis more accurate and strengthen the results. Since this thesis builds on available data free of charge, it was impossible to obtain more detailed data. Particularly, the age-group-gender and sector-specific variables were not available in a more comprehensive set.

Second, the properties of the diverse variables made it difficult to decide on a VAR or a vector error correction model (VECM). Since almost none of the variables were I(0) in their original format, it was required to use the concept of first differencing to receive I(1) variables. Additionally, preliminary tests for cointegration delivered unclear results due to the various combinations of variables in the diverse models; hence, it resulted in the decision to use a VAR model in first differences, which is appropriate if one is only interested in the effect of the short-run. However, with this type of approach, it is neither possible nor economically meaningful to trace out any causal findings for the long-run since the possible results found for the long-term relationship would be biased.

Third, Lütkepohl (2005) stresses that defining the relevant impulses to a system is not the only difficulty in impulse response analysis. Additionally, he warns of potential incompleteness due to omitted variables. There are likely other economic variables, for example, consumer confidence which may have explanatory power for responses of other variables.

Even though the system is still useful for forecasting, these omitted variables weaken interpretations due to a distortionary impact on the impulse response functions. Moreover, estimation results and impulse response functions may be influenced by measurement errors and "the use of seasonally adjusted or temporally and/or contemporaneously aggregated variables" (Lütkepohl, 2005, p. 63).

Finally, it is necessary to consider external validity. Pointing out that an analysis with data from a different country with a different labor market system may deliver different results. Therefore, it is inappropriate to conclude that these findings will also hold for the same age-gender-specific groups in other countries. It is also possible that significant results can be obtained for any sector depending on the economy of the observed country.

8 Conclusion

Private consumption is one of the main drivers in the macroeconomy and, therefore, an important variable of each country's economy. This paper connected diverse labor market data with consumption data to find that the latter has a considerable impact on the other variables. Shocks to consumer spending growth positively affect the change in unfilled job vacancies and, on the top of that, negatively influence the variation in the unemployment rate. Additionally, in model 1, at the beginning, real GDP growth is positively impacted by a shock to consumer spending change.

However, since this is just the baseline case, the study also focuses on the labor market in more detail by including age-gender-specific and sector-specific variables. Even though the picture in these analyses is a bit less clear, it is still possible to discover some interesting findings. On the one hand, it seems that a positive consumer spending growth shock has a positive effect on the overall employment rate growth of 15 to 64 years old females. On the other hand, the group of 25 to 54 years old females is most significantly affected in the short-term. On the contrary, for the male employment rates, a shock in consumption expenditure growth in the system most substantially increases the rate of 15 to 24 years old people.

When looking at the sector-specific case, it turns out that only for the service sector a substantial positive effect is recognized after a consumer spending growth shock. The graphical results of the impulse response functions are backed by significant Granger Causality tests and a significant correlation between the variables themselves.

The robustness check indicates that the findings remain stable even if consumer sentiment, praised in the literature as one major indicator of consumption behavior, is included.

Nevertheless, it is essential to interpret the results carefully since the models have their drawbacks. Moreover, it is impossible to make any long-term conclusions since the effects would be biased in the long-run. Thus, it would be an interesting and helpful opportunity to extend this work with a long-run analysis of the Austrian labor market or to conduct a similar analysis in another country with a different labor market system.

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A Appendix Tables

Table 8

Results augmented Dickey-Fuller tests			
	Test in level form	Test in logarithmic form	Test in first differences
PCE		-0.947	-5.178
		0.7720	0.0000***
JOV		0.180	-2.901
		0.9711	0.0452**
UNR	-2.325		-4.779
	0.1641		0.0001***
GDP		-1.335	-4.698
		0.6130	0.0001***
ER15_24f	-1.305		-5.337
	0.6267		0.0000***
ER25_54f	-1.533		-4.603
	0.5169		0.0001***
ER55_64f	0.406		-5.599
	0.9817		0.0000***
ER15_64f	-1.138		-4.291
	0.6997		0.0005***
ER15_24m	-2.394		-4.136
	0.1435		0.0008***
ER25_54m	-2.172		-3.866
	0.2167		0.0023***
ER55_64m	-0.127		-3.329
	0.9467		0.0136**
ER15_64m	-2.739		-4.077
	0.0676*		0.0011***
Agri		-0.604	-4.596
		0.8701	0.0001***

Cons		-2.028	-4.467
		0.2744	0.0002***
Indu		-2.236	-4.354
		0.1933	0.0004***
Manu		-2.249	-4.222
		0.1888	0.0006***
Serv		-0.958	-3.939
		0.7682	0.0018***

Note. The unemployment rate and the age-group employment rates of both genders can be used in level form since they are already percentage rates. The other variables were transformed into logarithmic values before the tests for unit roots were conducted.

Table 9

Results Philips-Perron tests			
	Test in level form	Test in logarithmic form	Test in first differences
PCE		-1.265	-12.061
		0.6453	0.0000***
JOV		0.281	-5.007
		0.9765	0.0000***
UNR	-2.323		-8.350
	0.1645		0.0000***
GDP		-1.724	-12.578
		0.4188	0.0000***
ER15_24f	-3.086		-13.403
	0.0276		0.0000***
ER25_54f	-1.412		-12.614
	0.5764		0.0000***
ER55_64f	0.724		-12.578
	0.9903		0.0000***
ER15_64f	-0.885		-12.358
	0.7930		0.0000***
ER15_24m	-2.982		-10.812
	0.0366		0.0000***

ER25_54m	-1.922		-9.424
	0.3219		0.0000***
ER55_64m	0.120		-10.681
	0.9674		0.0000***
ER15_64m	-2.598		-9.332
	0.0934*		0.0000***
Agri		-1.209	-9.671
		0.6696	0.0000***
Cons		-3.095	-11.241
		0.0269**	0.0000***
Indu		-2.094	-10.172
		0.2468	0.0000***
Manu		-2.010	-10.087
		0.2822	0.0000***
Serv		-0.946	-9.850
		0.7724	0.0000***

Note. The unemployment rate and the age-group employment rates of both genders can be used in level form since they are already percentage rates. The other variables were transformed into logarithmic values before the tests for unit roots.

Table 10

Lag-order selection criteria: Model 1			
Lag number	AIC	HQC	SIC
0	-14.3617	-14.3149	-14.2451
1	-15.2381	-15.0039	-14.6552*
2	-15.2712	-14.8498	-14.2221
3	-15.2691	-14.6603	-13.7537
4	-15.8004	-15.0042	-13.8187
5	-16.1571	-15.1737*	-13.7091
6	-16.1277	-14.9569	-13.2134
7	-16.1154	-14.7573	-12.7348
8	-16.4199*	-14.8745	-12.5731

Note. * denotes the optimal lag suggestion. In the analysis, a maximum number of 8 lags was allowed.

Table 11

Lagrange multiplier test for autocorrelation			
VAR Model	Number of lags	test statistic (chi squared)	p-value
Model 1	1	18.9515	0.27118
Model 1	2	12.2985	0.72319
Model 1	3	29.9604	0.01821
Model 1	4	24.7554	0.07426
Model 1	5	25.6803	**0.05870**
Model 2: female	1	61.7456	0.00481
Model 2: female	2	46.1566	0.11962
Model 2: female	3	31.3685	0.68851
Model 2: female	4	40.7572	0.26910
Model 2: female	5	36.7047	**0.43603**
Model 2: male	1	53.5504	0.03006
Model 2: male	2	44.0349	0.16809
Model 2: male	3	43.5469	0.18107
Model 2: male	4	43.4361	0.18412
Model 2: male	5	40.3984	**0.28213**
Model 3	1	60.8504	0.11932
Model 3	2	57.8454	0.18108
Model 3	3	60.4806	0.12590
Model 3	4	63.0894	0.08505
Model 3	5	48.5156	**0.49267**

Note. The test statistic and the p-values underlie a chi-squared distribution. The bold values indicate the p-value at the selected lag order of 5 lags, which was selected in each model. For further information regarding the process and the underlying structure of the test, see Breusch and Pagan (1980).

Table 12

Granger causality Wald test: Model 2 females

Equation	Excluded	test statistic	p-value
PCE	ER15_24f	10.023	0.075*
PCE	ER25_54f	13.059	0.023**
PCE	ER55_64f	12.283	0.031**
PCE	ER15_64f	14.206	0.014**
PCE	GDP	31.945	0.000***
PCE	ALL	85.426	0.000***
ER15_24f	PCE	10.318	0.067*
ER15_24f	ER25_54f	7.1988	0.206
ER15_24f	ER55_64f	4.0381	0.544
ER15_24f	ER15_64f	2.0444	0.843
ER15_24f	GDP	2.9288	0.711
ER15_24f	ALL	53.722	0.001***
ER25_54f	PCE	12.158	0.033**
ER25_54f	ER15_24f	15.412	0.009***
ER25_54f	ER55_64f	8.9289	0.112
ER25_54f	ER15_64f	12.412	0.030**
ER25_54f	GDP	13.349	0.020**
ER25_54f	ALL	56.438	0.000***
ER55_64f	PCE	2.9757	0.704
ER55_64f	ER15_54f	12.82	0.025**
ER55_64f	ER25_54f	18.788	0.002***
ER55_64f	ER15_64f	16.219	0.006***
ER55_64f	GDP	5.3224	0.378
ER55_64f	ALL	39.662	0.032**
ER15_64f	PCE	11.115	0.049**
ER15_64f	ER15_54f	8.5546	0.128
ER15_64f	ER25_54f	7.9306	0.160
ER15_64f	ER55_64f	5.0286	0.412
ER15_64f	GDP	9.3634	0.095*
ER15_64f	ALL	44.682	0.009***

GDP	PCE	7.9296	0.160
GDP	ER15_54f	9.684	0.085*
GDP	ER25_54f	10.854	0.054*
GDP	ER55_64f	3.6729	0.597
GDP	ER15_64f	11.587	0.041**
GDP	ALL	50.779	0.002*

Note. The variables are in the same format as they will be used in the VAR estimation. This means that all variables are already in first differences. Moreover, PCE and GDP are in logarithmic format.

Table 13

Granger causality Wald test: Model 2 males			
Equation	Excluded	test statistic	p-value
PCE	ER15_24m	4.1272	0.531
PCE	ER25_54m	6.9383	0.225
PCE	ER55_64m	9.6183	0.087*
PCE	ER15_64m	8.864	0.115
PCE	GDP	27.098	0.000***
PCE	ALL	60.613	0.000***
ER15_24m	PCE	24.649	0.000***
ER15_24m	ER25_54m	24.955	0.000***
ER15_24m	ER55_64m	14.008	0.016**
ER15_24m	ER15_64m	20.223	0.001***
ER15_24m	GDPALL	11.386	0.044**
ER15_24m		74.623	0.000***
ER25_54m	PCE	3.942	0.558
ER25_54m	ER15_24m	12.169	0.033**
ER25_54m	ER55_64m	8.1995	0.146
ER25_54m	ER15_64m	11.705	0.039**
ER25_54m	GDP	3.3681	0.643
ER25_54m	ALL	39.694	0.031**

ER55_64m	PCE	4.9581	0.421
ER55_64m	ER15_54m	14.801	0.011**
ER55_64m	ER25_54m	9.9848	0.076*
ER55_64m	ER15_64m	9.7096	0.084*
ER55_64m	GDP	1.8296	0.872
ER55_64m	ALL	39.907	0.030**
ER15_64m	PCE	8.6452	0.124
ER15_64m	ER15_54m	13.691	0.018**
ER15_64m	ER25_54m	4.2992	0.507
ER15_64m	ER55_64m	5.6888	0.338
ER15_64m	GDP	5.4359	0.365
ER15_64m	ALL	36.11	0.070*
GDP	PCE	10.741	0.057**
GDP	ER15_54m	3.7626	0.584
GDP	ER25_54m	4.4187	0.491
GDP	ER55_64m	5.3657	0.373
GDP	ER15_64m	6.8497	0.232
GDP	ALL	31.866	0.162

Note. The variables are in the same format as they will be used in the VAR estimation. This means that all variables are already in first differences. Moreover, PCE and GDP are in logarithmic format.

Table 14

Granger causality Wald test: Model 3			
Equation	Excluded	test statistic	p-value
PCE	Agri	21.106	0.001***
PCE	Cons	13.299	0.021**
PCE	Indu	7.6473	0.177
PCE	Manu	7.4597	0.189
PCE	Serv	.62359	0.987
PCE	GDP	19.571	0.002***
PCE	ALL	85.897	0.000***

Agri	PCE	8.7102	0.121
Agri	Cons	4.4945	0.481
Agri	Indu	11.225	0.047**
Agri	Manu	11.894	0.036**
Agri	Serv	8.2966	0.141
Agri	GDP	9.0326	0.108
Agri	ALL	54.997	0.004***
Cons	PCE	9.6553	0.086*
Cons	Agri	9.4187	0.093*
Cons	Indu	17.144	0.004***
Cons	Manu	20.312	0.001***
Cons	Serv	8.4017	0.135
Cons	GDP	26.319	0.000***
Cons	ALL	141.34	0.000***
Indu	PCE	4.4103	0.492
Indu	Agri	13.996	0.016**
Indu	Cons	7.6956	0.174
Indu	Manu	6.6517	0.248
Indu	Serv	9.9852	0.076*
Indu	GDP	3.0247	0.696
Indu	ALL	44.802	0.040**
Manu	PCE	5.8176	0.324
Manu	Agri	17.957	0.003***
Manu	Cons	10.054	0.074*
Manu	Indu	10.368	0.065*
Manu	Serv	12.915	0.024**
Manu	GDP	4.0955	0.536
Manu	ALL	56.362	0.002***
Serv	PCE	11.17	0.048**
Serv	Agri	6.6216	0.250
Serv	Cons	2.4865	0.779
Serv	Indu	1.5509	0.907
Serv	Manu	2.8536	0.723
Serv	GDP	12.511	0.028**
Serv	ALL	35.539	0.224

GDP	PCE	6.9309	0.226
GDP	Agri	16.639	0.005***
GDP	Cons	17.818	0.003***
GDP	Indu	4.3392	0.502
GDP	Manu	4.4585	0.485
GDP	Serv	.66696	0.986
GDP	ALL	63.013	0.000***

Note. The variables are in the same format as they will be used in the VAR estimation. This means that all variables are already in first differences. Moreover, PCE and GDP are in logarithmic format.

Table 15

Forecast error variance decomposition: Model 2 females

Forecast error in the the growth of	Forecast horizon (in quarters)	Proportions of forecast error variance h periods ahead accounted for by innovations in					
		ϵ_P	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_G
PCE	1	1	0	0	0	0	0
	4	70.0	9.9	9.19	2.81	1.66	6.44
	8	59.0	14.13	9.02	3.46	4.17	10.22
	12	57.45	13.93	10.32	3.44	4.9	9.96
ER15_24f	1	0.24	99.76	0	0	0	0
	4	2.29	85.7	6.66	2.61	0.6	2.14
	8	11.55	69.59	10.15	4.75	0.98	2.98
	12	18.38	59.68	8.7	5.0	1.94	6.3
ER25_54f	1	60.86	0.7	38.44	0	0	0
	4	45.2	7.85	30.31	4.31	3.21	9.12
	8	41.4	10.16	28.38	5.52	5.43	9.11
	12	40.51	9.9	27.97	5.96	6.81	8.85
ER55_64f	1	7.8	2.55	5.81	83.84	0	0
	4	8.12	2.71	9.39	71.84	6.72	1.22
	8	8.5	4.93	9.93	63.71	7.52	5.41
	12	8.54	5.36	9.61	61.34	8.38	6.77

ER15_64f	1	43.06	16.38	32.13	4.74	3.69	0
	4	32.14	19.51	31.5	5.86	4.71	6.28
	8	31.13	20.19	31.26	5.97	4.58	6.87
	12	31.84	20.19	30.08	5.93	4.4	7.56
GDP	1	78.09	2.9	0.11	0.85	0.29	17.76
	4	59.43	10.28	7.8	3.25	1.32	17.92
	8	55.69	11.98	9.05	3.31	2.98	16.99
	12	54.68	12.24	10.14	3.19	3.67	16.08

Note. Variance decomposition of model 2 for females. Variables are in first differences and PCE and GDP are in logarithmic format. The variables ϵ_1, ϵ_2, ϵ_3, ϵ_4 denote the percentage proportions for the four age-gender-specific groups.

Table 16

Forecast error variance decomposition: Model 2 males							
Forecast error in the the growth of	Forecast horizon (in quarters)	Proportions of forecast error variance h periods ahead accounted for by innovations in					
		ϵ_P	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_G
PCE	1	1	0	0	0	0	0
	4	78.51	0.35	2.04	0.95	2.57	15.58
	8	67.59	1.39	5.54	1.66	5.02	18.8
	12	65.58	1.39	6.47	2.78	5.69	18.09
ER15_24m	1	24.43	75.57	0	0	0	0
	4	18.55	57.29	2.17	4.7	14.31	2.98
	8	21.05	47.06	5.12	4.18	14.84	7.75
	12	22.87	43.9	5.0	4.21	14.61	9.41
ER25_54m	1	28.48	2.35	69.17	0	0	0
	4	24.63	3.03	58.87	6.07	5.1	2.3
	8	22.23	3.04	56.41	6.67	9.16	2.49
	12	22.51	3.37	54.91	6.91	9.05	3.25
ER55_64m	1	2.77	0.22	5.56	91.45	0	0
	4	3.93	4.81	6.93	79.17	4.35	0.81
	8	5.61	6.37	9.98	67.86	7.5	2.68
	12	6.32	7.04	9.97	64.1	9.03	3.54

ER15_64m	1	25.91	10.36	43.73	14.94	5.06	0
	4	21.39	12.42	35.64	17.85	10.64	2.06
	8	21.68	11.95	34.56	16.31	11.81	3.69
	12	22.6	12.32	32.7	15.9	12.04	4.44
GDP	1	80.92	0.99	0.55	0.32	0.72	16.5
	4	65.24	0.74	2.11	2.39	3.25	26.27
	8	59.62	1.34	6.67	3.3	4.93	24.14
	12	59.17	1.35	6.88	4.0	5.19	23.41

Note. Variance decomposition of model 2 for males. Variables are in first differences and PCE and GDP are in logarithmic format. The variables ϵ_1, ϵ_2, ϵ_3, ϵ_4 denote the percentage proportions for the four age-gender-specific groups.

Table 17

Forecats error variance decomposition: Model 3

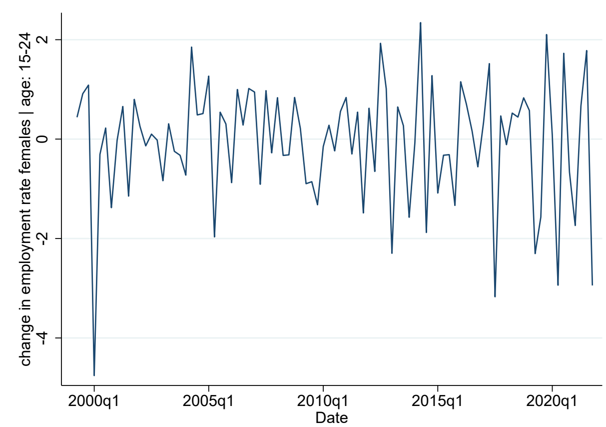
Forecast error in the the growth of	Forecast horizon (in quarters)	Proportions of forecast error variance h periods ahead accounted for by innovations in						
		ϵ_P	ϵ_A	ϵ_C	ϵ_I	ϵ_M	ϵ_S	ϵ_G
PCE	1	1	0	0	0	0	0	0
	4	74.71	8.46	2.73	0.91	0.83	0.99	11.37
	8	62.90	11.11	3.83	4.07	5.49	1.18	11.42
	12	61.54	12.44	4.4	4.16	5.1	1.83	10.53
Agri	1	0.45	99.55	0	0	0	0	0
	4	0.94	86.63	0.38	0.49	5.66	4.04	1.86
	8	8.34	69.4	2.54	1.76	6.38	5.99	5.59
	12	10.42	61.44	3.25	1.64	6.75	6.83	9.67
Cons	1	11.14	0.11	88.75	0	0	0	0
	4	28.4	3.05	54.45	0.71	4.64	2.97	5.78
	8	26.69	4.76	45.73	5.92	4.61	5.15	7.14
	12	30.18	6.87	40.14	6.33	4.16	5.11	7.21
Indu	1	1.52	18.97	0.06	79.45	0	0	0
	4	6.22	24.17	0.46	61.27	1.66	3.57	2.65
	8	6.76	22.60	3.32	56.43	1.77	6.56	2.56
	12	9.73	21.67	3.23	53.29	1.95	6.19	3.94

Manu	1	1.71	19.3	0.07	75.64	3.28	0	0
	4	7.24	25.48	0.25	57.08	3.58	3.68	2.69
	8	7.87	22.56	3.37	52.58	3.8	7.42	2.4
	12	10.66	21.43	3.29	49.68	3.9	7.11	3.93
Services	1	23.56	0.05	0.24	4.9	1.5e-04	71.24	0
	4	23.12	1.65	1.36	4.95	1.5	60.86	6.56
	8	21.83	4.66	1.46	8.23	3.39	54.17	6.26
	12	25.01	5.06	1.67	8.5	4.48	48.85	6.43
GDP	1	83.66	0.55	0.24	0.03	0.48	0.13	14.91
	4	61.25	8.79	2.18	2.15	5.58	1.43	18.62
	8	57.3	10.03	5.26	3.35	5.73	2.0	16.33
	12	55.72	11.5	5.34	4.01	5.51	2.79	15.13

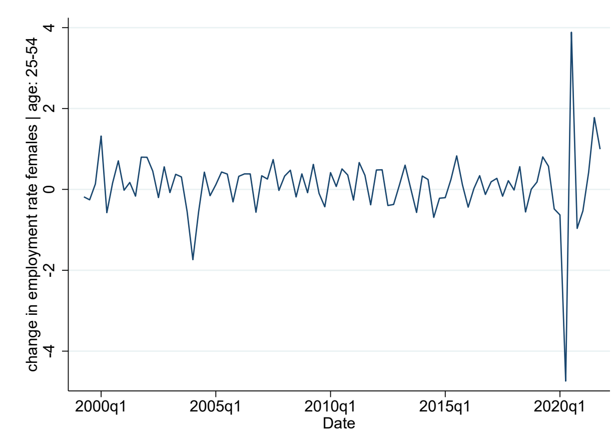
Note. Variance decomposition of model 3. Variables are in first differences and PCE and GDP are in logarithmic format. ϵ_A, ϵ_C, ϵ_I, ϵ_M and ϵ_S denote the percentage proportions for the sector related variables.

B Appendix Figures

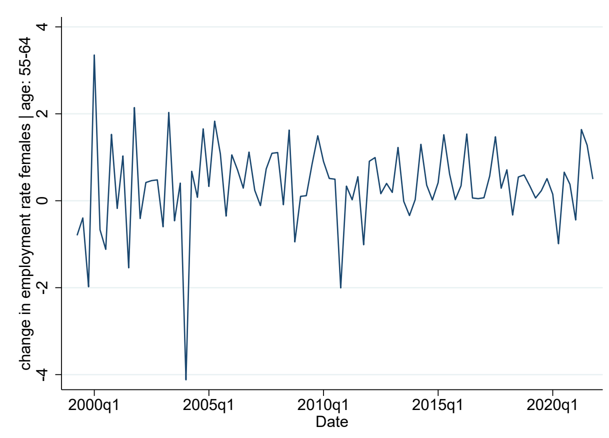
Figure 10



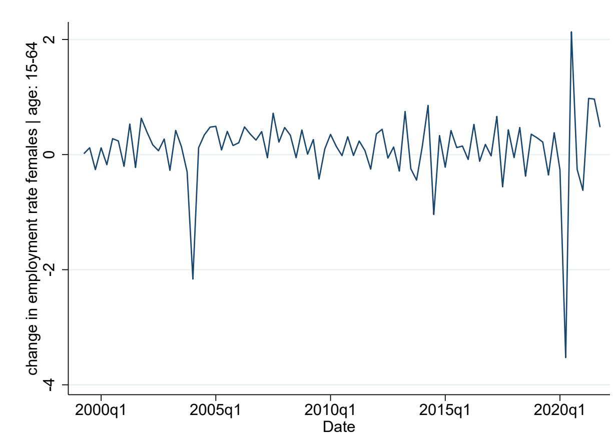
(a) Model 2: I(1) 15-24 female variable



(b) Model 2: I(1) 25-54 female variable



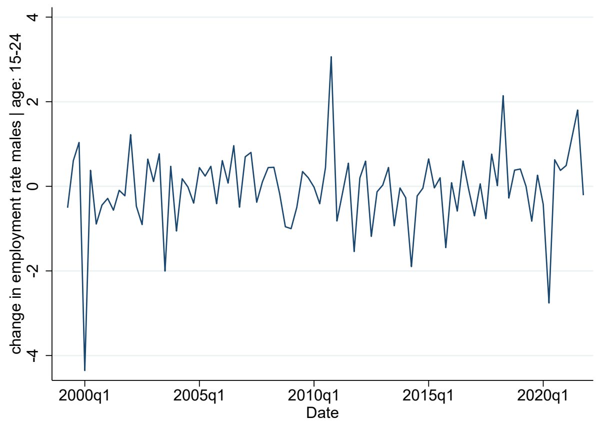
(c) Model 2: I(1) 55-64 female variable



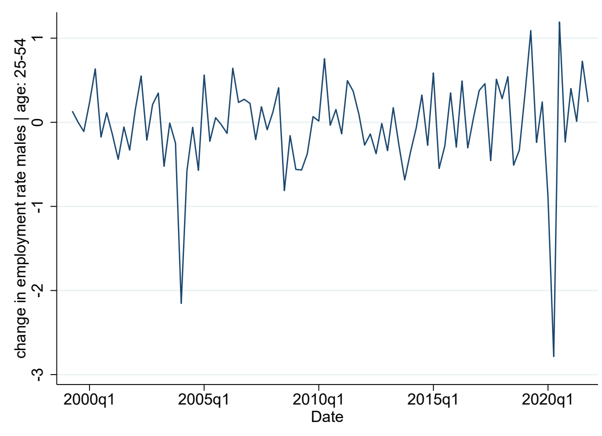
(d) Model 2: I(1) 15-64 female variable

Note. These are the first differenced female variables of model 2.

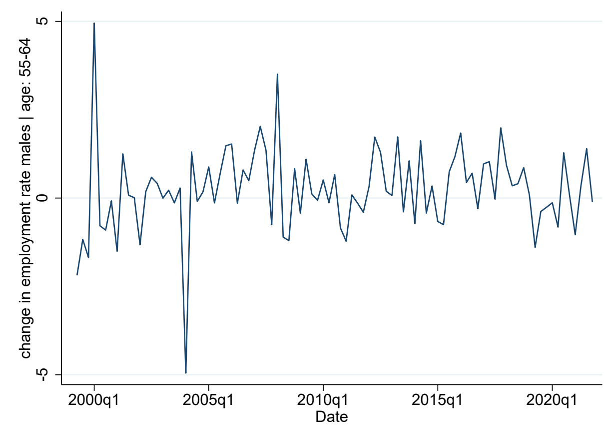
Figure 11



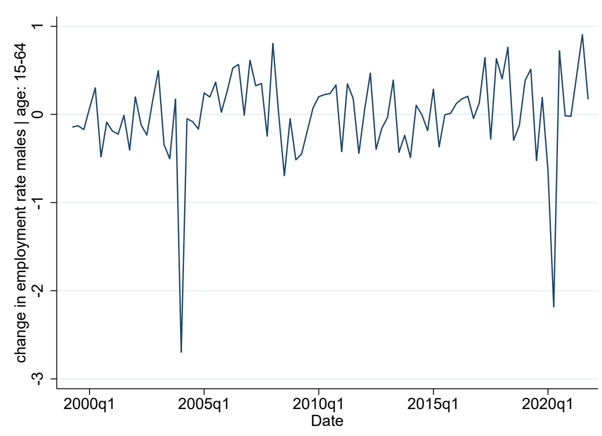
(a) Model 2: I(1) 15-24 male variable



(b) Model 2: I(1) 25-54 male variable



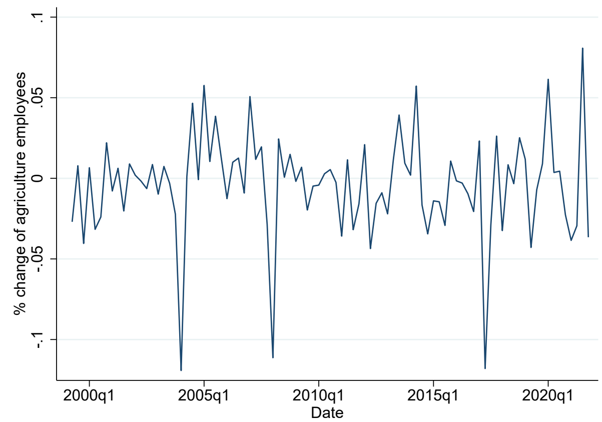
(c) Model 2: I(1) 55-64 male variable



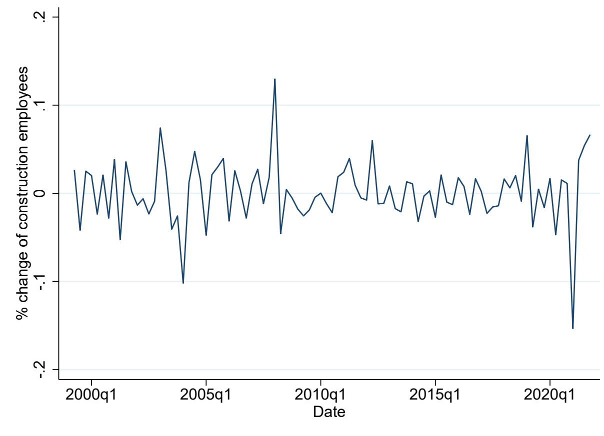
(d) Model 2: I(1) 15-64 male variable

Note. These are the first differenced male variables of model 2.

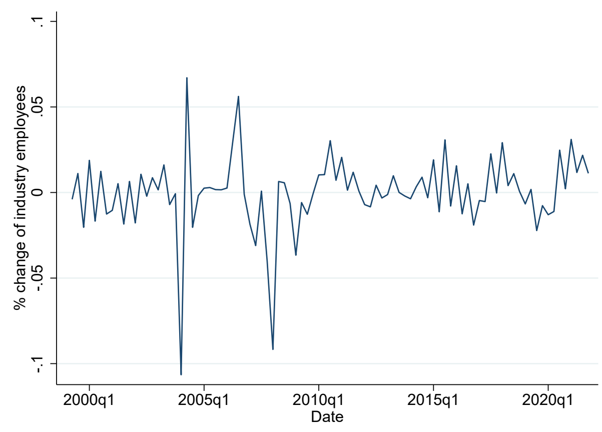
Figure 12



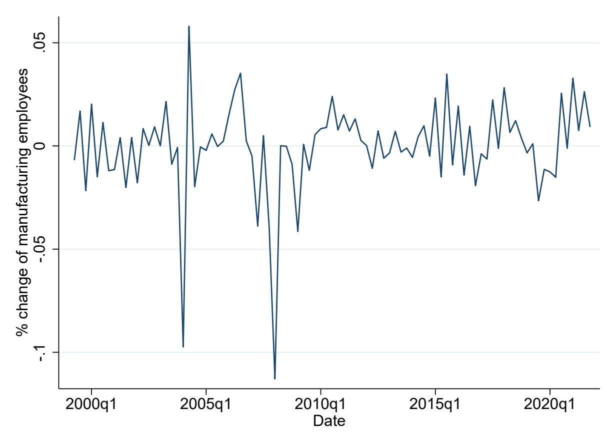
(a) Model 3: I(1) Agriculture variable



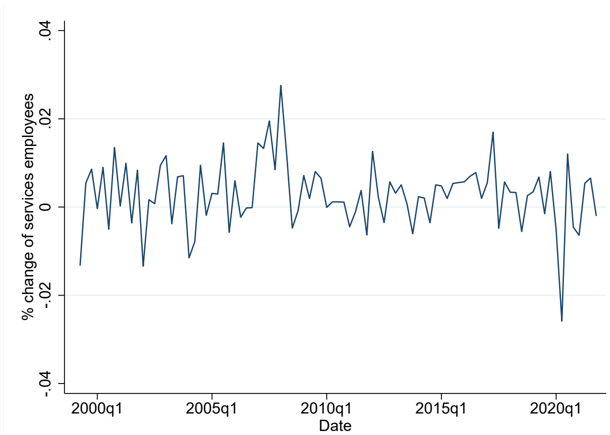
(b) Model 3: I(1) Construction variable



(c) Model 3: I(1) Industry variable



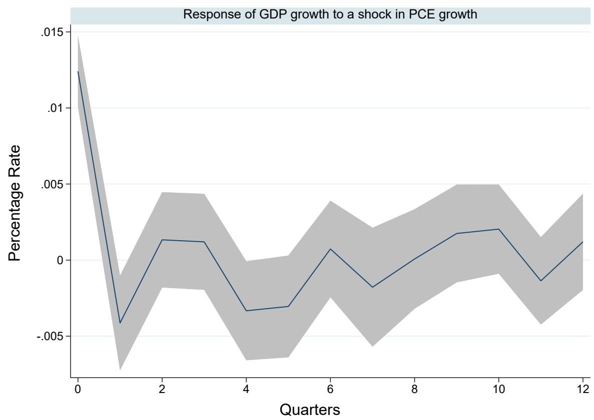
(d) Model 3: I(1) Manufacturing variable



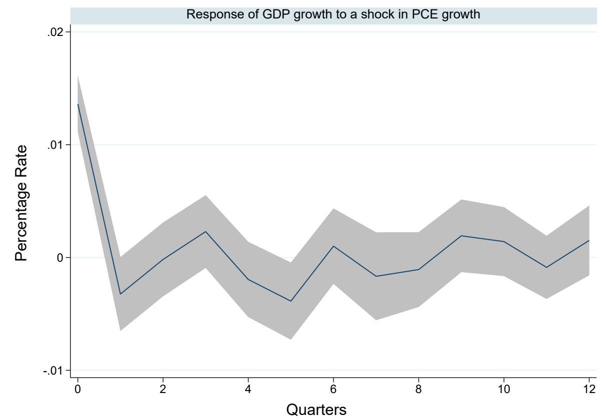
(e) Model 3: I(1) Services variable

Note. These are the logarithmic and first differenced sector variables of model 3.

Figure 13



(a) IRF GDP: female model



(b) IRF GDP: male model

Note. Impulse response functions for GDP of model 2 for females and males. GDP is in logarithmic and first difference format.