AN ANALYSIS OF IMPACTS OF ECONOMIC UNCERTAINTY AND COVID 19 OUTBREAK ON THE LABOR FORCE OF TURKEY BY EDUCATION LEVEL: SVAR APPROACH

A THESIS
SUBMITTED TO ABDULLAH GÜL UNIVERSITY
SOCIAL SCIENCES INSTITUTE
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF SCIENCE

By
Edanur Kılıç
June, 2022
Kayseri, Turkey

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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis titled "An Analysis of Impacts of Economic Uncertainty and Covid 19 outbreak on Labor Force of Turkey by Education Level: SVAR Approach" has been prepared in accordance with the Graduate Thesis Preparation Guidelines of the Abdullah Gül University, Social Sciences Institute.

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ABSTRACT

The economic downturns affect the fluctuations in the labor force participation rate. The pandemic brings about many changes in different areas and the labor force participation rate is one of them. This study analyses the impact of economic uncertainty innovations on the labor force participation rate in Turkey for the period January 2011 to November 2019. We also consider different educational attainment, which consists of five categories, because finding a job gets hard in recent years and there is no academic study on whether education level matters or not in Turkey.

We obtain an economic uncertainty index to analyze the effect of Covid-19 and generate multivariate models (SVAR) to determine the relationship between uncertainty and labor force participation rate. We examine labor force statistics at different educational attainment levels to understand whether there are any changes or not. Thus, the main research question is that "How is the impact of uncertainty shocks on labor force participation rate in different levels of education in Turkey?". The results show that the labor force participation rate decreases, while the unemployment rate increases in such an economic downturn.

Keywords: uncertainty, labor force market, unemployment, principal component analysis, Covid-19 outbreak

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Tez Başlığı :Ekonomik Belirsizlik ve Covid 19 Salgınının Türkiye'de Eğitim Durumuna göre İşgücüne Etkisinin Analizi : SVAR Yaklaşımı

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ÖZET

Ekonomik durgunluk, işgücü piyasasındaki dalgalanmaları etkilemiştir. Pandemi de farklı alanlarda birçok değişikliği beraberinde getirmiş ve işgücü piyasasını etkilemiştir. Pandeminin süresinin bilinmemesi nedeniyle belirsizlik göz önünde bulundurulmalıdır. Bu çalışmada Türkiye'de Covid-19'un işgücüne katılım oranına etkisi 01/2011-11/2019 dönemi için sadece ekonomik faktörlerin etkisi değil, belirsizliği ve eğitim düzeyinin etkisini ölçülmüştür. Ayrıca son yıllarda iş bulmanın zorlaşması ve eğitim düzeyinin önemli olup olmadığı konusunda kesin bir bilgi bulunmadığından, bu etkiler farklı eğitim düzeyleri için analiz edilmiştir.

Ekonomik faktörler ile işgücü arasındaki ilişkiyi belirlemek için çok değişkenli modeller (SVAR) kullanılmış ve Covid-19 salgınının etkisini analiz etmek için belirsizlik endeksi elde edilmiştir. Herhangi bir değişiklik olup olmadığını anlamak için işgücü istatistikleri farklı eğitim seviyelerinde analiz edilecektir. Bu çalışma, belirsizlik endeksi ile farklı eğitim seviyelerine göre işgücüne katılım oranları arasındaki ilişkiyi incelemiştir. Dolayısıyla sorulması gereken soru şudur: "Türkiye'de farklı eğitim düzeylerinde belirsizlik şoklarının işgücüne katılım oranı üzerindeki etkisi nasıldır?". Sonuçlar, böylesine bir ekonomik durgunlukta işgücüne katılım oranlarının azaldığını, işsizlik oranının ise arttığını göstermektedir.

Anahtar kelimeler: belirsizlik, işgücü piyasası, işsizlik, temel bileşen analizi, Covid-19 salgını

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller Test
AIC	Akaike Information Criterion
BRSA	Banking Regulation and Supervision Agency
CBRT	Central Bank of the Republic of Turkey
CPI	Consumer Price Index
ECI	Economic Confidence Index
EPU	Economic Policy Index
GDP	Gross Domestic Product
HQIC	Hannan-Quinn Information Criterion
IGM	Initiative on Global Markets
ILO	International Labour Organization
IMF	International Monetary Fund
ISE	Istanbul Stock Exchange
LFPR	Labor Force Participation Rate
PCA	Principal Component Analysis
PPI	Producer Price Index
SME	Small and Medium-sized Enterprises
SOEP	Socio-Economic Panel
SVAR	Structural Vector Autoregression
TURKSTAT	Turkish Statistical Institute
USA	United States of America
VAR	Vector Autoregression
VIX	Volatility Index
WB	World Bank
WUI	World Uncertainty Index

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1. INTRODUCTION

The Covid-19 outbreak is one of the biggest health crises in modern times in the world. Coronavirus causes major health problems, serious losses and deaths, and threatens people's social and physical well-being. It has been affecting all countries and changes the flow of life to an extraordinary extent, although the epidemic started to influence countries at different times. That is why fast and effective decisions are taken all over the world and in Turkey. Economic activity abruptly slowed, and there were severe falls in income and consumption. In this case, the health crisis created by the pandemic evolved into a serious social and economic crisis, the impact of which may deepen. In the countries affected by the epidemic, education was suspended in schools, services such as restaurants, cafes, hotels and the activities of small and medium-sized enterprises (SMEs) working in the tourism sector stopped. Production has stopped in many sectors and consumption has decreased significantly.

Given the global nature of the pandemic, it is unavoidable that the outbreak has significant economic and social consequences both globally and in Turkey. The global economy contracted by 4.0 percent in the first half of 2020, roughly double the decline experienced during the global financial crisis (Oxford Economics, 2020). The Covid-19 outbreak had a far higher macroeconomic impact than the previous 40 years' worth of economic crises and calamities (Ludvigson et al., 2020). The worldwide crisis caused/will be triggered by the pandemic is expected to be far deeper and more persistent than past global crises. Despite increased numbers of new coronavirus infections, global gross domestic product (GDP) growth predictions raise by 0.1 percentage point to 6.1 percent in 2021 and 4.3 percent in 2022 (Oxford Economics, 2021). As a matter of fact, since life could not return to normal in a short time, there was a loss of workforce and bankruptcies in the medium term, especially in SMEs (Bartik et al, 2020).

The Covid-19 outbreak led economies around the world to a serious contraction (IMF, 2020). The main reasons for this shrinkage can be grouped under the following headings, based on the views of the Initiative on Global Markets (IGM) Economic Experts Committee, which consists of world-renowned economists:

- Labor and income losses, especially of temporary workers,
- Direct labor loss and health expenses caused by those who have the disease,
- Labor and income losses due to social distance and quarantine practices taken by governments,
- Serious reductions in household consumption trends and firms' investment tendencies resulting from quarantine and extreme uncertainty,
- Widespread pessimistic expectations and uncertainty about the future and general state of the economy make it impossible to return to the pre-crisis economic situation.
- Disruptions and pauses in international trade and supply chain

This crisis creates a serious supply and demand shock simultaneously as can be inferred from the above items. (Baldwin and di Mauro, 2020). The loss of purchasing power and the sudden decrease in expenditures can create a spiral effect. Therefore, quarantines and disruptions in supply chains reduces supply. In addition, demand decreases due to the increase in uncertainty, the effect of loss of income and the tendency of households to increase precautionary savings. With the decline in demand for goods, the sales of firms fall further and the supply contraction deepens, which reduces demand with more firms closing, more workforce loss and reduced purchasing power (more people being unemployed). As a result, the contraction in supply and demand creates a multiplier effect with a mechanism that feeds each other, leading to a recession.

An impact and duration of the shocks caused by the outbreak cause a high degree of uncertainty in the economy, because it is not clear or predictable (Ludvigson et al., 2020). Uncertainty is an important factor that influences economic activity on expectations. As it is known, uncertainty causes both the households to delay their consumption and the firms to delay investments, and therefore causes an economic downturn (Bloom, 2009). The extreme uncertainty created by this outbreak brings about a lot of play in commodities and financial markets. In terms of companies, it is unclear how long the outbreak will last and whether the supply chains can be repaired. In addition, as a result of the slowdown in economic activity, individuals' revenues decrease and the uncertainty of the outbreak causes individuals to further reduce their expenditure. It is therefore important to measure the level of uncertainty with a precise indicator.

One of the biggest effects of the pandemic is on unemployment and household income. Although the International Labor Organization (ILO) predicts in its report at the beginning of April that 25 million people would be unemployed in the world. As a matter of fact, the figures revise in the report published by the ILO on September 23, 2020, and it shows that the loss of workforce in 2020 may be much higher, there was a loss of 17.3% working hours in the 2nd quarter worldwide and it is predicted that it will be 12.1% in the 3rd quarter. This figure corresponds to the loss of working hours (assuming 48 hours a week) of 495 million full-time workers in the 2nd Quarter and 345 million in the 3rd Quarter of 2021. Again, according to the report of the ILO, heavier labor losses are estimated especially in upper-middle-income countries, including Turkey. However, the acceleration of labor market recovery from the pandemic shock declines during 2021 globally, with little improvement since the fourth quarter of 2020 (ILO, 2021). According to the eighth edition of the Covid-19 report of ILO, global working hours are expected to remain much lower in 2021 than in the previous quarter, at –4.5% (equal to 131 million full-time jobs) in the first quarter, –4.8% (140 million full-time jobs) in the second quarter, and –4.7% (137 million full-time jobs) in the third quarter. This aggregate image, however, conceals significant differences between countries. Working hours in high- and upper-middle-income countries tend to recover in 2021, while both lower-middle and low-income countries continue to suffer large losses (ILO 2021, 27 October).

However, it should be noted here that most of these estimates are a lower limit, so the actual losses can be far higher. Because the economic measures and aid packages taken by countries only delay the loss of workforce and closure of workplaces for a while. Therefore, these restrictions influence the labor force participation rate. The sudden slowdown and contraction in the economy causes heavier losses sooner or later and influences the labor market. For this reason, economic uncertainty index and forecasts are required for Turkey to develop policies by recognizing the impact of education degrees. In this research, we add the statistics of workplaces closed to our model in order to understand the impact of the pandemic on the workforce on a monthly basis. Considering that the pandemic is still ongoing, having an index on a monthly basis is important in understanding the impact of emergency measures policies and renewing these policies when necessary.

This study generates a new economic uncertainty index (EUI) by using principal component analysis (PCA). This index is an important indicator in terms of monitoring the changes in politics and the economy. We measure the impact of the uncertainty shocks on the labor force participation rate and compare these effects among education levels by creating vector autoregression (VAR) and structural vector autoregression (SVAR) models. Educational attainment in Turkey is classified into five categories: illiterate, lower than high school, high school, vocational high school, and higher education degree. We compare the labor force participation rate among five different education degrees in Turkey by using bivariate VAR models. We include educational attainment in this study because the labor force rate of high school graduates and primary school graduates may differ from each other. High school graduates have 4.8 percent points higher participation rate in comparison with primary school graduates (Liu, 2012). We also compare the impact of uncertainty innovations on the unemployment rate and labor force participation rate (LFPR). The unemployment rate includes those who are not working but are looking for a job (Curtis and Irvine, 2021). The labor force includes people who are working as well as those who are unemployed but actively seeking work. In other words, discouraged workers are excluded from the unemployment rate measure. Therefore, we do not expect a sudden jump in the unemployment rate during business cycles. This is why we use LFPR as our main variable of interest.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 explains the methodology. Section 5 explains the construction of EUI. Section 6 examines seasonality and Section 7 shows and discusses the analysis and results. Section 8 concludes.

2. LITERATURE REVIEW

2.1. Uncertainty Index

There are studies to create uncertainty indicators by using financial data and macro uncertainty indices in the literature. Index-based research in the literature can be classified into three categories that aim to quantify uncertainty: uncertainty indices generated by using macro data set via principal component analysis, news-based uncertainty measures, and uncertainty measures based on the discrepancy in expectation. In uncertainty studies on financial markets, implied volatility is generally used to proxy the future volatility of an asset to measure market expectations (Bekaert et al., 2013). As an example, in the US, the VIX index reflects a 30-day forecast of volatility for Treasuries.

Bachman et al. (2013) and Klößner and Sekkel (2014) stated that Bloom (2009) pioneer economic studies to measure uncertainty. Bloom, (2009) claims that uncertainty is an intangible idea, even though it is a significant component influencing economic activity. Consequently, Bloom carries out different uncertainty studies. Baker et al. (2016) construct a new index of economic policy uncertainty (EPU) based on the frequency of news coverage. In an addition, the world uncertainty index (WUI) is developed that illustrates innovations like the Euro debt crisis and the Covid pandemic, and Bloom et al. (2022) observe that developments in the WUI portend critical decreases in yield in a panel vector autoregressive setting. This impact is more substantial and more lasting in nations with worse institutional quality, and in areas with tighter budgets.

Atkeson (2020) emphasizes the uncertainty regarding the combined distribution of the initial number of active patients and the fatality rate, while Lewis et al. (2020) analyze the "weekly economic index" they had previously created to measure the impact of the Covid-19 epidemic on the US economy. They create this index based on the first fundamental component from 10 different weekly time series using the PCA method. Ludvigson et al. (2020) state the unexpected Covid-19 shock shook the global economy, creating a significant amount of uncertainty.

2.2. Uncertainty Studies in Turkey

Ermişoğlu and Kanık (2013) apply the same method for Turkey as in Baker et al.'s (2016) study which creates an economic policy index based on newspaper coverage frequency for the US. Arslan et al. (2011) examine the relationship between economic activity and uncertainty in Turkey. The data of the Business Tendency Survey, which is a trend survey that includes the expectations of the companies in the manufacturing industry, are taken as the basis for uncertainty. Yıldırım and Alkan (2018) use the concept of volatility for uncertainty. Acting on the assumption that an increase in the volatility of financial variables also increases the uncertainty, they create a macroeconomic uncertainty index based on the volatility of financial indicators such as exchange rate, interest rate, and stock markets.

Unlike other studies, instead of measuring uncertainty, Erdem and Yamak (2016) create an optimal macroeconomic uncertainty index for Turkey. Using quarterly data and within the framework of a small structural macroeconomic model, after three different econometric estimations, an optimal uncertainty index is created with the optimization algorithm which minimizes the Central Bank's loss function.

Studies in the literature for Turkey generally aim to create an uncertainty index based on financial data. However, financial data is more volatile than macro data, and their use in the macro uncertainty index may dominate macro data due to the overrepresentation of financial data in the created index (Jurado et al., 2015). In addition, the economic crisis caused by the Covid-19 epidemic is a crisis that directly affects the real sector and income, rather than the financial sector. Including only financial data can lead the wrong impression to interpreting the impact of Covid on labor force participation rate, because the pandemic involves both supply and demand shocks (Baldwin and Di Mauro, 2020). Therefore, it would be more realistic to create an index based on real and macro data when analyzing a real crisis. A good example of the fact that financial data (such as stock markets) does not always represent the economic situation well is the fact that the stock markets in the USA did not fall very much despite the Covid-19 outbreak (see Krugman, 2020).

This research differs from the studies mentioned above in terms of both the method and the datasets used. However, this study follows the method of Mugaloğlu et al. (2021), in which an economic uncertainty index and sectoral uncertainty indices are created to measure the impact of pandemic shocks on output in Turkey. Mugaloglu et al. (2021) employ a PCA dimension reduction approach with 14 macroeconomic indicators including January 2011 to July 2020 time span. Their economic uncertainty index proxy for Turkey composes of the first main component, which represents 52% of total variation in the whole sample. Their EUI detects important economic and political events in Turkey. They conduct a structural VAR model where they find a significant decline in industrial production. They prove that sub-indices of industrial production imply a similar response to Covid- 19 shocks. Different from Mugaloglu et al. (2021) this research examines the impact of uncertainty on labor force participation rate (LBFR) and compares FPR by educational degree by using bivariate SVAR models. Since the Covid-19 epidemic influence the whole world and Turkey differently from previous crises, our study will be more effective and useful in analyzing the impact of the pandemic on labor force participation rate.

2.3. Principal Component Analysis

Principal component analysis (PCA) is a multivariate statistical technique widely used by almost all scientific disciplines (Abdi & Williams, 2010). Principal component analysis is mostly used for dimension reduction in the literature (Ringnér, 2008; Jolliffe & Cadima, 2016). Abdi and Williams (2010) state four goals for PCA: to get the most important information from the data, to reduce the size of the data set, to summarize the description of the data, and to analyze the structure of each variable and observation. Principal components analysis calculates the orthogonal principal components representing the data set with four steps described in the literature: calculating the mean, calculating the covariance (or correlation) matrix, calculating the eigenvectors and eigenvalues of the covariance (correlation) matrix, selecting the component, and obtaining the final data set. (Abdi and Williams, 2010; Hotelling, 1933; Lauro and Palumbo, 2000; Shlens, 2014; Smith, 2002; Wold, 1987). However, before taking these steps, the stationarity of the data should be checked (Drakos, 2002; Ludvigson, 2015).

Esmaeili and Shokoohi (2011) analyze the movement of macroeconomic index and food prices together. Seven main products are selected to measure the impact of macroeconomic variables (crude oil prices, food production index, GDP and consumer price index); meat, milk, eggs, oilseeds, sugar, wheat and rice. Esmaeili and Shokoohi (2011) conclude that food prices are indirectly affected by crude oil prices. Drakos (2002) investigates the integration problem in the Euro currency. Principal component analysis is used to measure whether the common (dynamic) set of factors affects the European currency. The findings prove that the Euro money market is integrated both in the short and long run if interest rates are sensitive to dynamic factors (Drakos, 2002). Radovanovic et al. (2018) obtain the Energy Security Geo-economic index using principal component analysis, since national economies are associated with a dynamic international economy when external shocks have an impact on energy security and energy prices. Principal component analysis is used to separate banks into different operational strategies to analyze the impact of financial shocks arising from internet banking services on the performance of Romanian banks, taking into account the context in which banks can gain competitive advantage through financial shocks (Stoica, Mehdian, & Sargu, 2015).

2.3.1. PCA in Different Disciplines

This multivariate statistical technique is used in different disciplines to create predictive models using data reduction. Lolli and Di Girolamo (2015) claim that it is difficult to develop a reliable, cost-effective securities network, so they created a composite index that includes the performance of the security, taking into account scientific, economic and operational factors. Researchers argue that the index created will help policy makers' decision-making process in evaluating cost-effective, reliable securities networks. Greyling (2003) creates a composite index to measure and compare the quality of life of different socio-economic and demographic groups in South Africa (across the Guteng city area). As a result, male, high-income, Asian and Caucasian, urban, and younger participants have higher quality of life scores than the other groups, according to the dimensions that explain the most variance. Olawale and Garwe (2010) examine barriers to the growth of new SMEs in South Africa using principal component analysis. Sherazi et al. (2013) address the same issue for Pakistan.

South Africa has the highest failure rate for SMEs, so Olawale and Garwe (2010) identify five barriers, both internal and external: financial (domestic), economic (external), markets (external), governance (internal), infrastructure (external). The financial component is the largest, due to the burdens of the first component explaining financial variables such as lack of access to finance. The first suggestion is that government support agencies can assist new SMEs with financing and training to raise awareness. (Olawale and Garwe, 2010). Sherazi et al. (2013) classify barriers into six groups: financial, corruption, social and technological, education, management and infrastructure. Filmer and Pritchett (2001) construct a linear index of wealth ownership indicators to explain the relationship between household welfare and children's school enrollment in India using principal component analysis.

There is a study that presents an alternative decision model to evaluate the performance of suppliers with various inputs and outputs. Petroni and Braglia (2000) produce components containing information of different ratio measures. Principal component analysis is used to facilitate data size reduction by calculating components that represent subsets of neuropsychological measures for mild traumatic brain injury (mTBI). Levin et al. (2013) identify four components for patients: verbal memory, cognitive processing speed, visual memory, and a symptom composite representing post-concussion and stress symptoms. Heng (2009) searches catalogs of gravitational waveforms to explain different waveforms with a set of orthonormal basis vectors. Heng (2009) concludes that the selected waveforms have very similar properties, as 12 principal components are required for minimum matching when the principal components are compared with the Gram-Schmidt basis vector. Anil, Anagha, and Karaca (2017) use PCA to understand the effects of transportation networks on the chemical composition of successive rain samples, so the aim is to determine the source area of the pollutant-generating routes present in the studied area. Balagué et al. (2016) examine the effects of different training methods and detraining on cardiorespiratory coordination (CRC) by identifying four training groups and comparing the initial components in three conditions (pre-training and post-training). Rodarmel and Shan (2002) present principal component analysis to improve hyperspectral image classification, and the results showed that with the use of the first few principal components, it can give an accurate classification rate of about 70%. Gottumukkal and Asari (2004) present a face recognition algorithm based on the modular PCA approach.

Facial recognition is enhanced with traditional PCA using facial images with large variations in facial expression and lighting direction, but modular PCA uses regional facial features because changes in pose, facial expression, and illumination do not greatly affect regional facial features and we expect the presented model to overcome these changes (Gottumukkal and Asari, 2004). The findings show that modular PCA performs better when there are large differences in expression and lighting.

2.3.2. Uncertainty Index and PCA

As Liu (2007) points out, uncertainty is important because of its role in areas such as risk analysis and decision theory. Bachman et al. (2013) and Klößner and Sekkel (2014) state that Bloom (2009) leads economic studies for measuring uncertainty. Major shocks such as the Cuban Missile crisis, the JFK assassination, the OPEC oil price shock and the September 11 terrorist attacks cause an increase in uncertainty, so Bloom (2009) aims to analyze the impact of these uncertainty shocks structurally. He states that the uncertainty causes a sudden decrease in employment and total output due to the temporary interruption in investments and hiring. The results show that short and sharp recessions and recoveries is caused by uncertainty shocks. Caggiano et al. (2014), Jurado et al. (2013), Leduc and Liu (2016), Bloom and Davis (2016), and Jurado, Ludvigson and Ng (2015) investigate uncertainty in the literature. Ludvigson et al. (2013) argue that previous studies did not provide information on how to measure uncertainty, so estimates differ from previous representatives of uncertainty with significant independent variation. The aim is developed to provide an assessment to explain which uncertainty shocks affect economic fluctuations. A macroeconomic uncertainty index proxy includes monthly basis macro data, and series are stationary. An economic uncertainty index is created by removing the predictable part of the series separately for each series. Their findings show that uncertainty indices are consistent with periods of economic downturn.

2.4. Labor Market Studies

The studies state that labor force is affected from various variables like age, education, health and uncertainties, in addition labor force can influence these variables. The researchers study mostly about labor for effect on fertility rate. Schmitt

(2021) analyzes the data from the German Socio-Economic Panel (SOEP) research from 1990 to 2015 to investigate the fertility behavior of men and women, and how risk attitude changes at a given uncertainty. Fertility behavior shows similarity for men and women, while women prefer family and parenthood path under the uncertain employment and uncertain career prospects (Schmitt, 2021). Consequently, the researchers determine economic uncertainty that is affected by labor market and output, to prove a negative impact of economic recessions and sharp increase in unemployment rate on fertility rate (Comolli, 2017; de Lange et al., 2014; Hondroyiannis, 2010; Dupray and Pailh´e, 2017; Pailh´e and Solaz, 2012).

Kohler, H. and Kohler, I. (2002) claim that there is a positive association between fertility and labor market uncertainty in Russia during 1990s. Results can differ from each other because of the data range. In these studies, uncertainty is determined as economic innovations. Economic activities are related with production and employment, yet there are various variables that impact economy and labor market.

Liu (2012) analyzes the labor market changes and employment in China by using the Chinese Household Inco Project (CHIP) survey due to the fact that GDP growth rates cause decrease in labor force participation rate, and increase in unemployment rate. As a result of logit model, Liu (2012) claims that education, age, communist-party membership and marital status are significantly related with employment opportunities and labor force participation. Giles et al. (2006) measure the nature and magnitude of innovations to employment and worker benefits under the economic restructuring from 1996 to 2001 by using China Urban Labor Survey includes five major Chinese cities. Economic restructuring increased unemployment, and declined labor force participation, in addition large employment shocks affect mostly older and women worker (Giles et al., 2006). The labor market analyzes is mostly done upon gender. For instance, Ince (2010) indicates that the distinction between male and female in education declines, however, there is a significant difference in employment opportunities in Turkey. Faridi et al., (2009) use logistic and logit regression models to analyze the trend between female labor force participation and education, which is resulted positive for Pakistan. Laplagne et al. (2007) measure the impact of health and education on labor force participation in Australia by using the Household, Income and Labor Dynamics in Australia (HILDA) survey data annually for 2001-2004. The authors use the standard multinomial logit model, the panel multinomial logit model and simultaneous equations model, conclude that good health and taking higher degree can increase the probability of attainment on labor force (Laplagne et al., 2007)

3. DATA

Data is taken from Turkish Statistical Institute (TURKSTAT), the Central Bank (CBRT), Istanbul Stock Exchange (ISE), Banking Regulation and Supervision Agency (BRSA) in this study. All data is accessible. This study uses 31 macroeconomic monthly data – that are seasonally adjusted- to create an uncertainty index from January 2011 to February 2022. The given content and details are presented in Table 3.1 below.

Table 3.1. Description of Variables

Variables	Source	Description
Economic Confidence Index	TURKSTAT	Economic confidence index contains 5 sub-indices. 1. Real Sector Confidence Index (%20) i) Total amount of orders (current situation) ii) Amount of stocks of finished goods (current situation) iii) Volume of output (next 3 months) iv) Total employment (next 3 months) v) Total amount of orders (past 3 months) vi) Export orders (next 3 months) vii) Fixed investment expenditure viii) General business situation 2. Consumer Confidence Index (%40) i) Financial situation of household at present compared to the last 12 months ii) Financial situation expectation of household over next 12 months iii) General economic situation expectation of household over next 12 months iv) Assessment on spending money on durable goods over next 12 months compared to the past 12 months 3. Services Confidence Index (%30) i) Business situation over past 3 months ii) Demand-turnover expectation over past 3 months iii) Demand-turnover expectation over next 3 months 4. Retail Trade Confidence Index (%5) i) Business activity sales over past 3 months ii) Current volume of stock iii) Business activity-sales expectation over next 3 months 5. Construction Confidence Index (%5)

		i) Current overall order books ii) Total employment expectation over next 3 months
Loan Rate	CBRT	1. Consumer Loan Rate (%) i) Personal Financial Loan Rate (%) ii) Mortgage Loan Rate (%) iii) Vehicle Loan Rate (%) 2. Commercial Loan Rate (%)
Price Indices	TURKSTAT	1. Consumer Price Index (CPI) 2. Producer Price Index (PPI) i) Domestic Producer Price Index (DPPI) ii) Foreign Producer Price Index (FPPI) iii) Agricultural Products Producer Price Index (AP-PPI)
Exchange Rate	CBRT	1. Real Effective Exchange Rate (CPI Based) 2. Real Effective Exchange Rate (DPPI Based)
	CBRT	Istanbul Stock Exchange 100 Index (ISE100)
	BRSA	Non-performing Loans to Total Loans Rate (%)
	TURKSTAT / CBRT	Capacity Utilization Rate (%)
	TURKSTAT	Real Retail Sales Index
	TURKSTAT	Real Turnover Index
Company Statistics	CBRT	1. Number of Opened Companies 2. Number of Closed Companies
Industrial Production Index	TURKSTAT	1. Total Industry 2. Intermediate Goods 3. Durable Consumer Goods 4. Non-durable Consumer Goods 5. Energy 6. Capital Goods
Labor force Statistics	TURKSTAT / CBRT	1. Labor Force Participation Rate (%) 2. Unemployment Rate (%) 3. Labor force participation rate by educational level 1. Illiterate 2. Less than high school 3. High School 4. Vocational high school 5. Higher education

Notes: The data range that are used for the uncertainty index is 01.2011-02.2022, however, labor force statistics by educational level is up to 07.2020. All data are monthly. In VAR analysis, 01.2011- 07.2020 data range was used because of data availability. Labor force status by education level data is not seasonally adjusted. Necessary transformations are done, in addition Istanbul Stock exchange, retail sales index and turnover index were transformed to real by dividing CPI.

3.1. Data for Uncertainty Index

The economic confidence index is a composite index that summarizes the evaluations, expectations and tendencies of consumers and producers regarding the general economic situation (TURKSTAT). It is formed by using seasonally adjusted consumer, real sector, service sector, retail sector and construction sector confidence indices. Seasonally adjusted and unadjusted sectoral confidence statistics (Services, Construction and Retail) are published on a monthly basis. These data include both the "confidence index" for each sector as a status indicator, and the past situation and future expectations, which are the sub-indices used to obtain confidence indices. For example, the sub-indices for the service sector confidence index are the business situation and demand for the last 3 months, the demand for services in the last 3 months and the expectation for the next 3 months demand. Industrial production index has also sub-indices as manufacturing, energy and intermediate goods. The details are given Table 3.1.1

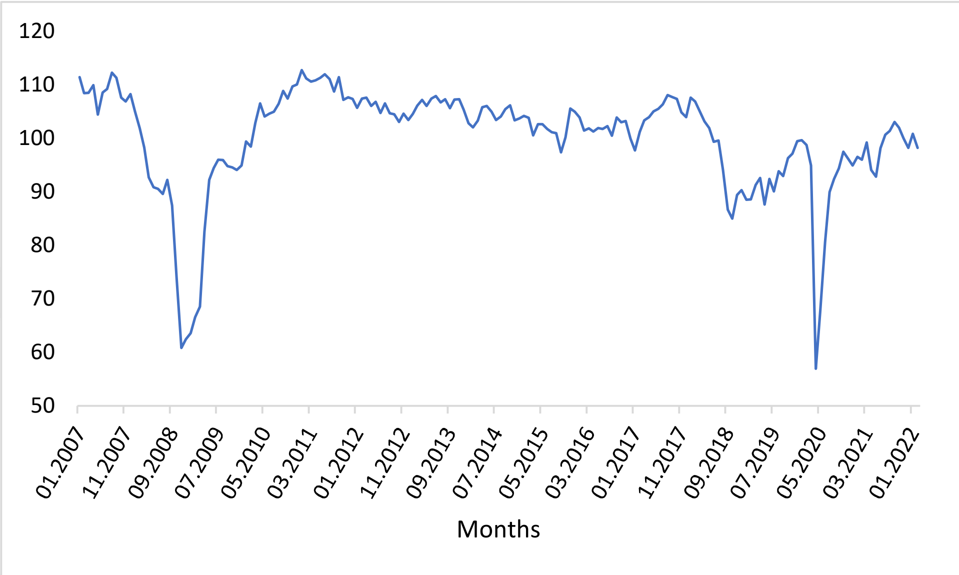
Table 3.1.1. Descriptive Statistics of data used for the uncertainty index

	Min	Max	Mean	SE Mean	Stdev	Skewness
Economic Confidence Index	56.96	112.77	101.65	0.76	8.18	-2.40
Customer Price Index	182.60	468.56	288.24	7.67	82.23	0.70
Domestic PPI	182.75	490.33	286.93	8.74	93.76	0.92
Capacity Utilization Rate	61.90	79.50	76.32	0.24	2.56	-3.47
Total Industry	77.41	120.78	99.61	1.20	12.88	-0.10
Intermediate Goods	77.61	119.52	99.01	1.04	11.13	-0.18
Durable Consumer Goods	58.68	127.21	99.46	0.92	9.82	-0.41
Non-Durable Consumer Goods	77.66	126.20	100.41	1.25	13.43	0.05
Energy	88.41	123.58	103.99	1.00	10.75	0.32
Capital Goods	66.32	128.02	97.90	1.81	19.44	-0.14
Number of Opened Company	2393	10591	5522.91	160.20	1717.97	0.64
Number of Closed Company	427	3113	1219.25	52.07	558.41	1.48
Personal Loan Rate	10.60	38.72	17.84	0.48	5.20	1.93
Vehicle Loan Rate	9.60	32.78	15.48	0.48	5.14	1.77
Mortgage Loan Rate	8.29	28.94	13.23	0.37	3.97	2.26
Commercial Loan Rate	8.41	34.87	15.23	0.47	5.10	1.72
Consumer Loan Rate	9.99	37.68	16.50	0.49	5.25	2.03
Foreign PPI	106.28	376.50	189.57	7.41	79.43	0.94
Effective Exchange Rate (CPI Based)	62.74	115.82	95.25	1.31	14.06	-0.58
Effective Exchange Rate (PPI Based)	70.98	108.64	93.46	0.85	9.15	-0.46
Non-Performing Loans to Total Loans Rate	2.65	5.35	3.26	0.06	0.68	1.72
Agricultural Products PPI	71.44	179.51	107.99	2.83	30.40	0.91
Istanbul Stock Exchange	1.99	3.92	2.98	0.04	0.43	-0.03
Retail Sales Index	0.19	0.44	0.36	0.01	0.06	-0.90
Turnover Index	0.29	0.52	0.40	0.01	0.06	0.25

Notes: *The data range is 01.2011 – 07.2020, and there are 150 observations for all variables. The data source is TURKSTAT. https://data.tuik.gov.tr*

Graph 3.1.1. illustrates the economic confidence index (ECI) that includes real, consumer, services, retail, and construction confidence index. In a global crisis, ECI decreases, at this point of view it is an adequate indicator to be included uncertainty index. In PCA analysis sub-indices of economic confidence index and industrial production index due to the importance level of components.

Graph 3.1.1. Economic Confidence Index



Notes: Data source is TURKSTAT (2022). https://data.tuik.gov.tr

The variables have to be stationary in PCA analysis (Drakos, 2002; Ludvigson, 2015). The augmented dickey fuller (ADF) test results are shown in Table 3.1.2. The integration level is 2 for the consumer price index, and 1 for all other variables. The data span is from March 2011 to February 2022, however, we contain a proxy uncertainty index between March 2011 and July 2020, because labor force statistics are published up to July 2020.

Table 3.1.2. Transformation of the variables

Description of the variable	**Level**	**1st difference**	**Transformation**
Consumer Confidence Index	-0.885	-10.098***	Δlnx
Real Sector Confidence Index	-0.056	-9.735***	Δlnx
Service Sector Confidence Index	-0.179	-9.215***	Δlnx
Retail Trade Confidence Index	-0.154	-10.040***	Δlnx
Construction Sector Confidence Index	-0.343	-9.867***	Δlnx

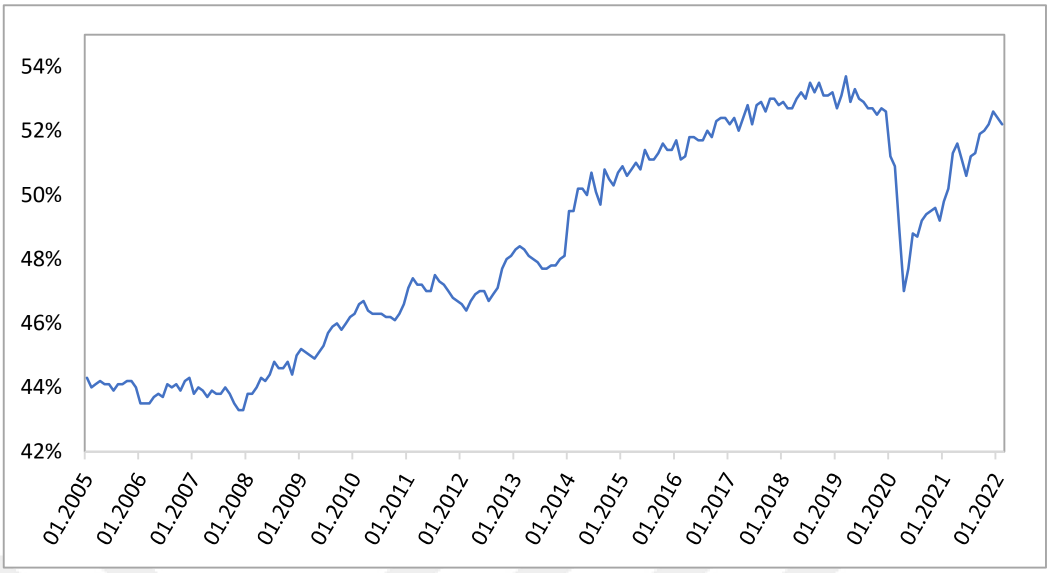
CPI (2003 based)	2.979	-1.628	Δ(Δlnx)
Domestic PPI	2.535	-3.299***	Δlnx
Mining and quarrying	0.908	-10.403***	Δlnx
Manufacturing	1.244	-10.088***	Δlnx
Electricity, gas, steam and air conditioning supply	1.272	-9.710***	Δlnx
Intermediate goods	1.150	-9.895***	Δlnx
Durable consumer goods	0.509	-10.486***	Δlnx
Non-durable consumer goods	1.410	-10.105***	Δlnx
Energy	1.234	-9.281***	Δlnx
Capital goods	1.192	-10.944***	Δlnx
Number of Opened Companies	0.293	-10.530***	Δlnx
Number of Closed Companies	-0.257	-11.238***	Δlnx
Capacity Utilization Rate	-0.579	-8.844***	Δlnx
Personal Loan Rate	-1.137	-5.431***	Δlnx
Vehicle Loan Rate	-1.116	-6.736***	Δlnx
Mortgage Loan Rate	-0.803	-7.386***	Δlnx
Commercial Loan Rate	-1.153	-5.888***	Δlnx
Consumer Loan Rate	-1.081	-5.917***	Δlnx
Foreign PPI	2.975	-6.586***	Δlnx
Real Effective Exchange Rate	-1.354	-9.179***	Δlnx
Real Effective Exchange Rate	-0.970	-8.656***	Δlnx
Non-performing loans to total loans rate	0.025	-5.816***	Δlnx
Agricultural Products PPI	2.757	-4.204***	Δlnx
Real Istanbul Stock Exchange	0.223	-8.559***	Δln(x/cpi)
Real Retail Sales Index	1.578	-9.039***	Δln(x/cpi)
Turnover Index	-1.662	-9.343***	Δln(x/cpi)

***Notes**: The necessary transformation for stationary condition. Retail sales index, Istanbul stock exchange and turnover index transformed in to real by dividing nominal variables to CPI. *** means the series are stationary at 99 percent significance level.*

3.2. Labor Force Statistics

The number of unemployed persons aged 15 and over decreased by 178 thousand persons in February 2022 compared to the previous month and became 3 million 579 thousand persons according to the results of the Household Labor Force Survey, on the other hand employment rate, decreased by 0.5 percentage points to 10.7 % (TURKSTAT, 2022).

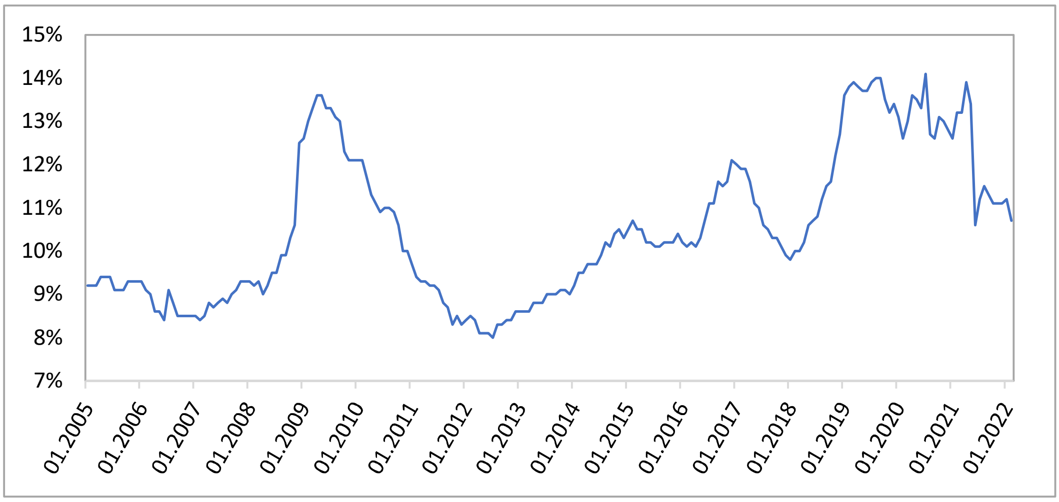
Graph 3.2.1 Labor force Participation rate (%)



Notes: Seasonaly adjusted labor force participation rate data between 01.2005 and 02.2022 taken from TurkSTAT.

Labor Force participation rate has an increasing trend over time in monthly basis, however in April 2020 it decreases to 47 percent after the first case of Covid-19 pandemic was announced on December 31, 2019 in Wuhan, while it is 52 percent on December 2019. The report of International Labor Organization (ILO) on October 27, 2021 supports the impact of pandemic on labor market by emphasizing on the significance of labor market slack.

Graph 3.2.2. Unemployment Rate (%)



Notes: Seasonaly adjusted unemployment rate data between 01.2005 and 02.2022 taken from TurkSTAT.

The unemployment rate does not show an increasing or decreasing trend like the labor force participation rate. The unemployment rate reaches its maximum by 4.1 percent in July 2020, it is 13.6 percent in May 2009. We expect that the unemployment rate increases when there is an economic recession because output falls (Curtis & Irvine, 2021). However, we cannot observe the sharp decline because as Mankiw (2020) indicates labor force participation rate includes the population who are not in the labor force.

4. METHODOLOGY

This study employs a Principal Component analysis, which is dimension reduction method to obtain an economic uncertainty proxy. We later use Vector autoregression models to examine the responses of labor force participation rates to uncertainty shocks, and to compare the results of th differtent educational attainment in Turkey by generating VAR model for each education level.

4.1. Principal Component Analysis

Principal Component Analysis (PCA) method, which is a dimension reduction method, is used to generate an uncertainty index. The PCA method is first used by Pearson (1901) and later Hotelling (1933) uses this term. Principal component analysis is an important unsupervised learning class of statistical techniques in multivariate time series due to the fact that it applies to either the covariance matrix or the correlation matrix as Abdi and Williams (2010) and Kim et al. (2002) claim. It uses smaller number of variables called principal components to explain high dimensional data. In practice, this method is used in many disciplines, especially in technical and computer sciences. Principal Components Analysis divides data consisting of many variables into vertical (orthogonal) components called principal components. The important point here is that the first component captures the most variance. Then, respectively, the 2nd, 3rd and other components capture the variance in decreasing proportions. In this way, the size of the data is reduced to a minimum, and its interpretability is increased.

The principal components are a sequence of n direction vectors in a real n dimensional space, where the first (i-1)th vectors are linearly uncorrelated with the ith vector that is the direction of the best fitting line. Ding et al. (2006) indicate that principal component analysis is sensitive to the presence of outliers and minimizes the sum of squared errors, therefore the minimization of the average squared distance from points to the line gives the best fitting line. The leading eigenvectors describe a series of uncorrelated linear combinations of the variables that contain most of the variance. A principal component analysis applies the eigen decomposition of the correlation matrix or covariance matrix of the variables.

Given n dimensional random variable $w = (w_1, \ldots, w_n)'$ with covariance matrix Σ_w, principal component anaylsis uses a few linear combinations of w_i, to explain the structure of covariance matrix. Let $z_i = (z_{i1}, \ldots, z_{in})'$ be an n dimensional real valued vector, where i = 1,2, ... , n. Then,

$$x_i = z_i' w \sum_{j=1}^{n} z_{ij} w_j$$

is a linear combination of the random vector w. the value z_{ij} gives the weigths of the jth variable, therefore the vector z_i is standardized due to the fact that multiplying a constant to z_{ij} does not influence the proportion of allocation assigned to the jth variable so that $z_i' z_i \sum_{j=1}^{n} z_{ij}^2 = 1$.

The equation below can be written by using specifications of a linear combination of random variables,

$$Var(x_i) = z_i' \Sigma_w z_i, \qquad i = 1, \ldots, n$$

$$Cov(x_i, x_j) = z_i' \Sigma_w z_j, \qquad i, j = 1, \ldots, n$$

PCA gets linear combinations z_i such that x_i, x_j are uncorrelated for i $i \neq j$ and x_i's variances are as large as possible. More particularly,

- The ith component of w is a linear combination of $x_i = z_i' w$,
  max Var (x_i)
  s.t. $z_i' z_i = 1$

$$\mathrm{Cov}(x_i, x_j) = 0 \qquad for\ \ j\ = 1, \ldots, i-1\ .$$

The covariance matrix must be expressed in terms of eigenvalues or eigenvectors because positive definiteness of the covariance matrix means that it is symmetrical and its eigenvalues are not negative. $\gamma_i = (\gamma_1, \gamma_2, \ldots, \gamma_n)$ and $\omega_i = (\omega_1, \omega_2, \ldots, \omega_n)$ are eigenvalue and eigen vector respectively, which is properly normalized. Consequently the i[th] component of w,

$$x_i = \omega_i' w \sum_{j=1}^{n} \omega_{ij} w_j\ ,\ \ where\ \ i = 1,2, \ldots, n$$

$$Var(x_i) = \ \omega_i' \sum\nolimits_w \ \omega_i\ = \gamma_i\ , \qquad i = 1,2, \ldots\ , n$$

$$Cov\big(x_i, x_j\big) = \ \omega_i \sum\nolimits_w \ \omega_j = 0\ \ , \qquad j = 1,2, \ldots\ , n$$

Moreover,

$$\frac{Var(w_i)}{\sum_{i=1}^{n} Var(w_i)} = \frac{\gamma_i}{\gamma_1 + \cdots + \gamma_n}$$

Thus, the ratio between the i'th eigenvalue and the sum of all the eigenvalues of the covariance matrix is the value representing how much of the total variance ratio in x is explained.

In this study, the first component obtained using the PCA method is used as uncertainty index. At this point, the “economic uncertainty index” is created, which reflects the uncertainty in the economy in general. Then, the effects of uncertainty shocks on labor force participation rate and unemployment rate are analyzed with structural vector auto regression (SVAR) models, in which this index and the variable indicating labor force participation rate is used.

4.2. Vector Autoregression & Structural VAR

When there is ambiguity whether a variable is exogenous or endogenous, it is a logical extension of transfer function analysis to consider each variable equally (Enders, 2008). We can allow present and past realizations of the x_t sequence to impact the time path of y_t, and we can allow current and past realizations of the x_t sequence to affect the time path of y_t in the two variable scenario. Consider the following basic bivariate system:

$$y_t = \alpha_{10} - \alpha_{12}x_t + \delta_{11}y_{t-1} + \delta_{12}x_{t-1} + \epsilon_{yt}$$

$$x_t = \alpha_{20} - \alpha_{21}y_t + \delta_{21}y_{t-1} + \delta_{22}x_{t-1} + \epsilon_{xt}$$

where it is assumed that

(1) x_t and y_t are stationary

(2) ϵ_{xt} and ϵ_{yt} are serially uncorrelated random vector with standard deviations of σ_x and σ_y .

The equation above generate a first order vector autoregression (VAR), however, it is useful for creating the multivariate higher order systems. Because x_t and y_t can impact each other, the system's structure involves feedback. For instance, $-\alpha_{12}$ represents the contemporaneous impact of a unit change in x_t on y_t, whereas δ_{12} represents the effect of a unit change in x_{t-1}on y_t. It should be noted that the words ϵ_{yt} and ϵ_{xt} are pure innovations in the terms y_t and x_t, respectively. Naturally, if α_{12} is greater than zero, ϵ_{yt} has an indirect simultaneous influence on y_t.

The SVAR model allows simultaneous interaction between endogenous variables by revealing that error terms are actually functions of shocks. In this research, a two-variable SVAR system generated to estimate the impact of uncertainty on labor force participation rate (LFPR).

When uncertainty measure is UNC_t, labor force participation rate indices are $LFPR_t$, and $Y_t = [UNC_t, LFPR_t]'$ is a $2x1$ vector of uncertainty measure, respectively the reduced form can be written as $\varphi(L)Y_t = \omega_t$, where $\varphi(L)$ is the autoregressive lag polynomial function, and ω_t is the forecast errors vector. If β_0 represents the contemporaneous impact,

$$\beta_0 Y_t = \beta_1 Y_{t-1} + \cdots + \beta_n Y_{t-n} + \epsilon_t, \qquad \epsilon_t \sim (0, \Sigma_\omega)$$

where ϵ_t captures the structural innovations related to elements of $\mathrm{Y_t}$. The forecast errors are the structural model can be written as below,

$$\begin{bmatrix} 1 & \alpha_{12} \\ \alpha_{21} & 1 \end{bmatrix} \begin{bmatrix} {\omega_t}^{UNC} \\ {\omega_t}^{LFPR} \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \begin{bmatrix} {\epsilon_t}^{UNC} \\ {\epsilon_t}^{LFPR} \end{bmatrix}$$

The above theoretical framework should include at least five limitations. Four constraints have already been applied in the equation above, implying that the diagonal elements of the contemporenous effect matrix are set as 1, and there is no connection between structural shocks $(b_{12}, b_{21} = 0)$. We introduce two models as follows, because one more restriction has to be applied:

Model(1): $\alpha_{12} = 0$, and α_{21} is unrestricted implies that the change in labor force participation rate has not impact on the uncertainty measure, while the labor force participation rate responds the changes in uncertainty.

Model(2): $\alpha_{21} = 0$, and α_{12} is unrestricted proposes that the change in uncertainty measure should not affect the labor force paticipation rate within the same month.

Economic factors determines the restrictions applied on the elements of $\mathrm{Y_t}$, rather than statistical identification of structural parameters (Kilian and Lütkepohl, 2017). Because there cannot be symmetrical relation between uncertainty and labor force participation rate, structural corrections are needed.

5. PCA RESULTS

The aim of using principal component analysis is obtaining economic uncertainty index for Turkey that is reflect economic situation, therefore we use 31 macroeconomic variables after we check the unit root and trend with Augmented Dickey Fuller test. Accordance with a ADF test, the second difference of CPI index, and the first difference of other variables are stationary. The stationary data is used to generate uncertainty index after they are scaled. Thus, each series are standardized as follows, standardized to have an expected value of 0 and a variance of 1. If the series in the PCA is w:

$$Z_i = \frac{w_i - E(w)}{\sigma_w} \quad ve \quad \overline{Z_i} = |Z_i|$$

Z_i standard normal scores are obtained for each series, showing how many standard deviations (σ_w) they differed from the expected values. Since these scores is used in the uncertainty index, they are included in the PCA analysis by taking their absolute values. Currently, econometric analysis packages provide outputs by standardizing the included batches when applying the PCA method by default. Since the study applies the PCA method to create the uncertainty index, it is structured like a volatility model and the variance of the series is taken into account instead of the mean value. For this reason, considering the non-negative variance ($\overline{Z_i}$), is used instead of Z_i and is not re-standardized.

Table 5.1 explains the first component includes 43.7 percent information of the variables. The first component has been chosen as uncertainty index that represent the economic fluctuations like Trump's sanction decision and Covid-19 health crisis.

Table 5.1. The importance level of components

Component Number	Sdev	Importance	Cumulative Importance
PC1	2.822	***0.437***	0.437
PC2	1.648	0.149	0.586
PC3	1.226	0.082	0.668
PC4	0.893	0.044	0.712
PC5	0.733	0.029	0.742
PC6	0.702	0.027	0.769
PC7	0.679	0.025	0.794
PC8	0.672	0.025	0.819

PC9	0.642	0.023	0.841
PC10	0.575	0.018	0.859
PC11	0.558	0.017	0.877
PC12	0.543	0.016	0.893
PC13	0.524	0.015	0.908
PC14	0.498	0.014	0.921
PC15	0.451	0.011	0.933
PC16	0.427	0.010	0.943
PC17	0.412	0.009	0.952
PC18	0.373	0.008	0.960
PC19	0.344	0.007	0.966
PC20	0.325	0.006	0.972
PC21	0.303	0.005	0.977
PC22	0.288	0.005	0.982
PC23	0.262	0.004	0.985
PC24	0.243	0.003	0.989
PC25	0.216	0.003	0.991
PC26	0.209	0.002	0.993
PC27	0.199	0.002	0.996
PC28	0.165	0.002	0.997
PC29	0.155	0.001	0.998
PC30	0.140	0.001	1
PC31	0.092	0.000	1

Notes: The components of the PCA. The first component is taken as uncertainty index.

The generated uncertainty index contains subindices of economic confidence index, capacity utilization rate, price indices, real Istanbul Stock Exchange 100 index, loan rates, number of opened and closed companies, real exchange rates, real retail sales index, real turnover index, and non-performing loans to total loans rate. Table 5.2 shows each data used in the index creation and their factor loadings. Real sector confidence index and manufacturing have high and positive loadings in first component.

Table 5.2 The macroeconomic data and factor loadings

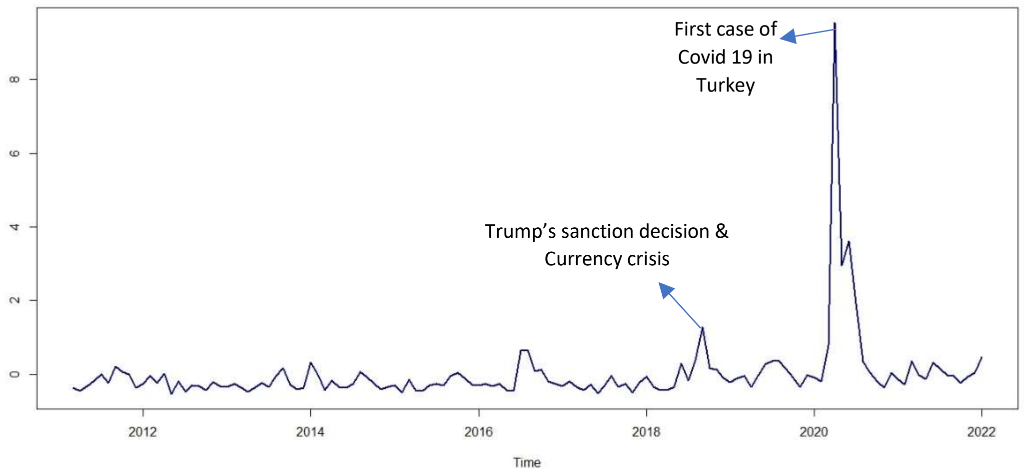
Description of the variable	PC1	PC2	PC3
Consumer Confidence Index	0.036	-0.152	0.094
Real Sector Confidence Index	**0.287**	0.015	-0.011
Service Sector Confidence Index	**0.314**	0.046	0.035
Retail Trade Confidence Index	**0.276**	0.026	0.016
Construction Sector Confidence Index	**0.273**	-0.013	-0.064
CPI (2003 based)	-0.005	**-0.304**	0.229
Domestic PPI	0.004	**-0.381**	0.250
Mining and quarrying	0.061	-0.004	-0.006
Manufacturing	**0.290**	0.068	0.025
Electricity, gas, steam and air conditioning supply	0.180	0.089	0.044
Intermediate goods	**0.281**	0.053	0.009

Durable consumer goods	0.241	0.063	0.036
Non-durable consumer goods	**0.259**	0.069	0.013
Energy	0.186	0.086	0.058
Capital goods	0.243	0.066	0.059
Number of Opened Companies	0.159	0.037	-0.031
Number of Closed Companies	0.034	-0.048	0.017
Capacity Utilization Rate	**0.277**	0.035	0.020
Personal Loan Rate	0.114	**-0.276**	**-0.351**
Vehicle Loan Rate	0.026	-0.235	**-0.323**
Mortgage Loan Rate	0.041	-0.222	**-0.445**
Commercial Loan Rate	0.042	-0.241	**-0.270**
Consumer Loan Rate	0.082	**-0.276**	**-0.372**
Foreign PPI	0.019	**-0.361**	**0.284**
Real Effective Exchange Rate	0.029	**-0.316**	0.226
Real Effective Exchange Rate	0.010	**-0.274**	0.215
Non-performing loans to total loans rate	0.077	-0.150	0.011
Agricultural Products PPI	-0.013	-0.166	0.156
Real Istanbul Stock Exchange	0.029	-0.043	0.054
Real Retail Sales Index	0.222	-0.153	0.107
Turnover Index	**0.255**	-0.014	0.066

Notes: There are 31 components, theree of components are represented.

Graph 5.1. illustrates uncertainty index between 03.2011-01.2022 that is obtained by PCA. Covid-19 crisis is 7 times of currency crisis. It also shows the 2016 United States presidential election, the coup attempts in July 2015, terrorist attack in capital city of Turkey in March 2016 and parliamentary election in June 2011.

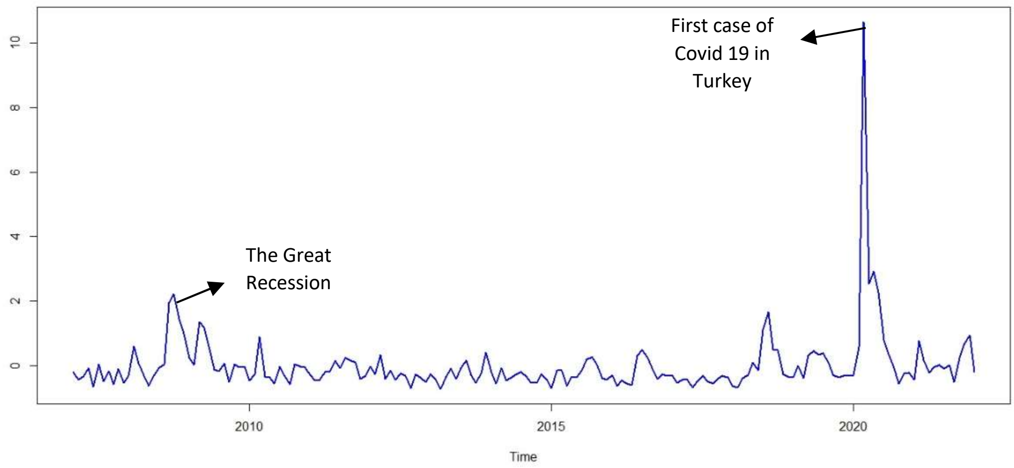
Graph 5.1. Uncertainty Index



Notes: The first component of the principal component analysis from 02.2011 to 01.2022.

Graph 5.1 shows the difference between Coronavirus crisis and the great recession. The data range of the uncertainty index in graph 5.2 is 2007-2022, however, it is not appropriate to include in analysis due to the shortage of the data. The percentage of included information drops 43 percent to 33.56 percent with 11 macroeconomic variables. Coronavirus innovation impact is four times of the great recession.

Graph 5.2. Uncertainty Index from 02.2007 to 01.2022



***Notes**: 11 macroeconomic variables have been used. All series are stationary at first difference.*

6. SEASONALITY

Weather, holidays, repeating promotions, and economic agents' activity induce seasonality that can be defined as a recurring pattern (Hylleberg, 1992). The seasonal and calendar effects prevent to observe the general tendency of the data when they are temporary effect. Zhang & Qi (2005) state that seasonal variations are the most important component in a seasonal time series due to the fact that they are in conjunction with a stochastic trend, and they create a significant impact on forecasting process. In the data containing seasonal movements, it is very difficult to understand whether the change in a certain period is due to the actual increase or decrease in the data or seasonal effects. In order to interpret monthly/periodical and annual changes in short-term indicators in an accurate way, it will be more significant to use seasonal and calendar adjusted indicators in comparisons to be made according to the previous month/period.

There are various seasonal adjustment methods have been developed. The most important and popular method is X-11 methods (Shiskin et al.,1967) that is generated by the Bureau of the Census in 1950s and 1960s which is evolved into X-12 ARIMA program (Findley et al., 1996), then the current X-13 ARIMA (Sax and Eddelbuettel, 2018). Seasonality of labor force participation rate series is adjusted by using X-13 ARIMA program in this study.

6.1. Labor Force Participation Rate by Educational Level

The labor force includes the population of working age who are or are willing to supply labor for the production of economic goods and services in the relevant reference period. In determining the workforce, activities that contribute to the production of goods and services that fall within the production limit in the United Nations System of National Accounts (SNA) are essential (TURKSTAT). The labor force represents the sum of the employed and the unemployed. Labor force participation rate is the ratio of the labor force to the non-institutional working-age population.

Table 6.1.1. Basic Statistics of Labor Force Status by educational level

	LFPR_IL	LFPR_LHS	LFPR_HS	LFPR_VHS	LFPR_HE
nobs	187	187	187	187	187
Minimum	**0.138**	0.416	0.459	0.591	**0.734**
Maximum	0.226	0.503	0.572	0.676	0.812
Mean	0.188	0.470	0.522	0.650	0.787
SE Mean	0.001	0.001	0.002	0.001	0.001
Variance	0.000	0.000	0.001	0.000	0.000
Skewness	-0.410	-0.551	-0.266	-1.217	-0.879
Kurtosis	0.225	-0.535	-0.432	3.724	1.205

Notes: *Labor force participation rate by education level data taken for TURKSTAT as monthly basis.*

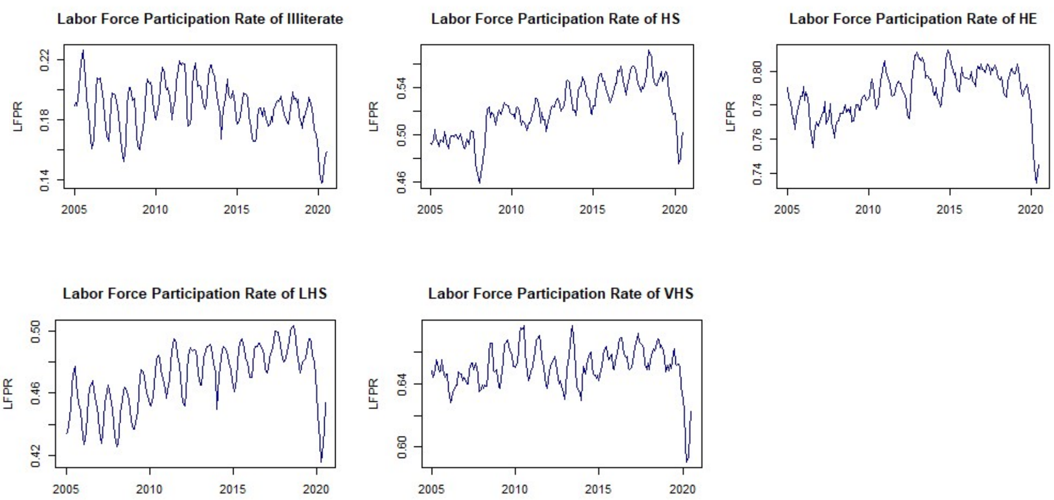
TURKSTAT classifies the information on the educational status of all individuals aged 6 and above in accordance with the International Standard Classification of Education (ISCED, 2011). There are four groups as follows:

- The illiterate

- Less than high school education
    - Those who can read and write and have not completed a school
    - Primary school
    - Primary education
    - Secondary or vocational secondary school
- High school or equivalent vocational school graduates
    - General high school
    - Vocational or technical high school
- Higher Education
    - College
    - University
    - Master and PhD

The labor force participation by educational level dataset takes vocational and general high school separately. Therefore, this study includes five groups for LFPR. The data is published from January 2005 to July 2020. There are 187 observations. Table 6.1.1. shows that the maximum labor force participation rate for illiterate people is 22.6 percent, while it is 81 percent for people who take their higher education degree.

Graph 6.1.1 LFPR by education level before seasonal adjusment



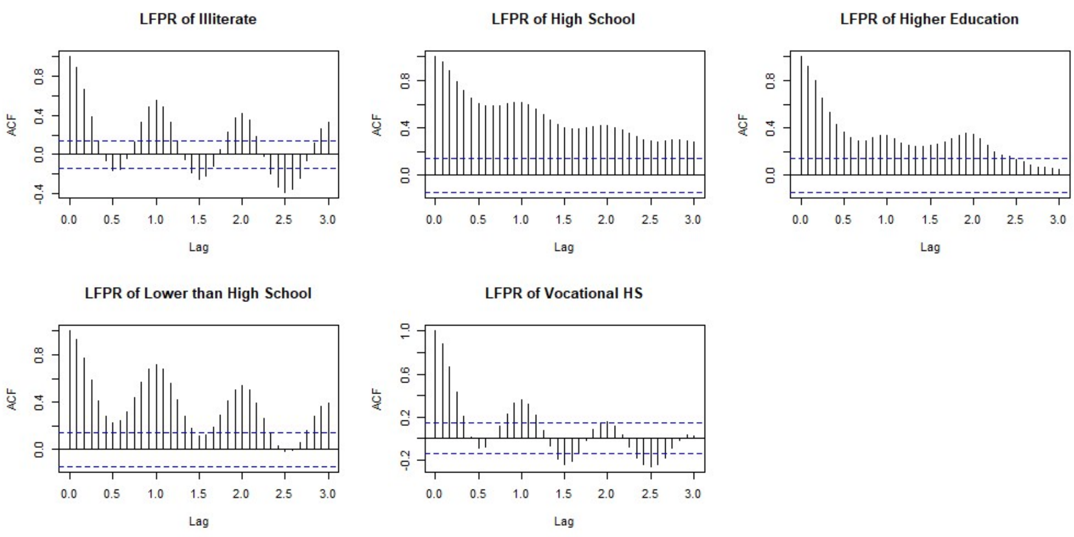
Notes: Non-Seasonally adjusted labor force participation rates are given from 01.2005 to 07.2020 in monthly basis. The education level of the left hand side graphs is illiterate, high school and higher education, on the left hand side is lower than high school and vocational high school respectively.

The graph 6.1.1 illustrates that the minimum labor force participation rate is equal to 13.8 percent among illiterate people, 41.6 precent in lower than high school level, 59.1 percent for vocational high school level, and 73.4 percent for higher education level in April 2020 with the impact of Covid-19 pandemic. However, LFPR for high school level's minimum value is 45.9 percent in January 2008 due to the fact that 2008 financial crisis.

6.2. Decomposition & Seasonality Results

TURKSTAT published seasonally unadjusted labor force status by educational level. Studies on seasonality indicate that the X-11 method introduced in 1957 by the US Census Bureau to adjust seasonality and that predictable cycles should be excluded from the analysis to obtain reliable results (Burman, 1980; Jain, 1989; Wallis, 1974; Ifrim and Mursa, 2009; Shiskin et al., 1967). We generate autocorrelation function (ACF) graphs (Graph 6.2.1) and decompositions of the series (Graph 6.2.2) to detect the seasonal effect.

Graph 6.2.1. Autocorrelation function graphs of the labor force participation rate series



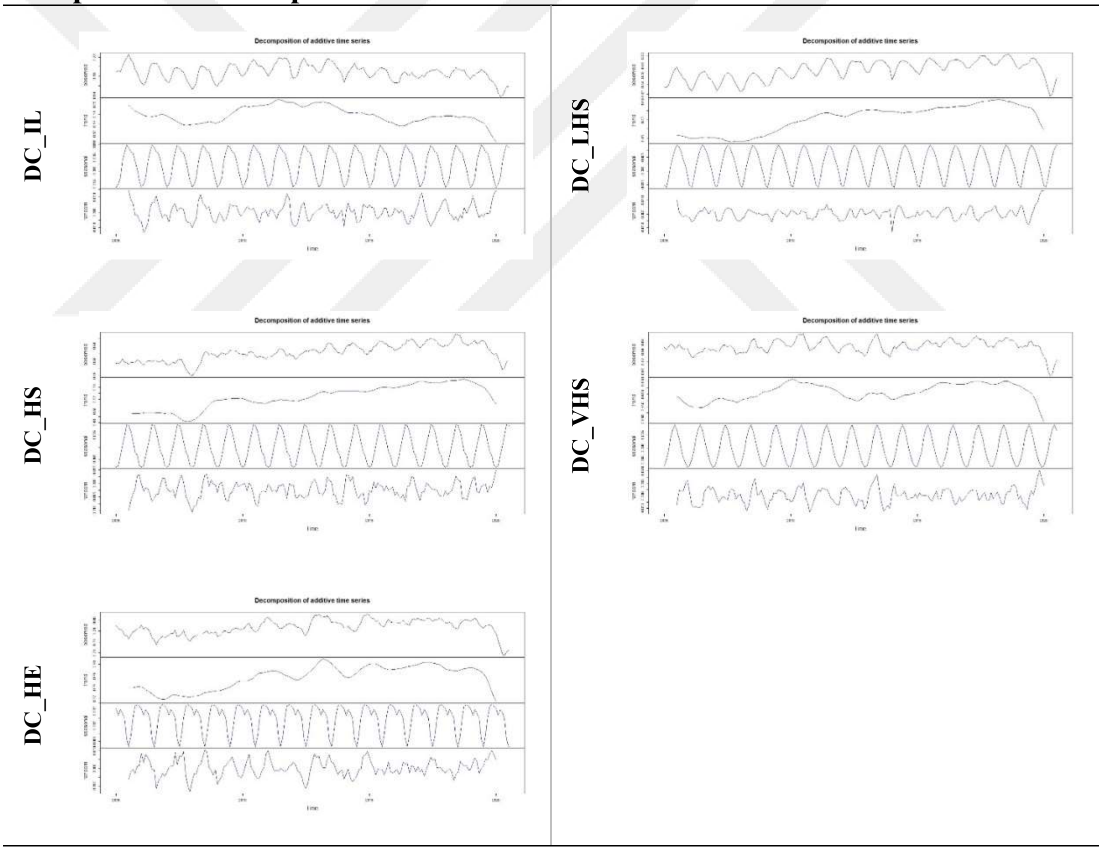
Notes*: ACF graphs of labor force status by education level. Lag is taken 36.*

ACF graphs give a clue about seasonality, however it cannot illustrate seasonality accurately. There is a recurring pattern for first three series. Decomposition illustrates the components of the series. The additive model can be written as follows:

$$X_t = T_t + S_t + \in_t$$

We use moving average to obtain trend component of the time series, while we utilize averaging to detect seasonal component. We appoint the error term after determining T_t, S_t. Graph 6.2.2 illustrates decompositions of time series.

Graph 6.2.2. Decompositons of the time series



Notes: Respectively, the series are labor force participation rate for illiterate, lower than high school, high school, vocational high school, and higher education.

We use Kruskal–Wallis test, QS test and Welch's ANOVA tests to identify seasonality. P values are less than 0.05, thus we cannot reject the null that means there is seasonality.

Based on the seas package there is seasonal impact for labor force statistic series by education level.

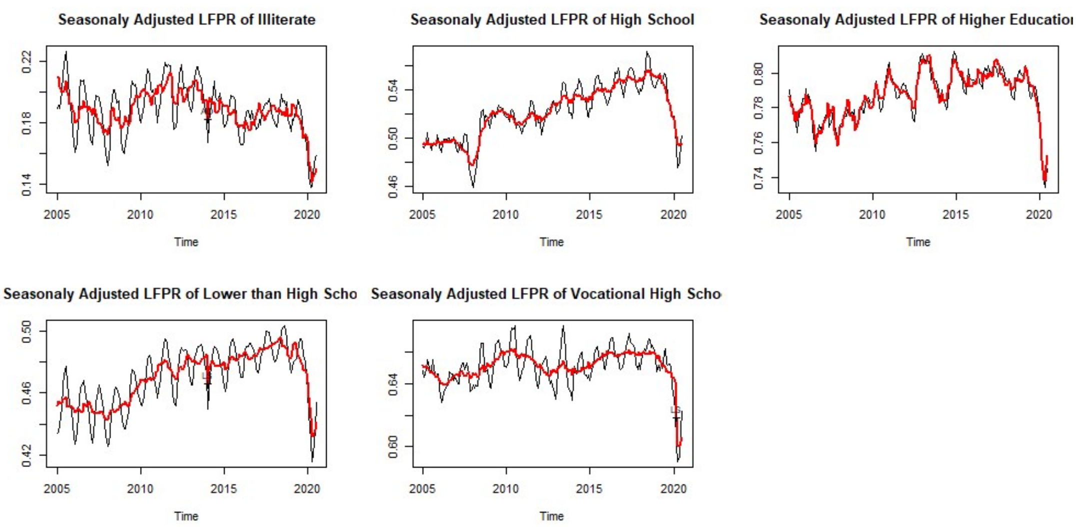
Table 6.2.1 Chosen RegARIMA model and test statistic of seasonal adjustment

Series	RegARIMA model	QS test Statistics	Durbin Watson of Residuals
LFPR (illiterate)	(0,1,1) (0,1,1)	157.537	2.002
LFPR (lhs)	(0,1,1) (0,1,1)	159.110	2.011
LFPR (hs)	(0,1,1) (1,0,0)	25.453	1.870
LFPR (vhs)	(2,0,0) (1,1,1)	48.548	1.997
LFPR (he)	(0,1,1) (0,1,1)	17.723	1.912

Notes: *RegARIMA model is determined automatically with seas function. There are 187 observations for all series.*

Durbin Watson results indicates that the generated model is adequate due to the fact that there is no autocorrelation among residuals in Table 6.2.1. The seasonally adjusted series are given in Graph 6.2.3.

Graph 6.2.3. Adjusment results



Notes*: Black line shows the observed data, while red line illustrates seasonaly adjusted series.*

Labor force participation rates decrease while coronavirus pandemic. There is negative correlation between LFPR by education level and health crisis. The great recession influenced high school graduates mostly, yet Covid-19 pandemic has significant impact on other education level.

7. VAR & SVAR MODELS

To measure the relation between uncertainty and labor force participation rate, we create Vector Autoregression models. According to the researchers, uncertainty have an impact on LFPR. Yet, they take expectations as uncertainty, so that they use survey data mostly in their research. We generate an uncertainty index by collecting macroeconomic data to analyze innovations and their impact on labor force participation rate.

We create a linear vector auto-regressive (VAR) system to measure the effects of random changes in the economic uncertainty index created by the PCA method on labor force participation rates. Accordingly, $Y_t = [UNC_t, LFPR_t]$ is a 2x1 vector consisting of uncertainty and labor force participation rate. We show the relationship of the VAR model with the lagged values of the Y_t vector as follows.

$$\beta_0 Y_t = \beta_1 Y_{t-1} + \cdots + \beta_n Y_{t-n} + \epsilon_t, \qquad \epsilon_t \sim (0, \Sigma_\epsilon)$$

β_0 is the 2x2 contemporaneous effect matrix between the economic uncertainty index and labor force participation rates. The parameter n represents the number of delayed values. ϵ_t represents the structural shocks and Σ_ϵ is the diagonal variance-covariance matrix. The reduced form of VAR system is as follows:

$$\varphi(L) Y_t = \omega_t \; ; \; \varphi_i = \beta_0^{-1} \beta_i \;\; and \;\; i = 1,2,\ldots,n$$

$\omega_t = [\omega_t^{UNC} \quad \omega_t^{LFPR}]'$ represents 2x1 reduced form autoregressive vector of equation errors. $\varphi(L) = I_2 - \varphi_1 L - \cdots - \varphi_n L_n$ is auto-regressive lag polynomial of reduced form and L is the delay operator. The error terms of the VAR equation (ω_t) imply that the structural shocks (ϵ_t) are the weighted average (Kilian, 2017). Here, since the number of parameters to be estimated with the β_0 matrix is more than the total number of equations, it is necessary to determine some constraints in the β_0^{-1} or β_0 simultaneous relations matrices, respectively, by using the $\beta_0^{-1}\epsilon_t = \omega_t$ or $\epsilon_t = \beta_0\omega_t$ equations. Blanchard and Perotti (2002) apply a structural model, where they can show these two approaches together, this study also uses same approach as follows.

$$\beta_0\,\omega_t = B\epsilon_t$$

It is necessary to create a constraint on at least 5 parameters in the β_0 and B matrices in order to obtain just identified model which is determined in the reduced form VAR equation. Economic assumptions or predictions determine which elements of the matrices will apply these constraints in addition to statistical significance. If the Σ_ϵ matrix is the unit matrix, $\Sigma_\epsilon = I_2$ and the diagonal elements of the simultaneous effects matrix equals to 1; in this case, it is necessary to create at least 3 more constraints on the matrices B and β_0. When the VAR system estimates the diagonal elements of the B matrix, the structural VAR system that explains the uncertainty and labor force participation rate is:

$$\underbrace{\begin{bmatrix} 1 & 0 \\ a_{21} & 1 \end{bmatrix}}_{\beta_0}\begin{bmatrix} \omega_t{}^{UNC} \\ \omega_t{}^{LFPR} \end{bmatrix} = \underbrace{\begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}}_{B}\begin{bmatrix} \epsilon_t{}^{UNC} \\ \epsilon_t{}^{LFPR} \end{bmatrix}$$

$$\Sigma_\epsilon = I_2 \quad ve \quad \Sigma_\omega = \beta_0^{-1}BB'\beta_0^{-1'}$$

This study predicts that the changes in the economic uncertainty index affect the changes in the labor force participation rates simultaneously, on the other hand, the changes in the labor force participation rates have no effect on the uncertainty in the period when it occurs. We expect that the effects of a shock that will cause a change in labor force participation rates will not have an effect on uncertainty simultaneously, and we expect to observe this change in the uncertainty index announced with the publication of labor force participation rates. While these assumptions explain how the simultaneous effect between uncertainty and labor force participation occurs, the dynamic interaction of the two does not suggest a change regarding the VAR system. Thus, taking into account the simultaneous relationships, we estimated the dynamic impulse-response functions between the labor force participation rate and the lagged values of the economic uncertainty index.

We determine VAR orders by using Akaike Information Criteria (AIC) test. The order (p) is 1, except participation rate of high school and vocational high school, which is 3 and 4 respectively. Table 7.1 summarizes the selection criteria and determined orders.

Table 7.1. Vector Autoregression order selection

	AIC(n)	*HQ(n)*	*SC(n)*	*FPE(n)*
LFPR (illiterate)	1	1	1	1
LFPR (lhs)	1	1	1	1
LFPR (hs)	3	2	2	3
LFPR (vhs)	4	2	2	3
LFPR (he)	1	1	1	1
LFPR	1	1	1	1
Unemployment Rate	1	1	1	1

Notes: We consider Akaike Information Criteria in Vector Autoregression analysis.

Table 7.2 gives serial correlation test results of VAR model. We can reject the null that there is serial correlation. The generates models have no serial correlation.

Table 7.2. Vector Autoregression serial test results

	Test stats	*P value*
LFPR (illiterate)	30.802	0.934
LFPR (lhs)	36.316	0.788
LFPR (hs)	47.757	0.187
LFPR (vhs)	43.894	0.078
LFPR (he)	40.153	0.637
LFPR	37.659	0.739
Unemployment Rate	53.651	0.151

We estimate the effect of structural shocks on the variables and the response of the variables in the 12-month period using impulse-response functions. Two structural shocks and four impulse-response values occur since there are two variables in the structural model. We present the effects of the structural shock created by the labor force participation rates on the uncertainty in the appendix section. We present the dynamic and cumulative effects of impulse response functions together.

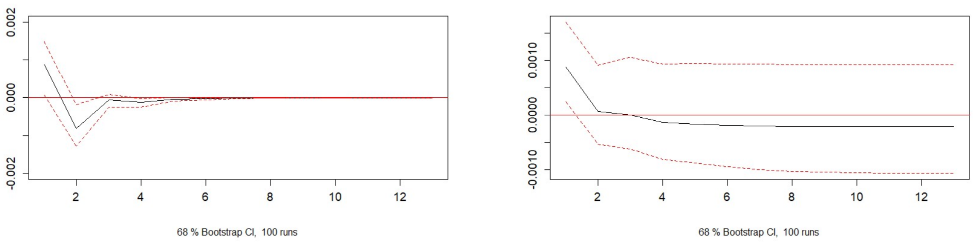
We repeat our analysis for both VAR and SVAR model specifications. For the sake of brevity, we just report SVAR results below since VAR impulse-response results are qualitatively similar to that of SVAR.

7.1. Labor Force Participation Rate

We perform an impulse response analysis (IRF) with the SVAR model created to measure the effects of uncertainty on labor force participation rates according to education level. Here, we graphically show and discuss how the labor force participation rates determined for each education level respond to shocks to the economic uncertainty index.

Figure 7.1.1 shows the effect of one standard deviation increase in the uncertainty index on the total labor force participation rate. The increase in the uncertainty index positively affects the labor force participation rate, but its impact turns negative after 1 month and disappears after 6 months (period) (left panel). Figure 7.1.1 right panel shows the cumulative effect of shocks on the economic uncertainty index. The initial total impact is negative, but it is statistically insignificant.

Graph 7.1.1 LFPR responses to uncertainty shocks.

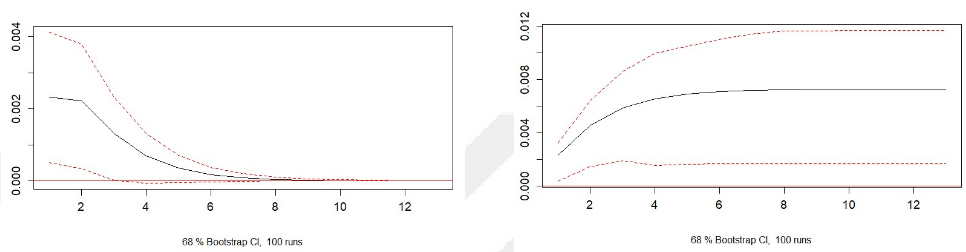


Notes: Left Panel: It is the dynamic response of labor force participation rate to the uncertainty shock. Right Panel: Cumulative response of labor force participation rate to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of labor force participation rate. The data is between 03/2011-11/2019 months.

7.2. Unemployment Rate

Graph 7.2.1 shows the unemployment rate responses to the EUI. There is positive impact of uncertainty on unemployment rate. The impact of uncertainty shocks disappears after 6 months. Right panel proves the total impact of the EUI is positive and statistically significant.

Graph 7.2.1 Unemployment rate responses to uncertainty shocks

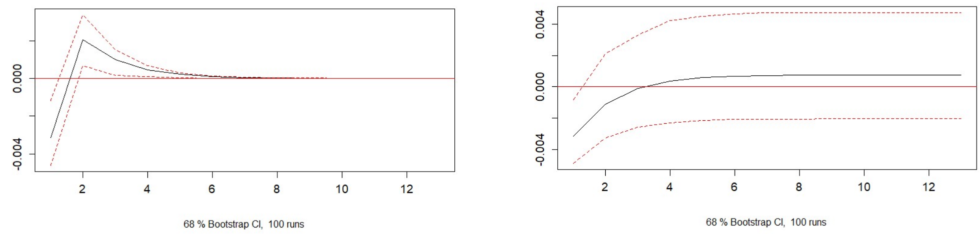


Notes: Left Panel: It is the dynamic response of unemployment rate to the uncertainty shock. Right Panel: Cumulative response of unemployment rate to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of unemployment rate. The data is between 03/2011-11/2019 months.

7.3. Illiterate

Figure 7.3.1 shows the effect of one standard deviation increase in the uncertainty index on the labor force participation rate of illiterate people. Right panel shows the cumulative responses. The increase in the uncertainty index negatively affects the labor force participation rate of illiterate people and the effect of the shock disappears after 6 months (period) (left panel). Figure 7.3.1 right panel shows the cumulative effect of shocks on the economic uncertainty index. Total effects are negative for up to 4 months.

Graph 7.3.1 LFPR_IL responses to uncertainty shocks

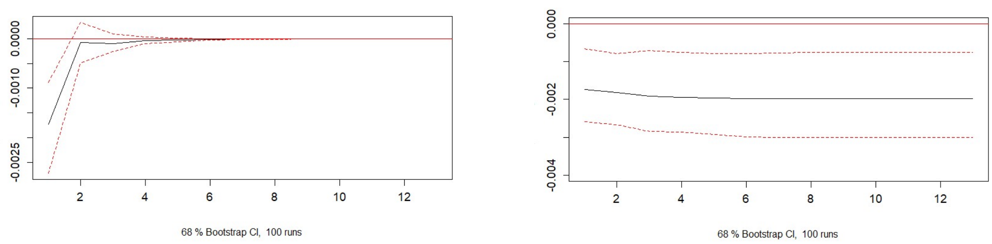


Notes: Left Panel: It is the dynamic response of labor force participation rate of illiterate people to the uncertainty shock. Right Panel: Cumulative response of LFPR_IL to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of LFPR_IL. The data is between 03/2011-11/2019 months.

7.4. Lower than High School Degree

Lower than high school category includes both secondary school graduate and primary school graduates. Uncertainty shock has a negative impact on their participation rate of labor force as in graph 7.4.1. The cumulative impulse response function (right panel) illustrates one standard deviation increase in economic uncertainty has negative impact on LFPR of lower than high school graduates.

Graph 7.4.1 LFPR_LHS responses to uncertainty shocks

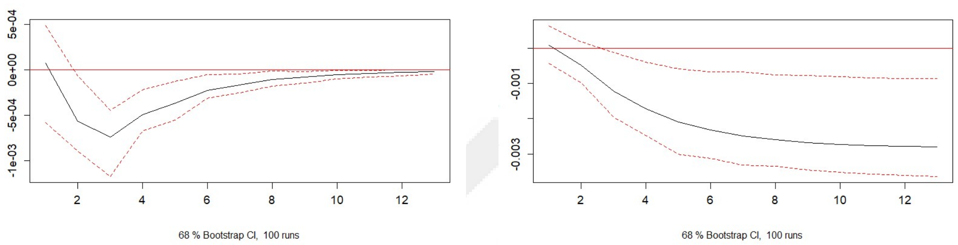


Notes: Left Panel: It is the dynamic response of labor force participation rate of people who get primary or secondary school degree to the uncertainty shock. Right Panel: Cumulative response of LFPR_LHS to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of LFPR_LHS. The data is between 03/2011-11/2019 months.

7.5. High School Degree

High school degree equals to 12 years educational background in Turkey. There is negative impact on participation rate of high school graduate. Graph 7.5.1. illustrates that one standard deviation increase in economic uncertainty decreases labor force participation rate of high school graduates in total (right panel).

Graph 7.5.1 LFPR_HS responses to uncertainty shocks



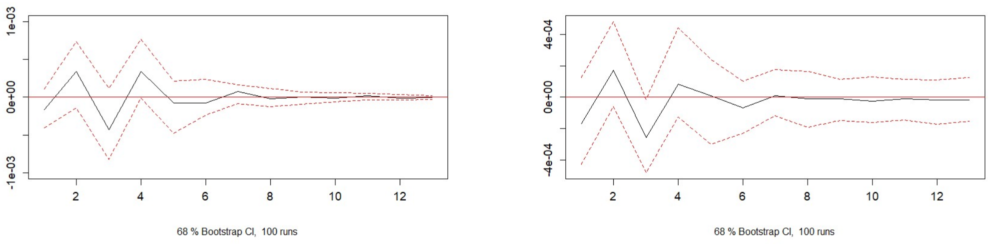
Notes: Left Panel: It is the dynamic response of labor force participation rate of people who get high school degree to the uncertainty shock. Right Panel: Cumulative response of LFPR_HS to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of LFPR_HS. The data is between 03/2011-11/2019 months.

The impact of uncertainty index on participation rate of high school graduates to labor is positive and the disappearance of the innovation takes a long time such 10 months.

7.6. Vocational High School Degree

The order (p) determined as 4 based on Akaike information Criterion (AIC), but Hannan Quinn Information Criterion (HQIC) it is equals to 2. There is no serial correlation in the model, however, the impact of economic uncertainty innovations is insignificant.

Graph 7.6.1 LFPR_VHS responses to uncertainty shocks

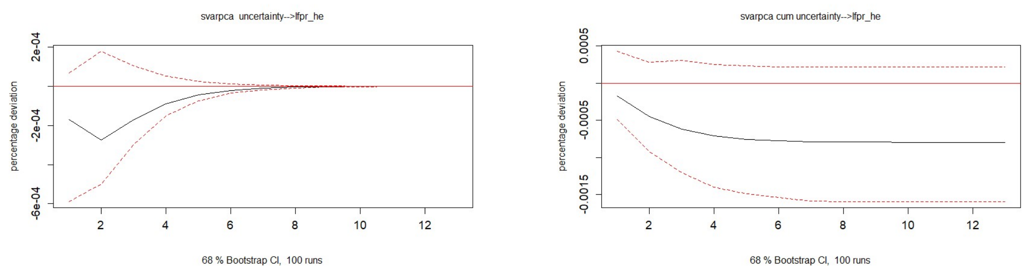


Notes: Left Panel: It is the dynamic response of labor force participation rate of people who get vocational high school degree to the uncertainty shock. Right Panel: Cumulative response of LFPR_VHS to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of LFPR_VHS. The data is between 03/2011-11/2019 months.

7.7. Higher Education Degree

Uncertainty innovation has a negative impact on participation rate of people who have a higher education degree. The direction of the impact is not parallel with the impact on the general labor force participation rate. However, the positive effect is insignificant (Graph 7.7.1). Thus, an increase in economic uncertainty shock decreases the participation rate of higher education graduates.

Graph 7.7.1 LFPR_HE responses to uncertainty shocks



Notes: Left Panel: It is the dynamic response of labor force participation rate of people who get higher education degree to the uncertainty shock. Right Panel: Cumulative response of LFPR_HE to uncertainty shock. The dashed lines indicate the error range of ±1standard deviation. The vertical axis is the percentage change of LFPR_HE. The data is between 03/2011-11/2019 months.

7.8. Forecast Error Variance Decomposition (FEVD)

The variance decomposition indicates the amount of information economic uncertainty shock contributes to labor force participation rates in the autoregression. Table 7.8.1 proves that economic uncertainty innovations have higher impact on people who graduated from primary or secondary school by 8 percent. Uncertainty has the least effect on the labor force participation rate of high school graduates.

Table 7.8.1. Forecast Error Variance Decompositions

	LFPR (illiterate)	*LFPR (lhs)*	*LFPR (hs)*	*LFPR (vhs)*	*LFPR (he)*	*LFPR*
1 month	0.0260	**0.0828**	**0.0003**	0.0044	0.0018	0.0173
4 months	0.0397	0.0828	0.0526	0.0229	0.0086	0.0301
8 months	0.0399	0.0828	0.0609	0.0237	0.0088	0.0301
12 months	0.0399	0.0828	0.0613	0.0237	0.0088	0.0301
24 months	0.0399	0.0828	0.0613	0.0237	0.0088	0.0301
36 months	0.0399	0.0828	0.0613	0.0237	0.0088	0.0301
48 months	0.0399	0.0828	0.0613	0.0237	0.0088	0.0301

Notes: The table presents the percentage decompositions of uncertainty shocks in the forecast error variance in the SVAR model to different labor force participation rates at 1, 2, 4, 8, 12, 36 and 48 months, respectively. The data estimate is in the range of 03/2011-11/2019.

8. CONCLUSION

Economic downturns have a significant impact on different areas like health, industrial production, labor market, and education. Due to the fact that economic recession creates some level of uncertainty, we measure the uncertainty by generating an index for economic uncertainty. The constructed proxy index detects the important political or economic changes between 03/2011 and 07/2022. The economic uncertainty index includes 43 percent information of thirty-one macroeconomic variables. Confidence indices and manufacturing, which is sub- index of industrial production index, have higher information in created index.

The Covid-19 pandemic crisis creates a serious supply and demand shock simultaneously. The loss of purchasing power causes more unemployed people. Therefore, we measure the impact of uncertainty on labor force participation rate in

Turkey. Different from previous studies, we include educational attainment. Unemployment rate is not enough to measure the impact of uncertainty on labor because unemployment rate excludes people who are looking for work. Although labor force participation rate shows sudden decline during Covid-19 pandemic, we cannot observe such a sudden increase in unemployment rate.

Educational attainment in Turkey consists of five categories: illiterate, lower than high school, high school, vocational high school, and higher education. Lower than high school includes both primary and secondary school graduates. Having higher education means getting bachelor's, master or Ph.D. degree. We expect to measure different levels of uncertainty shock impact on different labor force participation rates.

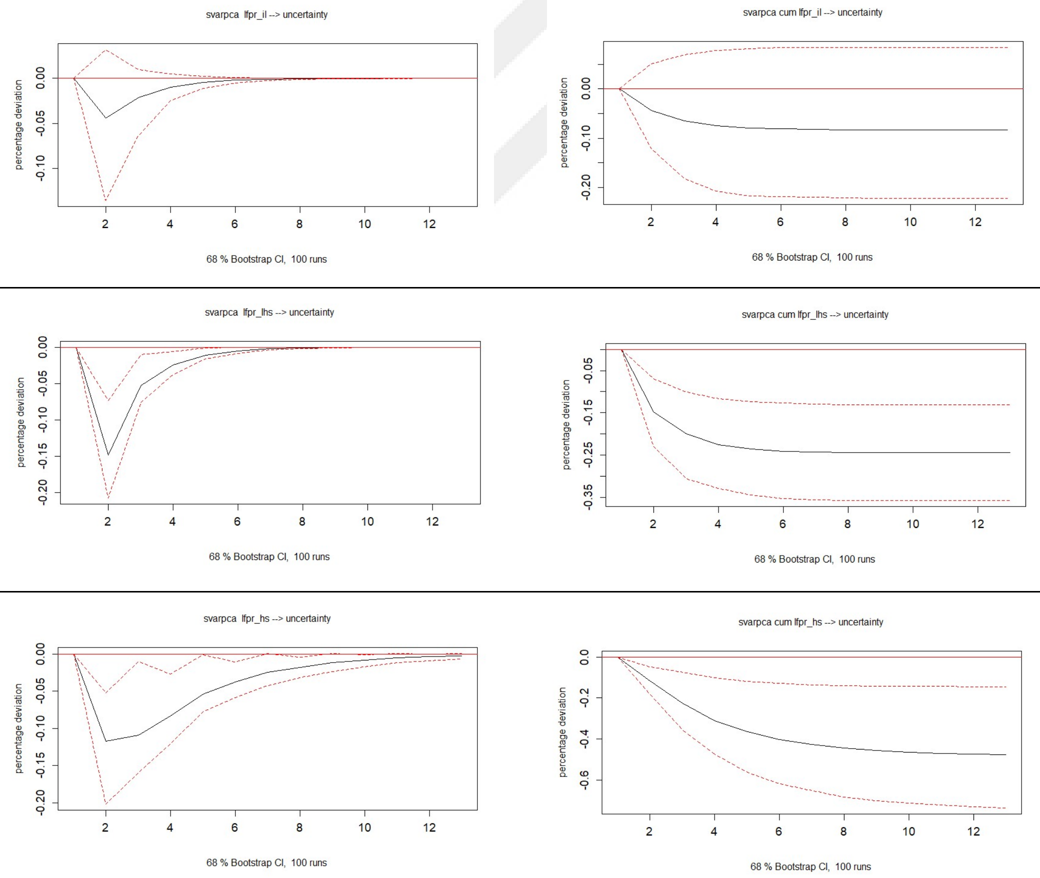
We develop a vector auto regression models to analyze the relationship between uncertainty shocks and LFPR. The economic uncertainty index included with limited data span, from March 2011 to November 2019. We exclude coronavirus period to relief of bias that can occur with high amount of uncertainty because first cases announced in December 2019. We also check stationarity of collected macroeconomic data. We use first difference of series (second difference for CPI). In addition, we adjust seasonality in labor force participation rate by education level data due to the fact that seasonal effect brings about improper forecast. We utilize X-13 ARIMA method to decompose the series and get adjusted series. Then, we developed bivariate VAR models for each level of education. VAR results shows that there is negative impact of uncertainty shocks on labor force participation rates. However, we expect labor force participation rate response uncertainty innovations after some time. It means simultaneous impact of uncertainty on LFPR should equals 0.

Finally, we construct a structural VAR to provide economic restrictions. The structural vector autoregression model results infer negative impact. Moreover, impulse response functions give both dynamic and cumulative impacts. The response of LFPR of vocational high school graduates is statistically insignificant. One standard deviation increase in uncertainty shock decreases labor force participation rate of the illiterate and less than high school graduates. Nevertheless, an initial impact of one standard deviation increase in uncertainty shock is positive. Forecast error variance decompositions explain the amount of uncertainty innovation information in labor force participation rate responses. LFPR of high school graduates' responses to uncertainty shock is less, while the influence of shocks on primary and secondary school graduates is high.

In further studies, co-integrations can be included in the analysis. Because there are insignificant impacts, there can be other variables that influence LFPR like health, age, and marital status. Bivariate VAR models can be generated after explaining the labor force participation rates economically. In addition, further studies can measure the forecast power.

9. APPENDIX

Graph 9.1 Uncertainty responses to LFPR shocks



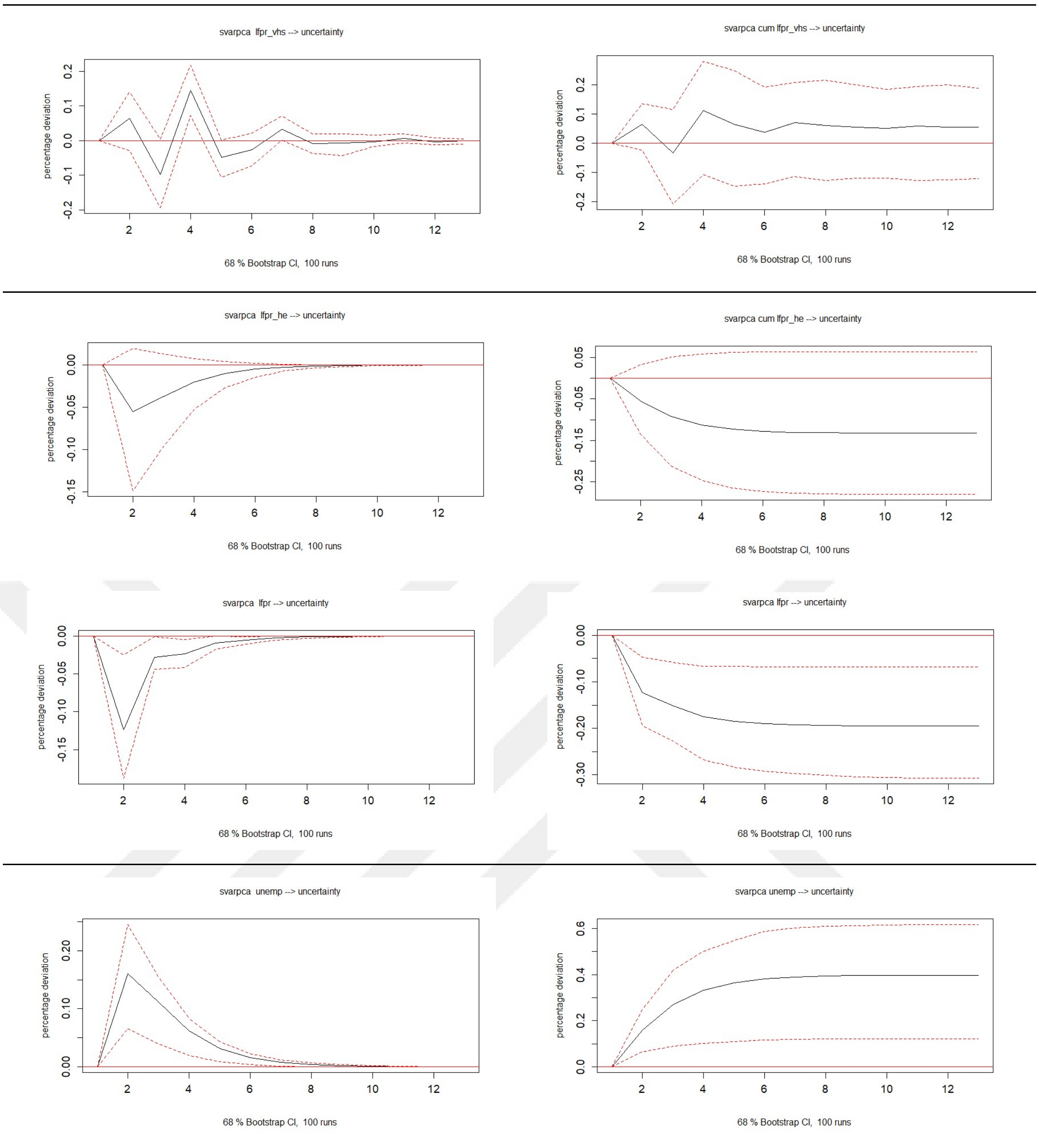


Table 9.1 Forecast Error Variance Decompositions of LFPR

	LFPR (illiterate)	*LFPR (lhs)*	*LFPR (hs)*	*LFPR (vhs)*	*LFPR (he)*	*LFPR*
4 months	0.0024	0.0247	**0.0315**	**0.0318**	0.0047	0.0163
8 months	0.0025	0.0248	0.0362	0.0351	0.0049	0.0164
12 months	0.0025	0.0248	0.0365	0.0352	0.0049	0.0164
24 months	0.0025	0.0248	0.0365	0.0352	0.0049	0.0164
36 months	0.0025	0.0248	0.0365	0.0352	0.0049	0.0164
48 months	0.0025	0.0248	0.0365	0.0352	0.0049	0.0164

Notes: The table presents the percentage decompositions of lfpr shocks in the forecast error variance in the SVAR model to the economic uncertainty at 1, 2, 4, 8, 12, 36 and 48 months, respectively. The data estimate is in the range of 03/2011-11/2019.

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