Response of Inflation to the Climate Stress: Evidence from Azerbaijan

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Abstract

This research is the first study that analyzes the effects of climate change-related factors on the inflation environment in Azerbaijan during 2005-2020 and forecasts annual inflation for the 2021-2030 period. For this purpose, considering the possible long-run cointegration relation among variables and limited historical observations, the chain impact of temperature on agricultural producer prices is analyzed through the BVAR model. Additionally, the transition requirements to the effects of green energy on inflation are examined through the exchange rate pass-through. Since the aim of the research is to reveal climate change's impact on the long-run trend of inflation, the study generates two climate scenarios for the 2021-2030 period and analyzes the inflation difference at the end of the horizon. According to the model results, climate change's contribution to inflation is expected to be 1.3 percentage points (pp) in the long run with the baseline scenario, where climate-related variables follow their historical trends. On the other hand, climate contribution to inflation is estimated to be 2.2 pp in the worst scenario of climate change, where 1.2 °C additional temperature anomaly deteriorates the trends. The results imply that climate change is not only the determinant of seasonality but the trend of inflation. In light of these results, the paper highlights the importance of a well-developed climate action plan set by the government and monetary incentives for transitioning to a green environment set by the Central Bank of the Republic of Azerbaijan.

Keywords: inflation, climate, fossil fuel, green energy, BVAR, forecasting

JEL Codes: E31, Q54, E37, E58, C32

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1. Background

The Central Banks (CB) are the major institutions to primarily maintain price stability and they are also in the charge of ensuring the financial stability of the economy. For this purpose, they have the authority to use several monetary tools to interfere with. However, set monetary policies' impacts on the economy are seen on a longer horizon (Friedman, 1972). Thus, CBs should foresee the economy for appropriate and on-time policies. On this path, they need to know the possibility of risks that threaten macroeconomic stability.

The CBs risk map includes well-known macroeconomic and financial sector-related risk factors such as asset balloons, soaring debts, supply chain, global demand, etc. However, the so-called climate change has been added to the recently updated risk map. But does the climate have enough direct effects on the economy to be accounted for as a risk factor?

Since temperature is the major impact variable of climate change, it distracts the precipitation balance, resulting in drought or extreme rainfall; moreover, a less productive environment for agricultural products and more physical damage such as heatwaves, wildfires, floods, etc. Thus, it is a potential risk factor. On the other hand, the Paris agreement to prevent climate-related disasters also potentially limits the growth of the fossil fuel sector. Overall, climate change and its related transition to a green environment impose some risk on the economies, especially fossil fuel exporters like Azerbaijan.

To answer the structural question, which is set above as climate change “has” or “has not” rather than “may” or “can,” this research deeply analyses the structural relations between climate-related factors and inflation in Azerbaijan from 2005 to 2020 in Section 2. Since the paper is the first one that accounts for climate risks on inflation in Azerbaijan, it brings new aspects to the determinants of inflation. In the end, consistent with the previous literature that accounted for climate impacts on other economies, this research concludes that climate has a significant impact on inflation that is now.

This research tries to prove that climate affects not only the seasonal part of inflation but also its trend, which will imply that it is a structural determinant of inflation. This paper analyses the exact impact of two climate scenarios between 2021 and 2030 in Section 3 to estimate the potential impact of climate change on inflation. The first scenario is called normal, which means everything will continue to be the same as it used to be. The second one is the worst scenario, which is based on five assumptions: i) average temperature will be 1.2 °C higher than the normal scenario in 2030 as projected by World Bank's (2014) Climate Change Program for Azerbaijan; ii) precipitation will be 4.8 percent lower, which is consistent with Asian Development Bank's estimates on droughts (2021); iii) per capita expenditures on environmental protection will be 15 percent higher than the current level; iv) zero fallow land, and v) cereal productivity 26 percent less consistent with the historical minimum level. These scenarios were integrated into the Bayesian Vector Autoregression (BVAR) model built to estimate inflation in Azerbaijan through an agricultural producer price index between 2021 and 2030. As a result, in 2030, with the worst scenario, water prices will become 2.2 times, and inflation will be 2.5 times higher than the assumed level in the normal scenario.

In addition, decreased oil production in compliance with the Paris agreement's main scope on global temperature has also created a threat to the exchange rate, which is one of the key factors in reducing inflation. According to United Nations-based research (UN) (2020), fossil fuel producer countries must cut 6 percent of fuel production to meet global temperature-limiting goals. In light of this condition and the World Bank's (2021) projections on oil prices, a new worst scenario was generated and implemented into the BVAR model to forecast inflation through Real Effective Exchange Rate (REER) between 2021 and 2030. According to the worst scenario, around 21 percent less fossil fuel revenue is expected from export, and inflation is around two times higher than the normal scenario. In the final step, a combination of the impact of climate change and the transition to a low-carbon economy by reducing fossil fuel production caused approximately 1.8 percent additional inflation each year during the periods of 2021 and 2030.

According to the model results, climate change became the proven risk for inflation that was never accounted for before in Azerbaijan. Moreover, similar results could also be obtained for the rest of the world while considering that history and future scenario paths are identical. At this point, this paper's BVAR modeling approach to forecasting climate change's impact on inflation (one of the first in the literature under our knowledge) could stimulate future inflation models that account for climate variables as a determinant factor.

After the proof that climate is the risk factor, the main task is to find intervention tools against climate-related inflation. Since the existing monetary tools only focus on macroeconomic variables, they have no impact on the reduction of temperature or increment in precipitation. However, these climate variables affect the inflation that central banks carry the responsibility for.

Thus, the toolbox of central banks should be widened consistently with their law-determined mandates. “Green quantitative easing” for green energy producer companies, incentives on green investments, or prudential norms in favor of green financing could be one of them. Although neither will reverse the climate change path, these tools could prevent economies from following the worst scenarios.

2. Climate risks on inflation

Since the early 1990s, Central Banks (CB) have been adopting inflation targeting (IT) regimes (Adam S. Posen, 1999), which led monetary authorities to use interest rate tools as a response to inflation and Gross Domestic Product (GDP) gap (Taylor, 1993). Moreover, the IT regime has become the primary mandate of Central Banks by official law. Alternatively, the countries that have not adopted the IT regime are also setting the CB’s mandate to maintain price stability, as in the case of the Republic of Azerbaijan. Thus, “*the main goal of the Central Bank is to maintain price stability within its authorities set by the Law*” (Central Bank of the Republic of Azerbaijan).

It is a common practice that CBs should consider the possible scenarios of future inflation. therefore, drivers of inflation, such as global commodity prices, and local factors that affect productivity, trade, demand, expectations, etc., attract immediate attention. However, exchange rate-targeting countries have a prior concern about the value of local currencies, which significantly impacts inflation through import prices. Henceforth, all possible risks that could affect future inflation through drivers should be considered while making today’s policy decisions. Then the revealed question is, what are the major risks, and with which transmission mechanism will they control inflation?

The unexpectedly high inflation of the post-pandemic period hustled us to worry about the other risks that were left unnoticed, such as climate change. Is it just a lead trending topic only related to “an environmental change,” or is it a real economic threat? If so, what is the impact mechanism of climate on macroeconomic variables? More importantly, will climate significantly affect the overall prices that CBs should maintain their stability?

The basic answer to the last question is “yes.” Climate, which uses average temperature as a “gun,” could be a serious determinant of inflation. When the temperature increases, the optimal environment for agricultural products changes, which affects the prices. Temperature also increases the risk of decreasing precipitation except for storm-affected areas, affecting the water demand and supply equilibrium. However, globally increased temperature is not an assumption. We observe an increase of 1 °C in 2020 compared to the 1951-1980 average temperatures (NASA Global Climate change, 2020).

Moreover, these conditions are expected to worsen, decreasing the productivity of land and the quality of agricultural products (Asian Development Bank, 2021) and increasing pressure on prices. Besides, climate-related natural disasters such as heatwaves, wildfires, and floods could threaten the insurance system. This risk will also be reflected in the overall prices through insurance prices.

The complex answer is also "yes." Transitioning to a low-carbon economy is a cost factor. It increases carbon taxes and forces companies to use more expensive green energy. As a result, part of "traditional" energy sources becomes unburnable. For instance, "*a third of oil reserves, half of the gas reserves, and over 80 percent of current coal reserves should remain unused from 2010 to 2050 in order to meet the target of 2 °C*" (McGlade & Ekins, 2015, p. 187). Thus, fossil fuel producer companies, their stockholders, and the natural source having countries will face negative results during the transition period. In this regard, Azerbaijan is one of those countries that strive to develop a non-fossil energy sector to hold a net exporter status.

However, one should note that the direct impact of climate change is and will be greater than the transition costs. For instance, the Bank of England (2021) estimates that transition could lower average annual output growth to 1.4 percent between 6-10 years of transition and increase afterward. On the contrary, no action to transition could gradually and continuously lower output growth to 1.2 percent in the following 26-30 years. Additionally, no action to transition brings significant physical risks, such as the natural disasters discussed above. One step further, extremely high temperatures and drought could worsen poorer communities' economic situation, whose income strictly depends on water infrastructure (Asian Development Bank, 2021).[3] Thus, following these significant economic structural impacts, the arguments related to ending the transition cost to reach today's best wealth level are not the subject of this paper.

The previous literature findings also indicate the importance of climate on inflation. Although the global literature is partially developed about the transmission mechanism of climate impacts, it has a significant gap in implementing climate factors into inflation forecasting. Under

[3] Explained in detail in Section 2.2.

the transmission mechanism, several researchers found a significant effect of climate-related disasters on inflation. For instance, according to Lesk, Rowhani, and Ramankutty (2016), droughts and heatwaves decrease global cereal productivity by 9-10 percent between 1964 and 2007. A step further, 1 °C increased temperature over a yearly average of 15 °C or above decreases the general productivity by 1.7 percent (Deryugina & Hsiang, 2014). Parker (2018) found that inflation immediately increases by 1.3 percentage points (pp) in response to drought by analyzing the relation between the frequency of disasters and inflation. The latest published research on climate and food inflation was made by Islam et al. (2022), proving that climate negatively affects food security, which is significantly related to inflation.

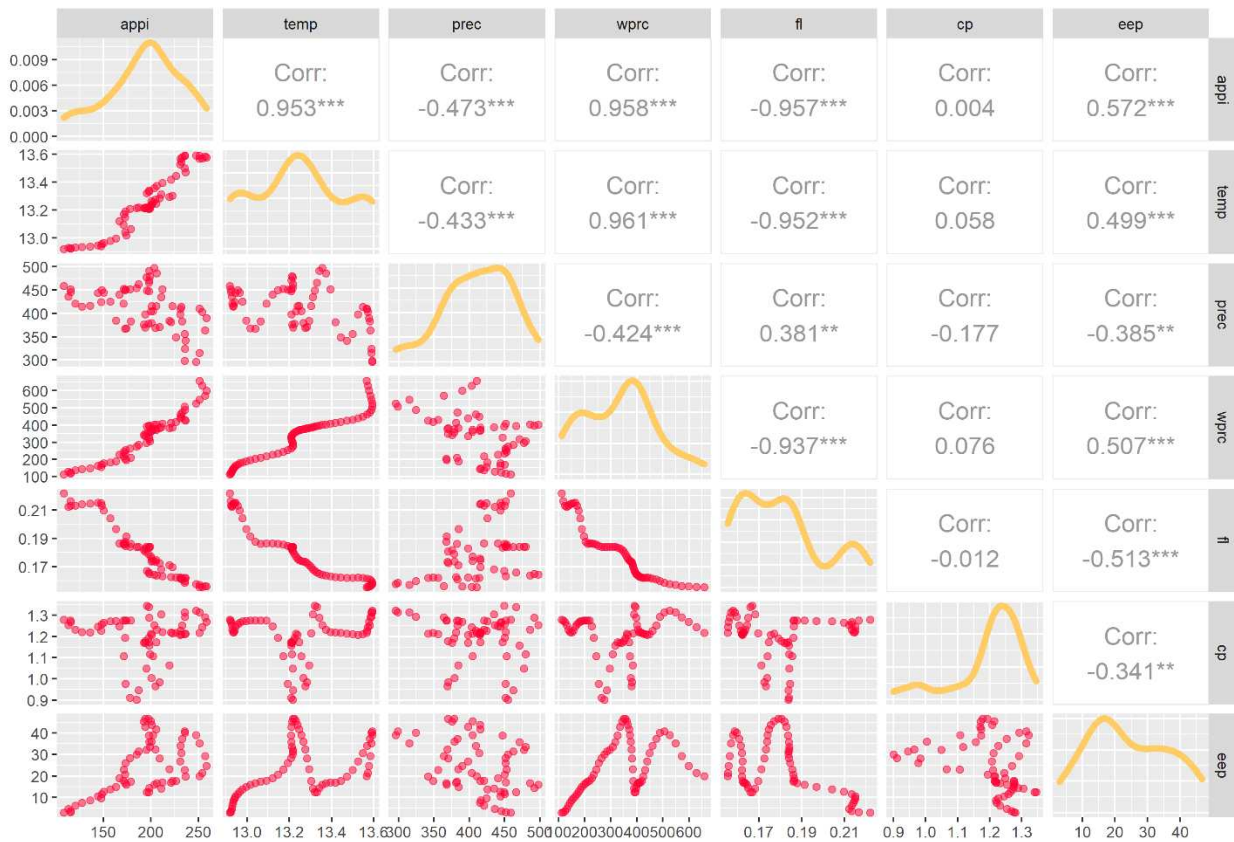
In sum, the climate is proven to have an impact on inflation through agricultural productivity. Moreover, globally transitioning to a low-carbon environment is risking fuel exporter countries and their currencies. Henceforth, the findings assure that the future of climate change carries a serious risk to inflation and the overall economy that should be estimated.

2.1. Data and descriptive statistics

The research is primarily based on exogenous temperature (temp) as a "gun" of climate change and precipitation (prec). Both data cover the period of 1901-2020 and are obtained from World Bank Climate Change Knowledge Portal as average annual observations. In relation to change in these variables, for the 2000-2020 period, the following scenario variables are per capita m^2 fallow land (fl), cereal productivity (cp) relative to population, and per capita expenditures on environmental protection (eep) that obtained annually from State Statistics Committee of the Republic of Azerbaijan (AzStat). The first set of focused endogenous variables are water price inflation (wprc) and agricultural producer price inflation (appi); both contain monthly observations during the period of 2005 and 2021 and are obtained from AzStat. The third primary endogenous variable is the Real Effective Exchange Rate (REER) during the period of 2000 and 2021, obtained as monthly observations from the CB of Azerbaijan Republic (CBAR). The scenario variable related to the REER model is fossil fuel revenues from export (oilr) received as yearly observations from AzStat between 2000 and 2021. The final exogenous variable is global oil price projections obtained as yearly observations from World Bank's Commodity Markets Outlook. The annual data sets were transformed into quarterly ones by Chow-Lin's (1971) methodology. The monthly data sets are converted to the quarterly base by summing or taking an average of three months

Since the literature proved the significant relationship between agricultural prices and climate-related drought, this research analyzes more detailed impact transmission mechanisms. In the beginning, descriptive statistics are used to ensure the relationship between inflation and climate variables and are displayed in Table 1.

Table 1. Correlogram



Source: AzStat, World Bank *** - if the p-value is < 0.001; ** - if the p-value is < 0.01; * - if the p-value is < 0.05

In Table 1, the variable abbreviations are as follows: appi - agricultural producer prices, temp – temperature, prec - precipitation, wprc - water prices, fl - per capita fallow land (m^2), cp- cereal productivity relative to population, eep - per capita expenditures on environmental protection. The lower triangular panel displays the correlation paths, and the upper panel shows the exact correlation values with their statistical significance. The diagonal is the density distribution of observations.

As seen in Table 1, the temperature negatively correlates with precipitation and fallow land; moreover, it has a positive and high correlation with agricultural product prices and water prices. It also has a positive correlation with per capita expenditures on environmental protection.

Thus, we address temperature as the "gun" of climate change. In the inflation dimension, temperature, water prices, and per capita expenditures on environmental protection observations provide a positive correlation; however, precipitation and per capita fallow land (m2) negatively correlate with agricultural product inflation, henceforth with overall price stability. Unlike other scenario variables, cereal productivity does not provide a significant relationship with any other. However, a step ahead, impulse response reveals its negative relation with inflation, discussed in detail in Section 2.4 and displayed in the Appendix.

The evidence from Azerbaijan displays that temperature is a factor of climate change directly and negatively affects the fallow land. Besides, the precipitation is falling,[4] which causes higher water supply prices and higher agricultural product prices. The Paris agreement continuously increases expenditures on environmental protection as a function of payments for releasing pollutants into the natural environment. In addition, decreasing oil production to meet the Paris agreement's main goal on global temperature is also creating a threat to the exchange rate.

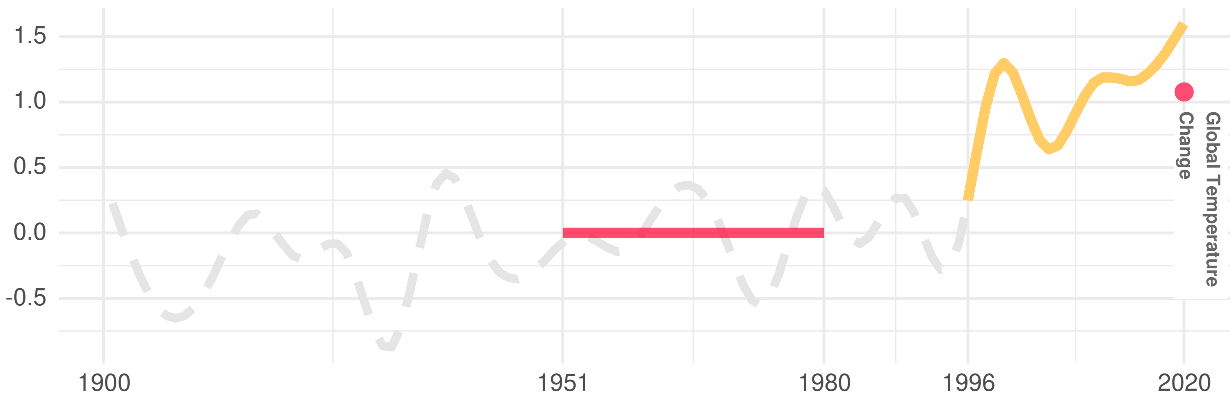
2.2. Changing climate conditions

According to NASA (2021), global temperature anomaly reached its historically high level (1.02 °C) in 2020 and decreased in 2021, which is the relative temperature of the current year versus the average temperature of the 1951-1980 pre-industrial period. Similarly, temperature anomaly in Azerbaijan also follows a parallel path but is above the world average. For instance, at the end of 2020, the mean annual temperature increased by 0.57 °C higher than the global average, ensuring that climate change has a more negative effect on Azerbaijan than on the world.

[4] It should be noted that increased temperature is expected to increase the extreme rainfall in Azerbaijan. However, extreme rainfall is not the source of agriculture required or a drinkable water supplier rainfall (Lawrence, 2018). Moreover, high temperature causes water evaporation and heavy rains, which reduce the "*water access for humans and ecosystems*" (Society, 2019).

Figure 1. Smoothed Mean Annual Temperature Change in Azerbaijan

relative to 1951-1980 average temperatures



Source: World Bank, NASA

High temperature causes high precipitation volatility and drought (Dore, 2005); moreover, less productive agricultural products (Lesk, Rowhani, and Ramankutty, 2016; Deryugina and Hsiang, 2014). As a result, decreased productivity directly affects food prices (Parker, 2018; Islam, et al., 2022). Due to high temperatures, arable land shrinks, and thus, fallow land decreases. Consistent with high volatile precipitation (extreme rainfall), drinkable water supplies fall (Lawrence, 2018), and water prices increase.

On the other hand, the water issue is also threatening the welfare structure of the country. According to ADB (2021), drought carries the possibility of worsening income inequality by reducing the revenues from "rain-fed" agricultural products. Since poor communities and farmers can not reach the local water supply, the rising temperature would have the most significant negative impact on them rather than on the rest of the population (Asian Development Bank, 2021).

Henceforth, understanding the potential climate risk to the economy is essential and requires an analysis of temperature's future path. In this scope, this paper develops two scenarios. The first one is a normal scenario, where the history of variables determines the future. The second is the worst scenario, where the variables' future is consistently determined by global projections. It should be highlighted that the normal scenario is not the best scenario that assumes no further change in the climate.

2.3. Normal scenario ARIMA model

The normal scenario variables' forecasts are built on Autoregressive Integrated Moving Average (ARIMA (p, q)) as below:

$$\boldsymbol{y_t = \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_p u_{t-q}} \quad \textbf{(1)}$$

where y_t is scenario variable (*temp; prec; fl; cp; eep; oilr*) and u_t is the error term.

Each variable's stationarity is checked by the Augmented Dickey-Fuller test, and random walk variables are transformed to stationary. Moreover, the Autocorrelation Function (ACF) denotes the MA (q), and the Partial Autocorrelation Function (PACF) determines the AR (p) lag orders. The model results are displayed in the following section.

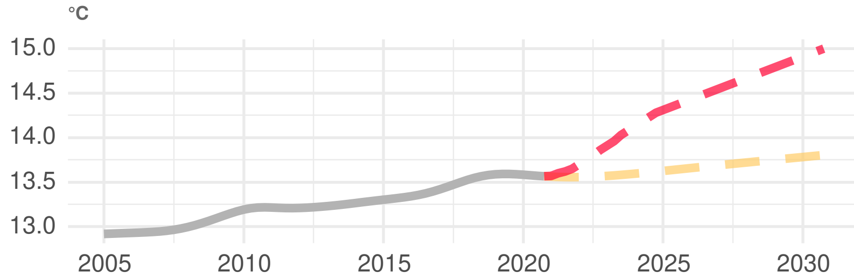
One thing should be noted that, in this research, the ARIMA models are not the main long-run forecast driver models. They are applied to obtain the trend of variables and provide continuation of them for the 2021-2030 period.

2.4. Climate stress scenarios

In the normal scenario based on previous data, scenario variable forecasts are determined by the ARIMA model discussed above. On the other hand, the worst scenario considers global forecasts and integrates them into local variables. As shown in Figure 2, the mean temperature is expected to grow on two quite different paths. The red forecasts that ended up at 15 °C indicate the worst scenario, based on the 50th percentile of the World Bank's SSP5-8.5 projections (2014). On the other hand, the yellow path indicates the normal scenario, where the temperature increases to 13.8 °C. Following the temperature rise, precipitation decreases to 395.6 mm (Figure 3) at the end of 2030, regarding the worst scenario. The normal scenario's precipitation forecast is 415.6 mm of rainfall for 2030.

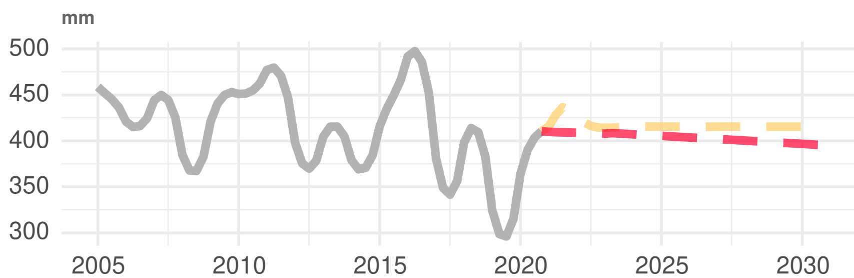
Associated with these changes, fallow lands will decrease in both scenarios (Figure 4). Moreover, in the worst scenario, we assume zero fallow lands, which is the extreme case. Since fallow land is the recovery of arable lands, it is significantly related to productivity.[5] However, productivity also depends on other factors, such as technology, and the quality of seeds. Thus, the history of productivity does not provide significant relations with previous variables. Notwithstanding the descriptive statistics, assuming zero technological change in productivity or seed quality, the worst scenario supposes that productivity will decrease to its historical minimum (Figure 5.).

Figure 2. Mean Temperature (temp)



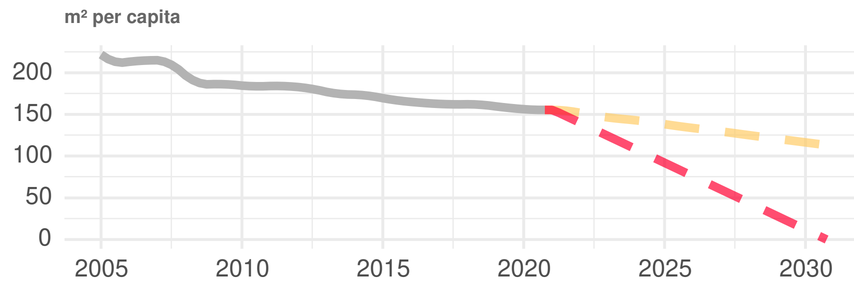
Source: World Bank

Figure 3. Precipitation (prec)



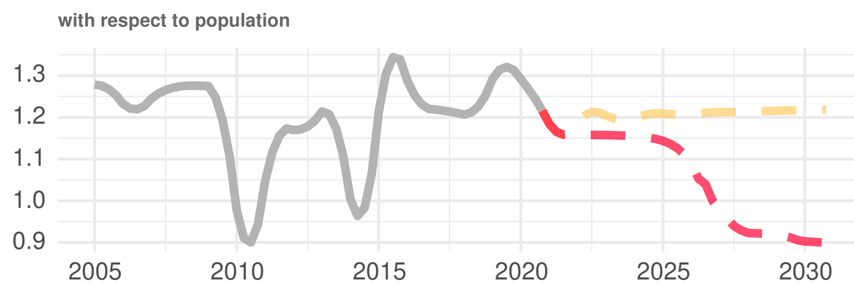
Source: World Bank

Figure 4. Fallow Land (fl)



Source: AzStat, CBAR Model result (forecast)

Figure 5. Cereal Productivity (cp)



Source: AzStat, CBAR Model result (forecast)

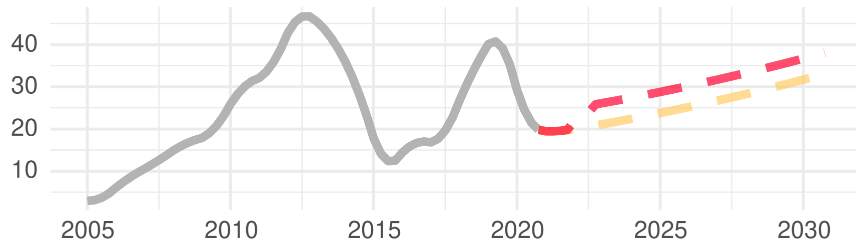
— worst scenario — normal scenario

[5] Fallow land is a farming technique in that arable land is left without sowing for several seasons. Since the land became intact, the soil became nutrient-rich and cause inclined productivity.

Another critical variable is per capita expenditures on environmental protection, which carries the impact of the Paris agreement. In the worst scenario displayed in Figure 6, *eep* is assumed to be 5 manats (constantly) higher starting from 2022 in accordance with being a more climate-friendly country. It should be noted that this assumption is entirely dependent on the researcher's initiative.

Figure 6. Expenditures on Environmental Protection (eep)

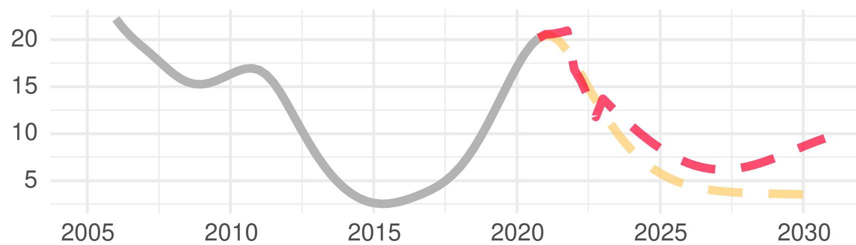
Manat per capita



Source: AzStat, CBAR Model result (forecast)

Figure 7. Water Price Inflation (wprc)

Annual Percent Change



Source: AzStat, CBAR Model result (forecast)

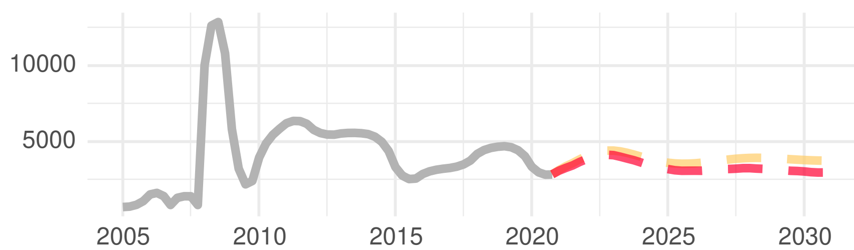
— worst scenario — normal scenario

As the result of climate change, Figure 7 displays the first important result of the BVAR model discussed in the following section. The figure shows that water price inflation is expected to rise sharply after 2027 and reach 9.51 pp at the end of 2030, whereas 3.5 pp is in the normal scenario. Henceforth, regardless of the scenario types, it clearly shows that water prices will create pressure on overall costs.

In the second dimension, the transition to a low-carbon economy with the Paris agreement, fossil fuel producer countries must decrease their production by 6 percent (UN, 2020). Considering Azerbaijan exports' fossil fuel dependency is extremely high (87 percent), reduced production will cause decrement in the export revenues at constant prices. Additionally, according to World Bank's commodity market projections (Commodity Markets Outlook, 2021), oil prices will gradually decrease from 74 USD in 2022 to 67.9 USD in 2030. That fact will be the second shock to the export revenues of Azerbaijan and the rest of other oil-exporting countries. Overall, these shocks are considered the worst scenario, as displayed in Figure 8, for a new model. According to the worst scenario, the fossil fuel revenues will be 21 percent lower than the normal scenario.

Figure 8. Export Revenue of Fossil Fuel

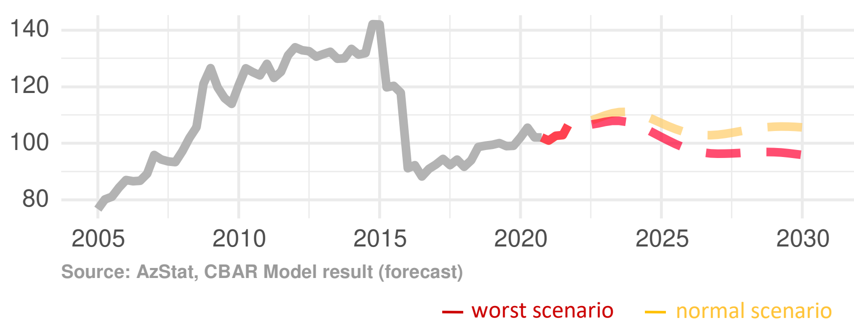
million USD



Source: AzStat, CBAR Model result (forecast)

Figure 9. Real Effective Exchange Rate (REER)

base year is 2000



Source: AzStat, CBAR Model result (forecast)

In Azerbaijan, fossil fuel revenues from export determine REER, and REER's contribution coefficient to inflation is high (-0.30).[6] Thus, this research analyzes fuel revenues' relation with REER through the second BVAR model. Without going further into details about the model in this section, Figure 9 displays the forecast for REER as a dependent variable for Fossil Fuel Revenue. According to the figure, the feeder environment started in 2018 for Azerbaijani manat's value would disappear after 2024. Moreover, the environment will continuously have the opposite effect in the worst scenario.

It should be noted that one can assume the worst scenario variables' future quite differently. Regardless of the values, the purpose here is to prove that the change in the climate scenario variables significantly alters the headline inflation in the end.

By combining temperature, precipitation, fallow land, cereal productivity, expenditures on environmental protection, and water price inflation variables regarding scenarios, this research firstly obtains a forecast of agricultural product price inflation (*appi*) by the BVAR model (BVAR1). Afterward, it converts *appi* to headline inflation by contribution coefficient (0.27). Besides considering the fossil fuel revenue scenarios, the paper forecasts REER by another BVAR model (BVAR2) and finds its' contribution to inflation. Finally, the contribution from climate change and the transition to the low-carbon

[6] The coefficient was obtained from non-published CBAR research written by R. Rahmanov and T. Yusifzada. It is achieved by a long-run coefficient of the ECM model for inflation decomposition.

environment with the Paris agreement are aggregated to obtain climate-related changes' total impact on inflation.

3. BVAR model

The BVAR model proposed by Litterman (1980) uses the Bayesian method described to estimate the VAR models. Unlike VAR models that treat parameters as fixed values, BVAR considers them as random variables with prior probabilities. By integrating the Bayes rule, it solves the dimensionality problem of VAR that resulted from the largeness of parameter numbers than the available number of observations (Öğünç, et al., 2013). Moreover, it increases in-sample fitting and out-of-sample forecasting performance (Dua & Ray, 1995), where observations are limited.

However, the main challenge in BVAR models is the selection of true priors (Öğünç, et al., 2013), where different priors result in different estimates (Blake & Mumtaz, 2007). Henceforth, in this paper, the selection of priors is based on the maximization of marginal likelihood proposed by Chib (1995).

Suppose $Y_t = (Y_{1,t}\ Y_{2,t} \ldots Y_{n,t})'$ is the random variable vector. Therefore, A VAR(p) model is specified as:

$$\boldsymbol{Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t} \quad \textbf{(2)}$$

where c is a vector of constants, $\phi_1, \phi_2, \ldots, \phi_p$ are lag matrices and ε_t is the white noise terms $\varepsilon_t \sim i.i.d.\ N(0, \Sigma_t)$.

The VAR (p) could be written in another format as:

$$\boldsymbol{Y_t = X_t \Phi + \varepsilon_t} \quad \textbf{(3)}$$

where Y_t is $t \times n$ matrix of model variables, $X_t = \{c, Y_{it-1}, Y_{it-2}, \ldots, Y_{it-p}\}$. Moreover, VAR equations have identical regressors that can be shown as:

$$\boldsymbol{y = (I_n \otimes X)\alpha + \varepsilon} \quad \textbf{(4)}$$

where $\varepsilon \sim (0, \Sigma_\varepsilon \otimes I_T)$, α is the vector of ϕ, and I_n is the identity matrix. The likelihood derived from equation 4 is:

$$\boldsymbol{L(\alpha, \Sigma_\varepsilon) \propto |\, \Sigma_\varepsilon \otimes I_T|^{-\frac{1}{2}} exp\{-\frac{1}{2}\,(y - (I_n \otimes X)\alpha)'(\Sigma_\varepsilon^{-1} \otimes I_T)(y - (I_n \otimes X)\alpha)\}} \quad \textbf{(5)}$$

Since the maximum likelihood provides unbiased estimates for α ($\alpha_{\mathrm{MLE}} = \alpha_{\mathrm{OLS}}$) and biased estimates for Σ_ε ($\Sigma_{\varepsilon\ \mathrm{MLE}} \neq \Sigma_{\varepsilon\ \mathrm{OLS}}$), we use Bayesian law in the lead of Blake and Mumtaz (2007), which gives an opportunity to introduce prior beliefs about the values of α and Σ_ε. These beliefs are integrated to the model by probability distributions such as:

$$\boldsymbol{p(\alpha|\Sigma_\varepsilon) \sim N(\hat{\alpha}_0, \Sigma_\varepsilon \otimes \mathrm{H})}$$

is the normal probability distribution of prior for α, where $\hat{\alpha}_0$ is prior mean and diagonal elements of $\Sigma_\varepsilon \otimes \mathrm{H}$ is the variance of the coefficient prior (high $\Sigma_\varepsilon \otimes \mathrm{H}$ indicates high uncertainty about prior). The diagonal elements for the coefficients on lags defined as $(\frac{\lambda_0\lambda_1}{l^{\lambda_3}\sigma_i})^2$ and for the constants are defined as $(\lambda_0\lambda_4)^2$ (Sims & Zha, 1998).

$$\boldsymbol{p(\Sigma_\varepsilon) \sim IW\,(\overline{S}\,, \delta)}$$

is the inverse Wishart distribution of prior for the covariance matrix of VAR, where δ is the prior degrees of freedom and $\overline{S}$ is a prior scale matrix (Blake & Mumtaz, 2007). The matrix for VAR(2) model used in this research is defined as follows:

$$\overline{S} = \begin{pmatrix} (\frac{\sigma_1}{\lambda_0})^2 & 0 \\ 0 & (\frac{\sigma_2}{\lambda_0})^2 \end{pmatrix}$$

The hyper-parameters used in this research are $\lambda_0 = 1$ (overall tightness of covariance matrix prior), $\lambda_1 = 0.2$ (overall tightness of coefficient priors on the first lag), $\lambda_3 = 1$ (lag decay) and $\lambda_4 = 100$ (control variable on constant) to maximize the marginal likelihood (Chib, 1995). Moreover, the Gibbs sampling algorithm is used to find marginal posterior distributions by setting the prior with initial observations and the sum of coefficient dummies. However, as suggested by Blake and Mumtaz (2007), initial prior values have a limited impact with larger Gibbs iterations. Gibbs sampling run for 100000 draws with 0.1 percent burn-in. Since the data is non-stationary $I(1)$, we set the prior's AR coefficient to 1.

In this research, BVAR1 random variables are:

$$y_t = [appi_t \;\; temp_t \;\; prec_t \;\; fl_t \;\; cp_t \;\; eep_t \;\; wprc_t]'$$

BVAR2 random variables are:

$$y_t = [reer_t \;\; oilr_t]'$$

The variables used in the model were transformed into quarterly observations by Chow-Lin (1971) and manually averaging or summing operations. Afterward, observations are seasonally adjusted by TRAMO-SEATS. Variable shocks are identified with Cholesky decomposition. Both models estimate quarterly variables from 2005 to 2020 and forecast endogenous variables (*wprc;*

appi; reer) for the 2021-2030 period. Exogenously given variables are the scenario variables discussed in Section 2.4.

Considering the possibility of a long-run equilibrium relationship between variables, to check the robustness of the model, the BVAR model is compared with Vector Error Correction Model (VECM) via Root Mean Squared Error (RMSE). Since the VECM's RMSE is 1.14 relative to BVAR (Table 2) for agricultural producer price inflation (*appi*), BVAR's *appi* forecasts outperform our research rather than VECM across forecasting horizons.

Table 2. Averaged 1 to 12 quarters ahead RMSE for BVAR and VECM

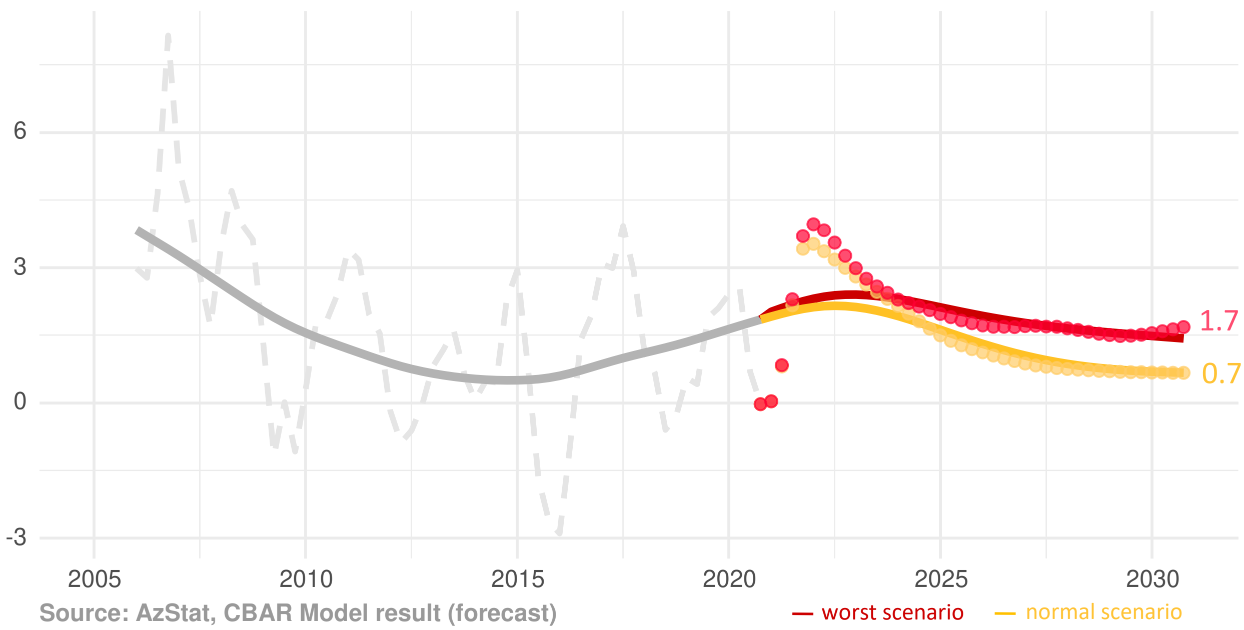
BVAR1		**VECM**		
Variable	RMSE	Variable	RMSE	RMSE in VECMRelative to RMSE in BVAR
APPI	5.795	APPI	6.630	1.144
CP	0.063	CP	0.040	0.634
EEP	7.881	EEP	10.275	1.304
FL	0.008	FL	0.001	0.572
PREC	42.393	PREC	35.850	0.846
WPRC	24.389	WPRC	15.466	0.634

Although in the long run, BVAR generally provides less forecast accuracy in the empirical literature works firstly proved by LeSage (1990), several ones prove BVAR's better or the same performance compared with VECM (Kato, 2021); (Giannone, Lenza, & Primiceri, 2018); (Félix & Nunes, 2003). Moreover, considering the relative RMSE of models displayed in Table 2 differs across variables, this research's main purpose is to forecast *appi* "given" other variables. Since RMSE is lower in BVAR1 than VECM for appi, the BVAR is taken as the main model, and impulse responses are displayed in the Appendix. Additionally, BVAR and VECM model output comparison for contribution to inflation is also displayed in the Appendix. It should be noted that VECM and BVAR provide near-identical estimations for REER and fossil fuel revenues model (Averaged 12 quarters ahead RMSE values are 12.83 in BVAR2 and 13.04 in VECM).

4. Result and Discussion

According to the BVAR1 model and scenarios discussed in Section 2, the agricultural producer price inflation forecast for the 2020-2030 period is generated.[7] Moreover, multiplying by the decomposition coefficient, the headline inflation is forecasted as in Figure 10.

Figure 10. Climate Change's Contribution to Inflation
Through Agricultural Producer Price Index



Source: AzStat, CBAR Model result (forecast)

Regarding the figure, the worst scenario indicates 1.7 pp additional inflation in 2030, assuming the rest of the inflation determinants will remain constant. Furthermore, the worst scenario is 1 pp higher than the history-based normal scenario, proving the impact of climate scenario variables on the inflation trend.

On the other hand, the transition to the low-carbon environment with the Paris agreement harms REER, considering the BVAR2 model. This impact was first shown in the sharp oil price decline in 2015,[8] where manat devaluation happened twice, and the cost of 1 USD rose to 1.7 manats from 0.78. As displayed in Figure 11, REER's contribution to

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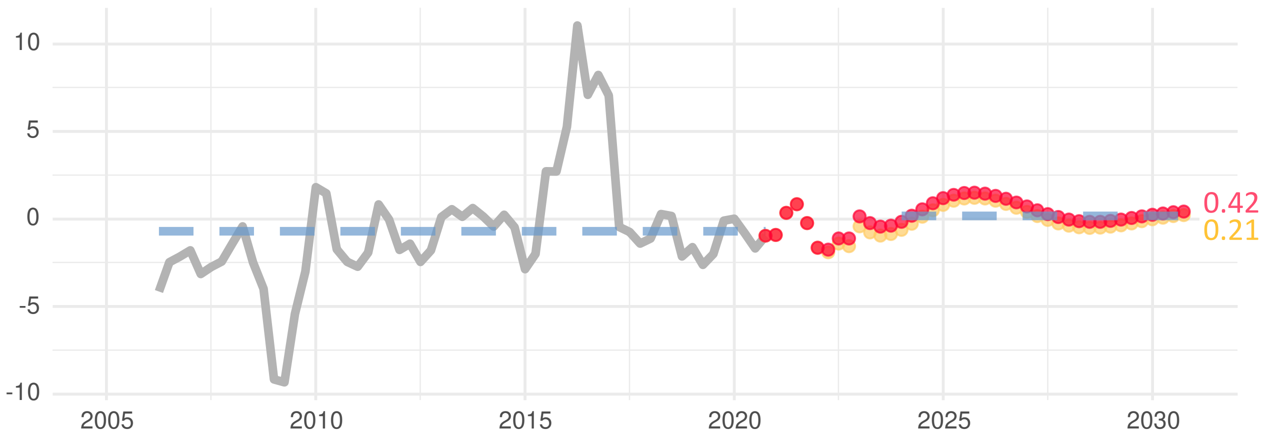
[7] Since its' share in the inflation is constant, the *appi* follows the identical path as the inflation contribution in Figure 10. Thus, its' direct forecast graph is not displayed in the paper.

[8] See Figure 8 and 9 simultaneously.

inflation reached its historical maximum (11 pp) in the second quarter of 2016 (Q2) due to the impact lag.

Figure 11. REER's Contribution to Inflation



Source: AzStat, CBAR Model result (forecast)

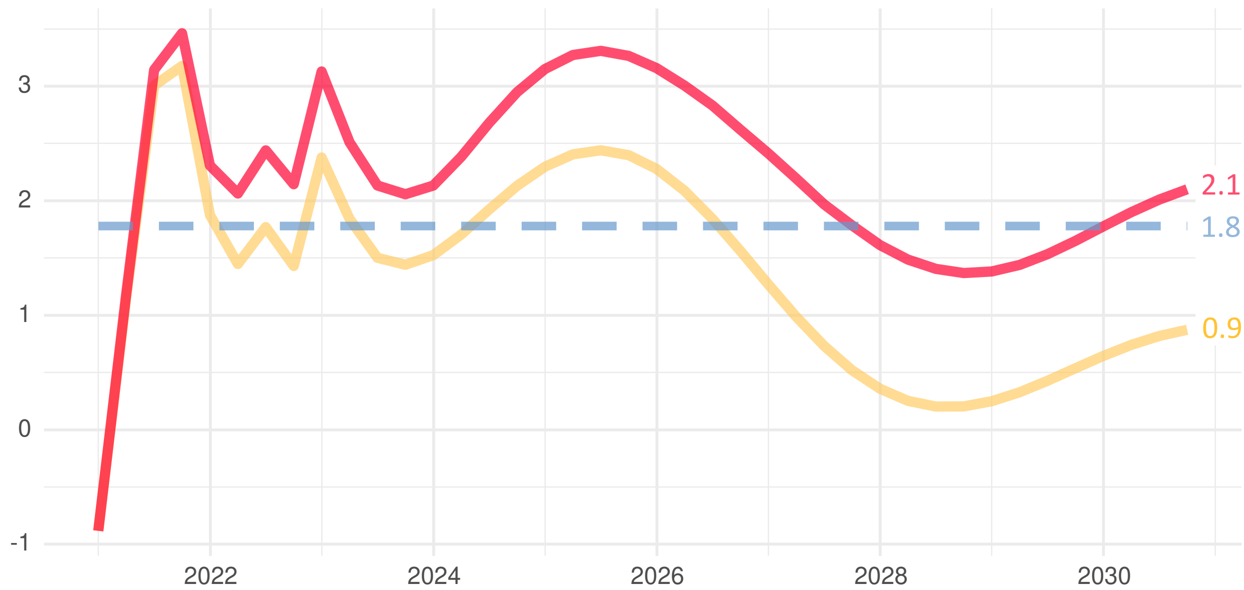
Overall, REER's long-run contribution to inflation was negative between 2005 and 2020, which gives it a bumper[9] function against inflation pass-through from trading partners. However, the transition to low-carbon seems to change this structure. For instance, model forecasts show that REER's contributions in both scenarios are minimally higher than the trend. Moreover, REER's contribution to inflation in the worst scenario is 2 times higher than the normal scenario due to declining fossil energy production to meet the Paris agreement's temperature anomaly goal. Considering the magnitude of impact, it may seem unimportant; however, losing of being the bumper function would have a more indirect effect on inflation that will be analyzed in further research.

Finally, combining both aspects of the paper, climate-related changes' total impact on inflation is aggregated in Figure 12.

[9] When inflation is high in trading partners, a relatively strong exchange rate of manat help to reduce imported product prices in manat terms. This mechanism prevents inflation pass-though from imported goods; hence it is called the bumper.

Figure 12. Response of Inflation to the Climate Stress

Aggregate contribution of climate change and the fossil fuel revenues to the inflation



Source: CBAR Model result

According to the figure, at the end of 2030, the worst scenario will create 2.1 pp inflation, 1.2 pp higher than the normal scenario, proving the response of inflation to climate factors. In general, regardless of the scenario types, climate change's impact on inflation is expected to be 1.8, as the long-run trend displays.

Overall, the literature findings and our findings display climate change's importance as another significant determinant of inflation. At this point, it is suggested that CBs with the mandate to maintain price stability or have IT regimes start to give attention to climate change and transition to a low-carbon economy. Henceforth, preserving price stability will require action against inflation, therefore, climate change. But how Central Bank can involve in its actions as an independent monetary organization?

European CB's President Christine Lagarde said that "g*overnments, not central banks, who are primarily responsible for facilitating an orderly transition, and who control the main required tools"* in July 2021 (France 24, 2021). Not primarily but secondarily, CBs could support governments' green and sustainable economic development plans by preserving their structural independence and law-determined mandates. For instance, "green quantitative easing" of CBs: purchasing of non-polluting sectors firms' bonds (Ferrari & Landi, 2020). Although Ferrari and Landi proved that green quantitative easing is ineffective in reducing pollution, it could permanently solve to reduce the balance sheet risks resulting from sectors with no bright future with the Paris agreement. As it is known that green energy will replace traditional ones sooner or later, fossil fuel companies' shares in balance sheets will lose their value, threatening financial stability (Campiglio, et al., 2018). Moreover, credit agencies that fund fossil fuel companies will also carry the risk of future shrinkage.

In practice, prudential tools could be considered to encourage lending to green sectors by Central Banks. Moreover, Central Bank may provide incentives for green investment funds and may support green energy exporter organizations through green quantitative easing. Not just to reduce pollution but also to reduce the negative impact of shrinkage risk on the fossil fuel market and reduce the risk possibility on the value of the local currency. Besides monetary policies' indirect impact opportunities, governmental development plans on the field such as Azerbaijan's 2022-2026 strategic plan on transitioning to a green environment, may affect the real economy fast and directly. Moreover, well coordination between fiscal and monetary authorities may result in smooth and more successful transitioning.

Conclusion

This research analyzed the climate risks that were previously "not considered valuable enough to be considered." By using historical relations, the paper provided the importance of climate as a derivative of inflation. In more detail, climate risk is considered under two aspects. At first, temperature performs as the main factor called a "gun" and affects inflation through chain impact on precipitation, fallow land, cereal productivity, expenditures on environmental protection, and water prices.

In relation to the first aspect, the historical trend is considered as the base for the 2021-2030 forecast horizon to obtain a normal scenario, and the World Bank's temperature change projection for Azerbaijan is taken into account as the driver of the worst scenario. Since the temperature is assumed to be 1.2 °C higher in the worst scenario than the normal scenario, precipitation, fallow land, and cereal productivity are supposed to be lower, and water prices have projected higher than in the normal scenario. Moreover, the Paris agreement causes additional costs on expenditures on environmental protection. As a result of climate change, the contribution to inflation is expected to be 1.7 pp in the worst and 0.7 pp in the normal scenario in 2030. The difference between scenarios ensures that climate factors determine the trend of inflation in Azerbaijan, which this study aimed to prove.

The second aspect is the Paris agreement's impact on fossil fuel production and the transition to a low-carbon environment's effects on oil prices. In this aspect, the worst scenario is built on continuously decreased 6 percent fossil fuel production and reduced oil prices from 74 USD in 2022 to 67.9 USD in 2030. By considering the high sensitivity of Azerbaijani manat on fossil fuel revenues, REER will no longer be able to neutralize high global product prices in the long run. Moreover, the model shows that after 2024 feeder environment for the value of Azerbaijani manat would disappear.

Overall, inflation's response to climate stress is alerting, according to 1.8 pp additional contribution of climate to inflation as the long-run trend while considering the inflation target. Thus, adding a climate action plan to its agenda could increase CBAR's future policy effectiveness until it has the mandate to maintain price stability.

One thing is clear CBs themselves have no power over temperature decrement. Under the knowledge of limited ability to have an impact on climate, the government of Azerbaijan and CBAR may be in search of alternative policies to prevent the economy from the damage risks. In this scope, the government's 2022-2026 mid-run strategic development plan would change the direction of energy exports from fossil fuel to green energy. Moreover, by green quantitative easing, CBAR's possible investments in green energy exporter companies worldwide may prevent its reserves against exchange rate shocks. Furthermore, CBAR may encourage local creditor organizations to change the direction of credits to green companies. By this policy, CBAR could avoid the risk of economic shrinking and prevents a more polluted environment that results in the worst scenario. However, the climate action plan and related cost-benefit analyzes should be well-developed and consistent with the rest of the world, which are left for future research.

List of abbreviations

ACF	Auto-correlation function
ADB	Asian Development Bank
APPI	Agricultural producer price inflation
AR	Auto-regressive
ARIMA	Autoregressive integrated moving average
AzStat	State Statistics Committee of the Republic of Azerbaijan
BVAR	Bayesian Vector Autoregression
CB	Central Bank
CBAR	Central Bank of the Republic of Azerbaijan
CP	Cereal productivity
ECM	Error Correction Model
EEP	Expenditures on environmental protection
FL	Fallow land
GDP	Gross Domestic Product
IT	Inflation Targeting
MA	Moving Average
OILR	Fossil fuel revenues from export
PACF	Partial auto-correlation function
pp	Percentage points
PREC	Precipitation
Q	Quarter
REER	Real Effective Exchange Rate
RMSE	Root Mean Square Error
TEMP	Temperature
USD	United States Dollar
VAR	Vector Autoregression
VECM	Vector Error Correction Model
WPRC	Water price inflation

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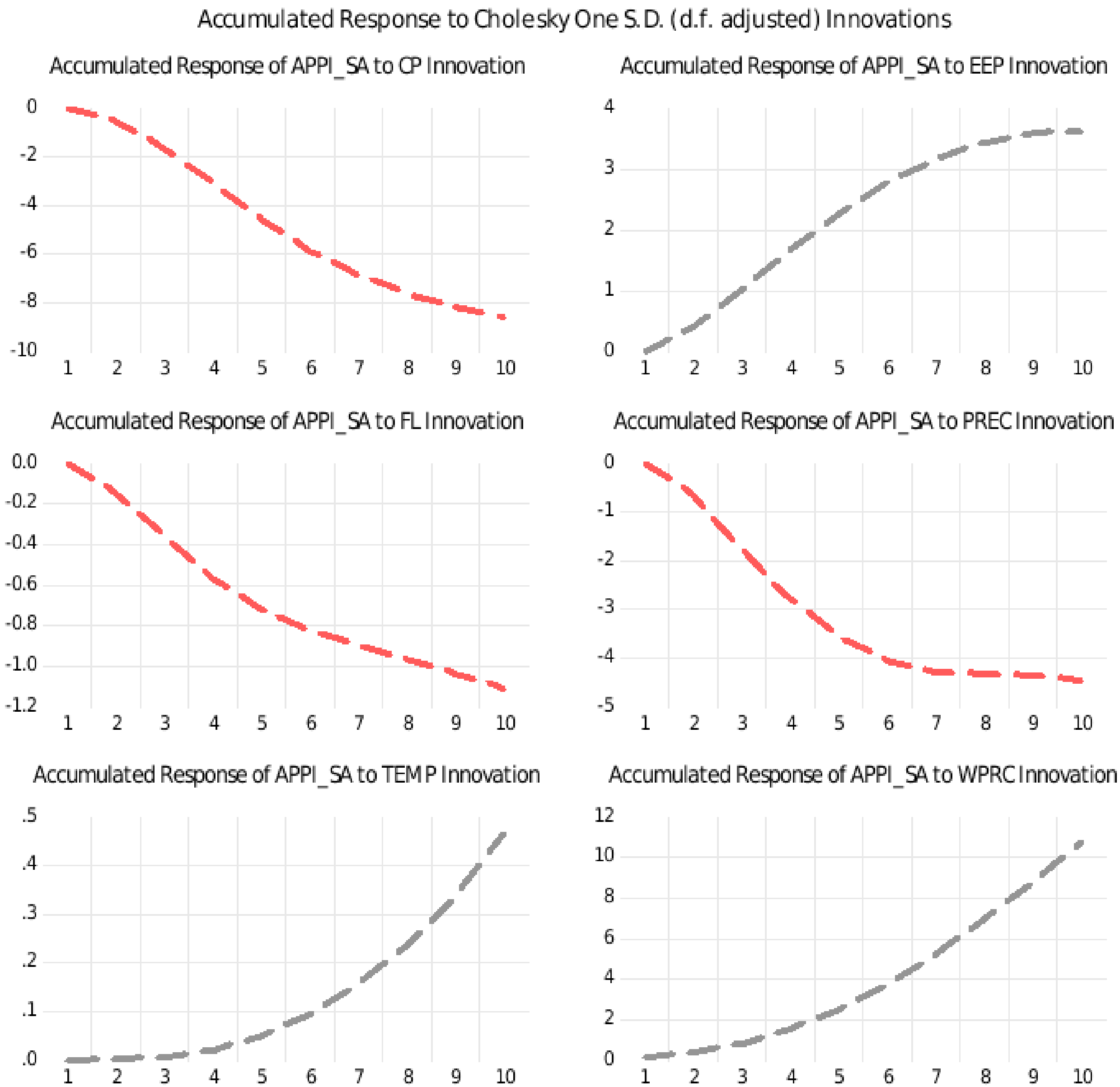
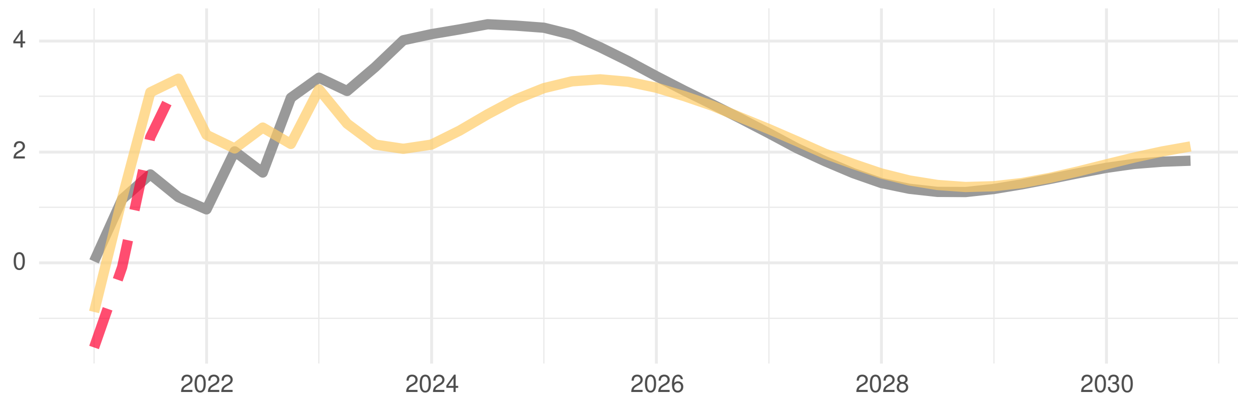
Appendix

1. Impulse Responses:



2. BVAR-VECM Forecast Comparison

Aggregate contribution of climate change and the oil revenues to the inflation in the worst scenario conditional on water prices in 2021



Source: CBAR Models' results

The long run contribution trend for worst scenario is 2.2 for BVAR and 2.4 for VECM.