# Introducing foresight to the stadard GTAP model: modeling capital allocation and stockholding under expected policy change

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**Abstract**

There is no doubt that the standard GTAP model has been tremendously useful in a wide range of policy analyses. Despite its success, one of the frequently mentioned drawback is the model's comparative static nature, where all shocks are executed at the same time with no visibility of the possible intertemporal interactions among the shocks. While a well-known dynamic version of the GTAP model exist—GDyn—it does not implement foresight, which prevents a proper treatment of expected future shocks. In this paper we develop a framework that introduces foresight to the standard GTAP model and solves the system with a determined level of limited foresight. We showcase this approach in the case of capital accumulation based on the actual expected values and in the case of stockholding in agriculture where we demonstrate that the presence of stocks dampens the size of productivity shocks, especially if the shocks are anticipated. The flexibility of our framework in permitting different foresight lengths and the introduction of shocks with different advance notice make it also useful for other dynamic behaviors in the model.

# 1 Introduction

General equilibrium is thought of as one of the crowning intellectual achievements of economics (Hertel et al. 2007). The models developed using that framework are known as computable general equilibrium (CGE) models—and are heavily used in policy analysis due to their ability to simulate potential impacts while taking into account inter-industry and global linkages (Beckman, Hertel, and Tyner 2011). Reasons for the increase in the use of CGE models include an increase in computational power and the availability of the underlying CGE data from the Global Trade Analysis Project (GTAP) (Aguiar et al. 2023). The models used could be either static—which considers a one-time shock, or dynamic—which shows how the economy evolves over time with respect to the shock.

There are numerous reasons why most literature involving CGE models use the static approach. The data available from GTAP is readily usable for a static model, using a dynamic model involves more data. The GTAP website notes that there is data available for their GDyn model, which augments the original data base with foreign income data. However, the available data is for the version 7 data base (which is 2004), while the static model has data available for version 11 (2017). In addition, more information is needed for the assumed economic path (i.e., the baseline data, such as projected GDP), although such data can be obtained from Fontagné, Perego, and Santoni (2022). In addition to the data needs, many of the modeling developments made by GTAP and others revolve around the static model.

But, a dynamic model can, at the minimum, consider the same shock as a static model—but it can also provide much more information on how the economy might change over time.[1] That is, consider a static shock using the Farm to Fork policies set out by the European Union and considered in numerous pieces of literature using CGE models (Baquedano et al. 2022; European Commission et al. 2021; Beckman et al. 2020, 2022; Beckman and Jelliffe 2022; Bremmer et al. 2021). One proposal from this policy is to reduce fertilizer usage by 20 percent by 2030. By using a static model, the above-mentioned papers can tell us how the EU and the global economy could be affected by the fertilizer reduction. However, these models tell us nothing about what happens after 2030. For example, does the use of fertilizer stay at the 20 percent reduction, or is the change even greater?[2] The static model is able to say how markets are impacted at 2030, but what about 2035 or 2040? Does the reduction in EU agricultural production resulting from the fertilizer decrease continue to impact global food security or does someone replace their loss production?

[1] One way of using a dynamic model is that laid out by Chappuis and Walmsley (2011) where one can compute the differences between a scenario where the policy examined is implemented—the policy simulation—and a counterfactual scenario where the policy examined is not implemented—the baseline scenario.

[2] Unfortunately, the path to the reduction is not laid out—otherwise, the dynamic model could provide information on the changes that occur along the path to the reduction.

Along with the difficulty with the data, the availabilities of models and model development is also less for dynamic models (especially from GTAP). The GTAP platform (i.e., the website and the Journal of Global Economic Analysis) allows modelers to upload or publish model developments.[3] However, most, if not all, of these are related to the static model. The main dynamic model featured by GTAP is known as Dynamic GTAP (GDyn) that was developed by Ianchovichina and McDougall (2000). There have been additions made to that model, such as the inclusion of a migration model (GMig2) (Aguiar and Walmsley 2010); G-RDEM—a recursive-dynamic model that is based on the standard GTAP model (Britz and Roson 2018); and GDyn-E-AEZ that brings in information on energy and land use to the GDyn model (Golub and Rose 2012).

In this work, we first propose and implement a forward-looking version of the dynamic GTAP model using the existing static GEMACK-based GTAP model, and open-source R framework. CGE models in the past have been predominately written in programming languages such as GEMPACK, GAMS, C++; but new languages, such as R, have become widely used due to its open-source nature. One motivation for this work is to show that we can reuse the standard GTAP model with minimal changes in a highly used model platform—thus making it easy to "update" the model after a new version of the static data base is released. The other motivation for our work is to make a more 'agriculture' focused dynamic model. Those mentioned in the previous paragraph have focused on migration and climate change issues; but agriculture presents a readily available experiment to implement in a dynamic framework through the concept of stockholding—i.e., should a farmer sale this year or next year? We demonstrate that forward-looking behavior may be introduced conveniently by replacing each variable whose value depends on the future with an exogenous value that is determined by the dynamic solver. For example, if the level of investment depends on the future return on capital (pm), we may introduce a new variable, e.g., future_pm, which will be exogenous to the current time model. It then becomes the task of the dynamic solver to assure that in the dynamic solution each future_pm is equal to pm in the future period.

Using our forward-looking dynamic framework, we demonstrate its application in two examples. First, we consider capital accumulation with foreseeing capital returns. Second, we implement stockholding behavior, again responding to the foreseen shocks in policy. To illustrate the new insights of the new dynamic framework in capital accumulation, we simulate an increase in Africa's internal trade efficiency by 100 percent. To show the implications of stock holding, we perform a sample simulation in which the European Union implements a hypothetical policy that reduces its available land by ten percent at a scheduled time in the future. In both examples, we demonstrate the implications of the shocks for the global markets in our dynamic framework.

[3] There are also other organizations who have dynamic models (e.g., the Envisage model of the World Bank), but access to these models is often less than those for GTAP.

## 2 Dynamics, foresight, and agriculture

Modeling foresight in CGE modeling is of great value: many policy changes and shocks are largely planned, allowing market players to prepare. For example, most impactful policies are generally subject to announcement, review and implementation which may take years. Unfortunately, not many dynamic CGE models incorporate true forward-looking expectations; for example, GDyn is a recursive model without forward-looking behavior (Ianchovichina and McDougall 2000). The lack of foresight is a serious drawback, as the reliance on the past values (as is done in recursive dynamic models) is not relevant for newly introduced shocks.

The omission of foresight precents modeling some of the key intertemporal relationship. For example, in the real world, stockholding by farmers can be used to help maintain stable agricultural prices, to help ensure global food security, and for farmers to try to maximize profits.[4] As noted by Wright and Williams (1982), storage is simply a productive activity, one that transfers a commodity from one period to the next. However, stockholding is not a typical feature of CGE models. Stockholding is not considered because in the static model, changes in stocks are typically eliminated in the initial data or subsumed into aggregate investment (Hertel, Reimer, and Valenzuela 2005). Hertel, Reimer, and Valenzuela (2005) offer a possible solution to stockholding in the static model, by specifying an exponential stock-holding function. But stockholding at its heart is a dynamic issue, where farmers can make decisions based on how they think future prices will change. Femenia (2015) realizes the importance of dynamics and introduces stockholding in a dynamic CGE model. But he acknowledges the difficulty with modeling stock-holding behavior, with uncertainty surrounding how to model agents' expectations.

Another important feature of our dynamic model is that its forward-looking behavior is not perfect. Instead of assuming that market players know the future perfectly all the way to the last period, we assume that market players possess an imperfect ability to expect the future for n future periods only. We also assume that the imperfection of foresight increases with the time distance—market players have perfect foresight for the immediate future period, the expectations for additional periods are discounted at a constant rate so that for the nth period the market players assume that the economy will be in a steady state with no additional shocks disturbing the system. This limited foresight, in addition to being realistic, also means that there is no connection among events beyond the nth period, which allows us to solve the dynamic system more easily.

[4] World Trade Organization (2023) notes that many developing countries have public stockholding programs where the government purchases, stockpiles, and distributes food. These programs can distort trade when they involve purchases from farmers at fixed prices. For our paper, we are primarily concerned with a representative farmer acting independently, i.e., private storage.

# 3 The forward-looking dynamic framework

Our forward-looking dynamic GTAP model is based on the standard GTAP model which we treat as a one-period transition function that moves the economy forward one period (year) to another. To serve as a forward-looking model, the only modification that is required is the introduction of the future variables to the model as exogenous variables. While any variable's future value may be introduced, forward-looking models are typically concerned with the future (expected) returns to capital or prices. In our implementation, we may therefore include `rorc_future` as a variable holding the future returns on capital, or `future_pm` as a variable holding the market price `pm` from the future period.

Formally, we define GTAP$(d_t, x_t)$ as a function of motion (e.g., the standard GTAP model) of input data $d_t$ and exogenous variables (shocks) $x_t$ that returns an updated data set for the following period $d_{t+1}$ and endogenous variables. We set up the dynamic system by linking the future variables to the expected variables with a level of imperfection in the foresight represented by discounting the future changes based on their distance from the present so that beyond the maximum level of foresight $f$ the future variables are ignored:

$$\forall_{n \in 1,2,\ldots f} \text{future\_variable}_t = \delta_n \text{variable}_{t+n} \tag{1}$$

where $\delta_n$ represents the weight of the future variable depending on its distance in the future. The value of $\delta_n$ would likely be anywhere between 0 and 1; however, it is possible that the true value might be lower than 0 or greater than 1 in case market players are unable to predict the future correctly—a value of $\delta > 1$ would mean that market players overestimate the true change in the future variables, while $\delta < 0$ would mean that market players get their forecasts completely wrong and expect the opposite of what the future brings.

In our examples in this paper, we assume that market players have a good understanding of the future and therefore $\delta_1 = 1$ (market players can predict the next period's variable changes without any bias). We then assume that for the foresight horizon, market players have a tendency towards information rigidity, where they assume that no more changes to any of the variables. Between the next period and the foresight horizon, we assume that the market players discount their expectations smoothly:

$$\forall_{n \in 1,2,\ldots f} \delta_n = \frac{n-1}{f} \tag{2}$$

Equations (1) and (2) mean that in the case of a model with a four-period foresight and expected (future) market prices, the solution to the dynamic system at time $t$ must be such, that the future prices (`future_pm`) at time $t$ be equal to the prices (pm) solved at time $t+1$ ($\text{future\_pm}_t = \text{pm}_{t+1}$ ), with an appropriate level of discount until the fourth period: $\text{future\_pm}_{t+1} = 0.75 \times \text{pm}_{t+2}$, $\text{future\_pm}_{t+2} = 0.5 \times \text{pm}_{t+3}$, $\text{future\_pm}_{t+3} = 0.25 \times \text{pm}_{t+4}$.

It is important to note that the fact that future variables are only connected to the following $f$ periods allows the calculation of the solution at periods $t$ by only considering the future $f$ periods. There is therefore no need for an infinite horizon terminal condition, which allows for the solution to be derived from the equation of motion alone.

It is also important to note that the variables in the GTAP model represent percentage changes from the original values. This means that a 100 percent discount of the future variable value simply means no further changes in the variable rather than setting the variable (e.g., price) to zero.

# 4 Solving the dynamic system in R

For the ease of implementation, the dynamic framework is formulated as a function in R. The R function is able to call the GTAP function of motion (i.e., the GEMPACK program) and therefore it can identify the values of each future variable that satisfy the condition expressed in Equations (1) and (2).

The formulation of the GTAP model as a simple mathematical function required us to to feed the results obtained from a GEMPACK simulation back to R. To do that, we take advantage of various tools made available on GitHub[5] that permit the reading of the GEMAPCK solutions and data files (.sl4 and .slc files) into R.

Solving of the dynamic system is certainly more computationally involved that solving a single-period model. With $n$ future variables and $f$ foresight periods, the dynamic system needs to solve a system of $n \times f$ non-linear equations (i.e.g, non-linear GTAP models as constraints). To solve for $t$ periods, this solution has to be repeated as many times.

The complexity of the solution is demonstrated in Figure 1 for solving the system in 2019 with a three-year foresight, which means that the solutions for the next three periods need to be taken into consideration. Instead of solving GTAP just for 2019, the model needs to be solved also for 2020, 2021 and 2022, so that the solved future variable values are equal to those assumed as exogenous in the previous period.

While the number of solutions required to solve the system for a large number of future variables and periods appears daunting, the fact that the changes to the GTAP database even after large shocks are not very large,

[5] https://github.com/mivanic/HARr

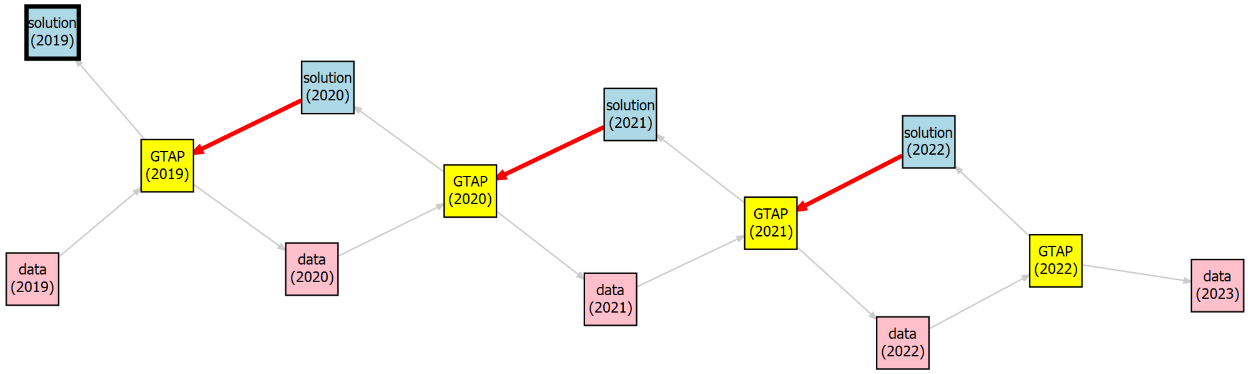


Figure 1: Overview of the solution structure

it is possible to solve the system fairly efficiently by calculating the Jacobian matrix of the errors (differences between the expected and actual future variables) and the future variables, and saving the Jacobian matrix for the future use (e.g., future periods). This means that the system may need to be solved only $f \times n$ times to obtain the Jacobian, which can then be used to solve the system at any future point in time in typically three iterations.

# 5 Examples

With the dynamic system with foresight set up, we present two examples of its use in policy-relevant settings. The first one is in capital accumulation, while the second one implements stocks in the GTAP model. In both of the examples, the dynamic of the model is driven by foreseeing the future, implemented in the standard (classic) GTAP model (version 6.2) by replacing the relevant variables with their future (expected) values.

## 5.1 Implementation of capital accumulation in the standard GTAP model with dynamic foresight

The first example involves the slight re-design of capital accumulation by considering the future (expected) capital returns to determine the distribution of investments across regions.

### 5.1.1 Change to the standard GTAP model

To introduce foresight and dynamic behavior to the standard GTAP model, we only add a variable to hold the future value of the capital returns `rorc` and modify the equation that links the future (expected) capital return to the expected value without changing anything else in the structure of the model:

```
variable (all,r,REG)  rorc_future(r);
```

```
Equation ROREXPECTED
# expected rate of return depends on the current return and investment (HT 58) #
(all,r,REG)
    rore(r) = rorc_future(r) - RORFLEX(r) * [ke(r) - kb(r)];
```

It is important to note that to make the dynamic system operate through the future (expected) value, it is necessary to switch the binary coefficient RORDELTA to 1; otherwise, the future (expected) return on capital would not be used in the capital allocation decision.

### 5.1.2 Scenario

A simple scenario that we run involves the expectation of improved efficiency of intra-African trade by 100 in 2025. The increase of trade efficiency in Africa not only increases the return to capital, resulting in greater capital accumulation, but also its expected increase results market adjustment in its anticipation.

The backdrop of the scenario is the global population and GDP growth and projected by CEPII. The growth is simulated by directly shocking the population levels and indirectly shocking the output efficiency (ao) to achieve the projected GDP growth. After solving for the required efficiency gains, the model then uses ao's as exogenous (prediced shocks).

The anticipated policy change is that of doubling the efficiency of trade in Africa by 100 percent in 2025. This is simulated by increasing the value of ams in the model by 100 percent.

### 5.1.3 Results

Figure 2 shows the accumulation of capital stock in Africa. Even though most of the increase in capital stock happens in 2025, that is driven by the returns to capital (its price). The consequence of the introduction of foresight in the model is demonstrated by a noticeable increase in capital accumulation in Africa one year before the positive shock; capital is moving to Africa because market players know that returns to capital in Africa will increase substantially in the following year.

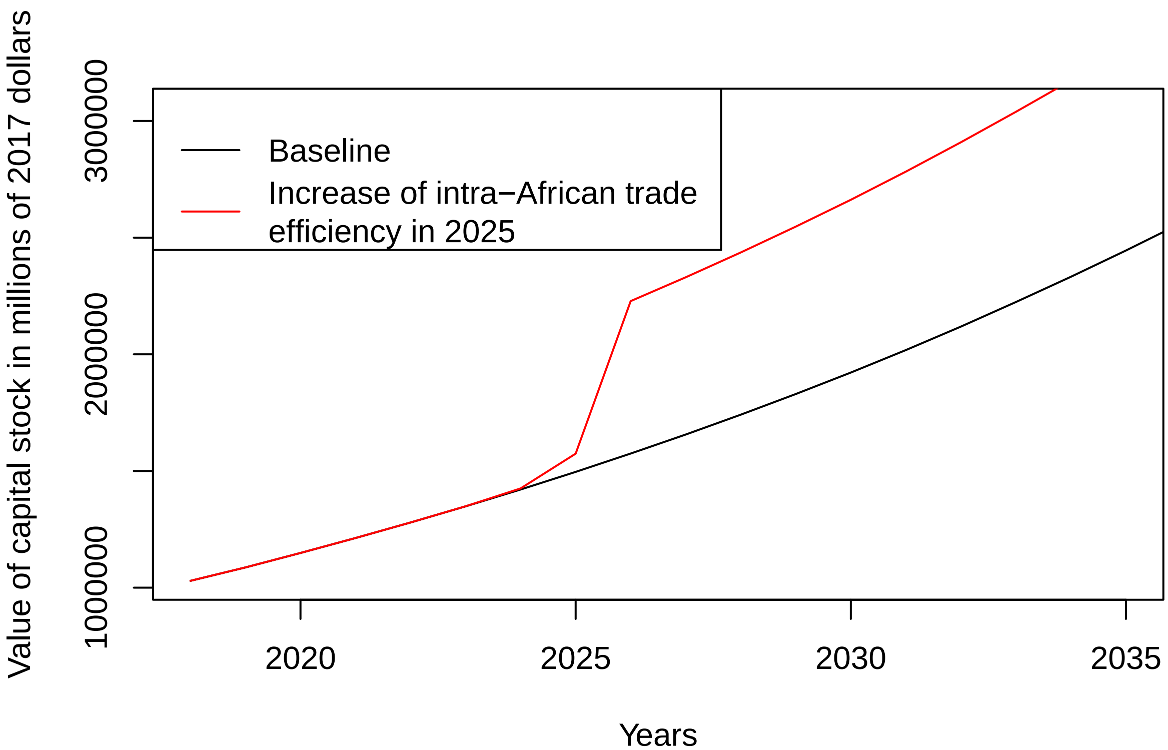


Figure 2: Value of capital stock in Africa

## 5.2 Implementation of stocks in the standard GTAP model with dynamic foresight

### 5.2.1 Change to the standard GTAP model

Our approach to implementing stockholding in GTAP is similar to that of Hertel, Reimer, and Valenzuela (2005). We also implement a key relationship between stock levels and the change of the price between periods, whereas stock are built when the future price rises and dissolved when the future price falls. Unlike the approach of Hertel, Reimer, and Valenzuela (2005) which was adopted for a comparative statics model, our approach considers the accumulation and dissolution of stocks at different periods (e.g., dissolving stocks in period $t$ if the price falls in period $t+1$). One important different from the approach of Hertel, Reimer, and Valenzuela (2005) is that we also assume that countries (i.e., governments, trade organizations) have a preferred level of stocks, which is demonstrated by the fact that stock ratios (stocks as a share of total domestic use) are typically stationary, i.e., mean reverting time series, rather than random walks which would be consistent with non-stationary prices.

Unlike most of the GTAP data which represents annual value flows (e.g., payments to factors, trade flows), stocks represent valuations at specific points of time. The interaction between the stocks and the value flows included in GTAP happens when stocks are dissolved or built, which impacts the product supply and the associated expenditures. The inclusion of stocks in GTAP, therefore requires the modification of two equations—market clearing condition and income equation—in addition to an equation of motion determining the changes in stocks.

First, we set up stocks in the model as a coefficient whose value updated by the change in stock quantity `qstock` and market price `pm`:

```
coefficient (all,i,TRAD_COMM)(all,r,REG)
    STOCKS(i,r);
Read
    STOCKS from file GTAPDATA header "STCK";
update (all,i,TRAD_COMM)(all,r,REG)
    STOCKS(i,r) = qstock(i,r) * pm(i,r);
```

The inclusion of stock changes in market clearing of margin and non-margin commodities (it is unlikely that margin commodities can be held in stock, as they are typically services)

```
Equation MKTCLTRD_MARG
```

```
# eq'n assures market clearing for margins commodities (HT 1) #
(all,i,MARG_COMM)(all,r,REG)
[VOM(i,r)+STOCKS(i,r)] * qo(i,r)
        =
        + STOCKS(i,r) * qstock(i,r)
        + VDM(i,r) * qds(i,r)
        + VST(i,r) * qst(i,r)
        + sum(s,REG, VXMD(i,r,s) * qxs(i,r,s))
        + tradslack(i,r);
```

```
Equation MKTCLTRD_NMRG
# eq'n assures market clearing for the non-margins commodities (HT 1) #
(all,i,NMRG_COMM)(all,r,REG)
[VOM(i,r)] * qo(i,r)
        =
        + STOCKS(i,r) * qstock(i,r)
        + VDM(i,r) * qds(i,r)
        + sum(s,REG, VXMD(i,r,s) * qxs(i,r,s))
        + tradslack(i,r);
```

Because dissolving stocks increases available income, while building stocks reduces it, we also need to change the regional income appropriately as well:

```
Equation REGIONALINCOME
# regional income = sum of primary factor income and indirect tax receipts #
(all,r,REG)
    INCOME(r) * y(r)
        = - sum(i,TRAD_COMM, STOCKS(i,r) * (qstock(i,r)))
        + FY(r) * fincome(r)
        + 100.0 * INCOME(r) * del_indtaxr(r)
        + INDTAX(r) * y(r)
        + INCOME(r) * incomeslack(r);
```

With these changes alone, we are able to change stocks exogenously while maintaining the model general equilibrium consistency (i.e., omitted market clearing).

To implement the endogenous change in stocks, we add an equation that relates the change in stocks to the difference between future market prices `future_pm` and the current market prices `pm` with a positive elasticity (`STOCKELAS`) and the difference of the current stocks (expressed as the ration of the domestic use) from the target stock share (`TARGETSTOCKS`) with a positive elasticity (`TARGETSTOCKE`). To make the equation operational, we introduce a scalar variable `unity` that is set exogenously to one in order to give effect to the second part of the equation.[6]

```
equation eq_stocks (all,i,TRAD_COMM)(all,r,REG)
    qstock(i,r) = STOCKELAS(i) * (future_pm(i,r)-pm(i,r))
                - (STOCKS(i,r)/[
                    VDPM(i,r)
                    +VDGM(i,r)
                    +sum(j,PROD_COMM,VDFM(i,j,r))] - TARGETSTOCKS(i,r))
                      * TARGETSTOCKE(i) * unity
    + qstock_slack(i,r);
```

Equation `eq_stocks` relies on variable `future_pm` which is an exogenous variable to the model as `pm` in the future period equals to `future_pm` in the current period. While this variable is not solved in the comparative static model, it allows the model to produce changes in stock in response to the expectations. In the next section, we show how the comparative static model may be placed into a dynamic framework which allows for `future_pm` to be endogenously determined.

#### 5.2.2 Scenario

To show the implications of stock holding, we perform a sample simulation in which the European Union implements a hypothetical policy that reduces its available land by ten percent at a scheduled time in the future (2025). We demonstrate the implications of this policy for the global markets in our dynamic framework. We then contrast the outcomes to the results obtained using the standard GTAP model (without stocks). In the second simulation, we show the importance of forward looking behavior by performing an alternative scenario where the shock to the EU agriculture is unexpected.

The time period that we consider in the experiment includes the ten years following the base period of the latest GTAP database 11 (2017) from 2018 through 2027. The baseline scenario includes only the growth in population and GDP as projected by CEPII.

[6] The need to introduce a unit shock to each simulation is just a quirk of GEMPACK, which requires that in equation each term contain a variable.

The GTAP aggregation considered for this work includes seven regions, eight commodities (with three grains) and five factors of production.

We used the FAO data on stocks in 2017, to estimate the levels of stocks of rice, wheat, and corn. We assume that the observed levels of stocks are the targeted levels (as shares of domestic consumption).

We consider a four year foresight, which means that market players are able to foresee the first future year perfectly, but discount the expectations of the following years uniformly to zero in the fourth year.

### 5.2.3 Results

Figure 3 shows the baseline and scenario results for wheat production, stocks and prices in the EU. The solid line shows the baseline values (normalized to 1 in year 2017), while the dashed line shows the implications of the shock at a scheduled time with the forward-looking behavior of the participants. The dotted lines shows the results when the shock is unanticipated (i.e. market participants are only made aware of it when it happens).

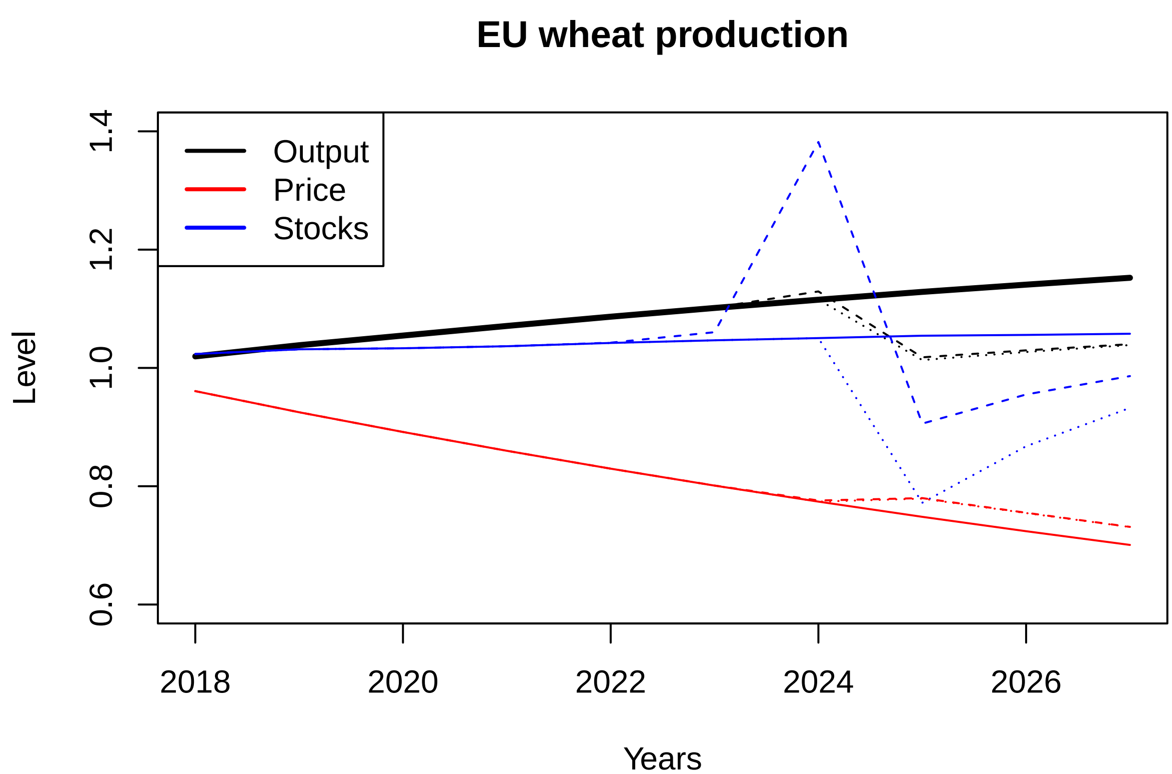


Figure 3: Implications of the shock for EU wheat market

# 6 Discussion

## 6.1 Importance of foresight in dynamic CGE models

There is great importance of including dynamics in CGE analysis. Frequently, policy change that are simulated represent large changes in taxes over a long periods of time (e.g., EU's Farm-to-fork, various FTAs). The most common approach has been to analyze the overall changes resulting from the policies in a comparative-static framework where the shocks are implemented and resolved fully in a single-period, long-term closure. While the results of such analyses are valid, they are unable to answer important question about the induced market impacts by the policy implementation, where market players respond to the expectation of the policy's implementation in advance of the actual implementation date.

Because market players are expected to respond to a known policy change in advance, it is very likely that most cases the policy change induces market impacts before its implementation. The size of the induced change is likely to depend on the level of foresight, the intertemporal discount rate, and the extent of possible action (e.g., movement of capital in anticipation of the change). If, for example, production is expected to fall at a future date in a specific region as a result of an anticipated policy change change, markets may respond by pulling capital out of the country (if its return is negatively impacted) and by building stocks (if future price is likely to rise), well before the policy is implemented.

It is important to note that the pre-adjustment to a future policy is likely to result in a smaller shock once the policy is actually implemented—the stocks that had been built or the capital that had been moved are likely to make the need for later adjustment smaller. The possible smoothing of the market impacts due to foresight may also be an important consideration of the policy as well.

While backward-looking dynamic models are able to provide useful insights in the intertemporal relationships among shocks and adjustements, they are unable to answer the market impacts of anticipation as well. The forward-looking dynamic framework presented in this paper represents therefore an important innovation to realistic dynamic CGE modeling.

## 6.2 Driving factors in dynamic CGEmodels

In this work, we have focused on the expectation of future prices as a driver of the model dynamics, e.g., the impact of the expected change in prices and capital returns on capital and stock accumulation. However, the flexibility of the system represented by the set of elasticities driving the behavior, i.e., the closure of the system, represents another important factor defining the response of the dynamic system.

The question of the closure is an important one due to its interplay with the time distance of the shock. If a shock is expected to happen sufficiently far in the future, it is likely that market players will be able to make all necessary adjustments to counter it in the most profit/welfare maximizing fashion. However, if a shocks is unexpected, or expected with little lead time, the adjustment would only be permitted where resources have not been fixed. To model the dynamics of a combination of immediate/unexpected and expected shocks properly, therefore requires the combination of closures, short-run for the unexpected shocks and a more long-run closure for the shocks where full adjustment is possible.

The inclusion of different closures in the dynamic model for different shocks (i.e., expected and unexpected) goes beyond the scope of the present paper; however, it represents an exciting research opportunity as it would add an additional layer of realism to the simulation results.

# 7 Conclusions

The introduction of foresight into dynamic CGE modeling is of great importance as it allows the simulations to shed light not only on the total impacts, but also on the likely distribution of the impacts of the time, and, importantly, any impacts due to the market's expectation of the change. This allows to provide a fuller picture of the multitudes of the impacts of any particular shock to the economy than a comparative static analysis can provide.

Despite providing many other useful insights, dynamic formulations of the GTAP model have not included foresight which has prevented such models from describing the induced impacts of policy changes. In our work, we have attempted to bridge this gap by formulating a dynamic GTAP model with foresight, which allows to include the expectations of the market players and their implications on the market outcomes before policy changes take effect.

We demonstrate the usefulness of the approach by applying the method to describe capital accumulation and stockholding in the standard GTAP model, with minimal change allowing for the foresight to operate, e.g., the inclusion of the future prices and future capital returns. We show that the ability of the market players to foresee a planned policy change can be properly translated into capital investments, and stock adjustments that results in smoother price and output changes.

Finally, we would like to emphasize an important feature of our approach that allows us to use the standard (classic) GTAP model with minimal changes in the code. We integrate the GEMPACK-formulated model in R as a user function, which allows us to solve solve the dynamic system in R with ease. Because the GTAP model is mathematically well behaved, we have demonstrated that it is possible to solve a dynamic GTAP model with foresight (i.e., linking expected variable values to the actually realized future values in several model results covering the foreseen future) very efficiently by recycling the Jacobian matrix of the solution across periods. This means that the our method may be used in the solving of fairly complex dynamic systems (e.g., with many future variables and foreseen periods.)

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