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# **The World Bank's MFMod Framework in Python with Modelflow**

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## *Foreword*

Lorem Ipsum “Neque porro quisquam est qui dolorem ipsum quia dolor sit amet, consectetur, adipisci velit...” “There is no one who loves pain itself, who seeks after it and wants to have it, simply because it is pain...”

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Indermit Gil World Bank Chief Economist



## **Part I**

# **The World Bank's MFMod Framework and Modelflow**





## INTRODUCTION

**Warning:** This Jupyter Book is work in progress.

This paper describes the implementation of the World Bank’s MacroFiscalModel (MFMod, see Burns *et al.* [2019]) using the open source solution program ModelFlow (Hansen, 2023).

The impetus for this paper and the work that it summarizes was to make available to a wider constituency the work that the Bank has done over the past several decades to disseminate Macro-structural models<sup>1</sup> – notably those that form part of its MFMod (MacroFiscalModel) framework.

## 1.1 The MFMod Framework at the World Bank

MFMod is the World Bank’s work-horse macro-structural economic modelling framework. It exists both a linked system of 184 country specific models that can be solved either independently or as a larger system (MFMod), and as a series of standalone customized models, known collectively as MFMod Standalones (MFMod SAs) that have been developed from the central model to the fit the specific needs of individual countries. Both modelling systems can be solved using the EViews modelling language, or through the intermediation of an easy-to-use excel front end developed by the Bank.

The main MFMod global model evolved from earlier macro-structural models developed during the 2000s to strengthen the basis for the forecasts produced by the World Bank. Some examples of these models were released on the World Bank’s isimulate platform early in 2010 along with several CGE models dating from this period. These earlier models were substantially extended into what has become the main MFMod (MacroFiscalModel) model during 2014. Since 2015, MFMod replaced the Bank’s RMSIM-X model ([Addison, 1989]), as the Bank’s main tool for forecasting and economic analysis, and is used for the World Bank’s twice annual forecasting exercise [The Macro Poverty Outlook](#).

The main documentation for MFMod are Burns *et al.* [2019].

<sup>1</sup> Economic modelling has a long tradition at the World Bank. The Bank has had a long-standing involvement in macroeconomic modelling, initially with linear programming polanning models [Chenery, 1971], and then CGE models []. Indeed, the popular modelling package GAMS, which is widely used to solve CGE and Linear Programming models, [started out](#) as a project begun at the World Bank in the 1976 [Addison, 1989].

### 1.1.1 Climate aware version of MFMod

Most recently, the Bank has extended the standard MFMod framework to incorporate the main features of climate change [Burns *et al.*, 2021]– both in terms of the impact of the economy on climate (principally through green-house gas emissions, like  $CO_2$ ,  $N_2O$ ,  $CH_4$ , ...) and the impact of the changing climate on the economy (higher temperatures, changes in rainfall quantity and variability, increased incidence of extreme weather) and their impacts on the economy (agricultural output, labor productivity, physical damages due to extreme weather events, sea-level rises etc.).

Variants on the model initially described in Burns *et al.* [2021], have been developed for [xx] countries and underpin the economic analysis contained in many of the World Bank's [Country Climate Development Reports](#).

## 1.2 Early steps to bring the MFMod system to the broader economics community

Bank staff were quick to recognize that the models built for its own needs could be of use to the broader economics community. An initial project `isimulate` made several versions of this earlier model available for simulation on the [isimulate platform](#) in 2007, and these models continue to be available there. The `isimulate` platform housed (and continues to house) public access to earlier versions of the MFMod system, and allows simulation of these and other models – but does not give researchers access to the code or the ability to construct complex simulations.

In another effort to make models widely available a large number (more than 60 as of June 2023) customized stand-alone models (collectively known as called MFModSA - MacroFiscalModel StandAlones) have been developed from the main model. Typically developed for a country-client (Ministry of Finance, Economy or Planning or Central Bank), these Stand Alones extend the standard model by incorporating additional details not in the standard model that are of specific import to different economies and the country-clients for whom they were built, including: a more detailed breakdown of the sectoral make up of an economy, more detailed fiscal and monetary accounts, and other economically important features of the economy that may exist only inside the aggregates of the standard model.

Training and dissemination around these customized versions of MFMod have been ongoing since 2013. In addition to making customized models available to client governments, Bank teams have run technical assistance program designed to train government officials in the use of these models, their maintenance, modification and revision.

## 1.3 Moving the framework to an open-source footing

Models in the MFMod family are normally built using the proprietary EViews econometric and modelling package. While offering many advantages for model development and maintenance, its cost may be a barrier to clients in developing countries. As a result, the World Bank joined with Ib Hansen, a Danish economist formerly with the European Central Bank and the Danish Central Bank, who over the years has developed `modelflow` a generalized solution engine written in Python for economic models. Together with World Bank, Hansen has worked to extend `modelflow` so that MFMod models can be ported and run in the framework.

This paper reports on the results of these efforts. In particular, it provides step by step instructions on how to install the `modelflow` framework, import a World Bank macrostructural model, perform simulations with that model and report results using the many analytical and reporting tools that have been built into `modelflow`. It is not a manual for `modelflow`, such a manual can be found [here](#) nor is it documentation for the MFMod system, such documentation can be found here [Burns *et al.*, 2019] and here [Burns *et al.*, 2021], [Burns *et al.*, 2021]). Nor is it documentation for the specific models described and worked with below.

## 1.4 Macrostructural models

The economics profession uses a wide range of models for different purposes. Macro-structural models (also known as semi-structural or Macro-econometric models) are a class of models that seek to summarize the most important interconnections and determinants of economic activity in an economy. Computable General Equilibrium (CGE), and Dynamic Stochastic General Equilibrium (DSGE) models are other classes of models that also seek, using somewhat different methodologies, to capture the main economic channels by which the actions of agents (firms, households, governments) interact and help determine the structure, level and rate of growth of economic activity in an economy.

Olivier Blanchard, former Chief Economist at the International Monetary Fund, in a series of articles published between 2016 and 2018 that were summarized in Blanchard [2018], lays out his views on the relative strengths and weaknesses of each of these systems, concluding that each has a role to play in helping economists analyze the macro-economy. Typically, organizations, including the World Bank, use all of these tools, privileging one or the other for specific purposes. Macrostructural models like the MMod framework are widely used by Central Banks, Ministries of Finance; and professional forecasters both for the purposes of generating forecasts and policy analysis.

### 1.4.1 A system of equations

Mathematically, macro-structural models are a system of equations comprised of two kinds of equations and three kinds of variables.

#### Types of variables in macro-structural models

- **Identities** are variables that are determined by a well defined accounting rule that always holds. The famous GDP Identity  $Y=C+I+G+(X-M)$  is one such identity, that indicates that GDP at market prices is definitionally equal to Consumption plus Investment plus Government spending plus Exports less Imports.
- **Behavioural** variables are determined by equations that typically attempt to summarize an economic (vs accounting) relationship. Thus, the equation that says Real Consumption =  $f(\text{Disposable Income, the price level, and animal spirits})$  is a behavioural equation – where the relationship is drawn from economic theory. Because these equations do not fully explain the variation in the dependent variable and the sensitivities of variables to the changes in other variables are uncertain, these equations and their parameters are typically estimated econometrically and are subject to error.
- **Exogenous** variables are not determined by the model. Typically there are set either by assumption or from data external to the model. For an individual country model, the exogenous variables would often include the global price of crude oil because the level of activity of the economy itself is unlikely to affect the world price of oil.

In a fully general form it can be written as:

$$y_t^1 = f^1(y_{t+u}^1, \dots, y_{t+u}^n, y_t^2, \dots, y_t^n, y_{t-r}^1, \dots, y_{t-r}^n, x_t^1, \dots, x_t^k, \dots, x_{t-s}^1, \dots, x_{t-s}^k) \quad (1.1)$$

$$y_t^2 = f^2(y_{t+u}^1, \dots, y_{t+u}^n, y_t^1, \dots, y_t^n, y_{t-r}^1, \dots, y_{t-r}^n, x_t^1, \dots, x_t^k, \dots, x_{t-s}^1, \dots, x_{t-s}^k) \quad (1.2)$$

$$\vdots \quad (1.3)$$

$$y_t^n = f^n(y_{t+u}^1, \dots, y_{t+u}^n, y_t^1, \dots, y_t^{n-1}, y_{t-r}^1, \dots, y_{t-r}^{n-1}, y_{t-r}^n, x_t^1, \dots, x_t^r, x_{t-s}^1, \dots, x_{t-s}^k) \quad (1.4)$$

where  $y_t^1$  is one of  $n$  endogenous variables and  $x_t^1$  is an exogenous variable and there are as many equations as there are unknown (endogenous variables).

Substituting the variable mnemonics Y,C,I,G,X,M for the simple model the above can be rewritten as as a system of 6

equations in 6 unknowns:

$$Y_t = C_t + I_t + G + t + (X_t - M_t) \quad (1.5)$$

$$C_t = c_t(C_{t-1}, C_{t-2}, I_t, G_t, X_t, M_t, P_t) \quad (1.6)$$

$$I_t = c_t(I_{t-1}, I_{t-2}, C_t, G_t, X_t, M_t, P_t) \quad (1.7)$$

$$G_t = c_t(G_{t-1}, G_{t-2}, C_t, I_t, X_t, M_t, P_t) \quad (1.8)$$

$$X_t = c_t(X_{t-1}, X_{t-2}, C_t, I_t, G_t, M_t, P_t, P_t^f) \quad (1.9)$$

$$M_t = c_t(M_{t-1}, M_{t-2}, C_t, I_t, G_t, X_t, P_t, P_t^f) \quad (1.10)$$

and where  $P_t, P_t^f$  (domestic and foreign prices, respectively) are exogenous in this simple model.

## MODELFLOW AND THE MFMOD MODELS OF THE WORLD BANK

At the World Bank models built using the MFMod framework are developed in EViews. When disseminated to clients, the models are operated in a World Bank customized EViews environment. But as a systems of equations and associated data the models can be solved, and operated under any system capable of solving a system of simultaneous equations – as long as the equations and data can be transferred from EViews to the secondary system. `Modelflow` is such a system and offers a wide range of features that permit not only solving the model, but also provide a rich and powerful suite of tools for analyzing the model and reporting results.

### 2.1 A brief history of ModelFlow

Modelflow is a python library that was developed by Ib Hansen over several years while working at the Danish Central Bank and the European Central Bank. The framework has been used both to port the U.S. Federal Reserve’s macro-structural model to python, but also been used to bring several stress-testing models developed by European Central Banks and the European Central Bank into a python environment.

Beginning in 2019, Hansen has worked with the World Bank to develop additional features that facilitate working with models built using the Bank’s MFMod Framework, with the objective of creating an open source platform through which the Bank’s models can be made available to the public.

This paper, and the models that accompany it, are the product of this collaboration.



### 2.2 Installation of Modelflow

Modelflow is a python package that defines the `model` class, its methods and a number of other functions that extend and combine pre-existing python functions to allow the easy solution of complex systems of equations including macro-structural models like MFMod. To work with `modelflow`, a user needs to first install python (preferably the Anaconda variant), several supporting packages, and of course the `modelflow` package itself. While `modelflow` can be run directly from the python command-line or IDEs (Interactive Development Environments) like `Spyder` or Microsoft’s `Visual Code`, it is suggested that users also install the Jupyter notebook system. Jupyter Notebook facilitates an interactive approach to building python programs, annotating them and ultimately doing simulations using MFMod under `modelflow`. This entire manual and the examples in it were all written and executed in the Jupyter Notebook environment.

### 2.2.1 Installation of Python

Python is an extremely powerful, versatile and extensible open-source language. It is widely used for artificial intelligence application, interactive web sites, and scientific processing. As of 14 November 2022, the Python Package Index (PyPI), the official repository for third-party Python software, contained over 415,000 packages that extend its functionality<sup>1</sup>. Modelflow is one of these packages.

Python comes in many flavors and modelflow will work with any of them. However, **users are strongly advised to use the Anaconda version of Python.**

The remainder of this section points to instructions on how to install the Anaconda version of python (under Windows, MacOS and under Linux). Modelflow works equally well under all three. This is followed by section that describes the steps necessary to create an anaconda environment with all the necessary packages to run modelflow.

#### Installation of Anaconda under Windows

The definitive source for installing Anaconda under windows can be found [here](#).

**Warning:** It is strongly advised that Anaconda be installed for a single user (Just Me) This is much easier to maintain over time. Installing “For all users on this computer” the other option offered by the anaconda installer will substantially increase the complexity of maintaining python on your computer.

#### Installation of Python under macOS

The definitive source for installing Anaconda under macOS can be found [here](#).

#### Installation of Python under Linux

The definitive source for installing Anaconda under Linux can be found [here](#).

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## 2.3 Installation of Modelflow

Modelflow is a python package that defines the modelflow class `model` among others. Modelflow has many dependencies. Installing the class the first time can take some time depending on your internet connection and computer speed. It is essential that you follow all of the steps outlined below to ensure that your version of modelflow operates as expected.

**Warning:** The following instructions concern the installation of modelflow within an Anaconda installation of python. Different flavors of Python may require slight changes to this recipe, but are not covered here.

Modelflow is built and tested using the anaconda python environment. It is strongly recommended to use Anaconda with modelflow.

If you have not already installed Anaconda following the instructions in the preceding section, please do so **Now**.

---

<sup>1</sup> [Wikipedia article on python](#)

### 2.3.1 Installation of modelflow under Anaconda

1. Open the anaconda command prompt
2. Execute the following commands by copying and pasting them – either line by line or as a single multi-line step
3. Press enter

```
conda create -n ModelFlow -c ibh -c conda-forge modelflow_pinned_development_test -y
conda activate ModelFlow
pip install dash_interactive_graphviz
conda install pyviews -c conda-forge -y
jupyter contrib nbextension install --user
jupyter nbextension enable hide_input_all/main
jupyter nbextension enable splitcell/splitcellcd
jupyter nbextension enable toc2/main
```

Depending on the speed of your computer and of your internet connection installation could take as little as 10 minutes or more than 1/2 an hour.

At the end of the process you will have a new conda environment called `modelflow`, and this will have been activated. The computer set up is complete and the user is ready to work with `modelflow`.

The following sections give a brief introduction to Jupyter notebook, which is a flexible tool that allows us to execute python code, interact with the `modelflow` class and World Bank Models and annotate what we have done for future replication.





## **Part II**

# **Some python essentials for using WorldBank models with modelflow**



## INTRODUCTION TO JUPYTER NOTEBOOK

Jupyter Notebook is a web application for creating, annotating, simulating and working with computational documents. Originally developed for python, the latest versions of EViews also support Jupyter Notebooks. Jupyter Notebook offers a simple, streamlined, document-centric experience and can be a great environment for documenting the work you are doing, and trying alternative methods of achieving desirable results. Many of the methods in `modelflow` have been developed to work well with Jupyter Notebook. Indeed this documentation was written as a series of Jupyter Notebooks bound together with Jupyter Book.

Jupyter Notebook is not the only way to work with `modelflow` or Python. As users become more advanced they are likely to migrate to a more program-centric IDE (Interactive Development Environment) like Spyder or Microsoft Visual Code.

However, to start Jupyter Notebooks are a great way to learn, follow work done by others and tweak them to fit your own needs.

There are many fine tutorials on Jupyter Notebook on the web, and [The official Jupyter site](#) is a good starting point. The following aims to provide enough information to get a user started. Another good reference is [here](#).

### 3.1 Starting Jupyter Notebook

Each time, a user wants to work with `modelflow`, they will need to activate the `modelflow` environment by

1. Opening the Anaconda command prompt window
2. Activate the ModelFlow environment we just created by executing the following command

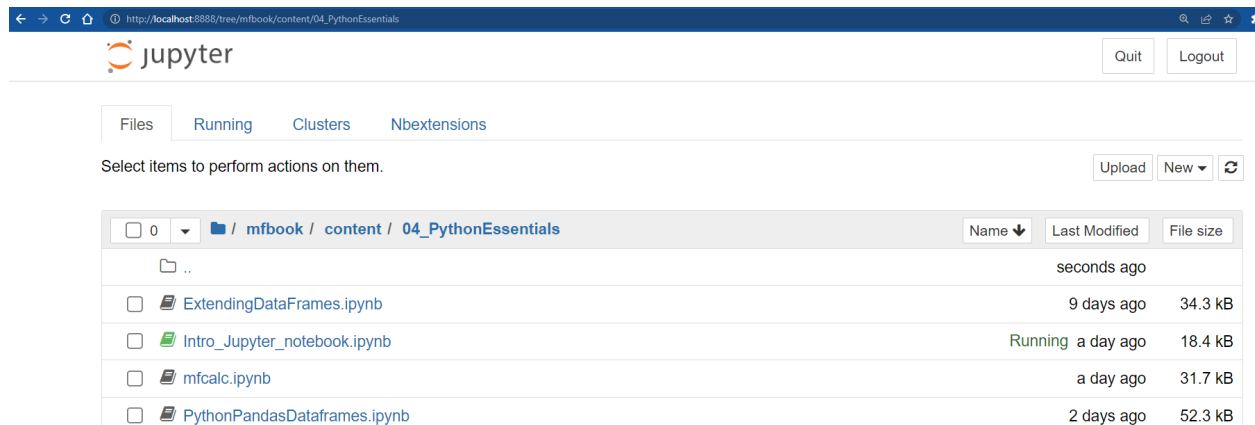
```
conda activate modelflow
```

From here, any number of mechanisms can be used to interact with `modelflow` and World Bank models.

**To use Jupyter Notebook** the Jupyter notebook, must be first started. Following steps 1-2 above, a user would need to execute from the conda command line:

```
jupyter notebook
```

This will launch the Jupyter environment in your default web browser, which should look something like this:



where the directory structure presented is that of the directory from the `jupyter notebook` command was executed.

**Warning:** Note the directory from which you execute the `jupyter notebook` **mfbook** in the example above will be the **root** directory for the jupyter session, and only directories and files below this root directory will be accessible by jupyter.

## 3.2 Creating a notebook

The idea behind jupyter notebook was to create an interactive version of the notebooks that scientists use(d) to:

- record what they have done
- perhaps explain why
- document how data was generated, and
- record the results of their experiments

The motivation for these notebooks and Jupyter notebook is to record the precise steps taken to produce a set of results, which if followed by others would allow the to generate the same results.

To create a notebook you must select from the Jupyter Notebook menu

File-> New Notebook

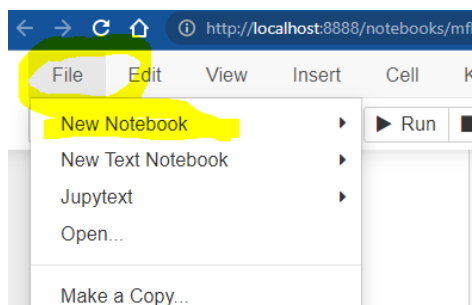


Fig. 3.1: A newly created Jupyter Notebook session

This will generate a blank unnamed notebook with one empty cell, that looks something like this:

```
! [NewCell] (./Newcell.png)
```

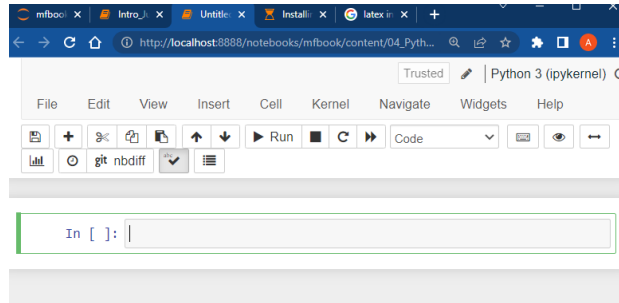


Fig. 3.2: A newly created Jupyter Notebook

**Warning:** Each notebook has associated with it a “Kernel”, which is an instance of the computing environment in which code will be executed. For Jupyter Notebooks that work with `modelflow` this will be a Python Kernel. If your computer has more than one “kernel’s” installed on it, you may be prompted when creating a new notebook for the kernel with which to associate it. Typically this should be the Python Kernel under which your `modelflow` was built – currently python 3.9 in April 2023.

### 3.3 Jupyter Notebook cells

A Jupyter Notebook is comprised of a series of cells.

*Jupyter Notebook cells can contain:*

- **computer code** (typically python code, but as noted other kernels – like Eviews – can be used with jupyter).
- **markdown text:** plain text that can include special characters that make some text appear as bold, or indicate the text is a header, or instruct Jupyter Notebook to render the text as a mathematical formula. All of the text in this document was entered using Jupyter Notebook’s markdown language
- Results (in the form of tables or graphs) from the execution of computer code specified in a code cell

**Every cell has two modes:**

1. Edit mode – indicated by a green vertical bar. In edit mode the user can change the code, or the markdown.
2. Select/Copy mode – indicated by a blue vertical bar. This will be the state of the cell when its content has been executed. For markdown cells this means that the text and special characters have been rendered into formatted text. For code cells, this means the code has been executed and its output (if any) displayed in an output cell.

**Users can switch between Edit and Select/Copy Mode by hitting Enter**

This entire book was generated using markdown cells, code cells and output cells from Jupyter Notebooks.

**Note:** Jupyter Notebooks were designed to facilitate *replicability*: the idea that a scientific analysis should contain - in addition to the final output (text, graphs, tables) - all the computational steps needed to get from raw input data to the results.

### 3.3.1 How to add, delete and move cells

The newly created Jupyter Notebook will have a code cell by default. Cells can be added, deleted and moved either via mouse using the toolbar or by keyboard shortcut.

#### Using the Toolbar

- **+ button:** add a cell below the current cell
- **scissors:** cut current cell (can be undone from “Edit” tab)
- **clipboard:** paste a previously cut cell to the current location
- **up- and down arrows:** move cells (cell must be in Select/Copy mode – vertical side bar must be blue)
- **hold shift + click cells in left margin:** select multiple cells (vertical bar must be blue)

#### Using keyboard short cuts

- **esc + a:** add a cell above the current cell
- **esc + b:** add a cell below the current cell
- **esc + d+d:** delete the current cell

### 3.3.2 Change the type of a cell

You can also change the type of a cell. New cells are by default “code” cells.

#### Using the Toolbar

- Select the desired type from the drop down. options include
  - Markdown
  - Code
  - Raw NBConvert
  - Heading

#### Using keyboard short cuts

- **esc + m:** make the current cell a markdown cell
- **esc + y:** make the current cell a code cell

#### Auto-complete and context-sensitive help

When editing a code cell, you can use these short-cuts to autocomplete and or call up documentation for a command.

- **tab:** autocomplete and method selection
- **double tab:** documentation (double tab for full doc)

## 3.4 Execution of cells

Every cell in a Jupyter Notebook can be executed, either by using the Run button on the Jupyter Notebook menu, or by using one of **two keyboard shortcuts**:

- **ctrl + Enter**: Executes the code in the cell or formats the markdown of a cell. The current cell retains the focus – cursor stays on cell executed.
- **shift + enter**: Executes the code in the cell or formats the markdown of a cell. Focus (cursor) jumps to the next cell

For other useful shortcuts see “Help” => “Keyboard Shortcuts” or simply press keyboard icon in the toolbar.

### 3.4.1 Executing python code

Below is a code with some standard python that declares a variable “x”, assigns it the value 10, declares a second variable “y” and assigns it the value 45. The final line of y alone, instructs python to display the value of the variable y. The results of the operation appear in Jupyter Notebook as an output cell Out[#]. By pressing **Ctrl-Enter** the code will be executed and the output displayed below.

```
x = 10
y = 45
y
```

45

#### The semi-colon “;” suppresses output in Jupyter Notebook

In the example below, a semi-colon “;” has been appended to the final line. This suppresses the display of the value contained by y; As a result there is no output cell.

```
x = 10
y = 45
y;
```

Another way to display results is to use the print function.

```
x = 10
print(x)
```

10

Variables in a Jupyter Notebook session are persistent, as a result in the subsequent cell, we can declare a variable ‘z’ equal to 2\*y and it will have the value 90.

```
z=y*2
z
```

90

## 3.5 Markdown cells and the markdown scripting language in Jupyter Notebook

Text cells in a notebook can be made more interesting by using markdown.

Cells designated as markdown cells when executed are rendered in a rich text format (html).

Markdown is a lightweight markup language for creating formatted text using a plain-text editor. Used in a markdown cell of Jupyter Notebook it can be used to produce nicely formatted text that mixes text, mathematical formulae, code and outputs from executed python code.

Rather than the relatively complex commands of html `<h1></h1>`, markdown uses a simplified set of commands to control how text elements should be rendered.

### 3.5.1 Common markdown commands

Some of the most common of these include:

symbol	Effect
#	Header
##	second level
###	third level etc.
<b>**Bold text**</b>	<b>Bold text</b>
<i>*Italics text*</i>	<i>Italics text</i>
* text	Bulleted text or dot notes
1. text	1. Numbered bullets

### 3.5.2 Tables in markdown

Tables like the one above can be constructed using `|` as separators.

The `|:-|:-----|` on the second line tells the Table generator how to justify the contents of columns. `:-` means left justify `:-` means center justify and `-:` means right justify.

Below is the markdown code that generated the above table:

```
| symbol          | Effect          |
| :-|:-----|          | # Specifies the justification for the
columns of the table.
| \#              | Header         |
| \#\#           | second level   |
| \*\*Bold text\*\* | **Bold text**  |
| \*Italics text\* | *Italics text* |
|
| 1\. text       | 1. Numbered bullets
```



### 3.5.3 Displaying code

To display a (unexecutable) block of code within a markdown cell, encapsulate it (surround it) with backticks `.

For a multiline section of code use three backticks at the beginning and end.

``` Multi line text to be rendered as code ```.

will be rendered as: text to be rendered as code.

```
Multi line
text to be rendered as code
```

For inline code references `a sigle back tick at the beginning and end suffices.

**This sentence:**

An example sentence with some back-ticked `text as code` in the middle.

**will render as:**

An example sentence with some back-ticked text as code in the middle.

### 3.5.4 Rendering mathematics in markdown

Jupyter Notebook's implementation of Markdown supports latex mathematical notation.

Inline enclose the latex code in \$:

An Equation:  $y_t = \beta_0 + \beta_1 x_t + u_t$  will renders as:  $y_t = \beta_0 + \beta_1 x_t + u_t$

if enclosed in  $\$ \$$  it will be centered on its own line.

$$y_t = \beta_0 + \beta_1 x_t + u_t$$

#### Complex and multi-line math

```
\begin{align}
Y_t &= C_t + I_t + G + t + (X_t - M_t) \\
C_t &= c_t(C_{t-1}, C_{t-2}, I_t, G_t, X_t, M_t, P_t) \\
I_t &= c_t(I_{t-1}, I_{t-2}, C_t, G_t, X_t, M_t, P_t) \\
G_t &= c_t(G_{t-1}, G_{t-2}, C_t, I_t, X_t, M_t, P_t) \\
X_t &= c_t(X_{t-1}, X_{t-2}, C_t, I_t, G_t, M_t, P_t, P^f_t) \\
M_t &= c_t(M_{t-1}, M_{t-2}, C_t, I_t, G_t, X_t, P_t, P^f_t)
\end{align}
```

The above latex mathematics code uses the & symbol to tell latex to align the different lines (separated by \\) on the character immediately after the &. In this instance the equals “=” sign.

$$Y_t = C_t + I_t + G + t + (X_t - M_t) \quad (3.1)$$

$$C_t = c_t(C_{t-1}, C_{t-2}, I_t, G_t, X_t, M_t, P_t) \quad (3.2)$$

$$I_t = c_t(I_{t-1}, I_{t-2}, C_t, G_t, X_t, M_t, P_t) \quad (3.3)$$

$$G_t = c_t(G_{t-1}, G_{t-2}, C_t, I_t, X_t, M_t, P_t) \quad (3.4)$$

$$X_t = c_t(X_{t-1}, X_{t-2}, C_t, I_t, G_t, M_t, P_t, P_t^f) \quad (3.5)$$

$$M_t = c_t(M_{t-1}, M_{t-2}, C_t, I_t, G_t, X_t, P_t, P_t^f) \quad (3.6)$$

### 3.5.5 links to more info on markdown

There are several very good markdown cheatsheets on the internet, one of these is [here](#)

## SOME PYTHON BASICS

Before using `modelflow` with the World Bank's MFMod models, users will have to understand at least some basic elements of `python` syntax and usage. Notably they will need to understand about packages, libraries and classes, how to access them.

### 4.1 Starting python in windows

To begin using `modelflow`, `python` itself needs to be started. This can be done either using the Anaconda navigator or from the command line shell. In either case, the user will need to start `python` and select the `modelflow` environment.

### 4.2 Anaconda navigator

1. Start Anaconda Navigator by typing Anaconda in the Start window and opening the Navigator (see Figure).
2. From Anaconda Navigator select the `Modelflow` environment (see figure)

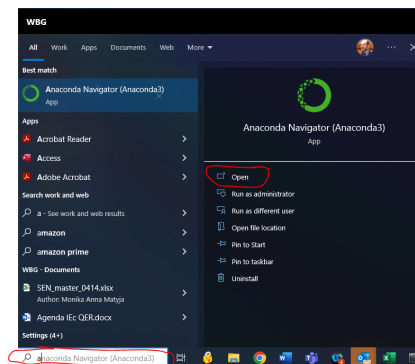


Fig. 4.1: A newly created Jupyter Notebook session

1. Once the environment is selected the user can either select a command line environment or start jupyter notebook by clicking on either the
  1. Jupyter Notebook environment
  2. The command line environment
  3. A programming IDE environment

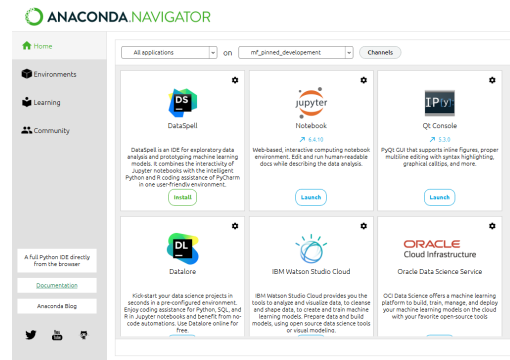


Fig. 4.2: A newly created Jupyter Notebook session

### 4.3 Python packages, libraries and classes

Some features of `python` are built-in out-of-the-box. Others build up on these basic features.

A **python class** is a code template that defines a python object. Classes can have properties [variables or data] associated with them and methods (behaviours or functions) associated with them. In python a class is created by the keyword `class`. An object of type class is created (instantiated) using the class's “constructor” – a special method that creates an object that is an instance of a class.

A **module** is a Python object consisting of Python code. A module can define functions, classes and variables. A module can also include runnable code.

A **python package** is a collection of modules that are related to each other. When a module from an external package is required by a program, that package (or module in the package) must be **imported** into the current session for its modules can be put to use.

A **python library** is a collection of related modules or packages.

`Modelflow` is a python package that *inherits* (build on or adds to) the methods and properties of other `python` classes like `pandas`, `numpy` and `matplotlib`.

---

**Note:** In `modelflow` the model is a class and we can create an instance of a model (an object filled with the characteristics of the class) by executing the code `mymodel = model(myformulas)` see below for a working example.

---

### 4.4 Importing packages, libraries, modules and classes

Some libraries, packages, and modules are part of the core python package and will be available (importable) from the get-go. Others are not, and need to be installed before importing them into a session.

If you followed the `modelflow` installation instructions you have already downloaded and installed on your computer all the packages necessary for running World Bank models under `modelflow`. But to work with them in a given Jupyter Notebook session or in a program context, you will also need to `import` them into your session before you call them.

---

**Note: Installation** of a package is not the same as **importing** a package. To be imported a package must be installed once on the computer that wishes to use it. Once it has been installed, the package must be imported into each python session where it is to be used.

---

Typically a python program will start with the importation of the libraries, classes and modules that will be used. Because a Jupyter Notebook is essentially a heavily annotated program, it also requires that packages used be imported.

As described above packages, libraries and modules are containers that can include other elements. Take for example the package Math.

To import the Math Package we execute the command `import math`. Having done that we can call the functions and data that are defined in it.

```
# the """ in a code cell indicates a comment, test after the # will not be executed
import math

# Now that we have imported math we can access some of the elements identified in the
# package,
# For example math contains a definition for pi, we can access that by executing the
# pi method
# of the library math
math.pi
```

```
3.141592653589793
```

#### 4.4.1 Import specific elements or classes from a module or library

The python package `math` contains several functions and classes.

If I want I can import them directly. Then when I call them I will not have to precede them with the name of their library. to do this I use the **from** syntax. `from math import pi, cos, sin` will import the `pi` constant and the two functions `cos` and `sin` and allow me to call them directly.

Compared these calls with the one in the preceding section – there the call to the method `pi` has to be preceded by its namespace designator `math`. i.e. `math.pi`. Below we import `pi` directly and can just call it with `pi`.

```
from math import pi, cos, sin

print(pi)
print(cos(3))
```

```
3.141592653589793
-0.9899924966004454
```

#### 4.4.2 import a class but give it an alias

A class and instead of using its full name as above or it can be given an alias, that is hopefully shorter but still obvious enough that the user knows what class is being referred to.

For example `import math as m` allows a call to `pi` using the more succinct syntax `m.pi`.

```
import math as m
print(m.pi)
print(m.cos(3))
```

```
3.141592653589793
-0.9899924966004454
```

### 4.4.3 Standard aliases

Some packages are so frequently used that by convention they have been “assigned” specific aliases.

For example:

#### Common aliases

Alias	aliased package	example	functionalty
pd	pandas	import pandas as pd	Pandas are used for storing and retrieveing data
np	numpy	import numpy as np	Numpy gives access to some advanced mathematical features

You don't have to use those conventions but it will make your code easier to read by others who are familiar with it.

## INTRODUCTION TO PANDAS DATAFRAMES

Modelflow is built on top of the Pandas library. Pandas is the Swiss knife of data science and can perform an impressive array of date oriented tasks.

This tutorial is a very short introduction to how pandas dataframes are used with Modelflow. For a more complete discussion see any of the many tutorials on the internet, notably:

- [Pandas homepage](#)
- [Pandas community tutorials](#)

### 5.1 Import the pandas library

As with any python program, in order to use a package or library it must first be imported into the session. As noted above, by convention pandas is imported as `pd`

```
import pandas as pd
```

Pandas, like any library, contains many classes and methods. The discussion below focuses on **Series** and **DataFrames** two classes that are part of the pandas library. Both `series` and `dataframes` are containers that can be used to store time-series data and that have associated with them a number of very useful methods for displaying and manipulating time-series data. Unlike other statistical packages neither `series` nor `dataframes` are inherently or exclusively time-series in nature. Modelflow and macro-economists use them in this way, but the classes themselves are not dated in anyway out-of-the-box.

### 5.2 The Pandas class series

A pandas series is class that can be used to instantiate an object that holds a two dimensional array comprised of values and an index.

The constructor for a `Series` object is `pandas.Series()`. The content inside the parentheses will determine the nature of the series-object generated. As an object-oriented language Python supports `overrides` (which is to say a method can have more than one way in which it can be called). Specifically there can be different constructors defined for a class, depending on how the data that is to be used to initialize it is organized.

### 5.2.1 Series declared from a list

The simplest way to create a Series is to pass an array of values as a Python list to the Series constructor.

**Note:** A list in python is a comma delimited collection of items. It could be text, numbers or even more complex objects. When declared (and returned) list are enclosed in square brackets.

For example both of the following two lines are perfectly good examples of lists.

```
mylist=[2,7,8,9] mylist2=["Some text","Some more Text",2,3]
```

The list is entirely agnostic about the type of data it contains.

In the examples below Simplest, Simple and simple3 are all series – although series3 which is derived from a list mixing text and numeric values would be hard to interpret as an economic series.

```
values=[7,8,9,10,11]
weird=["Some text","Some more Text",2,3]

# Here the constructor is passed a numeric list
Simplest=pd.Series([2,3,4,5,6])
Simplest
```

```
0    2
1    3
2    4
3    5
4    6
dtype: int64
```

```
# In this case the constructor is passed a variable that contains a list
simple2=pd.Series(values)
simple2
```

```
0    7
1    8
2    9
3   10
4   11
dtype: int64
```

```
# Here the constructor is passed a variable containing a list that is a mix of
# alphanumerics and numerical values
simple3=pd.Series(weird)
simple3
```

```
0      Some text
1  Some more Text
2              2
3              3
dtype: object
```

Note that all three series have different length.



Moreover, constructed in this way (by passing a list to the constructor) each of these `Series` are automatically assigned a zero-based index (a numerical index that starts with 0).

## 5.2.2 Series declared using a specific index

In this example the series `Simple` and `Simple2` are recreated (overwritten), but this time an index is specified. Here the index is declared as a(nother) list.

```
# In this example the constructor is given both the values
# and specific values for the index
Simplest=pd.Series([2,3,4,5,6],index=[1966,1967,1996,1999,2000])
Simplest
```

```
1966    2
1967    3
1996    4
1999    5
2000    6
dtype: int64
```

```
simple2=pd.Series(values,index=[1966,1967,1996,1999,2000])
simple2
```

```
1966     7
1967     8
1996     9
1999    10
2000    11
dtype: int64
```

Now the Series look more like time series data!

## 5.2.3 Create Series from a dictionary

In python a dictionary is a data structure that is more generally known in computer science as an associative array. A dictionary consists of a collection of key-value pairs, where each key-value pair *maps* or *links* the key to its associated value.

---

**Note:** A dictionary is enclosed in curly brackets {}, versus a list which is enclosed in square brackets [].

---

Thus `mydict={"1966":2,"1967":3,"1968":4,"1969":5,"2000":-15}` creates an object called `mydict`. `mydict` maps (or links) the key "1966" links to the value 2.

---

**Note:** In this example the Key was a string but we could just as easily made it a numerical value:

---

`mydict2={1966:2,1967:3,1968:4,1969:5,2000:-15}` creates an object called `mydict2` that links (maps) the key "1966" to the value 2.

The series constructor also accepts a dictionary, and maps the key to the index of the Series.

```
mydict2={1966:2,1967:3,1968:4,1969:5,2000:6}
simple2=pd.Series(mydict2)
simple2
```

```
1966    2
1967    3
1968    4
1969    5
2000    6
dtype: int64
```

### 5.3 Properties and methods of dataframes in modelflow

Any class can have both properties (data) and methods (functions that operate on the data of the particular instance of the class). With object-oriented programming languages like python, classes can be built as supersets of existing classes. The Modelflow class `model` inherits or encapsulates all of the features of the pandas dataframe and extends it in many important ways. Some of the methods below are standard pandas methods, others have been added to it by `modelflow` features

Much more detail on standard pandas dataframes can be found on the [official pandas website](#).

#### 5.3.1 dataframes

The dataframe is the primary structure of pandas and is a two-dimensional data structure with named rows and columns. Each columns can have different data types (numeric, string, etc).

By convention, a dataframe is often called `df` or some other modifier followed by `df`, to assist in reading the code.

#### 5.3.2 Creating or instantiating a dataframe

Like any object, a dataframe can be created by calling the constructor of the pandas class `DataFrame`.

Each class has many constructors, so there are very many ways to create a dataframe. The `pandas.DataFrame()` method is constructor for the `DataFrame` class. It takes several forms (as with `Series`), but always returns an instance of a (instantiates) `DataFrame` object – i.e. a variable that is a `DataFrame`.

The code example below creates a `DataFrame` of three columns A,B,C; indexed between 2019 and 2021. Macroeconomists may interpret the index as dates, but for pandas they are just numbers.

Below a `DataFrame` named `df` is instantiated from a dictionary and assigned a specific index by passing a list of years as the index.

```
df = pd.DataFrame({'B': [1,1,1,1], 'C': [1,2,3,6], 'E': [4,4,4,4]}, index=[2018,2019,2020,
↪2021])
df
```

```
      B  C  E
2018  1  1  4
2019  1  2  4
2020  1  3  4
2021  1  6  4
```

**Note:** In the `DataFrames` that are used in macrostructural models like MFMod, each column can be interpreted as a time-series of an economic variable. So in this dataframe, A, B and C would normally be interpreted as economic time series.

There is nothing in the `DataFrame` class that suggests that the data it stores must be time-series or even numeric in nature.

### 5.3.3 Adding a column to a dataframe

If a value is assigned to a column that does not exist, pandas will add a column with that name and fill it with values resulting from the calculation.

**Note:** The size of the object assigned to the new column must match the size (number of rows) of the pre-existing `DataFrame`.

```
df["NEW"]=[10,12,10,13]
df
```

	B	C	E	NEW
2018	1	1	4	10
2019	1	2	4	12
2020	1	3	4	10
2021	1	6	4	13

### 5.3.4 Revising values

If the column exists then the `=` method will revise the values of the rows with the values assigned in the statement.

**Warning:** The dimensions of the list assigned via the `=` method must be the same as the `DataFrame` (i.e. there must be exactly as many values as there are rows). Alternatively if only one value is provided, then that value will replace all of the values in the specified column (be broadcast to the other rows in the column).

```
df["NEW"]=[11,12,10,14]
df
```

	B	C	E	NEW
2018	1	1	4	11
2019	1	2	4	12
2020	1	3	4	10
2021	1	6	4	14

```
# replace all of the rows of column B with the same value
df['B']=17
df
```

	B	C	E	NEW
2018	17	1	4	11
2019	17	2	4	12
2020	17	3	4	10
2021	17	6	4	14

## 5.4 Column names in Modelflow

### Modelflow variable names

Modelflow places more restrictions on column names than do pandas *per se*.

While pandas dataframes are very liberal in what names can be given to columns, `modelflow` is more restrictive.

Specifically, in `modelflow` a variable name must:

- start with a letter
- be upper case

Thus while all these are legal column names in pandas, some are illegal in `modelflow`.

Variable Name	Legal in modelflow?	Reason
IB	yes	Starts with a letter and is uppercase
ib	no	lowercase letters are not allowed
42ANSWER	No	does not start with a letter
_HORSE1	No	does not start with a letter
A_VERY_LONG_NAME_THAT_IS_LEGAL_3	Yes	Starts with a letter and is uppercase

## 5.5 .index and time dimensions in Modelflow

As we saw above, series have indices. Dataframes also have indices, which are the row names of the dataframe.

In `modelflow` the index series is typically understood to represent a date.

For yearly models a list of integers like in the above example works fine.

For higher frequency models the index can be one of pandas datatypes.

**Warning:** Not all datatypes work well with the graphics routines of `modelflow`. Users are advised to use the `pd.period_range()` method to generate date indexes.

For example:

```
dates = pd.period_range(start='1975q1', end='2125q4', freq='Q')
df.index=dates
```

### 5.5.1 Leads and lags

In modelflow leads and lags can be indicated by following the variable with a parenthesis and either -1 or -2 two for one or two period lags (where the number following the negative sign indicates the number of time periods that are lagged). Positive numbers are used for forward leads (no +sign required).

When a method defined by the `modelflow` class encounters something like `A(-1)`, it will take the value from the row above the current row. No matter if the index is an integer, a year, quarter or a millisecond. The same goes for leads, `A(+1)` will return the value of `A` in the next row.

As a result in a quarterly model `B=A(-4)` would assign `B` the value of `A` from the same quarter in the previous year.

### 5.5.2 .columns lists the column names of a dataframe

The method `.columns` returns the names of the columns in the dataframe.

```
df.columns
```

```
Index(['B', 'C', 'E', 'NEW'], dtype='object')
```

### 5.5.3 .size indicates the dimension of a list

so `df.columns.size` returns the number of columns in a dataframe.

```
df.columns.size
```

```
4
```

The dataframe `df` has 4 columns.

### 5.5.4 .eval() evaluates calculates an expression on the data of a dataframe

`.eval` is a native dataframe method, which does calculations on a dataframe and returns a revised dataframe. With this method expressions can be evaluated and new columns created.

```
df.eval('''X = B*C
        THE_ANSWER = 42''')
```

	B	C	E	NEW	X	THE_ANSWER
2018	17	1	4	11	17	42
2019	17	2	4	12	34	42
2020	17	3	4	10	51	42
2021	17	6	4	14	102	42

```
df
```

	B	C	E	NEW
2018	17	1	4	11
2019	17	2	4	12
2020	17	3	4	10
2021	17	6	4	14

In the above example the resulting dataframe is displayed but is not stored.

To store it, the results of the calculation must be assigned to a variable. The pre-existing dataframe can be overwritten by assigning it the result of the eval statement.

```
df=df.eval('''X = B*C
            THE_ANSWER = 42''')
df
```

	B	C	E	NEW	X	THE_ANSWER
2018	17	1	4	11	17	42
2019	17	2	4	12	34	42
2020	17	3	4	10	51	42
2021	17	6	4	14	102	42

With this operation the new columns, x and THE\_ANSWER have been appended to the dataframe df.

---

**Note:** The `.eval()` method is a native pandas method. As such it cannot handle lagged variables (because pandas do not support the idea of a lagged variable).

The `.mfcalc()` and the `.upd()` methods discussed below are modelflow features that extend the functionalities native to dataframe that allows such calculations to be performed.

---

### 5.5.5 .loc[] selects a portion (slice) of a dataframe

The `.loc[]` method allows you to display and/or revise specific sub-sections of a column or row in a dataframe.

#### .loc[row,column] A single element

`.loc[row,column]` operates on a single cell in the dataframe. Thus the below displays the value of the cell with index=2019 observation from the column C.

```
df.loc[2019, 'C']
```

2

### `.loc[:,column]` A single column

The lone colon in a loc statement indicates all the rows or columns. Here all of the rows.

```
df.loc[:, 'C']
```

2018	1
2019	2
2020	3
2021	6

Name: C, dtype: int64

### `.loc[row,:]` A single row

Here all of the columns, for the selected row.

```
df.loc[2019, :]
```

B	17
C	2
E	4
NEW	12
X	34
THE_ANSWER	42

Name: 2019, dtype: int64

### `.loc[:,[names...]]` Several columns

Passing a list in either the rows or columns portion of the loc statement will allow multiple rows or columns to be displayed.

```
df.loc[[2018, 2021], ['B', 'C']]
```

	B	C
2018	17	1
2021	17	6

### `.loc` using the colon to select a range

with the colon operator we can also select a range of results.

Here from 2018 to 2019.

```
df.loc[2018:2020, ['B', 'C']]
```

	B	C
2018	17	1
2019	17	2
2020	17	3

### `.loc[]` can also be used on the left hand side to assign values to specific cells

This can be very handy when updating scenarios.

```
df.loc[2019:2020, 'C'] = 17
df
```

	B	C	E	NEW	X	THE_ANSWER
2018	17	1	4	11	17	42
2019	17	17	4	12	34	42
2020	17	17	4	10	51	42
2021	17	6	4	14	102	42

**Warning:** The dimensions on the right hand side of `=` and the left hand side should match. That is: either the dimensions should be the same, or the right hand side should be broadcasted into the left hand slice.

For more on broadcasting [see here](#)

### For more info on the `.loc[]` method

- [Description](#)
- [Search](#)

### For more info on pandas:

- [Pandas homepage](#)
- [Pandas community tutorials](#)



## MODELFLOW EXTENSIONS TO PANDAS

Modelflow inherits all the capabilities of pandas and extends some as well.

Data in a dataframe can be modified directly with built-in pandas functionalities like `.loc[]`, but `modelflow` extends these capabilities with in important ways with the `.upd()` and `.mfcalc()` methods.

### 6.1 `.upd()` method of modelflow

The `.upd()` method extends pandas by giving the user a concise and expressive way to modify data in a dataframe using a syntax that a database-manager or macroeconomic modeler might find more natural.

Notably it allows the user to employ formula's to do updates, and supports both lags and leads on variables.

`.upd()` can be used to:

- Perform different types of updates
- Perform multiple updates each on a new line
- Perform changes over specific periods
- Use one input which is used for all time frames, or a separate input for each time
- Preserve pre-shock growth rates for out of sample time-periods
- Display results

#### 6.1.1 `.upd()` method operators

Below are some of the operators that can be used in the `.upd()` method

##### Types of update:

Update to perform	Use this operator
Set a variable equal to the input	=
Add the input to the input	+
Set the variable to itself multiplied by the input	*
Increase/Decrease the variable by a percent of itself (1+input/100)	%
Set the growth rate of the variable to the input	=growth
Change the growth rate of the variable to its current growth rate plus the input value in percentage points	+growth
Specify the amount by which the variable should increase from its previous period level ( $\Delta = var_t - var_{t-1}$ )	=diff

**Danger:** Note: the syntax of an update command requires that there be a space between variable names and the operators.

Thus `df.upd("A = 7")` is fine, but `df.upd("A =7")` will generate an error.

Similarly `df.upd("A * 1.1")` is fine, but `df.upd("A* 1.1")` will generate an error.

## 6.1.2 .upd() some examples

## 6.1.3 Setting up the python environment

In order to use `.upd()` all of the necessary libraries must be **imported** into the python session.

```
%load_ext autoreload
%autoreload 2

# First import pandas and the model into the workspace
# There is no problem importing multiple times, though it is not very efficient.
import pandas as pd

from modelclass import model
# functions that improve rendering of modelflow outputs under Jupyter Notebook
model.widescreen()
model.scroll_off()
```

```
<IPython.core.display.HTML object>
```

Now create a dataframe using standard pandas syntax. In this instance with years as the index and a dictionary defining the variables and their data.

```
# Create a dataframe using standard pandas

df = pd.DataFrame({'B': [1,1,1,1], 'C': [1,2,3,6], 'E': [4,4,4,4]}, index=[2018,2019,2020,
↪2021])
df
```

	B	C	E
2018	1	1	4
2019	1	2	4
2020	1	3	4
2021	1	6	4

A somewhat more creative way to initialize the dataframe for dates would use a loop to specify the dates that get passed to the constructor as an argument.

Below a dataframe `df` with two Series (A and B), is initialized with the values 100 for all data points.

The index is defined dynamically by a loop `index=[2020+v for v in range(number_of_rows)]` that runs for `number_of_rows` times (6 times in this example) setting `v` equal to `2020+0, 2020+1,...,202+5`. The resulting list whose values are assigned to index is `[2020,2021,2022,2023,2024,2025]`.

The big advantage of this method is that if the user wanted to have data created for the period 1990 to 2030, they would only have to change `number_of_rows` from 6 to 41 and 2020 in the loop to 1990.

The second example simplifies further by just specifying the begin and end point of the range.

```
#define the number of years for which the data is to be created.
number_of_rows = 6

# call the dataframe constructor
df = pd.DataFrame(100,
                  index=[2020+v for v in range(number_of_rows)], # create row index
                  # equivalent to index=[2020,2021,2022,2023,2024,2025]
                  columns=['A','B']) # create column name
df

df1 = pd.DataFrame(200,
                  index=[v for v in range(2020,2030)], # create row index
                  # equivalent to index=[2020,2021,...,2030]
                  columns=['A1','B1']) # create column name
df1
```

	A1	B1
2020	200	200
2021	200	200
2022	200	200
2023	200	200
2024	200	200
2025	200	200
2026	200	200
2027	200	200
2028	200	200
2029	200	200

### 6.1.4 Use .upd to create a new variable (= operator)

With standard pandas a user can add a column (series) to a dataframe simply by assigning a adding to a dataframe. For example:

```
df['NEW2']=[17,12,14,15]
```

.upd() provides this functionality as well.

```
df2=df.upd('c = 142')
df2
```

	A	B	C
2020	100	100	142.0
2021	100	100	142.0
2022	100	100	142.0
2023	100	100	142.0
2024	100	100	142.0
2025	100	100	142.0

**Note:** Note that the new variable name was entered as a lower case 'c' here. Lowercase letters are not legal modelflow variable names. The .upd() method knows is part of modelflow and knows this rule, so it automatically translates lowercase entries into upper case so that the statement works.

## 6.1.5 Multiple updates and specific time periods

The modelflow method `.upd()` takes a string as an argument. That string can contain a single update command or can contain multiple commands.

Moreover by including a <Begin End> date clause in a given update command, the update will be restricted to the associated time period.

The below illustrates this, modifying two existing variables A, B over different time periods and creating a new variable.

**Danger:** Note that the third line inherits the time period of the previous line.

Note also the submitted string can include comments as well (denoted with the standard python `#` indicator).

```
df.upd("""
# Same number of values as years
<2021 2024> A = 42 44 45 46      # 4 years
<2020      > B = 200              # 1 year
c = 500                          # Same period as previous line
<-0 -1> D = 33                   # All years
""")
```

	A	B	C	D
2020	100	200	500.0	33.0
2021	42	100	0.0	33.0
2022	44	100	0.0	33.0
2023	45	100	0.0	33.0
2024	46	100	0.0	33.0
2025	100	100	0.0	33.0

### Time scope of `.upd()`

Made this a margin just to see

The update command takes a variety of mathematical operators `=`, `+`, `*`, `%` `=GROWTH`, `+GROWTH`, `=DIFF` and applies them to data for the period set in the leading `<>`.

If the user wants to modify a series or group of series for only a specific point in time or a period of time, she can indicate the period in the command line.

- If **one date** is specified the operation is applied to a single point in time
- If **two dates** are specified the operation is applied over a period of time.

The selected time period will persist until re-set with a new time specification. Useful to avoid visual noise if several variables are going to be updated for the same time period.

The time period can be reset to the full time-period by using the special `<-0 -1>` time period. More generally:

- Indicates the start of the dataframe use `-0`
- Indicates the end of the dataframe use `-1`

If no time is provided the dataframe start and end period will be used.

### 6.1.6 Setting specific datapoints to specific values

This example, demonstrates the equals operator. The = operator indicates that the variable a should be set equal to the indicated values following the = operator (42 44 45 46 in the first line, 200 in the second and 500 in the third). The dates enclosed in <> indicate the period over which the change should be applied.

Either:

- The number of data points provided must match the number of dates in the period, Or
- Only one data point is provided, it is applied to all dates in the period.

If only one period is to be modified then it can be followed by just one date.

Note that the final line inherited the time period set in the second line.

```
df.upd("""
# Same number of values as years
<2021 2024> A = 42 44 45 46      # 4 years
<2023      > B = 200             # 1 year
c = 500
""")
```

	A	B	C
2020	100	100	0.0
2021	42	100	0.0
2022	44	100	0.0
2023	45	200	500.0
2024	46	100	0.0
2025	100	100	0.0

### 6.1.7 Adding the specified values to all values in a range (the + operator)

NB: Here upd with the + operator indicates that we are adding 42.

```
df.upd('''
# Or one number to all years in between start and end
<2022 2024> B + 42      # one value broadcast to 3 years
''')
```

	A	B
2020	100	100
2021	100	100
2022	100	142
2023	100	142
2024	100	142
2025	100	100

### 6.1.8 Multiplying all values in a range by the specified values (the \* operator)

```
df.upd('''
# Same number of values as years
<2021 2023> A * 42 44 55
''')
```

	A	B
2020	100	100
2021	4200	100
2022	4400	100
2023	5500	100
2024	100	100
2025	100	100

### 6.1.9 Increasing all values in a range by a specified percent amount (the % operator)

In this example:

- A is increased by 42 and 44% over the range 2021 through 2022.
- B is increased by 10 percent in all years
- C is a new variable, is created and set to 100 for the whole range
- C is decreased by 12 percent over the range 2023 through 2025.

```
df.upd('''
<2021 2022 > A % 42 44
<-0 -1> B % 10          # all rows
C = 100                 # all rows persist
<2023 2025> C % -12     # now only for 3 years
''')
```

	A	B	C
2020	100	110.0	100.0
2021	142	110.0	100.0
2022	144	110.0	100.0
2023	100	110.0	88.0
2024	100	110.0	88.0
2025	100	110.0	88.0

### 6.1.10 Set the percent growth rate to specified values (=GROWTH)

```
res = df.upd('''
# Same number of values as years
<2021 2022> A =GROWTH 1 5
<2020> c = 100
<2021 2025> c =GROWTH 2
''')
print(f'Dataframe:\n{res}\n\nGrowth:\n{res.pct_change()*100}\n') # Explained b
```

```
Dataframe:
      A      B      C
2020 100.00  100 100.000000
2021 101.00  100 102.000000
2022 106.05  100 104.040000
2023 100.00  100 106.120800
2024 100.00  100 108.243216
2025 100.00  100 110.408080
```

```
Growth:
      A      B      C
2020   NaN   NaN   NaN
2021  1.000000  0.0  2.0
2022  5.000000  0.0  2.0
2023 -5.704856  0.0  2.0
2024  0.000000  0.0  2.0
2025  0.000000  0.0  2.0
```

### 6.1.11 Add or subtract from the existing percent growth rate (+GROWTH operator)

The below example is a bit more complicated.

The first line sets the growth rate of A to 1% in all periods beginning in 2021

The second command adds 2 3 4 5 6 to the growth rates in each period after 2021, resulting in growth rates of 3,4,5,6,7.

```
res =df.upd('''
<2021 > A =GROWTH 1 # All selected years set to the same growth rate
a +growth 2 # Add to the existing growth rate these numbers
''')
print(f'Dataframe:\n{res}\n\nGrowth:\n{res.pct_change()*100}\n')
```

```
Dataframe:
      A      B
2020 100  100
2021 103  100
2022 100  100
2023 100  100
2024 100  100
2025 100  100
```

```
Growth:
      A      B
2020   NaN   NaN
2021  3.000000  0.0
2022 -2.912621  0.0
2023  0.000000  0.0
2024  0.000000  0.0
2025  0.000000  0.0
```

### 6.1.12 Set the change in a variable to specific values (=diff operator)

$$\Delta = var_t - var_{t-1} = somenumber$$

Here sets the value of A in 2021 to 2 more than the value of 2020, and the 2022 value as 4 more than the **revised** value of 2021.

The second line creates a new variable “UPBY2” to the data frame and sets it equal to 100 for all periods,

The third line adds 2 to the previous periods value UPBY2.

```
df.upd('''
< 2021 2022> A =diff  2 4    # Same number of values as years
<2020 > UpBy2 = 100 # sets rows equal to the same number for all years in between
↪start and end
<2021 2025> UpBy2 =diff  2

''')
```

	A	B	UPBY2
2020	100	100	100.0
2021	102	100	102.0
2022	106	100	104.0
2023	100	100	106.0
2024	100	100	108.0
2025	100	100	110.0

### 6.1.13 Recall that we have not overwritten df, so the df dataframe is unchanged.

```
df
```

	A	B
2020	100	100
2021	100	100
2022	100	100
2023	100	100
2024	100	100
2025	100	100

---

**Note:** The method `.upd()` only operates on on variable. A command like `.upd('A = B')` would not work. For these kind of functions, use `.mfcalc()` (see next section).

---



### 6.1.14 Keep growth rates after the update time – the `-kg` option

In a long projection it can sometime be useful to be able to update variables for which new information is available, but for the subsequent periods keep the growth rate the same as before the update. In database management this is frequently done when two time-series with different levels are spliced together.

The `-kg` or `-keep_growth` option instructs modelview to calculate the growth rate of the existing pre-change series, and then use it to preserve the pre-change growth rates of the series for the periods that were **not** changed.

This allows to update variables for which new information is available, but keep the growth rate the same as before the update in the period after the update time.

#### The default `keep_growth` behaviour

The `upd()` method has a parameter `keep_growth`, which by default is equal to `False`.

`keep_growth` determines how data in the time periods after those where an update is executed are treated.

If `keep_growth` is `False` then data in the sub-period after a change is left unchanged.

if `keep_growth` is set to “True” then the system will preserve the pre-change growth rate of the affected variable in the time period *after the change*.

---

**Note:** At the line level:

- `keep_growth=True` can be expressed as `-kg`
  - `keep_growth=False` can be expressed as `-nkg`
- 

Let's see this in a concrete example. Consider the following dataframe `df` with two variables A and B, that each grow by 2% per period, with A initialized at a level of 100 and B at a level of 110 so that we can see each separately on a graph.

```
df = pd.DataFrame(100,
    index=[2020+v for v in range(number_of_rows)], # create row index
    # equivalent to index=[2020,2021,2022,2023,2024,2025]
    columns=['A', 'B'])

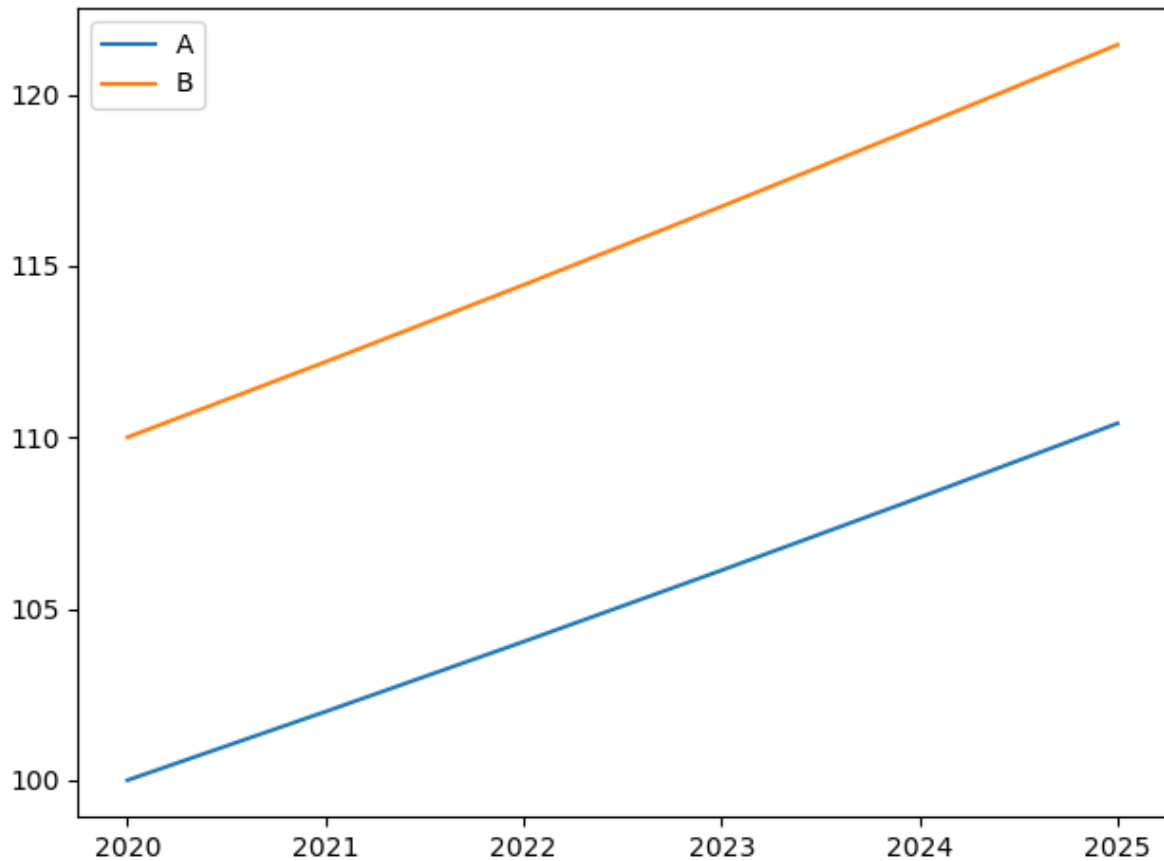
df=df.upd("""<2021 -1> A =growth 2
          <2020 -1>   B = 110
          <2021 -1>   B =growth 2
          """)

# Store these variables for later use in comparisons
df['A_ORIG']=df['A']
df['B_ORIG']=df['B']
df
```

	A	B	A_ORIG	B_ORIG
2020	100.000000	110.000000	100.000000	110.000000
2021	102.000000	112.200000	102.000000	112.200000
2022	104.040000	114.444000	104.040000	114.444000
2023	106.120800	116.732880	106.120800	116.732880
2024	108.243216	119.067538	108.243216	119.067538
2025	110.408080	121.448888	110.408080	121.448888

```
df[['A', 'B']].plot()
```

&lt;AxesSubplot: &gt;

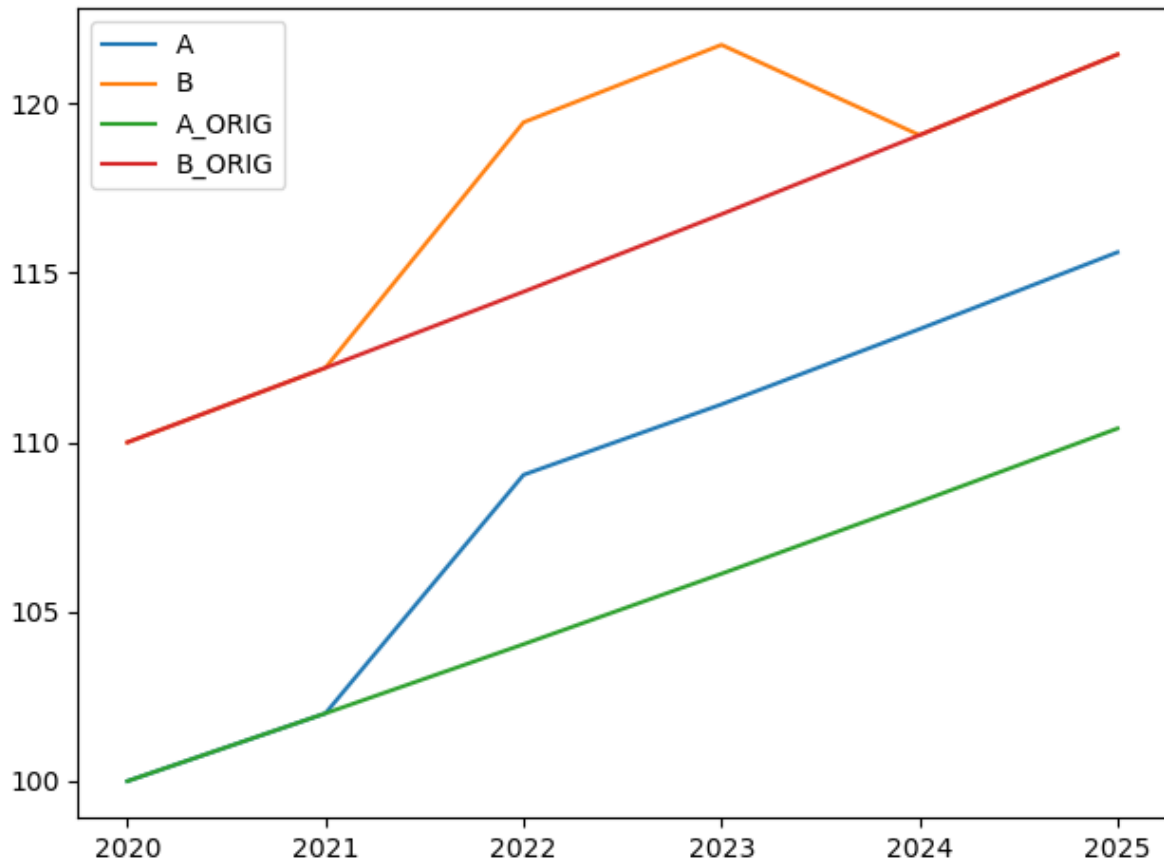


Now let's modify each by adding 5 to the level in 2022 and 2023. For B we will do setting the `keep_growth` option as False and for 'A' `keep_growth` positive. While the `keep_growth` is a global variable it can be set at the line level also using the `-kg` option (`keep_growth=True`) and `-nkg` option (`keep_growth=False`).

```
df=df.upd("""
    <2022 2023> A + 5 --kg
    <2022 2023> B + 5 --nkg
    """)

df[['A', 'B', 'A_ORIG', 'B_ORIG']].plot()
```

&lt;AxesSubplot: &gt;



In the first example 'A' (the green and blue lines) the level of A is increased by 5 for two periods (2021-2022). The subsequent values are also increased and they were calculated to maintain the growth rate of the original series.

For the 'B' variable the same level change was input but because of the `--nkg` (equivalent to `keep_growth=False`) the periods after the change were unaffected and retained their old values.

Below are plots the growth rates of the two transformed series.

Here the growth in both series accelerates in 2022, by slightly less than 5 percentage points because a) the base of each is more than 100, with the base of B being higher (it was initialized at 110). In 2023 the growth rate of A returns to 2 percent, while the growth rate of B is actually negative because the level (see earlier graph) has fallen back to its original level.

```
dfg=df[['A','B']].pct_change()*100
dfg.plot()
```

```
<AxesSubplot: >
```



### 6.1.15 .upd(,keep\_growth) some more examples

### 6.1.16 Initialize a new dataframe First make a dataframe with some growth rate

```
# instantiate a new dataframe with one column 'A' with avlue 100 everywhere and index
↳2020-2025
dfest = pd.DataFrame(100,
    index=[2020+v for v in range(number_of_rows)], # create row index
    # equivalent to index=[2020,2021,2022,2023,2024,2025]
    columns=['A']) # create column name

# Update a to have growth rate accelerationg linearly by 1 from 1 oercent to 5 percent
original = dfest.upd('<2021 2025> a =growth 1 2 3 4 5')
print(f'Levels:\n{original}\n\nGrowth:\n{original.pct_change()*100}\n')
```

```
Levels:
      A
2020 100.000000
2021 101.000000
2022 103.020000
2023 106.110600
2024 110.355024
2025 115.872775
```

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```
Growth:
      A
2020  NaN
2021  1.0
2022  2.0
2023  3.0
2024  4.0
2025  5.0
```

### 6.1.17 now update A in 2021 to 2023 to a new value

Below performs the same operation, the first time the updated value is assigned to the dataframe nkg and the default behaviour of keep\_growth is False

In the second example the -kg line option is specified, telling modelflow to maintain the growth rates of the dependent variable in the periods after the update is executed.

```
nokg = original.upd('''
<2021 2025> a =growth 1 2 3 4 5
<2021 2023> a = 120
''',lprint=0)

kg = original.upd('''
<2021 2025> a =growth 1 2 3 4 5
<2021 2023> a = 120 --kg
''',lprint=0)

kg=kg.rename(columns={"A":"KG"})          #rename cols to facilitate display
nokg=nokg.rename(columns={"A":"NOKG"})    #rename cols to facilitate display

combo=pd.concat([kg,nokg], axis=1)
combo

print(f'Levels\n{combo}\n\nGrowth\n{combo.pct_change()*100}')
```

```
Levels
      KG      NOKG
2020 100.00 100.000000
2021 120.00 120.000000
2022 120.00 120.000000
2023 120.00 120.000000
2024 124.80 110.355024
2025 131.04 115.872775

Growth
      KG      NOKG
2020  NaN      NaN
2021  20.0  20.000000
2022   0.0   0.000000
2023   0.0   0.000000
```

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```
2024    4.0   -8.03748
2025    5.0    5.00000
```

**Note:** In the first example where KG (keep\_growth) **was not set**, because the level was set constant for three periods at 120 the rate of growth was 0 for the final two years of the set period. But following this update, the level of A in 2023 is 120. With keep\_Growth=False (its default value) the level of A in 2024 remains at its unchanged (lower) level of 100.35. As a result, the growth rate in 2024 is negative.

In the **-kg** example, the pre-existing growth rate (of 4%) is applied to the new value of 120 and so the level in 2024 is  $(120 \times 1.04) = 124.8$  and 2025 is 131.04.

### .upd() with the option keep\_growth set globally

Above the line level option `--keep_growth` or `--kg` was used to keep the growth rate(or not) for a given operation.

This works because by default the option `Keep_growth` is set to false, implementing `--kg` at the line level temporarily set the `keep_growth` flag to true for the specific line (and those following).

The `keep_growth` flag can also be set globally for all the lines by setting the option in the command line.

`keep_growth=True`.

Now as default, all lines will keep the growth rate (unless overridden at the line level with `--nkg` or `--no_keep_growth`).

- c,d are updated in 2022 and 2023 and keep the growth rates afterwards
- e the `--no_keep_growth` in this line prevents the updating 2024-2025

```
# Create a data frame
dftest = pd.DataFrame(100,
    index=[2020+v for v in range(number_of_rows)], # create row index
    # equivalent to index=[2020,2021,2022,2023,2024,2025]
    columns=['A', 'B', 'C', 'D', 'E']) # create column_
↪name
df
```

	A	B	A_ORIG	B_ORIG
2020	100.000000	110.000000	100.000000	110.000000
2021	102.000000	112.200000	102.000000	112.200000
2022	109.040000	119.444000	104.040000	114.444000
2023	111.120800	121.732880	106.120800	116.732880
2024	113.343216	119.067538	108.243216	119.067538
2025	115.610080	121.448888	110.408080	121.448888

```
dfres = dftest.upd(''
<2022 2023> c = 200
<2022 2023> d = 300
<2022 2023> e = 400 --no_keep_growth
'',keep_growth=True) # <= Set keep_growth to True for the entirety of the command,
                    # except for e where it is overridden by the --no_keep_growth_
↪flag
print(f'Dataframe:\n{dfres}\n\nGrowth:\n{dfres.pct_change()*100}\n')
```

```
Dataframe:
      A      B      C      D      E
2020  100  100  100.0  100.0  100
2021  100  100  100.0  100.0  100
2022  100  100  200.0  300.0  400
2023  100  100  200.0  300.0  400
2024  100  100  200.0  300.0  100
2025  100  100  200.0  300.0  100

Growth:
      A      B      C      D      E
2020  NaN  NaN   NaN   NaN   NaN
2021  0.0  0.0   0.0   0.0   0.0
2022  0.0  0.0  100.0  200.0  300.0
2023  0.0  0.0   0.0   0.0   0.0
2024  0.0  0.0   0.0   0.0  -75.0
2025  0.0  0.0   0.0   0.0   0.0
```

### 6.1.18 Update several variable in one line

Sometime there is a need to update several variable with the same value over the same time frame. To ease this case .update can accept several variables in one line

```
df.upd('''
<2022 2024> h i j k =      40      # earlier values are set to zero by default
<2020>      p q r s =     1000     # All values beginning in 2020 set to 1000
<2021 -1>   p q r s =growth 2     # -1 indicates the last year of dataframe
''')
```

```

      A      B      A_ORIG      B_ORIG      H      I      J      K  \
2020  100.000000  110.000000  100.000000  110.000000  0.0  0.0  0.0  0.0
2021  102.000000  112.200000  102.000000  112.200000  0.0  0.0  0.0  0.0
2022  109.040000  119.444000  104.040000  114.444000  40.0  40.0  40.0  40.0
2023  111.120800  121.732880  106.120800  116.732880  40.0  40.0  40.0  40.0
2024  113.343216  119.067538  108.243216  119.067538  40.0  40.0  40.0  40.0
2025  115.610080  121.448888  110.408080  121.448888  0.0  0.0  0.0  0.0

      P      Q      R      S
2020  1000.000000  1000.000000  1000.000000  1000.000000
2021  1020.000000  1020.000000  1020.000000  1020.000000
2022  1040.400000  1040.400000  1040.400000  1040.400000
2023  1061.208000  1061.208000  1061.208000  1061.208000
2024  1082.432160  1082.432160  1082.432160  1082.432160
2025  1104.080803  1104.080803  1104.080803  1104.080803
```

### 6.1.19 .upd(,scale=<number, default=1>) Scale the updates

When running a scenario it can be useful to be able to create a number of scenarios based on one update but with different scale.

This can be particularly useful when we want to do sensitivity analyses of model results, depending on how heavily a shocked variable is hit

When using the scale option, scale=0 the baseline while scale=0.5 is a scenario half the severity.

In the example below the values of the dataframes are printed. We use the scale option (setting to 0, 0.5 and 1) to run three scenarios using the same code but where the update in each case is multiplied by either 0, 0.5 or 1.

**Note:** Here we are just printing the outputs, a more interesting example would involve the solving a model using different levels of a given shock.

```
print(f'input dataframe: \n{df}\n\n')
for severity in [0,0.5,1]:
    # First make a dataframe with some growth rate
    res = df.upd(''
<2021 2025>
a =growth 1 2 3 4 5
b + 10
'',scale=severity)
    print(f'{severity=}\nDataframe:\n{res}\n\nGrowth:\n{res.pct_change()*100}\n\n')
    #
    # Here the updated dataframe is only printed.
    # A more realistic use case is to simulate a model like this:
    # dummy_ = mpak(res,keep='Severity {severity}')      # more realistic
```

```
input dataframe:
      A      B  A_ORIG  B_ORIG
2020 100.000000 110.000000 100.000000 110.000000
2021 102.000000 112.200000 102.000000 112.200000
2022 109.040000 119.444000 104.040000 114.444000
2023 111.120800 121.732880 106.120800 116.732880
2024 113.343216 119.067538 108.243216 119.067538
2025 115.610080 121.448888 110.408080 121.448888
```

```
severity=0
Dataframe:
      A      B  A_ORIG  B_ORIG
2020 100.0 110.000000 100.000000 110.000000
2021 100.0 112.200000 102.000000 112.200000
2022 100.0 119.444000 104.040000 114.444000
2023 100.0 121.732880 106.120800 116.732880
2024 100.0 119.067538 108.243216 119.067538
2025 100.0 121.448888 110.408080 121.448888
```

```
Growth:
      A      B  A_ORIG  B_ORIG
2020 NaN      NaN      NaN      NaN
2021 0.0 2.000000 2.0      2.0
2022 0.0 6.456328 2.0      2.0
2023 0.0 1.916279 2.0      2.0
```

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```

2024  0.0 -2.189501      2.0      2.0
2025  0.0  2.000000      2.0      2.0

severity=0.5
Dataframe:
      A      B      A_ORIG      B_ORIG
2020 100.000000 110.000000 100.000000 110.000000
2021 100.500000 117.200000 102.000000 112.200000
2022 101.505000 124.444000 104.040000 114.444000
2023 103.027575 126.732880 106.120800 116.732880
2024 105.088126 124.067538 108.243216 119.067538
2025 107.715330 126.448888 110.408080 121.448888

Growth:
      A      B      A_ORIG      B_ORIG
2020 NaN      NaN      NaN      NaN
2021 0.5  6.545455      2.0      2.0
2022 1.0  6.180887      2.0      2.0
2023 1.5  1.839285      2.0      2.0
2024 2.0 -2.103118      2.0      2.0
2025 2.5  1.919399      2.0      2.0

severity=1
Dataframe:
      A      B      A_ORIG      B_ORIG
2020 100.000000 110.000000 100.000000 110.000000
2021 101.000000 122.200000 102.000000 112.200000
2022 103.020000 129.444000 104.040000 114.444000
2023 106.110600 131.732880 106.120800 116.732880
2024 110.355024 129.067538 108.243216 119.067538
2025 115.872775 131.448888 110.408080 121.448888

Growth:
      A      B      A_ORIG      B_ORIG
2020 NaN      NaN      NaN      NaN
2021 1.0 11.090909      2.0      2.0
2022 2.0  5.927987      2.0      2.0
2023 3.0  1.768240      2.0      2.0
2024 4.0 -2.023293      2.0      2.0
2025 5.0  1.845042      2.0      2.0

```

### 6.1.20 .upd(,lprint=True ) prints values the before and after update

The `lPrint` option of the method `upd()` is by default = `False`. By setting it true an update command will output the results of the calculation comapriong the values of the dataframe (over the impacted period) before, after and the difference between the two.

```

df.upd('''
# Same number of values as years
<2021 2022> A * 42 44
''',lprint=1)

```

```
Update * [42.0, 44.0] 2021 2022
A          Before      After      Diff
2021      102.0000     4284.0000    4182.0000
2022      109.0400     4797.7600    4688.7200
```

```

          A          B      A_ORIG      B_ORIG
2020  100.000000  110.000000  100.000000  110.000000
2021  4284.000000  112.200000  102.000000  112.200000
2022  4797.760000  119.444000  104.040000  114.444000
2023  111.120800  121.732880  106.120800  116.732880
2024  113.343216  119.067538  108.243216  119.067538
2025  115.610080  121.448888  110.408080  121.448888
```

### 6.1.21 .upd(,create=True ) Requires the variable to exist

Until now .upd has created variables if they did not exist in the input dataframe.

To catch misspellings the parameter `create` can be set to `False`. New variables will not be created, and an exception will be raised.

Here Python's exception handling is used, so the notebook will continue to run the cells below.

```
try:
    xx = df.upd(''
    # Same number of values as years
    <2021 2022> Aa * 42 44
    '', create=False)
    print(xx)
except Exception as inst:
    xx = None
    print(inst)
```

```
Variable to update not found:AA, timespan = [2021 2022]
Set create=True if you want the variable created:
```

## **Part III**

# **References**



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