

Applying Symbolic Mathematics in Stata using Python

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2020 Stata Conference

7/31/2020

Introduction

- Stata 16 includes integration with Python through the Stata Function Interface (SFI).
- This opens up opportunities to use Stata as a computer algebra system.
- I will demonstrate basic usage through an application substituting empirical elasticities into a dynamic labor supply model.

Computer Algebra Systems

- Commonly used via software like *Mathematica*.
- Represent mathematical expressions in an abstract symbolic (rather than numeric) form.
 - Allows exact evaluation of expressions like π or $\sqrt{2}$.
- Perform operations like expression evaluation, differentiation, integration, etc.
- Stata's Python integration allows performing symbolic computations in Stata via the *SymPy* library.

SymPy

SymPy is a Python library for symbolic mathematics. It aims to become a full-featured computer algebra system (CAS) while keeping the code as simple as possible in order to be comprehensible and easily extensible.

Info: <https://www.sympy.org/>



Figure 1: SymPy
Logo

SymPy Installation

- Part of many Python package managers (Anaconda, Pip, etc)

```
! pip install sympy
```

SymPy Usage

- Enter python environment, load module, and perform symbolic calculations:

• python

```
----- python (type  
> end to exit) -----  
>>> import sympy  
>>> x, y = sympy.symbols('x y')  
>>> expr = x + (y**2 / 2)  
>>> print(expr)  
x + y**2/2  
>>>  
>>>  
>>>  
>>>
```

SymPy Usage

```
>>> # prettier printing:
... sympy.init_printing(use_unicode=True)
>>> expr
      2
     y
x + —
     2
>>> expr * x**2
      (  2 )
  2 |   y |
x · | x + — |
      (  2 )
>>>
>>>
>>>
```

SymPy Usage

```
>>> # solver
... from sympy import solve, diff, sin
>>> solve(x**2 - 2,x)
[-√2, √2]
>>> diff(sin(x)+x,x)
cos(x) + 1
>>> end
```

Empirical Application

- In Lippold (2019), I develop a dynamic labor supply model that compares changes in work decisions after a temporary versus permanent tax change.
 - Agents decide each period whether to work based on wages, income, tax rates, etc.
 - My study uses a temporary tax change for identification, so want to estimate the response if the change was permanent.
- Formally, I relate the compensated steady-state elasticity of extensive margin labor supply ϵ_s to the intertemporal substitution elasticity ϵ_I .

Model

The model equation is

$$\varepsilon_I \approx \left(\frac{1 - \frac{\gamma W_t}{1-s_t} \left(1 - \frac{2\alpha}{1+r_t} + \frac{(2+r_t)\alpha^2}{(1+r_t)^2} \right)}{1 - \frac{\gamma W_t}{1-s_t}} \right) \varepsilon_s$$

where the relationship varies based on

- The coefficient of relative risk aversion γ
- The marginal propensity to save α (equal to $1 - \mu$, where μ is the marginal propensity to consume)
- The interest rate on assets r_t
- The savings rate s_t
- The percent change in post-tax income when working W_t

Empirical Estimates

- Using variation in tax rates from the Child Tax Credit, I compute ε_I with a regression discontinuity design in Stata.
- I then want to plug my results into my formula. The usual methods:
 - Enter into a calculator or Excel by hand. (Not programmatic, prone to error).
 - Solve an expression written using macros. (Hard to modify expression in future).
- The SFI creates a direct link from the empirical estimate to the symbolic formula.

Import LaTeX Formula

. python:

```
----- python (type  
> end to exit) -----  
>>> import sympy as sp  
>>> gamma, alpha, w, s, r = sp.symbols(r'\gamma \alpha W_{t}  
> s_{t} r_{t}')  
>>> formula = r"\frac{\left(1-\frac{\gamma W_{t}}{1-s_{t}}\right)\left(1-\frac{2\alpha}{1+r_{t}}+\frac{\left(2+r_{t}\right)\alpha^2}{\left(1+r_{t}\right)^2}\right)\left(1-\frac{\gamma W_{t}}{1-s_{t}}\right)}{\left(1-\frac{\gamma W_{t}}{1-s_{t}}\right)}"  
>>> # clean up for parsing  
... formula = formula.replace(r"\right", "").replace(r"\left"  
> , "")  
>>>  
>>>
```

Import LaTeX Formula

```
>>> # parse
... from sympy.parsing.latex import parse_latex
>>> multiplier = parse_latex(formula)
>>> multiplier
```

$$\begin{aligned}
 & W_{\{t\}} \cdot \gamma \cdot \left(\frac{\alpha \cdot (r_{\{t\}} + 2)}{(r_{\{t\}} + 1)^2} + \frac{2 \cdot \alpha}{r_{\{t\}} + 1} + 1 \right) \\
 & - \frac{1 - s_{\{t\}}}{1 - s_{\{t\}}} + 1
 \end{aligned}$$

$$\begin{aligned}
 & - \frac{W_{\{t\}} \cdot \gamma}{1 - s_{\{t\}}} + 1
 \end{aligned}$$

Import LaTeX Formula

```
>>> m = multiplier.subs([('gamma',1),(s,-0.02), ('alpha',0.7  
> 5), (r,0.073)])  
>>> m  
1 - 0.602791447544363·W_{t}  
-----  
1 - 0.980392156862745·W_{t}  
>>> end
```

Compute Empirical Values

After running my main analysis code, I have computed the following empirical values:

```
. scalar list
      W_t = .80264228
      epsilon_I = 1.0401141
```

I can then plug these values into the previous formula to get the desired statistic.

```
. python
----- python (type
> end to exit) -----
>>> import sfi
>>>
>>>
```

Compute Empirical Values

```
>>> # empirical elasticity
... epsilon_I = sfi.Scalar.getValue("epsilon_I")
>>> # empirical return to work
... W_t = sfi.Scalar.getValue("W_t")
>>> m.subs([(w,W_t)])
2.42226308973109
>>> epsilon_s = epsilon_I / m.subs([(w,W_t)])
>>> print(epsilon_s)
0.429397657197176
>>> end
```

Standard Errors via Bootstrapping

get_elasticity.ado:

```
prog def get_elasticity, rclass
    // analysis code...
    return scalar epsilon_I = //...
    return scalar W_t = //...
python script py_compute.py
```

end

py_compute.py:

```
# repeat earlier code to get multiplier 'm'...
epsilon_I = sfi.Scalar.getValue("return(epsilon_I)")
W_t = sfi.Scalar.getValue("return(W_t)")
epsilon_s = epsilon_I / m.subs([(w,W_t)])
result = sfi.Scalar.setValue('return(epsilon_s)',epsilon_s)
```

Run Bootstrap

```
. set seed 77984
```

```
. bs elasticity = r(epsilon_s), reps(50): get_elasticity
(running get_elasticity on estimation sample)
```

```
Bootstrap replications (50)
```

```
-----+----- 1 -----+----- 2 -----+----- 3 -----+----- 4 -----+----- 5
..... 50
```

```
Bootstrap results                               Number of obs   =       9,443
                                                Replications   =         50
```

```
command: get_elasticity
elasticity: r(epsilon_s)
```

	Observed	Bootstrap			Normal-based
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
elasticity	.4293977	.205351	2.09	0.037	.026917 .8318783

Conclusion

- Using SymPy with Stata 16 opens up exciting possibilities to incorporate symbolic mathematics into Stata computations.
 - Solve equations with computer algebra, then substitute returned results.
 - Close correspondence between LaTeX output and code
- New pystata features announced yesterday would allow using these methods in Jupyter notebooks.
- Code will be available at <https://www.kyelippold.com/data>

References

- Lippold, Kye. 2019. "The Effects of the Child Tax Credit on Labor Supply." *SSRN Electronic Journal*.
<https://doi.org/10.2139/ssrn.3543751>.

Sensitivity plots

```
from numpy import linspace
import matplotlib.pyplot as plt
substitutions = [('gamma', 1, 0, 2), (w, W_t, 0, 1), \
                 (s, -0.02, -.05, .1), ('alpha', 0.75, .5, .9), (r, 0.073, 0, .1)]
for param in substitutions:
    name = param[0]
    others = substitutions.copy()
    others.remove(param)
    sub = [(vals[0], vals[1]) for vals in others]
    expr = multiplier.subs(sub)
    lam_x = sym.lambdify(name, expr, modules=['numpy'])
    x_vals = linspace(param[2], param[3], 100)
    y_vals = lam_x(x_vals)
```

Sensitivity plots

```
plt.figure()
plt.plot(x_vals, y_vals)
plt.ylabel(r'$\frac{\epsilon_I}{\epsilon_S}$', \
           rotation=0, fontsize=12, y=1)
plt.xlabel(r'\${}\$'.format(name), fontsize=12, x=1)
plt.ylim(0,4)
#plt.show() # to see in session
disp_name = str(name).replace("\\", "").replace("_{t}", "")
plt.savefig('fig_{}.pdf'.format(disp_name))
plt.close()
```

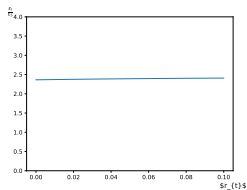
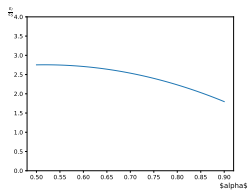
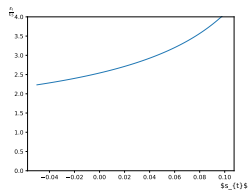
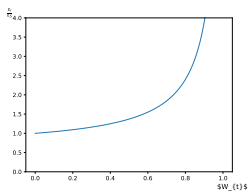
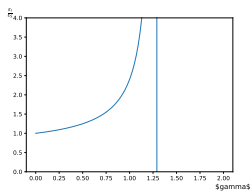
(a) r (b) α (c) s_t (d) W_t (e) γ

Figure 2: Sensitivity of Results to Parameter Values