# solve-transition

March 21, 2019

# 1 Steady states

Out[6]: true

### 1.1 Solving steady state solutions

Set up parameters and find the corresponding stationary solution:

Below are the results from the **updated** matlab calibration with the corresponding letters. Here I added the  $\mu$  parameter in the calibration routine to fit the firm dynamic moments. Fit improved a lot and it generated a negative drift term which is what we need to keep S from going negative.

Side note on previous version. Essentially, under this calibration, the parameters are very simmilar. Theta, chi, kappa are quite close to what we had in the prior version.

In [7]: # Define common objects.

#parameters = parameter\_defaults()

```
settings = settings_defaults()
        settings = merge(settings, (transition_penalty_coefficient = 1.0, ))
        z_grid = settings.z
        P = length(z_grid)
        d_0 = parameters.d # Here is the 10 percent tariff increase
        d_T = 1 + (parameters.d-1)*0.90
        d_{autarky} = 1 + (parameters.d-1)*2.5
        params_0 = merge(parameters, (d = d_0, )) # parameters to be used at t = 0
        params_T = merge(parameters, (d = d_T, )) # parameters to be used at t = T
        params_autarky = merge(parameters, (d = d_autarky, )) # parameters to be used in autar
        # initial value for numerical solver on (g, z_hat, Omega)
        initial_x = [0.02; 2; .57]
        # solve for stationary solution at t = 0
        stationary_sol_0 = stationary_algebraic(params_0, initial_x) # solution at t = 0
        stationary_sol = stationary_algebraic(params_T, initial_x) # solution at t = T
        stationary_autarky = stationary_algebraic(params_autarky, initial_x) # solution at t =
        _0 = stationary_sol_0.;
        _T = stationary_sol.;
In [8]: d_0
Out[8]: 5.0672
In [9]: print(stationary_sol.U_bar,'\n')
        print(stationary_sol_0.U_bar,'\n')
        print(stationary_sol_0.S,'\n')
        print(stationary_autarky.S,'\n')
31.960806397169257
25.335205621937796
0.08792930215911846
0.06111189985043804
In [10]: \#T = solved.t[end]
         lambda_ss = 100*(consumption_equivalent(stationary_sol.U_bar, stationary_sol_0.U_bar,
```

```
print("SS to SS welfare gain: ", lambda_ss,"\n")
    print("SS to SS welfare gain: ", stationary_sol._ii,"\n")

SS to SS welfare gain: 13.791679181400385
SS to SS welfare gain: 0.8650014500550756

In [11]: print("SS to SS welfare gain: ", stationary_sol.g,"\n")
SS to SS welfare gain: 0.011575084222623117
```

### 1.1.1 This is the autarky calculation

## 1.2 Welfare in Steady States

#### 1.2.1 Steady state at T

```
In [13]: stationary_sol.U_bar
Out[13]: 31.960806397169257
```

### 1.2.2 Steady state at 0

```
In [14]: stationary_sol_0.U_bar
Out[14]: 25.335205621937796
```

#### 1.2.3 Outstanding Issue #1: Sensitivity of growth to trade.

This is a big difference relative to previous version. As noted above, with parameter values that are quite similar to what we had before, the growth rate is changing a lot with only a very small change in trade flows. Why?

```
In [15]: @show stationary_sol.g, stationary_sol_0.g;
(stationary_sol.g, stationary_sol_0.g) = (0.011575084222623117, 0.008840735918269178)
```

# 2 Transition dynamics

Setup for optimizer:

#### 2.1 Welfare Gains

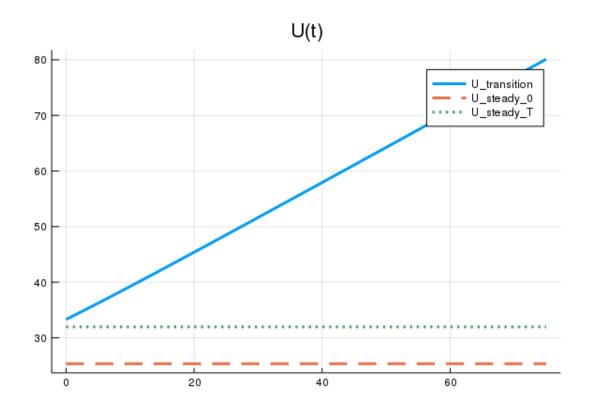
**Summary so far...** In the old paper, what we did was take U\_0\_ss at some date t, then compare it to U\_ss at the same date t. This is like an instantaneous jump to the new ss. This is what the first cell is looking at and note that this is like a 17 percent increase in utility. Higher than what we had in the paper, but in of the same order of magnitude.

The next cell reprots the utility just after the change. Utility here includes the future path of consumption and change in growth rate, so it "bakes in" the transition path. Here it goes up by much more than utility in the new SS. This is what I was expecting given the dynamics of consumption.

Just a reminder about how the function counsumption\_equivalent(U\_new, U\_old, parameters) works, it takes U\_new and then U\_old in that order, then evaluates the **gross** increase in consumption. 100 times this value **minus one** gives the permanent, percent increase in consumption required to make the agent indifferent between the two paths.

### 2.1.1 Relative to initial notebook computations

- SS to SS, the issue here is that we should compare at date 0 utility in the first ss vs. the second ss. This is what we must have been doing in the previous version of the paper. The previous calulation in the old notebook had consumption\_equivalent(solved.U[end], stationary\_sol\_0.U\_bar, parameters) which took date T utility and compard them. The problem is that this now depends on date T. So if we picked T to be arbitraily large, then utility will be arbitraily different.
- Following the same logic, the transition path should compare **date 0** utility with the initial value from the transition path. So what we want to do is to compare everything at 0. In the previous calculation, we had consumption\_equivalent(solved.U[1], stationary\_sol\_0.U\_bar, parameters) were comparing the initial utility relative to ss utility on the old path at date T. So the initial blue point below versues the last orange dashed point. **See the figure below**



## 2.1.2 Outstanding Issue #2: Welfare Gains still depend on T in transition path.

The stuff above I think is correct, the one issue is why does the welfare gains, inclusive of the transition path seem to depend on T??? So change T above from 40 to 75 or 100, then the welfare gains fall alot? Why?

## 2.2 Plotting

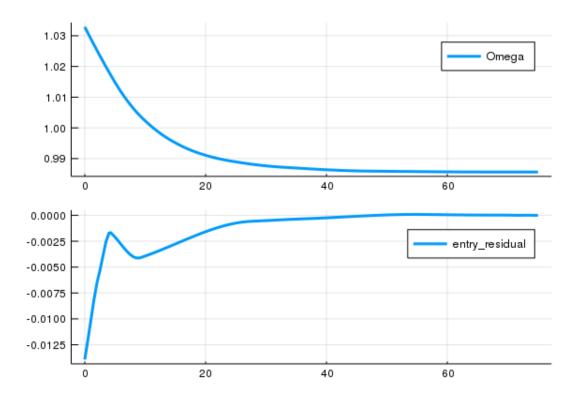
```
In [24]: solved.U[end]
```

Out [24]: 80.11612246846532

### 2.3 Plots for and residuals

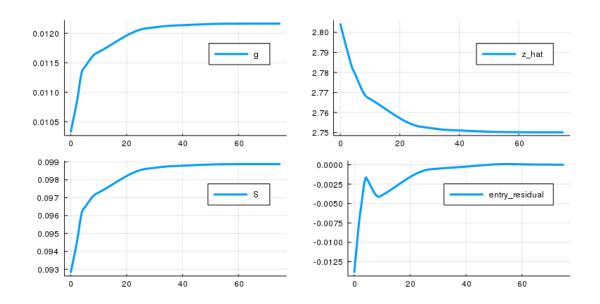
```
In [25]: #solved = solved.results;
    plot_ = plot(solved.t, solved., label = "Omega", lw = 3)
    plot_residual = plot(solved.t, solved.entry_residual, label = "entry_residual", lw = 3
    plot(plot_, plot_residual, layout = (2,1))
```

Out[25]:



# 2.4 Primary Plots

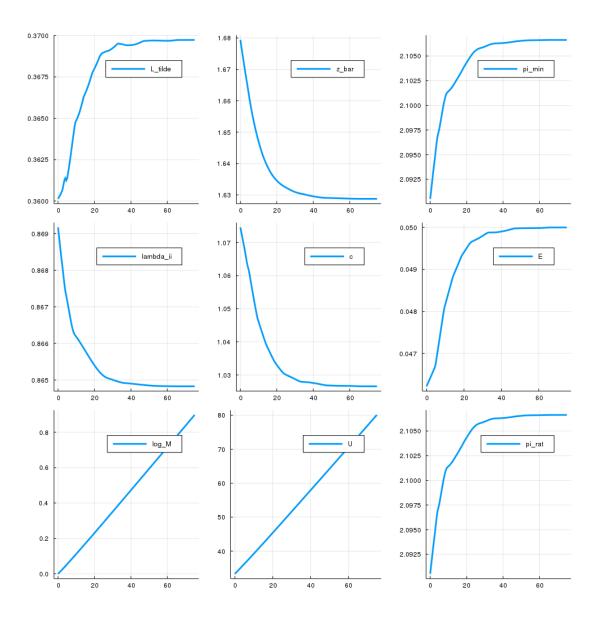
Out [26]:



# 2.5 Static Equations

```
In [27]: plot1 = plot(solved.t, solved.L_tilde, label = "L_tilde", lw = 3)
    plot2 = plot(solved.t, solved.z_bar, label = "z_bar", lw = 3)
    plot3 = plot(solved.t, solved._rat, label = "pi_min", lw = 3)
    plot4 = plot(solved.t, solved._ii, label = "lambda_ii", lw = 3)
    plot5 = plot(solved.t, solved.c, label = "c", lw = 3)
    plot6 = plot(solved.t, solved.E, label = "E", lw = 3)
    plot7 = plot(solved.t, solved.log_M, label = "log_M", lw = 3)
    plot8 = plot(solved.t, solved.U, label = "U", lw = 3)
    plot9 = plot(solved.t, solved._rat, label = "pi_rat", lw = 3)
    plot(plot1, plot2, plot3, plot4, plot5, plot6, plot7, plot8, plot9, layout=(3,3), size
```

Out [27]:



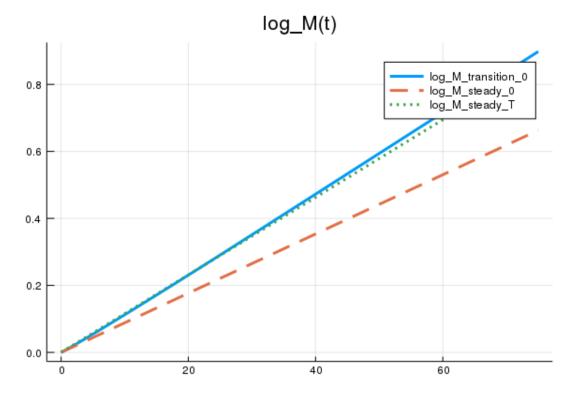
# 3 Welfare analysis

## $3.0.1 \log_M(t)$

```
In [28]: # define log_M with steady state g
    log_M_steady_0(t) = stationary_sol_0.g * t
    log_M_steady_T(t) = stationary_sol.g * t

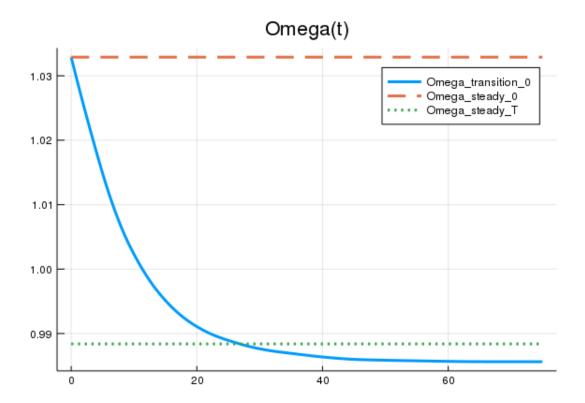
# generate the plot!
plot(solved.t,
    [solved.log_M, log_M_steady_0, log_M_steady_T],
    label = ["log_M_transition_0", "log_M_steady_0", "log_M_steady_T"] ,
    title = "log_M(t)", linestyle = :auto, lw = 3)
```

# Out[28]:



# 3.0.2 (t)

Out[29]:

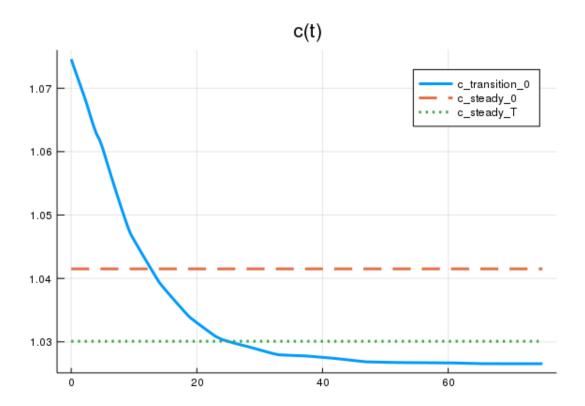


```
c_steady_0(t) = stationary_sol_0.c
c_steady_T(t) = stationary_sol.c

# generate the plot!
plot(solved.t,
       [solved.c, c_steady_0, c_steady_T],
       label = ["c_transition_0", "c_steady_0", "c_steady_T"] ,
       title = "c(t)", linestyle = :auto, lw = 3)
```

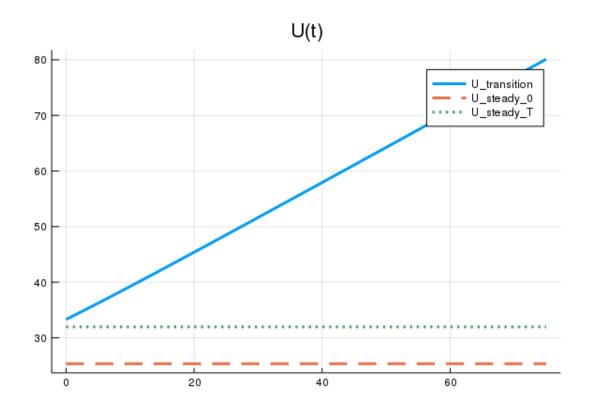
## Out[30]:

3.0.3 c(t)



### 3.0.4 U(t)

# Out[31]:



## 3.1 Consumption equivalent for search threshold (M(0))

See computational appendix for details.

## 3.1.1 M(0) by two steady states (autarky and steady state at T)

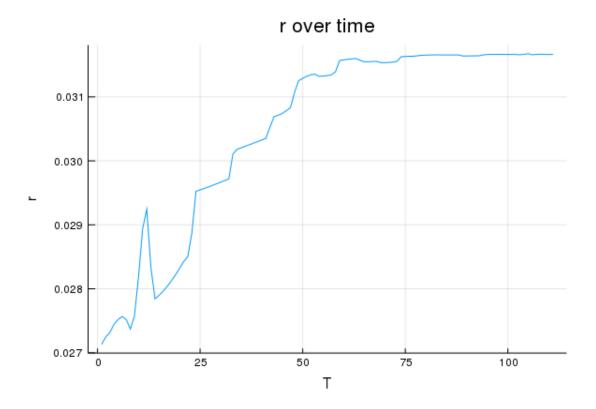
Out[32]: 2.9102176683529106

## 3.1.2 M(0) by autarky and transition from t=0

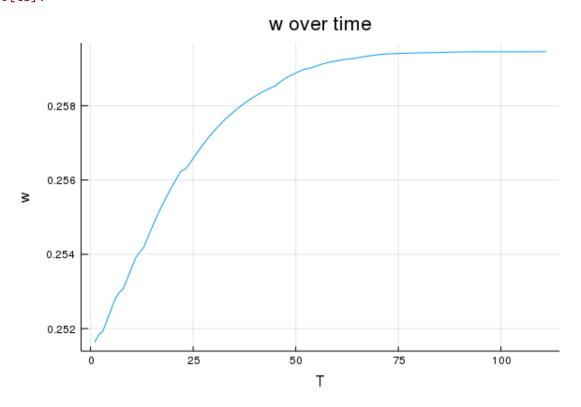
Out [33]: 1.1680672085349637

But if we include the transition path, this falls a lot. Like down to 13 percent gain.

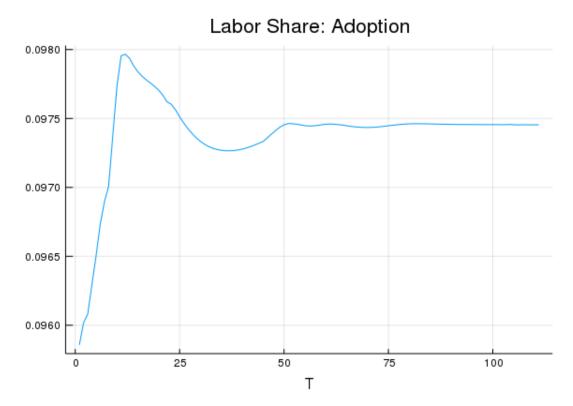
```
In [35]: using DataFrames
         df_stationary = DataFrame(t = -1.00, g =stationary_sol_0.g, _ii = stationary_sol_0._i
             _rat = stationary_sol_0._rat, L_tilde_a = stationary_sol_0.L_tilde_a, L_tilde_x =
In [36]: CSV.write("stationary_results.csv", df_stationary)
Out[36]: "stationary results.csv"
In [37]: df_transition = DataFrame(t = solved.t, g =solved.g, _ii = solved._ii, c = solved.c, !
             _rat = solved._rat, L_tilde_a = solved.L_tilde_a, L_tilde_x = solved.L_tilde_x, L
In [38]: CSV.write("transition_results.csv", df_transition)
Out[38]: "transition_results.csv"
In [39]: stationary_sol_0._rat
Out [39]: 1.7250561867295242
In [40]: df_welfare = DataFrame(steady_state = lambda_ss, transition_path = lambda_tpath, grow
         CSV.write("welfare_results.csv", df_welfare)
Out[40]: "welfare_results.csv"
In [41]: df_autarky = DataFrame(steady_state = lambda_ss_autarky, growth_rate = stationary_autarky)
         CSV.write("autarky_welfare_results.csv", df_autarky)
Out[41]: "autarky_welfare_results.csv"
3.1.3 R and W
In [42]: plot(solved.r, legend = false, title = "r over time", xlabel = "T", ylabel = "r")
Out [42]:
```



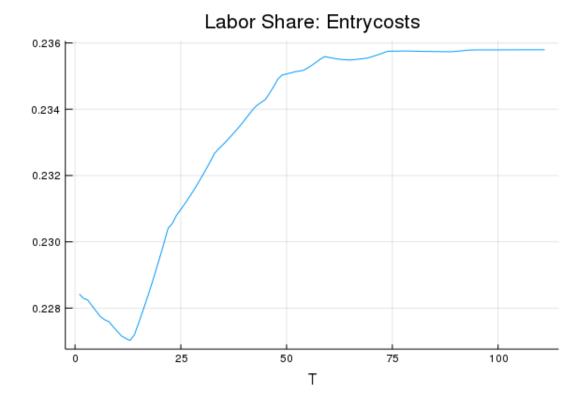
In [43]: plot(solved.w, legend = false, title = "w over time", xlabel = "T", ylabel = "w")
Out[43]:



In [44]: plot(solved.L\_tilde\_a, legend = false, xlabel = "T", title = "Labor Share: Adoption")
Out[44]:



In [45]: plot(solved.L\_tilde\_E, legend = false, xlabel = "T", title = "Labor Share: Entrycosts
Out[45]:



In [46]: plot(solved.L\_tilde\_x, legend = false, xlabel = "T", title = "Labor Share: Export")
Out[46]:

