## Problem Set 9: Simulated Method of Moments

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#### 1 Introduction

In this problem set, I will use Simulated Method of Moments (SMM) to estimate the parameters in the firms' problem. The codes I used in this problem set are benefited from the discussions with Foteini, Justin, Mathew, Zehra, Alex, and Destan. I appreciate their help in some parts of the codes, especially the simulation part. The structure of this problem set is as follows. In section 2, I will briefly go through the SMM method. Section 3 will explain the codes. Section 4 describes the estimation results.

### 2 Simulated Method of Moments

Simulated Method of Moments estimates the parameters of a structured model by simulating the model and minimizing the difference between the model moments and actual data moments.

The SMM estimator is:

$$\hat{\theta}_{S,T}(W) = \underset{\theta}{\operatorname{argmin}} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta))) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} \left[ \sum_{t=1}^{T} (\mu(x_t) - \frac{1}{S} \sum_{s=1}^{S} \mu(x(u_t^s, \theta)) \right]^T W_T^{-1} W_T^{-$$

The most important part is to simulate the moments under several restrictions regarding firm's optimization rules. In this problem set, the policy function k' = f(z, k) and the value function V = v(z, k) are used to simulate the moments.

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# 3 Explain The Codes

I have two separate codes to replicate Tables 2 (unconstraint) and 3 (with costly financing), respectively <sup>1</sup>. Because the only difference between them is that in Table 3, there is an additional parameter,  $\tilde{\phi}_0$ , that needs to be estimated. I will focus on demonstrating the steps in replicating Table 2.

There are three main steps to replicate Table 2. First, I need to solve out the partial equilibrium problem for the firm. I.e., given a guessed wage rate, I need to find the optimal investment decision rules. Second, I use the partial equilibrium equations to simulate the moments which are functions of  $\Theta$ . Third, I compare the simulated moments with the data moments and use a global minimizer to find the optimal  $\Theta$ , or  $\hat{\Theta}$  which returns the lowest difference between the simulated moments and the data moments.

# 4 Report The Results

This section reports the replication results. Table 1 reports estimated coefficients and standard errors calculated using identity matrix. Table 2 reports corresponding replication results of Table 3 in the paper.

**Table 1:** Replication Results of Table 2

	$\alpha_k$	$\psi$	ρ	$\sigma$
Point Estimates	0.023	0.101	0.026	0.004
Standard Errors	86.680	0.615	0.791	38.788

**Table 2:** Replication Results of Table 3

	$\alpha_k$	$\psi$	$\rho$	$\sigma$	$ ilde{\phi_0}$
Point Estimates	0.307	0.065	0.165	0.445	0.001
Standard Errors	3.297	2.269	2.382	12.770	< 0.001

<sup>&</sup>lt;sup>1</sup>It would be more efficient to combine them into one .py file. But I really have a time constraint and decide to improve it latter