Evaluating the Effects of the COVID-19 Outbreak: Modification of the Eaton, et al. (2016) Trade Model

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Abstract

I study the outcomes produced by counterfactuals in a simplified version of the trade model presented by Eaton, et al. (2016). There are various questions I attempt to answer: How does the recent COVID-19 outbreak, in causing declines in productivity and consumer demand, affect the U.S. and China? Are these effects magnified by modifying certain model parameters away from the original values used by Eaton, et al.? I use generalized method of moments to estimate these parameters, and run counterfactuals. I find that my differently-estimated parameter values affects the behavior of capital and GDP for the U.S. and China in two counterfactuals: 1) Random shocks to exogenous variables and 2) COVID-19 shocks to exogenous variables. The effects are seen not only in levels of the variables, but in how the variables change. This suggests that the parameter values in Eaton, et al. (2016) have a significant impact on the model's findings when it comes to applying counterfactuals. If my estimates for such parameters are more accurate than those originally used in the model, this would change the findings presented in Eaton, et al. (2016).

1 Introduction

Trade and the Global Recession by Eaton, Kortum, Neiman, & Romalis (2016) formulates a dynamic multi-country, multi-sector general equilibrium trade model that incorporates shocks to exogenous variables such as investment efficiency, productivity, consumer demand preferences, and labor supply. With the model and these shocks, the behavior of various endogenous variables such as capital, bilateral trade shares, sectoral price indices, and investment spending can be observed. The goal of this paper is to use the model to conduct counterfactuals in order to understand what led to the decline in international trade in manufactures during the 2008-2009 global recession. In general, however, the model can incorporate numerous counterfactuals in the form of shocks to exogenous variables, and observe their effect on endogenous variables.

The motivation of my research is to assess the appropriateness of some of the EKNR model's weakly calibrated parameters. I believe that some of these parameter values were not taken from appropriate studies, and am concerned because some of the sources of these values are not made clear. I will estimate these parameters using OLS and generalized method of moments, and compare outcomes of two counterfactuals, using my estimates, with those produced by using EKNR's weakly calibrated estimates. One of the two counterfactuals is chosen to mimic the impact of the COVID-19 pandemic of 2020. I will be using data from 2000 - 2019.

Given that the original model proposed by Eaton, et al. incorporates 21 countries and 4 sectors, the number of parameters explodes, as most are specific at the country-sector level. Thus, for the purposes of estimation, I will examine a simpler 2-country 2-sector version of the model.[1] This version of the model will hereon be referred to as the EKNR model.

The paper is organized as follows. Section 2 provides an overview of the EKNR model and the parameters to be estimated. Section 3 describes the theory behind estimating each parameter. Section 4 describes the data, and Section 5 describes the estimation strategy. Section 6 summarizes the estimation results. Section 7 shows how my estimated parameter values affect the outcomes of two counterfactuals, one given as an example by Eaton, et al., and the second, chosen to mimic the COVID-19 outbreak. These are compared to the results produced when the model uses the weakly calibrated parameters. Finally, section 8 concludes.

2 The EKNR Model and Parameters of Interest

What follows is a brief description of the relevant components of the EKNR model. A fuller description, released by Eaton, et al. is publicly available.[2]

The EKNR model is a two-country model that incorporates two sectors: durables and services. Durables, denoted by D, produces a capital good, while services, denoted by S, produces a consumption good. Durables can be traded, while services can not be. There are no intermediate inputs, and capital stock is used only for production.

Certain components of EKNR are standard of recent trade models. After defining firm production functions, consumer utilities, market constraints, and a capital law of motion, an Euler equation is derived. Assuming that all endogenous variables reach a steady state, the path of endogenous variables can be predicted, in response to shocks to exogenous variables. A planner's problem is used to characterize the solution.

Two central equations which rely on parameters I have chosen to estimate are:

$$Y_{n,t} = A^D_{n,t} L_n^{\beta_L} K_n^{\beta_K} \tag{1}$$

$$K_{n,t+1} = \chi_{n,t} \left(\frac{X^D_{n,t}}{p^D_{n,t}} \right)^{\alpha} (K_{n,t})^{1-\alpha} + (1-\delta) K_{n,t} \tag{2}$$

(1) is the production function in the durables sector, D, which features Cobb-Douglas technology and constant returns to scale. Production is a function of productivity in the durables sector, A^D, and two inputs, labor L and capital K. β_L and β_K denote the output elasticities of labor and capital, respectively. Endowments of labor and capital are not traded.

(2) is the capital law of motion (also known as capital accumulation equation). Next period's level of capital depends on investment efficiency, χ, investment spending in durables, X^D, the price index for durables, p^D, α, which governs adjustment costs, and capital depreciation rate, δ.

Above, the subscript n denotes the country of interest, and t denotes the time period.

The parameters in equation (1) are β_L and β_K. The exogenous variables are L and A^D, and the endogeneous variables are Y and K. EKNR weakly calibrates both parameter values.

The parameters in equation (2) are α, and δ. The exogenous variable is χ. X and K are endogenous. Lastly, p^D, the price index of the durables sector, is a function of a combination of parameters, endogenous, and exogenous variables. The derivation of p^D is described in Section 3.2. This derivation is necessary to

[1] I have obtained the values used by Eaton, et al. for the parameters in this version.

[2] Eaton, et al., "Illustrating the Methodology in EKNR (2016): Some Simple Examples", 2016.

understand the calibration procedure of α and δ. EKNR weakly calibrates α, δ, and the parameter, trade elasticity, denoted by θ, upon which p^D depends.

I am interested in estimating β_L, β_K, α, and δ, using GMM methods. There is a common misconception that production function coefficients can simply be estimated through standard regression analysis, but in reality, there are significant issues with endogeneity, spurious minima, and identification that arise with this approach (Olley & Pakes 1996; Levinsohn & Petrin, 2003; Ackerberg, Caves, & Frazer, 2015). I will base my approach on the methods developed by Ackerberg, Caves, and Frazer (2015), to account for these issues. My approach will differ from theirs in that I will specify that the production function is Cobb-Douglas and exhibits constant returns to scale. This is consistent with the production technology in EKNR.

The only parameter embedded in (1) or (2) that I will not be estimating is θ, which p^D in (2) depends on. Given that this is the trade elasticity measure and that I will be estimating my parameters using a two-country trade model, it does not seem that such an estimate would be meaningful. Additionally, there is plenty of literature that estimates θ to be approximately 2 (Backus, Kehoe, & Kydland, 1995; Eaton and Kortum, 2002). EKNR uses this value and shows that the model produces similar results with different values of θ.

After examining the sources of these weakly calibrated parameters, I have reason to suspect that some may not be appropriate for the EKNR model. I summarize the parameters and their sources of each parameter in Table 1.

	Description	EKNR Value	Bounds	Source
β_L	Labor Output Elasticity	0.66	[0,1]	Unclear
β_K	Capital Output Elasticity	0.33	[0,1]	Unclear
α	Adjustment Costs	0.55	[0,1]	Uncited literature
δ	Capital Depreciation	0.1	[0,1]	Greenwood, Hercowitz & Krusell (1997)

Table 1: Summary of EKNR parameters of interest

It is unfortunate that the sources of most of these values cannot be determined. For capital depreciation δ, Greenwood, Hercowitz & Krusell (1997) use a different, much more simple, capital accumulation equation involving δ and only variables available from the BEA. They solve their accumulation equation for δ, and take the average of δ over their sample years, 1954-1990, to obtain a number close to 0.1. This may not be appropriate, given that EKNR considers a more recent time period, 2000 - 2019, with a more complex accumulation equation, as shown in (2).

I will estimate the parameters in Table 1 using moments based on the EKNR model methodology. With these, I will conduct certain counterfactuals using the EKNR model and compare the outcomes using my estimates of the four parameters to those of the weakly calibrated values.

3 Theory

Now that I have established motivation for calibrating these parameters, I will describe the theory involved in deriving the moments of my GMM procedures. Since the output elasticities are estimated separately from the parameters characterizing equation (2), I will describe the theory and estimation procedures separately.

3.1 Production Function Estimation

The production function in EKNR is Cobb-Douglas with constant returns to scale. As previously mentioned, estimating production functions is not straightforward due to endogeneity, spurious minima, and identification issues. Literature on these issues over the past 25 years, most notably, Olley & Pakes (1996), Levinsohn & Petrin (2003), and Ackerberg, Caves & Frazer (2015) hereafter, ACF, has shown that, to counter these, it is necessary to introduce an intermediate input good. The theory described below uses ACF.
I estimate the following production function:

$$y_t = \beta_0 + \beta_L l_t + \beta_K k_t + \omega_t + \epsilon_t \tag{3}$$

where each lower case letter represents its uppercase corresponding letter in logs. For example, l_t denotes $\ln(L_t)$. ω_t represents an unobserved state variable that affects input and production levels. It is a function of k_t and m_t, and so l_t and k_t may be endogenous. Lastly, ϵ is an i.i.d. shock to production.

To address the endogeneity, I, as in ACF, introduce a proxy variable, m_t, which represents intermediate inputs. m_t is a function of l_t, k_t, and ω_t. The function to estimate, then becomes:

$$y_t = \beta_0 + \beta_L l_t + \beta_K k_t + h_t(l_t, k_t, m_t) + \epsilon_t = \hat{\phi}_t + \epsilon_t \tag{4}$$

Notice that m_t enters through the function h, where $\omega_t = h_t(l_t, k_t, m_t)$. The purpose of writing some of the terms as $\hat{\phi}$ is because estimation procedure will involve a standard OLS regression on this term, as a first step. Lastly, as in most production function estimation models, I assume that labor is chosen one period prior to other inputs. The impact of this assumption can be seen in the moments involved in estimating β_L and β_K. The moments will be described in Section 5.1.

3.2 Capital Law of Motion Derivation

The theory described below summarizes relevant components in the EKNR model for this paper. Estimating the parameters involved in the capital law of motion is not straightforward, for some variables are imputed from other data.
p^D from (2) can be restated as:

$$p^D_{n,t} = \left(\sum_{i=1,2} \left(\frac{b_{i,t} d_{ni,t}}{A^D_{i,t}} \right)^{-\theta} \right)^{-1/\theta} \tag{5}$$

Countries are indexed by n, i; time periods are indexed by t; and θ is the weakly calibrated trade elasticity measure, 2. $b_{i,t}$ represents the bundle of input factors, and $d_{ni,t}$ is the cost of trade for goods exported by country i to country n.

EKNR derives the following equation for bilateral trade shares:

$$\pi_{ni,t} = \left(\frac{b_{i,t} d_{ni,t}}{p^D_{n,t} A^D_{i,t}} \right)^{-\theta} \tag{6}$$

Bilateral trade shares can be thought of as the percentage of spending by country n in durables, that comes from imports from country i. (I do not involve a D superscript in this section, for legibility.) Notation of the order of countries in $d_{ni,t}$ and $\pi_{ni,t}$ is always importer (n), then exporter (i).

Lastly, $b_{i,t}$ the bundle of factors, is:

$$b_{i,t} = (w_{i,t})^{\beta_L} (r_{i,t})^{\beta_K} = \frac{Y_{i,t}}{L^{\beta_L}_{i,t} K^{\beta_K}_{i,t}} \tag{7}$$

Above, $w_{i,t}$ and $r_{i,t}$ are wage and rental rate, respectively. $Y_{i,t}$ is the total output, or GDP. Therefore, it is clear that the values of the output elasticities are inputs into b, and thus into the capital law of motion. To simplify computation, EKNR shows that shows that (2), and thus its related equations (5), (6) and (7), can be written in "changes" i.e. a ratio of the levels in the next period, to the current period. For a variable x, its form, in changes, is x_{t+1}/x_t.

With the notation in changes, (5) becomes:

$$\hat{p}^D_{n,t+1} = \left(\sum_{i=1,2} \pi_{ni,t} \left(\frac{\hat{b}_{i,t+1} \hat{d}_{ni,t+1}}{\hat{A}^D_{i,t+1}} \right)^{-\theta} \right)^{-1/\theta} \tag{8}$$

(6) becomes:

$$\hat{\pi}_{ni,t} = \left(\frac{\hat{b}_{i,t} \hat{d}_{ni,t}}{\hat{p}^D_{n,t} \hat{A}^D_{i,t}} \right)^{-\theta} \tag{9}$$

Given that $\hat{\pi}$, $\hat{X}$, $\hat{Y}$, $\hat{L}$, and $\hat{K}_{2001}$ can be computed or taken directly from data, $\hat{b}$, $\hat{d}$, $\hat{A^D}$ are exogenous, θ is taken as given, and β_L and β_K have previously been estimated, it is possible to solve for $\hat{p}^D$. With the capital law of motion written in changes:

$$\hat{K}_{n,t+2} = \hat{\chi}_{n,t+1} \left(\frac{\hat{X}^D_{n,t+1}}{\hat{p}^D_{n,t+1} \hat{K}_{n,t+1}} \right)^{\alpha} \left[\hat{K}_{n,t+1} - (1-\delta) \right] + (1-\delta) \tag{10}$$

It is possible to derive the path of K, and estimate α and δ via GMM. This procedure is described in Section 5.2.

4 Data

All moments will be calculated using annual data from the United States. This decision was based on the fact that the U.S. has readily accessible and reliable data on economic variables, and because the U.S. will be one of the two countries used in the counterfactuals run in Section 6.

To calculate the moments, data is needed on $\hat{X}$, $\hat{Y}$, $\hat{L}$, and $\hat{K}$ for the years 2000 - 2019. Data on investment spending in consumer durables, capital, and consumer durables GDP, is taken from the BEA NIPA database. Data on labor supply is taken from FRED.

Data is also needed to construct the bilateral trade shares, for these cannot be taken directly from the data. Following the methodology of Johnson & Noguera (2012) and Eaton, et al. (2016), it is necessary to obtain data on value added, sectoral shares of output, and gross output, from a combination of the OECD, WIOD, and CEPII BACI databases. A full description of how to construct π can be found in Appendix A.

5 Estimation Strategy & Results

The moments for each of the two GMM procedures are described below. For both, I use an identity weighting matrix. I chose not to use an alternative matrix, because, in production literature, this historically has not made a difference in estimation results, and in my estimation of α and δ, this led to no convergence, due to large values in the weighting matrix. I suspect that these large values resulted because the nature of these moments are in changes, and so the error matrix leads to very small values.

5.1 Output Elasticity Estimation

The estimation procedure is a modified version of ACF[3] and can be described in the following steps:

1. Estimate $\hat{\phi}$ by regressing y on inputs l, k, and m
2. Guess the the parameter vector for the inputs, $\boldsymbol{\beta} = (\beta_L, \beta_K)$ subject to CRS constraints[4]
3. Write the productivity shock as $\omega = \hat{\phi} - \boldsymbol{\beta x_t}$, where $\boldsymbol{x_t}$ is the vector of inputs
4. Assume ω follows a Markov process regress such that $\omega_t = g(\omega_{t-1}) + \eta_t$, where η is an innovation term[5]
5. Obtain $\hat{\eta}(\beta_L, \beta_K)$ by regressing $\beta_0 + \widehat{\omega_t(\beta_L, \beta_K)}$ on its lagged counterpart
6. Estimate $\boldsymbol{\beta}$ through GMM, with moments

$$\hat{\eta}_t(\beta_L, \beta_K) \times \begin{pmatrix} l_{t-1} \\ k_t \end{pmatrix} = 0$$

   * Labor in the previous period is involved, rather than labor in the current period, due to the assumption that labor is chosen prior to other inputs.

Thus, the GMM procedure for the estimation of the two output elasticities involves two moment conditions. The moment conditions are perfectly identified. For a more detailed summary on the derivation of these two moment conditions, please read Ackerberg, Caves, & Frazer (2015).

[3]ACF highlights concerns over the existence of spurious minima in their approach to production function estimation, but it has been shown in Kim, Luo and Su (2005) that this is only an issue when the true output elasticities take on extreme values (very close to 0 or 1). Thus, it is unlikely to affect my estimation, as I use real data.

[4]Flynn, Gandhi, & Traina (2019) show that making this assumption is fine for production function estimation.

[5]As with ACF, I use an AR(1) process.

5.2 Capital Law of Motion Parameter Estimation

Estimating α and δ involves a separate GMM procedure. To compute the model moments, it requires the data point $\hat{K}_{2000}$ to project a path for K.
The model moments are:

1. Average of $\hat{K}$: The average change, year-to-year in capital. The only years considered are years outside of the recession: 2001 - 2007, and 2013 - 2018.[6]

2. Average of $\frac{\hat{K}}{\hat{Y}}$: The average ratio of changes, year-to-year for capital to GDP (output). Again, only non-recession periods are considered.

3. $\text{Corr}(\hat{K}_{t+1}, \hat{K}_t)$: The correlation between the lagged and non-lagged path of capital. All years in 2001 - 2018 are considered.

The data moments are the analogous data terms (computed with $\hat{K}$ taken from the data, rather than computed using the capital law of motion in changes. Since we have three moments and two parameters to estimate, the moment conditions are overidentified. I use the euclidean distance for the error vector.

5.3 Dependency of GMM Procedures

Since β_L and β_K are inputs for a component in the capital law of motion, which is used to calculate model moments in the GMM procedure for α and δ, this second GMM procedure depends on the parameters from the first. Thus, I will examine exogenous shocks in four scenarios:

1. With all four parameters taking on the weakly calibrated values from EKNR, shown in Table 1

2. With β_L and β_K taking on the values shown in Table 1, and α and δ being computed via GMM

3. With β_L and β_K being computed via GMM, and α and δ taking on the values shown in Table 1

4. With all four parameters computed via GMM

These four scenarios are summarized in the tree diagram in *Figure 1.* I denote EKNR's estimates, from Table 1 by a dot $\dot{}$, and my estimates by a tilde $\tilde{}$. Since in scenarios 2 - 4, estimates of α and δ depend on estimates of β_L and β_K, α and δ, in these cases, will be denoted by two symbols, where the lower symbol denotes the methodology used for estimation of α and δ, and the upper symbol denotes the methodology used for estimation of β_L and β_K. For instance, $\dot{\tilde{\alpha}}$ denotes α that was estimated using EKNR's β values, and my GMM for estimation for α. Conversely, $\tilde{\tilde{\alpha}}$ denotes a parameter estimated using my methodology for both β values and α.

[6] This seemed appropriate, given the volatile behavior of various economic measures during the recession

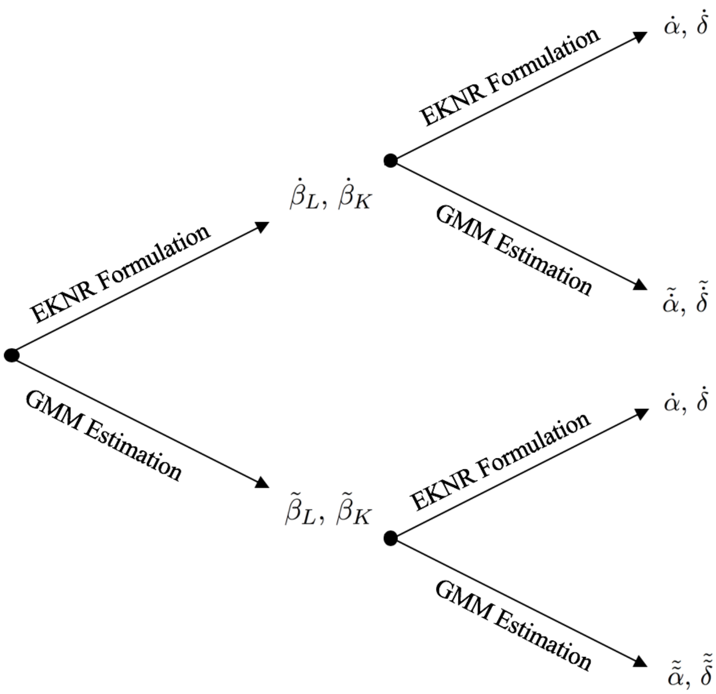

Figure 1: Four scenarios of parameter estimation

6 Estimation Results

The parameter values in all four scenarios are summarized in Table 2.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
β_L	0.66	0.66	0.672	0.672
β_K	0.33	0.33	0.328	0.328
α	0.55	0.4754	0.55	0.4747
δ	0.1	0.1225	0.1	0.1221

Table 2: Summary of Parameter Estimates

Given that the estimates of β_L and β_K are approximately the same as those used by EKNR, it is no surprise that the estimates of α and δ in scenarios 2 and 4 are roughly the same. What is interesting, however, is that the value estimated for adjustment cost α is about 14% different than that weakly calibrated in EKNR. This can be seen when comparing scenarios 2 and 4, to 1 and 3.

For Scenario 2, convergence occurred after 13 iterations, with a criterion value function of 0.0117. The errors were 0.000312, -0.000599, and 0.108 for moments 1, 2, and 3 respectively. For Scenario 4, the GMM procedure converged after 14 iterations, with a criterion value function of 0.0117. The errors were 0.000446, -0.000473, and 0.108 for moments 1, 2, and 3 respectively. Evaluation of the standard errors produced values of 12.8 for α and 24.7 for δ. This is quite large, however, I am wondering if this is again, due to the nature of the moments - that this may be a result of naturally small error vectors. Nevertheless, I continue, and present the counterfactuals.

7 Counterfactuals

To have a greater sense of how the parameter values affect the counterfactuals, for the following, I will compare the estimates in Scenario 1 and Scenario 4, from Table 2. In Figures 2 and 3, Scenario 1 will be denoted as "EKNR Parameters", and Scenario 4 will be denoted as "GMM Parameters."

7.1 Selection of Counterfactuals

I examine the output produced by the EKNR model in a setting where the two countries are China and the U.S. I use two different sets of shocks to exogenous variables:

1. Random shocks to the exogenous variables, given as an example by Eaton, et al.[7, 8] This is denoted as "Original Shocks" in Figure 2 and 3 below.
2. Exogenous shocks to productivity and consumer preferences, to simulate effects of the COVID-19 outbreak. This is denoted as "COVID-19 Shocks" in Figures 2 and 3 below. The rest of the shocks in this scenario are the same as the random shocks described in 1., above.

It is worth noting that as a result of these two sets of shocks being plotted, the effects on capital and GDP due only to the COVID-19 shocks can be backed out visually. These effects can be seen as the differences between analogous graphs for the endogenous variable and estimation procedure. For example, the COVID-19 shocks cause capital, shown in the upper left-hand figure in Figure 2, to behave as it does in the upper right-hand figure in Figure 2.

In simulating the counterfactual involving the COVID-19 outbreak, I choose to shock the exogenous variables productivity and consumer preferences. I will introduce a negative shock to productivity in durables in the U.S. of 15%. This is based on the behavior of real output in the U.S. manufacturing sector during the recession.[9] I will introduce an 8% negative shock to productivity in durables in China. This number is based on the behavior of the China Purchasing Managers Index during the recession, when compared to previous years.[10,11] Lastly, I will introduce a 4% negative shock to preferences for consumption (essentially a 4% negative shock to consumer durables expenditure) in China and the U.S. This number is based on the reported effects of pandemic influenza outbreaks on various economic measures.[12]

7.2 Results of Counterfactuals

The results of the counterfactuals can be seen graphically, below for each of two sets of shocks, and for each of the two countries. The paths of capital and GDP, in particular, are plotted. Note that the shocks are introduced in period 2. The choice of period 2 is arbitrary. The paths are shown for scenarios 1 and 4, from Table 2.

[7] A table of these shock values, given in changes, can be found in Appendix B

[8] Eaton, et al., "Illustrating the Methodology in EKNR (2016): Some Simple Examples", 2016.

[9] FRED

[10] Ycharts

[11] Although the data is from China and so may be unreliable, the purpose of this paper is to evaluate the effect of different calibration techniques for the parameters on the counterfactual outcomes. Thus it is the direction of the shock that matters, primarily.

[12] Loose, et al., "Economic and Policy Implications of Pandemic Influenza", 2010.

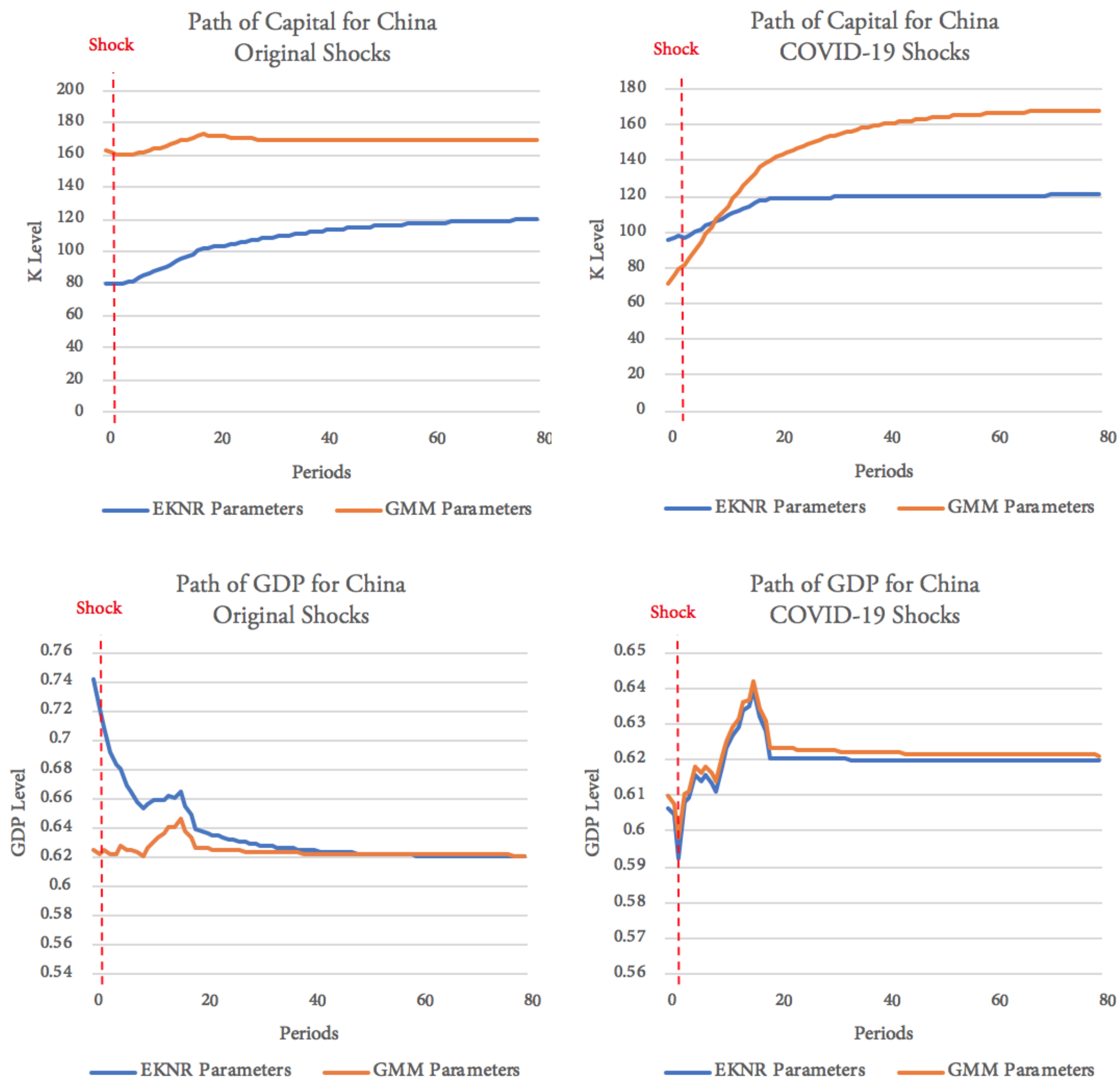

Figure 2: Comparison between EKNR method and GMM method of estimation of parameters on of behavior of capital and GDP for each set of shocks, for China

Note: The scales shown for capital and GDP are not meaningful for the purposes of this paper. It is more meaningful to examine the general trend of each path plotted, as well as how the EKNR and GMM paths behave relative to each other.

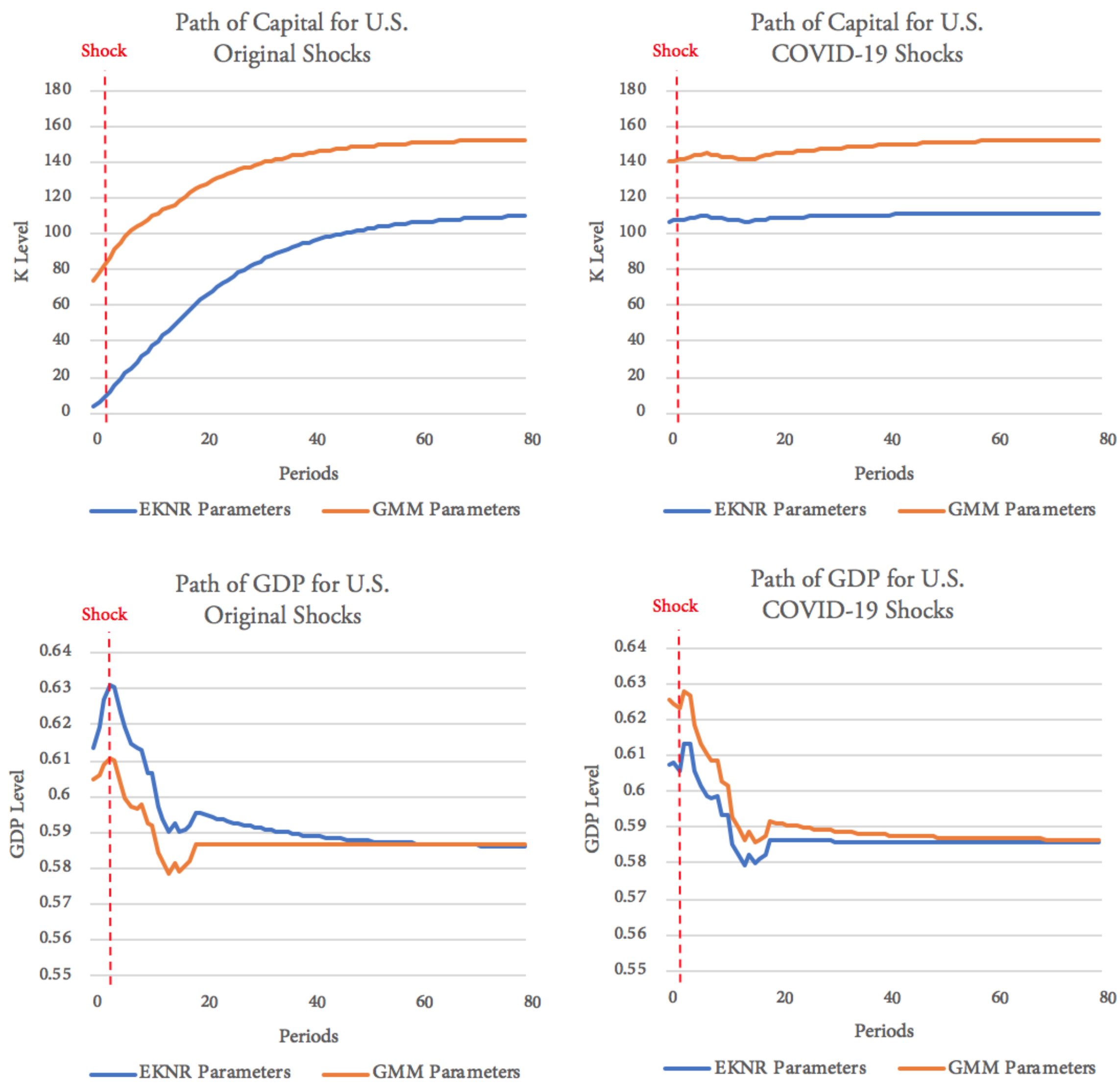

Figure 3: Comparison between EKNR method and GMM method of estimation of parameters on of behavior of capital and GDP for each set of shocks, for the U.S.

7.3 Discussion of the Effect of COVID-19

In the following discussion, it is important to keep in mind that since the EKNR model assumes a steady state, that the model involves "backing out" previous years' variable levels, such that a steady state can be reached. For this reason, we see that, across rows in each figure, that the paths reach the same level. For example, in the top row of Figure 2, in the GMM procedure, the steady state is around 168 in both shock scenarios. As the shocks are different, this leads to different paths of K, leading up to the steady state.

In assessing the behavior of capital and GDP when comparing the results in the original shock scenario and the COVID-19 shock scenario, the results are interesting. In Figure 2, the first row of figures indicates that the level of capital decreases with the COVID-19 shock. It decreases by about 50% initially in the GMM case (comparing across figures), but increases about 25% initially in the EKNR case. The second row of figures better aligns with the intuition in both estimation procedures: COVID-19 leads to a steep, negative drop, as soon as the shock kicks in. In Figure 3, capital experiences less growth over time with the COVID-19 shock, as seen in row 1. In the second row, notice that the relative position in levels of the EKNR and GMM cases swaps in the COVID case, compared to the original shock case.

7.4 Comparison of Counterfactuals for EKNR and GMM Estimation Methods

Since the EKNR model assumes a steady state, and this steady state depends on the parameters chosen, there may be very striking level differences between the EKNR and GMM methods of estimation. Thus, instead of purely comparing the estimation procedures on their level differences, it is also important to examine how the paths of K and GDP change in relative terms. In addition, in comparing the methods, it is more meaningful to compare them in the periods closer to the shock, rather than when each variable converges to its steady state in later periods.

Starting with Figure 2, there are differences when the original set of shocks is used. In this case, the GMM procedure seems to produce less volatile paths of capital and GDP. In the COVID-19 shock case, the path of GDP matches across the two estimation procedures pretty consistently, however, there seems to be a much faster recovery in capital, with the GMM case. This could be due to the fact that the GMM estimates include a lower measure of adjustment cost, α.

In Figure 3, which shows the same results but for the U.S., again, when the original set of shocks is used, the GMM method produces less volatile paths. In the COVID-19 shock case, the behavior of capital, in changes seems about the same, however the levels are much different. The GMM case predicts higher capital levels. Lastly, in the COVID-19 shock case, GDP seems to drop more steeply in the GMM case, although has a higher level overall.

8 Conclusion

Given that the effect of the estimation technique on the endogenous variables is not always consistent, this suggests that the four parameters estimated can affect the paths of capital and GDP in opposite directions. This is expected, given how the endogenous variables, in theory, rely on the parameters. Regardless, it seems clear that the parameters do have significant effects in certain cases, and so if the weakly calibrated EKNR variables are not in fact correct, this might raise concerns about the reliability in applying counterfactuals to the EKNR model, and thus the model presented by Eaton, et al.

Still, the GMM procedures presented above may not be optimal, for the results are accompanied by high standard errors. In addition, it is important to keep in mind that trade models involve many countries and sectors, and so it would be more applicable (although more tedious due to larger set of parameters) if I were to estimate the parameters in such a higher dimensional setting. As for addressing the effects of coronavirus, the exogenous shocks proposed may not be correct, as the situation is very active, and may have effects on various economic measures that are not similar to what the world has seen in previous recessions/pandemics. At the very least, I can be certain of the direction of the shocks, which is sufficient for examining the general behavior of capital and GDP.

My paper suggests that the parameter values in Eaton, et al. have a significant impact on the model's findings when it comes to applying counterfactuals. If my estimates for such parameters are more accurate than those originally used in the model, or more broadly, f the weakly calibrated values are not appropriate for the model, this would change the findings presented in Eaton, et al.

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Appendix

A. Construction of Bilateral Trade Shares

The following derivation of trade shares from the data involves subscript D, to denote durables. This is included here for clarity. As seen in Section 3, this superscript is relaxed, for legibility.

For the below, the notation is as follows:

- Value Added: VA
- Total expenditure: PE
- Total output: PY
- Net Exports: NX
- Gross Output: GO
- Trade Flow: TF (Note that the order of the countries, n and i, follows the same order as that in bilateral trade shares; n denotes the importer, and i denotes the exporter.)
- Bilateral Trade Share: π (Note that π^D_{nn} denotes country n's share of spending on durables, from itself.)

1. Collect/impute sectoral share of VA using methodology of Johnson & Noguera (2012)[13]
2. $VA^D =$ (Durable's Share of VA)(VA)
3. $P^D_{n,t}E^D_{n,t} = P^D_{n,t}Y^D_{n,t} - NX^D_{n,t}$
4. Impute right hand side of 3. : $\dfrac{VA^D_{n,t}}{\nu^D_n} - \displaystyle\sum_{i=1}^{2}\left(TF^n_{ni,t} - TF^n_{ni,t}\right)$

   where $\nu^n_i =$ Average of $\frac{VA^n_{i,t}}{GO^n_{i,t}}$
5. $\pi^D_{ni,t} = \frac{TF^D_{ni,t}}{P^D_{n,t}E^D_{n,t}}$
6. $\pi^D_{nn,t} = 1 - \displaystyle\sum_{i \neq n} \pi^D_{nit}$

[13] Johnson & Noguera, "Accounting for intermediates: Production Sharing and Trade in Value Added", Journal of International Economics, 2012

B. Shock Set 1, given by Eaton, et al.

	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10	t = 11	t = 12	t = 13	t = 14	t = 15	t = 16	t = 17	t = 18	t = 19	t = 20
Productivity in Durables Shocks																				
Country n	1.000	1.007	**0.990**	0.986	1.003	1.011	0.991	0.988	0.985	0.993	0.997	1.017	1.034	1.018	1.023	1.017	1.039	1.022	1.010	0.996
Country i	1.000	0.980	1.003	1.024	1.047	1.030	1.047	1.041	1.048	1.031	1.016	1.040	1.027	1.015	1.017	1.021	1.002	1.017	1.025	1.046
Chi Shocks																				
Country n	1.000	0.982	1.004	1.019	1.027	1.040	1.028	1.052	1.035	1.024	1.048	1.048	1.030	1.052	1.044	1.058	1.060	1.034	1.017	1.014
Country i	1.000	1.021	1.045	1.026	1.003	0.997	0.975	0.953	0.952	0.961	0.953	0.963	0.951	0.944	0.960	0.972	0.986	0.978	0.983	0.962
Trade Cost Shocks																				
n - i	2.000	1.974	1.967	1.961	1.937	1.967	1.938	1.928	1.898	1.877	1.891	1.888	1.875	1.856	1.837	1.844	1.819	1.835	1.832	1.820
i - n	2.000	1.991	2.010	1.993	1.966	1.995	2.000	1.983	2.004	1.974	1.984	1.993	1.997	2.013	2.025	2.017	2.036	2.065	2.064	2.060
Intertemporal Preferences Shocks																				
Country n	1.000	0.996	1.003	1.001	0.999	1.011	1.017	1.016	1.016	1.009	1.018	1.024	1.034	1.036	1.047	1.047	1.048	1.045	1.044	1.033
Country i	1.000	1.004	0.997	0.999	1.001	0.989	0.983	0.984	0.984	0.991	0.982	0.976	0.966	0.964	0.953	0.953	0.952	0.955	0.956	0.967