Distinguishing Across Models of International Capital Flows

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Preliminary and incomplete.

Abstract

We formulate and solve a range of dynamic models of international capital flows and risk sharing under imperfect capital markets. We feature both models of exogenously incomplete markets (debt with "tax" on borrowing or on capital outflows, non-defaultable debt) and models with endogenously incomplete markets (defaultable debt, limited commitment). All models share common preference and technology structure. We use computational methods based on mechanism design, linear programming, and maximum likelihood to estimate and statistically test across the alternative theories of imperfect international capital markets. Our methods work with both cross-sectional and panel data and allow for measurement error and unobserved heterogeneity. Our goal is to study which model fits the data best and also what type of data (income, investment, capital, consumption, or all together) is needed to distinguish across the proposed theoretical models. We use a panel dataset on GDP, government expenditure, consumption, capital stock and investment per capita for 175 countries in 1993-2002. Empirically, we find that, overall, the defaultable debt and autarky models fit the data best. The complete markets and limited commitment models are rejected in all estimation runs.

1 Introduction

International capital markets do not work perfectly. But are the imperfections severe enough that they need to be taken into account when modeling international capital flows? And if so, which of the many different possible forms or theoretical models of financial market imperfection best describe the data on international capital flows and, by extension, the data on international risk-sharing, consumption smoothing, and investment allocation? Moreover, given that different authors have emphasized different aspects of international data (e.g., consumption and income, or alternatively, savings and investment, etc.), to what extent are the conclusions that can be drawn regarding the form of financial constraints operating across countries dependent on the particular type of data used?

Towards an answer to these questions, in this paper we formulate a wide range of different theories of international financial market imperfections within a common modeling framework, and use a structural, simulated maximum likelihood approach to estimate and test across these theories. The theories we consider range from the benchmark of complete international financial markets, to theories of incomplete markets in which the countries' ability to trade is endogenously constrained by default risk or limited commitment, to models where the set of traded assets is limited by various forms of capital controls, all the way to international financial market autarky. We compute and estimate the corresponding dynamic models of cross-country financial markets on subsets of our data that emphasize consumption smoothing, or alternatively investment sensitivity to output fluctuations, as well as data on consumption, investment, capital and output jointly. We currently focus on the most recent decade of international capital flows for which data are available, but eventually plan to also consider historical data.

We emphasize two main preliminary findings. First, we find that models of imperfect international capital markets always outperform in terms of their likelihood fit the complete-markets benchmark, regardless of the type of data used in the estimation. Second, models of incomplete financial markets due to defaultable debt or borrowing frictions outperform all others in explaining international consumption smoothing behavior, while the autarky model outperforms the rest in explaining international investment smoothing behavior. Models that combine these features do best on the entire dataset. The limited commitment model implies too much consumption and investment smoothing in our calibration and is also rejected. Our answers to the question initially posed are thus that it is necessary, broadly regardless of the question of interest, to take into account financial market imperfections in modelling international capital flows, although the particular choice of a model of imperfect markets should depend on the question of interest to the researcher in the precise ways indicated.

Our methodology also allows us to eventually contribute to a number of other debates in the literature such as (i) the change in performance of international capital markets over time; (ii) differences in the degree of financial integration across countries stratified by income and (iii) differences across countries by degree of market integration overall (e.g., the European Union). Unlike much of previous work in the field, we use fully structural methods and simulated maximum likelihood based on the whole joint distribution (appropriately discretized for computational reasons) of the variables of interest, as opposed to particular moments or correlations.

The paper contributes to several distinct literatures. The first is the vast literature that examines the extent of international financial integration. Although the sheer size of that literature makes generalization difficult, the bulk of papers focus on a single dimension of the data and emphasize methods that place very little structure on the underlying economic model of financial market imperfections. For example, following the seminal papers by Feldstein and Horioka (1980) and Feldstein (1983), a substantial literature has examined the reduced form relationship between national savings and investment rates and concluded that the operation of international financial markets, although still far from perfect, has improved substantially since 1973. Similarly little structure on financial markets is imposed in comparisons of estimated marginal products of capital across countries (as in Harberger, 1978, Caselli and Feyrer, 2007, Ohanian and Wright, 2010).

More structure is imposed when comparing observed capital flows and estimated rates of return as in Lucas (1990), Gourinchas and Jeanne (2007), or Ohanian and Wright (2009, 2010), or when evaluating the degree of international risk sharing (as in Obstfeld, 1986, 1989, 1994; Lewis, 1996), although the focus on a single dimension of the data is maintained. The current paper complements the existing literature by applying fully structural methods, and by examining the extent to which our conclusions are maintained when different dimensions of the data are studied.

The rest of this paper is structured as follows. We first introduce our basic modeling environment and our implementation of each of the separate theories of imperfect capital markets in Section 2. Section 3 then describes our numerical and empirical methods as well as our data sources, while Section 4 presents the main results including their robustness to different assumptions and over different sub-groups of countries or time periods. The last section concludes.

2 Theory

In this section, we present the different theoretical models of capital flows that we confront with the international data later on in the paper. We begin by outlining the elements of the environment that are common across all theories and describing the problem with international autarky. We then turn to a discussion of theories in which the set of assets has been restricted either exogenously by restricting the set of traded securities, or endogenously by problems of limited commitment or strategic default. The case of complete financial markets (full set of state-contingent securities being traded) is also considered.

2.1 Environment

Consider a world populated by a large (but finite) number of small open economies. Where necessary, we index countries by $i = 1, ..., I$, but suppress this index for simplicity for the time being. Time is discrete, lasts forever, and is indexed by $t = 0, 1, ...$ Each economy is represented by an 'agent' who values state-contingent streams of per-capita consumption c and leisure l according to

$$\begin{aligned} & \sum_{t=0}^{\infty} \hat{\beta}^t \sum_{s^t} P\left(s^t | s_0\right) u\left(c\left(s^t\right), l\left(s^t\right)\right) n_t \\ = & \sum_{t=0}^{\infty} \beta^t \sum_{s^t} P\left(s^t | s_0\right) u\left(c\left(s^t\right), l\left(s^t\right)\right), \end{aligned}$$

where $\hat{\beta}$ is the discount factor and u the period utility function which are both common across countries, and n_t is the population of the country which grows exogenously at rate g with n_0 normalized to 1. We let $\beta = \hat{\beta}(1+g)$ be the discount factor of the country adjusted for population growth. All uncertainty is captured in the evolution of the 'productivity' state $s \in S$, with the notation $s^t = (s_0, s_, ..., s_t)$ denoting the history of realizations of s up to time t. The evolution of s is governed by the Markov transition probabilities $P(s'|s)$ and we use $P(s^t|s_0) = P(s_t|s_{t-1}) P(s_{t-1}|s_{t-2}) ...P(s_1|s_0)$ to denote the probability of observing history s^t given the initial state s_0.

In each period an economy has access to a production technology that uses capital and labor to produce per-capita output q of the single consumption good according to

$$q_t = f(s_t, k_t, 1 - l_t),$$

where we have normalized the total time endowment available to each representative agent to one. The dependence of the production function on s captures the presence of shocks to productivity, which is the only source of uncertainty in the model, and so we identify movements in the exogenous state with movements in productivity. Per-capita capital is accumulated according to

$$(1+g)\,k_{t+1} = (1-\delta)\,k_t + i_t,$$

where i_t is per-capita investment. The country begins with an initial endowment of physical capital k_0, and an initial endowment of foreign assets or debt, the notation for which will become clear as we explore the different financial markets environments below. In the empirical results below we currently consider the version of the model with inelastically supplied labor, $l = \bar{l}$.

The above framework admits multiple equivalent recursive representations. Here we adopt a representation in which the state vector of the country at the beginning of the period consists of the country's level of capital k, its level of foreign assets (the precise notation for which will vary across our models) and *last period's* realization of productivity s. It is important to stress that our state includes the previous period's productivity shock s, as this leads to a slightly different (but equivalent) recursive formulation than is often used in the literature. The reason for this choice of timing is that it allows for a more transparent comparison across the various financial market regimes and for an easier mapping to our empirical method, as we describe below. At the beginning of a new period the new state s' is observed, the country operates in the international financial market (if applicable) and chooses its current consumption c,current labor $1-l$ and next period's capital stock k'. Together with the new stock of foreign assets, the new productivity level s' and new capital stock k' then act as tomorrow's state.

We proceed to describe the alternative assumptions we consider under which each economy can access international financial markets.

2.2 Autarky

To begin, assume that each country has no access to international financial markets at all. In this case, if we let $V^A(k,s)$ denote the value function under autarky of the representative agent of a country with state (k,s) , the recursive representation of the country's problem is

$$V^A(k,s) = \max_{c(s'),l(s'),k'(s')} \sum_{s'} P(s'|s)\left\{u(c(s'),l(s')) + \beta V^A(k'(s'),s')\right\},$$

subject to

$$c(s') + (1+g)\,k'(s') + (1-\delta)\,k \le f(s',k,1-l(s')),$$

with k and s given.

Our choice of state space means that the above functional equation differs from the more common form in the literature, defined after observing the *current* state s'. Given the optimal policy function for our problem $k(k, s')$ it is straightforward to move back and forth between the two problems by noting that the autarky value *after* observing s', $\tilde{V}^A(k, s')$ for any $s' \in S$ is defined as

$$\tilde{V}^A(k, s') \equiv u\left(f\left(s', k, 1 - l\left(s'\right)\right) + (1-\delta)k - (1+g)k'(s'), l\left(s'\right)\right) + \beta V^A(k'(s'), s'). \quad (1)$$

2.3 Capital Controls and Exogenous Borrowing Limits

We next allow countries some form of access to an international market for non-contingent bonds. Let b denote the amount of zero-coupon bonds owed by the country, so that $-b$ denotes its asset holdings. The recursive representation state vector thus becomes (k, b, s). Also, let $1 + r^W$ be the (fixed) world interest rate. Suppose access to the market for foreign bonds is constrained by the presence of both borrowing constraints and capital controls which we model as 'taxes' or 'subsidies' on foreign bond holding. These taxes or subsidies could either have a literal interpretation (due to various policies) or could represent various costs/frictions or incentives operating in reality. The borrowing constraint consists of a lower bound on bond holdings $\underline{b}$ which may be set in either an ad hoc fashion, or at the natural borrowing limit (Aiyagari, 1998).

We consider two forms of 'taxes' (frictions) on capital flows. The first is a tax on holdings of foreign debt ('tax on borrowing', TB), which applies to the entire stock of foreign bonds b as long as it is positive. In this case, the problem of the representative agent is given by

$$V^{TB}(k, b, s) = \max_{c(s'), l(s'), k'(s'), b'(s')} \sum_{s'} P\left(s'|s\right) \left\{u\left(c\left(s'\right), l\left(s'\right)\right) + \beta V^{TB}\left(k'\left(s'\right), b'\left(s'\right), s'\right)\right\},$$

subject to

$$\begin{aligned} & c\left(s'\right) + (1+g)\,k'\left(s'\right) + (1-\delta)\,k - \left(1 - \tau_1 I_{\{b'(s')>0\}}\right) q b'\left(s'\right) \\ \leq \; & f\left(s', k, 1 - l\left(s'\right)\right) - b, \end{aligned}$$

and $b'\left(s'\right) \geq \underline{b}$ for all s', where $q = \left(1 + r^W\right)^{-1}$ denotes the price of these zero coupon bonds, τ_1 is the tax level, and $I_{\{b'>0\}}$ an indicator function that takes on the value 1 when future debt levels are strictly positive. This formulation can be also interpreted as representing various 'wedges' between the country's borrowing and lending interest rates.

The second incomplete market environment we consider here features a 'tax' on capital outflows (TO) which applies to the difference between the receipts on foreign investment today Rb and new purchases of foreign debt b'. In this case, the problem of the representative agent is given by

$$V^{TO}(k,b,s) = \max_{c(s'),l(s'),k'(s'),b'(s')} \sum_{s'} P(s'|s) \left\{ u(c(s'),l(s')) + \beta V^{TO}(k'(s'),b'(s'),s') \right\},$$

subject to

$$\begin{aligned} & c(s') + (1+g)k'(s') + (1-\delta)k \\ \leq \; & f(s',k,1-l(s')) + \left(1+\tau_2 I_{\{qb'(s')-b<0\}}\right)(qb'(s')-b), \end{aligned}$$

and $b'(s') \geq \underline{b}$ for all s'. Note that if $qb'-b$ is negative then capital is flowing out of the economy, and hence τ_2 increases the net resource loss for the economy. Obviously, setting either of τ_1 or τ_2 to zero yields the standard debt-financing model without default or other frictions which we also estimate (we call it 'non-defaultable debt/borrowing', B).

2.4 Defaultable Debt

In the above theories, the presence of borrowing constraints serves to ensure that the debtor was always able to repay its debts, and the possibility of strategic default is ruled out. We now consider a model in which the country can default strategically if it is in its interest. We assume that in the event of default, the country is excluded from financial markets forever and receives the autarky payoff, post-realization of the current state, $\tilde{V}^A(k,s')$ determined above.

In this case, the problem of a country which enters the period with state (k,b,s) and observes the new productivity level, s' is to first decide whether or not to repay its debt and, if it chooses to repay, how much to consume, work, invest and borrow in the next period. Formally, if we let $V^{DD,R}(k,b,s')$ be the value to the representative agent of acting optimally given that they have decided to repay *after* observing state s', then

$$V^{DD,R}(k,b,s') = \max_{c(s'),l(s'),k'(s'),b'(s')} u(c(s'),l(s')) + \beta V^{DD}(k'(s'),b'(s'),s'),$$

subject to

$$c(s') + (1+g)k'(s') + (1-\delta)k + q(k',b',s')b' \leq f(s',k,1-l(s')) + b.$$

The value function for the agent before the realization of s', and hence before the decision to default has been made, is then given by

$$V^{DD}(k,b,s) = \sum_{s'} P(s'|s) \max\left\{ \tilde{V}^{A}(k,s'), V^{DD,R}(k,b,s') \right\}. \tag{2}$$

Note that in the expression for V^{DD} we use the autarky value after observing the current productivity level s' as defined in (1).

Construct the indicator function $d(k,b,s')$ that takes on the value 1 whenever the country defaults. Then the probability of default tomorrow, given that the country is in state (k,b,s) today is

$$\phi(k,b,s) = \sum_{s'} P(s'|s)\, d(k,b,s').$$

Finally, creditors are assumed risk-neutral and behave competitively, so the equilibrium bond price q must satisfy the zero-profit condition,

$$q(k,b,s) = \frac{1-\phi(k,b,s)}{1+r^{W}}.$$

In practice, we solve problem (2) for a given bond price function, compute the resulting probabilities, ϕ and implied bond price function, q and look for a fixed point in the value function V^{DD} and the price function q jointly.

The form of the equilibrium bond price function q depends on the Markov transition matrix P; it will not, in general, be a concave function and so the constraint set for the problem of a country that repays its debts may not be convex. In addition, the binary decision to default or not default adds a further non-convexity. As a consequence, country welfare could be increased if it were able to convexify the environment by introducing randomization over its actions. The intuition is similar to that in G. Hansen's (1985) labor model. In addition, if the problem is non-convex, standard solution methods relying on first-order conditions may be inapplicable. Therefore, we show next how to introduce lotteries into this framework to address these issues.

2.4.1 Lotteries in the Defaultable Debt Model

Given any value of the state (k,b,s) and after observing the realization of the new productivity level s', the country must decide whether or not to default, as well as how much to work and how much capital and foreign debt to accumulate. Randomization over these choices is modeled by allowing the country to choose the probability of taking any possible actions

(l', k', b', d) given the productivity realization s' and the country's current state. Denote these probabilities (jointly with s' being realized) by

$$\pi\left(l', k', b', d, s'|k, b, s\right),$$

and let L, K, B and $D = \{0, 1\}$ denote the (discrete) sets or 'grids' of possible labor, capital, borrowing and default choices. We re-write the country's dynamic programming problem in the probabilities π in effect transforming the per-period problem into a linear program which is convex by construction. Our approach is thus the same as that of Prescott and Townsend (1984) or Phelan and Townsend (1991) used to compute information-constrained mechanism design problems.

The variables π must satisfy a number of intuitive restrictions. First, as they are probabilities, they must be non-negative, $\pi\left(l', k', b', d, s'|k, b, s\right) \geq 0$, and must sum to one,

$$\sum_{L \times K \times B \times D \times S} \pi(l', k', b', d, s'|k, b, s) = 1, \tag{3}$$

for all $(k, b, s) \in K \times B \times S$. They must also be Bayes-rule consistent with the (exogenous) evolution of the productivity process s, that is,

$$\sum_{L \times K \times B \times D} \pi\left(l', k', b', d, \bar{s}'|k, b, s\right) = P\left(\bar{s}'|s\right), \tag{4}$$

for all $\bar{s}' \in S$.

Taking as given the bond price function $q\left(k', b', s'\right)$, the country's problem can be then written as the following linear programming problem,

$$\begin{aligned} V^{DD}(k, b, s) \quad = \quad & \max_{\pi(l', k', b', s', d|k, b, s)} \sum_{L \times K \times B \times S \times D} \pi(l', k', b', s', d|k, b, s)[d\widetilde{V}^{A}\left(k, s'\right) + \\ & +(1-d)(u((1-\delta)k + f(s', k, 1-l') + q(k', b', s')b' - b - (1+g)k', l') + \\ & +\beta V^{DD}(k', b', s'))] \end{aligned}$$

subject to the non-negativity and adding-up constraints on the probabilities π, (3) and (4). Note that, since we have transformed the problem so that the country's choices are now over the probabilities π and since $\widetilde{V}^{A}\left(k, s'\right)$ does not vary with the probability chosen, the constraint set is now convex – all constraints are linear in the choice variables π and the objective function is also linear in the π's.

The solution to the defaultable debt problem is attained by the optimal policy function $\pi^*(l', k', b', d, s'|k, b, s)$ which depends on the bond price function q. From the optimal policy function we can determine the implied probability of default, and hence the implied equilibrium bond price function

$$q(k,b,s) = \frac{1}{1+r^W} \sum_{s'} P(s'|s)\pi^*(l', k', b', d=0, s'|k, b, s).$$

Iterating for a fixed point in V^{DD} and q above we obtain the equilibrium value, policy and bond price functions.

2.5 Limited Commitment

Next we allow for international markets in state-contingent Arrow securities subject to endogenous trading constraints due to limited commitment. To maximize consistency of notation with the earlier models, we use $b(s'|s)$ to denote obligations to repay one unit of the numeraire tomorrow in state s' given that today's state was s. We assume that all fluctuations in country productivity levels are idiosyncratic, so that these securities trade at prices $q(s'|s) = P(s'|s) / \left(1 + r^W\right)$.

Specifically, consider an environment in which access to the international market in state-contingent assets is restricted by the country's inability to commit to honoring contracts. Like in the defaultable debt model above, it is default risk that limits the country's access to financial markets, although unlike that model, here the optimal contract ensures that no default occurs in equilibrium.

There are multiple ways to formulate the limited commitment model, including the Arrow-Debreu market approach of Kehoe and Levine (1993) and the Arrow market approach of Alvarez and Jermann (2000). Here we adopt an equivalent optimal contracting approach in which a risk-neutral competitive financial intermediary designs a contract with the sovereign to maximize gains from trade subject to a limited commitment constraint. To obtain a recursive representation we follow Thomas and Worrall (1988) and introduce the state variable of 'promised utility', i.e., discounted value of future utility in the optimal contract which keeps track of history dependence in the limited commitment environment.

Formally, let $w \in W$ denote the initial promised utility of the country, so that its current state is given by (b, w, s). A financial intermediary (the world financial market) that trades with this country designs a system of state-contingent transfers to and from the country $\tau(s')$, recommended leisure and physical capital levels $l(s')$ and $k(s')$, and promised future utility levels $w(s')$ to maximize profits subject to providing the country with its promised utility level, w and subject to respecting the participation constraints that reflect the country's inability to commit to honoring contracts. The intermediary can carry funds over time at the world interest rate r^W. Letting $\Gamma(k, w, s)$ denote the optimal lifetime profits of the intermediary, then the optimal contracting problem is given by

$$\Gamma(k, w, s) = \max_{t(s'), l(s'), k(s') w'(s')} \sum_{s'} P(s'|s) \left[f(s', k, 1 - l') - \tau(s') + \frac{1}{1 + r^W} \Gamma(k'(s'), w'(s'), s') \right]$$

subject to the promise-keeping constraint

$$\sum_{s'} P(s'|s) \left[u\left(\tau(s') + (1 - \delta)k - (1 + g)k'(s'), l(s')\right) + \beta w'(s') \right] = w$$

and the (post realization of output) participation constraints

$$u\left(\tau(s') + (1 - \delta)k - (1 + g)k'(s'), l(s')\right) + \beta w'(s') \geq \tilde{V}^A(k, s'),$$

for all $s' \in S$.

The presence of the physical capital stock in the (concave) autarky value function on the right hand side of the participation constraints means that the constraint set for this problem may be, in general, not convex. As a consequence, as in the defaultable debt model, the intermediary may be able to increase its expected profits by randomizing over the allocation of resources to the country. In addition, convexifying the problem makes it easier to solve. This leads us to consider adding lotteries to this framework.

2.5.1 Lotteries in the Limited Commitment Model

Given the country's current state (k, w, s) and the productivity realization s', suppose the intermediary can randomize over the choice of transfers, leisure, capital levels, and promised utilities. Letting $\pi(\tau, l', k', w', s'|k, w, s)$ denote the probabilities of a given allocation, the problem of the intermediary is given by

$$\Gamma(k, w, s) = \max_{\pi(\tau, l', k', w', s'|k, w, s)} \sum_{T \times L \times K \times W \times S} \pi(\tau, l', k', w', s'|k, w, s) [f(s', k, 1 - l') - \tau + \frac{1}{1 + r^W} \Gamma(k', w', s')]$$

subject to the 'promise-keeping' constraint

$$\sum_{T \times L \times K \times W \times S} \pi(\tau, l', k', w', s'|w, k, s) [u(\tau + (1 - \delta)k - (1 + g)k', l') + \beta w'] = w,$$

the (post-realization of output) 'limited commitment' constraints,

$$\sum_{T\times L\times K\times W} \pi(\tau, l', k', w', \bar{s}'|w, k, s)[u(\tau + (1-\delta)k - (1+g)k', l') + \beta w'] \geq \tilde{V}^A(k, \bar{s}'),$$

for all $\bar{s}' \in S$, and subject to the usual restrictions on the probabilities, π of non-negativity, $\pi(\tau, l', k', w', \bar{s}'|w, k, s) \geq 0$, adding up

$$\sum_{T\times L\times K\times W\times S} \pi(\tau, l', k', w', s'|k, w, s) = 1,$$

and Bayesian consistency with the Markov productivity process,

$$\sum_{T\times L\times K\times W} \pi(\tau, l', k', w', \bar{s}'|k, w, s) = P(\bar{s}'|s),$$

for all possible realizations $\bar{s}' \in S$.

2.6 Perfect Capital Markets

In the limited commitment model, if the sequence of participation (limited liability) constraints never binds, it is easy to see that the country is fully insured against all country-specific risk. The same outcome would obtain if the country can fully commit to the ex-ante optimal contract. This is equivalent to the solution of the following contracting problem in which consumption, leisure, investment and obligations are chosen in the form of a complete array of state-contingent bonds $b(s'|s)$, subject to a flow budget constraint,

$$\begin{aligned} V^{CM}\left(k, \{b(s'|s)\}_{s'}, s\right) &= \max_{c(s'), l(s'), k'(s'), b'(s''|s')} \sum_{s'} P(s'|s)\left[u\left(c(s'), l(s')\right) + \right. \\ &\quad \left. + \beta V^{CM}\left(k(s'), \{b(s''|s')\}_{s''}, s'\right)\right], \end{aligned}$$

subject to

$$\begin{aligned} & c(s') + (1-\delta)k - (1+g)k'(s') - \sum_{s'} q(s''|s')\, b(s''|s') \\ \leq \quad & f\left(s', k, 1 - l(s')\right) - b(s'|s), \end{aligned}$$

for all $s' \in S$, given k and the full set of state-contingent obligations $\{b(s'|s)\}_{s'}$.

3 Empirical Method

In this section we describe our estimation strategy. We estimate via simulated maximum likelihood each of the alternative dynamic models of countries' international financial markets participation developed in Section 2. Our basic empirical method is as follows. We write down a likelihood function that measures the goodness-of-fit between the data and each of the alternative models of financial markets. We then use the maximized likelihood value for each model (at the MLE estimates for the parameters) and perform a formal statistical test (Vuong, 1989) about whether we can statistically distinguish between each pair of models relative to the data. We thus approach the data as agnostic about which theoretical model fits them best and let the data determine this. The results of the Vuong test, a sort of 'horse race' among the models, inform us which theory(ies) fits the data best and also which theories can be rejected as likely to have generated the observed data.

Denote the data by $\{\hat{y}_j\}_{j=1}^n$ where $j = 1, ...n$ denotes sample units (here, countries observed over a range of years). For each j, $\hat{y}_j$ is a vector that can consist of different variables from either a cross-section (e.g., consumption, income, capital, investment in a given year) or, if panel data is available as here, from different time periods (e.g., consumption and output at $t = 0$ and at $t = 1$). In this paper we have detailed country-level data on the per capita capital stock, investment, consumption and output, which we label $\{\hat{k}_{j,t}, \hat{\imath}_{j,t}, \hat{c}_{j,t}, \hat{q}_{j,t}\}$ respectively. In the estimation runs in Section 4, $\{\hat{y}_j\}$ refers to various possible sub-sets of these data, for example $\{\hat{c}_{j,0}, \hat{q}_{j,0}\}$. See Section 3.3 for more details.

We allow for the possibility that the data, $\hat{c}, \hat{q}, \hat{k}$ and $\hat{\imath}$ are measured with error. Assume the measurement error is additive and distributed $N(0, (\gamma_{me} r(x))^2)$ where $r(x)$ is the range of the grid X for variable x, i.e., $r(x) \equiv x_{\max} - x_{\min}$ where x is any of the variables of interest c, q, i, k. The reasoning behind this form is that for computational reasons we want to be as parsimonious with parameters as possible in the simulated likelihood. In principle, more complex versions of measurement error can be considered at the cost of computing time. The parameter γ_{me} is estimated in the simulated maximum likelihood routine.

3.1 The simulated likelihood function

1. Mapping model solutions to probability distributions

For any possible value of the state variables (e.g., k, w, s – the capital stock, the promised utility value and the productivity state for the LC model) and structural parameters ϕ^s (preferences, β, σ and technology, α, δ and the transition matrix for s) the model solution obtained from the respective linear program is a discrete joint probability distribution over the variable grids. For example, for the LC model the solution consists of the probabilities $\pi(\tau, k', w', s|k, w)$ over T, K, W, S where primes denotes future-period states. From this joint distribution we easily obtain (by manipulating the π's and summing over variables) the joint probability distribution over the desired variables to be used in the estimation, for instance $g_0(c, q, i|k, w, s; \phi^s)$.

In general, let's denote this distribution, for model m by $g_0^m(y^1|z^1, z^2, \phi^s)$ where y^1 is the non-state (e.g., in our application – any combination of c, q, i) data being fitted, z^1 is the vector of observable state variables and z^2 is the vector of unobservable state variables for that model. (We have $z^1 \equiv (k, s)$ for all models while $z^2 \equiv w$ or $z^2 \equiv b$ or z^2 absent, depending on the estimated model). The productivity data, $\hat{s}$ is backed out directly from the output, $\hat{q}$ and capital stock data, $\hat{k}$ using the production function specification. The unobservable states z^2 are sources of unobserved heterogeneity endogenous to the models.

2. Initialization and unobserved heterogeneity

(2a) To map the solution of each of the models to the data, we need to initialize the state variables. For the unobservable state variables, b and w we assume that they come from a parametric initial distribution $\Phi(.)$ (e.g. normal, mixture of normals) the parameters of which, ϕ^d will be estimated in the SMLE routine.[1] We first integrate the joint probability distribution $g_0^m(y^1|z^1, z^2; \phi^s)$ over the unobserved state variable (e.g., in the LC model this is the variable w on the grid W). This is done using the assumed parametric distribution for this variable, Φ discretized via a standard histogram function applied on the grid W. Call the result the joint distribution $g_1^m(y^1|z^1; \phi^s, \phi^d)$. For instance, this could be the joint distribution of c, q, i over $C \times Q \times I$ for each $(k, s) \in K \times S$ given by the LC model solution and integrated over the unobserved state distribution. Naturally, this step is not performed when we estimate the autarky model since it has no z^2 states.

(2b) For the observed state variables z^1 (here k, s) we take actual data $\hat{z}_j^1$ (i.e., $\hat{k}_j, \hat{s}_j$) and discretize it over the grid Z^1 (i.e., $K \times S$) via a histogram function. We call the resulting distribution $H(\hat{z}^1)$. If dynamic data is used in the MLE, the $\hat{z}^1$ data are taken from the initial period of data used. Within this step, we allow for the possibility that the actual z^1 data contains measurement error, as explained above. In practice, this means manipulating the theoretical joint distribution $g_1^m(y^1|z^1; \phi^s, \phi^d)$ from step (2a) to transform it into the distribution $g_2^m(y^1|z^1; \phi^s, \phi^d, \gamma_{me})$ which is the joint distribution of variables y^1 over the compound grid Y^1 (e.g., $y^1 = (c, q, i)$ over $C \times Q \times I$) in model m computed at

[1] In the baseline runs we assume that the unobserved state w in the LC model is distributed $N(\mu_w, \gamma_w^2)$ while the unobserved state b in the B and DD models is distributed $N(\mu_b, \gamma_b^2)$. This assumption is not essential – more general distributions can be incorporated at the computational cost of additional estimated parameters.

parameters ϕ^s, ϕ^d for each value of the state variables $z^1$and including measurement error in z^1 parametrized by γ_{me}.[2] It is computationally prohibitive to re-compute the model at non-grid points for z^1. The measurement error is applied sequentially and independently (see footnote above) to each observed state variable in z^1.

(2c) We next use the actual distribution of the observable states $\hat{z}^1$ in the data, $H(\hat{z}^1)$ (here, $z^1 \equiv (k, s)$ is discretized via a histogram function over the grids K and S) together with the distribution $g_2^m(y^1|z^1; \phi^s, \phi^d, \gamma_{me})$ obtained in step (2b) above to compute the joint distribution

$$f^m(y|\phi, H(\hat{z}^1))$$

over the grid Y that the estimated model m predicts conditional on $H(\hat{z}^1)$ and after allowing for measurement error in z^1 (here, k and s) and having integrated over unobserved heterogeneity z^2 (step 2a above). Here, we can have either $y = y^1$ (if the z^1 variables are not used in the estimation, in which case f^m is simply $g_2^m(.)$ integrated over z^1 with the probabilities from $H(\hat{z}^1)$ or we can have y contain a subset of z^1 (e.g., k) in which case f^m is the joint distribution of (y^1, z^1) over the compound grid $Y^1 \times Z^1$. Note that the distribution, f is a function of all parameters (measurement error, distributional for z^2 and structural), $\phi \equiv (\gamma_{me}, \phi^d, \phi^s)$ and the discretized distribution of the observed states $z^1 \equiv (k, s)$ from the data, $H(\hat{z}^1)$.

3. The simulated likelihood function

The next step is to allow for measurement error also in the remaining variables y^1 (here, c, q, i or subset thereof used in the estimation). That is, from the joint distribution f^m from step 2c above we obtain the distribution $\tilde{f}^m(y|\phi, H(\hat{z}^1))$ in which measurement error is allowed in each of the variables independently (as before, assumed normally distributed with $N(0, (\gamma_{me} r(x))^2)$ where $x = c, q, i$ or k). Focus on the case $y = y^1$ (the case when y contains variables from z^1 is handled analogously but the algebra is a bit more cumbersome since for each j we need to condition on its particular z^1 value).

Let $\Phi\left(.|\mu, \sigma\right)$ denote the pdf of $N\left(\mu, \sigma^2\right)$. Given the assumed measurement error distribution, the likelihood of observing data point $\hat{y}_j$ (e.g., $(\hat{c}_j, \hat{q}_j)$) relative to any model grid

[2] *Applying measurement error to a variable on a discrete grid.* Let x be a variable taking values on the discrete finite grid X. Let also ε be a continuous random variable distributed $\phi(\varepsilon)$ with $E(\varepsilon) = 0$ (we currently use Normal). Suppose $d(x) \equiv [d_1, d_2, ..., d_{\#X}]$ is the distribution (without error) over X where d_j denotes the probability mass on point $x_j \in X$ for $j = 1, ..\#X$ with $d_j \geq 0$ and $\sum_{j=1}^{\#X} d_j = 1$. Define ϖ as the operator which takes the distribution $d(x)$ into the distribution $\tilde{d}(x) \equiv [\tilde{d}_1, \tilde{d}_2, ..., \tilde{d}_{\#X}]$ where $\tilde{d}_j$ denotes the probability mass on point $x_j \in X$ for $j = 1, ..\#X$ with $\tilde{d}_j \geq 0$ and $\sum_{j=1}^{\#X} \tilde{d}_j = 1$ inclusive of measurement error. Basically, ϖ uses the measurement error's cdf to re-assign the probability mass d into $\tilde{d}$ by adding the appropriate mass falling into each discrete finite cell/point of X.

point $y_h \in Y$, for any $h = 1, ..., \#Y$ is:

$$\prod_{l=1}^{L} \Phi\left(\hat{y}_j^l | y_h^l, \sigma^l\right) \tag{5}$$

where $l = 1, ..., L$ indexes the variables in $\hat{y}$ and where $\sigma^l = \gamma_{me} r(y^l)$ is the measurement error standard deviation for each variable, as explained earlier. Expression (5) implies that the likelihood of observing data vector $\hat{y}_j$ (consisting of L components indexed by l) for model m, at parameters ϕ and initial conditions $H(\hat{z}^1)$ is

$$F^m\left(\hat{y}_j | H(\hat{z}^1), \phi\right) = \sum_h f^m(y_h | H(\hat{z}^1), \phi) \prod_{l=1}^{L} \Phi\left(\hat{y}_j^l | y_h^l, \sigma^l\right) \tag{6}$$

where we assume that measurement errors in all variables are independent from each other. We basically, sum over all grid points $h = 1, ...\#Y$, appropriately weighted by f^m, the likelihoods in (6). For example, for consumption and income cross-sectional data $\hat{y}_j = (\hat{c}_j, \hat{q}_j)$ we have $F^m\left(\hat{c}_j, \hat{y}_j | H(\hat{z}^1), \phi\right) = \sum_h f^m((c,q)_h | H(\hat{z}^1), \phi) \Phi\left(\hat{c}_j | c_h, \sigma^c\right) \Phi\left(\hat{y}_j | y_h, \sigma^q\right)$ where $(c,q)_h$ go over all elements of $C \times Q$, $h = 1, ..., \#C\#Q$.

Multiplying the individual likelihoods (6) over sample units (households) and taking logs, the simulated log-likelihood of the data $\{\hat{y}_j\}_{j=1}^n$, conditional on $H(\hat{z}^1)$ given parameters ϕ and allowing for measurement error is (normalized by n)

$$L_n^m\left(\phi | H(\hat{z}^1)\right) \equiv \frac{1}{n} \sum_{j=1}^{n} \ln F^m\left(\hat{y}_j | \phi, H(\hat{z}^1)\right). \tag{7}$$

The maximization of (7) over ϕ is performed by an optimization algorithm robust to local maxima (we use pattern search and polytope). Standard errors are computed via bootstrapping, repeatedly drawing with replacement from the data.

3.2 Testing and Model Selection

After we estimate and obtain the maximized likelihood (LL) for each model, we follow Vuong (1989) and compute an asymptotic test statistic that we use to formally distinguish (in bilateral comparisons) across the alternative theoretic financial regimes. The Vuong test does not require that either of the compared models be correctly specified. The Vuong test-statistic is normally distributed under the null hypothesis which is that the two models are equally close to the data. If the null is rejected (i.e., the Vuong Z-statistic is large enough in absolute value), we say that the higher likelihood model is closer to the data (in the KLIC sense) than the other.

More formally, suppose the values of the estimation criterion function being minimized (i.e., minus the log-likelihood) for two non-nested competing models ($m = 1$ or $m = 2$) are given by $L_n^1(\hat{\phi}^1)$ and $L_n^2(\hat{\phi}^2)$ where n is the (common) sample size and $\hat{\phi}^1$ and $\hat{\phi}^2$ are the respective SMLE parameter estimates.[3] The pairwise nature of the test conveniently allows us to obtain a complete ranking by likelihood of all models we study. Define the "difference in lack-of fit" statistic:

$$T_n = n^{-1/2}\frac{L_n^1(\hat{\phi}^1) - L_n^2(\hat{\phi}^2)}{\hat{\sigma}_n}$$

where $\hat{\sigma}_n$ is a consistent estimate of the asymptotic variance[4], σ_n of $L_n^1(\hat{\phi}^1) - L_n^2(\hat{\phi}^2)$ (the likelihood ratio). Under certain regularity conditions (see Vuong, 1989, pp. 309-13), if the compared models are strictly non-nested, the test-statistic T_n is distributed $N(0,1)$ under the null hypothesis. The test can be also applied for overlapping models, using a sum of chi-squared test-statistic distribution (see Vuong, 1989).

3.3 Data

We use data at an annual frequency for each country on the main national accounting expenditure aggregates (consumption, investment, government spending, exports, imports and gross domestic product), the labor market (population, employment, and hours worked), as well as the balance of payments and net foreign asset position. For most countries, our data begins in 1960, although for a subset we have data extending back to 1900 which allows for a more accurate estimate of the capital stock of the country.

The data come from a large number of sources, which are described briefly next; the Data Appendix (TO BE ADDED) presents the data and sources in greater detail. For OECD countries, our primary source is the *OECD Annual National Accounts*. For all other countries, our primary source is the World Bank's *World Development Indicators*. These sources were supplemented, where appropriate, using data from the International Monetary Fund's (IMF) *International Financial Statistics,* the *UN National Accounts Database*, the *Groningen Growth and Development Center Database*, the *Penn World Tables*, as well as a host of country-specific sources. Data on capital stocks was constructed from investment

[3]For the functional forms and parameter space we consider and use in the estimations, the regimes we study are statistically non-nested. Formally, following Vuong (1989), we say that model A nests model B, if, for any possible allocation that can arise in model B, there exist parameter values such that this is an allocation in model A. The Vuong model comparison test can be also used for "overlapping" models, i.e. neither strictly nested nor non-nested, in which case the test statistic has a weighted sum of chi-squares distribution (see Vuong, 1989, p. 322).

[4]In practice one can use the sample analogue of the variance of the LR statistic (see Vuong, 1989, p. 314).

data in a model-consistent fashion using the perpetual inventory method. Initial capital stocks were estimated under the assumption that the economy began in steady state, as in Caselli and Feyrer (2007), and were benchmarked against the estimates provided by Nehru and Dhareshwar (1993). For more details on the data construction see Ohanian and Wright (2010).

In the empirical results below we restrict attention to data from the period 1993 to 2002 for which period we have the largest possible balanced panel with available data. This results in a sample of 175 countries for which we have a balanced panel of complete data on each of consumption, output net of government expenditure, investment, capital and population size respectively, $\{C_{jt}, Q_{jt}, I_{jt}, K_{jt}, N_{jt}\}$ where $j = 1, ..., n$ denotes countries and $t = 1, ..., T$ denotes time.

Table 1 presents selected summary statistics of the data. The first column uses per capita data, measured (where applicable) in constant local currency units converted into 2000 US dollars (Ohanian and Wright, 2010). These data are not adjusted for productivity differences across the countries (e.g., evident in the high correlations between each of the variables c, q, i, k) and we cannot use them directly with our models assuming homogeneous production function across countries. The column serves simply as illustration of the data.

To try and adjust for productivity and other differences across countries and be able to map the data into the models from Section 2, we do the following. First, we compute an imputed 'productivity factor', A_{jt} for each country j and time t using a standard Cobb-Douglas aggregate production function: $A_{jt} = \frac{Q_{jt}}{K_{jt}^{\alpha} N_{jt}^{1-\alpha}}$ where Q is GDP net of government expenditure, K is the capital stock and N is the country's population (used here as proxy for labor). The parameter α is discussed below. We then construct the average relative productivity, a_j for each country j relative to the US defined as:

$$a_j = \frac{1}{T} \sum_{t=1}^{T} \frac{A_{jt}}{A_{US,t}} \text{ for all } j = 1, ..., n$$

Naturally, this procedure yields $a_{US} = 1$. We use the productivity factors a_j to compute the per-capita and productivity adjusted consumption c, output q, investment i and capital stock k in efficiency units of labor which we use in the MLE estimation results, as follows:

$$x_{jt} = \frac{X_{jt}}{N_{jt} a_j^{1/(1-\alpha)}}$$

where x can stand for each of c, q, i and k.

Column 2 in Table 1 displays the same summary statistics for the adjusted data. Note the reduction in the bivariate correlations as the variables c, q, i, k are effectively cleaned (in part) of common country factors affecting all of them simultaneously. Consumption and income and investment and income (in levels and in growth rates) are strongly positively correlated in the data suggesting imperfect risk sharing. Even after the productivity adjustment there remains very high persistence in all four variables in the data. [We are planning a robustness run after removing country and time fixed effects].

Figures 1 and 1a show the extreme lack of cross-country consumption and investment smoothing in the international data. For each country-year combination we plot the deviation between this country's income in a given year and the yearly average income across countries (the left two graphs). The same figure is plotted for consumption and investment on the right hand side panels of the figures. Figure 1 is in model-units, after the productivity adjustment described above, while Figure 1a is the same plot but for the per-capita raw data.

If countries were able to smooth completely all income variations across each other in terms of consumption (i.e., if perfect consumption smoothing or full risk-sharing held), which means that each country were to consume the average yearly consumption for the world in that year we should see the top-right panel of Figure 1 to be a flat plane at zero. Instead, we see very little consumption smoothing present in the data (note, the left and right panels use the same axes scale). This finding is in sharp contrast with household-level data within countries where typically the consumption plot is much smoother than that for income (e.g. see Townsend, 1994). The picture for investment (the lower two panels of Figures 1 and 1a) is not much different although there seems to be more investment smoothing going on across countries than consumption smoothing. Again, this is unlike what we typically see in micro-level data, e.g. across households running small businesses where investment is more volatile relative to income than consumption.

4 Results [preliminary and incomplete]

4.1 Functional forms, parameters and computation

To compute and structurally estimate the models we take functional forms standard for the literature. Assume preferences take the constant relative risk aversion form,

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

where $\sigma \geq 0$ and $u(c) = \ln c$ for $\sigma \to 1$. In the currently computed set of results presented below we assume labor is inelastically supplied and set $l = 1$. For each country the aggregate production function is Cobb-Douglas, with current output given by

$$q = s' k^{\alpha}$$

where $\alpha \in (0, 1)$.

For our benchmark runs, we calibrated the parameters governing preferences, technology and the evolution of productivity $P(s'|s)$ to values standard for an annual calibration. In particular, the world interest rate r^w is set to 0.04 and the discount fact of each country β was set to 0.96. The coefficient of relative risk aversion σ is set to 2. Depreciation rates δ are assumed to be 6%, and the capital share α is set to one-third. The productivity process for s is assumed to take a first order autoregressive form with autocorrelation 0.95 and a standard deviation of 2%. It is discretized over five states using Tauchen's method. The 'tax' or friction rate τ in the tax on borrowing (TB) and tax on outflows (TO) models is fixed at .1.

Given this calibration, the parameters we estimated in the simulated maximum likelihood runs below are the distributional parameters for the unobserved states, ϕ^d and the parameter governing the standard deviation of measurement error, γ_{me}. In the future plan to include structural parameters in the estimation as well but we are currently constrained by computation time considerations.

All data is first converted into per-capita units by dividing by each country's population. Output q is obtained from the GDP data by netting out government expenditure. All variables (c, q, i, k, as defined in the model description earlier) are further converted into 'model units' by dividing by 0.1 times the 90th percentile of capital k in the pooled data. To compute the alternative dynamic models of international financial markets we use the linear programming formulation (that is, allow for randomization/lotteries). While this is crucial in the defaultable debt and limited commitment models, we employ the same method for consistency in all other cases (see Appendix A for details).[5]

All model variables are assumed to lie on discrete grids, C, Q, I, K, W, B, S, etc. where capital letters denote the grid corresponding to the respective lower-case variable. Our baseline specification results presented below use a relatively coarse version of the models that allows faster computation (this version assumes five grid points for k). In addition, we did a robustness run with 'denser' grids using 25 grid points for k. All current estimation runs use a five-state process for the productivity shock, s using a transition matrix calibrated via Tauchen's method. This results in a five-point grid S. The benchmark K grid consists

[5]Non-convexities could be potentially an issue also in the tax on borrowing and tax on capital outflows models due to the presence of the max operator.

of five points set at the 10th, 30th, 50th, 70th and 90th percentile of the normalized whole sample data (respectively, 2.52, 4.04, 5.30, 6.73 and 10 model units). The Q and I model grids used in the MLE (see Section MLE) are determined endogenously, within the models, from the K and S grids. The consumption grid C used in the MLE (and also in the linear programs for the LC and CM models) consists of 25 linearly spaced points between 0.02 model units and the 95th percentile of the c data (2.6 model units). The lower bound of C is set slightly higher than zero for numerical reasons. The grid for promised utility, W in the LC and CM models is endogenously determined using the grid C and consists of 25 evenly spaced points. The grid for debt/savings B in the B, TB, TO, DD models consists of 25 evenly spaced points on the interval $[-2, 2]$ model units (to put this into perspective, remember from Table 1 that median income in our data is 1.94 model units). The bounds on B were determined in conjunction with the K, S and Q grids to ensure a numerical solution to each of these models exists for the parameters and functional forms we use.

Each model was computed using policy function iteration (Judd, 1998) with the exception of the defaultable debt model where this is not possible due to the necessity of jointly iterating on the bond price and value functions. At each stage of the iteration a linear programming problem must be solved. We use the commercial software CPLEX to perform this step. The objective functions and constraints are created in Matlab which is very efficient in handling large vectors and matrices.

4.2 Baseline estimation runs

Table 2 presents the baseline results. The Table reports the results from the Vuong (1989) test under the null hypothesis that the two compared models are 'equally close' in KLIC sense to the data (see section 3.2 for more details). Each row of the table presents a separate bilateral comparison between alternative dynamic models of international financial markets. In all tables that follow A denotes the autarky model, TB denotes the model with 'tax' (frictions) on debt/borrowing; TO denotes the model with a 'tax' (frictions) on capital outflows; B denotes the non-defaultable debt model; DD denotes the defaultable debt model; LC denotes limited commitment and CM stands for complete markets. Each column of Table 1 corresponds to a different sub-set of the overall panel data – by the type of variables used and/or by year. For instance, the caption *cq '93* stands for the estimation run using only data on consumption, c and output, q from 1993 as the vector $\hat{y}$ from Section 3.1.

Table 2 shows that using consumption and output data alone (either from 1993 or 2002; see the second column in each panel of Table 2), as in tests of international risk-sharing (although here we do more by fitting the whole discretized distribution of those variables in the data instead of running linear regressions) is not able to distinguish well among the models of exogenously incomplete markets. We are able to reject, however, the complete markets and limited commitment models. Using '93 data the defaultable debt (DD) model has the highest likelihood although it is statistically tied in the Vuong test with the TB and TO models. Adding investment into the set of variables used in the MLE helps a bit with distinguishing across the models in the ciq '93 run where TB and DD are tied for first place in terms of goodness of fit with the data.

Using investment and output data alone, as in a test of investment sensitivity to income fluctuations, we find, both with 1993 and 2002 data, that the autarky (A) model comes on top in terms of likelihood. The defaultable debt model ranks second in likelihood but is rejected by the Vuong test (at 10% or 1% significance level) as equally close to the data. Very similar results to those with investment and output data alone are obtained when adding the capital stock variable in the estimation (the runs kiq '93 and kiq '02).

Finally, using all available data (consumption, investment, income and capital) we find evidence favoring the defaultable debt, 'tax' on borrowing and autarky models. Unfortunately the we are unable to distinguish among them statistically in the cross-section which could be due to our sample size. We are working on a run utilizing better the panel dimension of the data, using data from two different years in our panel which, we hope can help us distinguish the models better.

Overall, Table 2 reports results from ten runs with different data sub-samples in which each model is tested six times against all alternatives, that is, 60 tests in total per model. The defaultable debt (DD) model is the 'statistical winner' (10% confidence level or better) in 39 of its 60 bilateral tests against other regimes. The autarky (A) model also wins 39 of its 60 bilateral comparisons. The TB model follows with 36 'wins'; the B model has 28; the TO model has 20 (only against CM and LC); the LC model has 10 (only against CM) and finally the complete markets models is always rejected against all alternatives.

To conclude – our baseline estimation runs with the whole sample of international data from 1993 and 2002 favor the autarky, defaultable debt and tax on borrowing regimes against the tax on capital outflows, non-defaultable debt, limited commitment and complete markets alternatives. The likelihood order among these three changes a bit, depending on the data used but overall they all feature among the top in best fit. The autarky model is strongly favored in the specifications not using consumption data. The limited commitment and complete markets models are rejected in all specifications.

The MLE parameter estimates for the 1993 run with (c, q, i, k) data are reported in Table 3. Remember, at the current stage we only estimate the standard error variance, γ_{me} and the distributional parameters, $\phi^d = (\mu_b, \gamma_b)$ or (μ_w, γ_w) for the distribution of unobserved heterogeneity (the state variable w in the CM and LC models and b in the B, TB, TO and DD models). All other parameters' values are fixed – see Section 4.1. The mean and standard deviation parameter estimates $\mu_{b/w}$ and $\gamma_{b/w}$ are reported relative to the range of the B and W grids, e.g. a value of $\mu_b = .5$ means that the mean of the initial b distribution equals $b_{\min} + .5(b_{\max} - b_{\min})$. Similarly, a value of $\gamma_b = .1$ means a standard deviation of b in the model equal to $\gamma_b(b_{\max} - b_{\min})$ where $b_{\max}$ and $b_{\min}$ denote respectively the upper and lower bound of the B grid in the model. The level of measurement error variance, γ_{me} relative to the variable range estimated in six of the seven models is very similar in value – around .10-.12. The exception is the complete market models which requires the largest standard error variance to match the data and yet still achieves the lowest likelihood. Note that while the parameter estimates differ quite a lot across the models, they remain relatively stable, for a given model, comparing 1993 and 2002 data.

4.3 Robustness [incomplete]

Data stratified by country per capita income

Next, in Table 4 we look at two stratifications of the whole sample data from 1993 used in Table 2, by country income level. We use World Bank's definition for these categories. In our sample, there are 58 'low-income' countries and 36 'high-income' ones. The results in Table 3 show some interesting differences between these country categories. Among the low-income countries the autarky (A) regime provides the best fit for all combinations of data variables. It is statistically significantly closer to the data according to the Vuong test when using *cqik*, *kiq*, *iq*, and *ciq* data. The only case it is tied with other regimes (all but LC and CM) is when only consumption and income data are used. The defaultable debt (DD) regime comes second in goodness of fit. In contrast, in the high-income sub-sample the non-defaultable debt regime with borrowing frictions (TB) has the highest likelihood whenever consumption data are used – in the *cqik*, *cq* and *ciq* data runs. This is not inconsistent with the whole sample data for the same year (see Table 2, left panel) where the TB model was tied for first in those runs but we are able to distinguish among TB and DD here despite the smaller sample size. When only investment, income and capital stock data are used, the autarky regime is once again best fitting, as in the baseline runs in Table 2.

Fixing the measurement error variance

Table 5, left panel presents the results from the estimation runs with 1993 data when we fix the level of measurement error across the models by setting the parameter γ_{me} which control the measurement error standard deviation (see Section 3.1) to $\gamma_{me} = .1$. The idea of this exercise is to study whether loading up on more vs. less measurement error in some of the regimes is driving our baseline results. Reassuringly, the results from the baseline run remain virtually the same, with the only exception of the *cq* results for 1993 where the B regime is now tied with TB, DD and TO. Looking back to the parameter estimates in Table 3, we see that the regime which is most 'hurt' by fixing the measurement error at 0.1 is the complete markets regime but it has the lowest fit with the data anyhow so the results are not affected.

Denser grid for capital

Table 5, right panel performs the same estimation runs as in Table 2 for 1993 data, but in the linear programming problems computation we use denser, 25-point linearly-spaced grid for the capital state variable on the interval between the 5th and 95th capital value in the data. The baseline results remain robust in general although, unexpectedly, we seem to lose some precision in the Vuong test results. The TB, DD and A models still tie for first in terms of fit with the *cqik* data but now the 'tax' on capital outflows (TO) model is tied with them too, unlike in the baseline. Using investment and output data, as in the *iq* and *kiq* estimation runs, the autarky (A) model still provides the best fit as in the baseline runs (Table 2) but it is tied with TO again in the *iq* data specification. The B and A model cannot be statistically rejected with the consumption-output data as best fitting but still the baseline 'winners' (the DD, TB and TO models) show up tied with them for best fit. One difference from the baseline is that the autarky model comes first in likelihood in the *ciq* run.

Per capita data

[TO DO]

...

Data with removed country and time fixed effects

[TO DO]

...

4.4 Peeking into the MLE 'black box' [preliminary]

To better illustrate the dimensions of the alternative dynamic models that our MLE procedure fits to the overall data, in this section we report the results of several exercises using simulated data from the seven models themselves, at the MLE best-fitting parameters and compare these simulated data to the cross-country data.

Table 6 computes the same set of summary statistics as in Table 1 for each of the seven models, using the MLE estimates for the 1993 benchmark runs. Overall, we found that the best-fitting models in terms of likelihood are the autarky (A) and the defaultable debt models (DD) – see Table 2. Table 6 clarifies further why this is the case. The DD model matches very closely the mean and median consumption and output in the data over all ten years. It somewhat underpredicts the capital and investment levels in the data. Most notably, however, is that it comes the closest to the data in terms of the consumption-income, consumption-capital stock and capital stock-income correlations. Contrast these with the LC and CM models which completely fail to match those features of the data. All models (but the complete markets model for c and k) match well the high autocorrelation of consumption, output and the capital stock. The DD model also comes closest to matching the relative volatility of consumption to output in the data. The autarky model is the only one to produce positive correlations between investment and other variables, as is the case in the data and also generates the closest to the data (c, q) and (k, q) correlations.

All models (with the exception of CM) match well the mean and median consumption in the data at their estimated parameters. However, they either underpredict (all but CM) or over-predict its variance (CM – this is counter-intuitive but the reason is the high measurement error estimate – see Table 3). All models fit well the mean and median k values, although CM and LC slightly over-predict those. Same applies for output. The CM and LC models match best the levels of investment in the data but over-predict the most its variance. Intuitively, these two models allow for most smoothing of consumption and investment from income shocks which explains the more volatile investment. The CM model severely underpredicts all bivariate correlations in the data, as well as the autocorrelation of consumption.

At their respective MLE parameters, neither of the seven models is able match several features of the data:

(i) the high standard deviation of the capital stock (A comes closest); Possible reasons are our coarse baseline k grid and 5-state process for s.

(ii) the low standard deviation of investment in the data (A comes closest); The likely reason is that in all models investment is allowed to be positive and negative, with no adjustment costs for large 'jumps' over the k grid. Adding investment adjustment costs can thus improve the fit in this dimension.

(iii) the high and positive correlations of investment with c, k, q in the data. Only the A model generates positive values for these correlations at the MLE parameters but they are too low. The possible reasons are related to point (ii) above.

(iv) the high autocorrelation of investment in the data (DD comes closest). Again, adjustment costs are a venue to explore.

(v) the high correlation between consumption and income changes in the data (the A model comes closest, followed immediately by DD). This correlation is related to the degree of consumption smoothing in the data, i.e., how much consumption adjusts from income changes. Apparently all our models over-predict the degree of cross-country consumption smoothing in the international data, or, in other words, underpredict the lack of smoothing of cross-country consumption.

Overall, the DD, TB and A models fit the various statistics in Table 6 best. In contrast, the worst fit is exhibited by the endogenously incomplete market model of limited commitment (LC) and the complete markets model which fail on many dimensions as they cannot match the lack of risk-sharing and investment smoothing in the international data. The TO and B model fall somewhere in between although much closer to the former group than the latter. These results match well with the likelihood values from Table 2.

Figures 2 plot the time paths for means and standard deviations of consumption, income and the capital stock in the productivity-adjusted data (in model units) and in each of the models using simulated data at the model's respective MLE estimates from the benchmark runs with 1993 c, q, i, k data. Note that the estimation uses only cross-sectional data from 1993 and yet the time paths for the variables' means and standard deviations for the next 9 years fit the data very close, especially for the models with the highest likelihood (DD, TB and A). These three models however somewhat underpredict the growth rate of capital. The complete markets model does worst in fit. All models severely underpredict the variance of the capital stock in the data (the first period is matched well since we initialize all models from the actual k distribution in 1993). The reason is the built-in convergence via the concave production function.

5 Conclusions

We formulate and solve a wide variety of dynamic models of international capital flows under perfect and imperfect capital markets. We set up and compare models of exogenously incomplete markets (debt with "tax" on borrowing or on capital outflows, non-defaultable debt) to models with endogenously incomplete markets (defaultable debt, limited commitment). All models share common preference and technology structure. We estimate and statistically test across the alternative theoretical models of imperfect international capital markets to study which model fits the data best and also what type of data (income, investment, capital, consumption, or all together) is needed to distinguish across the proposed theoretical models. Unlike much of previous work in the field, we use fully structural methods and simulated maximum likelihood based on the whole joint distribution of the variables of interest, as opposed to particular moments or correlations.

Empirically, we echo previous literature in rejecting the complete markets model with international data. We also use our detailed dataset to try go deeper and identify the most plausible source of financial market imperfections using different dimensions of the data used in previous work (consumption smoothing, investment smoothing or all data jointly). We find that the type of data used can matter to some extent for the end result although the overall evidence strongly and consistently favors the defaultable debt and autarky models. The limited commitment and complete market models are rejected in all the runs we did. They seem to provide too much smoothing and risk sharing relative to the international data.

In future work we plan to extend our results to earlier periods and various other data stratifications. Other variants of the incomplete markets models used here, such as allowing for adjustment costs in investment can be easily computed and estimated using our methods.

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6 Appendix A: Lotteries

In the main body of the paper, we showed how to introduce randomization (lotteries over possible allocations) into the defaultable debt and limited commitment models to convexify the countries' choice sets, which has the potential to be welfare improving and/or help us with solving the dynamic optimization problems. In the remaining theoretical frameworks for imperfect capital markets that we considered, the choice sets are convex and so allowing for randomization has no effect on welfare or the optimal contracts. Nonetheless, given our aim of estimating the models, and, most importantly, to ensure that our comparison across models is not subject to concerns about the use of different numerical solution algorithms, we solve these models using the lottery linear programming approach as well. The LP versions of the problems are stated in this Appendix.

6.1 Autarky

The problem of the country in autarky, formulated as a linear program in the probabilities over allocations $\pi(l, k', s')$, is

$$\begin{aligned} V^{A}(k,s) &= \max_{\pi(l',k',s'|k,s)} \sum_{L\times K\times S} \pi(l',k',s'|k,s)\left[u\left(f\left(s',k,1-l'\right)+(1-\delta)k-(1+g)k',l'\right)\right. \\ &\quad \left. +\beta V^{A}(k',s')\right], \end{aligned}$$

subject to Bayesian consistency

$$\sum_{L\times K} \pi(l',k',\bar{s}'|k,s) = P(\bar{s}'|s),$$

for all $\bar{s}' \in S$, adding up

$$\sum_{L\times K\times S} \pi(l',k',s'|k,s) = 1,$$

and non-negativity $\pi(l',k',s'|k,b,s) \geq 0$ for all $(l',k',s') \in L \times K \times S$.

Note that, whereas in the original statement of the problem choices of k' and l were explicitly conditioned on the realization of the current productivity shock s', this dependence is not explicitly written here. Instead, from the fact that lotteries are over combinations of (l', k', s'), this state contingency in choices is expressed in the equilibrium probabilities chosen over these combinations.

6.2 Exogenously Incomplete Markets

In this framework we introduce B as the set of possible values for debt holdings. Borrowing constraints are incorporated directly by choice of the set bounds. For the model with 'tax' on borrowing, when formulated using lotteries and after substituting for consumption from the resource constraint, the country's problem becomes

$$\begin{aligned} V^{TB}(k,b,s) \quad = \quad & \max_{\pi(l',k',b',s'|k,b,s)} \sum_{L\times K\times B\times S} \pi(l',k',b',s'|k,b,s)[u((1-\delta)k + f(s',k,1-l') + \\ & +(1-\tau_1 I_{b'>0})qb' - b - (1+g)k', l') + \beta V^{TB}(k',b',s')] \end{aligned}$$

subject to the familiar constraints on the probabilities $\pi(l', k', b', s'|k, b, s)$ of Bayesian consistency, adding-up and non-negativity.

For the model with 'tax' on capital outflows, the same process yields the problem of the country as

$$\begin{aligned} V^{TO}(k,b,s) \quad = \quad & \max_{\pi(l',k',b',s'|k,b,s)} \sum_{L\times K\times B\times S} \pi(l',k',b',s'|k,b,s)[u((1-\delta)k + f(s',k,1-l') + \\ & +(1+\tau_2 I_{qb'-b<0})(qb'-b) - (1+g)k', l') + \beta V^{TO}(k',b',s')] \end{aligned}$$

subject to Bayesian consistency, adding up and non-negativity as before. The non-defaultable debt (B) regime is obtained by setting either τ_1 or τ_2 to zero above.

6.3 Complete Markets

The solution to the limited commitment problem is identical to the solution to the complete markets problem as long as the participation constraints never bind. As a consequence, we can introduce lotteries into this framework in the same way that we did for the limited commitment model by simply dropping the participation (limited liability) constraints.

Table 1 - Data summary statistics

Statistic	1. Per capita USD	2. Model units[1]
mean consumption, c	3196	1.5623
median(c)	1092	1.5059
std(c)	4604	0.5680
kurtosis(c)	6.654	7.877
mean capital stock, k	13779	6.1187
median(k)	3848	5.3065
std(k)	22048	4.4887
kurtosis(k)	9.185	39.532
mean income, q	4679	1.9534
median(q)	1395	1.9248
std(q)	7028	0.4775
kurtosis(q)	6.9461	6.9279
mean investment, i	1287	0.5419
median(i)	356	0.4844
std(i)	1975	0.3022
kurtosis(i)	7.550	11.495
corr(c,k)	0.9502	0.5307
corr(c,q)	0.9749	0.5817
corr(k,q)	0.9681	0.7262
corr(i,k)	0.9584	0.6401
corr(i,q)	0.9577	0.5641
corr(i,c)	0.9264	0.3723
autocorr(c_t,c_{t-1})	0.8918	0.8918
autocorr(q_t,q_{t-1})	0.8949	0.8949
autocorr(i_t,i_{t-1})	0.8768	0.8768
autocorr(k_t,k_{t-1})	0.8931	0.8931
std(c)/std(q)	0.6551	1.1897
std(i)/std(q)	0.2810	0.6329
corr(Δc,Δq)	0.2411	0.5188
corr(Δk,Δq)	0.3734	0.1873

Note: 1. TFP and population adjusted data (normalized using the 90th percentile of k in the whole sample)

Table 2 - Model comparisons, baseline

Data used:	cqik, '93	cq, '93	kiq, '93	ciq, '93	iq, '93	cqik, '02	cq, '02	kiq, '02	ciq, '02	iq, '02
TB v. TO	TB***	tie	TB***	TB***	TB***	TB***	tie	TB***	TB***	TB***
TB v. B	TB*	tie	TB*	TB*	TB***	TB**	tie	TB***	tie	TB***
TB v. LC	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***
TB v. CM	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***
TB v. DD	tie	tie	DD**	tie	DD***	tie	tie	DD**	tie	tie
TB v. A	tie	tie	A***	TB**	A***	tie	tie	A***	tie	tie
TO v. B	B**	tie	B***	B***	B***	B*	tie	B**	B***	B**
TO v. LC	TO***	TO**	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***
TO v. CM	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***
TO v. DD	DD***	tie	DD***	DD***	DD***	DD***	tie	DD***	DD***	DD***
TO v. A	A*	tie	A***	tie	A***	A***	tie	A***	A**	A***
B v. LC	B***	B*	B***	B***	B***	B***	B***	B***	B***	B***
B v. CM	B***	B***	B***	B***	B***	B***	B***	B***	B***	B***
B v. DD	DD**	tie	DD**	tie	DD***	DD**	tie	DD***	tie	DD***
B v. A	tie	tie	A***	tie	A***	A***	tie	A***	tie	A***
LC v. CM	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***
LC v. DD	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***
LC v. A	A***	A**	A***	A***	A***	A***	A***	A***	A***	A***
CM v. DD	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***
CM v. A	A***	A***	A***	A***	A***	A***	A***	A***	A***	A***
DD v. A	tie	DD**	A***	DD*	A***	tie	tie	A***	tie	A*
Best fit:	*DD,TB,A*	*DD,TB,TO*	*A* *DD is second*	*TB,DD*	*A* *DD is second*	*A,TB,DD*	*TO,TB,B, A,DD*	*A* *DD is second*	*TB,DD,A, B*	*A* *DD is second*

Legend: TB = 'tax' on borrowing; TO = 'tax' on outflows; B = non-defaultable debt; LC = limited commitment; CM = complete markets; DD = defaultable debt; A = autarky

The better fitting regime in each bilateral test is listed; *** = 1%; ** = 5% and * = 10% confidence level (two-sided)

The "best fit" row lists the best-fitting (incuding ties) model, in order of log-likelihood, staring with the higest.

Table 3 - MLE parameter estimates, 1993 and 2002 cqik data

Model:	cqik '93 data γ_{me}	cqik '93 data $\mu_{b/w}$	cqik '93 data $\gamma_{b/w}$	cqik '02 data γ_{me}	cqik '02 data $\mu_{b/w}$	cqik '02 data $\gamma_{b/w}$
tax on borrowing (TB)	0.1032	0.5566	0.0029	0.1114	0.5258	0.0111
tax on outflows (TO)	0.1046	0.9909	0.4510	0.1222	0.6686	0.5733
non-defaultable debt (B)	0.1046	0.7435	0.0000	0.1274	0.6666	0.0542
limited commitment (LC)	0.1445	0.0000	0.4450	0.1341	0.1912	0.4777
complete markets (CM)	0.2489	0.9766	0.0049	0.2450	0.9837	0.0089
defaultable debt (DD)	0.1043	0.4922	0.0000	0.1138	0.4792	0.0000
autarky (A)	0.1003	n.a.	n.a.	0.1174	n.a.	n.a.

Table 4 - Model comparisons - Robustness I

	4.1 low income					4.2 high income				
Data used:	**cqik**	**cq**	**kiq**	**ciq**	**iq**	**cqik**	**cq**	**kiq**	**ciq**	**iq**
TB v. TO	tie	tie	TB***	TB*	TB***	TB*	TB**	tie	TB*	tie
TB v. B	tie	tie	TB***	TB*	TB***	TB***	TB**	B**	TB***	tie
TB v. LC	TB***	TB*	TB***	TB**	TB***	TB***	TB***	TB***	TB***	TB***
TB v. CM	TB***	TB**	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***
TB v. DD	tie	tie	tie	tie	DD**	TB**	TB***	DD**	TB***	DD**
TB v. A	A**	tie	A***	A**	A***	TB**	TB***	A***	TB***	A***
TO v. B	tie	tie	B*	tie	B***	tie	B**	B*	tie	tie
TO v. LC	TO***	TO*	TO***	TO**	TO***	TO***	tie	TO***	TO***	TO***
TO v. CM	TO***	TO**	TO***	TO***	TO***	TO***	TO***	TO***	BTO***	TO***
TO v. DD	DD**	tie	DD***	DD**	DD***	tie	TO***	tie	TO*	tie
TO v. A	A***	tie	A***	A***	A***	tie	TO***	A***	TO***	A**
B v. LC	B***	B*	B***	B**	B***	B***	B*	B***	B***	B***
B v. CM	B***	B**	B***	B***	B***	B***	B***	B***	B***	B***
B v. DD	tie	tie	DD***	DD**	DD***	tie	B***	tie	tie	tie
B v. A	A**	tie	A***	A***	A***	tie	B***	A***	B***	A**
LC v. CM	LC***	LC**	LC***	LC***	LC*	LC***	LC***	LC***	LC***	LC***
LC v. DD	DD***	DD*	DD***	DD**	DD***	DD***	tie	DD***	DD***	DD***
LC v. A	A***	A*	A***	A***	A***	A***	LC**	A***	A***	A***
CM v. DD	DD***	DD**	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***
CM v. A	A***	A**	A***	A***	A***	A***	A***	A***	A***	A***
DD v. A	A**	tie	A***	A**	A***	tie	DD**	A***	DD***	A***
Best fit:	*A*	*DD,TB,TO,*	*A*	*A*	*A*	*TB*	*TB*	*A*	*TB*	*A*
	DD is second	*B,A*	*DD is second*	*DD is second*	*DD is second*	*B is second*	*B is second*	*DD is second*	*TO is second*	*DD is second*

Legend: TB = 'tax' on borrowing; TO = 'tax' on outflows; B = non-defaultable debt; LC = limited commitment; CM = complete markets; DD = defaultable debt; A = autarky

The better fitting regime in each bilateral test is listed; *** = 1%; ** = 5% and * = 10% confidence level (two-sided)

The "best fit" row lists the best-fitting (incuding ties) model, in order of log-likelihood, staring with the higest.

Table 5 - Model comparisons - Robustness II

	5.1 fixed measurement error					5.2 denser grid				
Data used:	**cqik**	**cq**	**kiq**	**ciq**	**iq**	**cqik**	**cq**	**kiq**	**ciq**	**iq**
TB v. TO	TB***	tie	TB***	TB***	TB***	tie	tie	tie	tie	TO***
TB v. B	TB*	tie	TB**	TB**	TB***	TB**	tie	TB***	TB***	tie
TB v. LC	TB***	TB*	TB***	TB***	TB***	TB***	TB*	TB***	TB***	TB***
TB v. CM	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***	TB***
TB v. DD	tie	tie	DD***	tie	DD***	tie	tie	tie	tie	DD**
TB v. A	tie	TB***	A***	TB**	A***	tie	tie	A***	A***	A***
TO v. B	B**	tie	B***	B***	B***	TO***	tie	TO***	TO***	tie
TO v. LC	TO***	tie	TO***	TO***	TO***	TO***	TO**	TO***	TO***	TO***
TO v. CM	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***	TO***
TO v. DD	DD***	tie	DD***	DD***	DD***	tie	tie	tie	tie	tie
TO v. A	A*	TO***	A***	tie	A***	tie	tie	A***	A**	tie
B v. LC	B***	tie	B***	B***	B***	B***	B**	B***	B***	B***
B v. CM	B***	B***	B***	B***	B***	B***	B***	B***	B***	B***
B v. DD	DD**	tie	DD***	DD*	DD***	tie	tie	DD***	DD*	tie
B v. A	tie	B***	A***	tie	A***	tie	tie	A***	A***	A**
LC v. CM	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***	LC***
LC v. DD	DD***	tie	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***
LC v. A	A***	tie	A***	A***	A***	A***	A**	A***	A***	A***
CM v. DD	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***	DD***
CM v. A	A***	A***	A***	A***	A***	A***	A***	A***	A***	A***
DD v. A	tie	DD**	A***	DD*	A***	tie	tie	A***	A***	A**
Best fit:	*DD,TB,A*	*TB,B,DD, TO*	*A* *DD is second*	*TB,DD*	*A* *DD is second*	*TO,A,TB, DD*	*DD,TB,B, TO,A*	*A* *DD is second*	*A*	*A,TO*

Legend: TB = 'tax' on borrowing; TO = 'tax' on outflows; B = non-defaultable debt; LC = limited commitment; CM = complete markets; DD = defaultable debt; A = autarky

The better fitting regime in each bilateral test is listed; *** = 1%; ** = 5% and * = 10% confidence level (two-sided)

The "best fit" row lists the best-fitting (incuding ties) model, in order of log-likelihood, staring with the higest.

Table 6 - Actual vs. simulated data, summary statistics

	Data	BTB(sim)	BTO(sim)	B(sim)	LC(sim)	CM(sim)	DD(sim)	A(sim)
mean consumtpion, c	**1.5623**	1.5231	1.5090	1.5314	1.5127	1.0946	1.5398	1.5923
median(c)	**1.5059**	1.5164	1.5171	1.5286	1.4709	0.7507	1.5348	1.5920
std(c)	**0.5680**	0.3750	0.3749	0.3513	0.4769	1.0635	0.3724	0.3326
kurtosis(c)	**7.877**	3.2400	2.9836	3.1238	3.4086	2.6413	3.3238	3.0357
mean capital stock, k	**6.1187**	5.3592	5.4910	5.6230	6.5390	6.7205	5.3735	5.3136
median(k)	**5.3065**	5.2082	5.5642	5.6006	6.5430	6.7918	5.1393	4.8704
std(k)	**4.4887**	2.3845	2.3479	2.1948	2.1375	2.5288	2.5208	2.9298
kurtosis(k)	**39.532**	115.2	120.8	156.0	157.5	76.5	92.5	51.7
mean output, q	**1.9534**	1.9225	1.9377	1.9605	2.0692	2.0827	1.9195	1.8961
median(q)	**1.9248**	1.9089	1.9428	1.9595	2.0702	2.0699	1.9034	1.8597
std(q)	**0.4775**	0.2997	0.3004	0.2809	0.3097	0.4307	0.3124	0.3557
kurtosis(q)	**6.928**	3.1695	2.9883	3.2305	3.6291	3.0834	3.0910	2.6980
mean investment, i	**0.5419**	0.3455	0.3644	0.4063	0.5107	0.5158	0.3598	0.2816
median(i)	**0.4844**	0.3788	0.3721	0.3784	0.4088	0.4551	0.3681	0.2894
std(i)	**0.3022**	1.5438	1.5504	1.5942	2.3021	3.6834	1.5415	1.4774
kurtosis(i)	**11.495**	3.2057	3.2354	3.3920	3.3835	2.9942	3.0515	2.8589
corr(c,k)	**0.5307**	0.5188	0.4785	0.4430	0.0230	0.0063	0.5207	0.4183
corr(c,q)	**0.5817**	0.5123	0.5128	0.4491	0.0021	-0.0165	0.5190	0.5406
corr(k,q)	**0.7262**	0.5869	0.5751	0.5150	0.3715	0.1904	0.6190	0.7280
corr(i,k)	**0.6401**	-0.0659	-0.0806	-0.1288	-0.2153	-0.1269	-0.0442	0.0361
corr(i,q)	**0.5641**	-0.0232	-0.0299	-0.0700	-0.1162	-0.0516	-0.0095	0.0252
corr(i,c)	**0.3723**	-0.0467	-0.0344	-0.0737	0.0102	0.0105	-0.0450	0.0136
autocorr(c_t,c_{t-1})	**0.8918**	0.8685	0.8654	0.8710	0.8403	0.5371	0.8662	0.8728
autocorr(q_t,q_{t-1})	**0.8949**	0.8921	0.8930	0.8944	0.8944	0.8757	0.8917	0.8940
autocorr(i_t,i_{t-1})	**0.8768**	0.0493	0.0683	0.0706	0.0580	0.0379	0.0679	-0.0033
autocorr(k_t,k_{t-1})	**0.8931**	0.8629	0.8630	0.8688	0.8647	0.8305	0.8619	0.8668
std(c)/std(q)	**1.1897**	1.2513	1.2480	1.2506	1.5399	2.4692	1.1921	0.9351
std(i)/std(q)	**0.6329**	5.1512	5.1611	5.6753	7.4333	8.5521	4.9344	4.1535
corr(Δc,Δq)	**0.5188**	0.1070	0.1177	0.1057	0.0513	0.0603	0.1194	0.1348
corr(Δk,Δq)	**0.1873**	0.0737	0.1215	0.1118	0.2366	0.0947	0.0896	0.0580

Notes: All simulated data are at their corresponding MLE estimates from the cqik 1993 run
All above results are based on an n = 175, T = 10 panel of actual or simulated data.
All units (where applicable) are model units.

Figure 1 − Data (model units): output, consumption, investment comovement

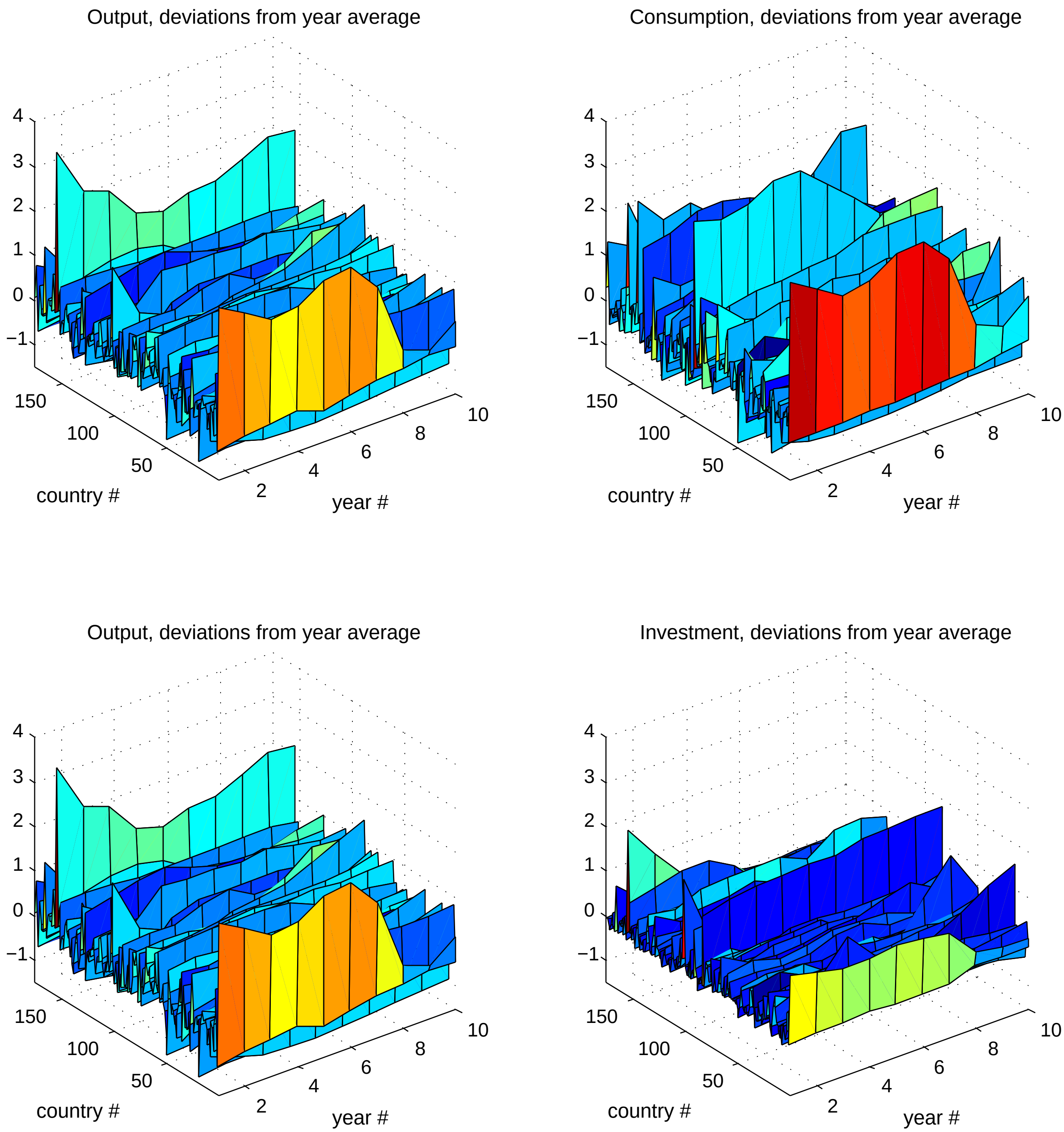
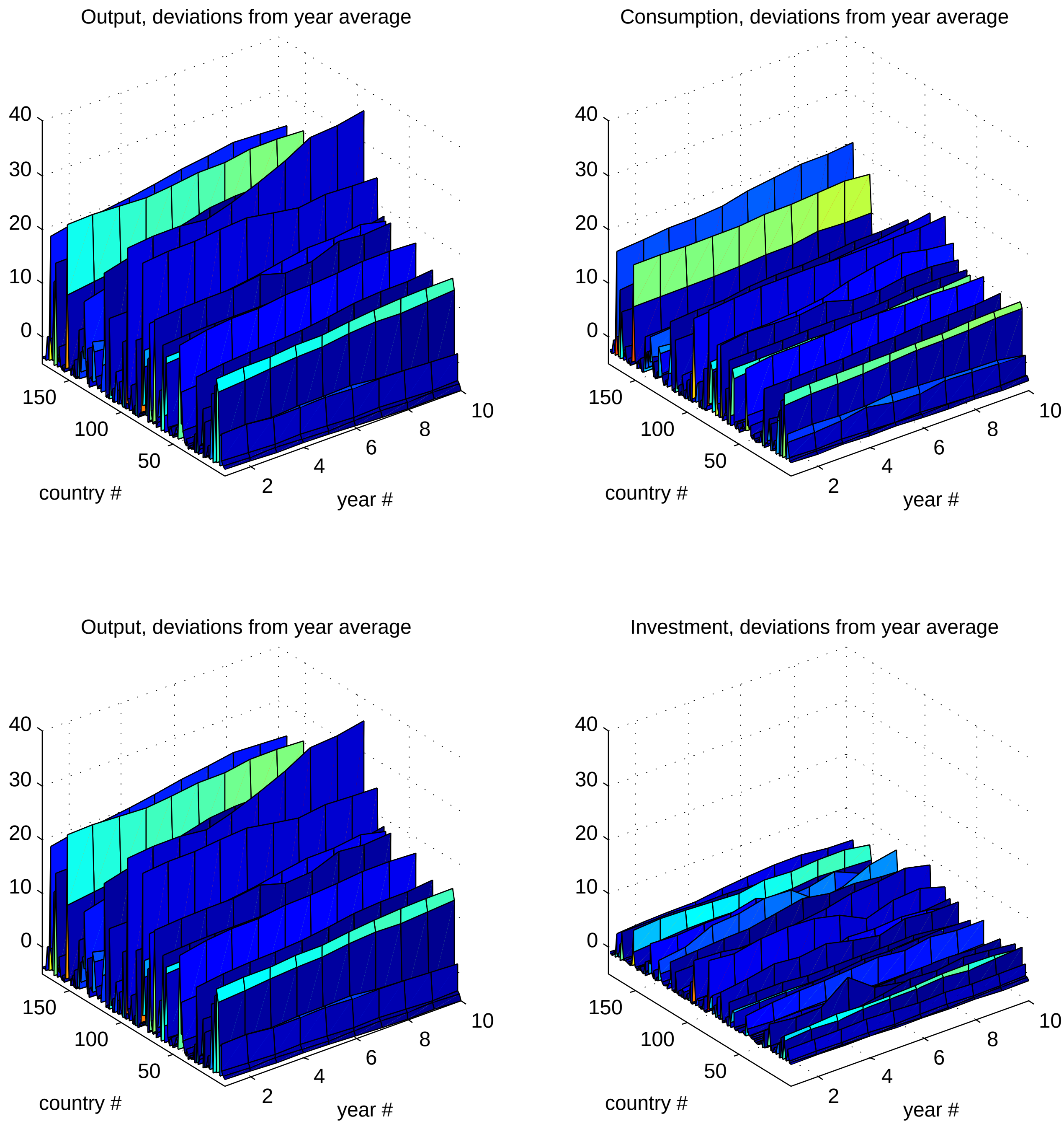
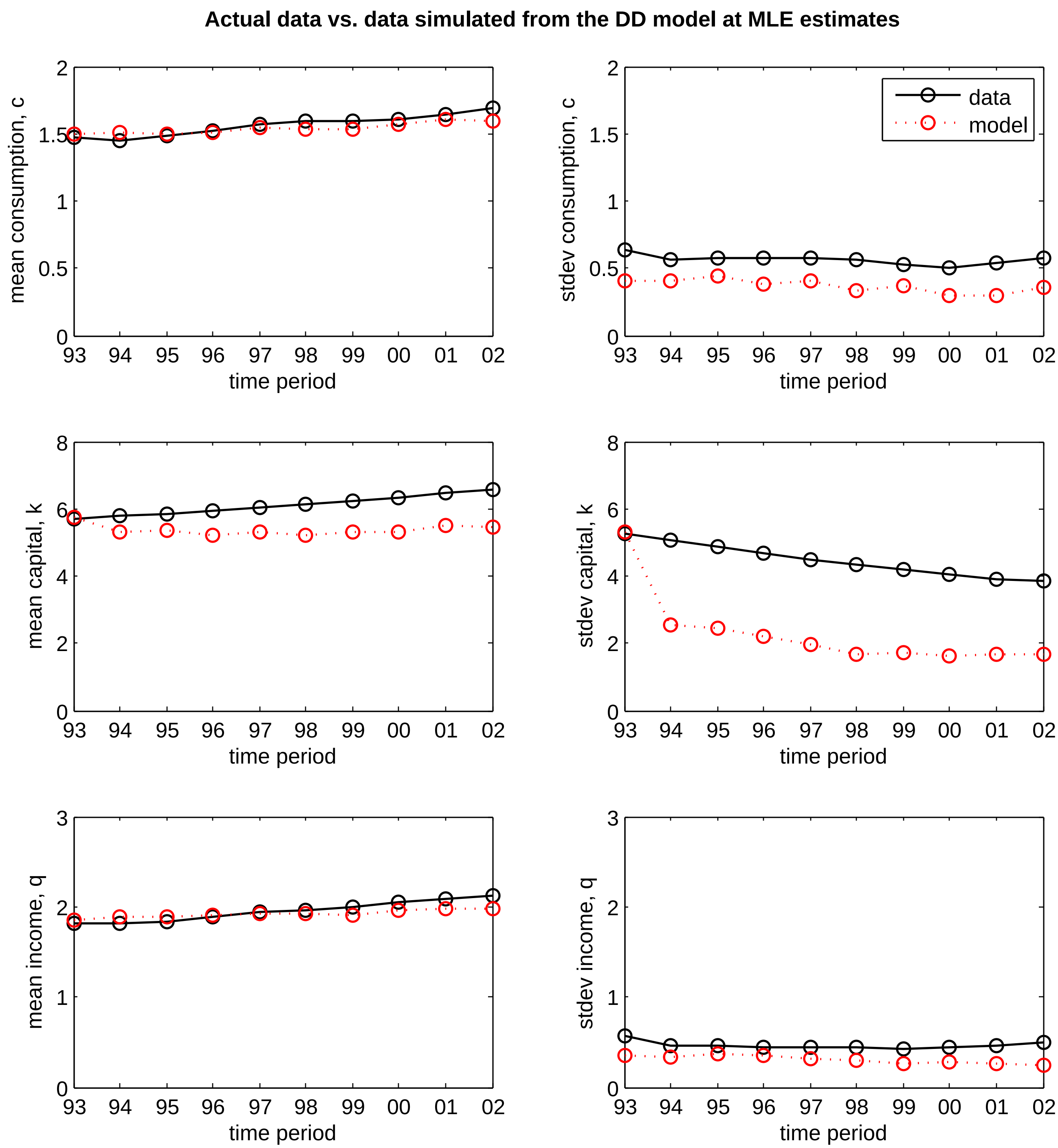


Figure 1a − Data: output, consumption, investment comovement ('000 USD)

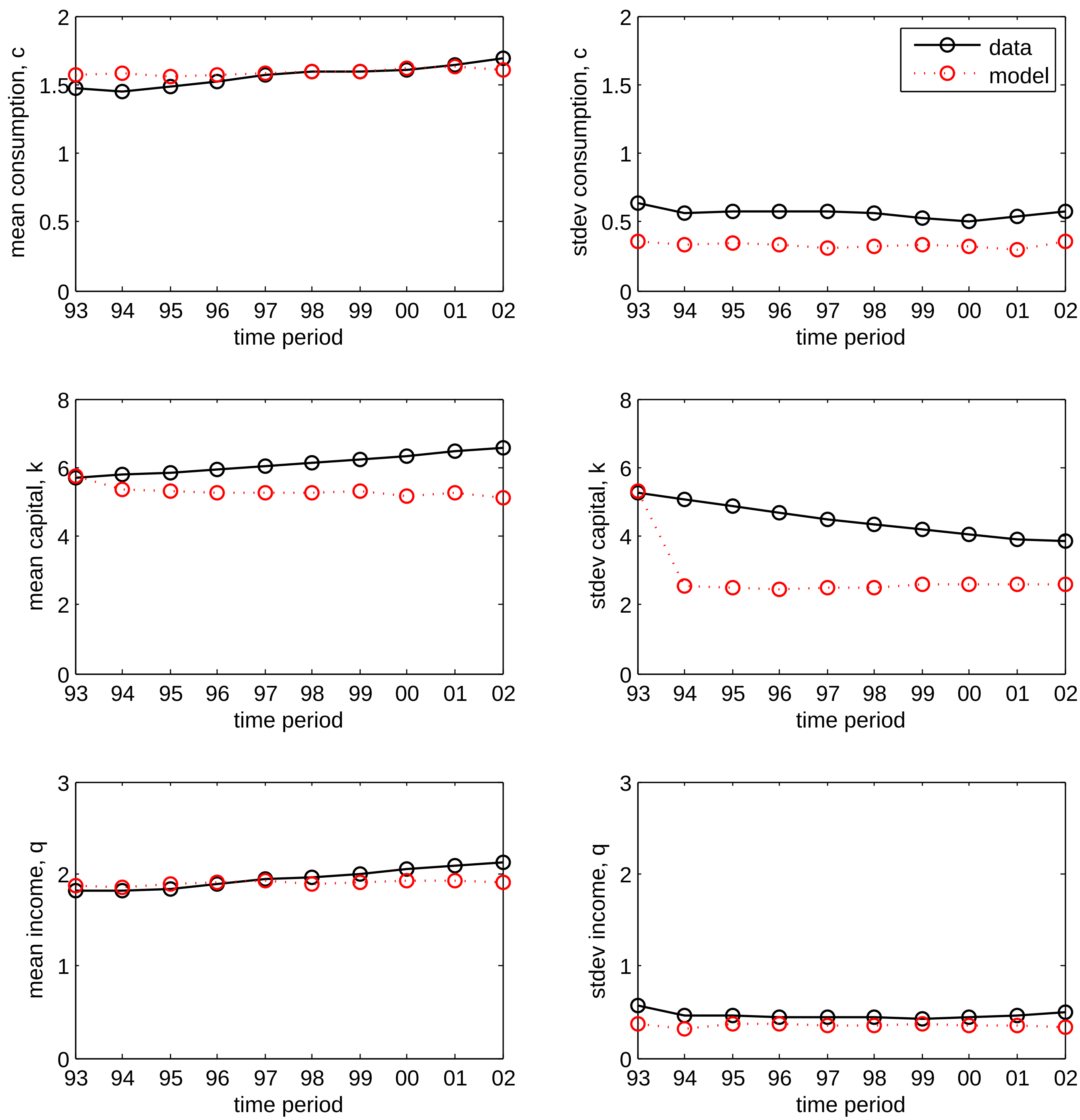


FIGURES 2

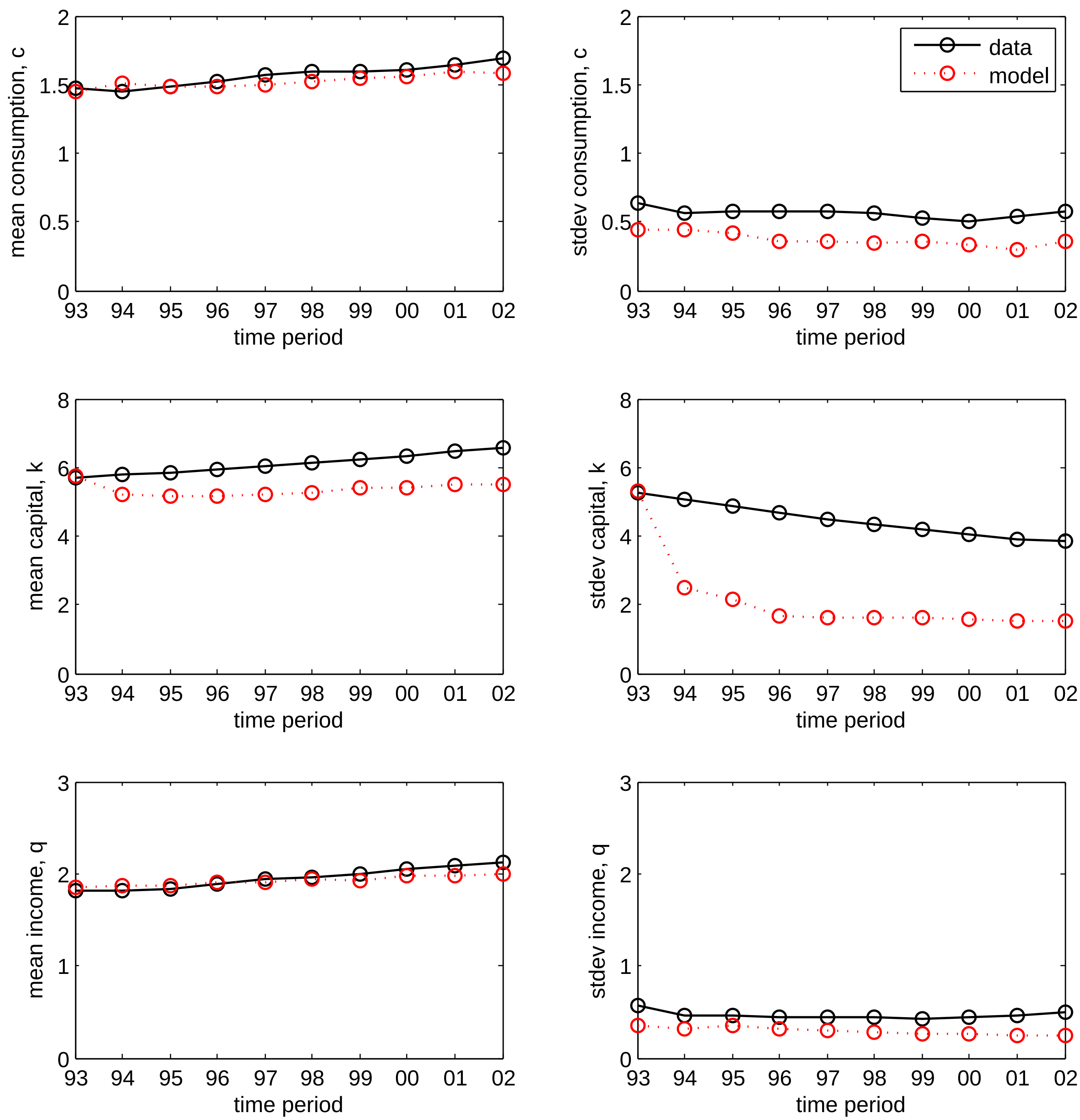


Actual data vs. data simulated from the DD model at MLE estimates
mean consumption, c
stdev consumption, c
data
model
mean capital, k
stdev capital, k
mean income, q
stdev income, q
time period
93 94 95 96 97 98 99 00 01 02

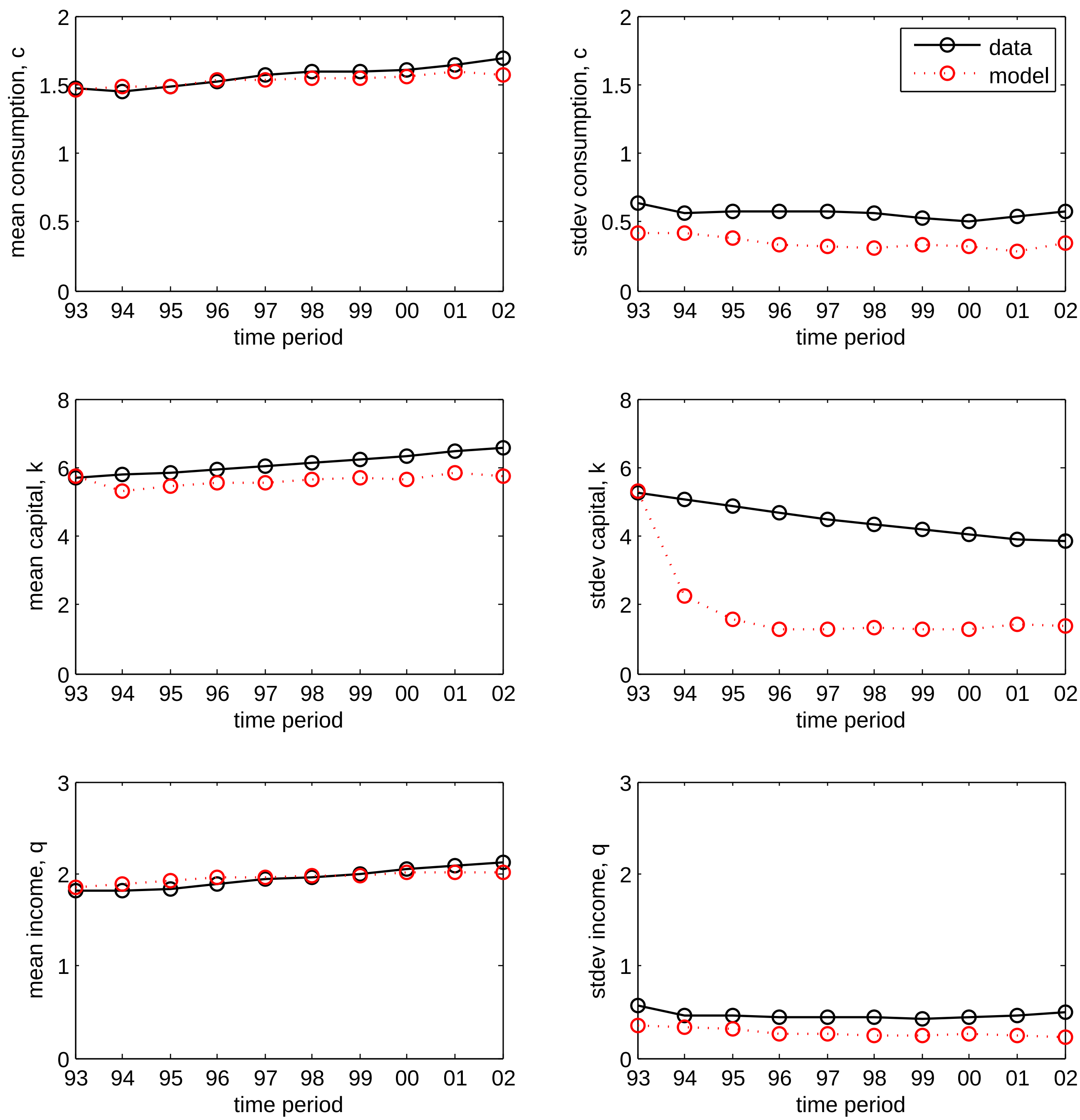
Actual data vs. data simulated from the A model at MLE estimates

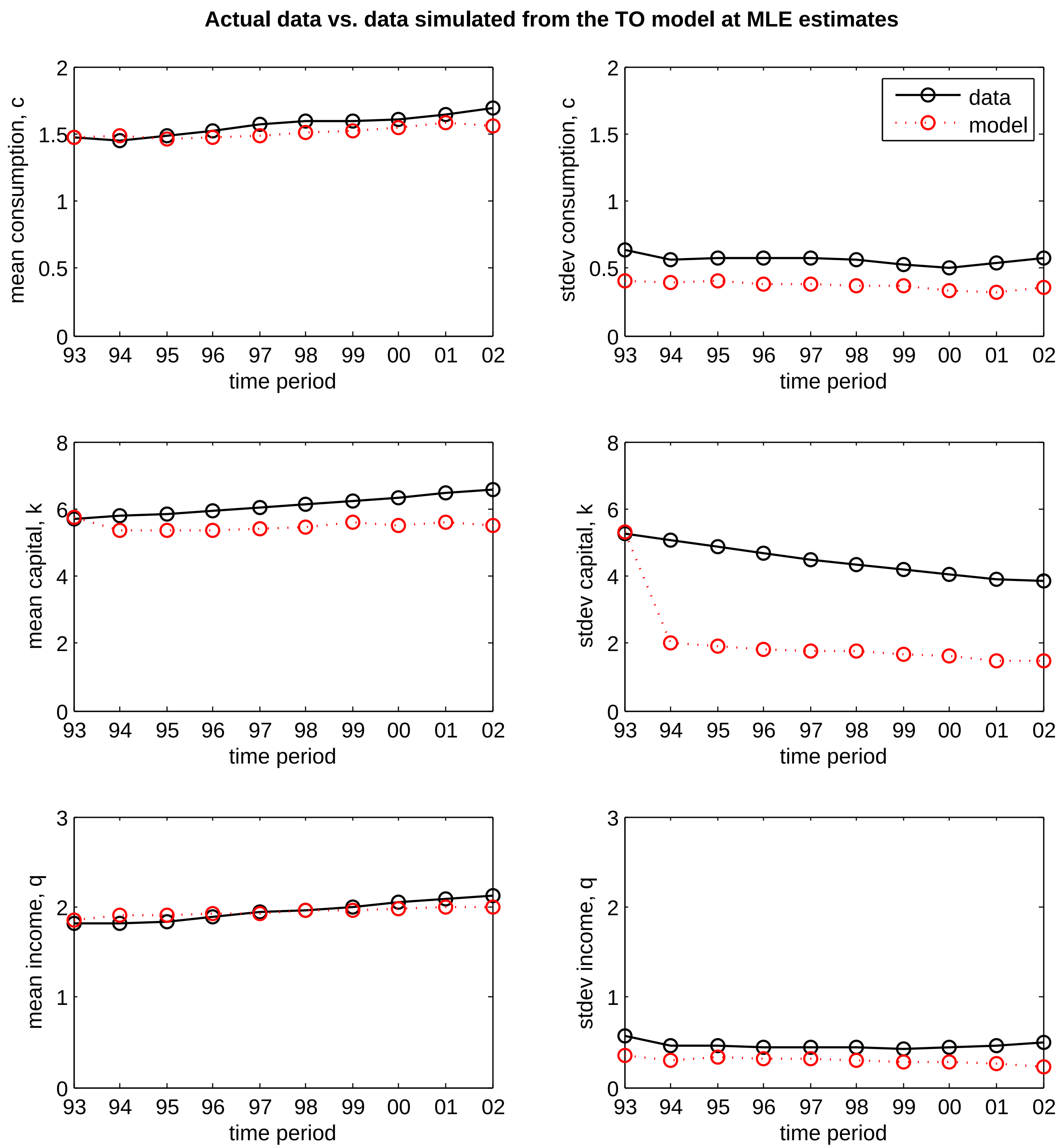


Actual data vs. data simulated from the TB model at MLE estimates

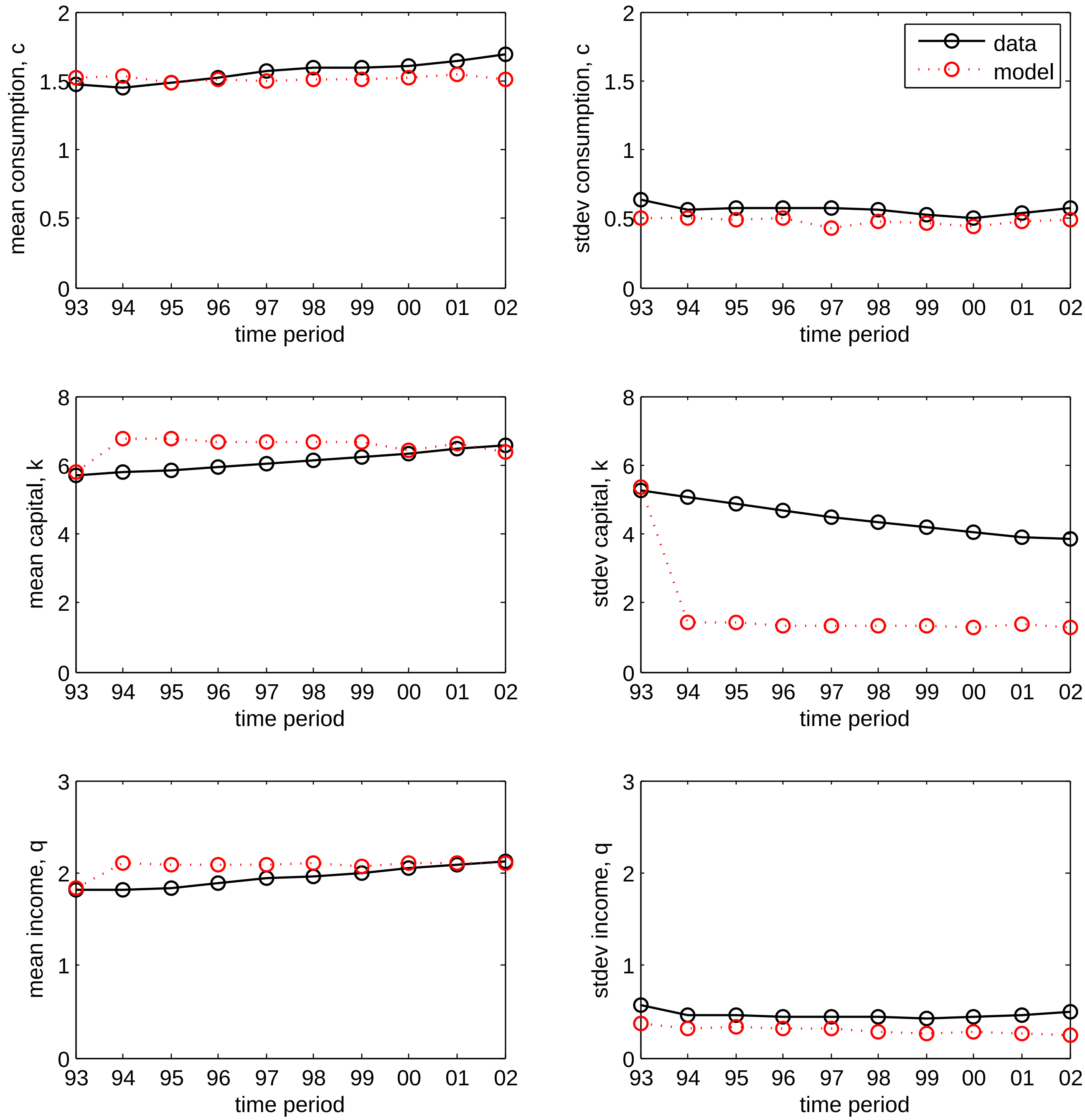


Actual data vs. data simulated from the B model at MLE estimates




Actual data vs. data simulated from the TO model at MLE estimates
mean consumption, c
stdev consumption, c
data
model
mean capital, k
stdev capital, k
mean income, q
stdev income, q
time period
93
94
95
96
97
98
99
00
01
02

Actual data vs. data simulated from the LC model at MLE estimates



Actual data vs. data simulated from the CM model at MLE estimates