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DYNAMIC FINANCIAL CONSTRAINTS: DISTINGUISHING MECHANISM DESIGN FROM EXOGENOUSLY INCOMPLETE REGIMES

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DYNAMIC FINANCIAL CONSTRAINTS: DISTINGUISHING MECHANISM DESIGN FROM EXOGENOUSLY INCOMPLETE REGIMES

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We formulate and solve a range of dynamic models of constrained credit/insurance that allow for moral hazard and limited commitment. We compare them to full insurance and exogenously incomplete financial regimes (autarky, saving only, borrowing and lending in a single asset). We develop computational methods based on mechanism design, linear programming, and maximum likelihood to estimate, compare, and statistically test these alternative dynamic models with financial/information constraints. Our methods can use both cross-sectional and panel data and allow for measurement error and unobserved heterogeneity. We estimate the models using data on Thai households running small businesses from two separate samples. We find that in the rural sample, the exogenously incomplete saving only and borrowing regimes provide the best fit using data on consumption, business assets, investment, and income. Family and other networks help consumption smoothing there, as in a moral hazard constrained regime. In contrast, in urban areas, we find mechanism design financial/information regimes that are decidedly less constrained, with the moral hazard model fitting best combined business and consumption data. We perform numerous robustness checks in both the Thai data and in Monte Carlo simulations and compare our maximum likelihood criterion with results from other metrics and data not used in the estimation. A prototypical counterfactual policy evaluation exercise using the estimation results is also featured.

KEYWORDS: Financial constraints, mechanism design, structural estimation and testing.

1. INTRODUCTION

WE COMPUTE, ESTIMATE, AND CONTRAST the consumption and investment behavior of risk averse households running small non-farm and farm businesses under alternative dynamic financial and information environments, including exogenously incomplete markets settings (autarky, savings only, non-contingent debt subject to natural borrowing limit) and endogenously constrained settings (moral hazard, limited commitment), both relative to full insurance. We analyze in what circumstances these financial/information regimes can be distinguished in consumption and income data, in investment and income data, or in both, jointly. More generally, we propose and apply methods

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for structural estimation of dynamic mechanism design models. We use the estimates to statistically test the alternative models against each other with both actual data on Thai rural and also urban households and data simulated from the models themselves. We conduct numerous robustness checks, including using alternative model selection criteria and using data not used in the estimation in order to compare predictions at the estimated parameters and to uncover data features that drive our results. We also provide an example of how our estimation method and results could be used to evaluate policy counterfactuals within the model.

With few exceptions, the existing literature maintains a dichotomy, also embedded in the national accounts: households are consumers and suppliers of market inputs, whereas firms produce and hire labor and other factors. This gives rise, on the one hand, to a large literature that studies household consumption smoothing. On the other hand, the consumer-firm dichotomy gives rise to an equally large literature on investment in which, mostly, firms are modeled as risk neutral maximizers of expected discounted profits or dividends to owners. Here we set aside, for the moment, the issues of heterogeneity in technologies and firm growth and focus on a benchmark with financial constraints, thinking of households as firms generating investment and consumption data, as they clearly are in the data we analyze.

The literature that is closest to our paper, and complementary with what we are doing, features risk averse households as firms but largely *assumes* that certain markets or contracts are missing.[2] Our methods might indicate how to build upon these papers, possibly with alternative assumptions on the financial underpinnings. Indeed, this begs the question of how good an approximation are the various assumptions on the financial markets environment, different across the different papers. That is, what would be a reasonable assumption for the financial regime if that part, too, were taken to the data? Which models of financial constraints fit the data best and should be used in future, possibly policy-informing, work and which are rejected and can be set aside? The latter, though seemingly a more limited objective, is important to emphasize, as it can be useful to narrow down the set of alternatives that remain on the table without falling into the trap that we must definitely pick one model.

Relative to most of the literature, the methods we develop and use in this paper offer several advantages. First, we solve and estimate fully dynamic models of incomplete markets—this is computationally challenging but captures the complete, within-period and cross-period, implications of financial constraints

[2]For example, Cagetti and De Nardi (2006) followed Aiyagari (1994) in their study of inequality and assumed that labor income is stochastic and uninsurable, while Angeletos and Calvet (2006) and Covas (2006), in their work on buffer stock motives and macro savings rates, featured uninsured entrepreneurial risk. In the asset pricing vein, Heaton and Lucas (2000) modeled entrepreneurial investment as a portfolio choice problem, assuming exogenously incomplete markets in the tradition of Geanakoplos and Polemarchakis (1986) or Zame (1993).

on consumption, investment, and production. Second, our empirical methods can handle any number or type of financial regimes with different frictions. We do not need to make specific functional form or other assumptions to nest those various regimes—the Vuong model comparison test we use does not require this. Third, by using maximum likelihood, as opposed to reduced-form techniques or estimation methods based on Euler equations, we are, in principle, able to estimate a larger set of structural parameters than, for example, those that appear in investment or consumption Euler equations and also a wider set of models. More generally, the MLE approach allows us to capture more dimensions of the joint distribution of data variables (consumption, income, investment, capital), both in the cross-section or over time, as opposed to only specific dimensions such as consumption-income comovement or cash flow/investment correlations. Fourth, on the technical side, compared to alternative approaches based on first order conditions, our linear programming solution technique allows us to deal in a straightforward yet extremely general way with non-convexities and non-global optimization issues common in endogenously incomplete markets settings. We do not need to assume that the first order approach is valid or limit ourselves to situations where it is, assume any single-crossing properties, or adopt simplifying adjacency constraints. Combining linear programming with maximum likelihood estimation allows for a natural direct mapping between the model solutions, already in probabilistic form, and likelihoods which may be unavailable using other solution or estimation methods. Our approach is also generally applicable to other dynamic discrete choice decision problems by first writing them as linear programs and then mapping the solutions into likelihoods.

In this paper, we focus on whether and in what circumstances it is possible to distinguish financial regimes, depending on the data used. To that end, we also perform tests in which we have full control, that is, we know what the financial regime really is by using simulated data from the model. Our paper is thus both a conceptual and a methodological contribution. We show how all the financial regimes can be formulated as linear programming problems, often of large dimension, and how likelihood functions, naturally in the space of probabilities/lotteries, can be estimated. We allow for measurement error, the need to estimate the underlying distribution of unobserved state variables, and the use of data from transitions, before households reach steady state.

We apply our methods to a featured emerging market economy—Thailand—to make the point that what we offer is a feasible, practical approach to real data when the researcher aims to provide insights on the source and nature of financial constraints. We chose Thailand for two main reasons. First, our data source (the Townsend Thai surveys) includes panel data on both consumption and investment and this is rare. We can thus see if the combination of consumption and investment data really helps make a difference. Second, we also learn about potential next steps in modeling financial regimes. We know in particular, from other work with these data, that consumption smoothing is quite good, that is, it is sometimes difficult to reject full insurance, in the sense that the coefficient on idiosyncratic income, if significant, is small (Chiappori, Schulhofer-Wohl, Samphantharak, and Townsend (2014)). We also know that investment is sensitive to income, especially for the poor, but, on the other hand, this is to some extent overcome by family networks (Samphantharak and Townsend (2010)). Finally, there is a seeming divergence between high rate-of-return households, who seem constrained in scale, and low rate-of-return households, who seemingly should be doing something else with their funds. In short, intermediation is imperfect but varies depending on the dimension chosen.

While we keep these data features in mind, we remain ex ante neutral in what we expect to find in terms of the best-fitting theoretical model. Hence, we test the full range of regimes, from autarky to full information, against the data. We are interested in how these same data look when viewed jointly though the lens of each of the alternative financial regimes we model. We also want to be assured that our methods, which feature grid approximations, measurement error, estimation of unobserved distribution of utility promises, and transition dynamics, are as a practical matter applicable to actual data. This is our primary intent, to offer an operational methodology for estimating and comparing across different dynamic models of financial regimes that can be taken to data from various sources. We focus on the Thai application, first, but also use Monte Carlo simulations and a variety of robustness checks, including with data or metrics not used in the estimation.

We find that, by and large, our methods work with the Thai data. In terms of the regime that fits the rural data best, we echo previous work which finds that investment is not smooth and can be sensitive to cash flow fluctuations and that capital stocks are very persistent. Indeed, we find that investment and income data alone are most consistent with the saving only and borrowing and lending regimes, with statistical ties depending on the specification, and this is true as well with the combined consumption and investment data. We also echo previous work which finds that, with income and consumption data alone, full risk sharing is rejected, but not by much, and indeed the moral hazard regime is consistent with these data though sometimes statistically tied with limited commitment or savings only, depending on the specification. We find some evidence that family networks move households more decisively toward less constrained regimes.

In the urban data, we find that the best-fitting financial/information regime is less constraining overall. There is still persistence in the capital stock, though less than in the rural data, so, with production data alone, the saving only regime again fits best. But the consumption data are even smoother against income than in the rural sample and the moral hazard and even full insurance regimes fit well, with fewer ties with the more constrained regimes. Overall in the urban data, with combined production and consumption data, moral hazard provides the best fit, unlike in the rural sample. The autarky regime is rejected in virtually all estimation runs with both the rural and urban data.

We are also keen to distinguish across the financial/information regimes themselves, and not their auxiliary assumptions. So, in a major robustness check, we establish that imposing a parametric production function with estimated parameters does not drive our conclusions. Our primary specification uses unstructured histograms for input/output data, as our computational methods allow arbitrary functional forms. We also perform a range of additional runs with the Thai data that confirm the robustness of our baseline results—imposing risk neutrality, fixing the size of measurement error across regimes, allowing for quadratic adjustment costs in investment, running on data purged from household or year fixed effects, different grid sizes, different distributional assumptions on the unobservable state variable, and alternative assets and income definitions.

In another important robustness check, we perform Monte Carlo estimations with data simulated from the model. In these runs, we know what the financial regime really is, and what the true parameter values really are, but we run our estimation the same way as in the Thai data, as if we did not have this information. We find that our ability to distinguish between the regimes naturally depends on both the type of data used and the amount of measurement error. With low measurement error, we are able to distinguish between almost all regime pairs and recover the true regime. As expected, however, higher measurement error in the simulated data reduces the power of the model comparison test—some counterfactual regimes cannot be distinguished from the data-generating baseline and from each other. For example, using investment, assets, and income data, we cannot distinguish between the regimes (with the exception of autarky) when moral hazard generated the data. Using joint data on consumption, investment, business assets, and income, however, does markedly improve the ability to distinguish across the regimes, including with high measurement error in the simulated data. We also incorporate intertemporal data from the model, which we also find to significantly improve our ability to distinguish the regimes relative to when using cross-sections of the same data variables. We also show that the results with simulated data are robust to various modifications—different sizes of measurement error, different grid and sample sizes, and using data-generating parameters identical to the ones estimated from the Thai data. We also do runs allowing for heterogeneity in productivity, risk aversion, and interest rates but then ignoring this in the estimation, so that the model is misspecified. Our results remain robust.

Finally, we look back at some key features of our data and at how the alternative models do in fitting these features and in predicting moments and time paths not used in the estimation. We display the persistence of capital in the data and in the best-fitting financial/information regimes. This helps clarify why the saving only regime does best when there is substantial persistence (lack of adjustment), as in the rural, and to a less extent the urban, data. We also display the rate of return on assets as a function of assets. Again, the more limited financial regimes (saving only) do best in being consistent with the negative observed relationship in the rural data, that is, low-asset households have relatively high rates of return and households with higher assets, low rates. The urban data share some features with data simulated from a less constrained regime (moral hazard). We also simulate the time paths of the best-fitting financial regime at the estimated parameters. The means of consumption, business assets, and income fit the Thai data quite well. The standard deviations of these variables also fit, though there is more heterogeneity in the actual than simulated data (removing extreme outliers helps). We also simulate the path for savings in the model and compare, favorably, to financial net worth monthly data which were not utilized in the ML estimation.

In a further robustness check on our likelihood approach and its auxiliary assumptions, a mean squared error metric based on selected moments of the data picks out the savings regime as best fitting in the rural data, which is consistent with our MLE results. The urban data show substantially more smoothing and the ad hoc moments criterion picks out a less constrained regime. We also go beyond the MLE and Vuong tests by running GMM tests based on Euler equations with our data. The Ligon (1998) GMM test using consumption data alone or with business assets or income as instruments shows evidence in favor of either the savings/borrowing or moral hazard regimes, depending on the exact sample or instruments used, in other words, mixed results as in our MLE using consumption and income data alone. The Bond and Meghir (1994) investment sensitivity to cash flow GMM test rejects the null of no financial constraints, as we do in the MLE, but their method is unable to distinguish across the alternative constrained regimes.

Further Comparisons to the Literature

On the household side, our paper relates to a large literature that studies consumption smoothing.[3] On the firm side, there is an equally large literature on investment.[4] There are also papers attempting to explain stylized facts on firm growth, with higher mean growth and variance in growth for small firms, for example, Cooley and Quadrini (2001), among others. Albuquerque and Hopenhayn (2004) and Clementi and Hopenhayn (2006) introduced either private information or limited commitment but maintained risk neutrality.[5]

[3]There is voluminous work estimating the permanent income model, the full risk sharing model, buffer stock models (Zeldes (1989), Deaton and Laroque (1996)) and, lately, models with private information (Phelan (1994), Ligon (1998)) or limited commitment (Ligon, Thomas, and Worrall (2002)), among many others.

[4]For example, there is the adjustment costs approach of Abel and Blanchard (1983) and Bond and Meghir (1994), among many others. In industrial organization, Hopenhayn (1992) and Ericson and Pakes (1995) modeled entry and exit of firms with Cobb–Douglas or CES production technologies where investment augments capital with a lag, and output produced from capital, labor, and other factors is subject to factor-neutral technology shocks.

[5]Some applied general equilibrium models feature both consumption and investment in the same context (e.g., Rossi-Hansberg and Wright (2007)), but there the complete markets hypoth-

In terms of distinguishing across alternative financial constraints, here we set out to see how far we can get, going a bit deeper than most existing literature. For example, the adjustment costs investment literature may be picking up constraints implied by financing and not adjustment costs per se. The "pecking order" investment literature (Myers and Majuf (1984)) simply assumes that internally generated funds are least expensive, followed by debt, and finally equity, discussing wedges and distortions. Berger and Udell (2002) also had a long discussion in this spirit, on small versus large firm finance. They pointed out that small firms seem to be informationally opaque yet receive funds from family, friends, angels, or venture capitalists, leaving open the nature of the overall financial regime. Bitler, Moskowitz, and Vissing-Jorgensen (2005) argued likewise that agency considerations play an important role. The empirical work of Fazzari, Hubbard, and Petersen (1988) picked up systematic distortions for small firms, but, again, the nature of the credit market imperfection was not modeled, leading to criticisms of their interpretation of cash flow sensitivity tests (Kaplan and Zingales (2000)).[6]

In estimating both exogenously incomplete and endogenous information constrained regimes, there are few other similar efforts to which this paper relates. Ligon (1998) used GMM based on regular versus inverse Euler equations on Indian villages consumption data to distinguish between a moral hazard model and the permanent income hypothesis assuming CRRA preferences. A similar approach was used in Kocherlakota and Pistaferri (2009) to test between asset pricing implications of a private information model and a standard exogenously incomplete markets model in repeated cross-sections of consumption data from the United States, the United Kingdom, and Italy. Both papers found evidence in favor of the private information model. Meh and Quadrini (2006) compared numerically a bond economy to an economy with unobserved diversion of capital, while Attanasio and Pavoni (2011) estimated and compared the extent of consumption smoothing in the permanent income model to that in a moral hazard model with hidden savings (see also Karaivanov (2012)). Krueger and Perri (2011) used data on income, consumption, and wealth from Italy (1987–2008) and from the PSID (2004–2006) to compare and contrast the permanent income hypothesis versus a model of precautionary savings with borrowing constraints and concluded the former explains the dynamics of their data better. Broer (2011) used a simulated method of moments to estimate stationary joint distributions of consumption, wealth, and

esis justifies within the model a separation of the decisions of households from the decisions of firms. Alem and Townsend (2014) provided an explicit derivation of full risk sharing with equilibrium stochastic discount factors, rationalizing the apparent risk neutrality of households as firms making investment decisions.

[6]Under the null of complete markets, there should be no significant cash flow variable in investment decisions, but the criticism is that when the null is rejected, one cannot infer the degree of financial markets imperfection from the magnitude of the cash flow coefficient. One needs to explicitly model the financial regime in order to make an inference, which is what we test here.

income in a limited commitment versus a permanent income model with U.S. data and found evidence in favor of the permanent income model, including in a setting with production. Ai and Yang (2007) studied an environment with private information and limited commitment. The work of Schmid (2008) was also an effort to estimate a dynamic model of financial constraints but by using regressions on model data, not maximum likelihood as here. Dubois, Julien, and Magnac (2008) estimated semiparametrically a dynamic model with limited commitment to explain the patterns of income and consumption growth in Pakistani villages nesting complete markets and the case where only informal agreements are available. Kinnan (2011) tested inverse Euler equations and other implications of moral hazard, limited commitment, and unobserved output financial regimes.

Our methods follow logically from Paulson, Townsend, and Karaivanov (2006), where we model, estimate, and test whether moral hazard or limited liability is the predominant financial obstacle explaining the observed positive monotonic relationship between initial wealth and subsequent entry into business. Buera and Shin (2013) extended this to endogenous savings decisions in a model with limited borrowing, but did not test the micro underpinnings of the assumed regime. Here, we abstract from occupational choice and focus much more on the dynamics, as well as include more financial regimes. We naturally analyze the advantages of using the combination of data on consumption and the smoothing of income shocks with data on the smoothing of investment from cash flow fluctuations, in effect filling the gap created by the dichotomy in the literature.

2. THEORY

2.1. *Environment*

Consider an economy of infinitely lived agents heterogeneous in their initial endowments (assets), k_0, of a single good that can be used for both consumption and investment. Agents are risk averse and have time-separable preferences defined over consumption, c, and labor effort, z, represented by $U(c, z)$ where $U_1 > 0$, $U_2 < 0$. They discount future utility using discount factor $\beta \in (0, 1)$. We assume that c and z belong to the finite discrete sets (grids) C and Z, respectively. The agents have access to a stochastic output technology, $P(q|z, k): Q \times Z \times K \to [0, 1]$ which gives the probability of obtaining output/income, q, from effort level, z, and capital level, k.[7] The sets Q and K are also finite and discrete—this could be a technological or computational assumption. Capital, k, depreciates at rate $\delta \in (0, 1)$. Depending on the intended

[7]We can incorporate heterogeneity in productivity/ability across agents by adding a scaling factor in the production function, as we do in a robustness run in Section 6.2. Note also that q, as defined, can be interpreted as income net of payments for any hired inputs other than z and k.

application, the lowest capital level ($k = 0$) could be interpreted as a "worker" occupation (similarly to Paulson, Townsend, and Karaivanov (2006)) or as firm exit, but we do not impose a particular interpretation in this paper.

Agents can contract with a financial intermediary and enter into saving, debt, or insurance arrangements. We characterize the optimal dynamic financial contracts between the agents and the intermediary in different financial markets "regimes" distinguished by alternative assumptions regarding information, enforcement/commitment, and credit access. In all financial regimes we study, capital k and output q are assumed observable and verifiable. However, effort, z, may be unobservable to third parties, resulting in a moral hazard problem.[8] The financial intermediary is risk neutral and has access to an outside credit market with exogenously given and constant over time opportunity cost of funds R.[9] The intermediary is assumed to be able to fully commit to the ex ante (constrained-) optimal contract with agent(s) at any initial state while we consider the possibility of limited commitment by the agents.

Using the linear programming approach of Prescott and Townsend (1984), Phelan and Townsend (1991), and Paulson, Townsend, and Karaivanov (2006), we model financial contracts as probability distributions (lotteries) over assigned or implemented allocations of consumption, output, effort, and investment (see below for details). There are two possible interpretations. First, one can think of the intermediary as a principal contracting with a single agent/firm at a time, in which case financial contracts specify mixed strategies over allocations. Alternatively, one can think of the principal contracting with a continuum of agents, so that the optimal contract specifies the fraction of agents of given type or at given state that receive a particular deterministic allocation. It is further assumed that there are no technological links between the agents, the agents cannot collude, and there are no aggregate shocks.[10]

[8]In the working paper version (Karaivanov and Townsend (2013)), we also formulated, computed, and performed several estimation runs with a model of hidden output (q is unobservable) and a model of moral hazard and unobserved investment (the capital stock k and effort z are unobservable, resulting in a joint moral hazard and adverse selection problem). These regimes have heavier computational requirements than the six featured here, which prevented us from treating them symmetrically in the empirical part. We did find the exogenously incomplete borrowing and saving regimes dominating in the rural data. In the urban data, the hidden output regime fit best in a specification with the parametric production function. Both findings are thus consistent with our main results—exogenously incomplete markets in the rural data and mechanism design financial regimes in the urban data. A more complete summary of these results and the associated mechanism design problems is also available as a Supplemental Material (see Karaivanov and Townsend (2014)).

[9]The assumption of risk neutrality is not essential since there are no aggregate shocks and we can think of the intermediary contracting with a continuum of agents. We perform robustness runs varying the return R, including taking different values at different dates (see Section 6.1), and a run with simulated data varying R in different asset quartiles in the population (see Section 6.2).

[10]While conceptually we could allow for aggregate shocks by introducing another state variable in our dynamic linear programs and still be able to solve them using our method, this would

2.2. *Financial and Information Regimes*

We write down the dynamic linear programming problems determining the (constrained) optimal contract in many alternative financial and information regimes which can be classified into two groups. The first group are regimes with exogenously incomplete markets: *autarky* (A), *saving only* (S), and *borrowing and lending* (B). To save space, we often use the abbreviated names supplied in the parentheses. In these regimes, the feasible financial contracts take a specific, exogenously given form (no access to financial markets, a deposit/storage contract, or a non-contingent debt contract, respectively).

In the second group of financial regimes we study, optimal contracts are endogenously determined as solutions to dynamic mechanism design problems subject to information and incentive constraints. In the main part of this paper, we look at two such endogenously incomplete markets regimes—*moral hazard* (MH), in which agents' effort is unobserved but capital and investment are observed, and *limited commitment* (LC), in which there are no information frictions but agents can renege on the contract after observing the output realization.[11] All incomplete markets regimes are compared to the *full information* (FI) benchmark (the "complete markets" or "first best" regime). In Section 6.1, we also consider versions of all regimes in which capital changes are subject to quadratic adjustment costs.

2.2.1. *Exogenously Incomplete Markets*

Autarky. We say that agents are in (financial) "autarky" if they have no access to financial intermediation—neither borrowing nor saving. They can, however, choose how much output to invest in capital to be used in production versus how much to consume. The timeline is as follows. The agent starts the current period with business assets (capital) $k \in K$ which he puts into production. At this time he also supplies his effort $z \in Z$. At the end of the period, output $q \in Q$ is realized, the agent decides on the next period capital level $k' \in K$ (we allow downward or upward capital adjustments), and consumes $c \equiv (1-\delta)k + q - k'$. Clearly, k is the single state variable in the recursive formulation of the agent's problem, which is relatively simple and can be solved by standard dynamic programming techniques. However, to be consistent with the solution method that we use for the mechanism design financial regimes where nonlinear techniques may be inapplicable due to non-convexities introduced by the incentive and truth-telling constraints (more on this below), we

increase computational time beyond what is currently feasible at the estimation stage. We perform robustness estimation runs with data with removed year fixed effects to allow for possible common shocks and find almost identical results to the baseline results (see Section 6.1).

[11] Again, see footnote 8. The proofs that the optimal contracting problems can be written in recursive form and that the revelation principle applies follow from Phelan and Townsend (1991) and Doepke and Townsend (2006) and hence are omitted.

formulate the agent's problem in autarky (and all others) as a dynamic linear programming problem in the joint probabilities (lotteries) over all possible choice variables allocations $(q, z, k') \in Q \times Z \times K$ given state k,

$$v(k) = \max_{\pi(q,z,k'|k)} \sum_{q,z,k'} \pi(q, z, k'|k)\big[U\big((1-\delta)k + q - k', z\big) + \beta v(k')\big]. \tag{1}$$

The maximization of the agent's value function, $v(k)$ in (1), is subject to a set of constraints on the choice variables, π.[12] First, $\forall k \in K$ the joint probabilities $\pi(q, z, k'|k)$ have to be consistent with the technologically determined probability distribution of output, $P(q|z, k)$:

$$\sum_{k'} \pi(\bar{q}, \bar{z}, k'|k) = P(\bar{q}|\bar{z}, k) \sum_{q,k'} \pi(q, \bar{z}, k'|k) \quad \text{for all } (\bar{q}, \bar{z}) \in Q \times Z. \tag{2}$$

Second, given that the $\pi(\cdot)$'s are probabilities, they must satisfy $\pi(q, z, k'|k) \geq 0$ (nonnegativity) $\forall (q, z, k') \in Q \times Z \times K$, and "adding-up,"

$$\sum_{q,z,k'} \pi(q, z, k'|k) = 1. \tag{3}$$

The policy variables $\pi(q, z, k'|k)$ that solve the above maximization problem determine the agent's optimal effort and output-contingent investment in autarky for each k.

Saving Only/Borrowing. In this setting, we assume that the agent is able to either only save, that is, accumulate and run down a buffer stock, in what we call the *saving only* (S) regime; or borrow and save through a competitive financial intermediary, which we call the *borrowing* (B) regime. The agent thus can save or borrow in a risk-free asset to smooth his consumption or investment in a Bewley–Aiyagari manner, in addition to what he could do via production and capital alone under autarky. Specifically, if the agent borrows (saves) an amount b, then next period he has to repay (collect) Rb, independent of the state of the world. Involuntary default is ruled out by assuming that the principal refuses to lend to a borrower who is at risk of not being able to repay in any state (computationally, we assign a high utility penalty in such states). By shutting down all contingencies in debt contracts, we aim for better differentiation from the mechanism design regimes.

Debt/savings b is assumed to take values on the finite grid B. By convention, a negative value of b represents savings, that is, in the S regime the upper bound of the grid B is zero, while in the B regime the upper bound is positive.

[12]In (1) and later on in the paper, K under the summation sign refers to summing over k' and not k, and similarly for w' and the set W below.

The lower bound of the grid for b in both cases is a finite negative number. The autarky regime can be subsumed by setting $B = \{0\}$. This financial regime is essentially a version of the standard Bewley model with borrowing constraints defined by the grid B and an endogenous income process defined by the production function $P(q|k, z)$.

The timeline is as follows: the agent starts the current period with capital k and savings/debt b and uses his capital in production together with effort z. At the end of the period, output q is realized, the agent repays/receives Rb, and borrows or saves $b' \in B$. He also puts aside (invests in) next period's capital, k', and consumes $c \equiv (1-\delta)k + q + b' - Rb - k'$. The two "assets" k and b are assumed freely convertible into one another.

The problem of an agent with current capital stock k and debt/savings level b in the S or B regime can be written recursively as

$$(4)\qquad v(k, b) = \max_{\pi(q,z,k',b'|k,b)} \sum_{q,z,k',b'} \pi(q, z, k', b'|k, b) \times \left[U\big((1-\delta)k + q + b' - Rb - k', z\big) + \beta v(k', b')\right],$$

subject to the technological consistency and adding-up constraints analogous to (2) and (3), and subject to $\pi(q, z, k', b'|k, b) \geq 0$ for all $(q, z, k', b') \in Q \times Z \times K \times B$.

2.2.2. *Mechanism Design Regimes*

Full Information. With full information (FI), the principal fully observes and can contract upon an agent's effort and investment—there are no private information or other frictions. We write the corresponding dynamic principal-agent problem as an extension of Phelan and Townsend (1991) with capital accumulation. As is standard in such settings (e.g., see Spear and Srivastava (1987)), to obtain a recursive formulation we use an additional state variable—*promised utility*, w, which belongs to the discrete set, W. The optimal full-information contract for an agent with current promised utility w and capital k consists of the effort and capital levels $z, k' \in Z \times K$, next period's promised utility $w' \in W$, and transfers τ belonging to the discrete set T. A positive value of τ denotes a transfer from the principal to the agent. The timing of events is the same as in Section 2.2.1, with the addition that transfers occur after output is observed.

Following Phelan and Townsend (1991), the set of promised utilities W has a lower bound, $w_{\min}$, which corresponds to assigning forever the lowest possible consumption, $c_{\min}$ (obtained from the lowest $\tau \in T$ and the highest $k' \in K$), and the highest possible effort, $z_{\max} \in Z$. The set's upper bound, $w_{\max}$, in turn corresponds to promising the highest possible consumption, $c_{\max}$, and the lowest possible effort forever:

$$(5)\qquad w^{\mathrm{FI}}_{\min} = \frac{U(c_{\min}, z_{\max})}{1-\beta} \quad \text{and} \quad w^{\mathrm{FI}}_{\max} = \frac{U(c_{\max}, z_{\min})}{1-\beta}.$$

The principal's value function $V(k, w)$ when contracting with an agent at state (k, w) maximizes expected output net of transfers plus the discounted value of future outputs less transfers. We write the mechanism design problem solved by the optimal contract as a linear program in the joint probabilities $\pi(\tau, q, z, k', w'|k, w)$ over all possible allocations (τ, q, z, k', w'):

$$V(k, w) = \max_{\{\pi(\tau,q,z,k',w'|k,w)\}} \sum_{\tau,q,z,k',w'} \pi\big(\tau, q, z, k', w'|k, w\big) \times \big[q - \tau + (1/R)V\big(k', w'\big)\big]. \tag{6}$$

The maximization in (6) is subject to the "technological consistency" and "adding-up" constraints:

$$\sum_{\tau,k',w'} \pi\big(\tau, \bar{q}, \bar{z}, k', w'|k, w\big) = P(\bar{q}|\bar{z}, k) \sum_{\tau,q,k',w'} \pi\big(\tau, q, \bar{z}, k', w'|k, w\big) \quad \text{for all } (\bar{q}, \bar{z}) \in Q \times Z, \tag{7}$$

$$\sum_{\tau,q,z,k',w'} \pi\big(\tau, q, z, k', w'|k, w\big) = 1, \tag{8}$$

as well as nonnegativity: $\pi(\tau, q, z, k', w'|k, w) \geq 0$ for all $(\tau, q, z, k', w') \in T \times Q \times Z \times K \times W$.

The optimal FI contract must also satisfy an additional, *promise keeping* constraint which reflects the principal's commitment ability and ensures that the agent's present-value expected utility equals his promised utility, w:

$$\sum_{\tau,q,z,k',w'} \pi\big(\tau, q, z, k', w'|k, w\big)\big[U\big(\tau + (1 - \delta)k - k', z\big) + \beta w'\big] = w. \tag{9}$$

By varying the initial promise w, we can trace the whole Pareto frontier for the principal and the agent. The optimal FI contract is the probabilities $\pi^*(\tau, q, z, k', w'|k, w)$ that maximize (6) subject to (7), (8), and (9).

The full information contract implies full insurance, so consumption is smoothed completely against output, q (conditioned on effort z if utility is non-separable). It also implies that expected marginal products of capital ought to be equated to the outside interest rate implicit in R, adjusting for disutility of labor effort which the planner would take into account in determining how much capital k to assign to a project. The intermediary/bank (planner) has access to outside borrowing and lending at the rate R, but internally, within its set of customers, it can in effect have them "borrow" and "save" among each other, that is, take some output away from one agent who might otherwise have put money into his project and give that to another agent with high marginal product. A lot of this nets out, so only the residual is financed with (or lent to) the outside market. In contrast, the B/S regime shuts down such within-group transfers and trades, and instead each agent is dealing with the market directly.

Moral Hazard. In the moral hazard (MH) regime, the principal can still observe and control the agent's capital and investment (k and k'), but he can no longer observe or verify the agent's effort, z. This results in a moral hazard problem. The state k here can be interpreted as endogenous collateral. The timing is the same as in the FI regime. However, the optimal MH contract $\pi(\tau, q, z, k', w'|k, w)$ must satisfy an incentive-compatibility constraint (ICC), in addition to (7)–(9).[13] The ICC states that, given the agent's state (k, w) and recommended effort level $\bar{z}$, capital k', and transfer τ, the agent must not be able to achieve higher expected utility by deviating to any alternative effort level $\hat{z}$. That is, $\forall(\bar{z}, \hat{z}) \in Z \times Z$, we must have

$$(10) \qquad \sum_{\tau,q,k',w'} \pi(\tau, q, \bar{z}, k', w'|k, w)\big[U\big(\tau + (1-\delta)k - k', \bar{z}\big) + \beta w'\big]$$
$$\geq \sum_{\tau,q,k',w'} \pi(\tau, q, \bar{z}, k', w'|k, w)\frac{P(q|\hat{z}, k)}{P(q|\bar{z}, k)}$$
$$\times \big[U\big(\tau + (1-\delta)k - k', \hat{z}\big) + \beta w'\big].$$

Apart from the additional ICC constraint (10), the MH regime differs from the FI regime in the set of feasible promised utilities, W. In particular, the lowest possible promise under moral hazard is no longer the value $w^{\mathrm{FI}}_{\min}$ from (5). Indeed, if the agent is assigned minimum consumption forever, he would not supply effort above the minimum possible. Thus, the feasible range of promised utilities, W, for the MH regime is bounded by

$$(11) \qquad w^{\mathrm{MH}}_{\min} = \frac{U(c_{\min}, z_{\min})}{1-\beta} \quad \text{and} \quad w^{\mathrm{MH}}_{\max} = \frac{U(c_{\max}, z_{\min})}{1-\beta}.$$

The principal cannot promise a slightly higher consumption in exchange for much higher effort such that the agent's utility falls below $w^{\mathrm{MH}}_{\min}$ since this is not incentive compatible. If the agent does not follow the principal's recommendations but deviates to $z_{\min}$, the worst punishment he can receive is $c_{\min}$ forever.

The constrained optimal contract in the moral hazard regime, $\pi^{\mathrm{MH}}(\tau, q, z, k', w'|k, w)$, solves the linear program defined by (6)–(10). The contract features partial insurance and intertemporal tie-ins, that is, it is not a repetition of the optimal one-period contract (Townsend (1982)).

Limited Commitment. The third setting with endogenously incomplete financial markets we study assumes away private information but focuses on

[13]For more details on the ICC derivation in the linear programming framework, see Prescott and Townsend (1984). The key term is the "likelihood ratio," $\frac{P(q|\hat{z},k)}{P(q|\bar{z},k)}$, which reflects the fact that by deviating, the agent changes the probability distribution of output.

another friction often discussed in the consumption smoothing and investment literatures (e.g., Thomas and Worrall (1994), Ligon, Thomas, and Worrall (2000), among others)—*limited commitment* (LC). As in those papers, by "limited commitment" we mean that the agent may potentially renege on the contract after observing his output realization, knowing the transfer τ he is supposed to give to others through the intermediary. Another possible interpretation of this, particularly relevant for developing economies, is a contract enforcement problem. The maximum penalty for a reneging agent is permanent exclusion from future credit/risk-sharing—that is, our assumption is the agent goes to autarky forever.

Using the same approach as with the other financial regimes, we write the optimal contracting problem under limited commitment as a recursive linear programming problem. The state variables are capital, $k \in K$, and promised utility, $w \in W$. In this model regime, the set (here, a closed interval on $\mathbb{R}$) of feasible promised utilities, W, is an endogenous object to be iterated over during the dynamic program solution (Abreu, Pearce, and Stacchetti (1990)). We initialize the lower bound of W, $w^{\text{LC}}_{\min}$, as equal to the autarky value at $k_{\min}$ (see Section 2.2.1) and set the initial upper bound to $w^{\text{LC}}_{\max} = w^{\text{FI}}_{\max}$. A similar solution approach, including allowing for randomization over allocations, was used in Ligon, Thomas, and Worrall (2000).

Given the agent's current state (k, w), the problem of the intermediary is

$$V(k,w) = \max_{\pi(\tau,q,z,k',w'|k,w)} \sum_{\tau,q,z,k',w'} \pi\big(\tau,q,z,k',w'|k,w\big) \times \big[q - \tau + (1/R)V\big(k',w'\big)\big],$$

subject to the promise keeping constraint

$$\sum_{\tau,q,z,k',w'} \pi\big(\tau,q,z,k',w'|k,w\big)\big[U\big(\tau + (1-\delta)k - k', z\big) + \beta w'\big] = w,$$

subject to the limited-commitment constraints which ensure that reneging does not occur in equilibrium, respecting our timing that effort z is decided before output q is realized,[14]

$$(12) \qquad \sum_{\tau,k',w'} \frac{\pi(\tau,\bar{q},\bar{z},k',w'|k,w)}{\sum_{\tilde{\tau},\tilde{k}',\tilde{w}'} \pi(\tilde{\tau},\bar{q},\bar{z},\tilde{k}',\tilde{w}'|k,w)} \big(U\big(\tau + (1-\delta)k - k', \bar{z}\big) + \beta w'\big) \geq \Omega(k,\bar{q},\bar{z}) \quad \text{for all } (\bar{q},\bar{z}) \in Q \times Z$$

[14]The terms $\frac{\pi(\tau,\bar{q},\bar{z},k',w'|k,w)}{\sum_{\tilde{\tau},\tilde{k}',\tilde{w}'} \pi(\tilde{\tau},\bar{q},\bar{z},\tilde{k}',\tilde{w}'|k,w)}$ correspond to the respective probabilities *conditional on* $\bar{q}, \bar{z}$ having been realized.

and subject to nonnegativity $\pi(\tau, q, z, k', w'|k, w) \geq 0$, technological consistency, and adding-up,

$$\sum_{\tau,k',w'} \pi\big(\tau, \bar{q}, \bar{z}, k', w'|k, w\big) = P(\bar{q}|\bar{z}, k) \sum_{\tau,q,k',w'} \pi\big(\tau, q, \bar{z}, k', w'|k, w\big)$$

$$\text{for all } (\bar{q}, \bar{z}) \in Q \times Z,$$

$$\sum_{\tau,q,z,k',w'} \pi\big(\tau, q, z, k', w'|k, w\big) = 1.$$

In constraint (12), $\Omega(k, q, z)$ denotes the present utility value of the agent going to autarky forever with his output at hand q and capital k, defined as

$$\Omega(k, q, z) \equiv \max_{k' \in K} U\big(q + (1 - \delta)k - k', z\big) + \beta v\big(k'\big),$$

where $v(\cdot)$ is the autarky regime value function defined in Section 2.2.1.

3. COMPUTATION

3.1. *Solution Methods*

We solve the dynamic programs for all financial regimes numerically. Specifically, we use the linear programming (LP) methods developed by Prescott and Townsend (1984) and applied in Phelan and Townsend (1991) and Paulson, Townsend, and Karaivanov (2006), where, as shown in the previous section, the dynamic problems are written in terms of probability distributions ("lotteries"). An alternative to the LP method in the literature is the "first order approach" (Rogerson (1985)) whereby the incentive constraints are replaced by their first order conditions.[15] The public finance literature in the tradition of Mirrlees has adopted these latter methods to provide elegant characterizations of solutions to tax and insurance problems, or used ex post verification to show that simplified, less constrained problems can be solved without loss of generality (Abraham and Pavoni (2008), Farhi and Werning (2012), Golosov, Tsyvinski, and Werning (2006), Golosov and Tsyvinski (2006), Ai and Yang (2007)). A problem with that approach arises from possible non-convexities induced by the incentive or commitment constraints.[16] Here, by way of contrast, we operate in extremely general environments, following Fernandes and Phelan (2000) and Doepke and Townsend (2006). Our linear programming approach can be

[15]The first order approach requires imposing monotonicity and/or convexity assumptions on the technology (Rogerson (1985), Jewitt (1988)) or, alternatively, as in Abraham and Pavoni (2008), employing a numerical verification procedure to check its validity for the particular problem at hand.

[16]We found such non-convexities in some of our solutions for the mechanism design regimes and hence we cannot use the first order approach. See also Kocherlakota (2004).

applied for *any* preference and technology specifications since, by construction, it convexifies the problem by allowing any possible randomization (lotteries) over the solution variables. The only potential downside is that the LP method may suffer from a "curse of dimensionality" due to its use of discrete grids for all variables. However, as shown above, by judicious formulation of the linear programs, this deficiency can be substantially reduced.

To speed up computation, we solve the dynamic programs for each regime using policy function iteration (e.g., see Judd (1998)). That is, we start with an initial guess for the value function, obtain the optimal policy function, and compute the new value function that would occur if the computed policy function were used forever. We iterate on this procedure until convergence. At each iteration step, that is, for each interim value function iterate, we solve a linear program in the policy variables π for each possible value of the state variables.[17] In the limited-commitment regime, LC (see Section 2), the promised utilities set is endogenously determined and has to be iterated and solved for together with the value function during the solution process, due to the commitment or truth-telling constraints, which makes the LC regime computationally harder than the MH or FI regimes.

3.2. *Functional Forms and Grids*

Below are the functional forms we adopt in the empirical analysis. They are chosen and demonstrated below to be flexible enough to generate significant and statistically distinguishable differences across the financial regimes. As argued earlier, we can handle, in principle, any preferences and technology, including with non-convexities, but, of course, in practice we are limited by computational concerns (estimation time sharply increases with the number of estimated parameters). We also verify robustness by using different parameterizations and model specifications (see Section 6).

Agent preferences are of the CES form:[18]

$$U(c, z) = \frac{c^{1-\sigma}}{1-\sigma} - z^{\theta}.$$

The production function, $P(q|z, k): Z \times K \to Q$, represents the probability of obtaining output level, $q \in Q \equiv \{q_1, q_2, \dots, q_{\#Q}\}$, from effort $z \in Z$ and capital

[17]The coefficient matrices of the objective function and the constraints are created in Matlab, while all linear programs are solved using the commercial LP solver CPLEX version 8.1. The computations were performed on a dual-core, 2.2 GHz, 2 GB RAM machine.

[18]Our linear programming solution methodology does not require separable preferences. However, assuming separability is standard in the dynamic contracts literature, so we adopt it for comparison purposes. We perform a robustness run with a more general preference form with an additional parameter in Section 6.1.

TABLE I

PROBLEM DIMENSIONALITY[a]

Model	Number of: Linear Programs Solved per Iteration	Number of: Variables per Linear Program	Number of: Constraints per Linear Program
Autarky (A)	5	75	16
Saving/Borrowing (S, B)	25	375	16
Full information (FI)	25	11,625	17
Moral hazard (MH)	25	11,625	23
Limited commitment (LC)	25	11,625	32

[a]The numbers in this table are based on the following grid sizes used in the estimation: $\#Q = 5$, $\#K = 5$, $\#Z = 3$, $\#B = 5$, $\#T = \#C = 31$; $\#W = 5$.

$k \in K$. In our baseline runs with Thai data, we fit $P(q|z, k)$ nonparametrically using a histogram function from a subset of households in the rural sample for which we have labor time data.[19] In robustness runs (with both the rural and urban data), we also use a parametric form for $P(q|z, k)$ with parameters we estimate which encompasses production technologies ranging from perfect substitutes to Cobb–Douglas to Leontief forms (see Section 6.1 below for details).

To get an idea of the computational complexity of the dynamic contracting problems we solve, Table I shows the number of variables, constraints, and linear programs that need to be solved at each iteration for each regime for the grids we use in the empirical implementation. The number of linear programs is closely related to the grid size of the state variables, while the total number of variables and constraints depends on the product of all grid dimensions. The biggest computational difficulties arise from increasing $\#K$ or $\#Z$, as this causes an exponential increase in the number of variables and/or constraints. This is why we keep these dimensions relatively low, whereas using larger $\#T$ (or, equivalently, $\#C$) is relatively "cheap" computationally.

The grids that we use in the estimation runs reflect the relative magnitudes and ranges of the variables in the Thai data or simulated data. In our baseline estimation runs, we use a five-point capital grid K with grid points corresponding to the 10th, 30th, 50th, 70th, and 90th percentiles in the data. The same applies for the output grid Q. The baseline grid for promised utility, W, consists of five uniformly spaced points over the respective bounds for the MH, FI, or LC regimes. Table II displays the grids we use in the estimation runs with Thai rural data. Further specific details on how all grids are determined

[19]Specifically, we map output, q, assets, k, and time worked, z, data onto the model grids and set $P(q|z, k)$ equal to the fraction of observations in each (q, k, z) grid cell. For the baseline runs with urban data, for data availability reasons we used the same data on z but the actual urban sample values for q and k.

TABLE II

BASELINE VARIABLE GRIDS USED IN THE ESTIMATION

Variable	Grid Size (# Points)	Grid Bounds and Spacing
Income/cash flow, Q	5	[0.04, 1.75], from data percentiles
Business assets, K	5	[0, 1], from data percentiles
Effort, Z	3	[0.01, 1], uniform
Savings/debt, B	5 (6 for B regime)	S: uniform on $[-2, 0]$, B: uniform on $[-2, 0.82]$ including 0
Transfers/consumption, C	31	MH/FI/LC: uniform on $[0.001, 0.9]$; B/S/A: endogenous
Promised utility, W	5	regime-dependent bounds, uniformly spaced values

are given in Section 5.2. We can use (and do robustness runs with) finer grids, but the associated computational time cost is extremely high at the estimation stage because of the need to compute the linear programs and iterate at each parameter vector during the estimation. This is why we keep dimensions relatively low at present.

4. EMPIRICAL METHOD

In this section, we describe our estimation strategy. We estimate via maximum likelihood each of the alternative dynamic models of financial constraints 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 model regimes. 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 if agnostic about which theoretical model fits them best and let the data themselves determine this. The results of the Vuong test, a sort of "horse race" among competing models, inform us which theory(ies) fits the data best and also which theories can be rejected in view of the observed data.

This is a structural estimation and model comparison paper, and so naturally this poses the question of distinguishing between testing or rejecting the imposed model structure (functional and parametric forms) versus testing the actual relationships between the features we are interested in (the financial and information regimes). In all structural MLE runs, these two dimensions are tested jointly by construction. We try to deal with this issue in several ways. First, in the robustness Section 6, we explore some alternative functional forms or parameterizations and perform the empirical analysis for different data samples and variable definitions. Runs with data simulated from the model are also performed to test the validity of our estimation method. Second, in

Section 7, we supplement the maximum likelihood and Vuong test results with additional graphs, tables, and alternative criteria of fit to better illustrate and provide further supporting evidence for the robustness of the main results. Finally, we use flexible and standard functional forms for preferences and the unobservable states distribution which are held constant across the alternative regimes; that is, any differences in likelihood are due to the nature of financial constraints imposed by the model, not due to differences in functional forms.

The financial regimes we study have implications for both the transitional dynamics and long-run distributions of variables such as consumption, assets, investment, etc. Given our application to Thailand—an emerging, rapidly developing economy, we take the view that the actual data are more likely to correspond to a transition than to a steady state.[20] Thus, estimating initial conditions (captured by the initial state variables distribution) is important for us, as well as fitting the subsequent trajectories using intertemporal data. In addition, our simulations show slow dynamics for the model variables in the mechanism design regimes, and, theoretically, some regimes can have degenerate long-run distributions (e.g., "immiseration" in the moral hazard model). These are further reasons to focus on transitions instead of steady states in the estimation. We explain the details below.

4.1. *Maximum Likelihood Estimation*

Suppose we have panel data $\{\hat{x}_{jt}\}_{j=1,t=1}^{n,T}$, where $j = 1, \dots, n$ denotes sample units and t denotes time (in our application, sample units are households observed over seven years). The data are assumed i.i.d. across households, j. In this paper, we use various subsets of data collected from rural and urban Thai households running small businesses on their productive assets, consumption, and income, $\{\hat{k}_{jt}, \hat{c}_{jt}, \hat{q}_{jt}\}$, where $t = 0, \dots, 6$ correspond to the years 1999–2005. We also construct investment data as $\hat{\imath}_{jt} \equiv \hat{k}_{jt+1} - (1-\delta)\hat{k}_{jt}$ for $t = 0, \dots, 5$. See Section 5.1 for more details.

For each household j, call $\hat{y}_j$ the vector of variables used in the MLE. In the various runs we do, this vector can consist of different cross-sectional variables (e.g., $t = 0$ consumption and income; that is, $\hat{y}_j = (\hat{c}_{j0}, \hat{q}_{j0})$ or $t = 6$ consumption, income, investment, and capital; that is, $\hat{y}_j = (\hat{c}_{j6}, \hat{q}_{j6}, \hat{\imath}_{j6}, \hat{k}_{j6})$) or can consist of variables from different time periods (e.g., consumption and income at $t = 0$ and $t = 1$; that is, $\hat{y}_j = (\hat{c}_{j0}, \hat{q}_{j0}, \hat{c}_{j1}, \hat{q}_{j1})$).

The data $\hat{y}$ may contain measurement error. Assume the measurement error is additive and distributed $N(0, (\gamma_{\text{me}}\chi(x))^2)$, where $\chi(x)$ denotes the range of the grid X for variable x, that is, $\chi(x) \equiv x_{\max} - x_{\min}$, where x is any of the variables used in the estimation (e.g., consumption). The reasoning is that, for

[20]We do a robustness estimation run in Section 6.2 with simulated data drawn after running the model a large number of periods, approximating a steady state.

computational time reasons, we want to be as parsimonious with parameters as possible in the likelihood routine while still allowing the measurement error variance to be commensurate with the different variables' ranges. In principle, more complex versions of measurement error can be introduced at the cost of computing time. The parameter γ_{me} will be estimated in the MLE.

Call s^1 the vector of observable state variables and s^2 the vector of unobservable state variables. We have $s^1 = k$ for all models while $s^2 = w$ or $s^2 = b$ or s^2 absent, depending on the financial regime. In the estimation runs that follow, there are two cases depending on whether or not the set of variables y used in the estimation includes s_0^1—the initial values of the observed state. Call $y^1 \equiv y \setminus s_0^1$, that is, all variables in y which are not s_0^1. For example, in the runs with $y = (c_0, q_0)$ data in Sections 5 and 6 below, we have $y = y^1$ since $k_0 = s_0^1$ is not among the variables y, while in the runs with $y = (k_0, i_0, q_0)$ data we have $y \neq y^1$ since $k_0 = s_0^1$ is among the variables y used in the estimation (see below for more discussion on this).

4.1.1. *Model Solutions and Joint Probabilities*

For each possible value of the state variables, s^1 and s^2 over the grids S^1 and S^2 in a given model regime (e.g., k, w—the capital stock and promised utility for the MH, FI, or LC models) and given structural parameters ϕ^s in the preferences and technology functions, the model solution obtained from the respective linear program (see Section 2) is a discrete joint probability distribution, $\pi(\cdot|s^1, s^2)$. For example, the MH model solution consists of the joint probabilities $\pi(\tau, q, z, k', w'|k, w)$. Using the LP solution $\pi(\cdot|s^1, s^2)$, we can easily obtain, essentially by summing over the different variables and probabilities (see Appendix A for more details), the theoretical joint probability distribution in model m over any set of variables y^1 used in the MLE; for instance, y^1 could be $t = 0$ consumption and income (c_0, q_0). Call this probability distribution $g^m(y^1|s^1, s^2; \phi^s)$.

4.1.2. *Initialization of Observable and Unobservable State Variables*

Let $h(s_0^1, s_0^2; \phi^d)$ denote the initial discrete joint distribution of the state variables over their corresponding grids, the parameters of which, ϕ^d, will be estimated in the MLE. To initialize the observed state variable s^1 (capital k in all models), we take the actual data $\{\hat{k}_j\}_{j=1}^n$ for the initial period used in the estimation and discretize it over the grid K via histogram function. Call the resulting discrete probability distribution $h(s_0^1)$—the marginal distribution of s_0^1.[21] The initial values of the unobservable state s_0^2 (b or w, depending on the

[21]In constructing the discrete initial distribution $h(s_0^1)$ (or $h(s_0^1, s_0^2)$, in general), we allow for the possibility that the $\hat{k}$ data contain measurement error, with the same additive Normal specification parameterized by γ_{me} assumed above. We use essentially the method described in (15)

regime) are treated as a source of unobserved heterogeneity. Their distribution and possible dependence on s_0^1 are parameterized by ϕ^d. In our baseline estimation runs with the Thai data in Section 5, we assume that the initial distributions of the state variables s^1 and s^2 are independent.[22] We relax this assumption in robustness runs (see Section 6.1 and Table IX), where we allow the initial unobserved state s_0^2 (e.g., initial promised utility) to be correlated with the initial distribution of s_0^1 (initial assets) via an additional estimated parameter. Note that we do not assume that the states s^1 and s^2 are independent beyond the initial period—they evolve endogenously with the model dynamics.

4.1.3. *The Likelihood*

To form the likelihood of model m with observations from variables y (e.g., consumption and income), denote by $h^m(y^1, s_0^1|s_0^2; \phi^s)$ the joint density of all observables conditional on all unobservables. Then, "integrate" over the initial distribution of the unobservable state, that is, form $\sum_{s_0^2} h^m(y^1, s_0^1|s_0^2; \phi^s)h(s_0^2; \phi^d)$, where $h(s_0^2; \phi^d)$ is the marginal distribution of s_0^2. In our baseline specification with independent initial states s_0^1 and s_0^2, we have $h(s_0^2; \phi^d) = \Omega(s_0^2, \phi^d)$ and the summation over s_0^2 is done using a histogram function over the grid S^2 (e.g., W in the MH model). Naturally, since the only state in autarky (k) is observable, this step is not performed when we estimate the A model. We have

$$
(13)\qquad \sum_{s_0^2} h^m\big(y^1, s_0^1|s_0^2; \phi^s\big)h\big(s_0^2; \phi^d\big)
$$
$$
= \sum_{s_0^2} g^m\big(y^1|s_0^1, s_0^2; \phi^s\big)h\big(s_0^1|s_0^2\big)h\big(s_0^2; \phi^d\big)
$$
$$
= \sum_{s_0^2} g^m\big(y^1|s_0^1, s_0^2; \phi^s\big)h\big(s_0^1, s_0^2; \phi^d\big) \equiv f^m\big(y^1, s_0^1; \phi^s, \phi^d\big).
$$

Above, $f^m(y^1, s_0^1; \phi^s, \phi^d)$ is the joint distribution of y^1 and s_0^1 in model m given parameters ϕ^s, ϕ^d. For instance, this could be the theoretical joint distribution of c, q, i, and k in the MH model for initial state distribution $h(s_0^1, s_0^2; \phi^d)$ over

below to compute the probability mass at each grid point. This step is done upfront since we need the discretized distribution $h(s_0^1, s_0^2)$ to obtain, using the LP solution, the joint distribution of the variables y^1 used in the MLE (see f^m and F^m below).

[22]Specifically, in these runs we assume that the unobserved state w in the MH, FI, LC models is distributed $\Omega(s_0^2, \phi^d) = N(\mu_w, \gamma_w^2)$ and the unobserved state b in the B and S models is distributed $\Omega(s_0^2, \phi^d) = N(\mu_b, \gamma_b^2)$. Thus, in the independence case, we have $h(s_0^1, s_0^2; \phi^d) = h(s_0^1)\Omega(s_0^2, \phi^d)$. Assuming Normality of the initial b or w distributions is not essential for our method, and more general distributional assumptions can be incorporated at the computational cost of additional estimated parameters. We perform a robustness run with a Gaussian mixture distribution in Section 6.1.

the grid $K \times W$. In the runs in which s_0^1 is not among the variables y used in the MLE (e.g., the runs with c, q data), we further "integrate out" the initial distribution of the observable state to obtain the joint distribution in model m of the variables y,

$$f^m(y; \phi^s, \phi^d) = \sum_{s_0^1} \sum_{s_0^2} g^m(y^1 | s_0^1, s_0^2; \phi^s) h(s_0^1, s_0^2; \phi^d). \tag{14}$$

We also allow for measurement error in the variables in y^1. Let $\Phi(\cdot|\mu, \sigma)$ denote the p.d.f. of $N(\mu, \sigma^2)$. Given the assumed measurement error distribution, the likelihood of observing data $\hat{y}_j^1$ (for instance, $\hat{c}_j, \hat{q}_j$), relative to any grid point $y_r^1 \in Y^1$, for any $r = 1, \dots, \#Y^1$, is

$$\prod_{l=1}^{L} \Phi(\hat{y}_j^{1,l} | y_r^{1,l}, \sigma^l(\gamma_{\text{me}})), \tag{15}$$

where $l = 1, \dots, L$ indexes the different elements of y^1 or $\hat{y}^1$ (e.g., $L = 2$ for $y^1 = (c, q)$) and where $\sigma^l(\gamma_{\text{me}}) = \gamma_{\text{me}} \chi(y^l)$ is the measurement error standard deviation for each variable, as explained earlier.

Focus on the case $y = y^1$; the case $y = (y^1, s_0^1)$ is handled analogously but the algebra is more cumbersome since, for each j, we need to condition on its s_0^1 value in the grid S^1. Expression (15) implies that the likelihood of observing data vector $\hat{y}_j$ (consisting of L data variables indexed by l) for model m, at parameters $\phi \equiv (\phi^s, \phi^d, \gamma_{\text{me}})$ and initial states distribution $h(s_0^1, s_0^2; \phi^d)$, is

$$F^m(\hat{y}_j; \phi) \equiv \sum_{r=1}^{\#Y} f^m(y_r; \phi^s, \phi^d) \prod_{l=1}^{L} \Phi(\hat{y}_j^l | y_r^l, \sigma^l(\gamma_{\text{me}})), \tag{16}$$

where $f^m(y_r; \phi^s, \phi^d)$ is the value of (14) at y_r, that is, the probability mass which model m puts on grid point r, and where we assume that measurement errors in all variables are independent from each other. We basically sum over all grid points, appropriately weighted by f^m, the likelihoods in (15). For example, for cross-sectional consumption and income data $\hat{y}_j = (\hat{y}_j^1, \hat{y}_j^2) = (\hat{c}_j, \hat{q}_j)$, we have

$$\begin{aligned} F^m(\hat{c}_j, \hat{q}_j; \phi) = \sum_r & f^m((c, q)_r; \phi^s, \phi^d) \\ & \times \Phi(\hat{c}_j | c_r, \sigma^1(\gamma_{\text{me}})) \Phi(\hat{q}_j | q_r, \sigma^2(\gamma_{\text{me}})), \end{aligned}$$

where r goes over all elements of the joint grid $C \times Q$, $r = 1, \dots, \#C\#Q$ and where $l = 1$ in (16) refers to consumption c and $l = 2$ refers to income q.

Multiplying (16) over the sample units (households) and taking logs, the normalized by n log-likelihood of data $\{\hat{y}_j\}_{j=1}^n$ in model m with initial state distribution $h(s_0^1, s_0^2; \phi^d)$ at parameters ϕ is

$$(17) \qquad \Lambda_n^m(\phi) \equiv \frac{1}{n}\sum_{j=1}^n \ln F^m(\hat{y}_j; \phi).$$

The maximization of the log-likelihood (17) over ϕ is performed by an optimization algorithm robust to local maxima.[23] Standard errors are computed using bootstrapping, repeatedly drawing with replacement from the data.

4.2. *Testing and Model Selection*

We follow Vuong (1989) to construct and compute an asymptotic test statistic that we use to distinguish across the alternative models using simulated or actual data. The Vuong test does not require that either of the compared models be correctly specified. The null hypothesis of the Vuong test is that the two models are asymptotically equivalent relative to the true data-generating process, that is, cannot be statistically distinguished from each other based on their "distance" from the data in KLIC sense. The Vuong test statistic is normally distributed under the null hypothesis. 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 KLIC sense) than the other.

More formally, suppose the values of the estimation criterion being minimized, that is, minus the log-likelihood, for two competing models are given by $L_n^1(\hat{\phi}^1)$ and $L_n^2(\hat{\phi}^2)$, where n is the sample size and $\hat{\phi}^1$ and $\hat{\phi}^2$ are the parameter estimates for the two models.[24] The test allows us to rank the likelihoods with the data of all studied models pairwise, although this ranking is not necessarily transitive (model A may be preferred to model B, which may be preferred to model C, but A and C can be tied). Define the difference in lack-of fit statistic:

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

[23] We first perform an extensive grid search over the parameter space to rule out local extrema and then use non-gradient based optimization routines (Matlab's function *patternsearch*) to maximize the likelihood.

[24] For the functional forms and parameter space we use in the estimation, the models we study are statistically non-nested. Formally, following Vuong (1989), if two models are represented by the parametric families of conditional distributions $\mathcal{F} = \{F_{Y|Z}(\cdot, \cdot|\phi^1) : \phi^1 \in \mathbb{R}^{d_{\phi^1}}\}$ and $\mathcal{G} = \{G_{Y|Z}(\cdot, \cdot|\phi^2) : \phi^2 \in \mathbb{R}^{d_{\phi^2}}\}$ where $\{Y_i, Z_i\}_{i=1}^n$ is i.i.d. data, they are non-nested if $\mathcal{F} \cap \mathcal{G} = \emptyset$. The Vuong test can be also used for overlapping models, that is, neither strictly nested nor non-nested, in which case a two-step procedure is used (see Vuong (1989, p. 321)).

where $\hat{\sigma}_n$ is a consistent estimate of the asymptotic variance, σ_n, of the log of the likelihood ratio, $\Lambda_n^1(\hat{\phi}^1) - \Lambda_n^2(\hat{\phi}^2)$.[25] Under regularity conditions (see Vuong (1989, pp. 309–313) for details), if the compared models are strictly non-nested, the test statistic T_n is distributed $N(0, 1)$ under the null hypothesis.

5. APPLICATION TO THAI DATA

5.1. *Data*

In this section, we apply our estimation method to actual household-level data from a developing country. We use the Townsend Thai Data, both the rural Monthly Survey and the annual Urban Survey (Townsend, Paulson, and Lee (1997)). Constrained by space and computation time, we report primarily on the rural data, but, where possible, compare and contrast results with the urban data.

The Monthly Survey data were gathered from 16 villages in four provinces, two in the relatively wealthy and industrializing Central region near Bangkok, Chacheongsao and Lopburi, and two in the relatively poor, semi-arid Northeast, Buriram and Srisaket. That survey began in August 1998 with a comprehensive baseline questionnaire on an extensive set of topics, followed by interviews every month. Initially consumption data were gathered weekly, then bi-weekly. All variables were added up to produce annual numbers. The data we use here begin in January 1999, so that technique and questionnaire adjustments were essentially done. We use a balanced panel of 531 rural households who run small businesses observed for seven consecutive years, 1999 to 2005.

Consumption expenditures, c, include owner-produced consumption (rice, fish, etc.). Income, q, is measured on accrual basis (see Samphantharak and Townsend (2010)), though at an annual frequency this is close to cash flow from operations. Business assets, k, include business and farm equipment, but exclude livestock and household assets such as durable goods. We do perform a robustness check with respect to the asset definition—see Section 6.1. Assets other than land are depreciated. All data are in nominal terms, but inflation was low over this period. The variables are not converted to per-capita terms, that is, household size is not brought into consideration (though we do a robustness check below). We construct a measure of investment using the assets in two consecutive years as: $i_t \equiv k_{t+1} - (1 - \delta)k_t$ for each household.

The monthly data measure transfers and borrowing/lending among households within a village, and so we are able to construct measures of financial networks. Gifts and especially loans are large when they occur, averaging 9% and 60% of household consumption, respectively. From an initial census, we also have the location of parents, siblings, adult children, and parents' siblings

[25] We use for $\hat{\sigma}_n$ the sample analogue of the variance of the LR statistic (see Vuong (1989, p. 314)).

of each surveyed household and his/her spouse, and so we can construct an indicator of family-connected households in each village.

From the Urban Survey which began later, in November 2005, we use a balanced panel of 475 households observed each year in the period 2005 to 2009 from the same four provinces as in the rural data, plus two more, Phrae province in the North of Thailand and Satun province in the South. We use the same variables—consumption expenditure, business assets, and income—as in the rural data, though in this case the variables are annual to begin with, so the recall period is different. Note that there is an overlap in years for 2005, and we do use that year for comparable estimation results with the rural and urban data.

Table III displays summary statistics of these data in thousands Thai baht for both the rural and urban samples (the average exchange rate in the 1999–2005 period was 1 USD = 41 Baht). All magnitudes are higher in the urban sample because those households are richer on average. Business assets, k, and investment, i, are very unequally distributed as reflected in the high standard deviations and ratio between mean and median. There are many observations with zero or close to zero assets and few with quite large assets. More detail is reported in Samphantharak and Townsend (2010, Chapter 7) for the monthly data.

TABLE III

THAI DATA SUMMARY STATISTICS[a]

	Rural Data, 1999–2005	Urban Data, 2005–2009
Consumption expenditure, c		
Mean	64.172	148.330
Standard deviation	53.284	131.710
Median	47.868	115.171
Income, q		
Mean	128.705	635.166
Standard deviation	240.630	1,170.400
Median	65.016	361.000
Business assets, k		
Mean	80.298	228.583
Standard deviation	312.008	505.352
Median	13.688	57.000
Investment, i		
Mean	6.249	17.980
Standard deviation	57.622	496.034
Median	0.020	1.713

[a]Notes: 1. Sample size in the rural data is 531 households observed over seven consecutive years (1999–2005). 2. Sample size in the urban data is 475 households observed over five consecutive years (2005–2009). 3. All summary statistics in the table are computed from the pooled data. Units are ’000s Thai baht.

Figure 1 plots, for both the urban and rural data, deviations from the sample year averages for income, consumption, and investment. As in Townsend (1994), the figure visualizes the relative degree of consumption and investment smoothing relative to income fluctuations. We see that there is a significant degree of consumption smoothing in the data, but it is not perfect as the full insurance hypothesis would imply (if all households were identical, the right hand panel should be flat at zero). Investment should not move with cash flow fluctuations either, controlling for productivity, but should move with investment opportunities. This is more so in the urban data.

Figure 2 plots the relationships between consumption level changes and asset level changes, each relative to income level changes, as in Krueger and Perri (2011). We sort the data into twenty bins by average income change over the seven years (using quantiles) and report the average consumption and assets change corresponding to each bin (each marker corresponds to a bin). The comovement between consumption changes and income changes, Δc and Δq in the figure, can be viewed as a measure of the degree of consumption smoothing in the data. For the rural data, the top left panel shows a positive relationship between consumption and income changes (correlation of 0.11), but the slope of the consumption change line is smaller than that found in Krueger and Perri for Italian non-durable consumption data, indicating more consumption smoothing. This pattern is stronger, that is, the line is flatter, in the urban data (bottom left panel). The top right panel shows that changes in business assets in the rural data are positively correlated with changes in contemporaneous income, although this general pattern does not hold at the two extremes of very high or very low income level changes (possibly due to measurement error or large outliers). The comovement between assets and income changes is stronger in the urban data (bottom right panel).

5.2. *Structural Estimation Results*

We convert all data from Thai currency into "model units" by dividing all currency values by the 90th percentile of the assets distribution in the sample (this is 179,172 Thai baht for the rural sample). The normalized asset values are used to define a five-point assets grid,[26] K corresponding to the 10th, 30th, 50th, 70th, and 90th percentiles in the data (e.g., for the rural sample, we have $K = \{0, 0.02, 0.08, 0.33, 1\}$). The unequal spacing reflects the skewness of the asset distribution in the data. Similarly, from normalized income q, we define a five-point grid corresponding to the 10th, 30th, 50th, 70th, and 90th income percentiles (for the rural sample, $Q = \{0.04, 0.17, 0.36, 0.75, 1.75\}$). The grids for assets, k, and income, q, endogenously imply an upper bound of 0.82 model units for the borrowing/savings B grid in the B regime—higher values of b

[26]We use a standard histogram function based on distance to the closest grid point (Matlab's command `hist`).

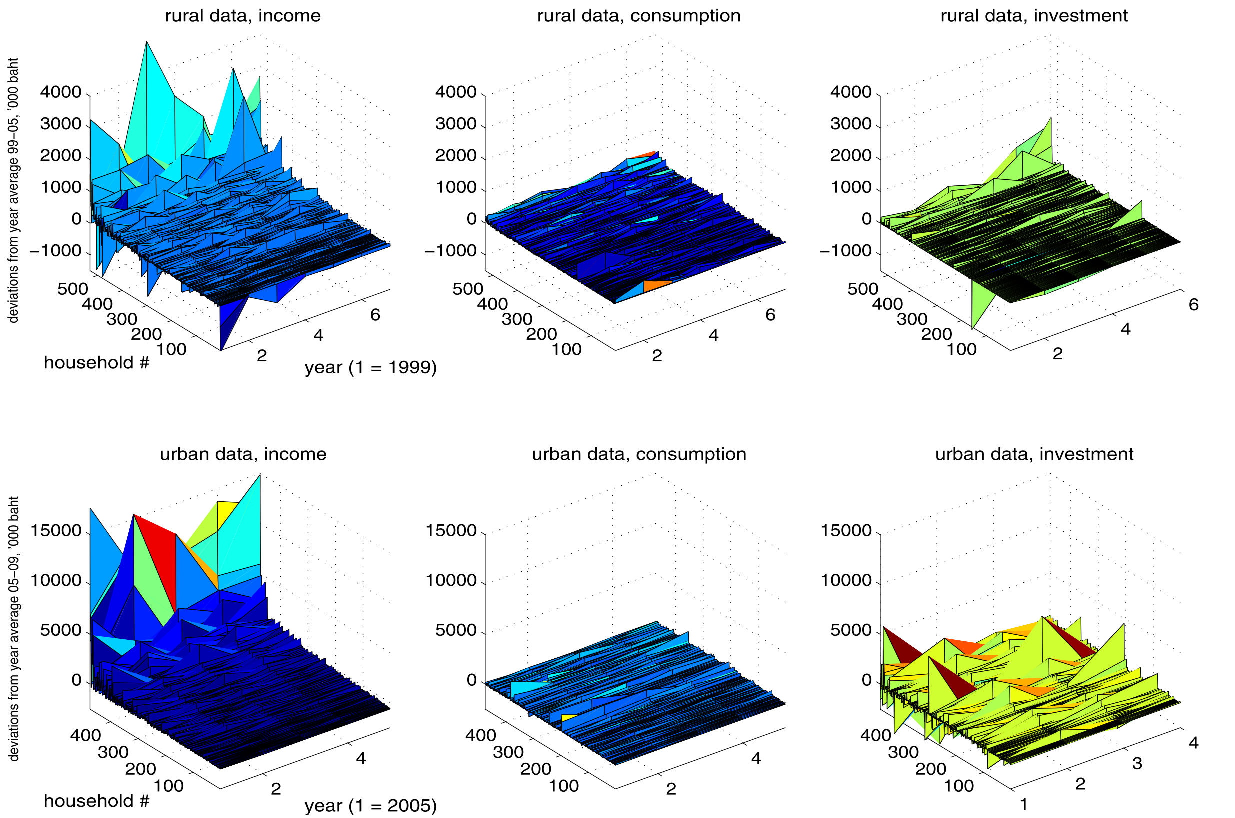

FIGURE 1.—Thai data—income, consumption, and investment comovement. Each panel displays differences from year averages of income, consumption, or investment for each household and year in the Thai rural or urban data. Households are ordered by increasing income in the first sample year.

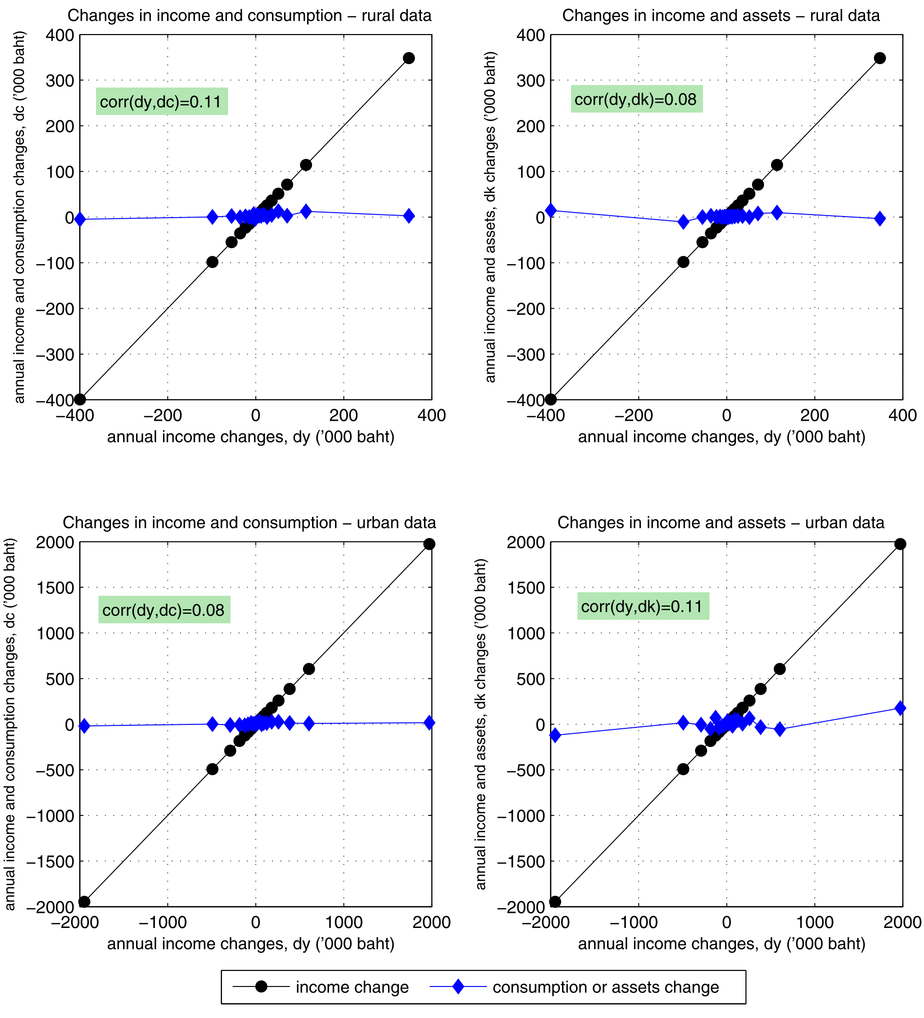

FIGURE 2.—Thai data—income, consumption, and assets changes. Each panel plots the relationships between consumption level changes or business asset level changes each relative to income level changes. We sort the data, using quantiles, into twenty bins defined by the average income change over the sample years. Each marker corresponds to the average consumption change or assets change in each income change bin.

would result in default. The consumption grid used to compute the moral hazard, full information, and limited commitment models consists of thirty-one equally spaced points on the interval $[0.001, 0.9]$ model units, which covers the range of consumption expenditure in the data. In the other regimes (B, S, and A), consumption is a residual variable, not independently chosen but obtained from the k and b grids. The promised utility grid, W in the MH, FI, and LC models, consists of five uniformly spaced points over the endogenously determined intervals derived in Section 2.2. Table II describes all grids used in the baseline estimation runs.

We use the algorithm described in Section 3 to estimate each model. We obtain estimates of the structural parameters, σ (risk aversion) and θ (effort curvature); the distributional parameters, μ_w and γ_w (respectively, μ_b, γ_b for B or S); and the measurement error size parameter, γ_{me}. The discount factor, β, the risk-free rate, R, and the depreciation rate, δ, are fixed at $\beta = 0.95$, $R = 1.05$, and $\delta = 0.05$. We also perform robustness runs with alternative values for R and δ. For robustness purposes, we perform the runs with cross-sectional (c, q) or (k, i, q) or (c, q, i, k) data using the first or the final available year of the sample.[27] In the cross-sectional runs for year t (e.g., 2004), we act as if the data start in 2004; that is, the initial k distribution $h(s_0^1)$, discussed in Section 4.1, is formed using the 2004 k data. We also perform runs in which we initialize the models with 1999 k data, run them for a number of periods, and estimate with later periods' data (see below).

Parameter estimates and bootstrap standard errors are displayed in Section 5.2.1 and Table IV, reported for the 1999 rural data runs only to save space. We then turn to the model comparisons in Section 5.2.2 and Table V.

5.2.1. *Parameter Estimates*

Table IV reports the parameter estimates for each model and its maximized likelihood (in the last column) using the 1999 Thai rural data. The best-fitting model is marked with an asterisk in the first column. We first discuss its estimates. We find that the saving only (S) regime is the best-fitting (achieves the highest likelihood) with (k, i, q) or (c, q, i, k) data. The moral hazard (MH) model achieves highest likelihood with the (c, q) data and is statistically tied with the FI and LC models. The estimates for the S regime show that the estimate for γ_{me}—the relative measurement error size parameter—is relatively small (in the range 0.09–0.13 depending on the data used, with small bootstrap standard errors). This corresponds to measurement error with standard deviation of 9% to 13% of the variables' range. The same applies for the estimate of γ_{me} for the MH model with c, q data. The estimates for the risk aversion parameter σ for the best-fitting regime indicate a relatively high degree of curvature in consumption for S (5.7 with (k, i, q) and (c, q, i, k) data) and 1.03 for MH with (c, q) data. The parameter θ, which can be interpreted as capturing the extent to which households dislike variability in effort, is estimated

[27] Remember that we need k data from periods t and $t+1$ to construct investment i in period t. Thus, when we say below that we use "1999 (k, i, q) data," this means we take k and q from 1999 and, to obtain i in 1999, we also use k from 1999 and 2000. Similarly, when we say we use "2004 (k, i, q) data," we need the value of k from 2005 to construct the 2004 value of i. For the runs with (c, q) data, we use consumption and income data from 1999 or 2005 (the main results do not change using 2004 data).

TABLE IV

PARAMETER ESTIMATES USING 1999–2000 THAI RURAL DATA[a]

Model	γ_{me}	σ	θ	$\mu_{w/b}$[b]	$\gamma_{w/b}$	LL Value[c]
			Business assets, investment, and income, (k, i, q) data			
Moral hazard, MH	0.1632	0.0465	1.3202	0.4761	0.0574	**−3.1081**
	(0.0125)	*(0.0000)*	*(0.0000)*	*(0.0139)*	*(0.0005)*	
Full information, FI	0.1625	0.0323	1.1928	0.4749	0.0591	**−3.1100**
	(0.0132)	*(0.0060)*	*(0.0770)*	*(0.0351)*	*(0.0138)*	
Limited commitment, LC	0.1606	0.4390	1.2039	0.7010	0.0609	**−3.0994**
	(0.0115)	*(0.0001)*	*(0.0053)*	*(0.0456)*	*(0.0432)*	
Borrowing and lending, B	0.0950	4.2990	0.1091	0.8883	0.0065	**−2.5992**
	(0.0059)	*(0.0880)*	*(0.0000)*	*(0.0269)*	*(0.0153)*	
Saving only, S*	0.0894	5.7202	9.2400	0.9569	0.0101	**−2.5266**
	(0.0068)	*(0.0000)*	*(0.0000)*	*(0.0087)*	*(0.0075)*	
Autarky, A	0.1203	3.1809	9.2000	n.a.	n.a.	**−2.7475**
	(0.0046)	*(0.6454)*	*(0.0000)*	n.a.	n.a.	
			Consumption and income, (c, q) data			
Moral hazard, MH*	0.1240	1.0260	1.6057	0.7933	0.0480	**−0.8869**
	(0.0086)	*(0.0046)*	*(0.0584)*	*(0.0053)*	*(0.0007)*	
Full information, FI	0.1242	0.9345	1.9407	0.7938	0.0464	**−0.9008**
	(0.0082)	*(0.0002)*	*(0.0000)*	*(0.0055)*	*(0.0000)*	
Limited commitment, LC*	0.1337	1.0358	7.7343	0.0188	0.0672	**−0.9116**
	(0.0109)	*(0.0076)*	*(0.5142)*	*(0.0070)*	*(0.0000)*	
Borrowing and lending, B	0.1346	4.3322	1.8706	0.8397	0.0311	**−1.0558**
	(0.0130)	*(0.0197)*	*(0.0000)*	*(0.0045)*	*(0.0004)*	
Saving only, S	0.1354	2.9590	0.0947	0.9944	0.0516	**−1.0033**
	(0.0074)	*(0.0343)*	*(0.8556)*	*(0.0133)*	*(0.0180)*	
Autarky, A	0.1769	1.2000	1.2000	n.a.	n.a.	**−1.1797**
	(0.0087)	*(0.0000)*	*(4.2164)*	n.a.	n.a.	
			Business assets, consumption, investment, and income, (c, q, i, k) data			
Moral hazard, MH	0.1581	0.0342	0.9366	0.3599	0.0156	**−2.8182**
	(0.0073)	*(0.0000)*	*(0.0000)*	*(0.0013)*	*(0.0010)*	
Full information, FI	0.1434	0.1435	1.0509	0.5608	0.1244	**−2.8119**
	(0.0083)	*(0.0018)*	*(0.0009)*	*(0.0112)*	*(0.0105)*	
Limited commitment, LC	0.1626	0.8035	1.0179	0.0142	0.0630	**−2.8178**
	(0.0075)	*(0.0102)*	*(0.0147)*	*(0.0074)*	*(0.0003)*	
Borrowing and lending, B	0.1397	1.0831	8.1879	0.9571	0.0398	**−2.5582**
	(0.0071)	*(0.1102)*	*(0.2536)*	*(0.0359)*	*(0.0267)*	
Saving only, S*	0.1245	5.6697	0.1114	0.9839	0.0823	**−2.3825**
	(0.0077)	*(0.0225)*	*(0.0744)*	*(0.0248)*	*(0.0432)*	
Autarky, A	0.1394	1.6922	9.2000	n.a.	n.a.	**−2.6296**
	(0.0050)	*(0.3157)*	*(0.0000)*	n.a.	n.a.	

[a]Bootstrap standard errors are in parentheses below each parameter estimate.

[b]$\mu_{w/b}$ and $\gamma_{w/b}$ (the mean and standard deviation of the w or b initial distribution) are reported relative to the variables' grid range.

[c]Log-likelihood values are normalized by dividing by the sample size n; higher values imply better fit.

* Denotes the best-fitting regime (including ties).

to be relatively high (9.2) when using (k, i, q) data alone, but lower (0.11 for S and 1.6 for MH) when including consumption data, in the respective (c, q, i, k) and (c, q) data runs. Since effort z takes values on $(0, 1)$, values for θ close to zero imply relatively high effort disutility z^θ over the whole effort range, while high values of θ imply low effort disutility at low z levels increasing sharply at high effort levels. This parameter is sometimes not very precisely estimated (relatively large bootstrap standard errors). The final two parameters reported in Table IV, $\mu_{w/b}$ and $\gamma_{w/b}$, determine the mean and standard deviation of the initial distribution of unobserved heterogeneity in the models captured by the state variables' promised utility, w (for the MH, FI and LC models) or debt/savings, b (for the B and S models). Their estimates are reported relative to these variables' grid ranges, for example, $\mu_w = 0.79$ estimated for the best-fitting MH regime with (c, q) data means that the initial promised utility distribution is estimated to have a mean of $w_{\min} + 0.79(w_{\max} - w_{\min})$. Similarly, γ_w refers to the estimate of the standard deviation of the initial distribution of w, again relative to its grid range (e.g., $\gamma_w = 0.05$ means a standard deviation of $0.05(w_{\max} - w_{\min})$ around the mean μ_w). The estimates of μ_b for the S regime are high and in a very narrow range (0.96–0.99) for all data subsets, which means putting the mean of the unobserved initial savings distribution close to zero savings (the upper limit of the B grid). The standard deviation parameter γ_b is estimated relatively small for the S model, in the range 0.01–0.08 depending on the data used, with standard errors in the 0.01–0.04 range.

More generally, Table IV shows that the estimates differ across the regimes as the MLE optimization adjusts the parameters for each model to attain best fit with the Thai data. The estimates for the measurement error size, γ_{me}, across all regimes and data types are in a relatively narrow range, 0.09–0.18. This corresponds to measurement error with standard deviation of 9% to 18% of the variables' grid ranges. The bootstrap standard errors on this parameter are low. The highest-likelihood model in each subsection of Table IV accommodates the smallest measurement error size. In contrast, the regimes that obtain the lowest likelihoods generally feature high estimated level of measurement error (e.g., the MH, FI, LC regimes with (k, i, q) data have estimates for γ_{me} larger than 0.16 vs. 0.089 for S). The likely explanation is that, to compensate for the bad fit, the MLE routine is raising the level of measurement error. The estimates for the risk-aversion parameter σ vary in the range 0.03 to 5.7 depending on the model and data used. The MH, LC, and FI regimes seem to require less risk-aversion to fit the data (σ below 1.04), while the B and S models produce estimates above 2.9 (with one exception, B with (c, q, i, k) data). A possible reason is that the mechanism design models need to impose less curvature in consumption to explain the data; higher curvature would lead to excessive smoothing in these models relative to the data. There is substantial variation in the estimates for the effort-curvature parameter θ across the six regimes. For example, with the (c, q, i, k) data, they range from 0.11 for saving only to 9.2 for autarky. Table IV also shows that, in order to fit the data, the

B and S regimes estimate the parameter of the unobserved debt/savings distribution, μ_b, in the range 0.84 to 0.99, which implies putting the mean initial b close to the borrowing limit $b_{\max}$ in the B model or to zero savings in the S model. In contrast the range of the estimates for μ_w is wider (between 0.01 for LC with c, q, i, k data and 0.79 for MH and FI with c, q data). The variance parameter, $\gamma_{b/w}$, is estimated to be relatively low, below 0.08 of the w or b grid ranges, with the FI, (c, q, i, k) data case the sole exception.

5.2.2. *Model Comparisons—Vuong Test Results*

Business Assets, Investment, and Income Data. We first explore the implications of the different models on the production side alone by using the joint distribution of assets, investment, and income, (k, i, q), in the data. When estimated from (k, i, q) 1999 cross-sectional data (see footnote 26), the regimes rank in decreasing order of likelihood as: S, B, A, LC, MH, FI (Table IV, last column). The saving only (S) model wins all its bilateral model comparisons at the 1% significance level in the 1999 data (Table V, row 1.1), while the B and S regimes are tied for best fit in the 2004 data (row 1.2). The MH, LC, FI, and A regimes obtain the worst likelihoods and are rejected at the 1% significance level in all comparisons with the best-fitting regime(s).

Consumption and Income Data. We next test whether we can distinguish between the regimes based solely on the degree of consumption smoothing they imply relative to the data using the (c, q) joint cross-sectional distribution (Table V, section 2). The Thai consumption and income data alone seem to be unable to pin down precisely the best-fitting regime—we have a tie between MH and LC with the 1999 data and between S, LC, and MH with the 2004 data.

Business Assets, Investment, Consumption, and Income Data. We also evaluate the gains from using combined data on assets, investment, income, and consumption as opposed to using the (k, i, q) or the (c, q) data on their own. This captures both the consumption and production side of the household/enterprise problem as shaped by the postulated financial constraints (section 3 of Table V). Theoretically, the classical separation between consumption and production/investment decisions fails with incomplete markets, and so empirically, joint data on the consumption and investment side of the model should be helpful to distinguish the regimes better. Adding the consumption data to the set of variables, we observe an improvement in our ability to distinguish the regimes relative to using (k, i, q) data or especially the (c, q) data alone, and we are able to pin down S as the single winner in both the 1999 and 2004 samples.

TABLE V

MODEL COMPARISONS[a] USING THAI RURAL DATA—BASELINE VUONG TEST RESULTS

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Using* (k, i, q) *data*																
1.1. Year: 1999[†]	MH*	LC**	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	S***	B***	S***	S
1.2. Year: 2004[†]	MH***	MH***	B***	S***	A***	tie	B***	S***	A***	B***	S***	A***	tie	B***	S***	B, S
2. *Using* (c, q) *data*																
2.1. Year: 1999	MH**	tie	MH***	MH***	MH***	tie	FI***	FI**	FI***	LC***	LC**	LC***	S***	B***	S***	MH, LC
2.2. Year: 2005	tie	tie	tie	tie	tie	LC***	tie	S***	tie	tie	tie	LC*	S**	tie	S***	S, LC, MH
3. *Using* (c, q, i, k) *data*																
3.1. Year: 1999[†]	tie	tie	B***	S***	A**	tie	B***	S***	A**	B***	S***	A**	S***	tie	S***	S
3.2. Year: 2004[†]	FI***	MH***	B***	S***	A***	FI***	B***	S***	A**	B***	S***	A***	S***	tie	S**	S
4. *Dynamics*																
4.1. (c, q) panel, years: 1999 and 2000	MH***	LC***	B***	S***	MH**	LC***	B***	S***	tie	LC*	tie	LC***	tie	B***	S***	LC, S
4.2. (c, q) panel, years: 1999 and 2005	MH***	MH***	tie	tie	MH***	FI***	B***	S***	tie	B***	S***	A**	tie	B***	S***	B, S, MH
4.3. c time series, years 1999–2001	tie	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	B***	S***	A***	S***	B***	S***	FI, MH
4.4. c time series, years 2003–2005	MH***	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	B***	S***	A***	S***	B***	S***	MH
4.5. 99 k distribution and 04 (c, q, i, k)	FI***	MH***	B***	tie	tie	FI***	B***	tie	FI*	B***	S***	A***	B***	B***	S**	B
4.6. 99 k distribution and 05 (c, q)	tie	MH***	tie	tie	MH***	FI***	tie	tie	FI***	B***	S***	A**	tie	B***	S***	S, B, FI, MH
4.7. 99 k distribution and 04 (k, i, q)	FI***	LC***	B***	S**	MH**	tie	B***	S*	FI**	B***	S*	LC**	B***	B***	S***	B

[a] *** = 1%, ** = 5%, * = 10% two-sided significance level, the better fitting model abbreviation is displayed. [†] k data from 2000 is also used to construct 1999 investment, i; k data from 2005 is also used to construct 2004 investment, i.

Dynamics. We next use the panel structure of the data to estimate and test across the alternative regimes targeting differences in the variables' dynamics across the models. Our empirical method, based as it is on repeatedly computing discrete joint distributions of model variables during the estimation, is heavy on computer time and memory when we use several years of data at a time. For example, if we wanted to use three periods of (k, i, q) data in the estimation, we would have a discretized joint distribution f^m in (14) of dimension (total number of mutually exclusive probability cells) equal to $(\#K)^3(\#I)^3(\#Q)^3$ (this equals almost two million with our baseline grids).[28] For these reasons, we only use (c, q) data from two periods in the runs reported below. We did, however, manage to run our MLE with three-period-long consumption time series data using the baseline grids (see below). We also did a robustness run with a five-year time series of consumption data, 1999–2003, but needed to use coarser grids (see Table IX).

Restricting ourselves to using two years of (c, q) data at a time (see rows 4.1 and 4.2 in Table V), the regimes' likelihood ordering is consistent with results discussed above. The ability to distinguish across the regimes with the 1999/2000 (c, q) panel data is similar to that in the single 1999 (c, q) cross-section but worsens with the gap between years included in the panel—three regimes, B, MH, and S, are statistically tied when the 1999/2005 (c, q) panel is used. In rows 4.3 and 4.4 of Table V, we perform a run using three consecutive years (1999–2001 and 2003–2005) of consumption data alone, as in a time series. The result, MH best-fitting (tied with FI in 4.3), is consistent with the runs with (c, q) data in rows 2.1–2.2.

In addition, we did runs (Table V, rows 4.5–4.7) where we used the 1999 distribution of k to initialize the models but 2004–2005 data in the MLE. That is, each model was run for six (seven in the case of c, q data) periods and its predictions for the joint distributions of (k, i, q), (c, q), or (c, q, i, k) at the final period were matched with actual data from the corresponding year of the panel. Once again, the evidence points to the exogenously incomplete market regimes fitting best (B, followed by S) when using the production-side (k, i, q) and the joint (c, q, i, k) data, while we are unable to distinguish those two regimes from FI and MH with the (c, q) data alone. We discuss further the models' ability to match the dynamics of the data in the robustness Section 6.

Rural Networks. In Table VI, we also perform runs with subsamples of the Thai rural data with various definitions of networks between households. We

[28] In terms of memory requirements, with our baseline grids, computing the MLE with three periods of (k, i, q) data would involve manipulating repeatedly vectors and matrices (some for each k, w) with size $(\#K)^3(\#I)^3(\#Q)^3 = 1{,}953{,}125$, as opposed to $(\#C)^2(\#Q)^2 = 24{,}025$, when using two periods of (c, q) data (a factor of 81) and size $(\#C)(\#Q) = 155$ when using (c, q) cross-sections. In terms of computer time, the baseline MLE runs with the slowest-to-run LC regime and two periods of (c, q) data or with three periods of c data require 10–15% more time than those with (c, q) cross-sections, but the run with five periods of c data (Table IX, row 5.13) required 50–60% more time.

TABLE VI

MODEL COMPARISONS[a] USING THAI RURAL DATA—NETWORKS

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Networks by friend or relative*																
1.1. (c, q) data, in network, $n = 391$	tie	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	LC***	tie	LC***	S***	B***	S***	MH, FI
1.2. (k, i, q) data, in network	tie	tie	B***	S***	A***	tie	B***	S***	A***	B***	S***	A***	S**	B**	S***	S
1.3. (c, q, i, k) data,in network	tie	tie	B***	S***	A**	tie	B***	S***	A***	B***	S***	A**	S***	tie	S**	S
1.4. (c, q) data, not in network, $n = 140$	tie	tie	tie	tie	tie	LC**	tie	tie	tie	LC**	LC*	LC**	tie	B*	S**	LC, MH
1.5. (c, q, i, k) data, not in network	tie	MH***	tie	S***	tie	FI***	tie	S***	A**	B**	S***	A***	S***	tie	S*	S
2. *Networks by gift or loan*																
2.1. (c, q) data, in network, $n = 357$	tie	tie	MH***	MH*	MH***	tie	FI***	FI**	FI***	LC***	tie	LC***	S***	B***	S***	FI, MH, LC
2.2. (k, i, q) data, in network	tie	tie	B***	S***	A***	tie	B***	S***	A***	B***	S***	A***	S**	B**	S***	S
2.3. (c, q, i, k) data, in network	tie	MH***	B***	S***	A**	FI***	B***	S***	A**	B***	S***	A***	S***	tie	S**	S
2.4. (c, q) data, not in network, $n = 174$	tie	tie	tie	tie	MH**	LC*	tie	tie	FI*	tie	tie	LC**	tie	B**	S***	S, LC, MH, FI, B
2.5. (c, q, i, k) data, not in network	tie	tie	B***	S***	tie	tie	B***	S***	tie	B***	S***	tie	S**	B*	S***	S

[a] $^{***} = 1\%$, $^{**} = 5\%$, $^{*} = 10\%$ two-sided significance level, the better fitting model abbreviation is displayed. † k data from 2000 is also used to construct 1999 investment, i; k data from 2005 is also used to construct 2004 investment, i.

first focus on a set of households ($n = 391$) who are related by blood or marriage (section 1 of Table VI). Compared to the whole sample results and likelihoods in Table V, with consumption and income cross-sectional data alone, this networked subsample allows us to narrow down the best-fitting regime as moral hazard (tied with FI). Evidently, family networks help in consumption smoothing, as in Chiappori et al. (2014). LC is, however, the best-fitting regime in the (c, q) subsample of unrelated households (tied with MH, but note the small number of observations). In contrast, including the production side, the results with 1999 (k, i, q) and (c, q, i, k) data still indicate that the S regime remains best-fitting in all stratifications, as in the whole sample. This is also true in the subsample of households not related by blood or marriage (line 1.5).

A re-estimation with another data subsample of 357 households related via observed personal loans or gifts (see Kinnan and Townsend (2012) for details) and the 1999 (c, q) data puts the FI regime on top in terms of likelihood (row 2.1 in Table VI), tied with MH and LC, compared to less information for those not in networks—S has highest likelihood (but tied with many other models, possibly due to the small number of observations). Again, this effect is not present when using the production-side data in the same subsamples—S wins, as in the whole sample.

Urban Data. We also ran our estimation routines on the more recent panel data from the Thai Urban Surveys on households in urban areas. Results are displayed in Table VII. Now the moral hazard (MH) regime is identified as the best-fitting using the complete data on consumption, income, investment, and assets (c, q, i, k) from both 2005 and 2008 (see Table VII, section 1).

In fact, the moral hazard regime appears as winning in all sections of Table VII, with one exception—when using data on the production side alone—the (k, i, q) specification (Table VII, section 3), where we recover the saving only (S) regime, the same as in the rural data. Again, the results with joint production and consumption data (c, q, i, k) are more decisive and an endogenously incomplete (MH) rather than exogenously incomplete regime is chosen. Urban households seem to be doing better than the rural in terms of smoothing consumption and investment. We come back to this in Section 7.

6. ROBUSTNESS

6.1. *Additional Estimation Runs With Thai Data*

In this section, we report on a large number of additional estimation runs we did to check the robustness of the baseline results and shed more light onto the regime likelihood patterns with consumption versus investment versus joint data. Here we restrict most of our robustness checks to the rural data.

TABLE VII

MODEL COMPARISONS[a] USING THAI URBAN DATA—VUONG TEST RESULTS

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Using* (c, q, i, k) *data*																
1.1. Year: 2005†	MH***	MH***	MH***	MH***	MH***	LC***	B***	S***	FI*	tie	S***	LC***	S***	B***	S***	MH
1.2. Year: 2008†	MH***	MH***	MH***	MH***	MH***	LC***	B***	S***	tie	LC**	tie	LC***	S***	B***	S***	MH
2. *Using* (c, q) *data*																
2.1. Year: 2005	tie	MH**	MH***	MH***	MH***	tie	FI***	FI**	FI***	LC***	LC**	LC***	S***	B***	S***	MH, FI
2.2. Year: 2009	MH***	tie	MH***	MH***	MH***	tie	FI***	FI***	FI***	LC***	LC***	LC***	S***	B***	S***	LC, MH, FI
3. *Using* (k, i, q) *data*																
3.1. Year: 2005†	tie	MH*	tie	S***	tie	tie	tie	S***	tie	tie	S***	tie	S***	tie	S**	S
3.2. Year: 2008†	FI*	tie	B***	S***	A***	FI*	B***	S***	tie	B***	S***	A***	tie	tie	S*	S, B
4. *Two-year panel*																
4.1. (c, q) data, years: 2005 and 06	tie	MH***	MH***	tie	MH***	FI***	FI***	tie	FI***	tie	S***	LC**	S***	B**	S***	S, MH, FI
4.2. (c, q) data, years: 2005 and 09	MH***	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	B***	S***	tie	S***	B***	S***	MH

[a] $^{***} = 1\%$, $^{**} = 5\%$, $^{*} = 10\%$ two-sided significance level, the better fitting model abbreviation is displayed. † Business assets k data from year $t + 1$ is also used to construct year t investment i.

Using Parametric Production Function

We redo the baseline estimation runs from Table V using an alternative, parametric production function. The advantage of doing this is that we can take into account the endogeneity in production decisions determined jointly with the financial regime. The disadvantage is that we are jointly testing the financial regime with the assumed parametric form. We assume the following parametric form for $P(q|z,k)$:

$$(18)\qquad P(q=q_1|z,k)=1-\left(\eta k^\rho+(1-\eta)z^\rho\right)^{1/\rho},$$
$$P(q=q_i|z,k)=\frac{1}{\#Q-1}\left(\eta k^\rho+(1-\eta)z^\rho\right)^{1/\rho}\quad\text{for}\quad i=2,\dots,\#Q,$$

where q_1 is the lowest output level. The probability of obtaining each output level is bounded away from zero or 1 by setting it equal to 0.01 if it is lower and 0.99 if higher. We estimate ρ but fix $\eta=1/2$ for computational time reasons. This functional form encompasses a range of production technologies ($\rho=1$—perfect substitutes technology; $\rho\to 0$—Cobb–Douglas; and $\rho\to-\infty$—Leontief). Note that $P(q|z,k)$ determines expected, not actual, output and so the CES parameter ρ here is not comparable to values from the macro literature.[29]

Table VIII reports the results from the Vuong test model comparisons with this production function specification. Using the production side of household operations, (k,i,q) data from either 1999 or 2004 (Table VIII, rows 1.1 and 1.2) reveals the saving only (S) regime (tied with B in one run) as best-fitting, consistent with the baseline runs (Table V, section 1). Using the consumption side, (c,q) data (rows 1.3–1.4), the B regime comes on top but, in 1.3, is tied with S and MH, which was the best-fitting regime in Table V. The combined consumption, income, investment, and assets data runs (Table VIII, rows 1.5–1.6) show as best-fitting (tied with B in one run) the S regime, the dominant regime in the corresponding part of Table V. The results with two-year panels of (c,q) data (Table VIII, rows 1.7–1.8) are similar to those in Table V, with many tied regimes.

We also perform the same exercise with the parametric production function with the urban data (Table VIII, section 2). As with the rural data, the results are once again similar to the corresponding baseline runs (in Table VII for the urban data), although there are more ties and the LC regime is doing better when using consumption data. The moral hazard regime ties for best-fitting with FI and LC using the urban 2005 (c,q,i,k) data; MH, LC, and FI are also tied when only the (c,q) data are used. The S regime still fits best with the

[29]In an earlier version of the paper, we also did runs with a version of this production function with an extra parameter that allowed differential probability for output levels different from the lowest. This did not affect the results in terms of best-fitting regime.

TABLE VIII

MODEL COMPARISONS[a] USING PARAMETRIC PRODUCTION FUNCTION

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Rural data*																
1.1. (k, i, q), year: 1999†	FI**	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	tie	B***	S***	S, B
1.2. (k, i, q), year: 2004†	MH***	MH***	B***	S***	A***	FI***	B***	S***	A***	B***	S***	A***	S***	tie	S**	S
1.3. (c, q), year: 1999	MH***	MH***	tie	tie	MH***	FI***	B***	S***	FI*	B***	S***	tie	tie	B***	S***	B, S, MH
1.4. (c, q), year: 2005	MH**	MH**	B***	S***	tie	tie	B***	S***	A**	B***	S***	A**	B**	B**	tie	B
1.5. (c, q, i, k), year: 1999†	tie	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	tie	tie	B***	S***	B, S
1.6. (c, q, i, k), year: 2004†	MH***	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	S*	B**	S***	S
1.7. (c, q) panel, years: 1999 and 2000	MH***	tie	tie	S**	MH***	LC***	B***	S***	FI***	B*	S***	LC***	tie	B***	S***	S, B
1.8. (c, q) panel, years: 1999 and 2005	MH*	tie	tie	tie	MH***	LC**	tie	tie	FI***	tie	tie	LC***	tie	B***	S***	LC, B, MH, S
2. *Urban data*																
2.1. (c, q, i, k), year: 2005†	tie	tie	MH**	MH***	MH***	tie	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	FI, MH, LC
2.2. (c, q), year: 2005	tie	tie	MH***	MH***	MH***	tie	FI***	FI*	FI***	LC***	tie	LC***	S***	B***	S***	MH, FI, LC
2.3. (k, i, q), year: 2005†	tie	LC**	tie	S**	tie	LC**	tie	S***	tie	tie	S**	tie	S***	tie	tie	S, A

[a] *** $= 1\%$, ** $= 5\%$, * $= 10\%$ two-sided significance level, the better fitting model abbreviation is displayed. † Business assets k data from year $t+1$ is also used to construct year t investment i.

urban (k, i, q) data, although now tied with autarky. The bottom line is that most, if not all, the results are similar to the baseline, and so we conclude that assumptions about the production function are not driving the regime comparisons.

Robustness Runs—Risk Neutrality, Fixed Measurement Error, Adjustment Costs, Fixed Effects, etc.

We perform a number of robustness checks with several variations of our baseline specification. The results are displayed in Table IX. Unless stated otherwise, Table IX uses 1999 data. First, a re-estimation imposing risk neutrality, that is, fixing $\sigma = 0$ instead of estimating σ (Table IX, section 1), produces similar results to the baseline runs allowing for risk aversion. One difference, however, is that the saving only regime shows as sole winner with the 1999 (c, q) data (row 1.1). Apparently, not allowing for risk aversion worsens the fit of the endogenously incomplete regimes which came on top with (c, q) data in Table V. Otherwise, with the production side data, imposing risk neutrality yields the borrowing or saving only regimes as best-fitting, as in the baseline.

Re-estimating with fixed size of measurement error (in these runs, we set the standard deviation parameter γ_{me} to 0.1) naturally reduces the regimes' likelihood values, especially for autarky, but preserves the MH model's best fit (tied with FI and LC) with the Thai data on consumption and income (see Table IX, section 2). The saving only (S) regime emerges as the single best-fitting regime with (k, i, q) and (c, q, i, k) data, exactly as in the 1999 baseline runs.

In section 3 of Table IX, we allow quadratic adjustment costs in investment. The bottom line here is that the introduction of adjustment costs does blur the distinction across the financial regimes, especially, endogenous versus exogenously incomplete markets regimes, or can pick out a different regime entirely. The full information regime with adjustment costs corresponds to the standard adjustment costs model in the literature (Bond and Meghir (1994), among many others) though we are allowing risk aversion. It appears as best-fitting in a tie with S using the joint production and consumption data (line 3.3). Production data alone (k, i, q) actually has S tied with autarky, A (line 3.2). The moral hazard and limited commitment regimes are tied with the borrowing regime with adjustment costs as fitting the consumption-income data best (line 3.1), though B was dominated when adjustment costs were not included, as in Table V. It is true that the likelihoods of some regimes improve, but there are more parameters. We do not come away convinced that adjustment costs offer a better underlying specification than the baseline. An exception, dealing with the persistence of capital, is discussed below.

In section 4 of Table IX, we perform a series of estimation runs with the data from which we removed year or year and household fixed effects and replaced them with average values. The issue here is that there might be more heterogeneity in the raw data than what the models are designed to accommodate.

TABLE IX

MODEL COMPARISONS[a] USING THAI DATA—ROBUSTNESS RUNS—VUONG TEST RESULTS

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Risk neutrality*																
1.1. (c, q) data	MH***	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	S***	B**	S***	S
1.2. (k, i, q) data	tie	tie	B***	S***	A***	tie	B***	S***	A***	B***	S***	A***	B***	B***	A***	B
1.3. (c, q, i, k) data	MH***	tie	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	S**	tie	S***	S
2. *Fixed measurement error variance*																
2.1. (c, q) data	tie	tie	MH***	MH***	MH***	tie	FI***	FI***	FI***	LC***	LC**	LC***	S***	B***	S***	MH, FI, LC
2.2. (k, i, q) data	tie	MH***	B***	S***	A***	FI***	B***	S***	A***	B***	S***	A***	S***	B***	S***	S
2.3. (c, q, i, k) data	FI***	tie	B***	S***	A***	FI***	B***	S***	A*	B***	S***	A***	S***	tie	S***	S
3. *Investment adjustment costs*																
3.1. (c, q) data	MH**	tie	tie	MH*	MH***	tie	tie	tie	FI***	tie	tie	LC***	B*	B***	S***	MH, B, LC
3.2. (k, i, q) data	tie	LC**	B***	S***	A***	LC**	B***	S***	A***	B***	S***	A***	S*	A*	tie	S, A
3.3. (c, q, i, k) data	tie	MH***	tie	S**	MH**	FI***	tie	tie	FI***	B***	S***	A***	S**	B***	S***	S, FI
4. *Removed fixed effects*																
4.1. Year fixed effects, 1999 $cqik^\dagger$	tie	tie	B***	S***	A***	tie	B***	S***	A***	B***	S***	A*	S*	tie	S*	S
4.2. Year fixed effects, 2004 $cqik^\dagger$	MH***	MH***	B***	S***	A**	LC**	B***	S***	A***	B***	S***	A***	tie	B***	S***	B, S
4.3. Year fixed effects, $cqik$ urban	MH***	MH***	MH***	MH***	MH***	LC***	B***	S***	tie	LC***	LC***	LC***	B***	B***	S***	MH
4.4. Year + hh fixed effects, kiq	tie	tie	B*	S***	A***	tie	B*	S***	A***	B*	S***	A***	S***	A***	S*	S
4.5. Year + hh fixed effects, cq	MH*	MH***	MH***	MH***	MH***	tie	FI***	FI**	FI***	LC***	LC***	LC***	S***	B***	S***	MH
4.6. Year + hh fixed effects, $cqik$	MH***	tie	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	S***	B***	S***	LC, MH
4.7. Year + hh fixed effects, param. prod. fn	FI**	LC***	tie	tie	MH***	LC***	tie	tie	FI***	LC***	LC***	LC***	tie	B***	S***	LC

(*Continues*)

TABLE IX—*Continued*

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
5. *Other robustness runs (with 1999*[†] c, q, i, k *data unless otherwise indicated)*																
5.1. Correlated initial states, 1999 $cqik$	FI**	LC**	B***	S***	A**	tie	B**	S***	tie	B***	S***	tie	S***	tie	S***	S
5.2. Correlated initial states, 1999 cq	tie	tie	MH***	MH***	MH***	tie	FI***	FI***	FI***	LC***	LC***	LC***	S**	B***	S***	FI, MH, LC
5.3. Correlated initial states, 1999 kiq	FI***	MH***	B***	S***	A*	FI***	B***	S***	A*	B***	S***	A***	S**	B***	S***	S
5.4. Alternative assets definition	tie	MH***	MH**	S***	tie	FI***	FI**	S***	tie	B***	S***	A***	S***	A***	tie	S, A
5.5. Alternative income definition	MH***	MH***	tie	S*	tie	FI***	B**	S***	A***	B***	S***	A***	S***	tie	S***	S
5.6. Alternative interest rate, $R = 1.1$	tie	tie	B***	S***	A*	tie	B***	S***	A*	B***	S***	A**	tie	B***	S***	S, B
5.7. Interest rate $R = 1.025$; 2004 $cqik$[†]	MH***	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	tie	B*	S**	S, B
5.8. Alternative depreciation rate, $\delta = 0.1$	FI***	LC***	B***	S***	A***	FI*	B***	S***	A**	B***	S***	A***	tie	B*	S***	S, B
5.9. Coarser grids	MH***	MH***	B***	S***	A***	FI***	B***	S***	A***	B***	S***	A***	B**	B***	S***	B
5.10. Denser grids	MH***	LC***	B***	S***	A***	LC***	B***	S***	A***	B***	S***	A***	tie	B***	S***	B, S
5.11. More general effort disutility form	FI***	tie	B***	S***	A*	tie	B***	S***	tie	B***	S***	tie	S***	B***	S***	S
5.12. Mixture of normals b, w distributions	MH***	MH***	B***	S***	tie	FI***	B***	S***	A*	B***	S***	A***	S***	tie	S***	S
5.13. 1999–2003 c time series (coarse grid)	MH*	MH***	MH**	MH***	MH***	FI***	FI***	FI***	FI***	LC***	LC***	LC***	S**	B***	S***	MH

[a] $^{***} = 1\%$, $^{**} = 5\%$, $^{*} = 10\%$ Vuong (1989) test two-sided significance level. Listed is the better fitting model or "tie" if the models are tied. Sample size is $n = 531$; data are for 1999 unless noted otherwise. [†] k data from 2000 is also used to construct 1999 investment, i; k data from 2005 is also used to construct 2004 investment, i.

Removing only year fixed effects (Table IX, lines 4.1–4.3) can be thought of as "purging" the data from aggregate shocks. Our baseline results remain robust. Using the 1999 (c, q, i, k) rural data reassuringly produces almost identical results in all bilateral comparisons as the corresponding baseline run with the raw data (compare line 4.1 in Table IX with line 3.1 in Table V), with the S regime coming on top. The run with 2004 (c, q, i, k) data with removed time fixed effects results in a tie between B and S for best fit, which is again consistent with the baseline (Table V, line 3.2). The run with 2005 (c, q, i, k) urban data with removed year fixed effects (line 4.3) yields MH as the best-fitting regime, exactly as in the corresponding baseline run in Table VII, line 1.1.

Removing both year and household fixed effects (Table IX, row 4.4) reveals S as the best-fitting regime with the (k, i, q) data, also as in the baseline. The MH regime has the highest likelihood with the 1999 consumption and income data from which year and household fixed effects have been removed (line 4.5), which is again consistent with the corresponding baseline run in Table V, where MH was tied for best fit with LC. The run with (c, q, i, k) data where LC and MH are revealed as best-fitting (row 4.6 in Table IX) is the only one that does not reproduce the baseline result where S is best-fitting (row 3.1 in Table V). Naturally, removing time and household fixed effects from the Thai data and replacing them with averages produces a "smoother" data set, so perhaps the better fit of the LC and MH models is not surprising (this applies also to row 4.7 with the parametric production function). We do not use this specification as the baseline, since the fixed effects may, at least partially, be endogenous to the financial regime in the data which we are trying to uncover. We come back to this question in the estimation runs with simulated data from one of the models (Section 6.2 below). In some of these runs, we deliberately generate simulated data with heterogeneity in risk aversion, in productivity, or in interest rates, and estimate the models as if this heterogeneity did not exist. In another run, we took out the time and household-level heterogeneity the model is generating endogenously, and the results echo what we find above.

In section 5 of Table IX, we perform thirteen additional robustness runs. We first check robustness with respect to our baseline assumption of independent initial states. Specifically, the runs in Table IX, rows 5.1–5.3 allow for correlation between the initial distributions of k and w or k and b used to initialize the respective model regimes. This introduces an extra estimated parameter, slowing down computation considerably. The results from these three runs confirm that our respective baseline results remain robust. In the runs with 1999 (c, q, i, k) and (k, i, q) data, the S regime is best-fitting, just like in the baseline (see Table V, rows 3.1 and 1.1). In the run with (c, q) data, the three mechanism design regimes (MH, FI, and LC) are statistically tied for best fit, as in the baseline (compare with Table V, row 2.1).

Next, we check robustness with respect to our definitions of assets and income in the Thai data (Table IX, row 5.4). That is, we re-estimate using the 1999 (c, q, i, k) data including all household assets and livestock in the definition of k. The sample size drops to 297, but the best-fitting regime (S) from the baseline, Table V, row 3.1, does not change (now tied with A, possibly due to the smaller sample size). In row 5.5, we check robustness with respect to the income definition by excluding labor income from the value of q for all 531 households. The baseline results remain robust. Re-estimating fixing the lender risk-free rate to $R = 1.1$ instead of the baseline value 1.05 in the baseline or the depreciation rate $\delta = 0.1$ instead of 0.05 in the baseline (Table IX, rows 5.6 and 5.8) does not affect our findings either—the S regime is still best-fitting, although in these runs we cannot discern it from the B regime. To address possible change in the rate R over time, we also did a run (Table IX, row 5.7) with the 2004 (c, q, i, k) data and $R = 1.025$, that is, a net interest rate equal to half of the baseline value. When viewed together with the runs using $R = 1.05$ (Table V, line 3.1 with 1999 c, q, i, k data) or using $R = 1.1$ (run 5.6 above, also with 1999 c, q, i, k data), this lower value of R can be thought of as proxying the gradual fall in interest rates in Thailand over the period 1999–2004. Our results remain robust.

Re-estimation using either grids coarser than the baseline (3 points) or denser than the baseline (10 points) produces similar results (see rows 5.9 and 5.10). The next robustness check (row 5.11) introduces an additional estimated preference parameter, ξ—in this run, we use the functional form $U(c, z) = \frac{c^{1-\sigma}}{1-\sigma} - \xi z^{\theta}$. The result is identical to the baseline—the S regime is best-fitting. We also do a run (row 5.12) where we assume that the initial distribution of the unobservable state (w or b) is a mixture of two Normals, instead of our univariate Normal baseline. This introduces extra parameters to be estimated in the MLE and slows down computation considerably, which is why we were not able to use it as baseline. The best-fitting regime remains saving only. Finally, in Table IX, row 5.13, we use a five-year-long time series of consumption data alone but, for computational reasons, we had to reduce the dimensionality of the C grid from 31 to 11 points. The best-fitting regime, MH, is consistent with our findings from the baseline run with a three-year consumption time series (Table V, row 4.3).

We also did MLE runs with 2000 and 2002 data and with data stratified by region, by bank access, and by "net wealth" (the latter constructed from household accounts as in Samphantharak and Townsend (2010)). We are not reporting details since we did not find systematic patterns or differences with the baseline.

6.2. *MLE With Simulated Data*

Because of the analytical complexity of the dynamic models we study, it is not possible to provide identification proofs while keeping the setting general. To show that our procedure works, we use a numerical verification algorithm consisting of the following steps: Step 1—take a baseline model; Step 2—generate simulated data from the baseline model at a baseline vector of parameters, ϕ^{base}; Step 3—estimate the baseline model with the data from Step 2 using our method from Section 4, with grids determined by the simulated data percentiles and the same maximization routine, to obtain ML estimates, $\hat{\phi}^{\text{base}}$; Step 4—check whether the estimates from Step 3 are close to the baseline ϕ^{base} within the standard error bands and whether the Vuong test recovers the actual data-generating regime. In short, we use data simulated from the model itself to check that our estimation method performs as it should.

While we have done our best to argue robustness, this section is purely intended as a validation exercise of our empirical method and further support for our results with the Thai data, not a proof of identification. Nonetheless, this section is important since we fully control the data used in the estimation. This enables us to test the robustness of our method to features that we do not currently model such as various forms of heterogeneity (in risk aversion, productivity, or interest rates) or sensitivity to the grids.

6.2.1. *Baseline Results*

We adopt as baseline model the moral hazard regime (MH) and simulate from it a panel data set with $n = 1{,}000$ and $T = 7$, which we then use to estimate and test across all regimes, including MH. Details on how the data are simulated are in Appendix B. All runs in this section use the parametric production function specification, (18) from Section 6.1. The reported results are representative of many more runs that we did, including with alternative parameterizations and functional forms. We discuss some of these runs in Appendix C, though obviously we are limited by space in what we can report. We use two specifications differing in the size of measurement error added to simulated data—"low measurement error," with $\gamma_{\text{me}}^{\text{base}} = 0.1$ (i.e., measurement error with standard deviation equal to 10% of the variables grid ranges) and a "high measurement error" specification, with $\gamma_{\text{me}}^{\text{base}} = 0.2$. Table X reports parameter estimates for the low measurement error specification, while Table XI reports the Vuong test results.

Business Assets, Investment, and Income. Using data on assets, investment, and income (k, i, q), Table X shows that, when estimating the data-generating MH regime, the baseline parameter values used to simulate the data (in italics) for γ_{me}, σ, and ρ are recovered relatively well, but the estimates for θ, μ_w, and γ_w inclusive of bootstrap standard errors are off.[30] The estimates in Table X differ across the regimes but, in general, are quite close between FI and MH, allowing for standard errors. The A regime requires much higher measurement error (0.3) to approach the data compared to the baseline value (0.1).

[30]How well we recover the baseline parameters at which the model is computed should be judged taking into account that two nontrivial sources of noise are added to the theoretical solution when we simulate data from the model—the random draws from the LP probabilities π and sizeable measurement error (10% or 20% of the range for each variable).

TABLE X

PARAMETER ESTIMATES USING SIMULATED DATA FROM THE MORAL HAZARD (MH) MODEL[a]

Model	γ_{me}	σ	θ	ρ	$\mu_{w/b}$[b]	$\gamma_{w/b}$	LL Value[c]
			Assets, investment, and income, (k, i, q) data				
Moral hazard, MH*	0.0935	0.6557	0.1000	0.2212	0.8289	0.0778	**−1.0695**
	(0.0019)	*(0.0144)*	*(0.0001)*	*(0.0079)*	*(0.0008)*	*(0.0029)*	
Full information, FI*	0.0937	0.5495	0.1000	0.2720	0.8111	0.1078	**−1.0692**
	(0.0019)	*(0.0648)*	*(0.0011)*	*(0.0291)*	*(0.0081)*	*(0.0105)*	
Limited commitment, LC	0.0929	0.0000	1.9202	2.3012	0.2000	0.2371	**−1.1015**
	(0.0020)	*(0.0032)*	*(0.0311)*	*(0.1623)*	*(0.0002)*	*(0.0266)*	
Borrowing & lending, B	0.1011	1.0940	1.0811	−1.5783	0.0096	0.9995	**−1.1821**
	(0.0021)	*(0.0782)*	*(0.1352)*	*(2.6279)*	*(0.0003)*	*(0.0683)*	
Saving only, S	0.0972	0.5000	1.2043	−1.8369	0.5184	0.1697	**−1.1407**
	(0.0025)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0104)*	*(0.0076)*	
Autarky, A	0.2927	0.0000	2.0000	2.2117	n.a.	n.a.	**−2.5390**
	(0.0046)	*(0.1431)*	*(0.5000)*	*(1.4179)*	n.a.	n.a.	
Baseline parameters	*0.1000*	*0.5000*	*2.0000*	*0.0000*	*0.5000*	*0.3500*	
			Consumption and income, (c, q) data				
Moral hazard, MH*	0.1041	0.4851	2.7887	−0.2338	0.4780	0.2867	**−0.1462**
	(0.0022)	*(0.0188)*	*(0.0742)*	*(0.6062)*	*(0.0098)*	*(0.0117)*	
Full information, FI	0.1102	0.4462	0.0934	−1.2892	0.5056	0.2644	**−0.1784**
	(0.0027)	*(0.0000)*	*(0.0001)*	*(11.694)*	*(0.0108)*	*(0.0180)*	
Limited commitment, LC	0.1097	0.4990	1.5704	1.5944	0.1287	0.6126	**−0.1710**
	(0.0022)	*(0.0072)*	*(0.1311)*	*(0.0493)*	*(0.0352)*	*(0.0685)*	
Borrowing & lending, B	0.1160	0.6007	0.1544	−1.5090	0.5202	0.3489	**−0.2182**
	(0.0023)	*(0.0000)*	*(0.0043)*	*(0.0170)*	*(0.0178)*	*(0.0312)*	
Saving only, S	0.1077	0.0000	1.9849	3.0075	0.4204	0.4527	**−0.1842**
	(0.0020)	*(0.0000)*	*(0.4816)*	*(0.0445)*	*(0.0278)*	*(0.0272)*	
Autarky, A	0.1868	0.0276	0.9828	0.2036	n.a.	n.a.	**−0.7443**
	(0.0122)	*(0.0124)*	*(0.0004)*	*(0.0271)*	n.a.	n.a.	
Baseline parameters	*0.1000*	*0.5000*	*2.0000*	*0.0000*	*0.5000*	*0.3500*	

(*Continues*)

The FI and MH regimes achieve the highest likelihoods, followed by LC, S, B, and finally autarky. The Vuong tests (Table XI, section 1) show that, in the low measurement error specification, we are unable to distinguish between the data-generating MH regime and FI, but we can reject the rest at the 1% significance level. We also distinguish at the 1% level within all pairs of counterfactual regimes. That is, even if the researcher incorrectly believed that the data were, for example, generated from the FI regime, he/she can still distinguish it from the LC, B, S, or A regimes. In contrast, with high measurement error, the distinction between the regimes is blurred and the Vuong test cannot discern statistically between MH and all regimes but autarky. In all cases, including those with high measurement error, the non-autarky regimes are distinguished at the 1% level from autarky.

TABLE X—*Continued*

Model	γ_{me}	σ	θ	ρ	$\mu_{w/b}$[b]	$\gamma_{w/b}$	LL Value[c]
			Assets, consumption, investment, and income, (c, q, i, k) data				
Moral hazard, MH*	0.0952	0.5426	2.1951	0.2267	0.5005	0.3464	**−0.8952**
	(0.0020)	*(0.0079)*	*(0.0889)*	*(0.0162)*	*(0.0119)*	*(0.0097)*	
Full information, FI	0.1358	0.5436	0.0967	−6.4718	0.5567	0.2862	**−1.4184**
	(0.0029)	*(0.0167)*	*(0.0021)*	*(1.3883)*	*(0.0127)*	*(0.0082)*	
Limited commitment, LC	0.1267	1.6114	1.1028	−8.8824	0.2549	0.5510	**−1.2773**
	(0.0022)	*(0.0004)*	*(0.0114)*	*(0.1380)*	*(0.0165)*	*(0.0154)*	
Borrowing & lending, B	0.1339	1.2000	7.7164	−3.0189	0.4048	0.3238	**−1.5624**
	(0.0036)	*(0.2416)*	*(0.0000)*	*(20.484)*	*(0.0135)*	*(0.0134)*	
Saving only, S	0.1678	0.0000	0.0727	−1.1738	0.3818	0.2771	**−1.7803**
	(0.0040)	*(0.0000)*	*(0.0004)*	*(0.0028)*	*(0.0212)*	*(0.0230)*	
Autarky, A	0.3302	1.2000	0.1000	0.4681	n.a.	n.a.	**−3.0631**
	(0.0042)	*(0.3634)*	*(0.2738)*	*(0.6550)*	n.a.	n.a.	
Baseline parameters	*0.1000*	*0.5000*	*2.0000*	*0.0000*	*0.5000*	*0.3500*	

[a] Bootstrap standard errors are in parentheses below each parameter estimate.

[b] $\mu_{w/b}$ and $\gamma_{w/b}$ (the mean and standard deviation of the w or b initial distribution) are reported relative to the variables' grid range.

[c] Log-likelihood values are normalized by dividing by the sample size n; higher values imply better fit.

* Denotes the best-fitting regime (including tied). All runs use data with sample size $n = 1{,}000$ generated from the MH model at the baseline parameters.

Consumption and Income. We next estimate using the simulated data on consumption and income (c, q). The maximized likelihood values (see Table X) are ordered MH, LC, FI, S, B, and A from highest to lowest. We recover the data-generating parameters better than with the (k, i, q) data (compare the MH estimates with the values in italics in Table X). In contrast, the estimates for the exogenously incomplete regimes in many instances differ significantly from the parameters at which we ran the model. With low measurement error, the data-generating MH regime is distinguished at the 1% significance level from all alternatives (Table XI, section 2), though ties appear between some counterfactual pairs (FI and LC, FI and S, LC and S). With high measurement error, we are, however, unable to recover MH as best-fitting (LC is). The autarky regime is statistically distinguished from all others, including in the high measurement error specification.

Business Assets, Consumption, Investment, and Income. The estimates with the (c, q, i, k) simulated data are reported in Table X, section 3. The data-generating regime (MH) is best-fitting and its estimates are close to the baseline values reported in italics—compare with the (k, i, q) case in particular, especially the estimates for θ, $\mu_{w/b}$, $\gamma_{w/b}$. All parameters are relatively precisely estimated for the MH regime, with small bootstrap standard errors relative to the point estimates. The regimes' likelihood order is MH, LC, FI, B, S, A. The incorrect regimes require higher measurement error to fit the data compared

TABLE XI

MODEL COMPARISONS USING SIMULATED DATA[a] VUONG TEST RESULTS

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
1. *Using* (k, i, q) *data*																
1.1. Low measurement error	tie	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	LC***	LC***	LC***	S**	B***	S***	FI, MH
1.2. High measurement error	tie	tie	tie	tie	MH***	FI***	B**	tie	FI***	B***	tie	LC***	tie	B***	S***	All but A
2. *Using* (c, q) *data*																
2.1. Low measurement error	MH***	MH**	MH***	MH***	MH***	tie	FI**	tie	FI***	LC***	tie	LC***	S**	B***	S***	MH
2.2. High measurement error	FI***	LC***	B*	MH*	MH***	LC***	tie	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	LC
3. *Using* (c, q, i, k) *data*																
3.1. Low measurement error	MH***	MH***	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
3.2. High measurement error	tie	tie	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	LC, MH
4. *Dynamics*																
4.1. $t = 0, 1$ (c, q) panel, low meas. error	MH***	MH***	MH***	MH***	MH***	FI**	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
4.2. $t = 0, 1$ (c, q) panel, high meas. error	tie	tie	MH***	MH***	MH***	LC**	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	LC, MH
4.3. $t = 0, 50$ (c, q) panel, low meas. error	MH***	MH***	MH***	MH***	MH***	FI***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
4.4. $t = 1{,}000$ (c, q) data, low meas. error	tie	tie	MH*	MH***	MH***	FI*	tie	FI**	FI***	tie	tie	LC***	B***	B***	S***	MH, FI, LC
5. *Runs with heterogeneity in the simulated data*																
5.1. Heterogeneous productivity	MH***	MH***	MH***	MH***	MH***	LC***	tie	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
5.2. Heterogeneous risk aversion	MH***	MH***	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
5.3. Heterogeneous interest rates	MH***	MH***	MH***	MH***	MH***	LC***	tie	FI***	FI***	LC**	LC***	LC***	B***	B***	S***	MH

(*Continues*)

TABLE XI—*Continued*

Comparison	MH v FI	MH v LC	MH v B	MH v S	MH v A	FI v LC	FI v B	FI v S	FI v A	LC v B	LC v S	LC v A	B v S	B v A	S v A	Best Fit
6. *Robustness runs with simulated data*[b]																
6.1. Sample size $n = 200$	MH***	MH**	MH***	MH***	MH***	LC***	tie	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
6.2. Sample size $n = 5{,}000$	MH***	MH***	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
6.3. Coarser grids	MH***	MH***	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B***	B***	S***	MH
6.4. Denser grids used to simulate data	MH***	MH***	MH***	MH***	MH***	LC***	FI***	FI***	FI***	LC***	LC***	LC***	B**	B***	S***	MH
6.5. No measurement error in simul. data	MH***	MH***	MH***	MH***	MH***	FI***	FI**	FI***	FI***	B***	S***	LC***	B***	B***	S***	MH
6.6. Data simulated at MLE estimates	MH***	tie	MH***	MH***	MH***	LC***	tie	tie	FI***	LC***	LC***	LC***	tie	B***	S***	LC, MH
6.7. Sim. data from S, removed fixed effects	MH***	tie	B***	S***	tie	LC***	B***	S***	A***	B***	S***	tie	S***	B***	S***	S

[a] *** = 1%, ** = 5%, * = 10% two-sided significance level, the better fitting model regime's abbreviation is displayed. Data-generating model is MH and sample size is $n = 1{,}000$ unless stated otherwise.

[b] These runs use (c, q, i, k) data simulated from the MH model and low measurement error ($\gamma_{me} = 0.1$) unless stated otherwise.

to the 0.1 baseline. Table XI, section 3 shows that our ability to distinguish the data-generating MH regime from all alternatives is excellent (at the 1% level) with low measurement error in the simulated data, but MH is tied with LC for best-fitting with high measurement error. These results, compared to those using (c, q) or (k, i, q) data, demonstrate that using joint data on consumption and production yields an improvement, especially with high measurement error. The ability to distinguish between counterfactual regimes also improves significantly relative to when using (c, q) or (k, i, q) data alone—the total number of ties falls from eight or four to two.

Dynamics. We use simulated data on the joint distribution of consumption and income (c, q) in two different periods, $t = 0$ and 1 (rows 4.1 and 4.2 in Table XI) or $t = 0$ and 50 (row 4.3) as in a two-year panel. Compared to Table XI, section 2, which uses a single (c, q) cross-section, section 4 of Table XI demonstrates that using multi-period data improves our ability to distinguish the regimes (both the MH and counterfactual)—the number of ties diminishes and MH is always recovered as best-fitting (in one case with high measurement error, tied with LC). The improvement in our ability to discern the regimes is comparable to when (c, q, i, k) data were used (compare with rows 3.1–3.2). In row 4.4, we first run the MH model for 1,000 periods to approximate a steady state and then estimate using simulated (c, q) data from the 1,000th period. In this run, MH comes up first in likelihood but is statistically tied with LC and FI.

We also report in Appendix C on additional runs with the simulated data which explore sensitivity to the grids, sample size, and measurement error size.

6.2.2. *Allowing for Heterogeneity*

Heterogeneity in Productivity. We test the robustness of the baseline results with simulated data by allowing for productivity differences across households (Table XI, row 5.1). In contrast, remember that, in the baseline runs, initial heterogeneity across agents exists only in their assets, k, debt/savings, b, or promised utility, w. Specifically, to capture productivity heterogeneity, we draw ten values from a uniform distribution on [0.75, 1.25] and compute the MH regime multiplying the income grid Q by each of these ten productivity "factors." We draw and pool simulated data from these ten runs, ending up with (c, q, i, k) data that correspond to a mixture of households with different productivities. We then estimate all six regimes as if those differences in productivity did not exist (i.e., as if we mistakenly treat the data as generated without such differences, like we do in our runs with actual data in Section 5). The results show that allowing for this additional source of unobserved heterogeneity, and thus, misspecification, in the model does not affect the robustness of the baseline findings. Significantly, we still recover MH as best-fitting and it is still distinguished at the 1% level from all alternatives. Compared to the homogeneous productivity baseline (Table XI, row 3.1), there is only one difference—a tie between the counterfactual regimes FI and B. The parameter estimates are also quite close to the baseline in Table X; for the MH regime with productivity heterogeneity, we obtain $\gamma_{\text{me}} = 0.103$, $\sigma = 0.5$, $\theta = 2.36$, $\rho = 0.26$, $\mu_w = 0.51$, and $\gamma_w = 0.34$.

Heterogeneity in Risk Aversion. We also test robustness to heterogeneity in preferences in the data by simulating data from the MH regime at three different values for the risk aversion parameter, $\sigma = 0.62$, 0.78, and 1.4, holding the rest of the parameters at their baseline values. The σ values are taken from the actual range of risk aversion values estimated in Chiappori et al. (2014). Similarly to the robustness run with productivity differences above, a mixed sample of size $n = 1{,}000$ is generated from the simulations. We then run our MLE routine with these data as if all sample units shared the same risk aversion parameter. We find that our baseline results (compare Table XI, row 5.2 with row 3.1) are not sensitive to allowing for this type of preference heterogeneity—we recover the data-generating MH regime as best-fitting and we are able to distinguish it from all alternatives at the 1% confidence level. The parameter estimates for the MH regime (with the exception of θ) are very close to their baseline values: $\gamma_{\text{me}} = 0.098$, $\sigma = 0.70$, $\theta = 9.9$, $\rho = 0.21$, $\mu_w = 0.49$, and $\gamma_w = 0.35$. Note that the σ estimate is in the intermediate range used to generate the data.

Heterogeneity in Interest Rates. In Table XI, row 5.3, we test the robustness of our method to heterogeneity in interest rates in the data. As in the previous two runs exploring heterogeneous samples, we first simulate the MH regime at four different values for the financial intermediary interest rate parameter, R, taken from another study using a different part of the Thai data (Cunha, Townsend, and Wang (2012)), namely, $R = 1.038, 1.026, 1.016$, and 1.009. These four values correspond roughly to the interest rates faced by the quartiles of households ordered by increasing assets. The rest of the model parameters are held at their baseline values. We create a heterogeneous sample of size $n = 1{,}000$ applying the respective R value to the households in our sample falling within the corresponding asset quartiles. We then run our MLE routine on the heterogeneous but pooled data using the same fixed interest rate set equal to the average of the four values above, that is, assuming counterfactually that the data came from a homogeneous sample. Once again, as in the runs with heterogeneity in productivity or risk aversion, we are able to recover the data-generating MH regime as best-fitting and distinguish it from all alternatives at the 1% significance level. The MH MLE parameter estimates (except that for ρ) are close to the data-generating values: $\gamma_{\text{me}} = 0.11$, $\sigma = 0.47$, $\theta = 2.97$, $\rho = -2.64$, $\mu_w = 0.499$, and $\gamma_w = 0.24$.

7. INSIDE THE MLE "BLACK BOX"

7.1. *Comparing Actual and Simulated Data*

In this section, we use simulated data from the model at the MLE parameter estimates to assess the dimensions in which the alternative models of financial and information constraints fail or succeed in matching the Thai data. The purpose of this section is to give a better idea why the omnibus MLE approach picks one regime in favor of another in terms of likelihood with the data, as well as to evaluate the fit of the highest-likelihood regime with data outside of the subsample we use to estimate.

Thai versus Simulated Data—Assets' Persistence

The different financial regimes impose endogenous constraints on the ability of agents to adjust assets or, in other words, endogenize the degree of persistence of assets/capital k. For example, the FI regime stipulates that an agent, facing no financial constraints, could immediately adjust to the first-best capital level k^{fb}, no matter what his initial k is. Such adjustment is subject to incentive compatibility constraints in the MH regime, to self-enforcement constraints in the LC regime, and to even more stringent borrowing constraints (e.g., zero borrowing under savings only and autarky) in the exogenously incomplete markets regimes. A salient feature of the Thai rural data is that investment events are infrequent (Samphantharak and Townsend (2010)). Likewise, as is evident from Table III, capital is very persistent—the median yearly investment i, computed from the data as $i_t = k_{t+1} - (1-\delta)k_t$, is close to zero (20 Baht). This persistence in assets favors the S (and sometimes B) regimes overall. It may also be the reason why, in our robustness runs with quadratic adjustment costs, the likelihood of the FI regime improves with (c, q, i, k) data (see Table IX, row 3.3), though this is not the case with (k, i, q) data in row 3.2.

Figure 3 helps visualize these observations. We plot the fractions of all possible k_t to k_{t+1} transitions between any pair of points in the assets grid K for the whole panel. Remember the grid points in K correspond to the 10th, 30th, 50th, 70th, and 90th percentiles of assets in the data. We see that in the Thai Monthly (rural) data (the top left panel), basically all transitions are on the main diagonal, that is, no movement at all, or the diagonals immediately next to it, which indicates very high persistence in assets. In contrast, in the urban data (the top right panel), there is still persistence (the main diagonal), but also many more households transitioning across capital levels each year. The bottom two panels of Figure 3 plot the same transition fractions, but for the simulated data at the MLE estimates with the rural data for the S and MH regimes from our baseline runs. We see that the S regime manages to come the closest to the rural data in terms of the diagonal pattern, although not perfectly. The moral hazard (MH) model, in contrast, predicts too many off-diagonal transitions, unlike what we see in the rural data, but closer to what the urban data look like. We view this as supportive, independent evidence for

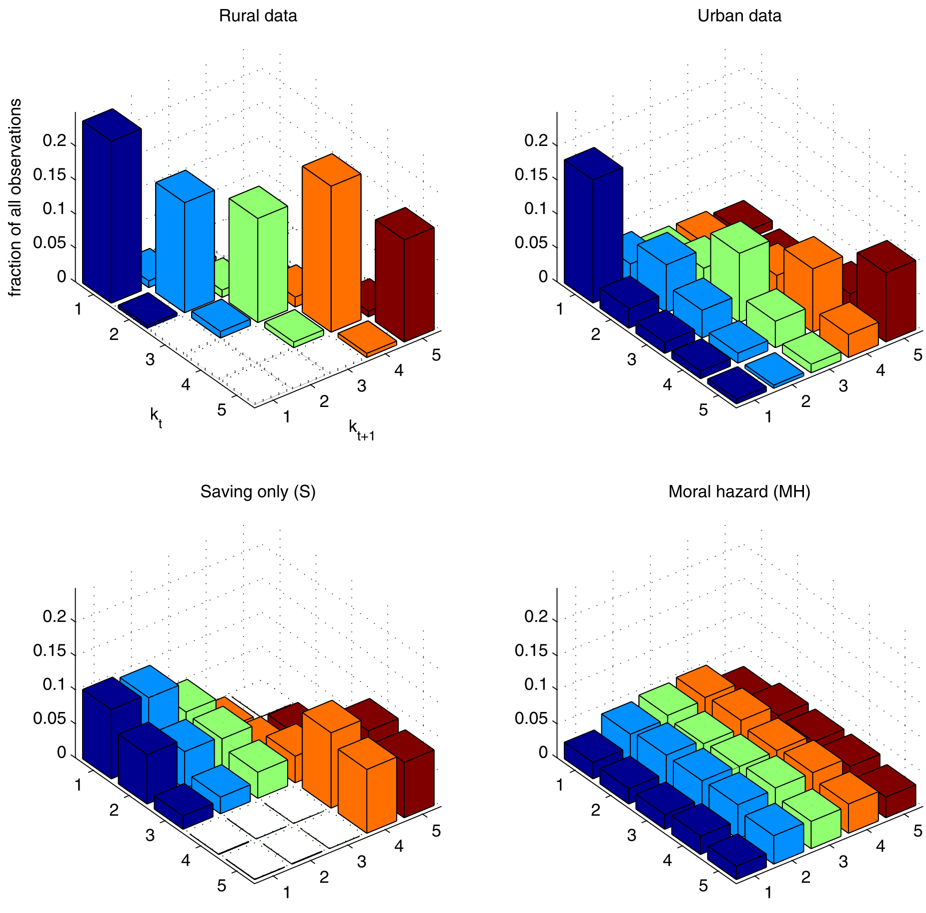

FIGURE 3.—Thai versus simulated data; business assets transition matrix. The axis labels correspond to business assets (k) percentiles at consecutive periods t and $t+1$, pooled over all sample years, "1" corresponds to the 10th percentile, "2" to the 30th, "3" to the 50th, "4" to the 70th, and "5" corresponds to the 90th percentile. Only values larger than $4(10^{-3})$ are plotted in color.

our baseline results with rural data (Table V; where S wins) and urban data (Table VII; where MH wins with (c, q, i, k) data and comes much closer in likelihood to S with (k, i, q) data compared to rural).

Thai versus Simulated Data—Time Paths

Figure 4 explores how well the highest-likelihood regime matches the paths of the mean and standard deviation (in model units) of consumption, c, business assets, k, and income, q, over the entire panel 1999–2005, that is, using far more data than in any MLE estimation run. To match the data time span,

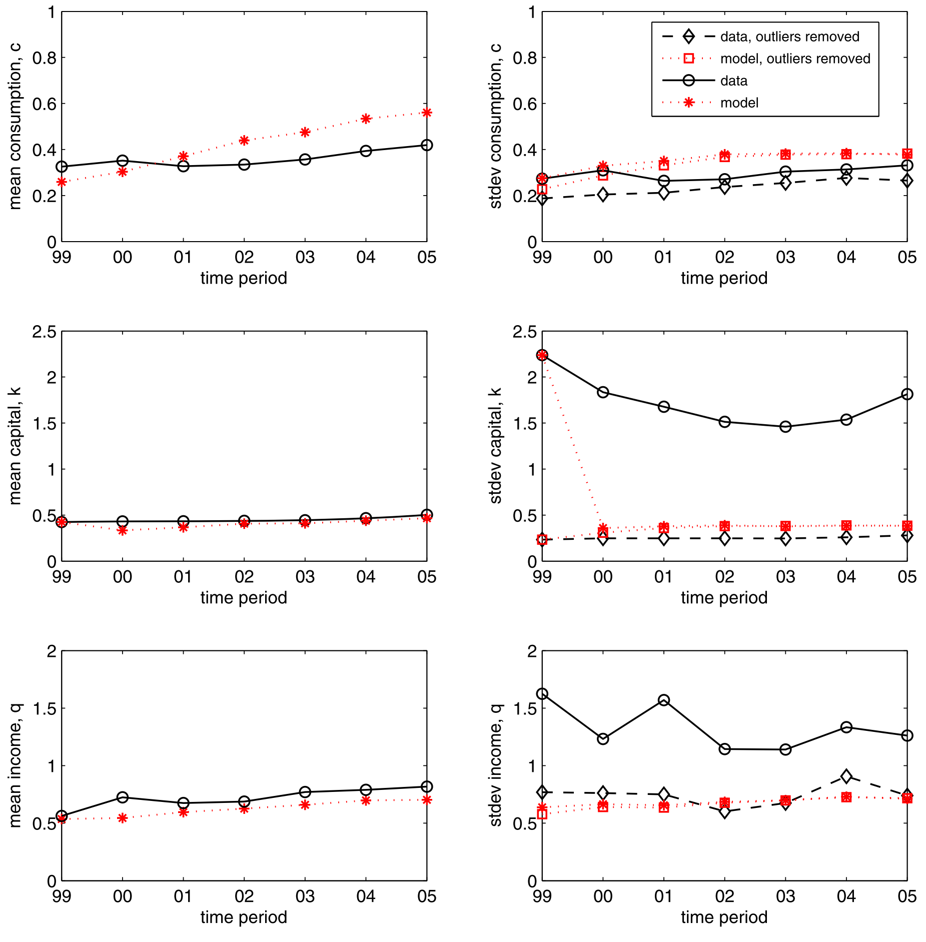

FIGURE 4.—Thai versus simulated data—time paths. The lines plot cross-sectional averages or standard deviations of consumption, capital, and income for each time period. The "data" lines use the Thai rural sample. The "model" lines use simulated data from the B regime at the MLE estimates from run 4.5 in Table V. The lines labeled "outliers removed" exclude observations larger than the 90th percentile of the plotted data.

we use the MLE estimates from row 4.5 in Table V, where we used the initial 1999 k distribution and the 2004 (c, q, i, k) data. Figure 4 shows that the best-fitting regime in this run (B) tracks extremely well the time paths of the means of all three variables, c, k, and q, over the complete sample period. In terms of standard deviations, the model traces relatively well that for consumption, but understates the variance of output in the Thai data and, even more significantly, the variance of assets after the initial period. The reason is the very skewed k and q distributions in the data, with few extremely large observations that are lumped on the highest grid point of the K and Q grids. When we plot the standard deviations excluding observations with average assets above the 90th percentile in the data (there are 54 such observations, or 10% of the sample)—see the right panels of Figure 4, the dashed lines, the standard deviations of k and q in the model come within 0.1 model units of those in the data.

Thai versus Simulated Data—Alternative Measure of Fit

We use the MLE estimates with 1999 (c, q, i, k) data to simulate data from each model, as explained in Section 6.2. We then compute a set of 22 summary statistics or "moments" (mean, median, standard deviation, skewness for each of the four variables c, k, i, q plus the six bilateral correlations between them) for each of the regimes and the same statistics (in model units) for the Thai data panel years used in the MLE estimation (here, 1999 data for c, q, and k and 1999 and 2000 k data used to compute investment i). Our MLE criterion is not fitting these moments per se. Nevertheless, as a robustness check that the auxiliary assumptions of our MLE are not explaining the results, we compute an ad hoc goodness-of-fit measure between actual and simulated data as $D^m = \sum_{j=1}^{\#s} \frac{(s_j^{\text{data}} - s_j^m)^2}{|s_j^{\text{data}}|}$, where s_j^m, $j = 1, \dots, 22$, denotes each of the computed moments in model m and s_j^{data} is the corresponding value in the 1999 Thai data. Table XII reports the value of the measure D^m for each of the six models (smaller values indicate better fit).

We see that the S regime achieves the lowest D^m measure (best fit), while the LC regime has the highest measure (worst fit). This is consistent with the baseline results with (c, q, i, k) data from Table IV using the MLE criterion. We also do the same robustness exercise with the urban data (Table XII, second row). In contrast to the rural data, we found that a less constrained regime (full information, FI) attains the lowest criterion value (32), followed by the other regimes all bunched in the 35–38 range.

Thai versus Simulated Data—Financial Net Worth

Figure 5 compares the implications of the best-fitting regime with 1999 (c, q, i, k) data (the S regime; see row 3.1 in Table V) for the time path of sav-

TABLE XII

THAI VERSUS SIMULATED DATA—MEAN SQUARED CRITERION

	Model, $m =$					
	MH	FI	B	S	A	LC
Criterion value (rural data), $D^m =$	321.1	395.4	38.5	20.8	28.1	520.1
Criterion value (urban data), $D^m =$	36.8	32.0	36.4	35.3	35.4	38.0

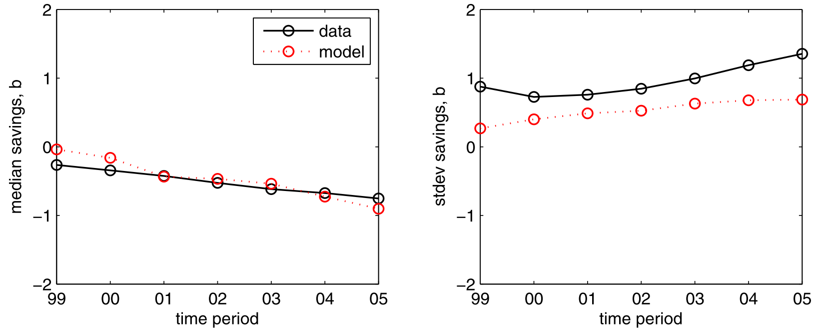

FIGURE 5.—Thai versus simulated data—savings. The "model" line is data simulated from the S regime at the MLE estimates from line 3.1 in Table V. The "data" line plots a measure of households' "financial net worth" as computed in Pawasutipaisit and Townsend (2011). Excluded are "outliers" with more than three model units of savings or more than one model unit of debt (1 "model unit" = the 90th percentile of business assets in the Thai data).

ings in the model and the data. Remember, in our baseline estimation runs we assumed that initial savings are distributed normally with mean and variance that we estimate, but we did not use actual savings data to maintain symmetry with the MH, FI, LC regimes. Figure 5 compares the median and standard deviation of savings, as computed from the S model, with a measure of "financial net worth" from the data (see Pawasutipaisit and Townsend (2011)).[31] To plot the figure, and since the data are very skewed again, we exclude "outliers" with more than three model units of savings or one model unit of debt (remember, one model unit equals the 90th percentile of business assets in the data). Figure 5 shows that the model is able to match the out-of-sample financial net worth data relatively well.[32]

Thai versus Simulated Data—Return on Assets

Figure 6 plots realized gross "return on assets" (ROA), defined as income per unit of productive assets, $\frac{q}{k}$, in the Thai data, rural and urban, and compares it with the corresponding simulated values from the S and MH models computed at the MLE estimates from 1999 (c, q, i, k) data (Table IV, section 3). We compute the gross ROA for each year in the panel and plot the

[31]We did not use these data to initialize the b distribution in the estimation routine for two reasons: (i) we want to keep the B and S regimes on even ground with the MH, LC, and FI regimes where the state variable w distribution is unknown, and (ii) these data only became available recently, after the baseline MLE runs were completed.

[32]We also plotted (not included in the paper to save space) the initial savings distribution in the S regime at the MLE parameters versus in the financial net worth data. Both the actual and estimated distributions have most of the mass around zero savings and a long left tail toward large savings.

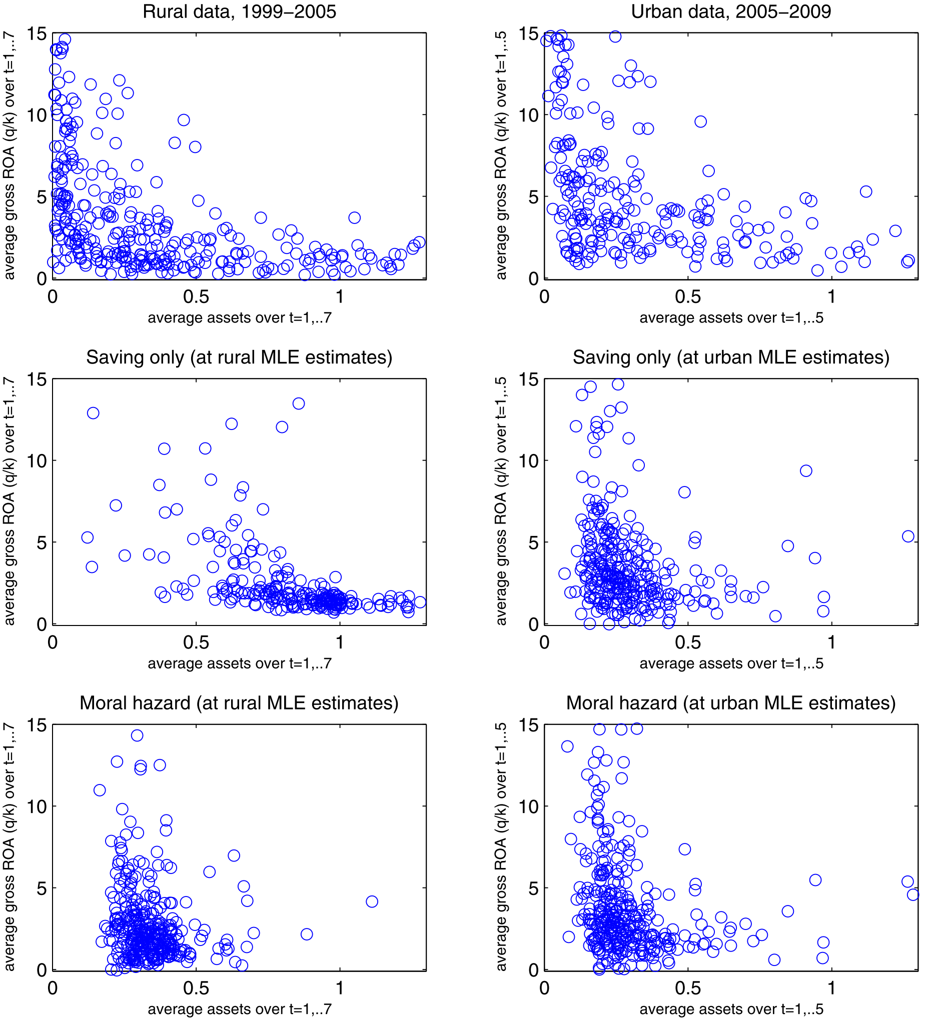

FIGURE 6.—Thai versus simulated data—return on assets. Each circle represents a household. The rural MLE estimates are from the run with (c, q, i, k) data in Table IV and Table V, line 3.1. The urban MLE estimates are from the run in Table VII, line 1.1.

average for each household over all years against the household's average business assets holdings over that time period. We see that, for the rural data, the S model, which we found best-fitting in the MLE (Table V, row 3.1), fits the general pattern (convex and downward-sloping) better than the MH model, which exhibits a lot of bunching in the relatively low k, low ROA range. The urban data appear to share visual features with both the MH and S panels—bunching at low k and the hyperbola shape.

7.2. *Euler Equations GMM Estimation*

In this section, we report results from two robustness estimation runs that use a GMM approach based on Euler equations. These results supplement our MLE results by using a different method to assess the fit of the alternative models of dynamic financial constraints with the Thai data.

7.2.1. *Consumption Euler Equations*

Following Ligon (1998), we test moral hazard versus "permanent income" (borrowing and lending in a risk-free asset) models based on their implications for the path of consumption over time. The permanent income hypothesis (PIH) implies the Euler equation,

$$u'(c_{it}) = \beta R E_t\big(u'(c_{it+1})\big),$$

which we estimate using our consumption panel data, $\{c_{it}\}$, $i = 1, \ldots, N$, $t = 1, \ldots, T$. Suppose u is CRRA, with coefficient $\gamma > 0$, that is, $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ and $u'(c) = c^{-\gamma}$. Let also $\beta R = 1$. Denoting $\eta_{i,t} \equiv \frac{c_{i,t+1}}{c_{i,t}}$ for $i = 1, \ldots, N$ and $t = 1, \ldots, T-1$ and $h(\eta_{i,t}, b) \equiv \eta_{i,t}^b - 1$ where $b = -\gamma$ (minus the coefficient of relative risk aversion), we have the moment conditions

$$E_t h(\eta_{i,t}, b) = 0.$$

On the other hand, as shown in Rogerson (1985), among others, the corresponding "inverse" Euler equation for the repeated moral hazard model is

$$\frac{1}{u'(c_{it})} = \frac{1}{\beta R} E_t\left(\frac{1}{u'(c_{it+1})}\right).$$

With CRRA utility and $\beta R = 1$, the above equation can be written as

$$E_t h(\eta_{i,t}, b) = 0, \tag{19}$$

where now $b = \gamma$ (the coefficient of relative risk aversion). As proposed by Ligon (1998), conditions (19) can be used in a GMM (following his paper, we actually use as moment restriction the unconditional expectation $E(h(\eta_{i,t}, b)) = 0$) to: (i) estimate the parameter b, and (ii) use the sign of the estimate of b from step (i) to infer which model (PIH vs. private information) holds in the data. Essentially, assuming households are risk averse, a positive estimate for b would indicate that the private information model is consistent with the data, while if the b estimate is negative, the PIH model is consistent with the data. A version of (19), $E(h(\eta_{i,t}, b)\zeta_{i,t}) = 0$ using variables $\zeta_{i,t}$ that are in the information set of household i at time t as instruments, is also estimated (see Ligon (1998) for details).

We ran the GMM estimation described above on our rural and urban samples. The GMM results are somewhat sensitive to the choice of sample years or instruments. In the rural data, we obtain a negative estimate for b when using all available consumption data (from 1999 to 2005), including in the specifications with different sets of instruments such as predetermined income and assets data (see Table XIII, lines 1–5).[33] This is consistent with PIH-type models (non-contingent debt or savings), such as our B and S regimes, which are tied for best fit in several MLE runs with (c, q) data (see Table V, lines 2.2, 4.1, and 4.2). However, we also ran the GMM using only the consumption data from 1999 to 2001 (see Table XIII, lines 6 and 7). The result (a positive b estimate) is consistent with the private information model (compare with Table V, row 4.3). The runs with instruments also yield positive estimates (not reported in the table).

In the urban sample, the GMM test results also vary. The run without instruments produces $b = -0.23$, which is evidence in favor of the PIH, but when we use predetermined income alone and income and assets as instruments, we obtain $b = 8.53$ and $b = 4.73$, respectively, which is suggestive of moral hazard. The run from Table XIII, line 4 (with three instruments) produced a singular matrix so we cannot report b. The bottom line: it is hard to distinguish the regimes, whether via the Euler equation GMM or our structural MLE methods, when restricting attention to the consumption data (jointly with income and/or instruments).

7.2.2. *Investment Euler Equations*

We follow Bond and Meghir (1994) and Bond, Elston, Mairesse, and Mulkay (2003) to test a model with quadratic adjustment costs and no financial constraints versus the alternative of financial constraints. Specifically, we estimate the following equation, obtained from the model's Euler equation, using GMM methods proposed by Arellano and Bond (1991):

$$\left(\frac{i}{k}\right)_{jt} = \beta_1\left(\frac{i}{k}\right)_{jt-1} + \beta_2\left(\frac{i}{k}\right)^2_{jt-1} + \beta_3\left(\frac{q}{k}\right)_{jt-1} + d_t + \eta_j + \varepsilon_{jt},$$

where j denotes household, t is time, and i, k, q are respectively investment, capital, and income (cash flow). Bond et al. (2003) showed that, under the null of no financial constraint, we must have $\beta_1 \geq 1$, $\beta_2 \leq -1$, and $\beta_3 < 0$. The focus in this literature (not without controversy; e.g., see Kaplan and Zingales (2000)) has been on the cash flow coefficient β_3. A positive β_3 estimate, suggesting that investment, i, is "sensitive" to fluctuations in cash flow, q, has been interpreted as indicating the presence of financial constraints.

Table XIV contains the results from the above estimation using the Stata function *xtabond2* and the rural sample. We obtain an estimate for β_3 that is

[33]The run in line 5 uses separate moment conditions for each $t = 1, \dots, T - 1$.

TABLE XIII

CONSUMPTION EULER EQUATION GMM TEST AS IN LIGON (1998), RURAL SAMPLE[a]

Instruments	b	Std. Error	[95% Conf. Interval]		J-Test p-Value
1. None	−0.336*	0.044	−0.423	−0.249	n.a.
2. Income	−0.333*	0.044	−0.418	−0.248	0.251
3. Income, assets	−0.340*	0.043	−0.424	−0.257	0.248
4. Income, assets, average consumption	−0.332*	0.041	−0.413	−0.252	0.312
Other specifications					
5. $t = 1, \ldots, T - 1$ moment conditions	−0.356*	0.030	−0.415	−0.296	0.000
6. 1999–2001 data only	0.062	0.113	−0.159	0.283	n.a.
7. 1999–2001 data, $t = 1, \ldots, T - 1$ moment conditions	0.037*	0.008	0.021	0.054	0.000

[a]1. b is the estimate of the risk aversion coefficient; assuming households are risk averse, a negative b suggests the correct model is B (standard EE); a positive b suggests MH (inverse EE). 2. The estimates are obtained using continuous updating GMM (Hansen, Heaton, and Yaron (1996)). * denotes significantly different from zero at the 5% confidence level.

TABLE XIV

INVESTMENT EULER EQUATION GMM TEST AS IN BOND AND BOND AND MEGHIR (1994), RURAL SAMPLE. DYNAMIC PANEL DATA ESTIMATION, ONE-STEP DIFFERENCE GMM USING LAGS OF 2 OR MORE AS INSTRUMENTS[a]

Dependent Variable $= i_t/k_t$	Coef.	Robust St. Err.	z	$P > \|z\|$	[95% Conf.	Interval]
i_{t-1}/k_{t-1}	0.3233	0.0595	5.43	0.000	0.2066	0.4399
$(i_{t-1}/k_{t-1})^2$	−0.0965	0.2778	−0.35	0.728	−0.6410	0.4479
q_{t-1}/k_{t-1}	0.0002	0.0003	0.77	0.440	−0.0003	0.0008
Year dummies	Included					

Arellano–Bond test for AR(1) in first differences: $z = -1.87$, $\Pr > z = 0.061$
Arellano–Bond test for AR(2) in first differences: $z = -0.48$, $\Pr > z = 0.628$
Arellano–Bond test for AR(3) in first differences: $z = 1.25$, $\Pr > z = 0.211$
Hansen test of overid. restrictions: chi2(17) = 22.29, Prob > chi2 = 0.174

[a]Observations with yearly assets (k) less than 400 Baht were excluded. Group variable: household. Time variable: year. Number of instruments = 24. Number of observations: 1,552. Number of groups: 388. Observations per group: 4.

positive and statistically insignificant from zero instead of negative. Both estimates of the coefficients β_1 and β_2 also do not satisfy the theoretical restrictions $\beta_1 \geq 1$ and $\beta_2 \leq -1$ under the null. This indicates that the data reject the null of no financial constraints. Compared to our MLE results with (k, i, q) data allowing for adjustment costs (Table IX, line 3.2), where S and A with adjustment costs are tied for best fit, we reach a similar conclusion which we view as further supporting evidence for the MLE findings in favor of the exogenously incomplete financial regimes when using the investment, income, and assets data. Unfortunately, the shorter panel length does not allow us to use this method on the urban sample.

7.2.3. *Euler Equations—Summary*

In sum, both the GMM and MLE methods have their advantages and disadvantages. The advantage of the GMM approach is its simplicity and, aside from the CRRA assumption in the Ligon (1998) case or sign restrictions on the parameters in the Bond et al. (2003) case, not requiring additional structure.[34] Advantages of our MLE/Vuong test approach include: (i) being able to estimate more parameters than the coefficient of risk aversion; (ii) being able to distinguish among more financial regimes; and (iii) being able to use more data variables than those appearing in the Euler equations (e.g., consumption alone in Ligon (1998)). Naturally, these advantages need to be weighed against the need for fully specified dynamic programs and much heavier computational requirements.

[34]Some limitations to estimating parameters from consumption Euler equations were discussed in Carroll (2001).

7.3. *Policy Evaluation in the Model—An Example*

In this section, we present a simple stylized example of how the structural estimation and model comparison results can be potentially used as ingredients in "policy experiments" within the context of the model. Here we would like to emphasize not so much the particular policy exercise we perform but, instead, the welfare implications of having or not having uncovered the best-fitting model of financial constraints among the many possible alternatives.

Specifically, here is what we do. Suppose the model economy is at our baseline value for the risk-free gross interest rate R $(= 1.05)$. Take the saving only (S), borrowing and lending (B), moral hazard (MH), and full information (FI) models at their corresponding MLE parameter estimates with the 1999 (c, q, i, k) data (Table V). Holding all other parameters fixed, we reduce the gross risk-free interest rate parameter R to 1.025, as if a "subsidization" of interest rates or simply a change in domestic or international rates. We then recompute the four chosen models at the new, lower R.

The top-row panels of Figure 7 plot the welfare gains or losses from the interest rate reduction, expressed as fractions of first-period consumption, for each value of assets k and savings b in the S and B models at their respective MLE estimates. For the B model, we do not plot the welfare gains for positive values of b (being in debt) to be able to compare directly with the S regime where being in debt is not possible.[35] Looking at the figure, savers (those with $b < 0$ in both the S and B models) naturally lose from the reduction in R, with their losses ranging from 0 to 40% in terms of $t = 1$ consumption, depending on the current k and b. The rightmost panel shows the relative difference, however, a complicated, non-monotone picture of gains and losses from +15% to −10%. For the MH and FI models, computed at their respective MLE estimates (the bottom-row panels of Figure 7), we plot the corresponding welfare gains or losses in terms of business assets k, holding fixed present-value profit levels for the principal, $V(k, w)$ (see Section 2.2.2), at their level from before the policy change. Evaluating at fixed profit level is needed since, unlike in the S and B models, if we were to evaluate welfare at fixed value for the state variable w, we would be unable to identify the welfare effect of the policy on households, since, by construction, the agent's discounted utility in the optimal contract must equal w either before or after the policy. Higher values of initial profits V correspond to lower initial present value utility for agents. We see a complex picture of winners and losers, especially in the moral hazard regime and in the difference between MH and FI.

The main take-away from Figure 7 is that evaluating who benefits and who loses from a given policy depends critically on knowing which financial or information regime is likely true in the data. If we took one specific regime as given

[35]The gains for borrowers, especially those initially near the natural borrowing limit (the upper bound of the grid B, i.e., maximum possible initial debt), are very high—up to 9 times first-period consumption.

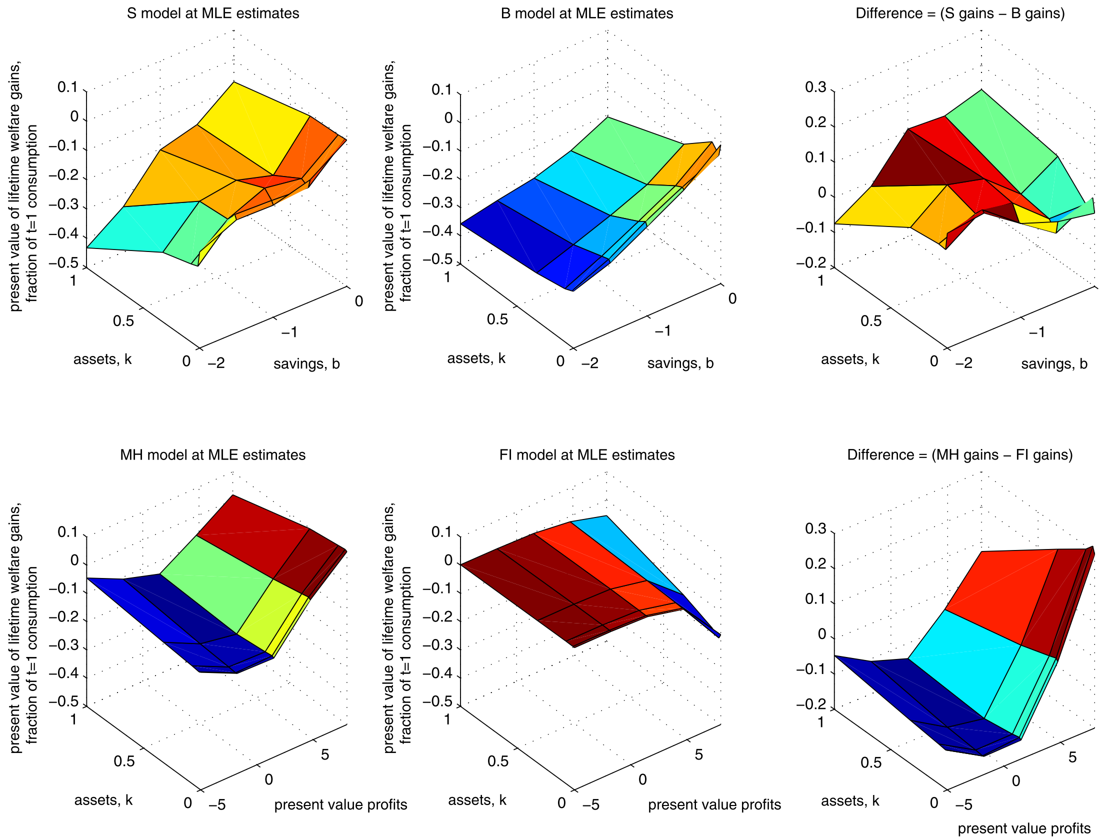

FIGURE 7.—Policy experiment—reduction in the gross interest rate R from 1.05 to 1.025. Data simulated from the S, B, MH, and FI models are at the MLE estimates from run 3.1 in Table V with 1999 (c, q, i, k) data.

(i.e., if we assumed financial constraints take a particular form, as in much of the literature) and used MLE to estimate it and evaluate a policy counterfactual, we would come up with a certain policy recommendation. However, the assumed regime might have been incorrect; another regime may fit the data better, which, as Figure 7 illustrates, could have very different predictions on who wins or loses and how much from the policy.

8. CONCLUSIONS

We formulate and solve numerically a wide range of models of dynamic financial constraints with exogenous or endogenous contract structure that allow for moral hazard, limited commitment and unobservable output, capital, and investment. We develop methods based on mechanism design theory and linear programming and use them to structurally estimate, compare, and statistically test between the different financial regimes. Our methods can handle unobserved heterogeneity, grid approximations, transitional dynamics, and reasonable measurement error. The compared regimes differ significantly with respect to their implications for investment and consumption smoothing in the cross-section and over time. Combined consumption and investment data were found particularly useful in pinning down the financial regime.

We have established that our methods work on actual data from Thailand. We echo previous work which found that full risk sharing is rejected, but not by much, and indeed find that the moral hazard regime is not inconsistent with the rural income and consumption data, where limited commitment also does well, and with the joint business and consumption data in our urban sample. We also recover more sophisticated contract theoretic regimes (moral hazard constrained credit, tied with full information) if we restrict attention to family or gift/loan networks data, confirming related work by Chiappori et al. (2014) and Kinnan and Townsend (2012).

In terms of investment, we confirm previous work which found that investment is not smooth and may be sensitive to cash flow and, indeed, find that more constrained regimes such as saving only and borrowing and lending characterize best the investment and income data (both rural and urban), as well as the combined consumption, income, and investment data in the rural sample. The reasons for these findings are most likely the infrequent nature of investment in the Thai data, especially in the rural sample, and the relatively large size of investment compared to capital when investment takes place. On the other hand, the financial regimes we study postulate endogenous constraints on the ability of firms to adjust assets, including the degree of persistence. The feature of the Thai data that capital is persistent thus favors the S (or B) regimes in which assets adjustment is subject to more stringent constraints than in MH, LC, or FI. Evidently, we have learned something from our approach, beginning to distinguish, in a sense, capital adjustment costs from financial constraints.

Our results here can be put in perspective relative to our previous findings in Paulson, Townsend, and Karaivanov (2006), where we estimated a one-period model of occupational choice between starting a business and subsistence farming as a function of ex ante wealth. We found moral hazard rather than limited liability to be the predominant source of financial constraints for rural Thai entrepreneurs, but we did not test the borrowing and saving only regimes we study here. In contrast, in the current paper, we not only introduce full-blown dynamic mechanism design models but also significantly extend our previous work and estimate using cross-sections, time-series, or panels of consumption, investment, assets, and income, separately and jointly. Karaivanov (2012) found that, in a one-shot occupational choice setting similar to that of Paulson et al., one cannot distinguish statistically between a model of moral hazard versus a model of borrowing with default, but rejected a model of saving only. The good fit of the moral hazard regime is similar to what we find here in our results using consumption and income data alone. As discussed earlier, the saving only regime seems to fit better the production side of our data (e.g., the persistence in assets over time or the inability to smooth investment when income fluctuates). These features, for which a dynamic model is necessary, are not directly tested in the essentially static settings of Paulson, Townsend, and Karaivanov (2006) and Karaivanov (2012), where the focus was instead on the one-off decision of becoming an entrepreneur. The reasons for the differences in the results, therefore, are both the different data on which we fit, which here, using the joint distribution of consumption and investment data variables together, are much richer than the binary occupational choice data from our previous work, and the fact that here we estimate models of fully dynamic constraints on consumption and investment smoothing versus a one-time constraint on business start-ups.

One important finding from the robustness runs with simulated data from one of the models is that, using consumption and investment data jointly, we can readily distinguish exogenously incomplete financial regimes from endogenously incomplete ones, where the latter are solutions to mechanism design problems with private information or limited commitment. As the literature we surveyed in the Introduction typically takes one route or the other, we believe this ability to distinguish will prove helpful in future research and the applications of others. We are also able to distinguish within these regime groups, though this depends on measurement error, the available data variables, or whether or not we have more than a single cross-section of data.

Of course, we do not claim that we cover all possible models of financial constraints, only six common prototypes. Natural extensions would include a model with unobserved productivity (adverse selection), allowing for distinctions across different technologies (fish, shrimp, livestock, business, etc.), or allowing for aggregate shocks (shrimp disease, rainfall, etc.). We would also like to return to the issue of entrepreneurial talent, as in our earlier work (Paulson, Townsend, and Karaivanov (2006)), and allow for heterogeneity in project returns. Related work (Pawasutipaisit and Townsend (2011)) showed that ROA varies considerably across households and is persistent. On the other hand, such data summaries have trouble finding consistent patterns with respect to finance, suggesting the data be viewed through the lens of revised models.

We are still somewhat limited on the computational side, though we are encouraged with recent advances we have made. In an ongoing collaboration with computer scientists, we have been exploring the use of parallel processing to speed up our codes and allow denser grids. What we have done thus far is, for want of better terminology, brute force. There would be further gains from more streamlined codes and more efficient search,for example, where to refine the grids, when to use nonlinear or mixed methods, the use of nested pseudo-likelihood methods, and so on. On the econometrics side, recent developments by Kristensen and Salanie (2010) can be used to improve accuracy in the maximum likelihood computation.

We have our eyes on other economies as well, in part because we see more entry and exit from business in other countries, and in part because we can have larger sample size. Unfortunately, we do not typically find both consumption and investment data, which is why we chose the Thai data to begin with. Work in progress (Karaivanov, Ruano, Saurina, and Townsend (2012)) with data from Spain shows evidence that the number of non-financial firms' bank relationships matters for whether they exhibit excess cash flow sensitivity of investment. We use the computational and estimation methods developed here to evaluate which of four financial regimes (autarky, non-contingent debt, moral hazard, and complete markets) best characterizes the nature of financial constraints for unbanked, single-banked, and multiple-banked firms. Our methods allow, in principle, for transitions across financial regimes, which is another extension we plan.

APPENDIX A: COMPUTING JOINT DISTRIBUTIONS OF MODEL VARIABLES

Our linear programming solution method allows us to easily map to likelihoods and take to data the implications of the different model regimes through the policy functions, the probabilities $\pi^*(\cdot)$ that solve the dynamic programs in Section 2. We first construct the state transition matrix for each regime. Denote by $s \in S$ the current state—k in autarky, (k, b) in S/B, or (k, w) in the MH/FI/LC regimes. The transition probability of going from any current state s to any next-period state s' is computed from the optimal policy $\pi^*(\cdot)$, integrating out all non-state variables. For example, for the MH regime we have

$$\text{Prob}\big(k', w'|k, w\big) = \sum_{c,q,z} \pi^*\big(c, q, z, k', w'|k, w\big),$$

where we have replaced the transfer τ by consumption c (the problem is mathematically equivalent). Putting these transition probabilities together for all $s \in S$ yields the state transition matrix $\mathbf{M}$ of dimension $\#S \times \#S$ (e.g., for MH,

$\#S = \#K \times \#W$), with elements m_{ij}, $i, j = 1, \dots, \#S$ corresponding to the transition probabilities of going from state s_i to state s_j in S.

The matrix $\mathbf{M}$ completely characterizes the dynamics of the model. For example, we can use $\mathbf{M}$ to compute the cross-sectional distribution over states at any time t, $\mathbf{H}_t(s) \equiv (h_t^1, \dots, h_t^{\#S})$, starting from an arbitrary given initial state distribution, $\mathbf{H}_0(s)$, as

$$\mathbf{H}_t(s) = (\mathbf{M}')^t \mathbf{H}_0(s). \tag{20}$$

In our empirical application, we take $H_0(s)$ from the data. In practice, some elements of the state s may be unobservable to the researcher, for example here, the state variable w in the MH, LC, and FI regimes. We assume that the unobserved state is drawn from some known distribution, the parameters of which we estimate.

We use the state probability distribution (20) in conjunction with the policy functions $\pi^*(\cdot)$ to compute cross-sectional probability distributions $F_t(x)$ for any vector of model variables x (which could include k, k', z, τ, q, c, etc.), at any time period. For example, in the MH regime, the time-t joint cross-sectional distribution of consumption over the grid C with elements c_l, $l = 1, \dots, \#C$ and income q over the grid Q with elements q_h, $h = 1, \dots, \#Q$ is

$$\begin{aligned} F_t(c_l, q_h) &\equiv \text{Prob}_t(c = c_l, q = q_h | \mathbf{H}_0) \\ &= \sum_{j=1,\dots,\#S} h_t^j \sum_{z,k',w'} \pi_t^*\big(c = c_l, q = q_h, z, k', w' | s^j\big). \end{aligned}$$

We also use the time-t distribution over states $\mathbf{H}_t(s)$ and the transition matrix $\mathbf{M}$ to compute the transition probabilities, $\mathbf{P}_t(x, x')$, for any model variable x, at any time period, t. The transition and the cross-sectional probabilities are then easily combined to construct joint probability distributions encompassing several periods at a time, as in a panel.

APPENDIX B: SIMULATING DATA FROM THE MODEL

To simulate data from the moral hazard (MH) regime, we fixed the parameter values as follows: risk aversion, $\sigma = 0.5$, effort curvature, $\theta = 2$, and the production function parameter $\rho = 0$ (corresponding to Cobb–Douglas form). These parameters are representative, chosen from a large set of runs we did, and generate well-behaved interior solutions for the baseline grids chosen (we use a five-point k grid on $[0, 1]$, five-point q grid on the interval $[0.05, 1.75]$). The rest of the parameters are the same as discussed in Section 5.2. We simulate data from the MH model at the baseline parameters, ϕ^{base}, and grids described above. We take an initial distribution over the states (k, w) that has an equal number of data points for each grid point in the capital grid K and is normally distributed in w, that is, $w \sim N(\mu_w, \gamma_w^2)$ for each $k \in K$. In the

Thai data applications, we use the actual initial discretized distribution of assets in the data for the marginal distribution over k.[36] We set the mean μ_w to be equal to the average value in the promise grid, $\frac{w_{\max}+w_{\min}}{2}$, at the baseline parameters; the standard deviation is set to 0.35 of the w grid span. We next compute the data-generating regime (MH) at the baseline parameters, ϕ^{base}, given the drawn initial distribution over states (k, w) as described above, and use the LP solution π^* to generate, via a Monte Carlo procedure (with fixed random numbers across regimes), draw "data" on c, q, k and i to use in the estimation.

Consistent with the runs with actual data, the simulation allows for additive normally distributed measurement error in all variables. We perform all estimation runs and tests in this section for two measurement error specifications: "low measurement error," where we set the parameter $\tilde{\gamma}_{\text{me}}$ governing the size of measurement error relative to a variable's range equal to 0.1, and "high measurement error," with $\tilde{\gamma}_{\text{me}} = 0.2$ of the grid range.

APPENDIX C: ADDITIONAL RUNS WITH SIMULATED DATA

Table XI, section 6 contains results from several additional robustness runs using simulated (c, q, i, k) data from the MH regime with the low measurement error specification, unless stated otherwise. Rows 6.1 and 6.2 study the effect of varying the sample size, n. We find that reducing n from 1,000 to 200 produces more ties between counterfactual regimes (compare row 6.1 with row 3.1), but the data-generating MH regime is still distinguished at 1% confidence level. Increasing the sample size of simulated data to 5,000 achieves virtually the same results to the $n = 1{,}000$ baseline (compare rows 6.2 and 3.1). Row 6.3 of Table XI checks the sensitivity of the results to grid dimensionality. Reducing the size of all grids to three points does not affect the Vuong statistics and baseline results in any significant way, which is reassuring. In row 6.4, we instead use denser grids for K and W (10 points) to generate the simulated data, but then estimate with the baseline five-point grids obtained from data percentiles as explained previously. Our results are again not sensitive to the grid sizes.

In yet another run (row 6.5), we generate the simulated data without adding measurement error, but we then allow for measurement error in the MLE routine when estimating afterwards, as per our usual MLE routine. The Vuong test statistics show that, as in row 3.1, the data-generating MH model is distinguished at the 1% confidence level from the rest. In the next run (row 6.6), we use the MLE estimates from the rural (c, q, i, k) data from Table IV as data-generating parameters instead of the baseline parameters from Table X used

[36] We also perform a robustness run with a mixture of two normals distribution for b or w—see Table IX, row 5.12. Our methods allow any other possible distributional forms at the cost of additional parameters to be estimated and slower computation.

in the above runs. The data-generating regime MH is recovered as best-fitting, tied with LC. The last run (row 6.7) uses simulated data from the S regime at the 1999 (c, q, i, k) MLE parameters from which we remove household and period fixed effects, as discussed in Section 6.1 and Table IX, section 4. We recover S as best-fitting (we also did a run without removing the fixed effects, with the same result).

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