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DYNAMIC COMPLEMENTARITIES: A QUANTITATIVE ANALYSIS

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ABSTRACT

This paper considers the importance of dynamic complementarities as an endogenous source of propagation in a dynamic stochastic economy. Dynamic complementarities link the stocks of human and organizational capital, which are influenced by past levels of economic activity, to current levels of productivity. We supplement an otherwise standard dynamic business cycle model with both contemporaneous and dynamic complementarities. The model is calibrated using estimates of these effects. Our quantitative analysis identifies empirically relevant dynamic complementarities as a source of propagation for both technology and taste shocks.

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Dynamic Complementarities: A Quantitative Analysis

I. Introduction

This paper seeks to address a major difficulty in the current literature on business cycles: the lack of endogenous propagation of aggregate shocks. As is documented in numerous studies (e.g. King, Plosser and Rebelo [1988a]), the propagation mechanism in the standard neoclassical growth model is quite weak: transitory technology shocks imply that the serial correlation in output is less than .03. This is quite low relative to the observed serial correlation of output in U.S. data. This problem affects not just models of the real business cycle genre but others that rely on quite different sources of fluctuations, such as demand side impulses caused by monetary disturbances.

One remedy, adopted in many real business cycle models, is to simply build in the serial correlation through the exogenous process. Reported statistics for real business cycle models with serially correlated shocks are much closer to those observed for the U.S. economy.

An alternative, which is more attractive if one wishes to study temporary demand variations, is to search for endogenous mechanisms beyond the process of physical capital accumulation that generate serial correlation. This paper contributes to this effort by investigating a stochastic growth model supplemented by contemporaneous and dynamic complementarities in the representative agent's production function. The main point is to provide a quantitative analysis of dynamic complementarities with emphasis on the propagation of temporary shocks.[1]

This paper complements the work by Baxter and King [1991] who provide a quantitative evaluation of the influence of contemporaneous complementarities operating through a production spillover, following the example by Bryant [1983]. The theme here is that individual agents are more productive the higher the production level of other agents. The Baxter and King analysis emphasizes the magnification of shocks through contemporaneous complementarities.

Our model induces propagation from dynamic complementarities: i.e. the presence of strategic complementarities, discussed in Cooper and John [1988], that operate through time rather than contemporaneously. These dynamic complementarities are intended to capture aspects of learning-by-doing spillovers and changes in the stock of organizational capital that take place at business cycle frequencies.[2] Moreover, we focus on complementarities that are external to the production process of an individual agent. Our analysis allows for the presence of both forms of complementarity and, as we demonstrate below, their interaction produces rich dynamics.

The next section of the paper provides a theoretical overview of dynamic complementarities with reference to papers that provide explicit models of these interactions. The third section discusses our approach to the quantitative analysis, including the estimation

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[1] There are other studies that proceed in this same direction. Chatterjee and Cooper [1993] uses product space variations over the business cycle to induce endogenous serial correlation in output. Beaudry and Devereux [1993] construct an economy with internal increasing returns to scale and find that monetary shocks lead to persistent deviations from the steady state. Stadler [1990] constructs a reduced-form business cycle model which relies on human capital accumulation as a source of propagation as well.

[2] Beaudry-Devereux [1995] also examine a model in which organizational capital is relevant. Relative to our model, they stress the accumulation of organizational capital as an alternative to production rather than as a complement.

of these interactions. The fourth section presents our results which indicate that relatively small dynamic linkages can create substantial serial correlation in the aggregate variables.

Overall, we find empirical support for the presence of both contemporaneous and dynamic complementarities from both aggregate and plant-level data. The aggregate empirical evidence comes from estimation of the parameters using sectoral (2-digit) output and input measures. The validity of the estimation routine is evaluated using Monte Carlo techniques with data simulated from a real business cycle model without complementarities. The plant-level data comes from the Longitudinal Research Database (LRD) and documents the presence of complementarities for automobile assembly plants.

When these aspects of the production process are included in the version of the stochastic growth model used by King, Plosser and Rebelo, the contemporaneous complementarities magnify shocks and the dynamic complementarities propagate them. For example, consider an economy in which fluctuations are driven by iid technology shocks. In an economy without any complementarities, there is little serial correlation in output. When both complementarities are present, the standard deviation of output increases by a factor of almost 5 and the serial correlation in output increases to .95 from .02.

We also consider fluctuations driven by demand variations, modeled here as shocks to an agent's marginal rate of substitution between consumption and leisure. In a competitive economy with no externalities, iid taste shocks have quite counterfactual implications: consumption and investment are negatively correlated and there is no consumption smoothing. As discussed by Baxter and King, these effects are somewhat attenuated by the introduction of contemporaneous complementarities. When both complementarities are set at empirically relevant levels, the economy displays rather rich dynamics in response to an iid taste shock. Initially, investment and output expand as in the economy without complementarities. After the initial expansion, the rise in the stock of human capital implies a rise in productivity which sustains the boom for some time. Eventually, the human capital effects are overwhelmed by the transition of the economy back to its steady state. However, investment remains negatively correlated with output and the standard deviation of consumption remains above that of output.

II. Theoretical Structure

Our approach is to focus on a fairly general specification of a dynamic complementarity rather than to assess any particular formulation. We first present the basic model and then turn to interpretations found in papers that motivate our analysis.

Consider an economy in which the representative agent solves the following dynamic optimization problem:

$$\max \quad E\sum_{t=0}^{\infty} \beta^t u(c_t - \Delta_t, 1-n_t)$$

$$\text{s.t.} \quad c_t + i_t \leq y_t$$

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

$$y_t = A_t n_t^{\alpha} k_t^{\phi} Y_t^{\epsilon} Y_{t-1}^{\gamma}$$

where Y_t is average aggregate activity in period t. In the objective function, current utility depends on consumption in period t (c_t), a taste shifter (Δ_t) and leisure ($1-n_t$), so that hours worked is n_t. The resource constraint and capital accumulation constraints, which hold in all time periods, are standard. The production function allows two forms of interactions across agents. The first is through the influence of current aggregate activity (Y_t) on the output of an individual producer (y_t), parameterized by ϵ. This is the complementarity that forms the basis of Baxter and King [1991]. The second influence is through lagged activity (Y_{t-1}) and is parameterized by γ. Stated in terms of this model, the goal of the paper is to estimate ϵ and γ and then to evaluate the quantitative implications of the model with particular emphasis on the propagation of shocks.

This form of a production function has been used extensively in both the business cycle and growth literatures. For business cycles, the influential paper by Bryant [1983] described a coordination problem in which multiple Pareto ranked Nash equilibria could emerge due to the presence of complementarities in the production process. That example was static but serves as motivation for the contemporaneous production complementarities found in Baxter and King [1991] and Klenow [1991].[3]

As discussed in Cooper and John [1988] and Cooper and Haltiwanger [1994], this representation nests other forms of interactions. As in Howitt [1985], one can consider costs of transactions that fall as the level of activity increases. These "thick market" effects can be viewed as arguments in a production process that converts inputs into consumption without being specific about the trading process. Further, in models of monopolistic competition, as in Blanchard and Kiyotaki [1987] or Kiyotaki [1988], the demand curve facing an individual producer depends on the level of demand for that period which, in turn, will depend on the

[3] Benhabib and Farmer [1994] take this specification a step further and argue that if the production complementarity is strong enough, the steady state may become locally stable and sunspot equilibria may emerge.

aggregate level of economic activity. This would again yield a similar specification though the interpretation of the parameters would relate more to preferences than technology.

In terms of the lagged output term, Durlauf [1991] considers dynamic complementarities which are motivated by learning-by-doing interactions within and across sectors of activity. In Durlauf's formulation, complementarities are local in that a single sector interacts with only a subset of other sectors. Still the aggregate economy is affected by sectoral shocks through the local interactions. In our formulation, the distinction between local and aggregate complementarities is lost since we do not explicitly focus on sectoral or plant-specific shocks.[4] Thus the lagged output term in our technology represents the learning spillovers in Durlauf's models. However, in our empirical implementation, we follow Durlauf and consider the dynamic complementarity as reflecting local linkages associated with learning by doing. Gale [1996] also uses the assumption of lagged complementarities to study the timing of investment decisions.

In a related paper, Stadler [1990] considered very similar effects of past production on current productivity though in his formulation current human capital depended on past human capital, lagged average labor productivity and lagged labor input. This specification is rationalized by arguments concerning the accumulation of organizational capital, the acquisition of new skills and so forth. As with our analysis, Stadler's main point was to understand the propagation of shocks. A central difference in the papers concerns the underlying economic model. Stadler focuses on the specification of the technology and

[4] Of course, one of the main points of Durlauf's analysis is to consider the interaction across sectors when they are not identical. Introducing heterogeneity of that form is not part of this exercise.

assumes particular forms for labor supply and a quantity equation for aggregate demand while our model is identical to the stochastic growth model except for the specification of the technology.

Finally, Drazen [1985] explores the effects of output fluctuations on the natural rate of unemployment. In this model, workers must train to become productive at the firm. By causing working-firm separations, fluctuations reduce the aggregate stock of human capital and thus have longer run effects.

In the growth literature, considerable attention has been paid to externalities in the accumulation and utilization of knowledge, as in Lucas [1988] and Romer [1986] and the literature that followed. In Romer [1986], the accumulation of knowledge is financed by foregone consumption while in Lucas [1988] human capital is accumulated by schooling rather than working and there is a human capital externality in the production function at the individual level.

If we interpret Y_{t-1} in the production function as a proxy for human capital, then our model can be viewed as an attempt to focus on the higher frequency implications of a specific version of these human capital accumulation models. In particular, our stock of human capital is determined solely as a function of the previous period's level of aggregate economic activity. Of course Y_{t-1} incorporates information about all the past levels of output through the dynamic complementarity. Klenow [1993] considers a related model in which there is both exogenous human capital depreciation as well as accumulation related to the level of employment. Both our paper and Klenow's take the view that current employment levels can have an immediate impact on the efficiency of individual workers in an economy. In contrast, King, Plosser and Rebelo [1988b] specify a business cycle model in which the accumulation of human capital provides an alternative use of time rather than a byproduct of the production of goods.

More generally, high activity in the past is a way to create organizational capital which goes beyond the idea of a single worker learning how to undertake a particular task. Some of this capital is undoubtedly internal to an organization but in periods of high activity, links are created with suppliers and customers (as in a more dynamic version of Howitt's transactions cost model) that reduce costs of marketing in future periods.

Our approach is not to rely specifically on one of these particular models but rather to use the specification of technology as primitive and determine the quantitative influence of these interactions. If there is no support for these effects in the empirical analysis or if the propagation effects from the simulations are relatively minor, then we would argue that this class of model is not worth exploring further. Alternatively, if these effects are significant and economically meaningful, then further work developing and testing the various models described here seems justified.

In this optimization problem, the representative agent takes as given the state dependent level of average aggregate output since agents are small relative to the economy. The first order conditions are:

$$\frac{u_l(c_t-\Delta_t,1-n_t)}{u_c(c_t-\Delta_t,1-n_t)} = A_t \alpha n_t^{\alpha-1} k_t^{\phi} Y_t^{\epsilon} Y_{t-1}^{\gamma} \tag{2}$$

$$u_c(c_t-\Delta_t,1-n_t) = \beta E u_c(c_{t+1}-\Delta_{t+1},1-n_{t+1})[A_{t+1} \phi n_{t+1}^{\alpha} k_{t+1}^{\phi-1} Y_{t+1}^{\epsilon} Y_t^{\gamma} + (1-\delta)] \tag{3}$$

$$c_t + [k_{t+1} - (1-\delta)k_t] = A_t n_t^{\alpha} k_t^{\phi} Y_t^{\epsilon} Y_{t-1}^{\gamma} \tag{4}$$

As there are no idiosyncratic shocks, finding an equilibrium simply requires imposing equality between individual and aggregate variables in the system of first order conditions. In particular, $y_t = Y_t$ so that, in equilibrium, the production relationship becomes

$y_t = [A_t n_t^{\alpha} k_t^{1-\alpha} y_{t-1}^{\gamma}]^{\eta}$ where $\eta \equiv 1/(1-\epsilon)$.[5] Using this relation in determining the individual marginal products, (2)-(4) become:

$$\frac{u_l(c_t - \Delta_t, 1-n_t)}{u_c(c_t - \Delta_t, 1-n_t)} = \alpha\, [A_t n_t^{\alpha} k_t^{\phi} y_{t-1}^{\gamma}]^{\eta}/n_t \tag{5}$$

$$u_c(c_t - \Delta_t, 1-n_t) = \beta\, E u_c(c_{t+1} - \Delta_{t+1}, 1-n_{t+1})\, [\phi\, (A_{t+1} n_{t+1}^{\alpha} k_{t+1}^{\phi} y_t^{\gamma})^{\eta}/k_{t+1} + (1-\delta)] \tag{6}$$

$$c_t + [k_{t+1} - (1-\delta)k_t] = [A_t n_t^{\alpha} k_t^{\phi} y_{t-1}^{\gamma}]^{\eta} \tag{7}$$

The underlying economics should be clear from this system. First, the presence of a contemporaneous production complementarity serves to magnify shocks to the system. This comes about because variations in A_t have an exponent of $\eta > 1$ and the marginal returns to variations in inputs is also influenced by this production externality parameter, as in (5) and (6). Second, the marginal products of labor and capital (again in (5) and (6)) are affected by the level of activity from the past, parameterized by $\gamma > 0$. This effect is the source of

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[5] Note of course that this is not the production relation from the perspective of the individual since each agent takes the level of aggregate activity as given in all periods. Hence, the equilibrium production relation is used to simplify the first-order conditions <u>not</u> the optimization problem of the representative agent.

propagation in our economy. Thus, not surprisingly, the key to the analysis is the magnitude of these two parameters.

Following King, Plosser and Rebelo [1988a], we analyze the equilibrium path of the economy by constructing a log linear approximation around the steady state.[6] Ultimately, this gives us a linear system dependent on the state vector $(A_t, \Delta_t, y_{t-1}, k_{t-1})$ and the initial values of the capital stock and output. This linear system can be analyzed and paths for the aggregate variables determined. For given stochastic processes for A_t and Δ_t, conditional expectations are then used instead of future values of these random variables in determining the evolution of the system. All relevant moments can then be computed from this linear system. Details on this approach are given in King, Plosser and Rebelo [1988a].

III. Parameterization and Estimation

To perform the quantitative analysis, we must specify and parameterize functional forms for the utility and production functions and set other parameters of the model economy. As our goal is to understand the effects of dynamic complementarities relative to models without this feature, we specify our model so that the real business cycle framework used in King, Plosser and Rebelo is a special case. In particular, we assume that utility is $\log(c_t) + \chi\log(l_t)$. For the production function, we have already specified a Cobb-Douglas form implying constant factor shares. We first discuss the parameterization of our production function since it represents the main difference between this and related exercises and then

[6] For the parameterizations we explore, there is a unique, saddle path stable steady state so that unlike Benhabib and Farmer [1994], the issue of the steady state becoming a sink does not arise here. However, as in that paper, there are parameter values (e.g., large values of ϵ combined with elastic labor supply) that will change the fundamental dynamics.

summarize our choices of the other parameters.

A. Production Function Estimation

This sub-section is devoted to estimating the production technology of the model specified above. This involves estimating the external returns parameter as well as the dynamic complementarities parameter along with the return to own inputs. We consider two alternative procedures for estimating the production function. The first involves direct estimation of the production function using aggregate (2-digit) data while the second obtains estimates from plant-level data. These are discussed in turn.

(i) *Aggregate Production Function Estimation*

Consider the following Cobb-Douglas production function in logs, which corresponds to the technology specified above,

$$y_t = \alpha n_t + \phi k_t + \epsilon Y_t + \gamma Y_{t-1} + a_t \tag{8}$$

where a_t is the productivity index.

One approach is to estimate this aggregate production function using data on output and inputs. While simple, this approach has three well known drawbacks. The first is the identification of the parameters, the second involves the correlation between productivity shocks and the inputs and the third relates to the measurement of capital services.

To understand the identification problem, recall that in the representative agent framework, a necessary condition for equilibrium was $y_t = Y_t$ for all t. Using this, the production function reduces to:

$$y_t = \frac{\alpha}{1-\epsilon}n_t + \frac{\phi}{1-\epsilon}k_t + \frac{\gamma}{1-\epsilon}y_{t-1} + \frac{1}{1-\epsilon}a_t = \alpha^* n_t + \phi^* k_t + \gamma^* y_{t-1} + a_t^* . \tag{9}$$

Notice that it is not possible to disentangle the returns to own inputs from the external effect using aggregate data. In terms of (9), it is possible to obtain estimates of α^* and ϕ^* but these cannot be separated into α, ϕ, and ϵ. If attention is restricted to aggregate data, an identifying assumption is required to determine the parameters.

Baxter and King [1991], for example, identify ϵ by imposing constant returns to scale. Hence they estimate

$$y_t = \frac{1}{1-\epsilon}x_t + v_t \tag{10}$$

where x_t is an index of inputs weighted by their long run sample average factor shares.

Instead of imposing such restrictions, it is possible to overcome the problem of identifying these parameters by taking advantage of the cross sectional variation available at the two digit industry level. To do so requires us to depart slightly from the theoretical model we have specified since the identification rests on the existence of sector specific movements in productivity.

Consider an economy in which aggregate manufacturing is divided into sectors indexed by $j = 1,\ldots,J$, each with a share δ_j of total value added. Then the sectoral production functions can be written as

$$y_{jt} = \alpha n_{jt} + \phi k_{jt} + \epsilon Y_t + \gamma y_{jt-1} + a_{jt} \tag{11}$$

where ϵ captures the externality from aggregate manufacturing to the two digit sector and γ

captures the impact of last period's production within the sector.[7] Summing over the j sectors gives exactly the aggregate production function specified in equation (8), as long as the shares do not vary from one period to another. Assume that the productivity shock can be decomposed into a sector specific shock and an aggregate shock which are orthogonal,

$$a_{jt}=\bar{a}_t+u_{jt} \tag{12}$$

then (11) can be written as

$$y_{jt}=\alpha n_{jt}+\phi k_{jt}+\epsilon y_t+\gamma y_{jt-1}+\bar{a}_t+u_{jt}. \tag{13}$$

The key element from the perspective of disentangling ϵ from α and ϕ is the presence of sector specific elements in the disturbance term. In the absence of these, the sectoral production functions are identical and, using $y_t=\sum\delta_j\, y_{jt}$ in (13), the same identification problem arises as in the aggregate data.

The second problem is common to this literature and arises from the correlation between the productivity shocks and the inputs. The nature of the problems created by this correlation depends on the amount of serial correlation in the productivity shock.[8] In particular, if the serial correlation of the productivity shock is low, then the labor input should be highly correlated with the shock reflecting intertemporal substitution effects. At the other extreme, a highly serially correlated technology shock implies a much smaller labor response

[7] As in Durlauf [1991], the learning-by-doing effects are assumed to be sector specific. Estimates of the model in which the lagged complementarity are aggregate does not qualitatively change our empirical results.

[8] We are grateful to Mark Watson for clarifying our thinking on these issues.

but more movements in capital. The biases produced by an OLS regression will then reflect the amount of serial correlation in the shock through the responses of labor and capital.

The usual procedure, which we follow, for dealing with this problem is to use instrumental variables. Following Burnside, Eichenbaum and Rebelo [1995] and Christiano, Eichenbaum and Evans [1996], we use lags of monetary policy innovations as instruments. The procedure for obtaining these innovations is discussed at length in these papers.[9] The idea is to use as instruments the innovations to monetary policy variables (specifically nonborrowed reserves and the federal funds rate) obtained by regressing these policy instruments on variables in agents' information sets. These information sets are constructed so that the innovations to the policy variables are not likely to be correlated with productivity shocks. As discussed by Burnside, Eichenbaum and Rebelo, these instruments are highly correlated with inputs into the production process.

These instruments are constructed using quarterly data. For our annual data, we follow Burnside, Eichenbaum and Rebelo and use the values of the quarterly shocks from the previous year. That is, the instruments used in year t are the 4 quarterly innovations to nonborrowed reserves and the 4 quarterly innovations to the federal funds rate from year t-1.

The third problem encountered in this type of estimation is the measurement of capital services. Frequently, estimation of a value added production function with capital and labor inputs results in a zero or even negative coefficient for capital. This contrasts with the long run capital share of around .36. One longstanding interpretation is that the flow of capital

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[9]We are grateful to Burnside, Eichenbaum and Rebelo for sharing their data with us.

services is not the same as the capital stock and instead reflects the utilization of this factor. Recently, Burnside, Eichenbaum and Rebelo deal with this point by using electricity consumption as a proxy for capital services. We follow this approach in our estimation as well though we also report results using the capital stock.

Our data-set was obtained from a variety of sources. Annual 2-digit value added, capital, and labor series were obtained from Hall and are discussed in detail in Hall [1988]. These series run from 1952 to 1986. The annual 2-digit data on sectoral electricity consumption runs from 1972 to 1992 and was obtained from Burnside, Eichenbaum and Rebelo. The quarterly series on innovations to the federal funds rate and to non-borrowed reserves runs from 1960 to 1992. These series were also obtained from Burnside, Eichenbaum and Rebelo. Thus, unless reported otherwise, our results use annual data for 1972-86.

Using data for US manufacturing, we estimate (13) for a number of different specifications using Seemingly Unrelated Regressions.[10] For all of these regressions, all coefficient except the constants are forced to be equal across sectors.[11] Here we use value added as our output measure as it conforms to the theoretical model we have specified. Further, the model assumes perfect competition and thus we are not interested in estimating markups. Therefore, some of the criticisms of Hall [1988] raised by Basu-Fernald [1995] do not directly pertain. However, for completeness we also report results using gross output

[10] The presence of common shocks in the model implies that the errors are likely to be correlated across sectors. Taking this into account leads to a dramatic improvement in efficiency over single equation methods as is evident from the low standard errors reported in Table 1.

[11] For computational reasons, we are unable to include all sectors in these regressions. The results are reported for the following (2-digit) industries: 25,26,27,28,31,32,33,34,35,36,37,38,39. The exact coefficient estimates do depend on the included sectors though for all sets of industries explored the complementarities are significant. A split of the data between durables and nondurables reveals a larger contemporaneous complementarity for durables and a dynamic complementarity that is larger for nondurables.

rather than value added data. Also, in keeping with a deterministic growth model, we linearly detrend the data.[12] Though again we include some results from a specification in growth rates for comparison with related work in the literature.

Table 1 summarizes our empirical results. The first row of Table 1 reports the results obtained from using ordinary least squares (OLS) to estimate our system of sectoral production functions with electricity consumption used as a proxy for capital services. Note that both forms of complementarities are significant. The estimate of the contemporaneous complementarity is fairly large and we find decreasing returns to scale with regards to own inputs with a labor coefficient of only .31. Burnside, Eichenbaum and Rebelo also find relatively low values for the labor coefficient (see their Table 4) using annual manufacturing data. However, the results are not directly comparable as we are using a value added measure of output and our data is linearly detrended while they use gross output and first difference their data.

Though it is likely that these results are biased due to the correlation between inputs, aggregate output and the productivity shock as well as the presence of a lagged dependent variable among the right hand side variables, we include the OLS results for completeness. The next row attempts to correct for these biases by using an instrumental variable procedure.

Row 2 presents results from the three stage least squares estimation where all coefficients across sectors are constrained to be equal. The use of the instruments raised the coefficient on labor and lowers the coefficient on electricity considerably. The external effects

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[12] We tested the input and output series for unit roots and rejected the unit root hypothesis for these series using a Dickey-Fuller test. In fact, the results indicate that the serial correlation in the series is less than one so that regressions in first differences are overdifferenced. This is particularly important if we want to distinguish dynamic complementarities from the serial correlation of underlying shocks.

parameter, ϵ, is .62 which is still quite high relative to other studies (summarized below) while the dynamic complementarity parameter is basically unaffected by the use of instruments.

One concern with these results is that the lagged output term is simply picking up the serial correlation in a productivity shock. However, the contemporaneous and lagged output terms are being instrumented with lagged measures of monetary innovations which are, by construction, independent of the lagged technology shocks. We investigated this further by lagging the instrument set an additional year. The results are reported in Table 1 in row 3, IV-lagged. Here again we find significant complementarities though the coefficient estimates are clearly sensitive to the instrument list.[13]

Row 4 (Dyn. Only) focuses attention on the dynamic complementarity by forcing $\epsilon=0$. Here too, the instruments are lagged two years as in row 3. In this case, we find constant returns to scale with the coefficients on labor and electricity much closer to the observed factor shares for labor and capital. Note that again there is evidence of a significant dynamic complementarity.

We also investigate the importance of proxying for capital services through the inclusion of electricity. Row 5, IV-capital, presents the instrumental variables estimates when the capital stock is used instead of electricity. Here, as expected the coefficient on capital is essentially zero and that on labor is lower than in the row 2 specification while the estimates of the complementarities are a bit larger. A natural conjecture would be that the contemporaneous complementarity was partially picking up unmeasured factor utilization so that the inclusion of

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[13]In a previous version of this paper we report a regression in growth rates in which we use a non-linear estimation routine to jointly identify the complementarity and the degree of serial correlation in the technology shock. In that specification, we estimated the lagged complementarity at .15 and the contemporaneous one at .5.

electricity would bring down the estimate of that coefficient a lot. That is, the row 2 estimate of the contemporaneous complementarity coefficient should be much lower than the row 5 estimate. It is quite surprising that the estimate drops so little, though it is possible that there still remains unmeasured factor utilization. One way of addressing this issue further is to force constant returns to scale in own inputs and see if the coefficient on the contemporaneous externality remains significant.

The final row in Table 1, IV-CRS, is a regression in the spirit of Baxter-King [1991] that forces constant returns to scale. To do so, we create an input measure from a weighted average of labor (.64) and electricity (.36). This input measure is subtracted from output to create a measure of the Solow residual which is then regressed on the two complementarities. The results provide additional support for the presence of both complementarities: the coefficient estimate for the contemporaneous complementarity is .24 (.024) and .32 (.018) for the dynamic complementarity.

Overall the results reported in Table 1 paint a fairly consistent picture in terms of the magnitudes of the production complementarity parameters. In particular, there is evidence in favor of both dynamic and contemporaneous complementarities in all of the specifications. Put differently, we reject the hypothesis of no complementarities in all specifications. The estimate of the dynamic complementarity seems fairly robust to specification while the estimate of the contemporaneous complementarity is much more sensitive. It should be recognized though that this evidence simply shows that these complementarities are present in a very reduced form sense. Clearly, there is no attempt here to discriminate the many potential sources of complementarity as alternative models.

(ii) *Comparison to other Studies*

A number of other studies have attempted to estimate production functions with productive complementarities. These are of the general form of (8), however they all force $\gamma=0$. This corresponds to the assumption that there is no dynamic complementarity.

One approach that is closest to ours is Caballero-Lyons [1992] who report estimates of three stage least squares exercises for the following system

$$y_{jt}=\theta x_{jt}+\epsilon y_t+v_{jt} \tag{14}$$

and

$$y_t=\frac{\theta}{1-\epsilon}x_t+\frac{1}{1-\epsilon}v_t \tag{15}$$

Substitution yields their estimation equation

$$y_{jt}=\theta x_{jt}+\frac{\epsilon v}{1-\epsilon}x_t+\frac{1}{1-\epsilon}v_t+v_{jt}. \tag{16}$$

They report an estimate of $\epsilon=.32$.

Baxter-King [1991] estimates (10) using data on total private industry rather than manufacturing. Their OLS estimate of ϵ was .33 under the restriction of constant returns to scale. Using a variety of instruments they obtain estimates of ϵ ranging from .09 to .45.

Braun-Evans [1991], use seasonal variations in order to jointly estimate a contemporaneous production complementarity along with labor hoarding. Using a method of moments procedure they jointly estimate their model and find $\epsilon=.24$. Note that their model did include unobserved variations in the utilization of labor.

Cooper-Haltiwanger [1996] also use seasonal variations (the data was monthly) as an instrument in regressions of sectoral output (industrial production) on labor input find evidence of short run increasing returns to labor in total manufacturing and in many 2-digit sectors. Further, adding manufacturing output as another independent variable, Cooper-Haltiwanger find large and statistically significant contemporaneous complementarities in many sectors. Note though that these results did not include electricity or other proxies for capital utilization.

In a recent paper, Burnside explores the presence of complementarities acting through employment rather than output. He finds no evidence for this form of a complementarity. Basu-Fernald [1995] presents similar findings using aggregate input growth as the externality. We have experimented with a specification using lagged employment and contemporaneous output as reported in the first row of Table 2. Again we find support for complementarities though the lagged complementarity through labor is quite small.[14]

One concern with our evidence and that provided in these other studies is the use of value added as a measure of output. As noted earlier, Basu-Fernald [1995] argue that in the presence of imperfectly competitive markets, value added production functions may be misspecified. We considered two specifications (rows 2 and 3 of Table 2,IV-Gross and IV-Gross-Growth) in which the output measure was gross output rather than value added using, again, labor and electricity as inputs. The data covers the 1972-92 period. The two specifications differ in the method of detrending, where IV-Gross used linear detrending and IV-Gross-Growth uses growth rates. The main problem with this regression is that materials is

[14] In a specification with both complementarities acting through employment, we find evidence of a contemporaneous complementarity but not a dynamic complementarity.

excluded though it is a significant input into gross output. Burnside, Eichenbaum and Rebelo assume that gross output is a Leontief function of value added and materials. Under this assumption, the regression is not misspecified. There are two things to note from our regression results. First, as in our other specifications, the hypothesis of no complementarities is rejected. Second, note that the results from the IV-Gross specification and those reported in row 2 of Table 1 should, under the fixed coefficient hypothesis, be the same but clearly this is not the case. This seems, to us, to indicate problems with the fixed coefficient hypothesis.

(iii) Microeconomic Evidence

To supplement our estimates based on aggregate data, we have also explored the relevance of contemporaneous and dynamic complementarities at the plant level. The data set is the Longitudinal Research Database (LRD) which provides plant level data for U.S. manufacturing. For this analysis, we estimated the production functions for automobile assembly plants (sector 3711). Our panel consisted of the 48 plants that were continuously operating over the 1972-89 period. We used real value added as our dependent variable, total production worker hours as a measure of labor input and electricity consumption at the plant as a proxy for the flow of services from capital.

The use of panel data is particularly challenging due to the presence of structural heterogeneity across the plants and the measurement of capital services. For the estimation, we assume that the basic production function for real valued added is Cobb-Douglas with capital and labor as inputs. This production function may, in general, be subject to plant specific and common shocks. Further, the plant specific shocks can represent, at one extreme, structural heterogeneity and, at the other, temporary plant specific shocks to the production process. In our estimation, we allow for plant specific unobservable heterogeneity through a fixed effects estimation strategy.

In terms of the measurement of capital services, we use electricity consumption at the plant as a proxy. Thus, a plant that utilizes its capital more intensively, say due to the addition of a second shift, would then require more electricity input. This proxy may still miss improvements to capital quality which make the machines more productive without requiring additional energy input. Our measure of output is real valued added which we construct at the plant level given data on shipments and changes in finished goods inventories, deflated by a shipments price index, less deflated material purchases. The data are in logs and are not detrended.

The results are summarized in Table 3. All of the specifications included fixed effects through the use of plant specific dummies as indicated in the table. The first specification had labor input as the only independent variable. The point estimate of .86 indicates some short run increasing returns in that this coefficient exceeds labor share in this sector. Without the fixed effects included, this point estimate is .99 with a standard error of .02 (not reported in the table) indicating the expected omitted variable bias.[15] The second column provides estimates from a specification that is close to that used in our aggregate regressions: labor and electricity are the only inputs. Here we see that the coefficient on labor input is lower presumably because it was reflecting unmeasured utilization of capital. The point estimates of these coefficient sum of 1.06 and we are unable to reject constant returns to scale. This

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[15] That is, more productive plants will generally use more labor and this will bias the coefficient on labor upwards unless fixed effects are included.

evidence seems quite consistent with that presented by Burnside, Eichenbaum and Rebelo [1995].

The next two columns present our estimates of contemporaneous and lagged complementarities for this sector using sectoral output as the source of this external effect. Here we see additional support for both types of complementarities in this sector. In fact, the point estimate of the coefficient on contemporaneous output seems incredibly large. This could reflect the presence of common shocks, a common trend or unobserved factor utilization that is not correlated with electricity use.

On the issue of detrending, the estimates thus far are for raw data. Thus, a common deterministic trend in productivity could lie behind the estimated complementarities. To capture this, we added a time trend to our set of independent variables. Thus the sectoral output measures would reflect complementarities that are not perfectly correlated with time. The last two columns of Table 3 show our results. For both columns (5) and (6), the contemporaneous complementarity is significant and reasonably close to the aggregate results. The coefficient on the lagged complementarity terms is now much lower than in the regressions without the time trend and is also not significantly different from zero. Thus it appears that the inclusion of the year drives the coefficient on lagged sectoral output to zero. Interestingly, the coefficient on electricity has also fallen to zero.

We also experimented with a specification that is outside of our model in which the lagged level of plant output is included instead of lagged sectoral output. This captures learning by doing that is internal to the plant. For this regression, which included the time trend as well, the coefficient on own lagged output is .2 (.02) and the coefficient on contemporaneous sectoral output is .26 (.06). Thus we see evidence of internal learning by doing.[16] Bahk and Gort [1993] find evidence of learning in their study of plant level data as well.

(iv) Monte Carlo Exercises

To evaluate our estimation procedure, we carried out a Monte Carlo exercise. Since we use the standard real business cycle model as the data generating mechanism, it is best to contrast these results with the more aggregate evidence provided in Table 1. Put differently, our simulations do not include the rich heterogeneity prevalent in the plant level data and in the results reported in Table 3.

Our objective is to address the following concern. If the economy had neither contemporaneous nor dynamic complementarities would an OLS estimation procedure on aggregate data nonetheless find significant complementarities? Though we have stressed results using IV estimation, the OLS results in this and other papers are also interesting to the extent that there is concern over the validity of the instruments.

To address this question, we use the basic neoclassical real business cycle model with <u>persistent</u> technology shocks (eg. King, Plosser and Rebelo [1988a]) and no complementarities in production to generate 100 simulated series on capital, labor and output, each of length 100 periods.[17] A number of regressions were run with these data. The results reported below are the means and standard deviations of the parameter distribution.

With these data, we followed Baxter and King by regressing output on an index of

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[16] There is some concern however with the inclusion of lagged dependent variables in regressions with fixed effects in small samples.

[17] The data created in this way are deviations from a deterministic trend so that our regressions were run on the "raw" data.

inputs (x_t). Using an OLS procedure we find an average coefficient on inputs of 2.16 with a standard error of .0785. This implies a value of the contemporaneous complementarity (ϵ) of .54 even though the data was generated by an economy without any contemporaneous complementarity.[18] The bias reflects the contemporaneous correlation between the shock and x_t.

In a second regression using the same data, we added lagged output as another explanatory variable. The coefficient on lagged output was estimated at -.0344 which was not significantly different from zero, while the estimate of contemporaneous effects was .55, again significantly different from zero. Overall, there is a tendency to find a contemporaneous complementarity when it isn't there but no such bias in the estimate of the dynamic complementarity.

As one might expect, if the data is generated using a taste shock instead of a technology shock, there is no correlation between capital and labor and the errors so that the production function is estimated without bias. This just confirms the point that in the presence of powerful instruments, there would be no bias in the estimation of the production function directly.

(v) Summary

In summary, using either aggregate or plant level data, we see evidence against the hypothesis that neither contemporaneous nor dynamic complementarities are present. This is true for 2-digit data and at the plant level for sector 3711. In terms of the parameterization of

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[18] It is interesting that the bias in this procedure is much higher when an index of inputs is used as compared to when the input coefficients are determined freely as in the first three rows of table 1. For that case, the estimate of ϵ falls to about .35 if calculated off of the labor coefficient. (The estimated coefficient on labor is 1.5 while on capital it is .65).

our production function, we work with a number of different specifications and discuss how sensitive the results are to alternative parameterizations. While the parameters of the production function change across treatments, the other parameters of the model remain unchanged. These are reported in the following section.

b. Other Parameters

As noted earlier, since our goal is in part of evaluate the effects of dynamic complementarities relative to a well-known benchmark, we have chosen our parameters to be close to those used by King, Plosser and Rebelo. In particular, we set the utility function parameter (χ) so that the average fraction of time spent working is .2 Further, δ equals 10% and β is chosen so that the real rate of interest is 6.5% on an annual basis.

The model includes two stochastic variables: technology and taste shocks. For comparison purposes, we set the standard deviation of the both the technology and taste shocks at .0075. The level of this standard deviation is actually immaterial since we only report correlations and relative standard deviations and make no attempt to compare the level of volatility in our economy with observation.

V. Results

In what follows we use three estimates of the production technology. The first is the conventional model without complementarities and assuming constant returns to scale with labor's share set at .64. The other specifications retain internal constant returns to scale but allow for external effects. In particular, the second specification is from row 4 of Table 1 in which the dynamic complementarities parameter is estimated at .37 and there are no contemporaneous effects. The final specification is from row 6 of Table 1 where we force constant returns to scale and allow for both forms of externalities to be present.

For each of these parameterizations, there are two treatments: iid taste shocks and iid technology shocks. Our principal findings are summarized in Tables 4 and 5, for technology and taste shocks respectively. In addition, Figures 1-6 present the impulse response functions for the various treatments.

Our analysis emphasizes the main macroeconomic variables of interest: consumption, investment, hours, output and the capital stock. In addition, we focus on the implications of our economies for the "Solow residual". Previous real business studies typically calculate a Solow residual from a production function without any complementarities, i.e.

$$SR_t = \log(Y_t) - \phi \log(K_t) - \alpha \log(N_t). \tag{17}$$

These studies generally find a highly persistent productivity shock process which is positively correlated with output. As we shall see, this Solow residual will display considerable persistence even if the true exogenous process is iid when there are dynamic complementarities in the production technology which have been ignored. Since we are emphasizing endogenous mechanisms of persistence, we present the moments of SR_t for various models.

(i) *Technology Shocks*

Row 1 of Table 4 summarizes the moments for the basic real business cycle model with iid technology shocks. As is well known, this model reproduces some of the basic features of the business cycle such as procyclical productivity and consumption smoothing. It also does well in capturing the stylized fact that investment is more volatile than output, which is more volatile than consumption. However, the baseline model does poorly on a number of accounts. Compared to the moments for postwar US data (last row), hours are too procyclical and consumption not enough. Further, the model generates virtually no endogenous persistence; thus the need to rely on persistent shocks to match the data better. The impulse response functions for this parameterization and a 1% technology shock, Figures 1a and 1b, confirm this basic feature: the only significant action in the variables occurs in the period of the temporary shock. As explained below, note that employment is actually below steady state as capital is above its steady state value during the transition.

As seen from row 2 of Table 4, the economy with dynamic complementarities displays a significant amount of persistent: the serial correlation in output has risen to .72. As expected, the increased persistence increases the standard deviation of consumption relative to output while reducing the volatility of employment relative to output. Note from the table that the Solow residual is highly correlated with output and has an autocorrelation coefficient of .69. The propagation of the initial technology shock comes from the effects of accumulated human capital on the production process. That is, the burst of activity caused by the initial productivity shock increases the stock of human capital in the following period and thus creates a basis for increased work, consumption and investment in future periods.

The impulse response functions in Figures 2a and 2b indicate this richer response to the temporary productivity shock. From Figure 2a, note that output and the Solow residual all remain above steady state levels for at least 15 periods. Employment is above steady state for the first 8 periods and then drops below the steady state. This behavior of employment reflects the interaction of the two state variables, physical and human capital. As seen in Figure 2b, the burst of productivity causes both physical and human capital to rise and both are above steady state for the 15 periods shown in the figure. However, the impact of these variables on employment is somewhat complicated. As is well understood (see King, Plosser and Rebelo [1988a] for a detailed explanation), employment is below steady state during the transitional dynamics of the neoclassical growth model if the physical capital stock is above steady state. This is essentially the response of employment to the relatively low intertemporal return caused by the large capital stock. For the economy with dynamic complementarities, there is an additional influence from the large stock of human capital: the increased human capital causes agents to work more. Thus, for the initial 7 periods, the employment increasing effect of the larger stock of human capital dominates and then the transitional dynamics take over.

The economy with both contemporaneous and dynamic complementarities contains both elements of magnification and propagation. As in the Baxter-King economy, the contemporaneous complementarity magnifies the technology shock. From row 3 of Table 4, the standard deviation of output is much larger for this economy than the others. Further, the propagation of the shock is actually stronger even though the parameter of the dynamic complementarity is lower in this parameterization than in the previous economy. Not surprisingly, consumption is even more volatile and employment less volatile.

The interaction of these two influences is brought out in the impulse response functions for this economy, Figures 3a and 3b. Note first that, relative to Figure 2a, the effect of the technology shock in period 1 is much larger for the economy with both types of complementarities. Further, we see that employment stays above its steady state value longer for this parameterization reflecting the large buildup in the stock of human capital (Figure 3b).

(ii) Taste Shocks

Table 5 reports the implications of an iid taste shock instead of an iid technology shock. A taste shock causes changes in the marginal rate of substitution between consumption and leisure. The increased urgency to consume should lead to more volatile consumption and relatively less procyclical labor hours as well as a tendency to substitute consumption for investment, compared to the results from an iid technology shock. This intuition is borne out in row 1 of Table 5 and in the impulse responses, Figures 4-6.

This effect of a taste shock is clear from the behavior of consumption and investment given in Figure 4. At the time of the taste shock, consumption rises sharply to the point that investment is negative (agents consume their capital). At the same time they substitute between consumption and leisure: hours worked increases and output is higher. In the periods after the shock, consumption is below steady state levels and investment is above, in an effort to build up the capital stock. The lower than steady state capital stock yields lower output despite hours worked remaining above their steady state level along the transition path. These negative correlations are brought out in the statistics reported in Table 5. Further, note that both consumption and investment are more volatile than output. Similar patterns are reported by Baxter-King though they focus too on an economy with serially correlated taste shocks.

In the model with dynamic complementarities, the propagation effect is displayed once more as the serial correlation in output rises to .85. Further, the serial correlation in the Solow residual (mismeasured as it ignores the complementarities) is also .85. Still, the negative correlations from the baseline model remain. From the impulse responses shown in Figure 5, the dynamic complementarities actually prolong the expansion associated with the taste shock as output is above steady state for 3 periods. Hours stay above steady state throughout reflecting the fact that capital is below steady state following the reduction in investment at the time of the taste shock.

The model with both dynamic and contemporaneous complementarities displays much richer dynamics around the steady state. As indicated in Figure 6, in the impact period, hours, output and consumption rise while investment is negative. Despite the lower capital stock, output remains high for about 12 periods because of the presence of the increased stock of "human capital". From Figure 6a, the measured Solow residual is well above steady state through 12 periods as well. At the same time, consumption is below, and investment above, its steady state level during the transition in order to build back the capital stock as in the neoclassical model. Since both hours worked and human capital are falling, output eventually goes below its steady state level while the capital is being built up. This can be seen clearly in Figure 6b.

VI. Conclusions

Our goal in this paper was to explore the quantitative implications of dynamic complementarities. In our economy, the standard dynamic stochastic growth model is supplemented by the presence of two complementarities. One, as in Baxter and King, acting as a contemporaneous link across agents and a second, as in Durlauf, providing an intertemporal link. To us, the key question was whether this type of model could generate endogenous propagation of shocks for empirically reasonable parameters.

As a consequence, the paper contains a lengthy discussion of the estimation of these parameters, including some Monte Carlo exercises. Overall, we do find evidence of a dynamic complementarity that we are able to distinguish from persistence in technology shocks. Our quantitative exercises indicate that these complementarities, working together, can magnify and propagate shocks to technology and tastes.

There is much more work to be done along these lines. First, the construction of explicit models in which dynamic (rather than static) complementarities play a role is clearly of important to go beyond the "black-box" specification employed here. Second, these effects should be integrated into richer models of a demand impulse rather than relying on taste shocks as a source of fluctuations. Finally, an alternative model in which learning by doing is internal to the firm bears some consideration in light of our empirical findings at the plant level and those reported by Bahk and Gort [1993].

References

Bahk, B.H. and M. Gort, "Decomposing Learning by Doing in New Plants," Journal of Political Economy, 101 (1993), 561-83.

Bartlesman, E., R. Caballero and R. Lyons, "Customer and Supplier Driven Externalities," American Economic Review, 84 (1994), 1075-84.

Basu, S. and J.G. Fernald, "Are apparent Productive Spillovers a Figment of Specification Error?" Journal of Monetary Economics, 36 (1995), 165-88.

Baxter, M. and R. King, "Productive Externalities and Business Cycles," Institute for Empirical Macroeconomics, Federal Reserve Bank of Minneapolis, Discussion Paper #53, November 1991.

Beaudry,P. and M. Devereux, "Monopolistic Competition, Price Setting and the Effects of Real and Monetary Shocks," mimeo, 1993

____________________, "Towards an Endogenous Propagation Theory of Business Cycles", mimeo, University of British Columbia, Oct. 1995.

Benhabib, J. and R. Farmer, "Indeterminacy and Increasing Returns," Journal of Economic Theory, 63 (1994), 19-41.

Blanchard, O. and N. Kiyotaki, "Monopolistic Competition and the Effects of Aggregate Demand," American Economic Review, 77 (1987), 647-66.

Braun, R. Anton and C. Evans, "Seasonal Solow Residuals and Christmas: A Case for Labor Hoarding and Increasing Returns," Working Paper WP-91-20, Federal Reserve Bank of Chicago, October 1991.

Bryant, J. "A Simple Rational Expectations Keynes-Type Model," Quarterly Journal of Economics, 97 (1983), 525-529.

Burnside, C. "Production Function Regressions, Returns to Scale and Externalities,"World Bank, no date.

Burnside, C, M. Eichenbaum and S. Rebelo, "Labor Hoarding and the Business Cycle," Journal of Political Economy, 101 (1993), 245-73.

____________________, "Capital Utilization and Returns to Scale" in B. Bernanke and J. Rotemberg, eds., NBER Macroeconomics Annual, MIT Press: Cambridge, Ma., 1995, 67-123.

Caballero, R. and R. Lyons, "External Effects in U.S. Procyclical Productivity," Journal of Monetary Economics, 29 (1992), 209-225.

Chatterjee, S. and R. Cooper,"Entry and Exit, Product Variety and the Business Cycle," NBER Working Paper #4562,1993.

Chatterjee, S., R. Cooper and B. Ravikumar, "Strategic Complementarity in Business Formation: Aggregate Fluctuations and Sunspot Equilibria," Review of Economic Studies, 60 (1993), 795-811.

Christiano, L., M. Eichenbaum and C. Evans, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," REStat, 78 (1996), 16-34.

Cooper, R. and J. Haltiwanger, "Evidence on Macroeconomic Complementarities," REStat, 78 (1996), 78-93.

Cooper, R. and A. John, "Coordinating Coordination Failures in Keynesian Models," Quarterly Journal of Economics, 103 (1988), 441-63.

Diamond, P. "Aggregate Demand Management in Search Equilibrium," Journal of Political Economy, 90 (1982), 881-94.

Drazen, A. "Cyclical Determinants of the Natural Level of Economic Activity," International Economic Review, 26 (1985), 387-97.

Durlauf, S. "Multiple Equilibria and Persistence in Aggregate Fluctuations" American Economic Review, 81 (1991), 70-74.

Farmer, R. and J.T. Guo, "Real Business Cycles and the Animal Spirits Hypothesis," Journal of Economic Theory, 63 (1994), 42-72.

Gale, D., "Delay and Cycles," Review of Economic Studies, 63 (1996), 169-98.

Hall, R. "The relation between Price and Marginal Cost in U.S. Industry," Journal of Political Economy, 96(5), (1988), 921-47.

__________"Invariance Properties of Solow's Productivity Residual," in Growth/ Productivity/ Unemployment, edited by P.Diamond, Cambridge, MA,MIT Press, 1990.

Hart, O. "A Model of Imperfect Competition with Keynesian Features," Quarterly Journal of Economics, 97 (1982), 109-38.

Heller, W. "Coordination Failure Under Complete Markets with Applications to Effective Demand," in Equilibrium Analysis, Essays in Honor of Kenneth J. Arrow , Volume II, edited by Walter Heller, Ross Starr and David Starrett, Cambridge, Cambridge University Press, 1986.

Howitt, P. "Transactions Costs in the Theory of Unemployment," American Economic Review, 75 (1985), 88-101.

Howitt, P. and P. McAfee, "Stability of Equilibria with Externalities", Quarterly Journal of Economics, 103 (1988), 261-77.

King, R., Plosser, C. and S. Rebelo, "Production, Growth and Business Cycles: I. The Basic Neoclassical Model," Journal of Monetary Economics, 21 (1988a), 195-232.

_____________, "Production, Growth and Business Cycles: II. New Directions," Journal of Monetary Economics, 21 (1988b), 309-41.

Kiyotaki, N. "Multiple Expectational Equilibria Under Monopolistic Competition," Quarterly Journal of Economics, 103 (1988), 695-766.

Klenow, P. "Externalities and Economic Fluctuations," mimeo, Stanford University, 1991.

________"Not Learning by Not Doing," mimeo, University of Chicago, 1993.

Lucas, R. "On the Mechanics of Economic Development," Journal of Monetary Economics, 22 (1988), 3-42.

Romer, P. "Increasing Returns and Long-run Growth," Journal of Political Economy, 94 (1986), 1002-37.

Shapiro, M. "Assessing the Federal Reserve's Measures of Capacity and Utilization," Brookings Papers on Economic Activity, 1989 (1), 181-225.

Stadler, G. "Business Cycle Models with Endogenous Technology," American Economic Review, 80 (1990),763-78.

Tobin, J. "Stabilization Policy Ten Years After," BPEA, (1980), 19-71.

Table 1
Results from Annual 2-digit Data

Specification	labor	electricty	dynamic	contemp.
OLS	.31 (.01)	.26 (.02)	.25 (.02)	.57 (.02)
IV	.43 (.025)	.12 (.03)	.26 (.02)	.62 (.03)
IV-lagged	.22 (.017)	.38 (.024)	.37 (.029)	.49 (.05)
IV-Dyn. Only	.62 (.02)	.38 (.03)	.37 (.04)	
IV-capital	.28 (.03)	0.0001 (0.0001)	.33 (.03)	.7 (.03)
IV-CRS			.32 (.018)	.24 (.024)

* Standard errors are reported below the coefficient estimates

Table 2
Additional Results: Annual 2-digit Data

Specification	labor	electricity	dynamic	contemp.
IV- emp	.45 (.004)	.38 (.001)	.008 (.002)	.57 (.005)
IV - Gross	.14 (.014)	.21 (.02)	.67 (.02)	.39 (.03)
IV-Gross Growth	.49 (.04)	.32 (.036)	.09 (.02)	.24 (.05)

* Standard errors are reported below the coefficient estimates

Table 3
Microeconometric Evidence

Plant Level Regressions of Real Value Added in 3711 (standard errors in parentheses)						
variable	1	2	3	4	5	6
total hours	.86 (.051)	.67 (.054)	.784 (.036)	.814 (.035)	.938 (.037)	.94 (.037)
electricity		.388 (.048)	.113 (.033)	.104 (.03)	.042 (.031)	.042 (.03)
sectoral output			.889 (.028)	.55 (.07)	.312 (.065)	.27 (.078)
lagged output				.33 (.07)		.07 (.07)
fixed effects	yes	yes	yes	yes	yes	yes
time trend					.054 (.006)	.051 (.005)
nobs	764	764	764	764	764	764

Table 4
IID Technology Shocks

Treatment	Corr. with Y Contemporaneous				Standard Deviation Relative to Y				Statistics for Y	
	C	Hr	In	Sr	C	Hr	In	Sr	sd	sc
$\alpha=.64$, $\Phi=.36$, $\epsilon=0$, $\gamma=0$	.36	.98	.99	.99	.18	.76	4.0	.52	.015	.02
$\alpha=.62$, $\Phi=.38$, $\epsilon=0$, $\gamma=.37$	.63	.88	.94	.99	.48	.63	3.2	.53	.02	.72
$\alpha=.64$, $\Phi=.36$, $\epsilon=.24$, $\gamma=.32$	.91	.59	.86	.99	.83	.33	2.0	.58	.07	.95
U.S. Data	.85	.07	.6	.76	.69	.52	1.3	1.1	.06	.96

Table 5
IID Taste Shocks

Treatment	Corr. with Y Contemporaneous				Standard Deviation Relative to Y				Statistics for Y	
	C	Hr	In	Sr	C	Hr	In	Sr	sd	sc
$\alpha=.64$, $\Phi=.36$, $\epsilon=0$, $\gamma=0$	.86	.11	-.84	0	17	1.8	51	0	.0001	.2
$\alpha=.62$, $\Phi=.38$, $\epsilon=0$, $\gamma=.37$	.55	.05	-.45	.85	10.6	1.1	28.9	.37	.0007	.85
$\alpha=.64$, $\Phi=.36$, $\epsilon=.24$, $\gamma=.32$	.54	.89	-.4	.94	7.5	1.2	21.7	.54	.001	.82
U.S. Data	.85	.07	.6	.76	.69	.52	1.3	1.1	.06	.96

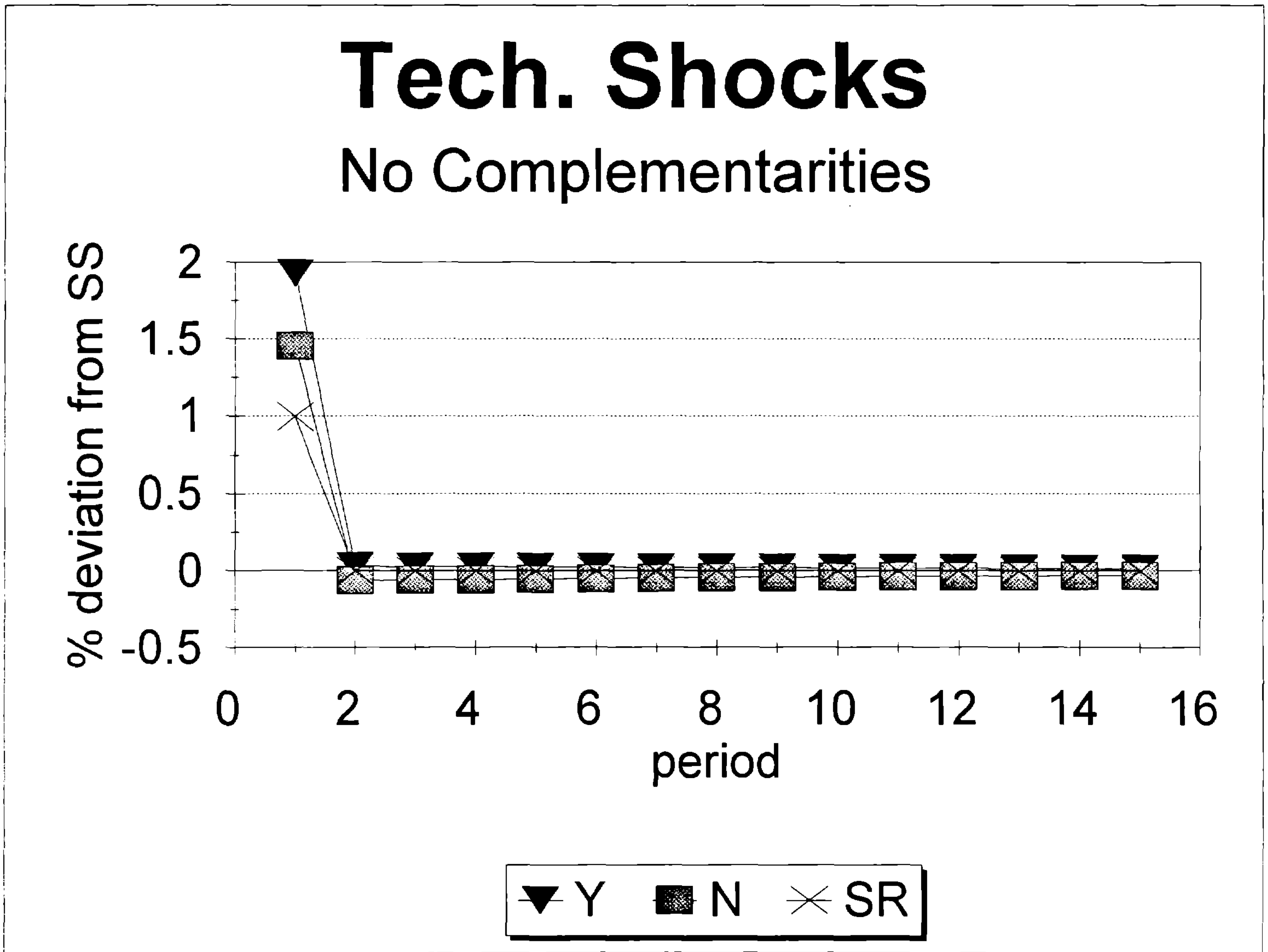
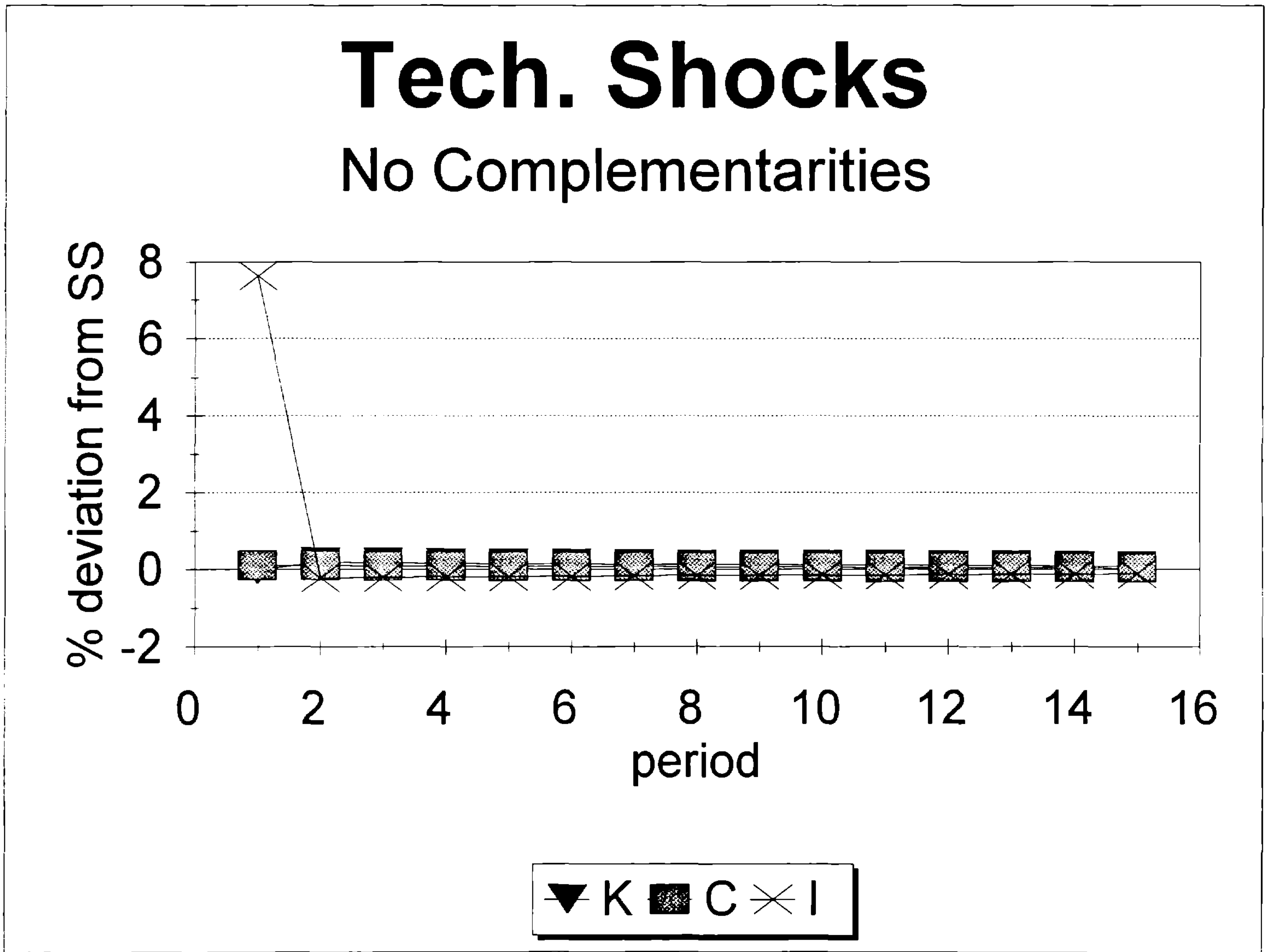

Tech. Shocks
No Complementarities
% deviation from SS
2
1.5
1
0.5
0
-0.5
0
2
4
6
8
10
12
14
16
period
Y
N
SR

Figure 1a



Tech. Shocks
No Complementarities
% deviation from SS
8
6
4
2
0
-2
0
2
4
6
8
10
12
14
16
period
K
C
I

Figure 1b

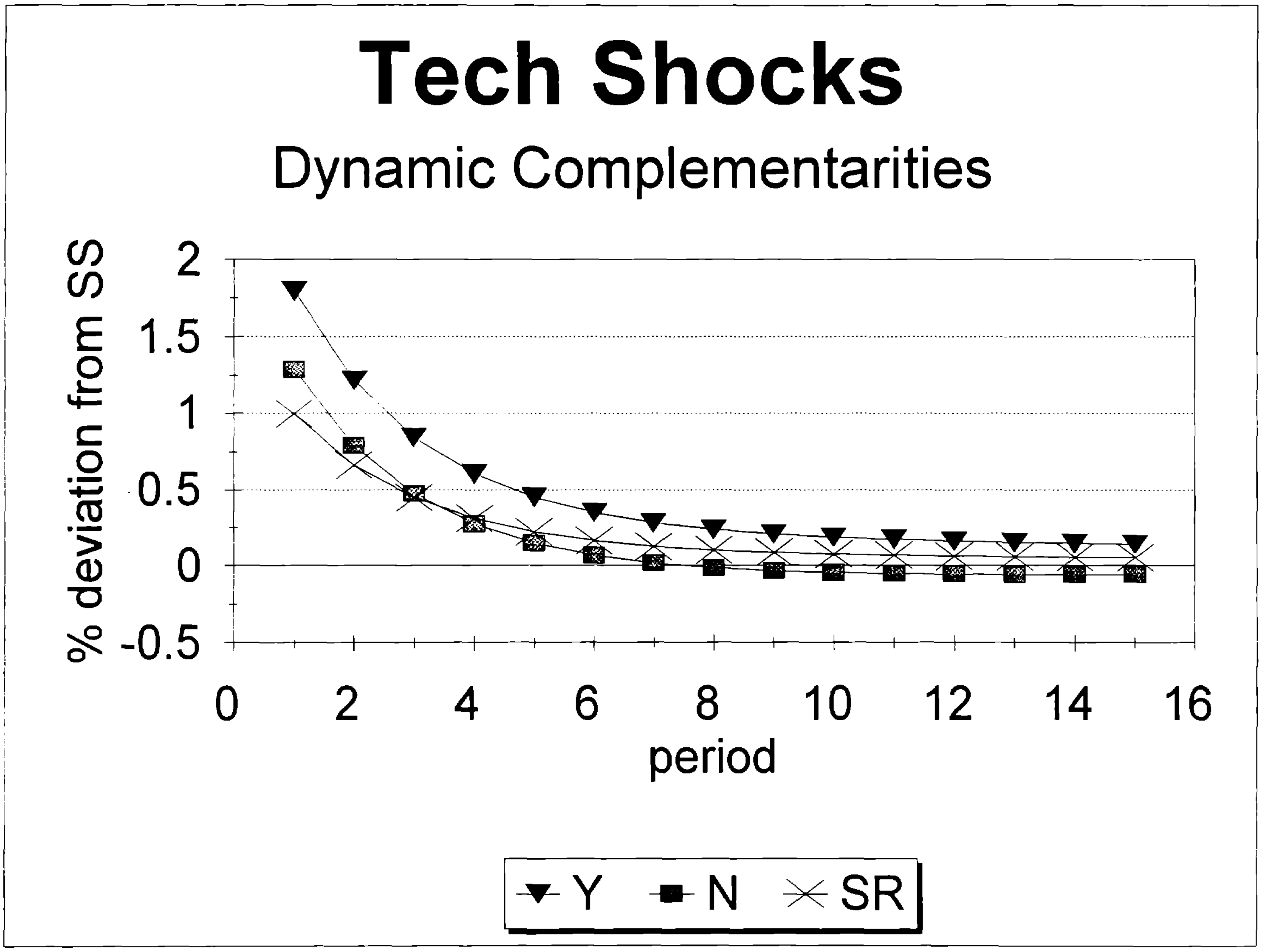

Tech Shocks
Dynamic Complementarities
% deviation from SS
2
1.5
1
0.5
0
-0.5
0
2
4
6
8
10
12
14
16
period
Y
N
SR

Figure 2a

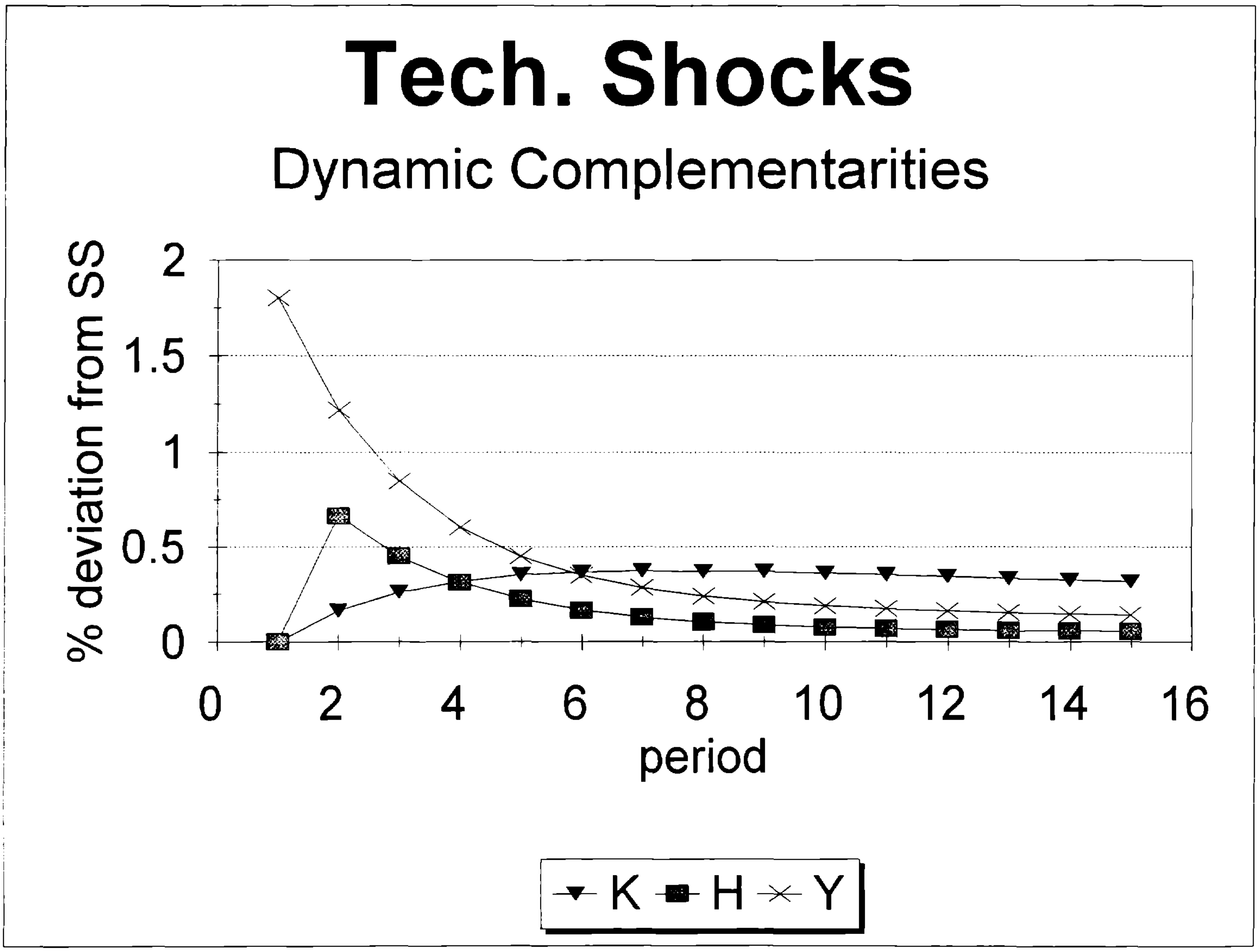

Tech. Shocks
Dynamic Complementarities
% deviation from SS
2
1.5
1
0.5
0
0
2
4
6
8
10
12
14
16
period
K
H
Y

Figure 2b

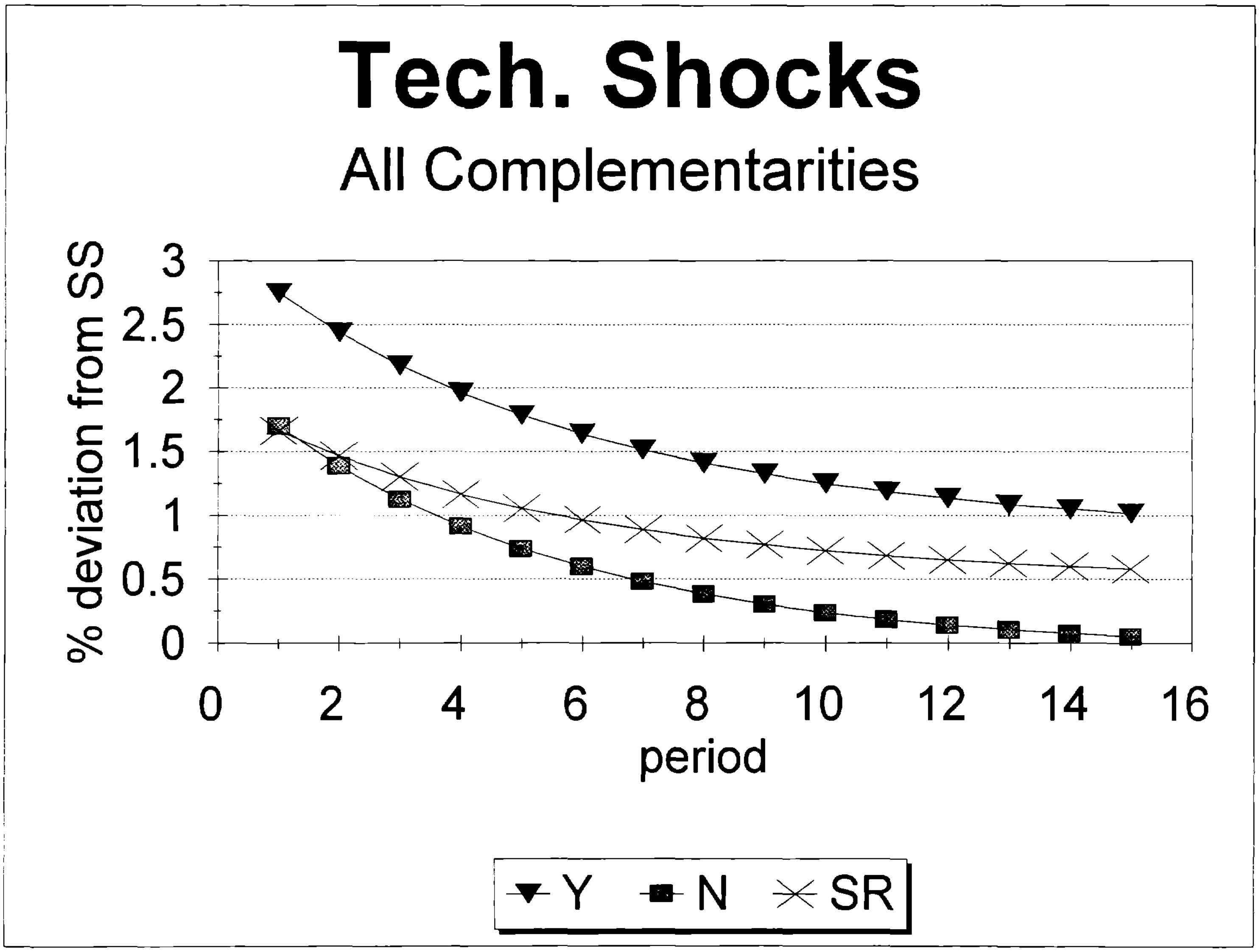

Tech. Shocks
All Complementarities
% deviation from SS
3
2.5
2
1.5
1
0.5
0
0
2
4
6
8
10
12
14
16
period
Y
N
SR

Figure 3a

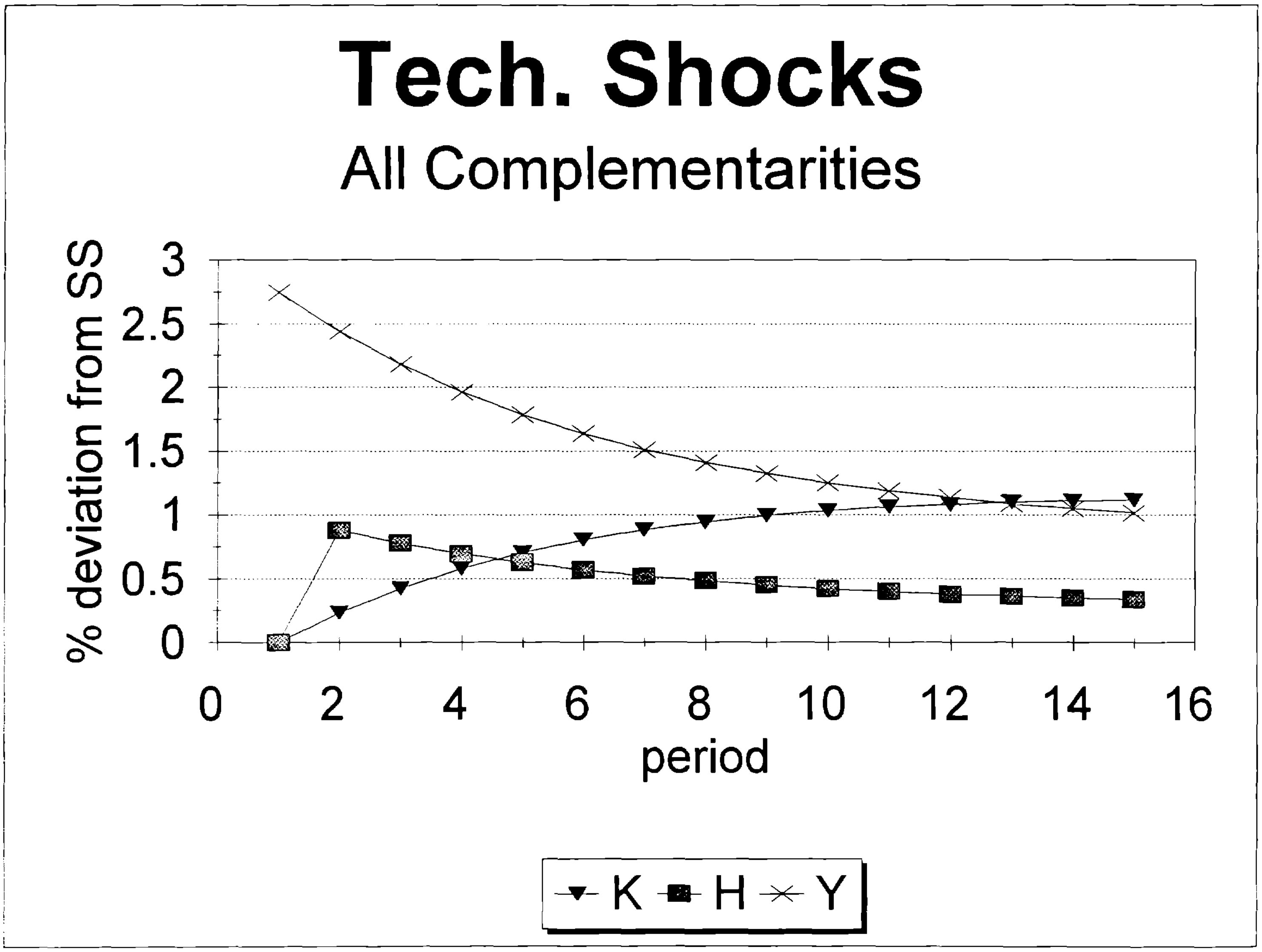

Tech. Shocks
All Complementarities
% deviation from SS
3
2.5
2
1.5
1
0.5
0
0
2
4
6
8
10
12
14
16
period
K
H
Y

Figure 3b

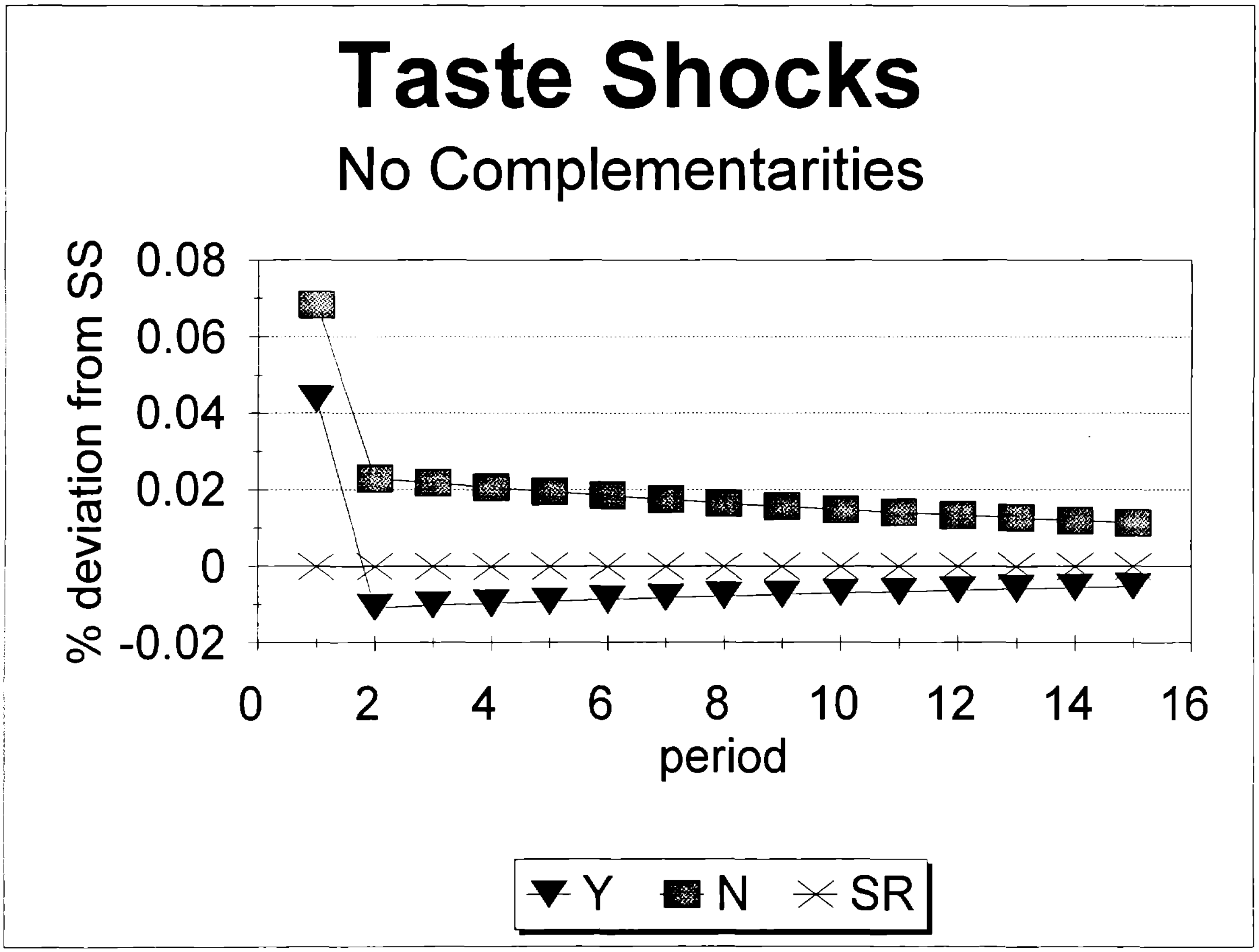

Taste Shocks
No Complementarities
% deviation from SS
0.08
0.06
0.04
0.02
0
-0.02
0
2
4
6
8
10
12
14
16
period
Y
N
SR

Figure 4a

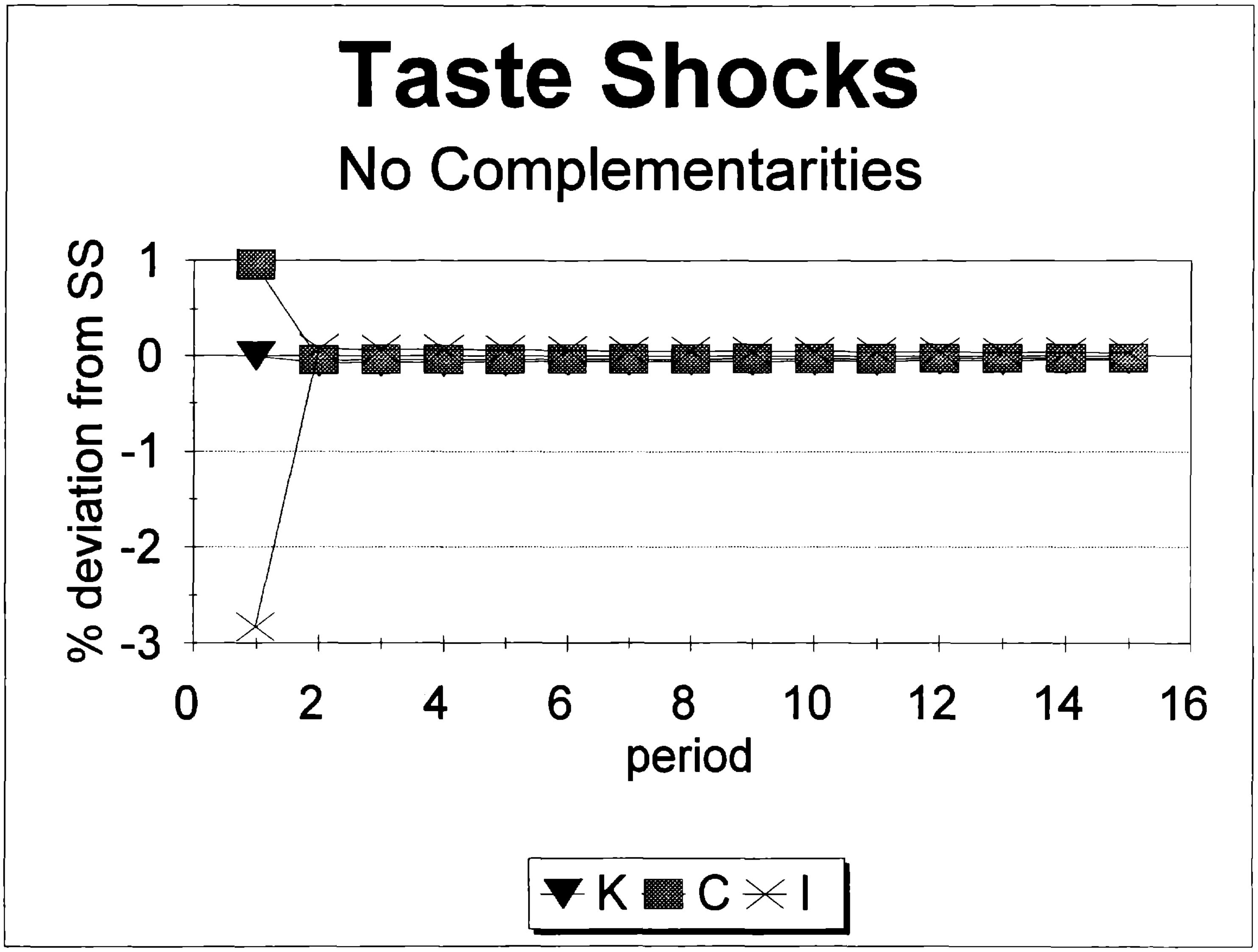
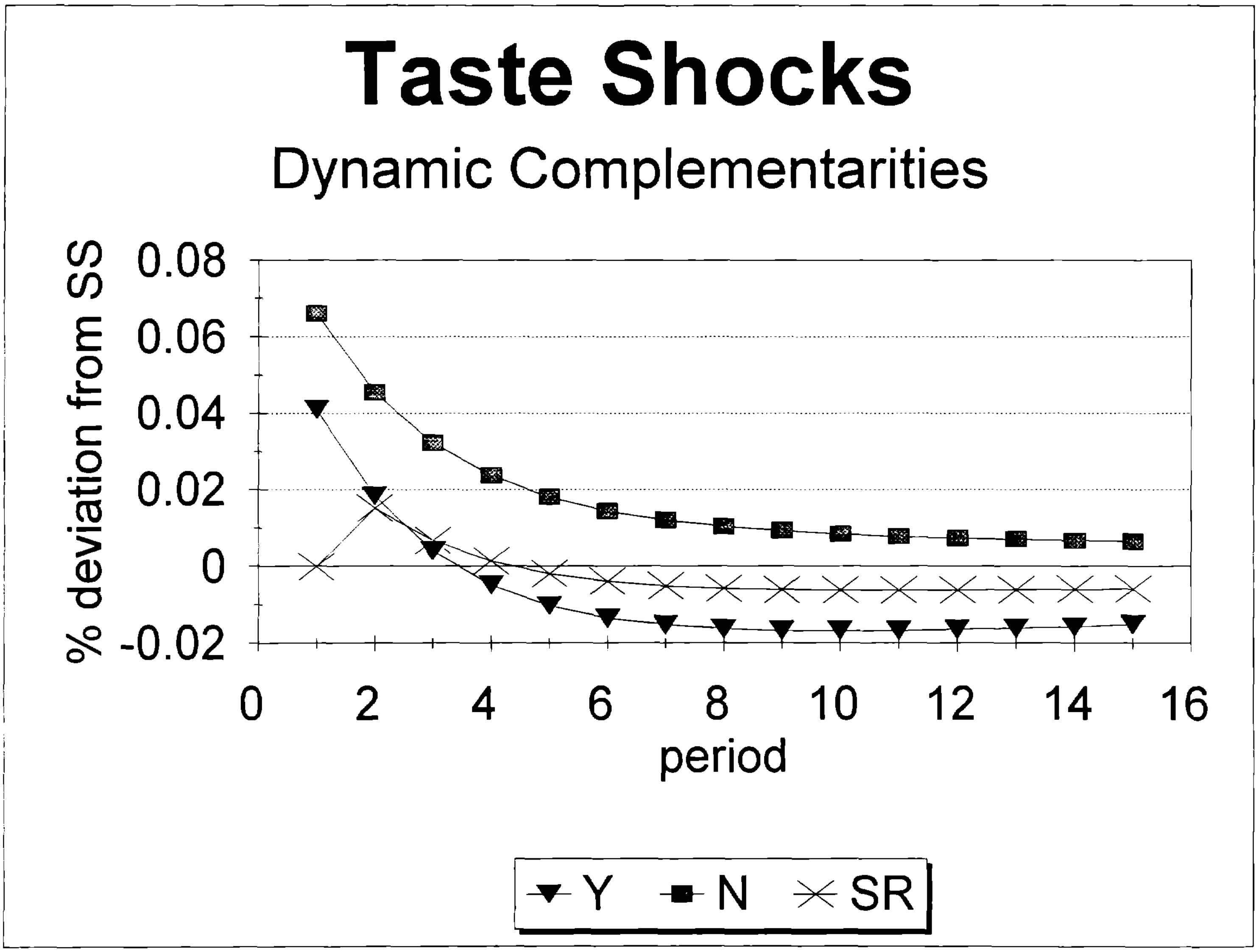

Taste Shocks
No Complementarities
% deviation from SS
1
0
-1
-2
-3
0
2
4
6
8
10
12
14
16
period
K
C
I

Figure 4b



Taste Shocks
Dynamic Complementarities
% deviation from SS
0.08
0.06
0.04
0.02
0
-0.02
0
2
4
6
8
10
12
14
16
period
Y
N
SR

Figure 5a

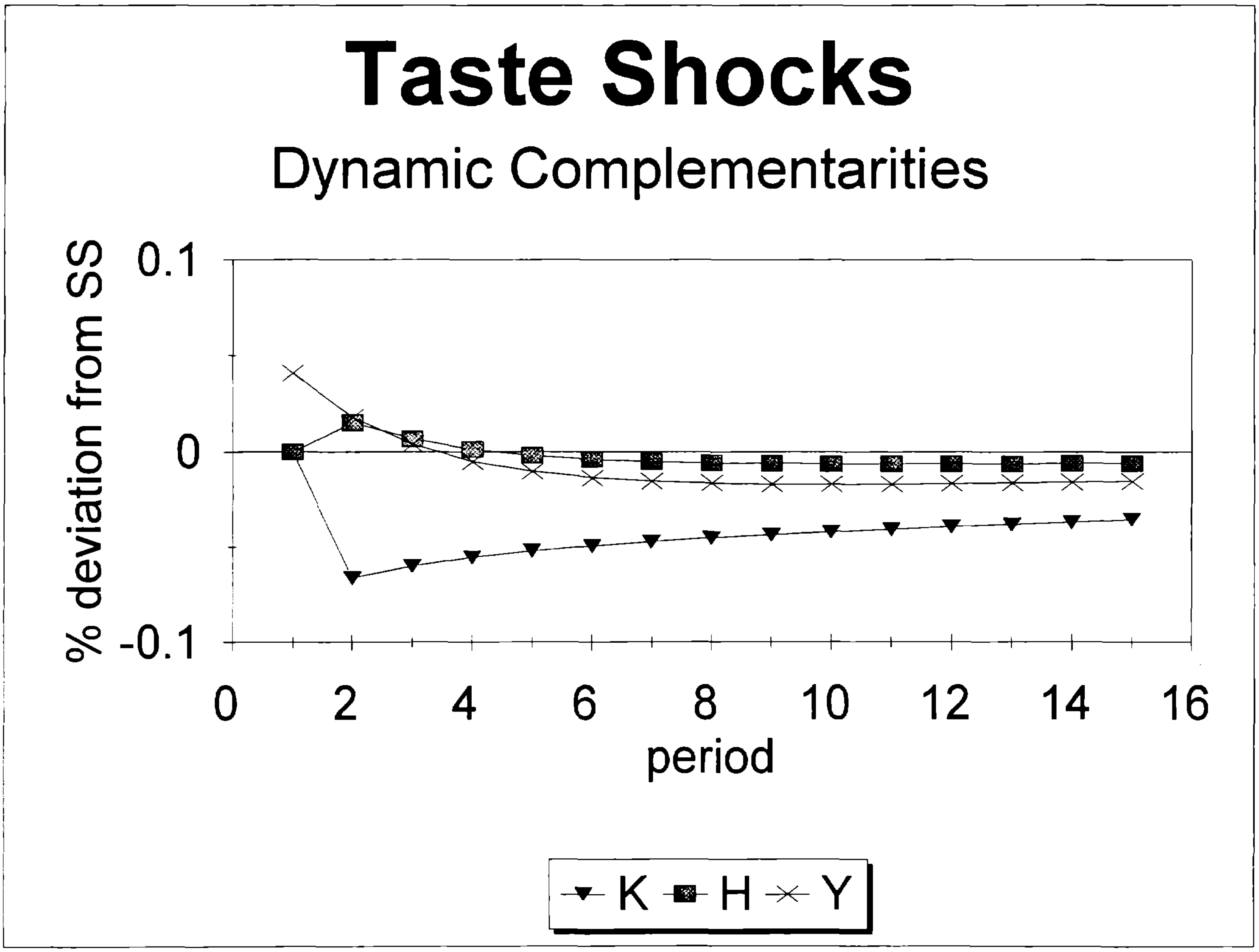
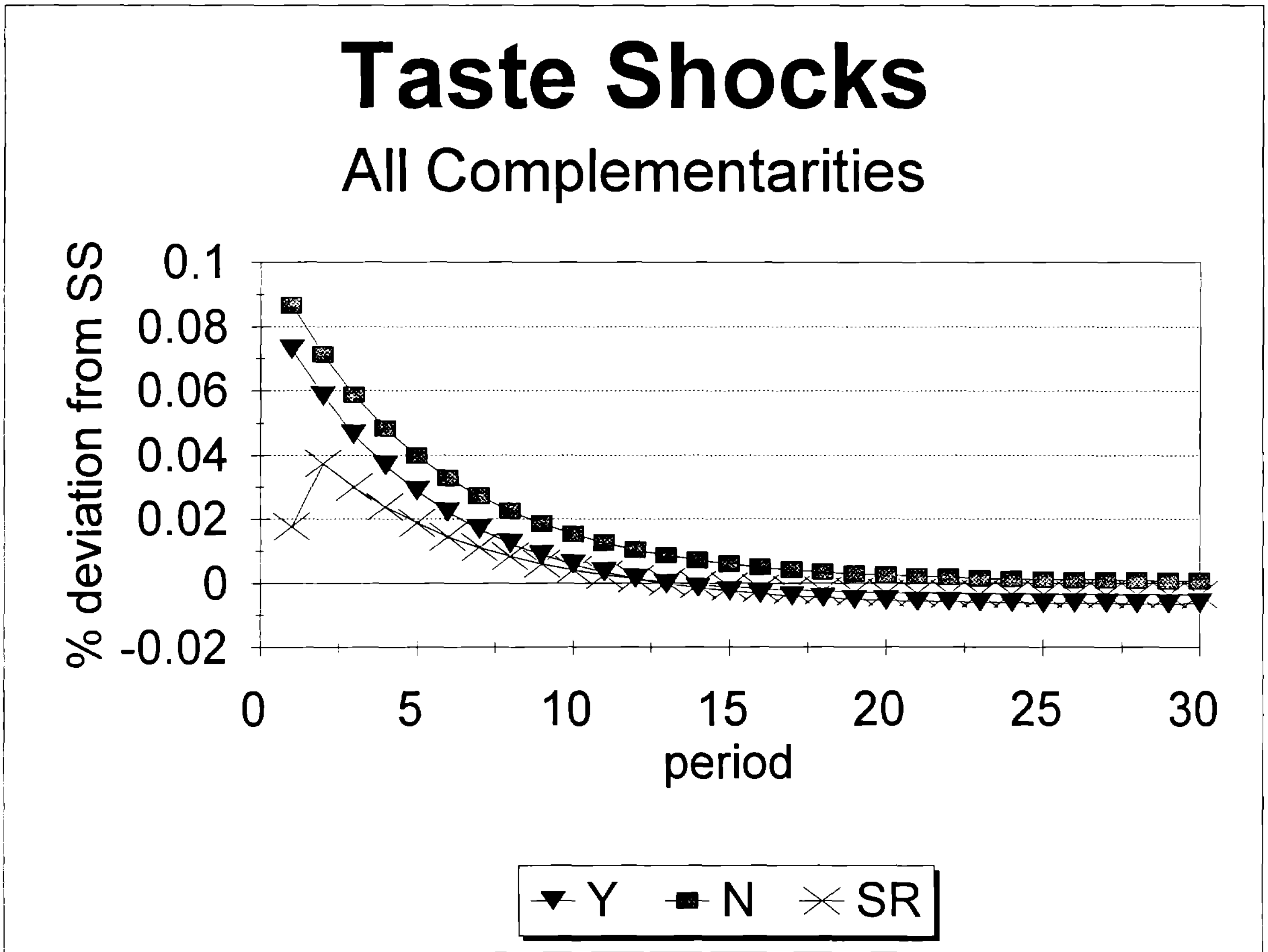

Taste Shocks
Dynamic Complementarities
% deviation from SS
0.1
0
-0.1
0
2
4
6
8
10
12
14
16
period
K
H
Y

Figure 5b



Taste Shocks
All Complementarities
% deviation from SS
0.1
0.08
0.06
0.04
0.02
0
-0.02
0
5
10
15
20
25
30
period
Y
N
SR

Figure 6a

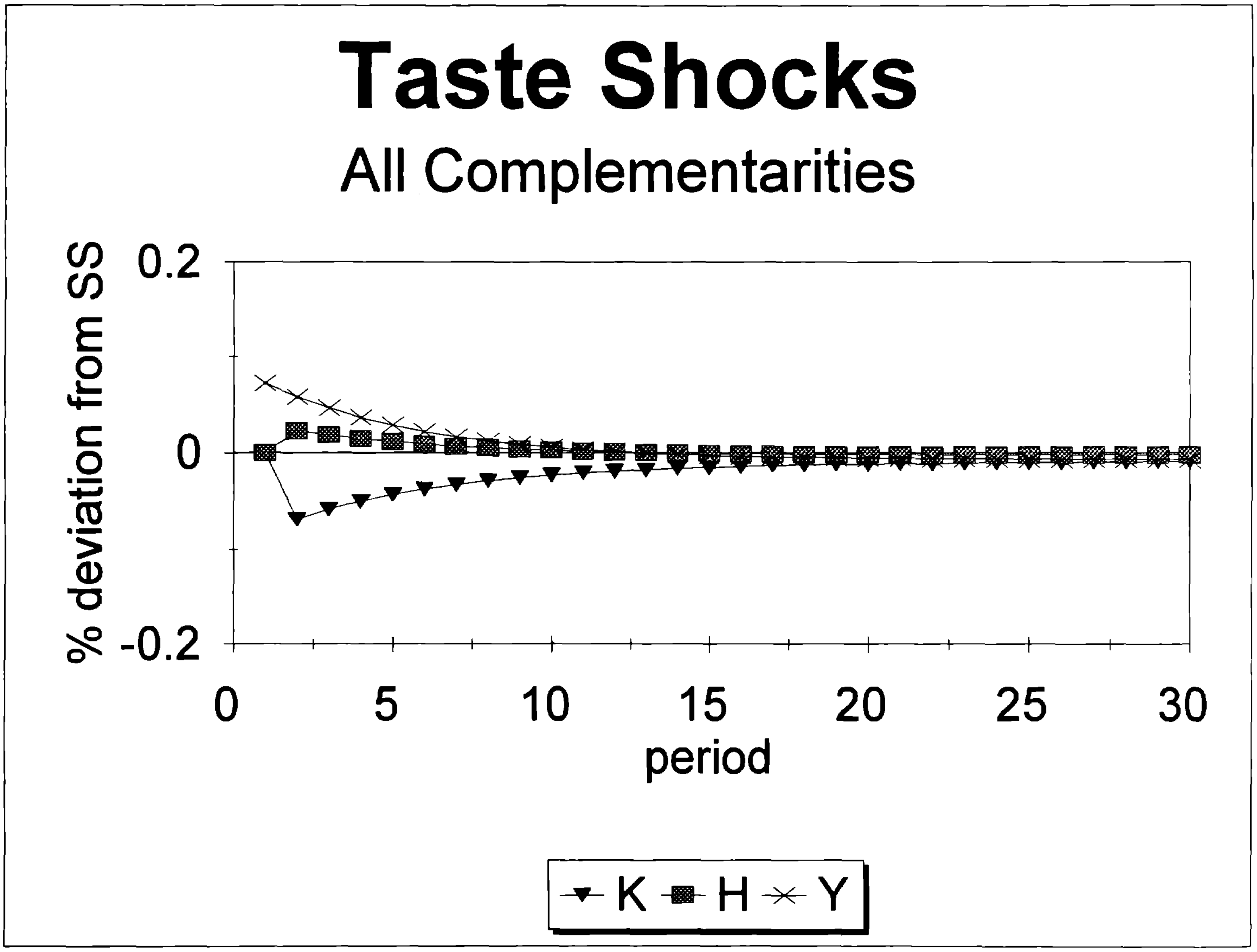

Taste Shocks
All Complementarities
% deviation from SS
0.2
0
-0.2
0
5
10
15
20
25
30
period
K
H
Y

Figure 6b