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A Flexible Price Explanation

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Abstract

I present empirical evidence of how the U.S. economy, including per-capita hours worked, responds to a technology shock. In particular, I present results based on permanent changes to a constructed direct measure of technological change for U.S. manufacturing industries.

Based on empirical evidence, some claim that hours worked declines and never recovers in response to a positive technology shock. This paper's empirical evidence suggests that emphasizing the drop in hours worked is misdirected. Because the sharp drop in hours is not present here, the emphasis rather should be on the small (perhaps negative) initial response followed by a subsequent large positive response. Investment, consumption, and output have similar dynamic responses.

In response to a positive technology shock, a standard flexible price model would have an immediate increase in hours worked. Therefore, such a model is inconsistent with the empirical dynamic responses. I show, however, that a flexible price model with habit persistence in consumption and certain kinds of capital adjustment costs can better match the empirical responses.

Some recent papers have critiqued the use of long run VARs to identify the dynamic responses to a technology shock. In particular they report that, when long run VARs are applied to data simulated from particular economic models, the point estimates of the impulse responses may be imprecisely estimated. However, based on additional simulation evidence, I find that, although the impact response may be imprecisely estimated, a finding of a delayed response is much more likely when the true model response also has a delayed response.

Keywords macroeconomic models, vector autoregressions, impulse responses, weak instruments, long-run identification assumption

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1 Introduction

Recent papers by Galí (1999), Basu, Fernald, and Kimball (2004), and Francis and Ramey (2003) have claimed that in response to an unexpected improvement in technology, hours spent working declines. This finding challenges the standard macroeconomic flexible-price model because that model predicts a strong positive correlation between employment and technology.

This paper's empirical evidence suggests that emphasizing the drop in hours worked is misdirected. Because the sharp drop in hours is not present in several of the data series examined here, the emphasis rather should be on the small (perhaps negative) initial response followed by a subsequent large positive responses. The paper also presents a flexible-price model that is broadly consistent with the empirical dynamic responses. The empirical evidence describes how the economy responds to shocks to a productivity measure that has been corrected for utilization and reallocation. For the quantities considered here (output, consumption, investment, and hours worked), a consistent pattern emerges. When the technology shock occurs, the variables respond only slightly. Over time, the variables' dynamic responses gain strength.

To be consistent with the empirical responses, the standard quantitative dynamic flexible-price model must be modified. The modifications pursued here are to make utility depend on past consumption (habit persistence) and to have capital adjustment costs.

Galí (1999) and Francis and Ramey (2003) measure productivity using aggregate labor productivity. Aggregate labor productivity, however, is a poor measure of technology because it can change for many reasons besides technological growth. In particular, in response to changes in the economy, workers sometimes vary their effort and, hence, output. Because this variation in the utilization of inputs is unobservable, changes in the utilization rate will appear as changes in productivity. To obtain an accurate measure of how technology increases productivity, one must control for these changes in utilization. In addition, reallocation of labor from an industry with low labor productivity to an industry with high labor productivity will also show up as in improvement in aggregate labor productivity that may not be due to increases in technology.

Combining the methods of Burnside, Eichenbaum, and Rebelo (1996) and Basu, Fernald, and Kimball (2004), the current paper constructs a quarterly measure of productivity that has been corrected for variations in utilization and also for reallocation between industries. In spite of the steps taken to remove endogenous influences, this productivity measure still might be influenced by other economic variables. To control for this endogeneity, I use the long-run approach of Galí (1999) to consider how the economy responds to exogenous shocks to the productivity series. The empirical results support the view that the immediate response to a technology shock is either negative or small. Although the initial responses are small, this paper shows that, within six quarters, the responses are positive and large.

The empirical work is presented with an emphasis on robustness. The paper considers responses to a technology shock identified under different identification assumptions. In addition, the paper reports confidence intervals for the impact response of a technology shock that are valid under the assumption of weak instruments. Although the resulting confidence intervals are wide, compared to the possible range associated with an unidentified shock, the identification scheme does restrict the possible responses.

Having documented how the economy responds to a technology shock, the challenge is to construct a model that has the same dynamic responses. The empirical responses are incompatible with a standard quantitative dynamic flexible-price model; because, in the standard model, the period of the technology shock is when the variables respond most. The model needs to be modified to generate a more realistic delayed dynamic response. Galí (1999) and Basu, Fernald, and Kimball (2004) propose to resolve the model's problem by including sticky prices. Basu (1998) presents a sticky price model that successfully matches the immediate small empirical responses to a technology shock but fails to match the medium-term empirical responses. With both sticky prices and wages, Altig, Christiano, Eichenbaum and Linde (2004) better match these responses. The current paper does not use sticky prices. Rather it uses a flexible-price model with modifications to both preferences and technology. Preferences are modified such that today's utility depends on the previous level of consumption, habit persistence. Habit persistence implies that consumption responds more slowly to an increase in technology. Just habit persistence, however, is not enough to match the data. The technology to transform investment into capital must be modified to dampen the responses by investment and output. The paper presents two specifications for the investment technology: time-to-plan and convex capital adjustment costs. When the capital adjustment costs depend on the ratio of new investment to capital, the model can match the initial period's responses but fails to match the subsequent increases. Having the adjustment costs depend on the growth rate of investment results in a better match to the long-run response. A time-to-plan model also matches but, with only one kind of investment good, its responses are somewhat too jagged. These last two specifications work better because although they constrain the initial response by investment they allow the subsequent responses to be strong.

Although these models can match the consumption, investment and hours worked responses, the models presented here have a difficult time matching the response of the real interest rate. Although there is some uncertainty with respect to the true real interest rate response, the empirical impulse responses, in general, indicate that the real interest rate increases in response to a positive technology shock. Chiefly because of habit persistence, in the reported economic models, the real interest rate instead falls in response to a positive technology shock. I show that a model with consumption adjustment costs can better match the real interest rate response. Even this model, however, does not completely capture the empirical response by the real interest rate.

Recent papers by Erceg, Guerrieri and Gust (2004) and Chari Kehoe and McGrattan (2004) have critiqued the use of long-run VARs to construct impulse responses. Using simulated data from particular economic models, they show that, for these particular models, the point estimates of long run VARs are imprecisely estimated. However, when I adopt their approach of simulating data from a benchmark model, I find further evidence in favor of studying the shape of the impulse responses. Although the impact response may be imprecisely estimated, a finding of a delayed response is much more likely when the true model response also has a delayed response.

2 Empirical Work

This paper's empirical work combines the two approaches taken in the literature to study productivity shocks. As in Basu Fernald and Kimball (2004), industry-level data is used to construct a utilization-corrected aggregate technology series. This series is then used as a variable in a vector autoregression, where, as in Galí (1998), exogenous technology shocks are identified under the assumption that only exogenous technology shocks affect the permanent level of productivity. In the first subsection, I describe how to use fluctuations in electricity usage (as in Burnside, Eichenbaum and Rebelo (1996)) and fluctuations in average hours (as in Basu Fernald and Kimball (2004)) to construct a quarterly utilization-corrected technology series. In the second subsection, I then use the same vector autoregression approach that Galí (1999) and Francis and Ramey (2003) used for labor productivity to calculate impulse responses to a permanent shock to my constructed technology series. The main findings are that the response by per capita hours worked is initially small but ,within two years, hours worked experiences a large increase.

2.1 Accounting For Utilization and Reallocation

Forces besides technological progress affect labor productivity. In particular, the effort expended by workers and machines can vary endogenously over time. One cannot always observe this time-varying utilization of inputs, which can be a serious issue in measuring technology growth because a change in utilization can be mistaken for a change in technology.

This section uses methods proposed by Basu, Fernald, and Kimball (2004) [BFK] and Burnside Eichenbaum and Rebelo (1996) [BER] to approximate the changes in utilization with changes in observable variables. BFK approximate changes in utilization by using changes in average hours worked. The intuition for this approximation is that a firm would choose to vary both workers' hours and utilization until the costs and the benefits are the same.[1] BER approximate changes in capital services by changes in electricity usage. In addition, because reallocation can increase aggregate productivity without requiring an increase in technology, one should also control for reallocation between industries. As is done in BFK, the aggregate productivity series is constructed by aggregating industry-level productivity series.

To calculate the productivity series at the quarterly frequency requires a few strong assumptions. Because the industry-level capital stock is unobservable at the quarterly frequencies, changes in electricity usage are used to approximate the changes in capital services. Because data on material usage is unavailable at the quarterly frequency, one must assume that there is very limited substitutability between materials and a mix of capital services and labor. BFK have been critical of estimating productivity without data on materials usage. In trying to measure quarterly productivity growth, it, however, is likely better to implement partially their methods than not use them at all.

Industry-Level Data The productivity equation is estimated using quarterly data at the industry level between 1972 to 2001. As in BFK, these industry-level productivity series are then aggregated to generate an economy-wide productivity series.[2] The industries used here are the eighteen two-digit SIC manufacturing industries. Their names and SIC codes are reported in Table 1.

[1] In more formal terms, using hours to approximate for utilization implies an assumption that, at least for empirically relevant values, the output expansion path is an upward sloping line. The assumption would be satisfied if output were produced, for example, by a homothetic production function (such as Cobb-Douglas) using hours and utilization with constant costs of increasing either input.

[2] A lack of data requires the use of this manufacturing-based technology measure to approximate the economy-wide fluctuations in technology.

Applying the methods of BER and BFK results in the following equation whose residual is a measure of productivity growth. Output and all the inputs are expressed in logged first differences of quarterly data. For each industry j, the growth rate at quarter t of the productivity series $\Delta z_{j,t}$ will be the residual from the following estimated equation[3]:

$$\Delta y_{j,t} = \mu_j \left(s^v_{k,j} \Delta k_{j,t} + s^v_{l,j} \left(\Delta h_{j,t} + \Delta e_{j,t} \right) \right) + \xi_j \Delta h_{j,t} + \Delta z_{j,t} \tag{1}$$

This output data Δy will be measured by the Federal Reserve's measures of industrial production. The capital services variable Δk will be approximated by data on electricity usage.[4] The average hours Δh and employment data Δe are taken from the corresponding BLS measure. The capital s^v_k and labor shares s^v_l are calculated as the average value-added shares from the BLS KLEMS database.[5] The values of μ and ξ are estimated. The values of μ and ξ are constrained to be the same for all durable good sectors and the same for all nondurable good sectors.

In aggregating these industry level estimates, the aggregation equation is the same as in BFK.[6] Aggregate productivity is calculated as

$$\Delta z_{\text{agg},t} = \sum w_j \frac{\Delta z_{j,t}}{1 - \mu_j s_{m_j}} \tag{2}$$

The weight w_j is the share of value added by industry j. The share of materials s_{m_j} is calculated using the materials share of gross-output reported in the KLEMS dataset.

The parameters are estimated using two-step GMM under the assumption that the values of Δz_{it} and Δz_{jt} are correlated but that there is no serial correlation. I use the three instruments that are commonly used in estimating this kind of production function. One of the instruments is the previous quarter's value of the Federal Funds shock resulting from the monetary VAR estimated in Christiano, Eichenbaum, and Evans (2001). The second instrument is the current and previous quarters' values of the difference between the aggregate GDP price deflator and the growth rate of the price of oil.[7] The third instrument is the current

[3] This equation is similar to that estimated in Burnside Eichenbaum and Rebelo (1996) and in Conley and Dupor (2003) except for two differences. First, these authors don't use the average hours correction, represented in Equation 2 by $\xi h_{j,t}$. Second, the value of μ is estimated as the sum of the shares of capital services and labor which are estimated separately. In other words, they don't use the information on KLEMS shares but rather just estimate the shares. Impulse responses generated using this approach were similar to the ones reported in the paper.

[4] Some might be concerned that electricity usage might be overly sensitive to weather fluctuations. Because the electricity usage data is on a national basis, geographic diversification should limit any dependence on weather.

[5] The KLEMS dataset is used to measure multi-factor productivity as the annual frequency. It and the Canadian equivalent are featured in Vigfusson (2003).

[6] This aggregation equation calculates the increase in aggregate technology resulting from industry-level technology growth holding the distribution of inputs among industries fixed.

[7] The results reported here use the IMF world price of oil, an average of international well-head prices. Other researchers including Basu, Fernald, and Shapiro (2001) have used the Producer Price Index for crude oil as an instrument. The Producer Price Index, however, only measures the price paid for domestic but not foreign oil. Not including foreign oil results in a very misleading price series because, between the summer of 1973 and January 1981, American produced oil was under government-imposed price controls. Because of these price controls, the PPI does not measure the true cost of oil. In particular, it does not capture the dramatic effect of the oil shocks of 1973 and 1979 that are observable in other series such as the IMF oil series or the Department of Energy's series, Refiner Acquisition Nominal Cost of Imported Crude Oil.

and previous quarters' growth rate in real defense spending.[8]

The GMM estimator requires an estimate of the variance-covariance matrix. Because, the estimation exercise is a system of equations for eighteen industries, the unconstrained version of the variance-covariance matrix requires a large (171) number of parameters. To reduce this number, one could place structure on the correlation between sectors. Conley and Dupor (2003) assume that the industries that use similar inputs have similar patterns of productivity. Given my interest in aggregated quantities, this correction has only a small effect on the aggregated results. [9]

2.1.1 Results

The coefficient estimates are reported in Table 2. For the nondurable goods producing sectors, the estimate of the mark-up parameter μ is less than one. The difference between the estimate and constant returns, however, is not statistically significant. Some of the estimates reported in BFK were also less than one. They argue (p.29) that one possible explanation for these low estimates of μ is the omitted variable bias that would result from not including an estimate of reallocation effects.

The estimates of ξ are positive and significantly different from zero. Positive coefficients imply that when utilization growth and, therefore, average hours growth are high, the growth in the utilization-corrected measure of productivity is less than the growth in the measure of uncorrected productivity.

Although the work here has tried to construct a technology series that corrects for utilization and reallocation, one may be concerned that the series is still affected by measurement error. A such, this estimated technology series will be combined with a long-run identification assumption to identify the part of this series that seems to have a long-run affect on the level of technology. The next section describes how to implement such a long-run identification assumption.

2.2 Estimating A Vector Autoregression with A Long Run Identification Assumption

Here, as in Galí (1999), a technology shock will be identified as a permanent shock to productivity.[10] These shocks and resulting impulse responses are computed in the following manner.

[8] To specify these variables as instruments requires an assumption that these variables are uncorrelated with the technology shocks. There are models in which this assumption would be violated. For example, if implementation cycles models (Shleifer 1986) were empirically relevant, then these variables may be correlated. In such a model, reductions in oil prices could result in an economic expansion that would cause people to implement their ideas increasing productivity.

[9] The aggregation, however, does obscure the important role played by industry-specific productivity growth that is found in US industrial production data in Conley and Dupor (2003) and again in KLEMS data for both Canada and the United States in Vigfusson (2003).

[10] Several recent papers have identified a technology shock using a long-run restriction. These papers include Gali (1999); Francis and Ramey (2003); Altig, Christiano, Eichenbaum, and Linde (2004); and Fisher (2002). Although these methods have proven popular, some researches have critiqued these methods. In particular, Faust and Leeper (1997) describe problems associated with constructing confidence intervals (see footnote 15 for more discussion), and the perils of excluding variables from the VAR. Erceg, Guerrieri,and Gust (2004) present model-based Monte Carlo evidence on the long-run identification assumption. Their work will be discussed in section 4.

Consider the following structural vector autoregression (VAR) for a vector of variables y_t

$$A_0 y_t = A(L) y_{t-1} + \begin{pmatrix} \varepsilon_t^z \\ v_t \end{pmatrix} \tag{3}$$

The vector y_t consists of n elements. The first element is the growth rate of a productivity measure, denoted by Δz_t. Galí measured productivity using labor productivity. Here, I will report results for both labor productivity and also for my constructed measure of technology. The next n-1 elements are the other variables in the VAR x_t.

$$y_t = \begin{pmatrix} \Delta z_t \\ x_t \end{pmatrix} \tag{4}$$

The shocks ε_t^z and v_t (where v_t has $n-1$ elements) are assumed to be independent. Galí identifies the technology shock by assuming that only the technology shock ε_t^z can have a permanent effect on the level of productivity z_t. All other shocks are assumed to have no long-run effect. To impose this restriction is to impose a restriction on the moving average representation of the data. Denote the moving average representation by:

$$\begin{pmatrix} \Delta z_t \\ x_t \end{pmatrix} = \begin{pmatrix} C_{11}(L) & [C_{1j}(L)]_{j=2}^n \\ [C_{j1}(L)]_{j=2}^n & [C_{jk}(L)]_{j,k=2}^n \end{pmatrix} \begin{pmatrix} \varepsilon_t^z \\ v_t \end{pmatrix} \tag{5}$$

the restriction that the long run impact on z_t is zero for all shocks except the first is that, for all the other shocks, the sum of moving average coefficients equals zero. (i.e $[C_{1j}(1)]_{j=2}^n = 0$ for all $j \geq 2$)

To actually estimate the structural VAR with this long-run restriction requires a restriction on the structural VAR coefficients. To make the notation clear, I rewrite the structural VAR as

$$\begin{pmatrix} a_{0,11} - A_{11}(L) & [a_{0,1j}]_{j=2}^n - [A_{1j}(L)]_{j=2}^n \\ [a_{0,j1}]_{j=2}^n - [A_{j1}(L)]_{j=2}^n & [a_{0,jk}]_{j,k=2}^n - [A_{jk}(L)]_{j,k=2}^n \end{pmatrix} \begin{pmatrix} \Delta z_t \\ x_t \end{pmatrix} = \begin{pmatrix} \varepsilon_t^z \\ v_t \end{pmatrix} \tag{6}$$

Because $(A_0 - A(1))$ equals $C(1)^{-1}$, the restriction on $C(1)$ is equivalent[11] to the following restriction on $A_0 - A(1)$

$$a_{0,1j} - A_{1j}(1) = 0 \text{ for all } j \geq 2 \tag{7}$$

To implement this restriction we estimate the equation[12]

$$\begin{pmatrix} a_{0,11} - A_{11}(L) & \tilde{A}(L)(1-L) \end{pmatrix} \begin{pmatrix} \Delta z_t \\ x_t \end{pmatrix} = \varepsilon_t^z \tag{8}$$

To estimate this equation, one has to instrument for Δx_t using x_{t-1}. An discussed in Christiano, Eichenbaum and Vigfusson (2003), if x_{t-1} is non-stationary, then x_{t-1} will be a weak instrument.[13] Section 2.4 considers the weak instrument problem.

[11] The equivalency can be seen by examination of the co-factor formula for the inverse of a matrix.

[12] This specification is the "double difference" approach described in King and Watson (1997).

[13] If the VAR is correctly specified, lagged Δx_{t-i}'s cannot be used as instruments for Δx_t. For a VAR with p lags, the first p values of Δx_{t-i} $\left(\{\Delta x_{t-i}\}_{i=1}^p\right)$ will also be in the equation. Hence, they cannot serve as instruments. Other values $\{\Delta x_{t-i}\}_{i=p+1}^\infty$ are not valid instruments by the definition of the VAR being correctly specified. Being correctly specified implies that these values cannot contain any information about Δx_t beyond that contained in $\{\Delta x_{t-i}\}_{i=1}^p$.

Estimating this equation results in a time series of the technology shocks. To calculate the impulse responses requires the moving average representation of y_t in terms of ε_t^z and v_t. One approach to calculate this moving average representations starts with the reduced form VAR[14]

$$y_t = B(L)y_{t-1} + u_t \tag{9}$$

where u_t is the vector of the n reduced-form residuals. A regression of u_t on ε_t^z results in γ, the first column of A_0^{-1}. The residuals from these regressions would be a linear combination of the other fundamental error terms v_t that are un-correlated with ε_t^z. The impulse response to a one standard-deviation technology shock σ_{ε^z} can be constructed using the column γ and the inverted reduced-form VAR coefficients. The formula for the impulse responses Γ is therefore

$$\Gamma = (I - B(L)L)^{-1}\,\gamma\sigma_{\varepsilon^z} \tag{10}$$

To summarize, the impulse responses can be calculated using the following four steps.

$$\begin{aligned} \begin{pmatrix} a_{0,11} - A_{11}(L) & \tilde{A}(L)(1-L) \end{pmatrix} \begin{pmatrix} \Delta z_t \\ x_t \end{pmatrix} &= \varepsilon_t^z \\ y_t &= B(L)y_{t-1} + u_t \\ u_t &= \gamma\varepsilon_t^z + v_t \\ \Gamma &= (I - B(L)L)^{-1}\,\gamma\sigma_{\varepsilon^z} \end{aligned} \tag{11}$$

2.3 Impulse Responses

The next section reports the dynamic responses to an exogenous shock to productivity. The measure of productivity is the result of using Equation 2 to aggregate the industry-level estimates calculated using Equation 1.

Two sets of results are reported. The first results correspond exactly to the methods used by Galí (1999) and Francis and Ramey (2003) except that I replace their use of labor productivity with my productivity measure. Compared to the initial response by hours when using labor-productivity, the initial response here is much more positive. Either hours declines less or it does not decline at all. The result reported here do not overturn earlier critiques of the standard quantitative dynamic flexible-price model. Hours still do not respond positively to the shock for the first year.

The second set of results report the dynamic responses by investment, output, and consumption as well as hours. These results are useful because they provide the basis upon which to characterize the ability of the macroeconomic model to match the data. These variables do not respond much in the period of the shock. In subsequent periods, the variables start to increase in response to the technology shock.

[14]Because there are no other restriction on the equation, the results calculated using the reduced form VAR are identical to results calculated using the structural VAR with coefficients A_0 and $A(L)$. Imposing additional restrictions on A_0 such as also identifying a monetary policy shock, as in Altig, Christiano, Eichenbaum, and Linde (2003), would require using the structural VAR to calculate impulse responses.

2.3.1 Bivariate VAR with Hours Worked

As in Galí (1999) and Francis and Ramey (2003), the impulse response are from a two-variable VAR on the growth rates of a productivity series and the growth rates of hours worked. Productivity is measured using two different time series: labor productivity and my constructed aggregate productivity series. In addition, impulse responses are calculated from a VAR of the constructed productivity series and the levels of per-capita hours worked. Christiano, Eichenbaum and Vigfusson (2003) argue that estimating the long-run VAR with hours in first differences is mis-specified relative to estimating a VAR with per-capita hours in levels. This section, however, reports both sets of results to maximize comparability with the earlier literature. Confidence intervals around the estimate are calculated using a bootstrapped approach. Sampling from the residuals with replacement, the estimated VAR is used as a data generating process to simulate time series. Using the simulated data, the VAR is estimated and the responses to a permanent positive increase in technology are calculated. After simulating the data 500 times, the variance of each period's impulse response is calculated. The resulting confidence interval is the estimated response plus or minus 1.96 times the standard deviation.[15]

Figure 1 reports the response of the three different VARs. The three different specifications have similar responses. Nothing much happens on impact. Subsequently, hours worked begins to increase. For all three VARs, the response on impact is much greater than that reported in Galí or in Francis and Ramey. These results, however, are not large enough to overturn the conclusions of previous work. Hours still do not respond much initially to a positive productivity shock. Therefore, the evidence is still against models that predict a large initial response to increases in productivity.

2.3.2 VAR with Hours Worked and Other Variables

To compare the model to the data, one needs to know how other variables in the economy respond to a technology shock. This section describes how other variables (output y_t, consumption c_t, investment i_t, and the real interest rate r_t)[16] respond to a technology shock. The approach taken here is to estimate the set of equations described in Section 2.2 . The

[15] Faust and Leeper (1997) note that the standard confidence intervals for impulse responses are not valid unless restrictive assumptions are made concerning the data generating process. For the bootstrapped confidence intervals considere here, the implicit assumption is the true data generating process actually is a six lag bivariate vector autoregression. Under such a restrictive assumption, the confidence intervals reported here would be valid.

[16] All variables are expressed in logs. The variables span the second quarter of 1972 to the end of 2001 and are taken from the DRI BASIC Economics (nee Citibase) database. The series with their mnemonics are as follows: real consumption (the sum of consumption of services GCS, nondurables GCN and government consumption divided by the gross output price deflator GDPD and consumption of durables GCD), real investment (gross private investment (GPI) and government investment divided by the output price deflator GDPD), output (nominal consumption and investment divided by GDPD), real interest rate (3 month Treasury Bill rate minus the growth rate of the GDP price deflator), and hours worked (nonfarm business hours LBMNU). All quantities are expressed in per-capita term by dividing by the population over 16. Deflating consumption and investment by the same price measure rather than using the separate published deflators for investment and consumption is deliberate. See Whelan (2000) for a discussion of using chain-weighted data.

vector of other variables is constructed as follows

$$x_t = \begin{pmatrix} h_t \\ r_t \\ \Delta y_t \\ i_t - y_t \\ c_t - y_t \end{pmatrix} \tag{12}$$

Cointegrating relationships are defined between investment and output, and consumption and output. There is no assumption of a cointegrating relationship between per-capita output and the technology series, in order to allow for other shocks to have a permanent effect on per-capita output. Besides this baseline VAR, I also report impulse responses for two other VARs. One uses the same reduced form VAR but identifies the technology shock not with a long-run identifying assumption but rather uses a standard recursiveness assumption with technology ordered first. In other words I estimate the same reduced form VAR but identify my technology shock ε_t^z as the first element in u_t. I then regress u_t on ε_t^z to find γ and then calculate the impulse responses as done earlier. Finally, I report another VAR where I consider permanent shocks to labor productivity rather than to my constructed productivity series.[17]

Figure 2 reports the data used in the VAR. The log of per-capita hours worked increases over this time period. This increase in hours worked is the result of two opposite trends. An increase in the labor force participation rate (from 60 to 67 percent over this time period) offsets the decline in average hours worked, (for production workers, the average work week has declined from 36 hours to 34 hours).

Figure 3 reports the implications for the technology growth series by applying the long-run identification assumption. The constructed technology series is presented along with the technology series implied by the VAR and allowing only permanent shocks to technology. In order to emphasize the role of the long run identification assumption, both series are presented with mean zero. Perhaps not surprising the series that results from the long run identification series is much less volatile than the original series.

Impulse responses for the baseline long-run VAR are reported in Figure 4. In general, quantities take time to respond to the technology shock. Hours worked responds only slightly in the impact period of the shock. It takes several quarters before hours worked has a strong response. Consumption only responds gradually over time. In the impact period, the response is only about half of what it will be 10 quarters later. In percentage terms, the investment response is stronger on impact but the strongest investment response is about four quarters later. The real interest rate, however, has a very different response. The real rate jumps 80 basis points on impact. It then steadily declines but it does take six years before the real rate returns to normal.

The results for the two other VARs are similar. Identify technology shocks with a short-run recursiveness assumption produces a few small differences. The largest difference is that the

[17]The labor productivity output series considers total output divided by business hours. As such, this definition of labor productivity is more like the work by Gali (1999) than the definition used in Francis and Ramey and Christiano, Eichenbaum, and Vigfusson (2003). As in CEV, I could have defined labor productivity as the ratio of business output to business hours worked. This has the advantage of avoiding the problem of increases in government spending being misconstrued as a technology shock. However, it comes at the cost of being less transparent concerning the imposed cointegration results.

real interest rate response is much weaker. Also, the consumption response is not as strong but the investment response is of greater size and duration. For this dataset, identifying a technology shock as a permanent shock to labor productivity again produces a very similar set of responses.

2.3.3 The Shape of the Impulse Responses

I have claimed that the delayed response to a positive technology shock is a robust feature of the data. The following section characterizes this robustness. Using the baseline VAR as the DGP process, Figure 5 reports that in the majority of cases the response by hours six quarters after a shock is greater than the response on impact.

Table 3 reports that for the majority of simulations, the impact period response for consumption, investment, or hours worked is much smaller than responses several periods later.

2.4 Weak Instruments And the Delay in the Hours Response

To identify a permanent change in technology requires estimating an instrumental variables regression. One may be concerned about whether the above conclusions concerning the shape of the impulse responses are robust to weak instruments. Although the actual instrumental variables regression may have problems with weak instruments, the evidence is that the conclusions concerning shape are more robust.[18]

When instruments are only weakly correlated with the explanatory variables, confidence intervals can often be much wider than those calculated using standard methods. In the equation estimated here, the lagged level of hours worked is used to instrument for the growth rate of hours worked. If hours worked has either a unit root or else approaches a unit root asymptotically, then hour worked would be a weak instrument.[19] Valid confidence intervals for estimation using weak instruments, however, were established by Anderson and Rubin (1949). In the present context, their method can be implemented as follows. Begin with the IV regression where any dependence on lagged values has been removed by a linear projection. All that is left is to estimate a_0, in the following equation,

$$\Delta z_t - \Delta x_t a_0 = \varepsilon_t^z$$

with the instruments x_{t-1}. The Anderson Rubin confidence interval can be described (Wright 2002) as the values of a_0 that satisfy the following condition:

$$\left\{ a_0 : \frac{(\Delta z - \Delta x a_0)' \left(x_{-1} \left(x'_{-1} x_{-1} \right)^{-1} x'_{-1} \right) (\Delta z - \Delta x a_0)}{(\Delta z - \Delta x a_0)' (\Delta z - \Delta x a_0)} \leq F_{\chi^2} (k, \alpha) \right\}$$

where Δz, Δx and x_{-1} are the vectors of Δz_t, Δx_t and x_{t-1} and F is the α percent critical value from a chi-squared distribution with k degrees of freedom, where k is the number of instruments. Figure 6 plots the results when Δz is the growth rate of the constructed

[18] Complementary to this work is a paper by Pesavento and Rossi (2003) where they calculate confidence intervals for impulse responses at long horizons.

[19] Addition detail is provided in Christiano, Eichenbaum and Vigfusson for the weak instruments problem that occurs when hours has a unit root.

technology series and x is the level of per-capita hours. The first panel of Figure 6 plots the criterion function. A 95 percent confidence interval for a_0 is very large ranging between -7 and 6.2. However, the value of a_0 is only important as it affects the measure of γ. Each a_0 maps into a value γ, the response by hours to a one standard deviation shock. The second panel plots the mapping from a_0 to γ. The third panel shows that this mapping implies that the confidence interval for the impact response of hours to a one-standard deviation shock is between -0.05 percent and 0.11 percent. Although this confidence interval is large, it does contain information. In particular, if the coefficient were unidentified, the confidence interval would be between $[-\sigma_u, \sigma_u]$, the variance of the reduced form residual.[20]

These confidence intervals are constructed holding as fixed the values of the reduced form VAR coefficients. Hence if we combine these estimates of the possible values of γ with the reduced form VAR, the resulting hours response six quarters later is between 0.05 and 0.27.

Similar calculations can be done for the six variable system. A grid search on all the possible values of a_0 would be particularly laborious for the larger system. For example, a five dimensional space with 100 grid points per dimension would be ten billion points. However, one can approximate the grid search by instead sampling over the parameter space. A random sample of the same space should be sufficiently informative.[21] Table 4 reports confidence intervals for γ_0 that result from those values of a_0 that belong to the AR confidence interval. Going from the bivariate autoregression to the multivariate regression seems to have both tightened and shifted upwards the confidence intervals on the hours worked response.

There appears to be a great deal of uncertainty of investment's response on impact. This uncertainty does not seem to be reflected in the standard bootstrap confidence intervals reported above. Perhaps the most surprising thing is the improvement of identification that results from using the constructed technology series.

The emphasis on the shape of the hours worked response can also be studied in the context of weak instruments. Consider Figure 7, which shows the connection between the response by hours on impact combined with its response six quarters later. The oval indicates all observed responses, holding the reduced form VAR coefficients $B(L)$ fixed. The grey area indicates those values that are associated with a value of the Anderson Rubin statistic less than the 95 percent critical value of 9.488. Although this oval does not take into account the sampling uncertainty of $B(L)$, the figure is supportive of placing a greater emphasis on the shape of responses.

The evidence from the weak instruments reinforces the view that the robust finding is

[20] The proof of this claim is straightforward. By definition the part of x_t that does not depend on lagged x_{t-i} is u_t. Given the previously described identity,

$$u_t = \gamma \varepsilon_t^z + v_t$$

the response by x_t to a one-standard deviation shock to ε_t^z is $\gamma\sigma_z$. But because ε_t^z and v_t are uncorrelated, the variance of u is the following

$$\sigma_u^2 = \gamma^2\sigma_z^2 + \sigma_v^2$$

and therefore, we have the result that

$$|\gamma\sigma_z| \leq \sigma_u$$

completing the proof.

[21] The following table is based on 20,000 samples over the parameter space. These results were then checked by making an additional 30,000 simulations. In no case did these additional samples change the results reported here.

that the hours response is initially small but grows over time. Models therefore should be constructed to attempt to match this finding.

2.5 Sensitivity of Results

The following sections report on the sensitivity to using different data and also to using different sample periods.

2.5.1 Ex ante Real Interest Rate

To check for data sensitivity, the empirical VAR is estimated using an ex ante measure of the real interest rate in place of the ex post measure. The ex ante real interest rate is based on the difference between the three month treasury rate and the forecasted inflation in the GDP deflator for the next quarter. The forecasted inflation is the median forecast from the Survey of Professional Forecasters. The results are presented in Figure 8. On impact, the ex ante real interest rate only increase 50 basis points rather than the ex post real interest rate increase of 100 basis points. However, all of the quantities experience responses that are similar to those reported in the baseline VAR.

2.5.2 Shorter Sample, Starting in 1983

One might wonder if the strong-interest rate response is stable over time. In particular, Galí, López-Salido and Vallés (2003) argue that monetary policy changed in the United States with Paul Volker and that therefore the responses to a technology shock look very different after 1983 than they did earlier. There are two ways to test the stability. The first is to calculate γ from a regression of just a subsample of the identified technology series on the reduced form residuals, estimated from the full-sample VAR. This method holds the VAR fixed but sees whether a particular episode drove the estimation results. These results, although not reported, are almost identical to the results in Figure 8. Therefore, we have evidence against any particular technology shock episode driving the results.

The second approach, which was used by Galí López-Salido and Vallés, is to re-estimate the entire VAR but begin in 1983. The impulse responses from this VAR are reported in Figure 8. For the first year after impact, these responses are quite different from the responses in the baseline VAR. For the shorter sample VAR, the variables are less responsive on impact. After two years, the responses by quantities are quite similar. These results emphasizes the robustness of describing the response to a technology shock as being a delayed response. One important difference between the two sets of results is that, with the shorter sample, the real interest rate does not respond to the technology shock.

The shocks identified using the post-1982 VAR are very different from the same shocks identified using the full sample of data. The full sample shocks are much more volatile. In addition, they are not closely related to the post-1982 shocks. The post-1982 shocks are the same sign as the full sample shocks only about 50 percent of the time.

The question is whether the full sample or the truncated sample correctly identifies the true technology shocks. Determining which is the correct set of responses is a difficult question. A simple likelihood ratio test would support using the truncated sample. However, to exclude three of the four recessions in the covered time period throws away a lot of information. As such, the analysis here will continue to use the benchmark responses, but with the caveat that other responses are possible.

3 Models

Having described the empirical responses, the next step is to develop a model that can match the data. The model presented here has two features that are different from a standard quantitative dynamic flexible-price model. The first is that the economic agent has habit persistence in the utility function. Thus, the previous period's level of consumption affects current utility. Habit persistence results in a slower response by consumption. (In order to match the real interest rate response, a model with consumption adjustment costs is also presented.) The second feature and the focus of the paper is how investment is transformed into capital. I consider two different specifications of this transformation: time-to-build and capital-adjustment-cost models. Both specifications have the property of preventing capital from adjusting quickly.[22] The time-to-build model has a lag between the decision to increase the capital stock and the actual increase in the capital stock. Likewise in the capital adjustment model, increasing investment is expensive and therefore an economic agent will have an incentive to smooth out investment.

All of these features have been used previously to explain other economic phenomena. In particular, Christiano and Todd (1995) and Christiano and Vigfusson (2003) document the properties of a particular parameterization of the time-to-build model, the time-to-plan model, where investment cannot respond much in the first period of a shock. Christiano and Vigfusson show that this model is much better than a standard quantitative dynamic flexible-price model in matching the output growth dynamics and the lead-lag relationship between output and business investment.[23] Models with capital adjustment costs that depend on the ratio of investment to capital have been used extensively in the Tobin's Q literature. (See Chirinko (1993) for a survey.) Boldrin, Christiano, and Fisher (2000) and Beaudry and Guay: (1996) document how adding capital adjustment costs and habit persistence allows a macroeconomic model to explain both business cycle facts and asset pricing issues. Topel and Rosen (1988) make capital adjustment costs depend on the growth rate of investment to explain housing investment. Christiano, Eichenbaum, and Evans (2001) use a similar specification to generate improved dynamics in a sticky price model. Francis and Ramey (2003) also consider a capital adjustment model to explain the low correlations between productivity and employment. In their model, capital adjustment costs depend on the ratio of investment to capital.

[22] Models with capital adjustment costs do have a similarity with models of marginal efficiency shocks (Dejong Ingram and Whiteman 2000). In both models, the amount of output required to produce a unit of capital (the marginal efficiency of investment) varies over time. The models differ in how they determine the marginal efficiency. In models with capital adjustment costs, the marginal efficiency varies endogenously as agents vary how much they invest. In Dejong Ingram and Whiteman (2000), the marginal efficiency is an exogenous random variable.

[23] Additional support for time-to-build models comes from Kovea (2000), which presents firm-level evidence of time-to-build being a feature of investment in structures. Based on reports from newspapers and trade journals on 106 randomly chosen firms, she estimates an average time-to-build for structures of about two years. Furthermore, she reports that very few of the projects that she examines were cancelled.

3.1 The Utility Function

The model has a representative agent who chooses consumption C and the fraction of time spent working H to maximize utility, where utility is defined as

$$E_t \sum \beta^j \left(\log\left(C_{t+j} - bC_{t+j-1}\right) + \eta \log\left(1 - H_{t+j}\right)\right) \tag{13}$$

The coefficient b describes the degree of habit persistence in the model.[24] The agent maximizes utility subject to two constraints. The first constraint is the aggregate resource constraint that for any period $t+j$, the resources used in that period must be no more than the amount of output produced. The constraint is:

$$C_{t+j} + I_{t+j} \leq F\left(\theta_{t+j}, K_{t+j}, H_{t+j}\right) \tag{14}$$

The amount of output produced depends on the amount of labor H, the amount of capital K, and the level of technology θ_t.

As an alternative to habit persistence, I also consider a model that features consumption adjustment costs. In this model, the habit persistence coefficient is set to zero and the resource constraint is the following.

$$C_{t+j} + I_{t+j} + \xi\left(\frac{C_t}{C_{t-1}} - x\right)^2 C_{t-1} + A(U_{t+j})K_{t+j} \leq F\left(\theta_{t+j}, K_{t+j}, H_{t+j}\right) \tag{15}$$

As will be discussed in the section on the real interest rate, consumption adjustment costs $\xi\left(\frac{C_t}{C_{t-1}} - x\right)^2 C_{t-1}$ are a useful alternative to habit persistence. This feature results in the same dampened consumption response without driving down the response of the real interest rate.

Two different production functions are considered here. As is common in the macroeconomic literature, I use a Cobb Douglas technology function.

$$F\left(\theta_{t+j}, K_{t+j}, H_{t+j}\right) = \theta_{t+j}\left(K_{t+j}\right)^{\alpha}\left(H_{t+j}\right)^{1-\alpha}$$

In addition, because of the strong interest rate response reported above, I also consider the following CES production function.[25]

$$F\left(\theta_{t+j}, K_{t+j}, H_{t+j}\right) = \left[\alpha^{1-\psi}\left(K_{t+j}\right)^{\psi} + \theta_{t+j}\left(1-\alpha\right)^{1-\psi}\left(H_{t+j}^{\psi}\right]^{1/\psi}$$

The second constraint specifies how investment is transformed into capital and will be described in Section 3.3

One difference between this model and Francis and Ramey is the specification of the utility for leisure. They used an indivisible labor model; whereas, here, the model has the standard

[24] The specification of habit persistence used here is standard in the literature. One drawback of this specification is that it requires that the level of consumption c_t must always be greater than the habit stock bc_t to avoid marginal utility being infinite. Carroll, Overland, and Weil (2000) discuss a different specification, where what matters is the ratio of current consumption to the lagged habit stock. Using the ratio avoids the problems of infinite marginal utility as long as consumption is positive.

[25] For the CES production function, technology is labor augmenting. This assumption is important for the normalization required when technology is a random walk.

divisible labor utility function. The two specifications imply very different values for the labor supply elasticity. The labor supply elasticity is much greater for the indivisible labor model, where the labor supply is infinitely elastic. With divisible labor, the labor supply would have an elasticity of about three.[26] Therefore, the labor supply will be less responsive in the specification studied here.

3.2 The Technology Shocks

In order to match the data, the model should have growth and therefore the level of technology should be nonstationary. The level of technology θ_t has the following functional form

$$\ln \theta_t = \mu + \ln \theta_{t-1} + \varepsilon_t \tag{16}$$

where ε_t has mean zero. The standard assumption is that the shock to the growth rate ε_t of technology is independent over time. An alternative specification allows the growth rate to be autoregressive

$$\varepsilon_t = \rho_z \varepsilon_{t-1} + u_t \tag{17}$$

where $|\rho_z|$ is strictly less than one and u_t is independent over time. Although most of the reported results are for a shock where ρ_z equals zero, some results reported in Section 3.6 are considered where ρ equals 0.7. The standard deviations of u_t is chosen so that the standard deviation of ε_t is 0.01.

3.3 Transforming Investment into Capital

This section describes how investment is transformed into capital. Three different specifications are considered. The first is the time-to-build model of Kydland and Prescott (1982). In this model, several quarters pass before a desired increase in the capital stock is realized. The second is the convex capital adjustment costs where the costs are a function of the ratio of investment to capital. The third has adjustment costs that depend on the growth rate of investment.[27]

3.3.1 Time-to-Build

In the time-to-build model (Kydland and Prescott 1982), the investment technology has two features. The first is that the time between the decision to increase the capital stock and the actual increase is greater than a quarter. In the current application, four quarters pass between making a decision to increase the capital stock and the actual increase. The second feature is that the increase in the capital stock is paid for over time. In other words, a project x_t initiated at quarter t results in an increase in the capital stock $K_{t+4} - (1-\delta)K_{t+3}$ four quarter later. The total cost of the project x_t equals the increase $K_{t+4} - (1-\delta)K_{t+3}$, but the

[26] Microeconomic evidence suggests that the labor supply elasticities are much smaller. The labor literature reports labor supply elasticities near zero for males and about 1 for females. Most macroeconomic models, however, require these larger estimates in order to match the data.

[27] The emphasis in this paper is on convex adjustment costs. Cooper and Haltiwanger (2000) emphasize that including firm-level non-convex costs (such as fixed costs) also matters for aggregate investment. Including such non-convexities is a goal for future work.

project is paid for in installments. Thus, investment consists of several different projects that are at various stages of completion. In particular, period t investment equals:

$$I_t = \phi_1 x_t + \phi_2 x_{t-1} + \phi_3 x_{t-2} + \phi_4 x_{t-3} \tag{18}$$

where $\phi_i \geq 0$ for $i = 1, 2, 3, 4$, and

$$\phi_1 + \phi_2 + \phi_3 + \phi_4 \equiv 1.$$

Resources in the amount $\phi_1 x_t$ must be applied in period t, $\phi_2 x_t$ must be applied in period $t+1, \phi_3 x_t$ must be applied in period $t+2$, and finally, $\phi_4 x_t$ must be applied in period $t+3$. Once initiated, the scale of an investment project cannot be expanded or contracted.

3.3.2 Capital Adjustment Costs

Two versions of capital adjustment costs are described here. The first, (which I will refer to as CIK), is the more common version where the cost of capital adjustment is a function of the ratio of current investment to capital

$$K_{t+1} + \gamma \left(\frac{I_t}{K_t} - \delta \right)^2 K_t - (1 - \delta) K_t - I_t \tag{19}$$

The second (which I will refer to as CII) is less common but it allows the adjustment costs to depend on the ratio of current investment to the previous period's investment.

$$K_{t+1} + \gamma \left(\frac{I_t}{I_{t-1}} - \exp \mu \right)^2 I_{t-1} - (1 - \delta) K_t - I_t \tag{20}$$

For the specifications given here, adjustment costs parameterized by γ, will not affect the steady state properties of the model. For the two models, these parameters, however, should be calibrated at different values. For comparable costs of adjustment, the value of γ for the investment growth rate specification should be δ times the value of γ in the investment to capital ratio specification [28]

3.4 Model Parameterization

At calibrated values, the standard RBC model fails to match the main facts discussed in the empirical section. In particular, all the variables respond to a positive technology shock most strongly on impact. Therefore, they completely miss the delayed response observed in the data.

Recent model estimation has often tried to match impulse responses by using a GMM weighting function. However, the goal of this paper is to show the flexibility of these macroeconomic models to match estimated technology impulse responses. As such, rather than attempting to match any particular set of responses, I will present a comparative analysis

[28] The difference in the two specifications can be seen by examining the cost of the investment adjustments costs when investment is $(1 + r)$ times greater than the steady state value. For the investment to capital ratio case, the adjustment costs would equal $\gamma (r\delta)^2 K$. For the investment growth rate case, the adjustment costs would equal $\gamma (r)^2 \delta K$. Hence, the values of γ must be different for the two specifications.

that will clarify how the flexible-price models are compatible with the responses observed both in this paper and in many of the other papers in the literature.

Figure 9 reports results for just the response of hours on impact and how the different models are able to capture the response of hours to a positive technology shock. For each of the different models, some of the model's coefficients were fixed and others were allowed to vary. The coefficients that were allowed to vary were the ones that characterize the newer features of the model. In particular, results are reported for different values of both the degree of habit persistence and the coefficients related to how investment is translated into capital, (i.e. the degree of investment adjustment costs γ or time-to-build weights ϕ.). The other coefficients were held constant.[29] The models were log-linearized and solved using the undetermined coefficients method of Christiano (2001).[30]

In Figure 9, there are several things to note. First, all three models have parameterization that are consistent with hours worked falling in response to a positive technology shock. Many, including Galí and Basu, Fernald, and Kimball, have argued that the earlier empirical claims of negative hours responses to a technology shock is evidence against flexible-price models. Clearly, the flexible-price models reported here can imply that hours fall on impact of a positive technology shock. Therefore, these previous criticism of flexible-price models, although valid for the standard RBC model, do not apply to these models. Furthermore, for all three models, different combinations of investment adjustment costs and habit persistence can generate a given hours response. Habit persistence and investment adjustment costs actually work against each other. Investment adjustment costs decrease the investment response and increase the consumption response, and habit persistence increases the investment response and decreases the consumption response.

Figure 10 illustrates these trade offs for the CII model and how consumption and investment impact responses depend on the degree of habit persistence and investment adjustment costs. The shaded areas indicate the bootstrap confidence intervals around the empirical impact effect. For investment, the width of the area suggest that the investment response is not very informative about the best values of habit persistence and the investment adjustment cost.

3.5 Dynamic Responses

Figure 11 reports on the ability of all three models to capture the dynamic response of hours worked, consumption, and investment. The benchmark empirical results from Figure 2 are reproduced here.

The first panel reports responses for a model with habit persistence and investment adjustment costs that depend on the growth rate of investment, the CII model. As seen in Figure 10, it is fairly easy to find model parameterization that match the consumption response. The investment response is somewhat more difficult with the response being too strong compared to the empirical response. The hours worked response is delayed. However, hours actually do not respond enough on impact and then responds too strongly afterwards. The differences in

[29] The value of η is 1.5.The following coefficients were taken from Christiano and Eichenbaum (1992). The vector (β, α, δ) equals $\left(1.03^{-0.25}, 0.36, 0.02\right)$.

[30] Because the model is assumed to have a unit root in the technology, in calculating a solution, the variables will be normalized by dividing through by the level of technology. Hence the model will be solved for $\{c_t, i_t, k_t, H_t\}$ where $\{c_t, i_t, k_t\}$ equals $\{C_t/\theta_t, I_t/\theta_t, K_t/\theta_{t-1}\}$.

responses, however, are within the standard bootstrapped confidence intervals, indicated by the shaded regions.

The second panel reports results from the time-to-build and CIK models. The CIK model can match the initial responses. However the CIK model can not match the increases in responses because the ratio of investment to capital does not quickly change. Without a change in the ratio of investment to capital, the investment adjustment costs remain high. The time-to-build model does better at creating responses that are small initially but then increase. The main problem with the time-to-build model is that the responses are too jagged. The jaggedness results from there being only one kind of capital with only a four period building period. A time-to-build model with much smoother responses can be found in Edge (2000) where there are many different kinds of capital goods, with each kind of capital requiring a different number of periods to build.[31]

3.6 Real Interest Rate Response

Although both the investment growth rate model and the time-to-plan model have done well in fitting the responses of consumption, investment and hours worked, this section makes clear that the models have a much harder time matching the strong interest rate response observed in the benchmark results. Figure 12 reports the real interest rate results from the empirical VAR and from the economic models. Given that consumption only slowly increases in both the CII and time-to-build models, it may seem puzzling that the real interest rate actually falls on impact. The explanation, however, involves the definition of marginal utility with habit persistence. First, the real interest rate can be expressed in terms of a ratio of marginal utilities. In particular, ignoring uncertainty, the real interest rate can be written as

$$(1 + R_t) = \frac{u'(C_t)}{\beta u'(C_{t+1})}$$

Assuming no growth, the interest rate would be below the steady state interest rate only if the current marginal utility is less than next period's marginal utility. For log utility and without habit persistence, we have that

$$(1 + R_t) = \frac{C_{t+1}}{\beta C_t}$$

and so the interest rate only falls below steady state if current consumption is more than future consumption. With positive investment adjustment costs but no habit persistence, consumption does spike on impact and then declines somewhat. Therefore, in this case, the real interest rate declines on impact. Adding habit persistence, however, deepens the puzzle because then consumption increases over time. With consumption increasing over time and log utility, the interest rate would increase. However, with habit persistence, marginal utility depends on both the level and the growth rate of consumption. Because the growth rate of consumption increase with the impact of a technology shock, the real interest rate falls.

[31] As is evident in Christiano and Vigfusson (2003), this jaggedness is not a problem when examining the spectrum implied by the time-to-plan model.

For further intuition, consider the real interest rate in a model of internal habit which drops the forward looking part of the external habit specification used here.[32]

$$(1 + R_t) = \frac{1}{\beta} \frac{(C_{t+1} - bC_t)}{(C_t - bC_{t-1})}$$

If the difference between C_t and bC_{t-1} is greater than the difference between C_{t+1} and bC_t then the model projects that the real interest rate will fall.

Modeling the production function as a CES production function, rather than Cobb-Douglas, does strengthen the growth rates of investment. However, this feature does not overcome the negative interest rate response generated by the habit persistence. Another option would be to have habit persistence depend on the difference between current consumption and a habit stock that only slowly evolved with current consumption. In other words, the new utility function is

$$\begin{aligned} U(C_t, X_t, H_t) &= \ln(C_t - bX_{t-1}) - \eta \ln(1 - H_t) \\ X_{t-1} &= (1 - \tau) X_{t-2} + \tau C_{t-1} \end{aligned}$$

Although adding a habit stock ameliorates the decline in the real interest rate, the real interest rate still falls in response to a positive technology shock.

One partial remedy to the falling real rate is to replace habit persistence with consumption adjustment costs. With consumption adjustment costs, one continues to delay the consumption response but, unlike habit persistence, consumption adjustment costs do not introduce the growth rate of consumption into marginal utility. As such, the real interest rate increases on impact. However, as seen in Figure 12, the rise is not as much or as persistent as the empirical point estimates.

Consumption adjustment costs may seem particularly ad-hoc. However, like investment adjustment costs, they help macroeconomic models match the empirical impulse response functions. Future work will be required to find a more structural mechanism to reduce how quickly both the level and the marginal utility of consumption increases in response to a positive technology.

Another possible solution would be to have serially correlated technology shocks. Although serially correlated shocks can result in a model with a stronger real interest rate response. Figure 13 reports results with the assumption that the autoregressive coefficient on the growth rate of technology ρ_z equals 0.7. As shown in Figure 13, in models with investment adjustment costs, the real interest rate increases almost 50 basis points on impact. [33] However, this real interest rate response is less than the estimated response. In addition, the responses of the other variables particularly investment and hours worked are now too weak compared to the

[32]With external habit, the real interest rate is a somewhat less tractable

$$(1 + R_t) = \frac{1}{\beta} \frac{\frac{1}{\left(c_t - b\exp(-\varepsilon_t)c_{t-1}\right)} + \beta \frac{-b\exp\left(-\varepsilon_{t+1}\right)}{\left(c_{t+1} - b\exp\left(-\varepsilon_{t+1}\right)c_t\right)}}{\frac{1}{\left(c_{t+1} - b\exp\left(-\varepsilon_{t+1}\right)c_t\right)} + \beta \frac{-b\exp\left(-\varepsilon_{t+2}\right)}{\left(c_{t+2} - b\exp\left(-\varepsilon_{t+2}\right)c_t\right)}}$$

[33]With serially correlated shocks,the standard flexible price model has a delayed response to the onset of a technology shock. The response on impact however seem to be too negative with both investment and hours worked falling sharply.

estimated responses. So any gain in better real interest rate fit is lost in worse fit of hours worked and the real interest rate.

The real interest rate response is a problem for these models. As mentioned in the empirical section, the interest rate response is somewhat uncertain with both a wide confidence interval and being sensitive to the sample period. Therefore, some may question the seriousness of a failure to match this response. In fact, many researchers have felt that a fall in real interest rates followed by a positive increase in output is a desirable characteristic in a technology driven model.

4 Criticisms of Long Run VARs

Recent papers by Erceg, Guerrieri and Gust (2004) and Chari Kehoe and McGrattan (2004) have criticized the use of long-run VARs to construct impulse response. Both papers have shown that, for particular model parameterizations, the point estimates of the impulse responses may be estimated imprecisely. This section provides some additional simulation evidence concerning the responses. I show for a particular set of models that, although, these authors do have a valid concern about the possible imprecision of the point estimates, the impulse responses are informative about the shape of the responses. Of specific relevance to the current paper, simulation evidence shows that these impulse responses can distinguish between a model where hours responds most on impact and a model where hours have a delayed (hump shaped) response. However, sign restrictions are not as informative. For the models considered here, the finding of a positive response is unlikely to allow us to discriminate between a model that has a positive hours response on impact and a model that has a negative hours response on impact.

The simulation evidence presented here comes from three models: a standard quantitative dynamic flexible-price model (where hours responds positively and with the largest response being immediate), a model with CII investment adjustment costs (where hours responds positively and with a delayed response), and a model with CII investment adjustment costs and habit persistence. In order to estimate a non-trivial bivariate VAR, each model has an additional shock ε_t^η that affects the labor preference parameter η. Hence the utility function becomes

$$E_t \sum \beta^j \left(\log \left(C_{t+j} - bC_{t+j-1}\right) + \eta \left(1 + \varepsilon_t^\eta\right) \log \left(1 - H_{t+j}\right)\right) \tag{21}$$

and the shock ε_t^η is assumed to be independent of the technology and shock and have the following autoregressive structure.

$$\varepsilon_t^\eta = \rho_\eta \varepsilon_{t-1}^\eta + \upsilon_t$$

where υ_t is i.i.d normal with variance σ_η^2. Using the standard quantitative dynamic flexible-price model and holding the standard deviation of the technology shock σ_z fixed at 0.01, the standard deviation and the persistence of the preference shock is estimated by maximum likelihood (as described in Christiano and Vigfusson (2003)), by matching the model-based spectrum of labor productivity growth and the log level of hours worked to the empirical spectrum of nonfarm business labor productivity and per capita hours worked.[34] Based on

[34] Appendix A describes briefly the estimation procedure.

data between 1959q1-2000q4, the standard deviation of the labor supply shock equals 0.0093 with a persistence coefficient of 0.975.[35]

Given these estimates, I then used each model to generate 500 data sets of 200 observations each on labor productivity and hours worked. For each simulated data set, I then estimated a long run VAR on the growth rate of labor productivity and the log level of hours worked. Figure 14 reports the theoretical model response for hours worked and also the average response estimated from the simulated data. For all models, the average responses are biased upwards, but the average responses are reasonably close. However, an interval that contains 90 percent of the simulated responses is very large. Figure 14 plots such an interval for the CII model. Given these wide intervals, one may be concerned that one could not distinguish between the models.

Some measures but not others are able to distinguish between the models. Figure 15 reports the probability of observing two results in each model. The top panel reports the probability of observing a positive impact response. Because of the wide confidence intervals and the upward bias in the hours response, all three models, including the model where the true response is negative, have a high probability of observing a positive value. Therefore, a finding of a positive response is not very informative about the true data generating model. As can be seen in the bottom panel of Figure 15, the shape results are much more informative. In the standard RBC model, the downward trend in the hours response is apparent in the small fraction of responses that are greater than the impact response. Likewise, in the model with investment adjustment costs, the hump-shaped response is readily apparent by the large fraction of responses that are greater than the impact response.

One way to quantify the difference between models would be with a posterior odds ratio. In particular given the observed data y, one would calculate the odds of model one M_1 being preferred over model two M_2 as follows.

$$\frac{P(M_1|y)}{P(M_2|y)} = \frac{P(y|M_1)P(M_1)}{P(y|M_2)\,P(M_2)}$$

Supposing that model one has coefficients θ_1, we could define the posterior probability $P(y|M_1)$ as follows

$$P(y|M_1) = \int P(y|\theta_1, M_1)P(\theta_1|M_1)d\theta_1$$

where $P(y|\theta, M_1)$ is the likelihood of observing y in model one given parameters θ and $P(\theta_1|M_1)$ is the prior belief about the distribution of θ. Instead of a full fledged Bayesian analysis, I will suppose that the data y is the fact that we observed a hump-shaped response and that our prior belief about the distribution $P(\theta_1|M_1)$ is that $P(\theta_1|M_1)$ equals zero for all θ_1 except for the calibrated values used here. Given these assumptions, one can calculate the odds ratio as being the ratio of the percentages reported in Figure 15. Therefore, based on the hump-shaped response, the odds in favor of the CII model relative to the standard quantitative dynamic flexible-price model are well over two to one. A similar calculation on the sign of the impact response is not as informative. Because of both the bias and the

[35] These values were calculated for the version of the flexible price model without any adjustment costs. As such, a richer structure might result in different parameter estimates. However, the goal of this section is to provide some evidence on the usefulness of long run VARs to discriminate between models, not a full maximum likelihood estimation.

imprecision of the point estimates, the observation of a positive impact response favors the standard quantitative dynamic flexible-price model over the CII model with habit persistence with odds of only 1.22 to one.

These calculations should be taken as only a guideline. Other models with more features or other shocks might give different results for both the identification of point estimates and response shapes. However, at least for these simple models where the criticisms of EGG and CKM are valid, studying the shape of the responses seems to be a valid way to use long-run VARS to learn about the economy.[36]

5 Conclusions

The main empirical conclusion of this paper is that, for the U.S. economy, the response by per-capita hours worked to a technology shock is initially small but subsequently increases. The small initial response is evidence against any model, including the standard quantitative dynamic flexible-price model, that predicts a large immediate response by employment to a technology shock. These results do not, however, completely invalidate the use of real technology shocks to explain business cycles since variables do respond in the medium term to these shocks. Therefore, the task is to develop models that can explain both the short-term and long-term responses to technology shocks.

The current paper presents quantitative dynamic flexible-price models that can be reconciled with the observed responses by quantities to a technology shock. Of course, this reconciliation is not a rejection of other possible explanations. These other possible explanations might include the examples provided by Basu, Fernald, and Kimball (2004): sticky-price models, multi-sector reallocation models, and cleansing models of recessions. All of these explanations should be scrutinized further to determine their relative merits.

The current paper has done three things. First, it has presented new empirical dynamic responses for models to match. Second, it has shown that the estimated shape of these dynamic responses may be more informative than the sign of the impact response. Third, it has put forward flexible-price models that better explain these delayed responses. In effect, it has raised the standard for criticisms of the flexible-price model. It was easy to show that the small initial response by hours worked was inconsistent with the standard flexible-price model. With the additional features discussed here, a flexible-price model can be made consistent with these observations concerning hours worked. The new challenge will be to build upon the improved fits described here.

[36] In the above results, I did not consider the effect of using the growth rate of hours in the long-run VAR. In these models, hours worked is stationary. As is discussed in CEV (2003), estimating a VAR after first differencing a stationary variable is a form of specification error. Hence using the first difference VAR on model-simulated data would be using a misspecficied VAR. As was found in CEV and CKM, I also found that applying the first difference VARs would result in a very high probability of a negative response by hours on impact.

A A Summary of Model Estimation by Maximum Likelihood in the Frequency Domain

In order to make the paper somewhat more self-contained, this appendix summarizes how to estimate a model by maximum likelihood in the frequency domain. For more details and application,. see Christiano and Vigfusson (2003).

Begin with a time series of data, $y = [y_1, ..., y_T]$, where y_t is a finite-dimensional column vector with zero mean. In this paper's analysis, the vector y_t is defined as

$$y_t = \begin{bmatrix} \Delta \log(Y_t/H_t) \\ \log(H_t) \end{bmatrix}, \tag{22}$$

where Y_t denotes output and H_t denotes hours worked.

It is well known (Harvey, 1989, p. 193) that for T large, the Gaussian likelihood for such a time series of data is well approximated by:

$$L(y, \Phi) = -\frac{1}{2} \sum_{j=0}^{T-1} \left\{ 2 \log 2\pi + \log \left[\det \left(F(\omega_j; \Phi) \right) \right] + tr \left(F(\omega_j; \Phi)^{-1} I(\omega_j) \right) \right\} \tag{23}$$

where $tr(\cdot)$ and $\det(\cdot)$ denotes the trace and determinant operators, respectively. Also, $I(\omega)$ is the periodogram of the data:

$$I(\omega) = \frac{1}{2\pi T} y(\omega) y(-\omega)', \; y(\omega) = \sum_{t=1}^{T} y_t \exp(-i\omega t), \tag{24}$$

and

$$\omega_j = \frac{2\pi j}{T}, \; j = 0, 1, ..., T-1.$$

Finally, $F(\omega; \Phi)$ is the spectral density of y at frequency ω, and Φ is a vector of unknown parameters.[37]

To estimate a model by frequency domain maximum likelihood, one needs the mapping from the model's parameters, Φ, to the spectral density matrix of the data, $F(\omega_j; \Phi)$. The following describes this mapping.

The first step is to solve a linearized version of the macroeconomic model. One can then use the linearized solution to write a linear approximation of the y_t process

$$y_t = \alpha(L; \Phi^r)\varepsilon_t = \alpha_0(\Phi^r)\varepsilon_t + \alpha_1(\Phi^r)\varepsilon_{t-1} + \alpha_2(\Phi^r)\varepsilon_{t-2} + ... \tag{25}$$

In the two-shock model, y_t is defined in (22), $\alpha(L; \Phi^r)$ is 2×2 matrix polynomial in L, and

$$\varepsilon_t = \begin{pmatrix} \eta_t \\ u_t \end{pmatrix}, \; V(\Phi^r) = \begin{bmatrix} \sigma_\eta^2 & 0 \\ 0 & \sigma_u^2 \end{bmatrix}.$$

[37]Let $C(k; \Phi) = E y_t y'_{t-k}$, for integer values of k. Then,

$$F(\omega; \Phi) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} C(k; \Phi) e^{-i\omega k},$$

for $\omega \in (0, 2\pi)$.

In this case, $\alpha(L;\Phi^r)$ is the infinite moving average representation corresponding to a vector ARMA model with 2 autoregressive and 2 moving average lags, i.e., a VARMA(2,2).

In all cases, I restrict Φ^r so that

$$\sum_{i=0}^{\infty} \alpha_i(\Phi^r) V(\Phi^r) \alpha_i(\Phi^r)' < \infty,$$

guaranteeing that the spectral density of y_t exists. We also restrict Φ^r so that $\det[\alpha(z;\Phi^r)] = 0$ implies $|z| \geq 1$, where $|\cdot|$ denotes the absolute value operator.

The spectral density of y_t at frequency ω is

$$F^r(\omega;\Phi^r) = \frac{1}{2\pi}\alpha(e^{-i\omega};\Phi^r)V\alpha(e^{i\omega};\Phi^r)',$$

where the superscript, r, on F indicates that the form of $\alpha(L;\Phi^r)$ is restricted by the model. Using this expression, one can then maximize the likelihood function with respect to the values of Φ^r. Christiano and Vigfusson (2003) describe the usefulness of the frequency domain approach in studying model fit.

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A Tables

Table 1: Manufacturing Industries

Durable Good Producers	SIC Code	Nondurable Good Producers	SIC Code
Lumber	24	Food	20
Furniture	25	Textiles	22
Glass Stone & Clay	32	Apparel	23
Primary Metals	33	Paper	26
Fabricated Metals	34	Printing	27
Industrial Machinery	35	Chemicals	28
Electrical Machinery	36	Petroleum	29
Transportation	37	Rubber and Plastics	30
Instruments	38		
Miscellaneous	39		

Table 2: Coefficient Estimates

	Coef	T-stat	Coef	T-stat
	NonDurable		Durable	
μ	0.82	-1.13	1.04	0.28
ξ	0.31	2.45	0.17	1.65

Results: 18 Manufacturing Industries 1972-2001
GMM Estimation with Asymptotic Standard Errors
T-stat for μ is test of μ equal to one.
T-stat for ξ is test of ξ equal to zero.
Degrees of Freedom Equal to 167

Table 3 Percent of Simulations where the response x periods after the shock is greater than the response on impact

x Periods After Shock	H	C	I
1	90.1	77.4	94.1
2	90.7	68.0	92.0
3	91.4	77.0	93.4
4	87.8	74.4	88.4
5	88.5	79.4	88.2
6	90.3	84.7	87.6
7	89.7	83.8	86.3
8	89.0	85.6	85.1
9	88.6	86.0	83.1

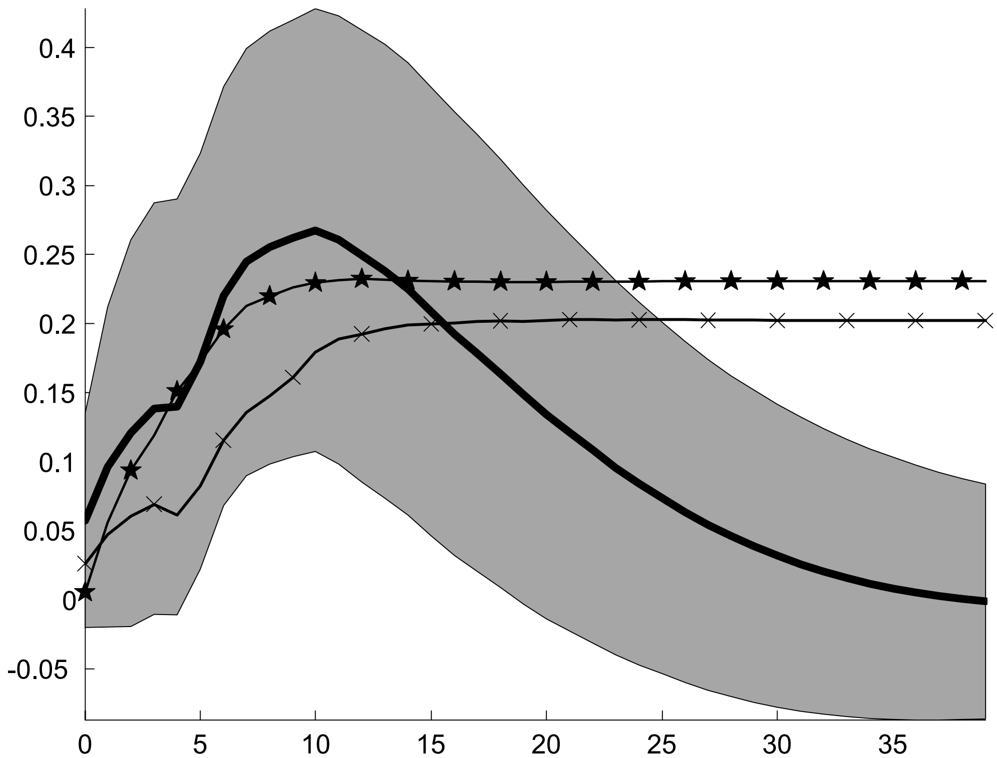
Table 4: Estimated Confidence Intervals and Theoretical Bounds on Impact Response to A Technology Shock

	Estimate Confidence Intervals		Theoretical Bounds	
	Technology	Labor Productivity	Technology VAR	Labor Productivity VAR
Labor Productivity	(-0.06, 0.38)	(-0.22, 0.36)	$\pm$0.518	$\pm$0.55
Hours Worked	(-0.007, 0.084)	(-0.09, 0.11)	$\pm$0.108	$\pm$0.124
Real Interest Rate	(28, 98)	(-38, 100)	$\pm$101.1	$\pm$102.6
Output	(-0.05, 0.42)	(-0.31, 0.45)	$\pm$0.564	$\pm$0.62
Consumption	(0.07, 0.32)	(-0.03, 0.20)	$\pm$0.469	$\pm$0.46
Investment	(-0.69, 1.08)	(-1.09, 1.30)	$\pm$1.32	$\pm$1.41

Notes: Confidence Intervals Constructed using 95 percent critical value of 11.07 for tech and 9.488 for labor productivity

B Figures

Figure 1: Hours Response



Thick Line VAR with Constructed Productivity Series and Hours In Levels
'X's: VAR with Constructed Productivity Series and Hours In Difference
Stars VAR with Labor Productivity and Hours in Differences
Grey Area: 95 Percent Bootstrapped Confidence Interval Centered Around VAR with Constructed Productivity Series and Hours In Levels

Figure 2: Data Used In the VAR Analysis

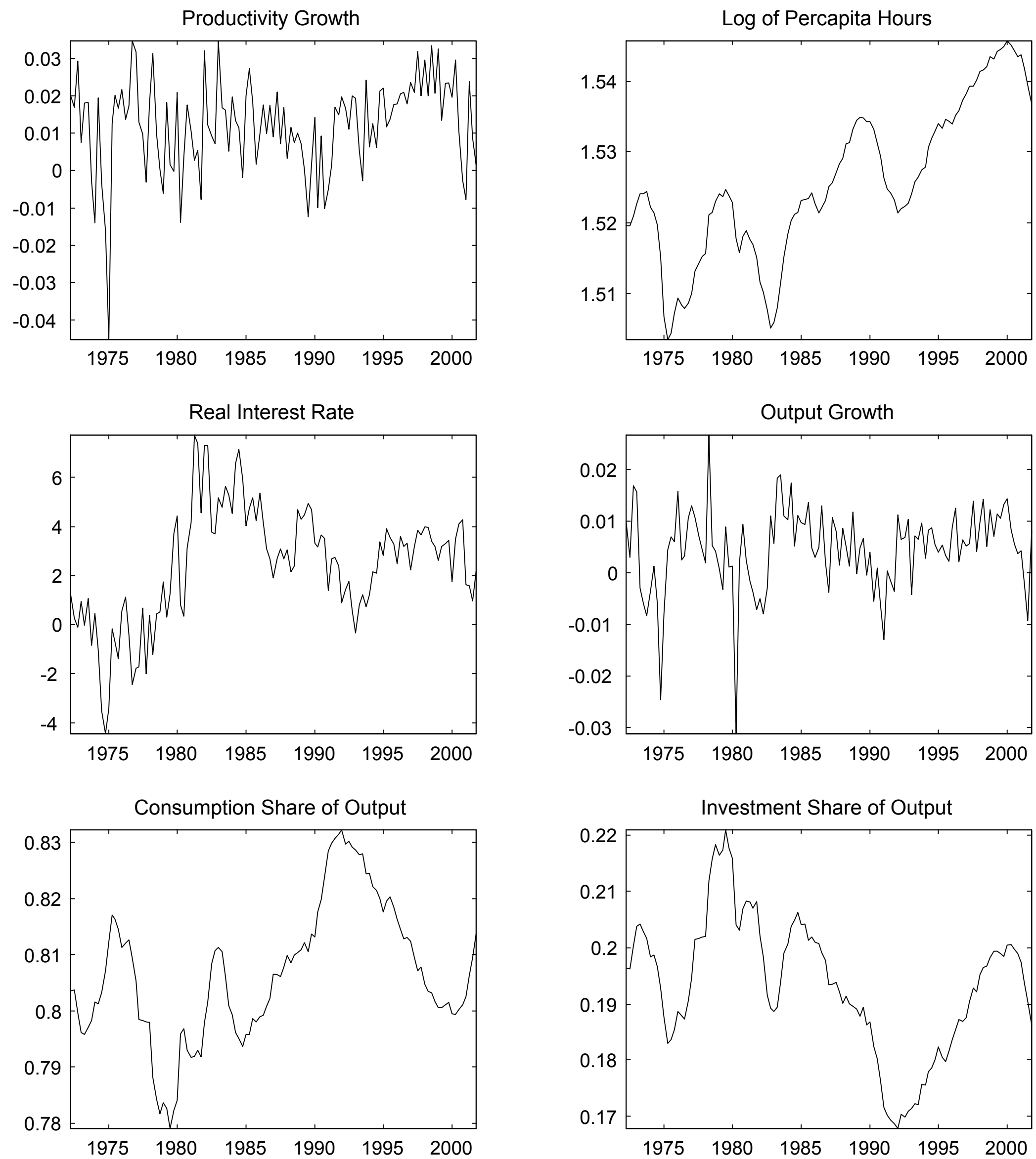
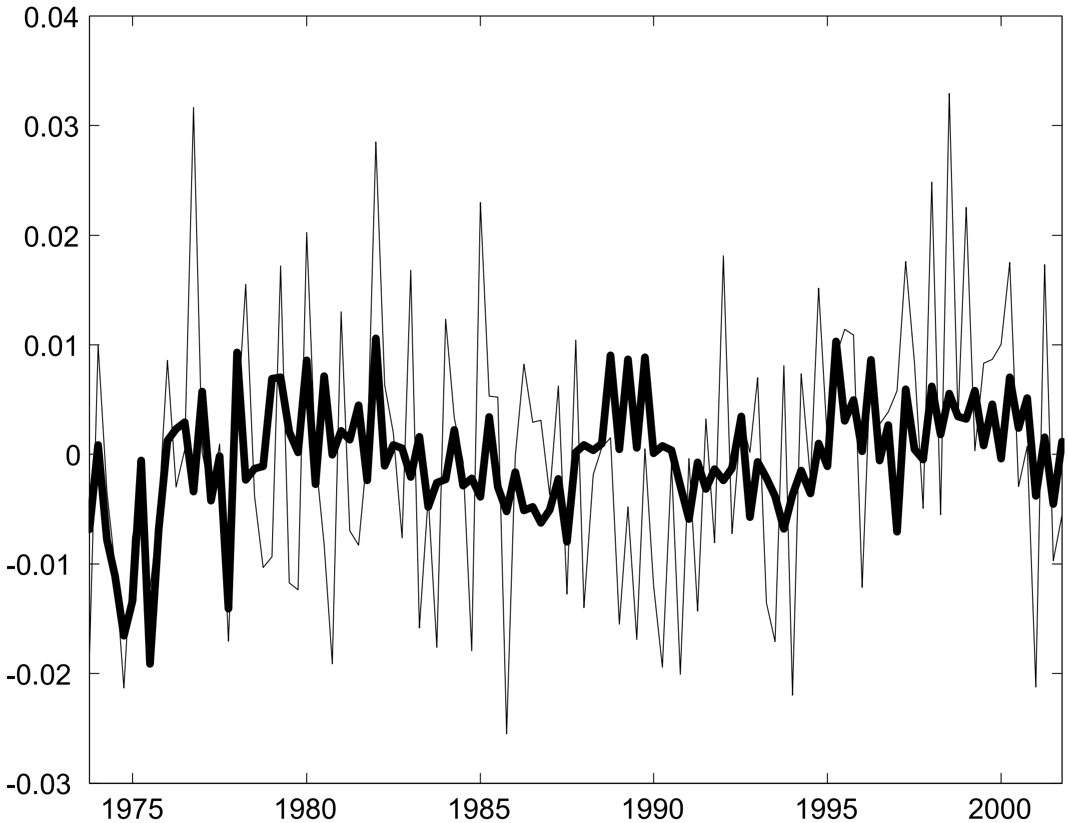
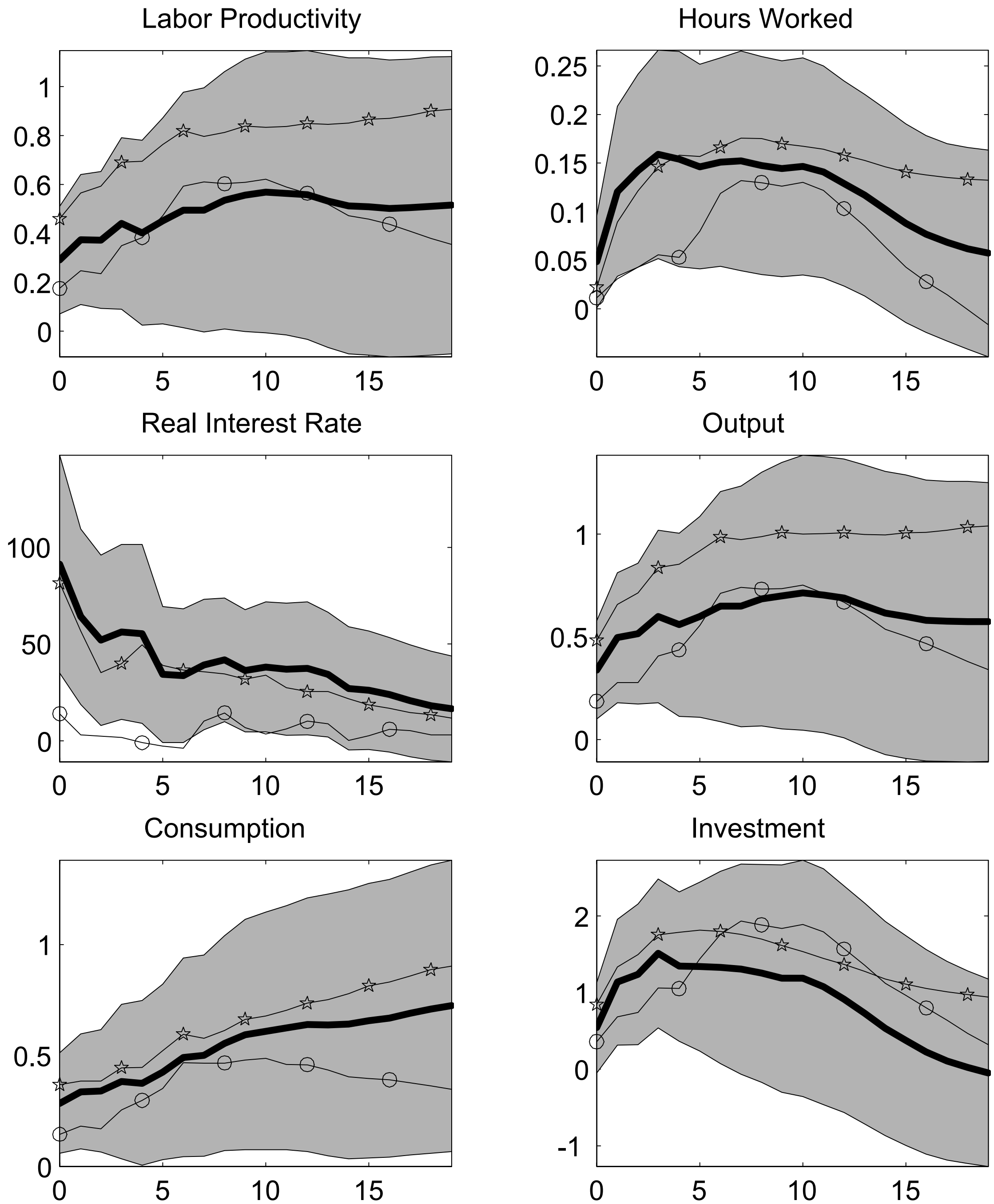


Figure 3: The Result of Applying The Long Run Identification Assumption



Thin Line Constructed Technology Growth Rate Series (Demeanded)
Thick Line: Technology Growth Rate Series (Demeanded) implied
by the Long Run Identification Assumption

Figure 4: Responses To Productivity Shock



Thick Line VAR with Constructed Productivity Series and Hours In Levels, with Long Run Identification Assumption
Grey Area: 95 Percent Bootstrapped Confidence Interval Centered Around VAR with Constructed Productivity Series and Hours In Levels
Circles VAR with Constructed Productivity Series and Hours In Levels, with Short Run Identification Assumption
'Stars's VAR with Labor Productivity and Hours in Differences with Long Run Identification Assumption

Figure 5: Shape of The Response of Hours

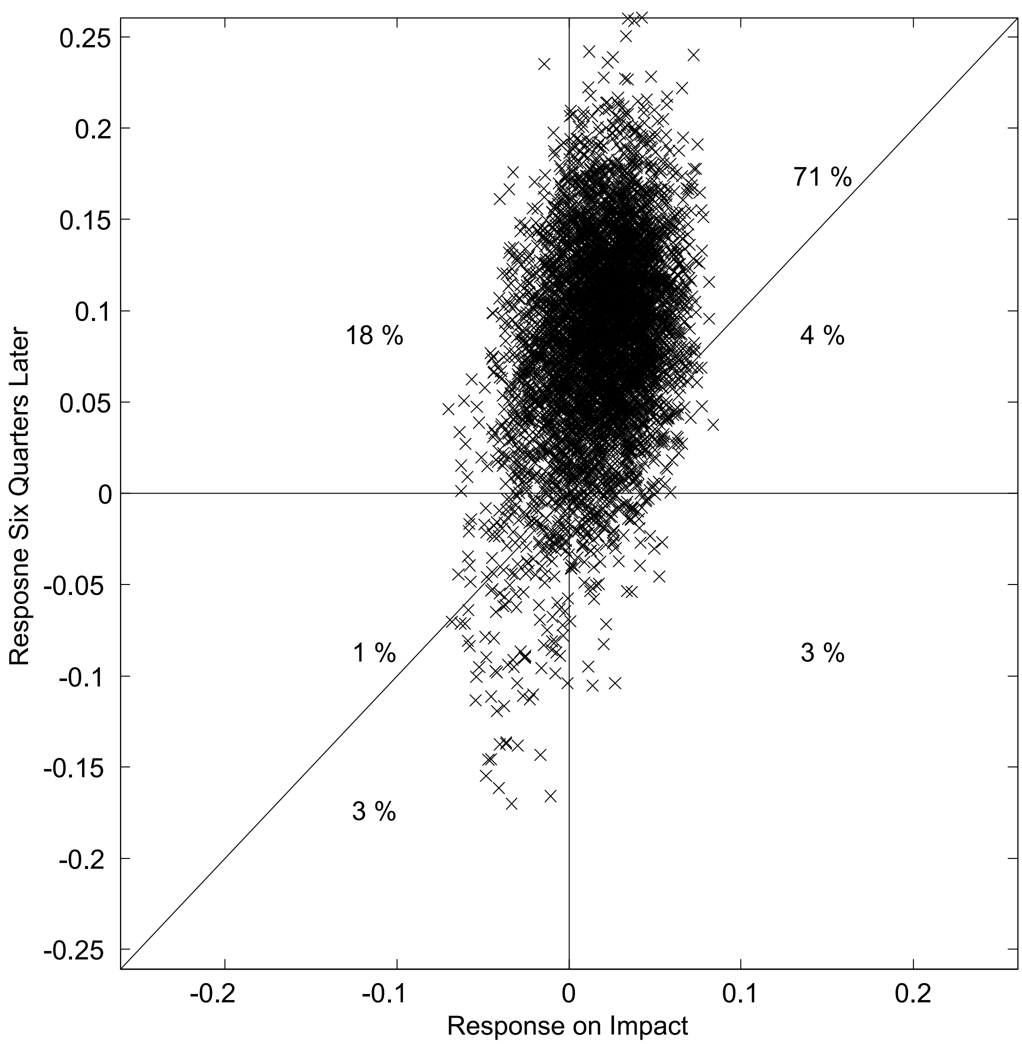
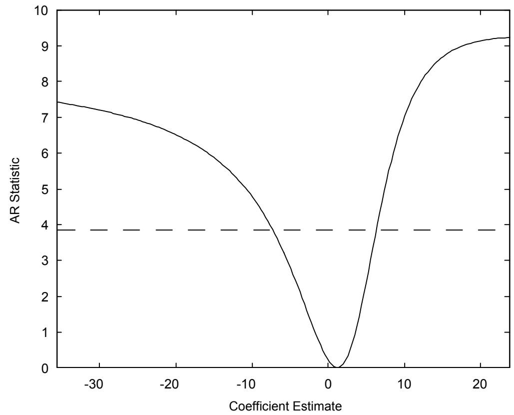
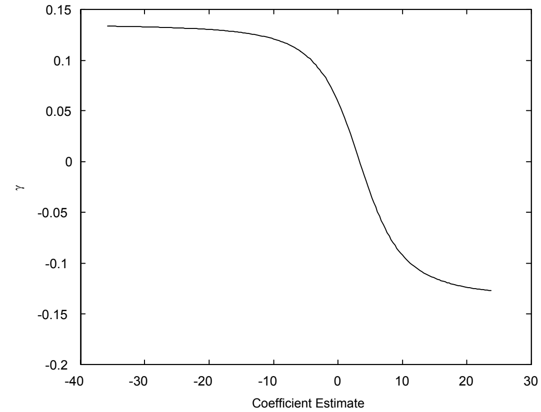


Figure 6: Confidence Intervals for a_0, Impact Response on Hours, and the Response Six Periods Later

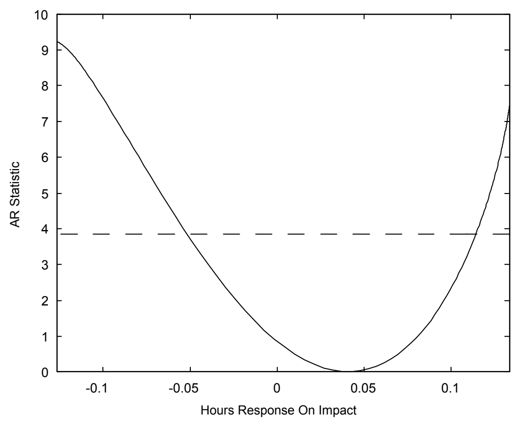
Anderson-Rubin Confidence Set for a_0



Mapping from a_0 to γ



Anderson-Rubin Confidence Set
for Hours Response On Impact



Anderson-Rubin Confidence Set
for Hours Response Six Periods Later

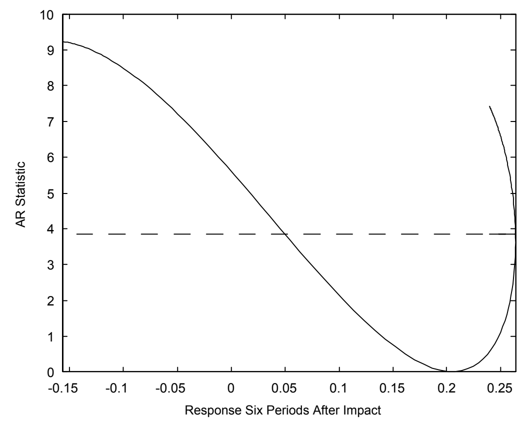
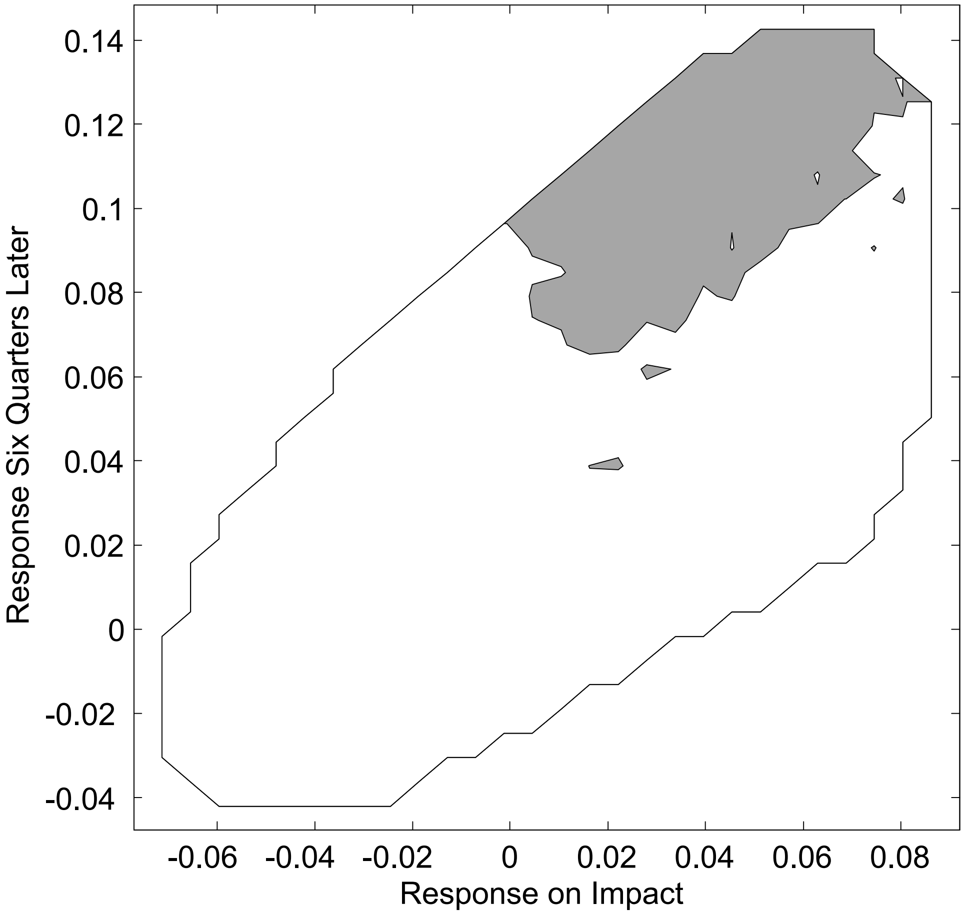
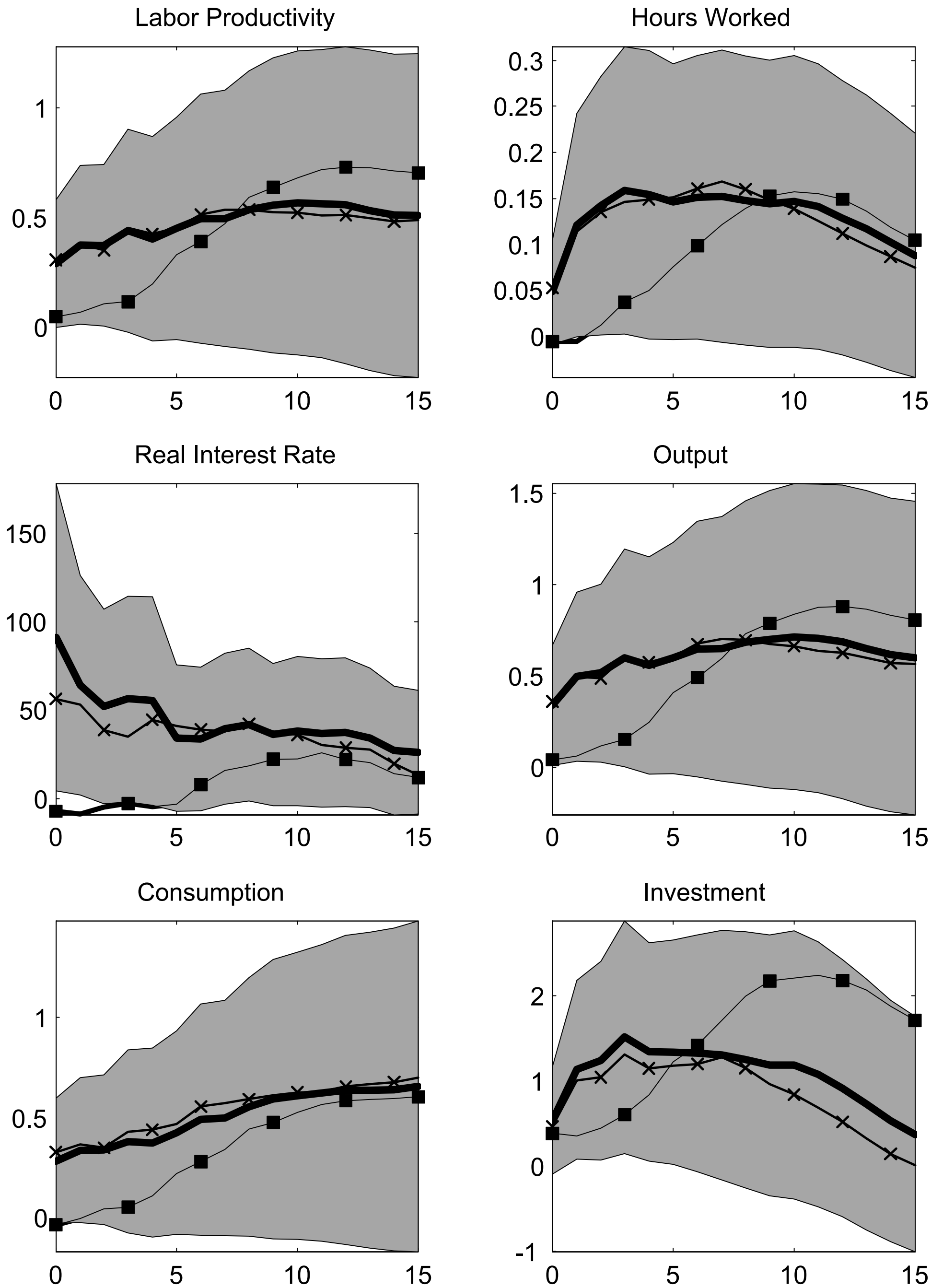


Figure 7: Anderson-Rubin Confidence Set



Thin Line indicated all possible combinations of $\gamma_{0,}^{H}$ and $\gamma_{6,}^{H}$
The grey area indicates those combinations with an Anderson-Rubin statistic less than the 95 percent critical value.

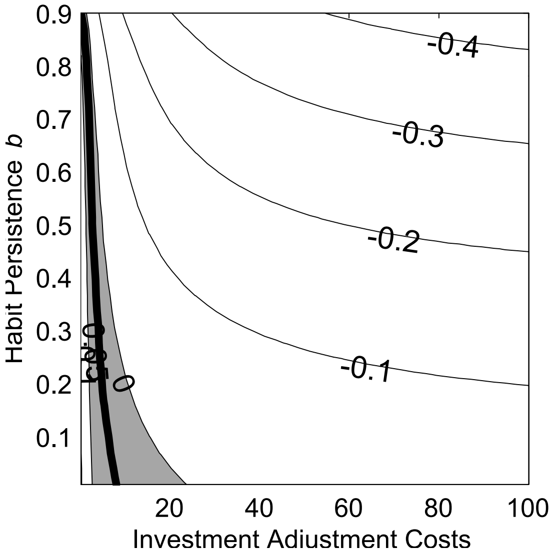
Figure 8: Robustness of Impulse Responses to Different Subsamples.



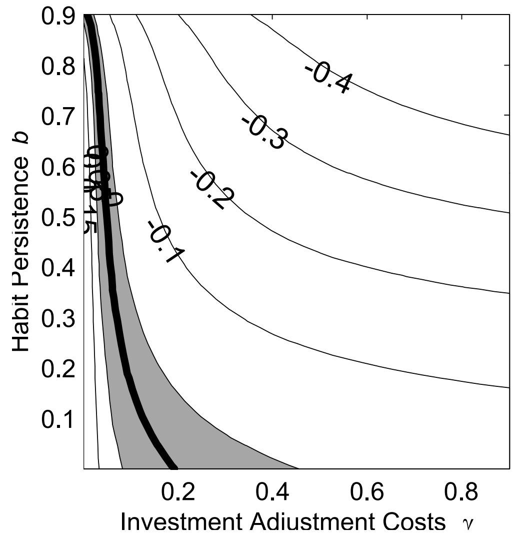
Thick Line VAR and Grey Area: Baseline Results replicated from Figure 4
'X's VAR with exante Real Interest Rate, full sample 1973-2001.
Squares VAR with exante Real Interest Rate, short sample 1983-2001.

Figure 9: How Hours Responds on Impact

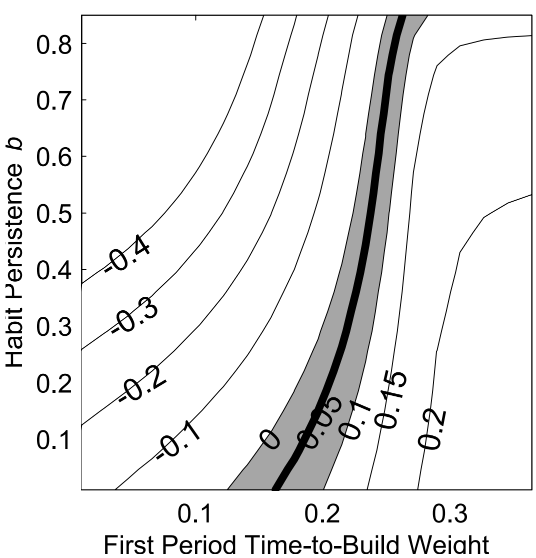
I/K Adjustment



ΔI Adjustment



Time to Build



Notes

Thick Black Line: Point Estimate of Response of Hours on Impact

Grey Area: 95 percent weak-instrument confidence interval as reported in Table 4.

Figure 10: The Trade-off Between
Investment Adjustment Costs and Habit Persistence

Consumption Investment Response

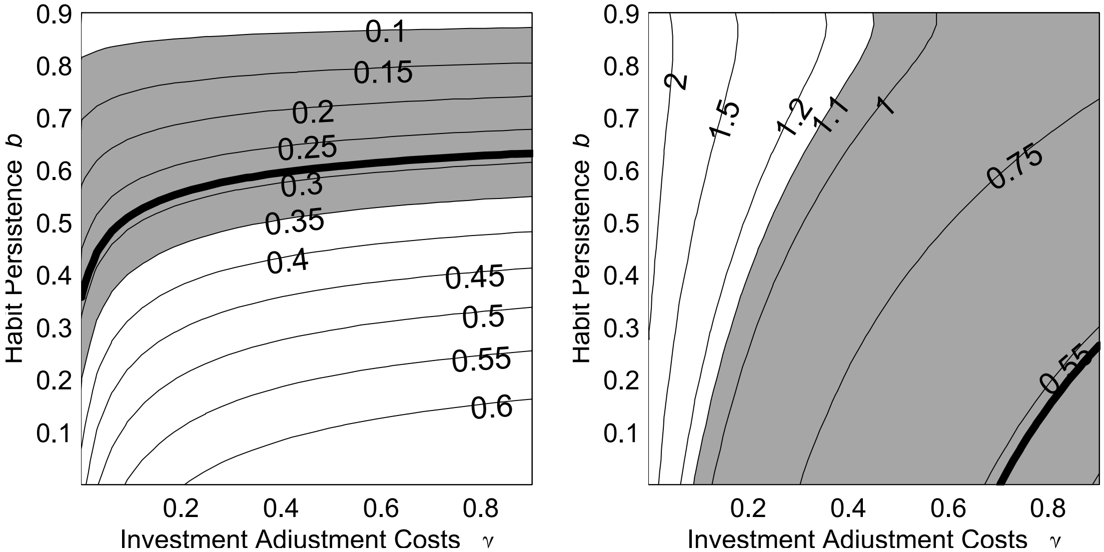
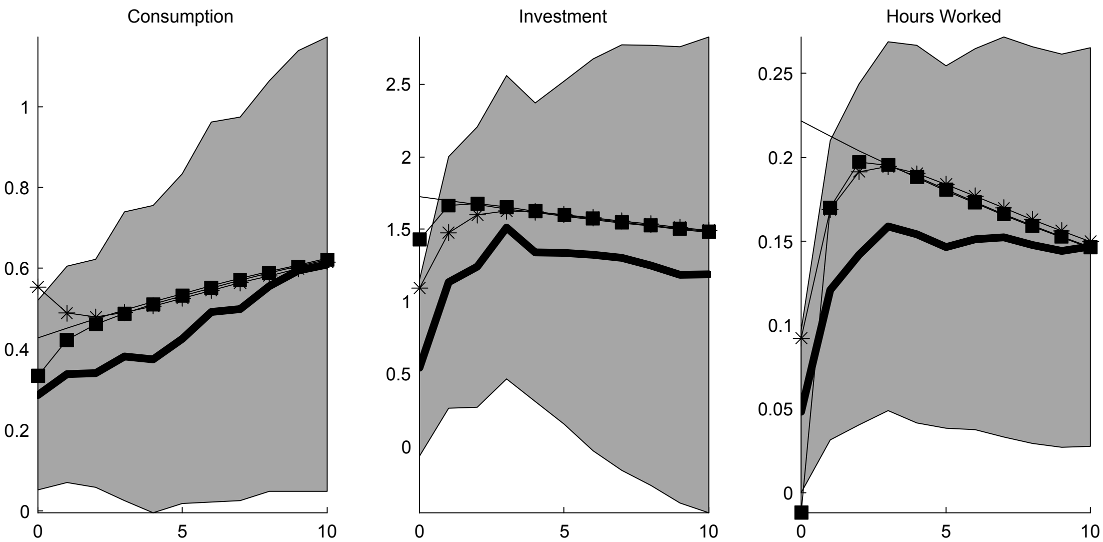
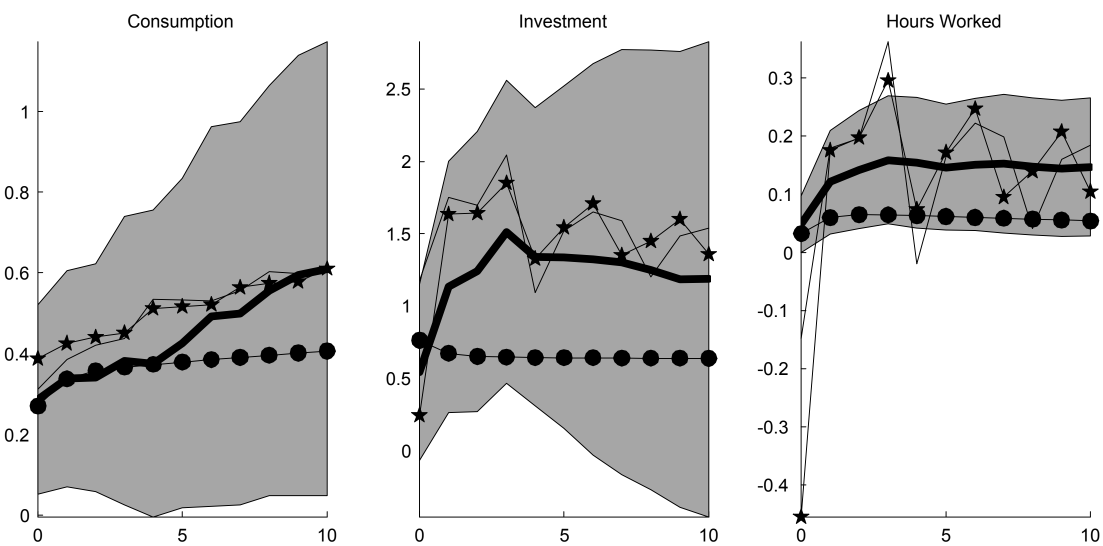


Figure 11: Dynamic Responses Comparing Models and Data
Investment Adjustment Costs as Function of Investment Growth

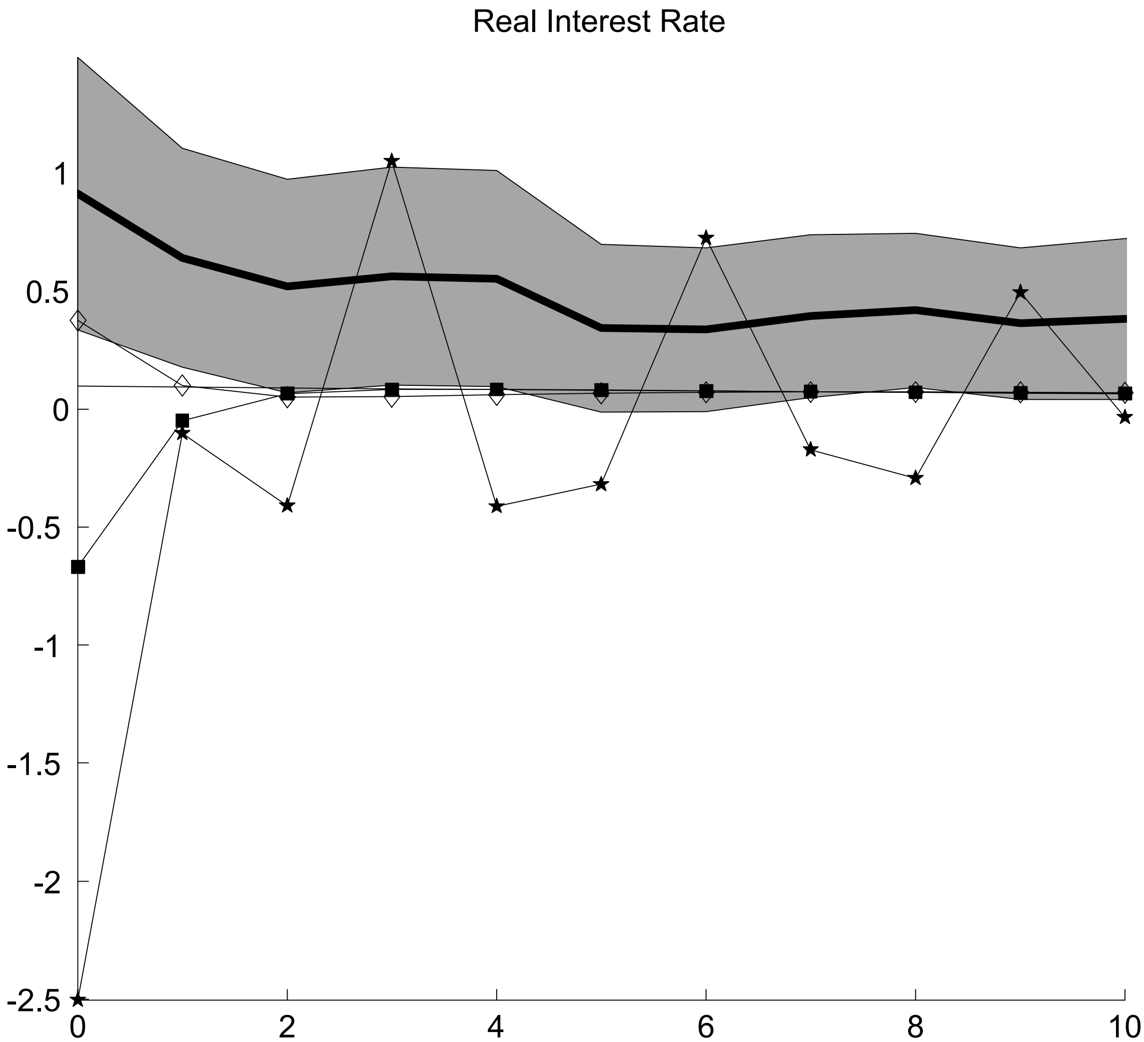


Thick Solid Line: Empirical Response, Thin Line, Standard flexible-price model $(b, \phi) = 0$
Squares: Model with habit persistence and investment adjustment Costs $(b, \phi) = (0.4, 0.09)$
'*'s Model with investment adjustment Costs $(b, \phi) = (0, 0.09)$



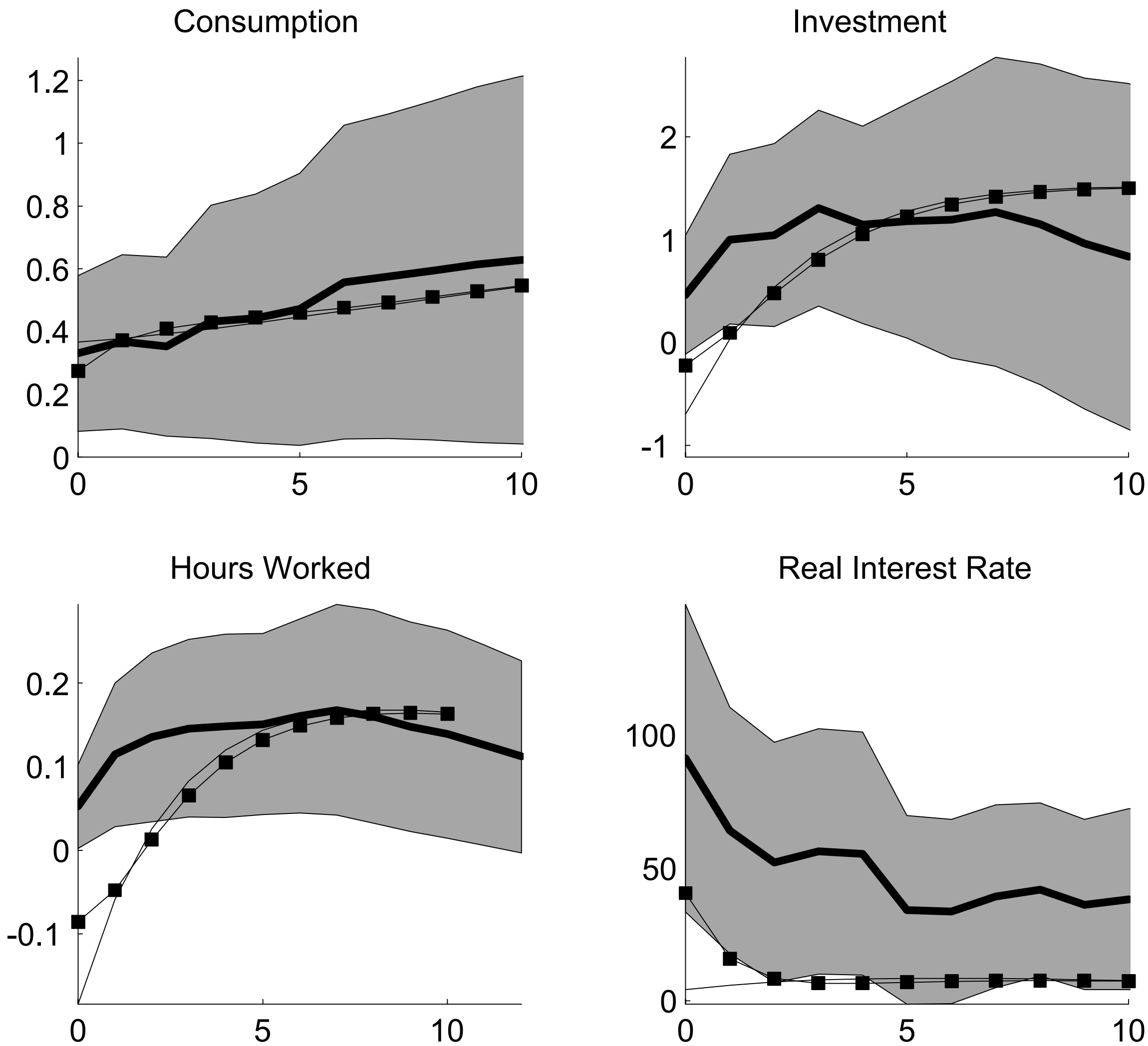
Thick Solid Line: Empirical Response, Stars: Model with habit persistence and Time to Plan $(b, \phi) = (0.5, 0.05)$
Thin Solid: Model with habit persistence and Time to Build $(b, \phi) = (0.5, 0.20)$
Line with Solid Circles, CIK model with habit persistence $(b, \phi) = (0.28, 5)$

Figure 12: Real Interest Rate Response



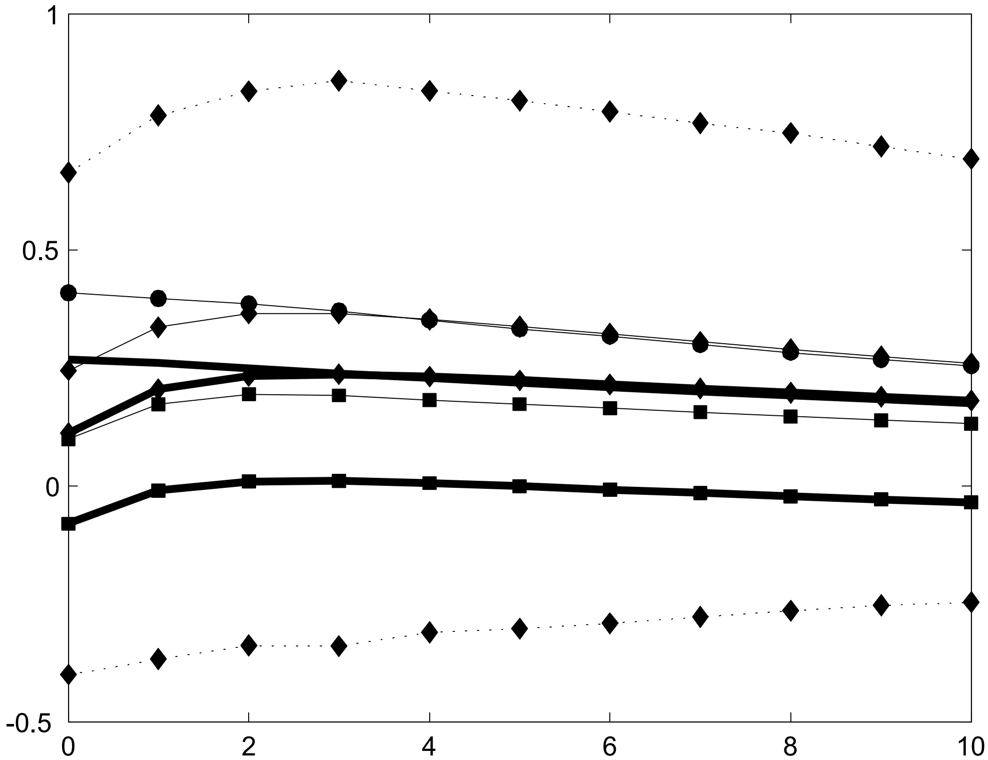
Thick Solid Line: Empirical Response, Thin Line, Standard flexible-price model $(b, \phi) = 0$
Squares: Model with habit persistence and investment adjustment Costs $(b, \phi) = (0.4, 0.09)$
Stars: Model with habit persistence and Time to Plan $(b, \phi) = (0.5, 0.05)$
Diamonds: Model with consumption adjustment costs and investment adjustment costs. $(b, \phi) = (0.4, 0.2)$

Figure 13: Model Responses with Correlated Shocks.



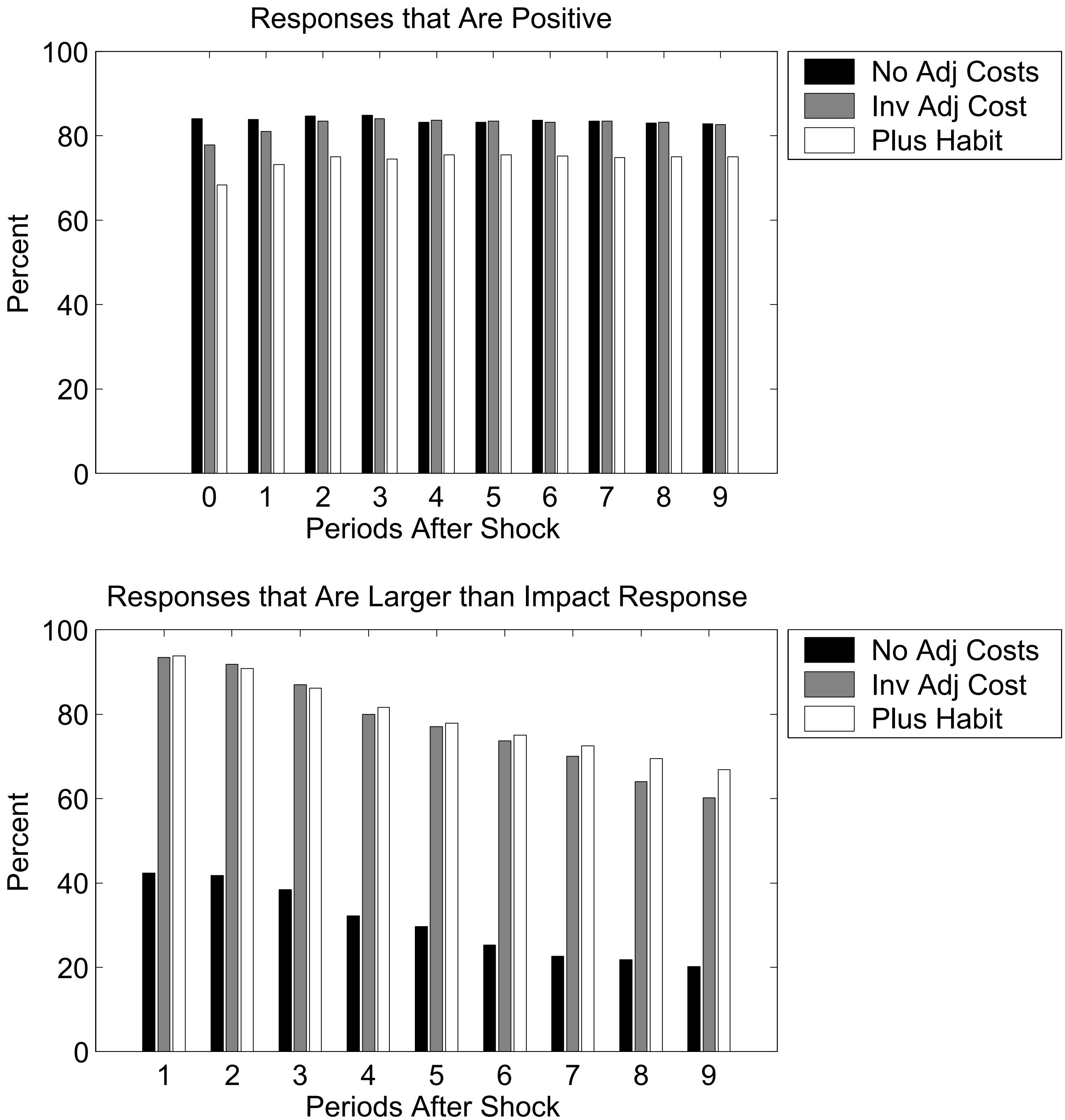
Thick Solid Line: Empirical Response, Thin Line, Standard flexible-price model $(b, \phi) = 0$ with $\rho_z = 0.7$
Squares: Model with habit persistence and investment adjustment Costs $(b, \phi) = (0.4, 0.09)$ with $\rho_z = 0.7$

Figure 14: Hours Response to A Technology Shock



Thick Lines, Model Responses, Plain Standard RBC, Diamonds CII Adjustment Cost, Squares, CII Adjustment and Habit
Thin Lines, Average Estimated Response, Plain Standard RBC, Diamonds CII Adjustment Cost, Squares, CII Adjustment and Habit
Dashed Lines, 90 Percent of all estimated responses for the CII Model
are contained within dashed lines

Figure 15: Simulations Results



No Adj Costs: Standard flexible-price model with no investment adjustment costs or habit persistence.
Inv Adj Costs: flexible-price model with CII-type investment adjustment costs ($\gamma = 0.01$)
Plus Habit flexible-price model with CII-type investment adjustment costs ($\gamma = 0.01$)
and with habit persistence coefficient ($b = 0.6$)