# Unemployment Insurance in a Sticky-Price Model with Worker Moral Hazard

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**Abstract**

This paper studies the role of unemployment insurance in a sticky-price model that features an efficiency-wage view of the labor market based on unobservable effort. The risk-sharing mechanism central to the model permits, but does not force, agents to be fully insured. Structural parameters are estimated using a maximum-likelihood procedure on US data. Formal hypothesis tests reveal that the data favor a model in which agents only partially insure each other against employment risk. The results also show that limited risk sharing helps the model capture many salient properties of the business cycle that a restricted version with full insurance fails to explain.

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# 1 Introduction

Unemployment is a ubiquitous feature of modern economies. Yet in a dynamic general equilibrium setting, unemployment does not emerge unless certain frictions, such as efficiency wages (e.g., Danthine and Donaldson, 1990; Gomme, 1999) or search externalities (e.g., Merz, 1995; Andolfatto, 1996), are built into the labor market. A frequent assumption underlying these models is that workers perfectly insure each other against variations in labor income resulting from job loss. The rationale is that insurance contracts make the intertemporal decisions independent of one's employment status, thereby circumventing complications that arise from heterogeneous work histories. Restoring homogeneity to the model, the argument goes, allows the researcher to focus on the role of labor market imperfections in accounting for unemployment and other important aspects of the data.

Notwithstanding the desire to highlight the labor market, the assumption of complete risk sharing has two potential drawbacks that have received little attention in the macroeconomic literature. First, there is no compelling evidence that points to full insurance as an empirically realistic premise. To the contrary, many studies show that brief unemployment spells cause a nontrivial decline in personal consumption spending (e.g., Dynarski and Sheffrin, 1987; Gruber, 1997). At the very least it would be useful to have a business cycle model that is more consistent with our understanding of the risk-sharing behavior of consumers. Second, the assumption of full insurance is appropriate provided its effect on the main conclusions of the model are negligible. It is difficult to determine whether full insurance meets this standard in the absence of a model that embodies alternative insurance possibilities.

In light of these issues, this paper estimates an equilibrium model of unemployment that incorporates a menu of different risk-sharing options, and by doing so, departs from the widespread practice of considering only the case of full insurance. More specifically, this paper asks whether the assumption of full insurance is sufficient to explain most of the key properties of the US business cycle, or whether limiting the insurance opportunities substantially improves the fit of the model. To that end, I construct a dynamic sticky-price model that gives prominence to a frictional labor market along the lines of Alexopoulos (2004). The central idea is that workers face a temptation to shirk that arises from firms' inability to monitor effort. Consequently, employers design a payment mechanism that discourages shirking. The outcome corresponds to an efficiency wage that exceeds the market-clearing level and makes unemployment an equilibrium feature of the economy.

Unemployment insurance enters the model by means of an income-pooling device that permits, but does not force, agents to fully insure each other against employment risk. Workers contribute a portion of their earnings into a fund that is redistributed equally to the unemployed. Individual contributions are governed by an exogenous function that defines the scope of insurance coverage. The specification used in the model can accommodate any one of a continuum of different arrangements, including both partial and full insurance cases.[1]

The paper proceeds by estimating the parameters of the model using a maximum-likelihood procedure with quarterly US data on per capita consumption, investment, the real wage, inflation, and the nominal interest rate. Two versions of the model are estimated that differ in their treatment of risk sharing. One leaves the insurance parameter unconstrained, allowing the data to ascertain the extent of risk sharing among agents. The second restricts this parameter prior to estimation to guarantee full insurance in equilibrium. Likelihood ratio tests provide the basis for a formal comparison of fit between the restricted, full insurance version and the unrestricted alternative that allows for partial insurance.

Econometric results indicate that the data prefer a model in which agents are only partially insured. Point estimates of the insurance parameter imply that individual consumption is about 40 percent less for unemployed members. A likelihood ratio test of the null hypoth-

[1] I avoid computational problems related to consumption heterogeneity by using a family construct that makes all decisions regarding asset accumulation (e.g., Alexopoulos, 2004; Danthine and Kurmann, 2004).

esis of full insurance is easily rejected at standard significance levels.

Although useful for comparing model fit, likelihood ratio tests are not very informative about precisely which features of the data are better explained by the inclusion of partial insurance. Imposing the full insurance restriction causes all of the parameters to deviate from their unconstrained estimates, so any discernable shift in empirical performance is the result of changes in all of the parameter values, not just in the degree of risk sharing. The log likelihood criterion alone is, therefore, not sufficient to identify the specific contribution of the partial insurance mechanism. To evaluate the role of insurance coverage independently from other features of the model, I conduct various simulations of the unconstrained model with partial insurance and compare the findings to those from an identical version with full insurance imposed after estimation. First, impulse response functions show that partial insurance, by altering the pattern of real wage dynamics, enables key structural shocks to have a bigger and more persistent effect on measures of real economic activity. Second, evidence from a broad survey of moments confirms that limited risk sharing helps match the low relative volatility of the real wage and the small correlation between wages and output observed in the data. It also boosts the degree of wage persistence, as reflected in the correlations between current and lagged real wages. Third, variance decompositions reveal that the unrestricted model with partial insurance is more consistent with the belief that monetary shocks have a modest impact on the business cycle, while investment-specific technology shocks play a dominant role in driving economic fluctuations.

## 1.1 Related Literature

There are a few recent papers showing that the performance of business cycle models can be improved in certain areas by restricting the insurance opportunities available to agents. Using a GMM procedure, Alexopoulos (2004) estimates a flexible-price model with unobservable effort driven by technology and fiscal shocks. Two distinct insurance arrangements are examined by imposing alternative calibrations on the wage-pooling equation. The first is the case of full insurance, and the second is a partial insurance plan whereby consumption declines by about 22 percent when unemployed. The results indicate that partial insurance helps amplify and propagate the responses to both shocks while improving the volatility and co-movement of real wages and employment. In a related paper, Alexopoulos (2007) shows that partial insurance also generates a more sluggish price response to monetary shocks from the perspective of a limited participation model.

Aside from the inclusion of sticky prices, this paper extends Alexopoulos' research by conducting statistical inference on the insurance component of the model. Alexopoulos bases her comparison of insurance schemes on an assortment of key second moments, leaving open the question of whether partial insurance actually improves the fit of the model. I impose greater econometric discipline by estimating the degree of risk sharing in an environment that nests full insurance as a special case. The maximum-likelihood strategy employed here enables the researcher to formally test the null hypothesis of complete risk sharing against the alternative of partial insurance.

Givens (2008) develops a monetary business cycle model that combines sticky prices with unobservable labor effort. Similar to the present study, his model features an insurance mechanism that allows for varying degrees of risk sharing. Through dynamic simulations, Givens finds that limiting the scope of insurance coverage leads to greater persistence in the path of output after a monetary shock and more sluggishness in the response of inflation.

By focusing on maximum likelihood estimation, this paper is different from Givens' study, the results of which are predicated on a less rigorous calibration of the parameters. In the course of taking the model to the data, several features are added that have been shown to enrich the dynamics of this class of models. These include capital accumulation with adjustment costs, habit formation in consumption, dynamic price indexation, and an interest rate rule for monetary policy. The model is also augmented by a richer set of disturbances, namely, neutral and investment-specific technology shocks, a preference shock, a cost-push shock, a monetary shock, and a labor supply shock affecting the hours margin. The inclusion of these elements is not meant to be an extension of Givens (2008) by and of itself, but rather a necessary step to implementing the econometric procedure described above. Simpler models that lack these ingredients often produce highly misspecified representations of the data generating process, which can lead to difficulties in interpreting the estimation results.[2]

# 2 The Economic Model

The model blends sticky prices with an efficiency-wage theory of the labor market based on unobservable effort. It is populated by five types of agents: a representative family, a continuum of family members, a competitive finished goods-producing firm, a continuum of intermediate goods-producing firms, and a government.

## 2.1 Families

The representative family has a continuum of members of measure one. Randomly selected $N_t$ members receive job offers every period, while the remaining $1 - N_t$ are unemployed. Because unemployment generates income dispersion, I follow Alexopoulos (2004) in assuming that the family accumulates assets over time. Denying individuals access to financial markets conserves the representative agent framework in an economy with positive unemployment.

The family brings $K_t$ units of capital and $R_{t-1}B_{t-1}$ units of nominal bond wealth into period $t$, where $R_t$ is the gross nominal interest rate between $t$ and $t+1$ on bond purchases $B_t$. It then leases its capital stock to a $[0, 1]$ continuum of intermediate good firms at a competitive rental rate $r_t^k$. At the end of the period, it receives a flow of real dividend payments $\int_0^1 D_t(i)di$ from ownership of those firms. Together with bond and dividend earnings, returns

[2] See Del Negro, Schorfheide, Smets, and Wouters (2007) for a discussion.

from capital are used to purchase a portfolio of new bonds $B_t$, investment goods $I_t$, and a stream of consumption benefits $C_t^f$ for the members. The family distributes consumption equally before jobs commence, making $C_t^f$ a lower bound on the amount of consumption available to members who face employment risk. The budget constraint is then given by

$$C_t^f + I_t + \frac{B_t}{P_t} \leq r_t^k K_t + \frac{R_{t-1}B_{t-1}}{P_t} + \int_0^1 D_t(i)di, \tag{1}$$

where $P_t$ denotes the price of the finished good that can be either consumed or invested.

The law of motion for the family's capital stock is given by

$$K_{t+1} = (1-\delta)K_t - \frac{\phi}{2}\left(\frac{I_t}{K_t} - \delta\right)^2 K_t + a_t I_t, \tag{2}$$

where the depreciation rate $\delta \in (0,1)$ and $\frac{\phi}{2}(\cdot)^2$ is an adjustment cost function with $\phi \geq 0$. In the spirit of Greenwood, Hercowitz, and Huffman (1988), the stochastic variable $a_t$ is an investment-specific technology shock that follows the autoregressive process

$$\log a_t = \rho_a \log a_{t-1} + \varepsilon_{a,t},$$

where $0 < \rho_a < 1$ and $\varepsilon_{a,t} \sim N(0, \sigma_a^2)$.

### 2.1.1 Family Members

Although members do not participate in asset markets, they can purchase additional consumption above the family minimum using wage income. Intermediate good firms offer one-period job contracts that specify an effort level $e_t$ and work hours $h_t$ in exchange for an hourly real wage $w_t$.[3] The inability to perfectly monitor effort, however, invites employed members to shirk. Following Alexopoulos (2004), workers receive a fraction $s$ of their total

[3] I drop firm-specific notation when discussing the characteristics of employment contracts. Because they share a common production technology, contracts will not vary across firms.

wages upon entry, while the final payment of $(1-s)h_t w_t$ is awarded at the end of the period if shirking goes undetected. Shirking is detected with exogenous probability $d$. The shift length $h_t$ is modeled as an exogenous stochastic process: $h_t = h\varepsilon_{h,t}$, where $h$ is the average length of work hours and $\log(\varepsilon_{h,t}) \sim N(0, \sigma_h^2)$[4]. Adding shocks to hours worked permits total hours to vary along the *intensive* margin through exogenous changes in $h_t$ and along the *extensive* margin through endogenous fluctuations in $N_t$.[5]

The government coordinates a fully funded insurance program to spread the risk associated with unemployment. Employees pay an insurance fee $F_t$ that is pooled into one large fund totaling $N_t F_t$ and distributed equally to unemployed members. Those who reject job offers are ineligible to receive unemployment benefits, ensuring that all offers are accepted and that unemployment will be strictly involuntary.[6] It follows that consumption will depend on one's employment status as well as the outcome of the firm's monitoring efforts. If an individual finds employment and is not detected shirking, his date-$t$ consumption will be

$$C_t^e = C_t^f + h_t w_t - F_t. \tag{3}$$

If caught shirking, his consumption will be

$$C_t^s = C_t^f + s h_t w_t - F_t \tag{4}$$

after forfeiting the end-of-period bonus. If unemployed, his date-$t$ consumption will be the

[4]As explained in detail in section 3, exogenous variation in hours worked prevents the forecast error covariance matrix of the observable variables from being rank-deficient. Earlier presentations of the model treat work hours as a constant (e.g., Alexopoulos, 2004; Alexopoulos, 2007; Givens, 2008).

[5]Most of the variation in US total hours occurs along the extensive margin (e.g., King and Rebelo, 1999).

[6]Equilibrium outcomes would not change if the family, instead of the government, was responsible for administering unemployment benefits.

sum of family-purchased consumption and an equal share of the insurance fund given by

$$C_t^u = C_t^f + \frac{N_t F_t}{1 - N_t}. \tag{5}$$

The insurance fee is characterized by an exogenous formula that encompasses a menu of different risk-sharing possibilities. Specifically,

$$F_t = \sigma(1 - N_t) h_t w_t, \tag{6}$$

where $\sigma \in [0, 1]$ quantifies the scope of the insurance program. The government can fully insure workers by setting $\sigma = 1$ since $C_t^e = C_t^u$ in this case. A partial insurance arrangement can be obtained by setting $0 < \sigma < 1$, guaranteeing that $C_t^f < C_t^u < C_t^e$ in equilibrium.

The utility function of a family member $j$ who consumes $C_t^j$ units of the finished good is

$$U(C_t^j - bC_{t-1}, e_t) = \log(C_t^j - bC_{t-1}) + \theta \log(T - \vartheta_t[h_t e_t + \xi]), \tag{7}$$

where $\theta \geq 0$, $T$ is the time endowment, and $\vartheta_t$ is an indicator function equal to one if employed and providing effort. The parameter $\xi$ measures fixed costs of exerting nonzero effort. As in Smets and Wouters (2003), consumption $C_t^j$ appears relative to an external habit variable $bC_{t-1}$. The parameter $b \in [0, 1]$ determines the degree of habit formation, where the reference variable corresponds to last period's average level of consumption $C_{t-1}$.[7] An alternative way to model consumption habits is to treat lagged individual consumption $C_{t-1}^j$ as an internal reference variable (e.g., Fuhrer, 2000; Christiano, Eichenbaum, and Evans, 2005). As illustrated by Dennis (2009), however, the two approaches display very similar business cycle properties in a new Keynesian model.

Because effort is imperfectly observable, workers encounter a moral hazard problem after

[7] Date-$t$ average consumption in the family is given by $C_t = (N_t - dN_t^s)C_t^e + dN_t^s C_t^s + (1 - N_t)C_t^u$, where $N_t^s$ denotes the fraction of members who shirk.

accepting job offers. Specifically, they must decide whether supplying the mandatory effort is optimal given knowledge of the firm's exogenous monitoring technology. Alexopoulos (2006a) demonstrates that employees will abide by the terms of the contract only if the resultant utility exceeds the expected utility from shirking. Workers will otherwise choose to elicit zero effort because any positive effort reduces utility and the wage forfeiture facing a detected shirker does not depend on the size of one's effort deficit. This means that workers will satisfy the conditions of employment provided they are *incentive compatible*, that is, if

$$U(C_t^e - bC_{t-1}, e_t) \geq dU(C_t^s - bC_{t-1}, 0) + (1-d)U(C_t^e - bC_{t-1}, 0). \quad (8)$$

It is clear from (8) that the precise definition of the habit variable will have important consequences for equilibrium real wages. Under an external habit setup, all non-shirking employees have the same utility, implying that firms can satisfy each worker's incentive compatibility constraint with a common wage. When individual consumption is the reference variable, current utility depends on the realization of random employment draws in earlier periods. If those outcomes are observable, firms seeking to discourage all shirking at the lowest possible cost will offer different wages to employees according to their idiosyncratic work histories.[8] Assuming that consumption habits are external keeps the model tractable and avoids complications arising from equilibrium wage dispersion.

#### 2.1.2 The Representative Family's Problem

The family's objective is to maximize the present value of the average utility of its members. The next section establishes that job contracts are always incentive compatible, so workers

[8]This is only true in the partial insurance case. With full insurance, family members consume equal quantities, implying that all individuals who receive job offers have the same utility.

will never shirk in equilibrium. Accordingly, family preferences take the form

$$E_0 \sum_{t=0}^{\infty} \beta^t g_t \left[ N_t U(C_t^e - bC_{t-1}, e_t) + (1 - N_t) U(C_t^u - bC_{t-1}, 0) \right], \tag{9}$$

where $\beta \in (0, 1)$ is the discount factor. Sequences $\{C_t^f, B_t, I_t, K_{t+1}\}_{t=0}^{\infty}$ are chosen to maximize (9) subject to (1), (2), (3), and (5). The family treats $N_t$ parametrically during optimization because it does not believe that its actions affect employment outcomes.[9] Finally, the stochastic variable $g_t$ is a shock affecting the time rate of preference and is governed by

$$\log g_t = \rho_g \log g_{t-1} + \varepsilon_{g,t},$$

where $0 < \rho_g < 1$ and $\varepsilon_{g,t} \sim N(0, \sigma_g^2)$. The preference shock appears in the Euler equation for $C_t^f$ linking current and expected future average marginal utility of consumption to the real interest rate. McCallum and Nelson (1999) argue that shocks like this one are similar to shocks originating in the goods market in traditional Keynesian IS-LM models.

## 2.2 Firms

Firms are of two types. The first type produces identical finished goods sold to families in competitive markets. The second type hires family members to produce intermediate goods that are sold to finished goods-producing firms in monopolistically competitive markets.

[9] Divorcing individuals from savings decisions raises another issue about the treatment of habit formation. From the members' perspective, past average consumption is viewed as an *external* reference variable. With the family managing assets, however, the impact of marginal changes to $C_t^f$ on average consumption are *internalized* in the decision period.

### 2.2.1 Finished Good Firms

A perfectly competitive firm manufactures finished goods $Y_t$ by assembling a $[0,1]$ continuum of intermediate goods indexed by $i$ using the technology described by Kimball (1995)

$$\int_0^1 G\left(\frac{Y_t(i)}{Y_t}\right) di = 1, \tag{10}$$

where $Y_t(i)$ measures the quantity of good $i$. The function $G$ is increasing and strictly concave, with $G(1) = 1$. The Kimball formulation generalizes the popular Dixit-Stiglitz aggregator by permitting the elasticity of demand for each good $i$ to be increasing in its relative price. This feature introduces a strategic complementarity in intermediate good firms' pricing decisions that helps the model achieve greater consistency with the micro-level evidence on the frequency of price adjustments (e.g., Eichenbaum and Fisher, 2007).

The finished good firm chooses $Y_t$ and $\{Y_t(i)\}_{i\in[0,1]}$ to maximize profits every period subject to (10). This leads to a demand curve for good $i$ of the form

$$Y_t(i) = G'^{-1}\left[\frac{P_t(i)}{P_t}\int_0^1 G'\left(\frac{Y_t(i)}{Y_t}\right)\frac{Y_t(i)}{Y_t}\,di\right] Y_t, \tag{11}$$

where $P_t(i)$ denotes the date-$t$ price of $Y_t(i)$.[10] The marginal cost of producing a unit of the finished good is $P_t$, which can be derived from the zero profit condition $P_tY_t = \int_0^1 P_t(i)Y_t(i)di$.

### 2.2.2 Intermediate Good Firms

The production technology for intermediate goods takes the form

$$Y_t(i) = z_t k_t(i)^\alpha([n_t(i) - n_t^s(i)]e_t(i)h_t)^{1-\alpha},$$

[10] $G'^{-1}(\cdot)$ denotes the inverse function of $G'(\cdot)$.

where the capital share $\alpha \in (0,1)$. The variable $z_t$ is a neutral technology shock that follows

$$\log z_t = (1-\rho_z)\log z + \rho_z \log z_{t-1} + \varepsilon_{z,t},$$

where $0 < \rho_z < 1$, $z > 0$, and $\varepsilon_{z,t} \sim N(0, \sigma_z^2)$. Inputs $k_t(i)$, $n_t(i)$, $n_t^s(i)$, and $e_t(i)$ represent the date-$t$ capital services, number of family members, number of shirkers, and effort levels employed by firm $i$, respectively. Given the timing of wage payments and the fact that shirkers produce no output, it is never profitable to hire workers who are inclined to shirk. As a result, firms design labor contracts that elicit effort from all employees.

During period $t$, firms select $\{k_t(i), n_t(i), w_t(i), e_t(i)\}$ to minimize unit production costs $k_t(i)r_t^k + n_t(i)h_t w_t(i)$ subject to $z_t k_t(i)^\alpha (n_t(i)e_t(i)h_t)^{1-\alpha} \geq 1$ and the incentive compatibility constraint (8). The latter constraint holds with equality because firms want to compensate employees no more than what is minimally needed to induce effort. By substituting (3), (5), and (7) into (8), effort can be expressed as a function of the real wage,

$$e_t(i) = e(w_t(i)) = \frac{T-\xi}{h_t} - \frac{T}{h_t}\left(\frac{C_t^f + h_t w_t(i) - F_t - bC_{t-1}}{C_t^f + sh_t w_t(i) - F_t - bC_{t-1}}\right)^{-d/\theta}. \tag{12}$$

Subject to (12), cost minimization yields the familiar Solow (1979) condition

$$\frac{w_t(i)e'(w_t(i))}{e(w_t(i))} = 1, \tag{13}$$

which implies that firms select the real wage to minimize costs per unit of effort.[11] The *efficiency wage* satisfying (13) will generally exceed the wage that would prevail in a Walrasian labor market with perfect monitoring. The result is positive unemployment in equilibrium.

After differentiating (12) with respect to the real wage, the Solow condition (13) implies that $(C_t^e - bC_{t-1})/(C_t^s - bC_{t-1})$ is fixed and depends only on the parameters $s$, $T$, $\xi$, and

[11] Firms take the government insurance fee and the habit variable as given when making wage decisions.

$d/\theta$. Specifically, one can show that this ratio satisfies

$$T\left(\frac{d}{\theta}\right)(1-s\tilde{C})(\tilde{C}-1)=(1-s)\left[(T-\xi)\tilde{C}^{1+d/\theta}-T\tilde{C}\right], \tag{14}$$

where $\tilde{C}\equiv(C_t^e-bC_{t-1})/(C_t^s-bC_{t-1})$. This result generalizes the findings of Alexopoulos (2004) to account for the impact of habit formation on wage contracts.

Although firms negotiate wages every period, price contracts can last for several periods. Using the Calvo (1983) formulation, a fraction $1-\chi$ of randomly selected firms adjust prices optimally in each period. The remaining $\chi$ firms reset prices according to a variant of the dynamic indexing rule proposed by Christiano *et al.* (2005)

$$P_t(i)=\exp(\varepsilon_{\pi,t})\pi_{t-1}P_{t-1}(i), \tag{15}$$

where $\pi_{t-1}$ is the inflation rate from dates $t-2$ to $t-1$. The stochastic term $\varepsilon_{\pi,t}$ is a shock to the indexation rule with distribution $\varepsilon_{\pi,t}\sim N(0,\sigma_\pi^2)$. Casares (2007) shows that exogenous variation in the indexation rule resembles, in equilibrium, a "cost-push" shock of the kind emphasized by Clarida, Galí, and Gertler (1999). Denote $\tilde{P}_t$ the price common to all firms that reoptimize during period $t$. Firms choose $\tilde{P}_t$ to maximize the present value of profits

$$E_t\sum_{j=0}^{\infty}(\chi\beta)^j\left(\frac{\lambda_{t+j}/P_{t+j}}{\lambda_t/P_t}\right)\left[\frac{\tilde{P}_t}{P_{t+j}}\left(\prod_{k=0}^{j-1}\exp(\varepsilon_{\pi,t+k+1})\pi_{t+k}\right)-mc_{t+j}\right]P_{t+j}Y_{t+j}(i), \tag{16}$$

where $mc_t$ is the real marginal cost of production and the term $\beta^j(\lambda_{t+j}/P_{t+j})/(\lambda_t/P_t)$ measures the family's date-$t$ nominal value of additional profits acquired at date $t+j$.

### 2.2.3 The No-Shirking Condition

The presence of unobservable effort means that the labor market can no longer be described in Walrasian terms. In the language of Shapiro and Stiglitz (1984), a "no-shirking condition" originating from the incentive compatibility constraint supplants the neoclassical labor supply curve. To derive the no-shirking condition, substitute (3) into (4) and apply the result that $(C_t^e - bC_{t-1})/(C_t^s - bC_{t-1})$ is constant in equilibrium to obtain

$$(1-s)\left(\frac{\tilde{C}}{\tilde{C}-1}\right) h_t w_t = C_t^e - bC_{t-1}. \tag{17}$$

For constant family consumption, (17) implies a positive relationship between $w_t$ and $N_t$.

The no-shirking requirement also implies a fixed relationship between employed and unemployed consumption. Combining (3), (5), (6), and (17) yields

$$\frac{C_t^u - bC_{t-1}}{C_t^e - bC_{t-1}} = \mu(\sigma) \equiv 1 - \frac{1-\sigma}{1-s}\left(\frac{\tilde{C}-1}{\tilde{C}}\right), \tag{18}$$

where $\mu$ is a scalar with an upper bound of one and increasing in $\sigma$. Because changes in $\sigma$ translate directly into changes in $\mu$ for fixed values of $s$ and $\tilde{C}$, the value of $\mu$ fully identifies the scope of insurance coverage. Under full insurance, $\mu(\sigma = 1) = 1$ and (18) collapses to $C_t^u = C_t^e$. Under partial insurance, $\mu(\sigma < 1) < 1$ and (18) implies $C_t^u = \mu C_t^e + (1-\mu)bC_{t-1}$.

## 2.3 The Government

The government conducts monetary policy through control of the one-period nominal interest rate $R_t$. Policy decisions are characterized by a generalized Taylor (1993) rule of the form

$$\log\frac{R_t}{R} = \theta_R \log\frac{R_{t-1}}{R} + (1-\theta_R)\left[\theta_\pi \log\frac{\pi_t}{\pi} + \theta_{Y0}\log\frac{Y_t}{Y} + \theta_{Y1}\log\frac{Y_{t-1}}{Y}\right] + \varepsilon_{R,t}, \tag{19}$$

which calls for a gradual adjustment of $R_t$ to steady-state departures of current inflation and current and past output with coefficients $\{\theta_\pi, \theta_{Y0}, \theta_{Y1}\}$. Lagged output is included in the policy rule to accommodate a response to movements in output growth, in which case $\theta_{Y0} = -\theta_{Y1}$. The coefficient $\theta_R$ captures the degree of interest rate smoothing. The purely random component of policy is summarized by the stochastic variable $\varepsilon_{R,t} \sim N(0, \sigma_R^2)$.

# 3 Equilibrium and Estimation Strategy

The optimality conditions, various identity and market-clearing conditions, laws of motion for the shocks, and the monetary policy rule form a system of nonlinear difference equations governing the dynamic equilibrium of the shirking model. When the shocks are fixed at their mean values, the equations jointly imply that all prices and quantities converge to a unique steady state. I log-linearize the difference equations around the steady state and solve the resulting system using the method developed by Klein (2000).[12] The solution takes the form

$$\mathbf{s}_t = \mathbf{\Pi}\mathbf{s}_{t-1} + \mathbf{\Omega}\varepsilon_t, \tag{20}$$

$$\mathbf{f}_t = \mathbf{U}\mathbf{s}_t, \tag{21}$$

where $\mathbf{s}_t$ is a vector of exogenous shocks and endogenous state variables, $\varepsilon_t$ contains the innovations $\varepsilon_{z,t}$, $\varepsilon_{g,t}$, $\varepsilon_{a,t}$, $\varepsilon_{\pi,t}$, $\varepsilon_{h,t}$, and $\varepsilon_{R,t}$, and $\mathbf{f}_t$ holds the endogenous flow variables. The elements of $\mathbf{\Pi}$ and $\mathbf{U}$ are functions of the structural parameters, and $\mathbf{\Omega}$ is a selector matrix.

As illustrated by Kim (2000) and Ireland (2001), a class of models with solutions of the form (20) - (21) are amenable to maximum likelihood estimation using the Kalman filtering algorithms described in Hamilton (1994, Ch. 13). With data on the model's observable variables, the Kalman filter compiles a history of innovations $\{\varepsilon_t\}_{t=1}^T$ that can be used to construct the sample likelihood function. Because the innovations depend on $\mathbf{\Pi}$ and $\mathbf{U}$, the structural parameters can in principle be estimated by maximizing the likelihood function.[13]

The structural parameters are estimated using data on consumption, investment, the

[12] Appendix A contains a list of the general equilibrium conditions, a derivation of the steady state, and the complete system of log-linear difference equations.

[13] Appendix B contains a detailed discussion of the estimation procedure.

real wage, inflation, and the nominal interest rate. With data on five variables, no fewer than five shocks must enter the econometric model to circumvent the stochastic singularity problem emphasized by Ruge-Murcia (2007). Preliminary estimation attempts with just five shocks (i.e., neutral and investment-specific technology shocks, a preference shock, a cost-push shock, and a policy shock) were successful under a partial insurance arrangement. Under full insurance, however, estimation failed because the forecast error covariance matrix of the data became singular. The reason is that the no-shirking condition (17) simplifies to $(1-s)(\tilde{C}/(\tilde{C}-1))h_t w_t = C_t - bC_{t-1}$ when $\mu = 1$, implying an exact deterministic relationship between consumption and the real wage in the absence of shocks to hours worked. Using data on both variables renders the covariance matrix rank-deficient. Permitting temporal variation in hours worked drives a stochastic wedge between consumption and the real wage, sidestepping the singularity problem that emerges in the presence of complete risk sharing. This makes it possible to estimate the partial and full insurance models with the same data.[14]

The key parameters of interest are those characterizing the labor market and the insurance scheme. Alexopoulos (2004) and Alexopoulos (2007) use an exactly identified GMM strategy to form inferences about their values. The central estimate in both studies is the ratio $d/\theta$ appearing in the incentive compatibility constraint (equation (12) in this paper). To identify this ratio, assumptions are made about the other parameters affecting labor supply. Specifically, $T$ and $\xi$ are calibrated to match the time resources available to workers every quarter, and $\tilde{C}$ is chosen to match the estimated decline in food consumption resulting from unemployment reported by Gruber (1997). With fixed values for $T$, $\xi$, and $\tilde{C}$ and an estimate of $d/\theta$, the value of $s$ is determined from the Solow condition (equation (14) in this paper). All five parameters jointly determine the average employment rate $N$.[15]

[14]An alternative strategy would be to augment the observable variables with a vector of measurement errors (e.g., McGratten, 1994; Hall, 1996; Ireland, 2004a). This approach is less appealing because measurement errors carry no structural interpretation and basically absorb specification error. Nevertheless, Appendix C reports estimation results from a version of the shirking model in which hours worked is constant and measurement errors are included in the observation equation.

[15]Alexopoulos (2006a) and Alexopoulos (2006b) demonstrate an alternative calibration strategy in which

A potential drawback of this strategy is that it forces the researcher to make assumptions regarding the scope of the insurance program before estimation. In both studies, two sets of estimates are obtained by placing competing restrictions on the risk-sharing parameter $\mu$, that is, on the equilibrium value of $C_t^u/C_t^e$. One case considers full insurance by restricting $\mu = 1$. The other case considers a specific amount of partial insurance in which $\mu = 1/\tilde{C}$. No other risk-sharing arrangements are considered during the course of estimation.[16]

This paper takes a different approach by leaving $\mu$ unrestricted and allowing the data to ascertain the true relationship between $C_t^u$ and $C_t^e$. One advantage of this strategy is that the researcher need not make assumptions regarding $T$, $\xi$, $\tilde{C}$, $d/\theta$, or $s$. It turns out that $s$ and $\tilde{C}$ appear only as the ratio $((1-s)\tilde{C})/(\tilde{C}-1)$, which can be expressed as a function of parameters that are estimated directly or calibrated prior to estimation.[17] Moreover, $T$, $\xi$, and $d/\theta$ serve only to determine steady-state employment $N$. I choose to insert $N$ into the linearized model rather than assign values to $T$, $\xi$, and $d/\theta$ because there is ample evidence about the size of the former but only sparse information about suitable values for the latter.

Most of the other parameters are estimated with US data spanning 1959:Q2 to 2005:Q4. Consumption is real personal consumption expenditures, and investment is real gross private domestic investment. To express the series in per capita terms, divide each by the civilian noninstitutional population, age 16 and over. The real wage corresponds to real compensation per hour in the nonfarm business sector. Inflation is the log first difference of the GDP deflator, and the nominal interest rate is the log of the gross return on three-month Treasury bills at a quarterly rate. All data except for the interest rate are seasonally adjusted.

To make the data conformable with the model, subtract the sample mean from observa-

survey evidence on the size of employee bonuses is used to uncover a value for $s$, while data on the unemployment rate is used to identify a value for the detection probability. The Solow condition is then used to back out an implied value for $\tilde{C}$.

[16]The interpretation of $\mu$ is slightly different in this paper due to the presence of habit formation.

[17]Appendix C explains how to back out implied values of $s$ and $\tilde{C}$ given knowledge of the other parameters and compares the findings to values reported in Alexopoulos (2004).

tions of inflation and the interest rate. Consumption, investment, and the real wage, exhibit positive trends, reflecting the long-run growth in the US economy. Following Rabanal and Rubio-Ramirez (2005), I regress the logs of each against a constant, a linear time trend, and a quadratic time trend. The resulting least squares residuals are used for estimation.

# 4 Maximum Likelihood Estimates

Some parameters are fixed prior to estimation because they are either difficult to identify or external information about their values is available. The discount factor $\beta$ is set to 0.9955 to ensure an annualized mean real interest rate equal to the ratio of the sample averages of inflation and the nominal interest rate. The capital share parameter $\alpha$ is set equal to 0.36 based on evidence from the NIPA. Absent data on the capital stock, the depreciation rate $\delta$ is fixed at $1.1^{1/4} - 1$ so that capital depreciates at a rate of 10 percent per annum. Steady-state employment $N$ is set equal to 0.941 to match the mean employment rate over the sample period. This parameter is calibrated rather than estimated because it has no effect on the dynamics of the linearized model under full insurance.[18] Finally, there are three parameters that only directly affect inflation dynamics: the price adjustment probability $\chi$, firms' steady state markup denoted $\eta$, and the elasticity parameter of the Kimball aggregator denoted $\epsilon$.[19] As shown in the appendix, all three parameters jointly determine the slope coefficient on real marginal cost in the Phillips curve. Forming inferences about the adjustment probability $\chi$, therefore, requires specifying fixed values for $\eta$ and $\epsilon$ before estimation. I set $\eta$ equal to 0.20 to deliver an average markup of 20 percent (e.g., Basu and Feranld, 1997) and fix $\epsilon$ at 33 to match the benchmark value used by Kimball (1995). With constant values for $\eta$ and $\epsilon$,

[18]See Appendix A for details.

[19]The Kimball parameter measures the percent change in a firm's elasticity of demand with respect to a one percent change in the relative price of its good, evaluated in the steady state. Let $\varepsilon = -\frac{G'(1)}{G''(1)}$ denote the steady-state elasticity of demand, implying that $\epsilon = \frac{\tilde{P}/P}{\varepsilon} \frac{\partial \varepsilon}{\partial \tilde{P}/P}$.

initial attempts to estimate $\chi$ unfortunately returned values that point to extremely high amounts of price rigidity. Consequently, I set $\chi$ equal to $0.\overline{55}$, implying that prices are reset optimally every 6.75 months on average.[20] This number corresponds to the midpoint of the micro-level estimates on the median frequency of price changes of 5.5 months reported by Bils and Klenow (2004) and 8 months by Nakamura and Steinsson (2008).[21]

Table 1 displays the point estimates and standard errors of the remaining parameters. The standard errors are computed by taking the square roots of the diagonal elements of the information matrix, obtained by inverting the matrix of second derivatives of the maximized log likelihood function. Two sets of estimates are reported. The first set considers partial insurance by leaving the risk-sharing parameter $\mu$ unconstrained. The second set examines the case of full insurance by restricting $\mu = 1$.

Point estimates of the capital adjustment cost parameter $\phi$ are large and statistically significant regardless of the insurance plan. The estimate of habit formation $b$ is 0.26 under partial insurance and 0.42 under full insurance. Both estimates are smaller than the ones reported by Fuhrer (2000) and Boldrin, Christiano, and Fisher (2001), but they are close to the values obtained by Levin *et al.* (2005) and Ireland (2007).

Concerning the policy rule, estimates of the smoothing coefficient $\theta_R$ are large and statistically significant, reflecting the Federal Reserve's tendency to adjust interest rates gradually in response to shocks. Estimates of $\theta_\pi$, $\theta_{Y0}$, and $\theta_{Y1}$ indicate a greater historical emphasis on stabilizing inflation than real output. Interestingly, the relative magnitudes of $\theta_{Y0}$ and $\theta_{Y1}$ suggest that policy responds more to fluctuations in the growth rate of output than to its absolute level. Both point estimates are statistically different from zero, but their sum is

[20] The average quarterly duration of price contracts is given by $(1-\chi)^{-1}$.

[21] The price adjustment coefficient is notoriously difficult to estimate in DSGE models using likelihood-based methods. Ireland (2004b) holds fixed this parameter during estimation because it converged to unreasonably large values when left unrestricted. Applying Bayesian priors that effectively penalize these areas of the parameter space, Smets and Wouters (2005) and Levin, Onatski, Williams, and Williams (2005) obtain estimates that far exceed the value used in this paper.

not. Finally, comparing estimates across both versions of the model reveals that the policy response to inflation and output growth is larger under partial insurance.

Turning next to the exogenous shocks, estimates of $\rho_z$, $\rho_a$, and $\rho_g$ indicate that neutral and investment-specific technology shocks as well as preference shocks are highly persistent. Levin *et al.* (2005) and Smets and Wouters (2007) also report persistent technology and preference shocks. Estimates of the standard deviations are statistically significant and not greatly affected by the insurance plan. There is one exception. The estimate of $\sigma_h$ is 0.0083 under partial insurance and 0.03 under full insurance. With complete risk sharing, the model requires large shocks to hours worked in order to fit the data. The reason for this is that full insurance forces the hours shock to absorb all of the variation in consumption and the real wage that is not explained by the deterministic component of the no-shirking condition (17). By contrast, partial insurance allows the same residual portion to be spread between work hours and fluctuations in employment.[22] This extra degree of freedom drives down the implied volatility of the hours shock. Because most of the variation in US total hours occurs along the extensive margin, I view this result as evidence in favor of partial insurance.

The estimate of the risk-sharing parameter $\mu$ is 0.49, implying that consumption less the habit stock for unemployed members is about one-half of what it is for employed members. To make a direct comparison with the insurance schemes considered in Alexopoulos (2004) and Alexopoulos (2007), it is necessary to determine what $\mu$ reveals about the relative consumption of the unemployed $C_t^u/C_t^e$. Both studies fix this ratio, which is constant in equilibrium, equal to 0.78 prior to estimation, ensuring that consumption declines by 22 percent when unemployed. Unfortunately, it is impossible to derive a parallel ratio for this model because the presence of habit formation makes $C_t^u/C_t^e$ time varying. In the absence

[22]See appendix A for details.

of shocks, however, $C_t^u/C_t^e$ eventually converges to a steady-state level given by

$$\frac{C^u}{C^e} = \frac{\mu(1-b) + [N + (1-N)\mu]b}{(1-b) + [N + (1-N)\mu]b}.$$

The estimates of $\mu$ and $b$ imply an estimate of $C^u/C^e$ equal to 0.62 with a standard error of 0.03. The interpretation is that unemployed members consume on average about three-fifths of what employed members consume. Estimates of the degree of risk sharing are, therefore, smaller than, but not totally inconsistent with, values commonly used in previous studies.[23]

To determine if the model with partial insurance can better account for the time series behavior of the data, I conduct a likelihood ratio test of the restriction imposed by full insurance. The likelihood ratio statistic is formed by subtracting the restricted value of the maximized log likelihood function from its unrestricted counterpart and multiplying the difference by two. It is asymptotically distributed as a chi-square random variable with one degree of freedom. Table 1 reports a value of the log likelihood function of 3135.44 in the unrestricted model and 3057.26 in the restricted model. Under the null hypothesis that $\mu = 1$, the test statistic is 156.36 with a $p$-value less than 0.01. Thus, incorporating limited risk sharing statistically improves the ability of the shirking model to fit the data.

# 5 Examining the Role of Partial Insurance

The preceding analysis makes clear that partial insurance strengthens the broad empirical performance of the model as measured by the likelihood function. But how exactly does the inclusion of limited risk sharing, the central mechanism under examination, facilitate an improvement in model fit? To address this question and gain insight into the role of insurance coverage *per se*, I compare simulation results from the unrestricted model estimated in the previous section to those from the same model with partial insurance replaced by

[23] A Wald test of the null hypothesis that $C^u/C^e = 0.78$ is rejected at standard significance levels.

full insurance. Three different simulation exercises are considered. The first one generates impulse response functions from the two models to see how the risk-sharing arrangement affects equilibrium dynamics. The second one assesses the effectiveness of each model in accounting for the overall volatilities and correlations found in the data. A side-by-side analysis allows one to identify the contribution of partial insurance in capturing the relevant moments. The third simulation computes variance decompositions to see whether predictions about the sources of economic fluctuations are sensitive to changes in the insurance scheme.

The key to understanding how partial insurance improves standard measures of fit is the behavior of the real wage. To provide intuition on this point before discussing the broader simulation results, I derive a log-linear expression for the no-shirking condition (17) that links the real wage to average consumption. The approximation reveals an interesting "employment effect" that influences the wage-setting process under partial insurance but vanishes under full insurance. This effect works to dampen the adjustment of wages to shocks that generate positive co-movement between employment and consumption while amplifying the response to those that produce negative co-movement. It turns out that wage dynamics under partial insurance contribute in a significant way to the propagation of various shocks and ultimately enhances the model's ability to match some prominent moments in the data.

To derive an expression for the wage, substitute into the no-shirking condition (17) the approximation of the risk-sharing condition (18) and the equation defining average consumption. After some rearranging, the linearized no-shirking condition becomes

$$\hat{w}_t = \frac{1}{1-b}\hat{C}_t - \frac{b}{1-b}\hat{C}_{t-1} - \tau \hat{N}_t - \hat{h}_t, \tag{22}$$

where $\tau = N(1-\mu)/[N(1-\mu)+\mu]$ and $\hat{x}_t$ denotes the log deviation of $x_t$ from steady state.

Two aspects of (22) stand out. First, the direct impact of employment on the real wage, as measured by $\tau$, depends on the scope of the insurance policy. Specifically, $\tau$ is a positive and decreasing function of the risk-sharing parameter $\mu$. In the limiting case of full insurance ($\mu = 1$), the employment effect disappears altogether as $\tau = 0$. Second, observe that employment enters (22) with a negative sign. Shocks that boost the real wage through higher average consumption will be partially offset if those shocks also expand employment. They will be amplified if higher consumption is accompanied by a reduction in employment.

To understand why the no-shirking condition implies an inverse relationship between the labor input and the real wage, consider the effects of a unit rise in employment. Under partial insurance, the average marginal utility of consumption across members falls since the utility function is concave and $C_t^e > C_t^u$. For a fixed marginal utility of wealth, the representative family wants to reduce average consumption by lowering $C_t^f$. It follows from (3) and (4) that, all else constant, $C_t^e$ and $C_t^s$ fall by equal amounts. Because detected shirkers forfeit a portion of their income, the percent decline in $C_t^s$ is larger than that of $C_t^e$, increasing the ratio $(C_t^e - bC_{t-1})/(C_t^s - bC_{t-1})$. This elevates the punishment from shirking and makes employees strictly prefer working under the current wage. Firms' incentive is to reduce wages to the point where the consumption ratio realigns with $\tilde{C}$ and employees are indifferent between working and shirking.

## 5.1 Impulse Response Functions

Evidence of the employment effect and its consequences for equilibrium dynamics appears in Figures 1 - 3, which graph the impulse response functions to some of the key structural shocks. Each panel illustrates the response profile in the unrestricted model with partial insurance (henceforth, the PI model) and, for comparison, the response in the same model with full insurance imposed after estimation (henceforth, the FI model). The latter are generated by setting $\mu = 1$ while preserving all other estimates from the PI model. The ensuing differences in model dynamics are, therefore, driven entirely by the scope of insurance coverage.

Consider first the effects of a cost-push shock in Figure 1. Monetary policy responds to the rise in inflation by lifting the real interest rate, causing output and consumption to fall, which, in turn, puts downward pressure on the real wage via the no-shirking condition. Because it also lowers employment, the downward wage adjustment in the PI model is smaller than the FI model for reasons discussed above. As will become clear in the next section, dampening the sensitivity of wages to cost-push shocks helps the shirking model lower the overall volatility of the real wage and weakens the high correlation with output that would otherwise occur under full insurance.[24] Less variation in the real wage also contributes to a diminished but more prolonged adjustment of marginal cost. Firms react to this by administering smaller price reductions in future periods, enabling the cost-push shock to have a larger and more persistent effect on inflation. The presence of higher inflation explains why the interest rate response is larger in the PI model in the aftermath of the shock. The extra tightening of monetary policy that emerges under partial insurance amplifies the contraction in output and employment relative to the full insurance case.

Turning next to the investment-specific technology shock in Figure 2, the consumption response is initially negative as families take advantage of higher returns to capital by expanding investment purchases. Increases in the capital stock boost the marginal product of labor, inducing firms to hire additional workers. As predicted by (22), the combination of falling consumption with rising employment causes the decline in real wages to be greater in the PI model than the FI model. A stronger countercyclical response to investment-specific shocks helps the model reduce the broad correlations between wages and output and wages and employment, a fact that will be made explicit in the next section. Lower real wages in the PI model also reinforces firms' desire to keep employment demand high for several periods after the shock. Persistent employment, through its effect on the production function and the no-shirking condition, ensures that both output and wages revert to steady state more

[24]Although not shown in the paper, a qualitatively similar response occurs after an interest rate shock and, in the opposite direction, a preference shock.

slowly under partial insurance. Stated differently, output and the real wage inherit considerable persistence from the employment series when risk sharing is incomplete, especially if investment-specific shocks are proven to be dominant source of economic fluctuations.

Finally, Figure 3 graphs the response to a neutral technology shock. All else constant, the increase in output relaxes the family's lifetime budget constraint, permitting average consumption to rise through a standard wealth effect channel. Investment spending also goes up as a result of intertemporal substitution. As is often the case in sticky-price models, employment contracts after a neutral technology shock because monetary policy does not fully accommodate the expansion in aggregate demand (e.g., Galí and Rabanal, 2004). Indeed, the offsetting rise in the interest rate guarantees that the implied percentage growth in output is less than the percentage growth in productivity, leading to a decline in total employment. Because consumption and employment move in opposite directions, the increase in the real wage is substantially larger in the PI model than the FI model. The gap between the two series persists for a period of about one year, allowing neutral technology shocks to have a greater impact on the short-run volatility of the real wage under partial insurance.

## 5.2 Volatilities and Correlations

This section assesses the role of partial insurance in capturing some basic features of the US business cycle. A set of empirical moments are calculated using the actual data and compared to ones generated from the PI model and the FI model. The full information approach used for estimation does not focus exclusively on replicating this small set of statistics, but rather on matching the broad aspects of the data embodied by the likelihood function. To see which features are more easily reconciled within a limited insurance framework, I examine what the PI and FI models imply for these common statistics.

Table 2 reports three sets of statistics. The first group contains the standard deviations of the logs of detrended $C_t$, detrended $I_t$, detrended $w_t$, $N_t$, $\pi_t$, and $R_t$. Each one is divided by the standard deviation of the log of detrended $Y_t$, defined in the models and the data as the sum of consumption and investment. The second set includes contemporaneous correlations with output, while correlations with the real wage form the third set.[25]

Looking first at the standard deviations, the PI model does a better job of matching the relative volatility of consumption. The standard deviation of investment, however, appears largely invariant to the scope of insurance coverage. Echoing the results of Alexopoulos (2004), the PI model also accounts well for the low relative volatility of the real wage. By contrast, imposing full insurance makes wage volatility almost as high as that of output. This confirms earlier findings from the impulse response analysis, namely, that wages adjust more sluggishly to cost-push, monetary policy (not shown), and preference shocks (not shown) in the PI model. Finally, both models overstate the variability of employment but explain well the low variation in inflation and the nominal interest rate.

The PI model is also generally more successful at replicating the correlations with output. The consumption and investment correlations, in particular, match closely their counterparts in the data. Similar to Alexopoulos (2004), allowing for partial insurance reduces the wage correlation (from 0.90 to 0.67) and increases the employment correlation (from 0.50 to 0.67) relative to the full insurance case. A major portion of these improvements can be attributed to the strong countercyclical wage and procyclical employment responses to investment-specific technology shocks produced by the PI model. Recall from the previous section, the adjustment of both variables is bigger in the impact period and more persistent thereafter under partial insurance. Finally, the FI model is better at capturing the positive correlation between inflation and output, but it falsely predicts the sign of the interest rate correlation.

The results are mixed regarding the covariation of wages. Under both insurance schemes, the correlation with consumption is too high. Alternatively, the PI (FI) model understates (overstates) the investment correlation. Both models correctly produce a positive correlation

[25]Employment is calculated in the data as the log of all employees in the nonfarm business sector.

with inflation and match closely the small negative correlation with the interest rate. Finally, the PI model generates a small, negative correlation (-0.03) between the real wage and employment, while the FI model generates a larger, positive correlation (0.31). Although the dataset used here indicates that the true correlation is 0.16, the PI model is more consistent with the Dunlop-Tarshis observation that wages move countercyclically with employment (e.g., Christiano and Eichenbaum, 1992). This finding can be traced to the behavior of the labor market following neutral and investment-specific technology shocks. Recall that while employment and wages move in opposite directions after either shock, the inverse co-movement between them is even more pronounced under partial insurance.

Figure 4 plots the autocorrelation functions for the logs of detrended $Y_t$, detrended $w_t$, $\pi_t$, and $R_t$ as implied by the data and the models. As in Fuhrer and Moore (1995), the autocorrelations for the data are from an unrestricted, fourth-order vector autoregression.

The PI model is better at reproducing several of the key autocorrelations involving the real wage. The degree of wage persistence, as measured by correlations between current and lagged real wages, is larger under partial insurance. Limited risk sharing also helps explain the cross correlations with output. The PI model captures reasonably well the positive and diminishing correlation between current output and the real wage one to two years in the past. It also matches the positive, hump-shaped correlation between the current real wage and past output, with the peak occurring at a two-year lag.

The PI model also improves the match with some of the correlations between nominal and real variables. For example, partial insurance helps capture the "inverted leading indicator" effect (e.g., King and Watson, 1996), that is, the negative correlation between output and lagged interest rates found in the data. The PI model also predicts the correct sign and magnitude of the correlation between the interest rate and past wages up to a one-year lag.

## 5.3 Variance Decompositions

This section evaluates the ability of the model to correctly identify the sources of business cycle fluctuations observed in the data. To that end, I compare forecast error variance decompositions of the PI model with those from the FI model. The goal is to determine in what way, and to what extent, limited risk sharing aids in matching the decompositions found in other studies that estimate the contributions of the same shocks appearing in this paper. For the PI and FI models, respectively, Tables 3 and 4 decompose the variances of output, consumption, investment, the real wage, employment, inflation, and the interest rate into shares attributed to each of the model's six orthogonal shocks. Panel I reports conditional variances at a one-year forecast horizon, panel II a three-year horizon, and panel III a ten-year horizon.

Consider first the contribution of monetary shocks. Using a structural VAR, Christiano *et al.* (2005) show that policy shocks have a modest effect on output fluctuations but a small impact on inflation and the real wage. Meanwhile, they have a sizeable effect on interest rate variability in the short run that diminishes at longer horizons.

Tables 3 and 4 reveal that policy shocks contribute less to output in the PI model. At a one-year horizon, they account for 7 percent of output variation under partial insurance but 10 percent under full insurance. Similarly, their contribution to real wage and inflation variability is smaller in the presence of limited risk sharing. Policy shocks are responsible for less than 1 percent of wage variation after one year in the PI model but more than 10 percent in the FI model. The PI model also attributes a greater share of interest rate variability to policy shocks than the FI model. At a one-year horizon, they account for approximately 29 percent of interest rate fluctuations in the former but only 17 percent in the latter.

Turning next to technology shocks, Fisher (2006) demonstrates, using an identified VAR, that neutral and investment-specific shocks jointly explain about 60 percent of output fluctuations at a forecast horizon of one year and 80 percent after eight years. From the perspective of an equilibrium model along the lines of Smets and Wouters (2003), Justiniano, Primiceri, and Tambalotti (2010) find that investment-specific shocks account for 50 percent of the variance of output and 80 percent of investment at business cycle frequencies. Neutral shocks, on the other hand, explain only 25 percent of output and less than 10 percent of investment.

The decompositions show that both models match closely the joint contribution of neutral and investment-specific shocks to output fluctuations. At a forecast horizon of one year, the two shocks together explain 65 percent of output volatility in the PI model and 61 percent in the FI model. The contributions rise to 83 and 86 percent, respectively, at a ten-year horizon. When it comes to matching the relative contributions, however, the PI model is more consistent with the findings of Justiniano *et al.* (2010). At a three-year horizon, investment-specific shocks alone account for 54 percent of the variance of output under partial insurance, while neutral technology shocks explain less than 22 percent. The FI model attributes only 37 percent of output variability to investment-specific shocks and more than 39 percent to neutral shocks.

Regarding cost-push shocks, Ireland (2004b), in the context of an estimated sticky-price model, attributes to them more than 60 percent of the movements in inflation at all forecast horizons. Cost-push shocks also account for 15 to 30 percent of the variance of the nominal interest rate between one and ten years.

The shirking model tells a different story about the importance of cost-push shocks depending on the insurance program. Across all horizons, they account for more than 60 percent of inflation variability in the PI model but around 40 percent in the FI model. Cost-push shocks are also a dominant source of interest rate volatility under partial insurance, accounting for 37 percent in the short run and 32 percent in the long run. They have a smaller effect under full insurance, explaining less than 15 percent of the variance of the interest rate at all horizons.

Finally, contributions of shocks to hours worked and the time rate of preference are broadly similar in both models. There is one difference, however, that appears to favor partial insurance. At a one-year horizon, preference shocks explain as much as 32 percent of inflation variability and 41 percent of interest rate variability in the FI model. By contrast, preference shocks are responsible for only 17 and 18 percent of fluctuations in these variables in the PI model. Primiceri, Schaumburg, and Tambalotti (2006) show that intertemporal disturbances affecting the representative household's time rate of preference account for only a small portion of inflation and interest rate variability. The shirking model is more consistent with these findings under a partial insurance specification.

# 6 Sensitivity Analysis

Below I examine the robustness of the principal findings to several changes in the data and the model. The main purpose is to determine whether the point estimates and results of the likelihood ratio test are sensitive to the following: subsample estimation, alternative values for price stickiness and average employment, the absence of habit formation, and the use of data on real GDP or total employment during estimation.[26]

## 6.1 Subsample Estimation

Table 5 reports estimates of the model using a subsample that begins in 1979:Q3. Numerous studies conclude that the stance of monetary policy changed considerably following the appointment of Paul Volcker to Chairman of the Federal Reserve (e.g., Clarida, Galí, and Gertler, 2000). As evidence of a regime shift, they point to structural breaks in the estimated coefficients of policy rules like (19) when the sample is divided into disjoint subsamples around 1980. It remains to be seen whether the parameters are significantly altered when

[26]In addition to the sensitivity analysis discussed below, Appendix C reports estimates from a basic sticky-price model without efficiency wage considerations to see how important the description of the labor market is for fitting the model to the data.

estimated over a period that coincides with a more stable monetary regime.

Under both insurance arrangements, the estimates of $\theta_\pi$, $\theta_{Y0}$, and $\theta_{Y1}$ are larger than those from the benchmark model employing the full sample, indicating a stronger response to inflation and output growth during the post-1979 period. Most of the other parameters are close to their full sample counterparts. The exceptions are capital adjustment costs $\phi$ and the standard deviation of investment shocks $\sigma_a$, the estimates of which are much larger for the post-1979 sample. Ireland (2003) also reports rising adjustment costs and bigger investment shocks after the period ending in 1979. Regarding the insurance behavior of consumers, the estimates of $\mu$ (0.38) and $b$ (0.30) jointly determine a steady-state consumption ratio $C^u/C^e$ equal to 0.56. Accounting for the likely regime shift in monetary policy that occurred after 1979 evidently has only a small effect on the degree of risk sharing implied by the data.

## 6.2 Varying the Degree of Price Stickiness

As explained in section 4, the adjustment probability $\chi$ is fixed prior to estimation because attempts to estimate it along with the other parameters delivered values that are inconsistent with credible amounts of price stickiness. In choosing $\chi = 0.\overline{55}$, I appealed to the midpoint of recent evidence on the frequency of price changes obtained by Bils and Klenow (2004) and Nakamura and Steinsson (2008). The calibration ensures that firms optimally adjust prices once every 6.75 months on average. Considering the difficulties in estimating $\chi$, it is important to check how robust the findings are to alternative values that span the full range of estimates reported in these two studies.

Table 5 presents estimates of the shirking model for $\chi$ equal to $0.\overline{45}$ and 0.625, values that correspond to price durations of 5.5 months and 8 months, respectively. Both the partial and full insurance schemes are estimated for each parameter setting. Excluding the policy coefficients, most of the estimates are not greatly affected by variations in the degree of price stickiness. The estimates of $\theta_\pi$, $\theta_{Y0}$, and $\theta_{Y1}$ suggest that higher values of $\chi$ (stickier prices) are associated with a weaker response to inflation and output growth. This relationship appears only in the partial insurance case. Estimates of the policy coefficients under full insurance do not change much with the value of $\chi$. Importantly, estimates of $\mu$ and $C^u/C^e$ are also quite stable, and the likelihood ratio test still rejects the full insurance restriction.

### 6.3 Varying the Average Employment Rate

By setting $N = 0.941$ to match the average unemployment rate, the model implicitly treats individuals who do not work in a given period as formally unemployed in the sense of belonging to the labor force. It follows that the total number of family members is correctly understood to reflect the size of the labor force (normalized to one). In the labor search literature, however, it is not uncommon to view those who are either unemployed or out of the labor force as equivalent for the purpose of calibrating $N$. Andolfatto (1996) and Hairault (2002), for example, set $N = 0.57$ to match the ratio of total employment to the civilian population instead of the labor force. Given the disagreements over the proper interpretation of $N$, I re-estimate the model using smaller values for steady-state employment.

Table 6 reports estimates for values of $N$ equal to 0.57 and 0.9399. The latter number corresponds to the estimate obtained by Alexopoulos (2004). Only estimates from the partial insurance case are presented because, as explained earlier, steady-state employment does not influence the dynamics of the model under full insurance. Comparing the results to the benchmark values in Table 5 shows that estimates of $\sigma_a$ and $\mu$ appear somewhat sensitive to large changes in the calibration of $N$. The insurance parameter $\mu$, in particular, declines by 22 percent from its benchmark value when $N = 0.57$. In terms of relative consumption $C^u/C^e$, the degree of risk sharing implies that members consume on average about 50 percent less during periods of unemployment. Finally, estimates of the model for $N = 0.9399$ are practically identical to the benchmark findings, indicating that small changes in average employment have virtually no effect on estimation.

## 6.4 No Habit Formation

Habit formation in consumption is one feature that distinguishes the present shirking model from the previous models of Alexopoulos (2004) and Alexopoulos (2007). Because it appears in the incentive compatibility constraint, consumption habits have a potentially sizable impact on equilibrium real wages and, therefore, the flow of transfers from employed to unemployed members. In what follows, I examine whether inferences about the size and significance of unemployment insurance are affected by the presence of habit formation.

Table 6 presents estimates of the model under partial and full insurance with the restriction $b = 0$ applied before estimation. A comparison with the benchmark analysis reveals several interesting results. First, dropping habit formation from the model with partial insurance has very little effect on estimates of the other parameters. The point estimate of $\mu$, for instance, is 0.49 in the benchmark model as well as the constrained version without consumption habits. Recall that when $b = 0$, however, $\mu$ simplifies to $C_t^u/C_t^e$, so implied values of the relative consumption of the unemployed are lower in the absence of habit formation. Second, removing habit formation in the full insurance case reduces estimates of the policy rule coefficients and the capital adjustment cost parameter. Third, tests of the null hypothesis of full insurance are still easily rejected at normal significance levels in the restricted model with $b = 0$. The relevant likelihood ratio statistic is 186.66 with a $p$-value less than 0.01. Lastly, incorporating habit formation improves the fit of the shirking model regardless of the scope of insurance coverage. The log likelihood values under partial insurance with and without habit formation imply a likelihood ratio statistic of 17.22 ($p$-value $< 0.01$). The corresponding statistic under full insurance is 47.52.

## 6.5 Using Real GDP Data for Estimation

In selecting which time series to use for estimation, I followed the strategy proposed by Ireland (2003) whereby data on consumption and investment are inserted into the Kalman filter rather than data on output alone. The rationale is that these series provide the most relevant information for estimating two parameters that are critical to the model's empirical performance, namely, the capital adjustment cost term $\phi$ (e.g., Kimball, 1995; Casares and McCallum, 2006) and the risk-sharing coefficient $\mu$. Ireland (2001) demonstrates that absent data on investment, it is difficult to identify the adjustment cost parameter in a class of models similar to the one presented here. Moreover, because unemployment leads to consumption disparity across members, per capita consumption is likely the preferred series for attaining the best possible estimate of $\mu$.

Despite sound reasons for excluding output during estimation, there are countless studies that estimate DSGE models using data on real GDP (e.g., Kim, 2000; Christiano *et al.*, 2005; Smets and Wouters, 2007). The belief is that GDP contains information on the cyclical properties of the US economy that is useful for obtaining estimates of key structural parameters. Considering the prevalence of this approach in the literature, it is reasonable to ask whether estimating the shirking model with data on real GDP significantly alters the main findings. Unless more shocks are built into the economy, however, output can not be added to the current list of observable variables without encountering the stochastic singularity problem discussed in section 3. As a result, I choose to drop investment from the set of observables and replace it with output.[27] This allows me to satisfy the full rank requirement without having to take a stand on new sources of exogenous variation in the model. The estimates are reported in Table 6.

Incorporating data on real GDP produces substantial changes in the estimates of several

[27] The output series used for estimation corresponds to the residuals from a least-squares regression of the log of per capita real GDP against a constant and both linear and quadratic time trends.

parameters, particularly in the case of partial insurance. For example, the policy response to output growth, measured by the joint values of $\theta_{Y0}$ and $\theta_{Y1}$, is about 50 percent larger when the dataset includes GDP. Employing output as an observable variable also drives $\rho_z$ towards the upper bound of the admissible parameter space where neutral technology shocks function like a random walk. Concerning the parameters describing private behavior, estimates of $\phi$ and $b$ indicate much higher capital adjustment costs in the model with partial insurance but a negligible role for habit formation. Finally, the estimates of $\mu$ (0.27) and $C^u/C^e$ (0.28) point to far less risk-sharing activity than what the benchmark estimation implies, with consumption falling by around 70 percent for members who enter the unemployment pool.

## 6.6 Using Employment Data for Estimation

There are a number of recent papers that estimate models emphasizing various labor market frictions using data on total employment (e.g., Alexopoulos, 2007; Trigari, 2009; Christoffel, Kuester, and Linzert, 2009). A common goal among these studies is to better understand the relationship between labor market activity and the broader macroeconomy. Employment data is potentially useful in this regard becuase it is a key indicator of current labor market conditions. Below I examine how sensitive estimates of the shirking model are to the use of data on aggregate employment. As discussed in the previous section, however, inserting another variable into the Kalman filter, all else equal, renders the model stochastically singular. To make estimation feasible without introducing additional shocks, I swap employment for investment in the vector of observables.[28] The results appear in Table 6.

Although some parameter estimates change dramatically with the use of employment data, inferences about the insurance component of the model remain largely unaltered. The estimates of $\mu$ (0.48) and $C^u/C^e$ (0.58) are close to the benchmark values, and a likelihood

[28]The employment series is constructed from the residuals of a least-squares regression of the log of total payrolls in the non-farm business sector against a constant and both linear and quadratic time trends.

ratio test rejects the null hypothesis of full insurance with a $p$-value less than 0.01. Under both risk-sharing arrangements, estimates of the capital adjustment cost parameter $\phi$ and the reaction coefficients $\theta_{Y0}$ and $\theta_{Y1}$ are much bigger when the dataset includes employment. By contrast, estimates of the standard deviation of neutral technology shocks $\sigma_z$ are an order of magnitude smaller than their counterparts from the benchmark model. For the case of partial insurance, designating $N_t$ as an observable variable amplifies the point estimate of $\sigma_h$. This occurs because the hours shock now has to absorb all of the joint variation in consumption, the real wage, and employment that does not satisfy the endogenous portion of the no-shirking condition (22). In the model with full insurance, using employment data lowers the estimate of habit formation $b$ by almost 60 percent.

# 7 Concluding Remarks

This paper estimates a sticky-price model that gives prominence to a shirking, efficiency-wage view of the labor market along the lines of Alexopoulos (2004). Central to the model is an insurance mechanism that allows, but does not require, agents to fully insure against income risk. The main objectives are to determine the extent of risk sharing implied by the data and to assess the importance of the insurance mechanism for improving model fit.

Maximum likelihood estimates reveal that the data prefer an arrangement in which individuals only partially insure. Likelihood ratio tests reject the hypothesis of full insurance. Simulations of models with and without full insurance provide additional, albeit less formal, evidence in favor of limited risk sharing. With partial insurance, for example, the model is better at capturing many sample volatilities and correlations involving the real wage.

Even though partial insurance improves empirical performance along numerous dimensions, some concerns remain that warrant further consideration. First, the model generates too much employment volatility. This problem could be addressed by using employment data during estimation while modifying the firms' decision problem to include labor adjustment costs. Second, the correlations between the real wage and inflation are inconsistent with the data and invariant to the scope of insurance coverage (see Figure 4). This fact suggests that the present shirking model lacks the right economic machinery needed to capture the true dynamic relationship reflected in the sample. A more sophisticated model featuring sticky nominal wages or limited participation could possibly correct this deficiency. Third, a more appealing model would allow for joint inference about the extent of risk sharing and the size of nominal rigidity. Data limitations make it difficult in the present study to identify the adjustment probability that governs the degree of price stickiness. Recent papers have had some success in identifying this parameter by using Bayesian methods. I believe that confronting these issues is an important task but properly the business of future research.

# Appendix A. Model Solution

## A.1 General Equilibrium Conditions

- Average marginal utility of consumption

$$X_t = g_t \left( \frac{N_t}{C_t^e - bC_{t-1}} + \frac{1 - N_t}{C_t^u - bC_{t-1}} \right) \tag{A.1}$$

- Euler equation for family-purchased consumption

$$\lambda_t = X_t - \beta b E_t X_{t+1} \tag{A.2}$$

- Euler equation for bond holdings

$$\lambda_t = \beta R_t E_t \left( \frac{\lambda_{t+1}}{\pi_{t+1}} \right) \tag{A.3}$$

- Euler equation for investment[29]

$$1 = q_t \left[ a_t - \phi \left( \frac{I_t}{K_t} - \delta \right) \right] \tag{A.4}$$

- Euler equation for capital

$$\lambda_t q_t = \beta E_t \lambda_{t+1} r_{t+1}^k + \beta E_t \lambda_{t+1} q_{t+1} \left[ 1 - \delta - \frac{\phi}{2} \left( \frac{I_{t+1}}{K_{t+1}} - \delta \right)^2 + \phi \left( \frac{I_{t+1}}{K_{t+1}} - \delta \right) \frac{I_{t+1}}{K_{t+1}} \right] \tag{A.5}$$

- Law of motion for capital

$$K_{t+1} = (1 - \delta) K_t - \frac{\phi}{2} \left( \frac{I_t}{K_t} - \delta \right)^2 K_t + a_t I_t \tag{A.6}$$

- No-shirking condition

$$(1 - s) \left( \frac{\tilde{C}}{\tilde{C} - 1} \right) h_t w_t = C_t^e - bC_{t-1} \tag{A.7}$$

- Consumption risk-sharing condition

$$C_t^u = \mu C_t^e + (1 - \mu) bC_{t-1} \tag{A.8}$$

- Average consumption

$$C_t = N_t C_t^e + (1 - N_t) C_t^u \tag{A.9}$$

[29] The variable $q_t$ is the lagrange multiplier for the capital accumulation equation.

- Aggregate resource constraint

$$Y_t = C_t + I_t \tag{A.10}$$

- Marginal product of capital[30]

$$r_t^k = \alpha mc_t z_t K_t^{\alpha-1}(N_t eh)^{1-\alpha} \tag{A.11}$$

- Marginal product of labor

$$h_t w_t = (1-\alpha) mc_t z_t K_t^{\alpha}(N_t eh)^{-\alpha} eh \tag{A.12}$$

- Aggregate production function[31]

$$Y_t \Delta_t = z_t K_t^{\alpha}(N_t eh)^{1-\alpha} \tag{A.13}$$

- Aggregate profit equation[32]

$$D_t = (1 - mc_t \Delta_t) Y_t \tag{A.14}$$

- Equilibrium family consumption

$$C_t^f = C_t - h_t w_t N_t \tag{A.15}$$

- Monetary policy rule

$$\log \frac{R_t}{R} = \theta_R \log \frac{R_{t-1}}{R} + (1-\theta_R)\left[\theta_\pi \log \frac{\pi_t}{\pi} + \theta_{Y0} \log \frac{Y_t}{Y} + \theta_{Y1} \log \frac{Y_{t-1}}{Y}\right] + \varepsilon_{R,t} \tag{A.16}$$

- Aggregate price index[33]

$$1 = (1-\chi) P_t^* G'^{-1}[P_t^* \tau_t] + (1-\chi) \sum_{j=1}^{\infty} \chi^j P_{t-j}^* \left( \prod_{k=0}^{j-1} \exp(\varepsilon_{\pi,t-k}) \frac{\pi_{t-k-1}}{\pi_{t-k}} \right) \times G'^{-1}\left[ P_{t-j}^* \left( \prod_{k=0}^{j-1} \exp(\varepsilon_{\pi,t-k}) \frac{\pi_{t-k-1}}{\pi_{t-k}} \right) \tau_t \right] \tag{A.17}$$

[30]The product of effort and hours worked is constant in equilibrium and satisfies $eh = T - \xi - T\tilde{C}^{-d/\theta}$.

[31]The price dispersion term is given by $\Delta_t = \int_0^1 G'^{-1}\left(\frac{P_t(i)}{P_t}\tau_t\right) di$, where $\tau_t = \int_0^1 G'\left(\frac{Y_t(i)}{Y_t}\right)\frac{Y_t(i)}{Y_t}\, di$.

[32]Total real profit from ownership of all firms is $D_t = \int_0^1 D_t(i) di$.

[33]The relative contract price chosen by all firms reoptimizing at date $t$ is denoted $P_t^* = \tilde{P}_t / P_t$.

- Price dispersion

$$\Delta_t = (1-\chi)G'^{-1}[P_t^*\tau_t] + (1-\chi)\sum_{j=1}^{\infty}\chi^j G'^{-1}\left[P_{t-j}^*\left(\prod_{k=0}^{j-1}\exp(\varepsilon_{\pi,t-k})\frac{\pi_{t-k-1}}{\pi_{t-k}}\right)\tau_t\right] \tag{A.18}$$

- Euler equation for the optimal relative contract price[34]

$$E_t\sum_{j=0}^{\infty}(\chi\beta)^j\lambda_{t+j}Y_{t+j}^*\left\{P_t^*\tilde{X}_{t,j} + \frac{\left(P_t^*\tilde{X}_{t,j} - mc_{t+j}\right)}{G'^{-1}[P_t^*\tilde{X}_{t,j}\tau_{t+j}]}\frac{G'\left(\frac{Y_{t+j}^*}{Y_{t+j}}\right)}{G''\left(\frac{Y_{t+j}^*}{Y_{t+j}}\right)}\right\} = 0 \tag{A.19}$$

## A.2 Steady State Equilibrium

Below is a derivation of the deterministic steady-state equilibrium of the model. A box around an equation indicates that the term on the lefthand side is a function of known estimated or calibrated parameters and possibly variables determined at an earlier stage. The boxed equations are written in the order needed to obtain the steady state numerically. The numbers to the left of the boxes indicate which general equilibrium equation the steady-state condition corresponds to. Boxed equations with multiple numbers on the lefthand side are obtained by combining the relevant steady-state conditions already determined.

$$\text{(A.3)}\quad \boxed{\beta = \frac{\pi}{R}} \tag{A.20}$$

$$\text{(A.6)}\quad \boxed{\frac{I}{K} = \delta} \tag{A.21}$$

$$\text{(A.4)}\quad \boxed{q = 1} \tag{A.22}$$

$$\text{(A.5)}\quad \boxed{r^k = \beta^{-1} - 1 + \delta} \tag{A.23}$$

[34]The output produced at date $t+j$ by firms who last reoptimized at date $t$ is given by $Y_{t+j}^* = Y_{t+j}G'^{-1}[P_t^*\tilde{X}_{t,j}\tau_{t+j}]$, where $\tilde{X}_{t,j} = \prod_{k=1}^{j}\exp(\varepsilon_{\pi,t+k})\frac{\pi_{t+k-1}}{\pi_{t+k}}$ for $j \geq 1$ and $\tilde{X}_{t,0} = 1$.

$$\text{(A.17)}^{35} \quad \boxed{P^* = 1} \tag{A.24}$$

$$\text{(A.18)} \quad \boxed{\Delta = 1} \tag{A.25}$$

$$\text{(A.19)}^{36} \quad \boxed{mc = 1 + \frac{G''(1)}{G'(1)} \equiv \frac{1}{1+\eta}} \tag{A.26}$$

$$\text{(A.11)} \quad \frac{K}{Neh} = \left(\frac{r^k}{\alpha mcz}\right)^{\frac{1}{\alpha-1}} \tag{A.27}$$

$$\text{(A.12)} \quad hw = (1-\alpha)mcz\left(\frac{K}{Neh}\right)^{\alpha} eh \tag{A.28}$$

$$\text{(A.14)} \quad \boxed{\frac{D}{Y} = 1 - mc} \tag{A.29}$$

$$\text{(A.8)} \quad C^u = \mu C^e + (1-\mu)bC \tag{A.30}$$

$$\text{(A.7)} \quad C^e = (1-s)\left(\frac{\tilde{C}}{\tilde{C}-1}\right) hw + bC \tag{A.31}$$

$$\text{(A.9)} \quad C = \left(\frac{1}{1-b}\right)(1-s)\left(\frac{\tilde{C}}{\tilde{C}-1}\right) hw[N + (1-N)\mu] \tag{A.32}$$

$$\text{(A.13)} \quad Y = z\left(\frac{K}{Neh}\right)^{\alpha} Neh \tag{A.33}$$

$$\text{(A.10)} \quad \boxed{(1-s)\left(\frac{\tilde{C}}{\tilde{C}-1}\right) = \frac{(1-b)\left[1 - \frac{\delta\alpha mc}{r^k}\right] N}{(1-\alpha)mc[N + (1-N)\mu]}} \tag{A.34}$$

$$\text{(A.21) (A.33)} \quad \boxed{\frac{I}{Y} = \frac{\delta\alpha mc}{r^k}} \tag{A.35}$$

$$\text{(A.28) (A.32) (A.33)} \quad \boxed{\frac{C}{Y} = 1 - \frac{I}{Y}} \tag{A.36}$$

$$\text{(A.28) (A.31) (A.33) (A.34) (A.35)} \quad \boxed{\frac{C^e}{C} = \left(\frac{1-b}{N + (1-N)\mu}\right) + b} \tag{A.37}$$

[35] In the steady state, the demand curve (11) implies $G'^{-1}(P^*\tau) = 1$.

[36] The firm's percent markup in the steady state is given by $\eta = -\frac{G''(1)}{G'(1)+G''(1)}$.

(A.30) (A.37) $$\boxed{\frac{C^u}{C} = \mu\left(\frac{1-b}{N+(1-N)\mu}\right) + b} \tag{A.38}$$

(A.1) $$\boxed{XC = \frac{N}{(C^e/C)-b} + \frac{1-N}{(C^u/C)-b}} \tag{A.39}$$

(A.2) $$\boxed{\lambda C = (1-\beta b)XC} \tag{A.40}$$

(A.15) (A.28) (A.33) $$\boxed{\frac{C^f}{Y} = \frac{C}{Y} - (1-\alpha)mc} \tag{A.41}$$

## A.3 The Complete Linearized System

- Linearizing the average marginal utility of consumption (A.1) gives

$$\begin{aligned}\frac{1-(1-\mu)N}{(C^u/C)-b}(\hat{X}_t - \hat{g}_t) &= \frac{-(1-\mu)N}{(C^u/C)-b}\hat{N}_t - N\left(\frac{C^e/C}{((C^e/C)-b)^2}\right)\hat{C}^e_t \\ -(1-N)\left(\frac{C^u/C}{((C^u/C)-b)^2}\right)\hat{C}^u_t &+ \left(\frac{N}{((C^e/C)-b)^2} + \frac{1-N}{((C^u/C)-b)^2}\right)b\hat{C}_{t-1}\end{aligned} \tag{A.42}$$

- Linearizing the family-consumption Euler equation (A.2) gives

$$(1-\beta b)\hat{\lambda}_t = \hat{X}_t - \beta b E_t \hat{X}_{t+1} \tag{A.43}$$

- Linearizing the Euler equation for bond holdings (A.3) gives

$$\hat{\lambda}_t = \hat{R}_t + E_t(\hat{\lambda}_{t+1} - \hat{\pi}_{t+1}) \tag{A.44}$$

- Linearizing the investment Euler equation (A.4) gives

$$\hat{q}_t + \hat{a}_t = \phi\delta(\hat{I}_t - \hat{K}_t) \tag{A.45}$$

- Linearizing the capital Euler equation (A.5) gives

$$\hat{\lambda}_t + \hat{q}_t = E_t\hat{\lambda}_{t+1} + \beta r^k E_t \hat{r}^k_{t+1} + \beta(1-\delta)E_t\hat{q}_{t+1} + \beta\phi\delta^2 E_t(\hat{I}_{t+1} - \hat{K}_{t+1}) \tag{A.46}$$

- Linearizing the law of motion for capital (A.6) gives

$$\hat{K}_{t+1} = (1-\delta)\hat{K}_t + \delta(\hat{I}_t + \hat{a}_t) \tag{A.47}$$

- Linearizing the no-shirking condition (A.7) gives

$$(C^e/C - b)(\hat{h}_t + \hat{w}_t) = (C^e/C)\hat{C}^e_t - b\hat{C}_{t-1} \tag{A.48}$$

- Linearizing the consumption risk-sharing condition (A.8) gives

$$(C^u/C)\hat{C}^u_t = \mu(C^e/C)\hat{C}^e_t + (1-\mu)b\hat{C}_{t-1} \tag{A.49}$$

- Linearizing the equation for average consumption (A.9) gives

$$\hat{C}_t = (C^e/C)N\hat{C}^e_t + (C^u/C)(1-N)\hat{C}^u_t + (1-\mu)((C^e/C) - b)N\hat{N}_t \tag{A.50}$$

- Linearizing the aggregate resource constraint (A.10) gives

$$\hat{Y}_t = (C/Y)\hat{C}_t + (I/Y)\hat{I}_t \tag{A.51}$$

- Linearizing the marginal product of capital (A.11) gives

$$\hat{r}^k_t = \hat{mc}_t + \hat{z}_t + (\alpha - 1)(\hat{K}_t - \hat{N}_t) \tag{A.52}$$

- Linearizing the marginal product of labor (A.12) gives

$$\hat{h}_t + \hat{w}_t = \hat{mc}_t + \hat{z}_t + \alpha(\hat{K}_t - \hat{N}_t) \tag{A.53}$$

- Linearizing the aggregate production function (A.13) gives

$$\hat{Y}_t + \hat{\Delta}_t = \hat{z}_t + \alpha\hat{K}_t + (1-\alpha)\hat{N}_t \tag{A.54}$$

- Linearizing the aggregate profit equation (A.14) gives

$$\hat{D}_t = \hat{Y}_t - \frac{1}{\eta}(\hat{mc}_t + \hat{\Delta}_t) \tag{A.55}$$

- Linearizing the equation for family consumption (A.15) gives

$$((C/Y) - (1-\alpha)mc)\hat{C}^f_t = (C/Y)\hat{C}_t - (1-\alpha)mc(\hat{h}_t + \hat{w}_t + \hat{N}_t) \tag{A.56}$$

- Linearizing the monetary policy rule (A.16) gives

$$\hat{R}_t = \theta_R\hat{R}_{t-1} + (1-\theta_R)\left[\theta_\pi\hat{\pi}_t + \theta_{Y0}\hat{Y}_t + \theta_{Y1}\hat{Y}_{t-1}\right] + \varepsilon_{R,t} \tag{A.57}$$

- Linearizing the equation for the aggregate price index (A.17) gives[37]

$$\hat{P}^*_t = \frac{\chi}{1-\chi}(\hat{\pi}_t - \hat{\pi}_{t-1} - \varepsilon_{\pi,t}) \tag{A.58}$$

[37]Linearizing (10) gives $\hat{Y}_t = \int_0^1 \hat{Y}_t(i)di$ which, in turn, implies $\hat{\tau}_t = \left(1 + \frac{G''(1)}{G'(1)}\right)\left(\int_0^1 \hat{Y}_t(i)di - \hat{Y}_t\right) = 0$.

- Assuming $\hat{\Delta}_{-1} = 0$, linearizing the equation for price dispersion (A.18) gives

$$\hat{\Delta}_t = 0 \tag{A.59}$$

- Combining the linear approximations to (A.17) and (A.19) gives the Phillips curve[38]

$$(\hat{\pi}_t - \hat{\pi}_{t-1}) = \beta E_t(\hat{\pi}_{t+1} - \hat{\pi}_t) + \frac{(1-\chi)(1-\beta\chi)}{\chi}\frac{1}{\eta\epsilon + 1}\hat{mc}_t + \varepsilon_{\pi,t} \tag{A.60}$$

- Linearizing the neutral technology shock gives

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_{z,t} \tag{A.61}$$

- Linearizing the time rate of preference shock gives

$$\hat{g}_t = \rho_g \hat{g}_{t-1} + \varepsilon_{g,t} \tag{A.62}$$

- Linearizing the investment-specific technology shock gives

$$\hat{a}_t = \rho_a \hat{a}_{t-1} + \varepsilon_{a,t} \tag{A.63}$$

- Linearizing the intensive margin shock gives

$$\hat{h}_t = \log(\varepsilon_{h,t}) \tag{A.64}$$

# Appendix B. Model Estimation

The data includes average consumption $C_t$, investment $I_t$, the real wage $w_t$, inflation $\pi_t$, and the one-period nominal interest rate $R_t$. These data can be used to collect a history of observations $\{\mathbf{d}_t\}_{t=1}^{T}$, where the vector $\mathbf{d}_t = [\hat{C}_t\ \hat{I}_t\ \hat{w}_t\ \hat{\pi}_t\ \hat{R}_t]'$. The reduced-form solution of the shirking model given by (20) and (21) takes the form of a state-space econometric model

$$\mathbf{s}_t = \mathbf{\Pi}\mathbf{s}_{t-1} + \mathbf{\Omega}\varepsilon_t, \tag{B.1}$$

$$\mathbf{d}_t = \mathbf{\Gamma}\mathbf{s}_t, \tag{B.2}$$

where $\mathbf{s}_t = [\hat{z}_t\ \hat{g}_t\ \hat{a}_t\ \varepsilon_{\pi,t}\ \hat{h}_t\ \varepsilon_{R,t}\ \hat{K}_t\ \hat{C}_{t-1}\ \hat{Y}_{t-1}\ \hat{\pi}_{t-1}\ \hat{R}_{t-1}]'$ and $\mathbf{\Gamma}$ is formed by pulling out

[38] Expressed as a function of $G$, $\epsilon = 1 - \frac{G'(1)}{G''(1)}\left(1 + \frac{G'''(1)}{G''(1)}\right)$.

the appropriate rows of $\mathbf{U}$ in (21). The vector of serially uncorrelated innovations $\varepsilon_t = [\varepsilon_{z,t}\ \varepsilon_{g,t}\ \varepsilon_{a,t}\ \varepsilon_{\pi,t}\ \log(\varepsilon_{h,t})\ \varepsilon_{R,t}]'$ is assumed to be mean-zero and normally distributed with diagonal covariance matrix $V = E\varepsilon\varepsilon_t' = [\sigma_z^2\ \sigma_g^2\ \sigma_a^2\ \sigma_\pi^2\ \sigma_h^2\ \sigma_R^2] \times I_6$.

The state-space representation (B.1) and (B.2) can be used to calculate the sample likelihood function with the Kalman filtering algorithms described in Hamilton (1994, Ch. 13). Denote $\Theta$ the vector of structural coefficients, the parameters governing the distributions of the shocks, and the policy rule coefficients. Log likelihood for a sample of size $T$ is

$$\log \mathcal{L}(\Theta|\mathbf{d}_1, \ldots, \mathbf{d}_T) = \frac{-5T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log|\mathbf{\Gamma}\hat{\Sigma}_{t|t-1}\mathbf{\Gamma}'|$$
$$-\frac{1}{2}\sum_{t=1}^{T}(\mathbf{d}_t - \mathbf{\Gamma}\hat{\mathbf{s}}_{t|t-1})'(\mathbf{\Gamma}\hat{\Sigma}_{t|t-1}\mathbf{\Gamma}')^{-1}(\mathbf{d}_t - \mathbf{\Gamma}\hat{\mathbf{s}}_{t|t-1}),$$

where $\hat{\mathbf{s}}_{t|t-1}$ and $\hat{\Sigma}_{t|t-1}$ are the one-step-ahead optimal forecasts of the mean and variance of $\mathbf{s}_t$. They are calculated recursively according to the following updating scheme:

$$\begin{aligned}
\mathbf{K}_t &= \mathbf{\Pi}\hat{\mathbf{s}}_{t|t-1}\mathbf{\Gamma}'(\mathbf{\Gamma}\hat{\Sigma}_{t|t-1}\mathbf{\Gamma}')^{-1}, \\
\hat{\mathbf{s}}_{t+1|t} &= \mathbf{\Pi}\hat{\mathbf{s}}_{t|t-1} + \mathbf{K}_t(\mathbf{d}_t - \mathbf{\Gamma}\hat{\mathbf{s}}_{t|t-1}), \\
\hat{\Sigma}_{t+1|t} &= (\mathbf{\Pi} - \mathbf{K}_t\mathbf{\Gamma})\hat{\Sigma}_{t|t-1}(\mathbf{\Pi} - \mathbf{K}_t\mathbf{\Gamma})' + \mathbf{\Omega}V\mathbf{\Omega}',
\end{aligned}$$

where $\mathbf{K}_t$ is the Kalman gain matrix. Parameter estimates are obtained by numerically maximizing the likelihood function over the elements of $\Theta$. The first three observations from the sample are used to initialize the Kalman filter and are not included in the value of $\log \mathcal{L}$.

# Appendix C. Miscellaneous Issues

## C.1 A Discussion of $s$ and $\tilde{C}$

What do the parameter estimates and calibration imply for the values of $s$ and $\tilde{C}$? Given estimates of $\mu$ and $b$ and fixed values for $\beta$, $\delta$, $\alpha$, $\eta$, and $N$, the steady-state condition (A.34) determines an inverse relationship between $s$ and $\tilde{C}$. Solving (A.34) for $\tilde{C}$ in terms of $s$ yields

$$\tilde{C} = \left(1 - (1-s)\frac{(1-\alpha)mc[N + (1-N)\mu]}{(1-b)\frac{C}{Y}N}\right)^{-1}. \tag{C.1}$$

It is easy to verify from (C.1) that $\tilde{C}$ is a decreasing function of $s$. This means that as the up-front portion of the wage payment falls (or as the end-of-period bonus rises), consumption minus the habit stock of workers relative to that of detected shirkers goes up.

Alexopoulos (2004) documents a similar relationship between $s$ and $\tilde{C}$, particularly in the partial insurance case. Without habit formation, however, $\tilde{C}$ simplifies in her model to $C_t^e/C_t^s$. To draw a better comparison with her results, one must examine what the level of $\tilde{C}$ in the present shirking model implies for $C_t^e/C_t^s$. Rearranging the identity for $\tilde{C}$ that follows from (14) and evaluating the resulting expression in the steady state gives

$$\frac{C^e}{C^s} = \tilde{C}\left(1 - (1-\tilde{C})b\frac{C}{C^e}\right)^{-1}, \tag{C.2}$$

where $C^e/C = ((1-b)/[N + (1-N)\mu]) + b$. Equations (C.1) and (C.2) jointly determine an inverse relationship between $s$ and $C^e/C^s$, which is depicted graphically in Figure 5 for values of $s$ ranging from zero to one. The results show that the steady-state consumption ratio is less than two for any $s$ greater than one-third. For $C^e/C^s$ equal to 1.285, the value considered in Alexopoulos (2004), I find a corresponding value of $s$ equal to 0.70. Alexopoulos' model produces a value of $s$ equal to 0.78.

## C.2 Incorporating Measurement Error

This section reports estimates of a version of the shirking model that treats work hours as a constant and incorporates measurement errors into the observation equation. The transformation involves setting $\sigma_h = 0$ and augmenting (B.2) with a vector of serially uncorrelated shocks $\nu_t = [\nu_{c,t} \ \nu_{i,t} \ \nu_{w,t} \ \nu_{\pi,t} \ 0]$ that is assumed to be mean-zero and normally distributed with diagonal covariance matrix $W = E\nu_t\nu_t' = [\varrho_c^2 \ \varrho_i^2 \ \varrho_w^2 \ \varrho_\pi^2 \ 0] \times I_5$. The nominal interest rate is not subject to measurement error. The results are reported in Table 7.

Some of the point estimates change considerably once measurement errors are included in the state-space model. In the case of partial insurance, for example, the capital adjustment cost parameter $\phi$ rises from 44 to 169, habit formation $b$ falls from 0.26 to 0.09, and the risk-sharing parameter $\mu$ drops from 0.46 to 0.12. The values of $\mu$ and $b$ jointly imply an estimate of $C^u/C^e$ equal to 0.19, meaning that consumption declines by about 80 percent for members who become unemployed. The parameters describing the structural shocks also change with the addition of measurement errors, particularly $\rho_z$, which suggests that neutral technology shocks basically follow a random walk. Estimates of the measurement shocks themselves point to a high degree of uncertainty in the investment equation but no uncertainty in the consumption and real wage equations. Finally, the presence of measurement errors does not alter the central conclusion that limiting insurance coverage improves model fit according to the log likelihood criterion. A likelihood ratio test of the null hypothesis of full insurance is rejected at standard significance levels.

## C.3 Comparison to a Basic Sticky-Price Model

Consider a business cycle model identical to the one developed in this paper but with the efficiency wage assumption replaced by a purely Walrasian treatment of the labor market. Household preferences are defined by the utility function

$$U(C_t, H_t) = \log(C_t - b\overline{C}_{t-1}) - \exp(\varepsilon_{L,t})\frac{H_t^{1+\varphi}}{1+\varphi}, \tag{C.3}$$

where $C_t$ is consumption, $\overline{C}_t$ is the average consumption of the population, and $H_t$ is hours worked. The term $\varphi \geq 0$ measures the inverse of the wage elasticity of labor supply, and $\varepsilon_{L,t} \sim N(0, \sigma_L^2)$ is a taste shock that distorts equality between the marginal rate of substitution and the marginal product of labor, the so-called "labor wedge" described by Chari, Kehoe, and McGratten (2007). Below I estimate the parameters of this model and compare them to values from the benchmark shirking model. The results are presented in Table 7.

Without efficiency wage considerations, the estimate of habit formation $b$ increases to 0.66 and estimates of $\theta_{Y0}$ and $\theta_{Y1}$ fall to 0.30 and -0.38, respectively. Point estimates of $\sigma_g$ (0.14) and $\rho_g$ (0.99) indicate that shocks to the household's time rate of preference are larger and more persistent in the basic sticky-price model. Regarding the labor supply parameters, the estimate of $\varphi$ is consistent with a wage elasticity of labor supply of about one, while the estimated standard deviation of the labor wedge shock $\sigma_L$ goes to zero. All of the remaining parameters are close to the benchmark estimates.

To compare the fit of the two models, I compute the Bayesian information criterion (BIC). The BIC is a consistent model-selection criterion that penalizes log likelihood by an amount that is increasing in the number of estimated parameters.[39] In contrast to likelihood ratio tests, it forms the basis for a valid comparison of fit between models that are parametrically non-nested like the ones examined in this section. The BIC for the shirking model with partial and full insurance is 3093.72 and 3018.15, respectively. The BIC for the sticky-price model is 3083.32. The shirking model with partial insurance, therefore, does a better job of explaining the joint time series properties of the data than the basic sticky-price model, which, in turn, does a better job than the shirking model with full insurance. These results show that efficiency wage frictions can improve the fit of an otherwise conventional sticky-price model provided it also permits departures from the assumption of full risk sharing.

[39] $BIC = \log \mathcal{L} - \frac{N_p}{2} \log(T)$, where $N_p$ is the number of estimated parameters and $T$ is the sample size.

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Table 1: Maximum Likelihood Estimates of the Benchmark Model

| Parameter | Partial Insurance | | Full Insurance | |
|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error |
| $\phi$ | 44.1014 | 11.3807 | 22.0684 | 6.0613 |
| $b$ | 0.2636 | 0.0543 | 0.4153 | 0.0456 |
| $\mu$ | 0.4875 | 0.0275 | $1^*$ | – |
| $\theta_R$ | 0.8534 | 0.0183 | 0.8063 | 0.0254 |
| $\theta_\pi$ | 1.8626 | 0.2312 | 1.6096 | 0.1550 |
| $\theta_{Y0}$ | 0.7004 | 0.1314 | 0.5699 | 0.0953 |
| $\theta_{Y1}$ | -0.7200 | 0.1336 | -0.5768 | 0.0959 |
| $\rho_z$ | 0.9482 | 0.0191 | 0.9465 | 0.0236 |
| $\rho_g$ | 0.8873 | 0.0221 | 0.8926 | 0.0341 |
| $\rho_a$ | 0.8866 | 0.0346 | 0.9128 | 0.0299 |
| $\sigma_z$ | 0.0093 | 0.0008 | 0.0131 | 0.0018 |
| $\sigma_g$ | 0.0221 | 0.0029 | 0.0169 | 0.0026 |
| $\sigma_a$ | 0.0469 | 0.0130 | 0.0279 | 0.0069 |
| $\sigma_\pi$ | 0.0057 | 0.0004 | 0.0036 | 0.0002 |
| $\sigma_h$ | 0.0083 | 0.0010 | 0.0302 | 0.0016 |
| $\sigma_R$ | 0.0020 | 0.0001 | 0.0021 | 0.0002 |
| $\log \mathcal{L}$ | 3135.4389 | | 3057.2626 | |

*Notes*: The superscript * denotes a parameter value that is imposed prior to estimation. The term $\log \mathcal{L}$ denotes the maximized value of the log-likelihood function.

Table 2: Volatilities and Correlations

| | $Y$ | $C$ | $I$ | $w$ | $N$ | $\pi$ | $R$ |
|---|---|---|---|---|---|---|---|
| I. *U.S. Data: 1959:Q2 - 2005:Q4* | | | | | | | |
| Relative Standard Deviation | 1.00 | 0.78 | 2.57 | 0.80 | 0.50 | 0.15 | 0.16 |
| Correlation with $Y$ | 1.00 | 0.95 | 0.89 | 0.58 | 0.62 | 0.17 | -0.06 |
| Correlation with $w$ | 0.58 | 0.62 | 0.40 | 1.00 | 0.16 | 0.47 | -0.06 |
| II. *PI Model* | | | | | | | |
| Relative Standard Deviation | 1.00 | 0.83 | 1.90 | 0.76 | 0.81 | 0.10 | 0.09 |
| Correlation with $Y$ | 1.00 | 0.93 | 0.88 | 0.67 | 0.67 | -0.07 | -0.27 |
| Correlation with $w$ | 0.67 | 0.87 | 0.28 | 1.00 | -0.03 | 0.13 | -0.04 |
| III. *FI Model* | | | | | | | |
| Relative Standard Deviation | 1.00 | 0.89 | 1.89 | 0.92 | 0.68 | 0.12 | 0.10 |
| Correlation with $Y$ | 1.00 | 0.91 | 0.82 | 0.90 | 0.50 | 0.13 | 0.03 |
| Correlation with $w$ | 0.90 | 0.98 | 0.50 | 1.00 | 0.31 | 0.13 | -0.03 |

*Notes*: Relative standard deviations are normalized by the standard deviation of output, defined in the model and the data as the sum of consumption and investment.

Table 3: Variance Decompositions in the PI Model

| | $Y$ | $C$ | $I$ | $w$ | $N$ | $\pi$ | $R$ |
|---|---|---|---|---|---|---|---|
| I. *1-Year Horizon* | | | | | | | |
| Neutral Technology | 16.77 | 34.89 | 1.36 | 53.67 | 5.23 | 0.83 | 3.52 |
| Preference | 1.82 | 21.01 | 4.36 | 10.70 | 2.44 | 17.31 | 18.05 |
| Investment-Specific | 48.49 | 2.36 | 84.74 | 23.42 | 50.96 | 1.21 | 12.58 |
| Cost-Push | 26.02 | 33.48 | 7.32 | 1.02 | 32.69 | 76.58 | 37.00 |
| Hours | 0.00 | 0.00 | 0.00 | 10.92 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 6.91 | 8.24 | 2.21 | 0.26 | 8.68 | 4.06 | 28.83 |
| II. *3-Year Horizon* | | | | | | | |
| Neutral Technology | 21.68 | 44.23 | 3.08 | 68.28 | 3.05 | 1.07 | 2.08 |
| Preference | 4.66 | 9.87 | 8.59 | 7.51 | 6.58 | 26.18 | 42.10 |
| Investment-Specific | 54.05 | 19.14 | 81.03 | 16.49 | 55.97 | 1.37 | 5.88 |
| Cost-Push | 16.81 | 23.20 | 6.11 | 0.85 | 29.23 | 65.37 | 36.16 |
| Hours | 0.00 | 0.00 | 0.00 | 6.70 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 2.81 | 3.56 | 1.18 | 0.17 | 5.16 | 6.00 | 13.77 |
| III. *10-Year Horizon* | | | | | | | |
| Neutral Technology | 22.02 | 36.91 | 4.57 | 53.81 | 2.83 | 1.35 | 2.45 |
| Preference | 5.12 | 6.72 | 8.99 | 4.77 | 8.15 | 25.65 | 47.91 |
| Investment-Specific | 61.26 | 43.02 | 80.59 | 36.99 | 57.18 | 2.51 | 5.29 |
| Cost-Push | 9.96 | 11.59 | 4.90 | 0.79 | 27.04 | 64.61 | 32.10 |
| Hours | 0.00 | 0.00 | 0.00 | 3.52 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 1.65 | 1.76 | 0.95 | 0.12 | 4.80 | 5.87 | 12.24 |

*Notes*: The numbers correspond to the percentage of the variance of each variable attributed to each shock.

Table 4: Variance Decompositions in the FI Model

| | $Y$ | $C$ | $I$ | $w$ | $N$ | $\pi$ | $R$ |
|---|---|---|---|---|---|---|---|
| I. *1-Year Horizon* | | | | | | | |
| Neutral Technology | 22.87 | 28.14 | 3.05 | 25.04 | 9.06 | 4.71 | 0.90 |
| Preference | 6.45 | 34.53 | 6.12 | 31.79 | 8.81 | 31.92 | 41.14 |
| Investment-Specific | 38.06 | 0.11 | 85.39 | 0.11 | 39.92 | 3.52 | 25.73 |
| Cost-Push | 22.20 | 25.52 | 3.61 | 22.23 | 28.69 | 45.48 | 14.77 |
| Hours | 0.00 | 0.00 | 0.00 | 9.92 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 10.41 | 11.70 | 1.83 | 10.90 | 13.52 | 13.38 | 17.47 |
| II. *3-Year Horizon* | | | | | | | |
| Neutral Technology | 39.29 | 55.51 | 6.13 | 49.50 | 7.57 | 4.55 | 1.69 |
| Preference | 6.14 | 18.55 | 10.29 | 19.44 | 11.72 | 33.54 | 57.55 |
| Investment-Specific | 37.17 | 3.15 | 80.14 | 3.05 | 41.19 | 4.37 | 23.05 |
| Cost-Push | 12.49 | 16.55 | 2.38 | 15.42 | 28.10 | 42.97 | 9.15 |
| Hours | 0.00 | 0.00 | 0.00 | 5.93 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 4.91 | 6.24 | 1.06 | 6.66 | 11.42 | 14.56 | 8.55 |
| III. *10-Year Horizon* | | | | | | | |
| Neutral Technology | 36.70 | 49.44 | 8.15 | 46.15 | 7.40 | 4.86 | 2.10 |
| Preference | 4.70 | 10.60 | 9.70 | 11.82 | 11.91 | 33.24 | 58.55 |
| Investment-Specific | 48.81 | 27.73 | 79.40 | 25.87 | 42.00 | 4.89 | 23.06 |
| Cost-Push | 7.04 | 8.89 | 1.91 | 8.91 | 27.53 | 42.57 | 8.43 |
| Hours | 0.00 | 0.00 | 0.00 | 3.41 | 0.00 | 0.00 | 0.00 |
| Monetary Policy | 2.76 | 3.34 | 0.84 | 3.84 | 11.16 | 14.45 | 7.85 |

*Notes*: The numbers correspond to the percentage of the variance of each variable attributed to each shock.

Table 5: Maximum Likelihood Estimates of Alternative Models

| Parameter | Benchmark | | 1979:Q3 - 2005:Q4 | | $\chi = 0.\overline{45}$ | | $\chi = 0.625$ | |
|---|---|---|---|---|---|---|---|---|
| | Partial | Full | Partial | Full | Partial | Full | Partial | Full |
| $\phi$ | 44.1014 | 22.0684 | 83.8186 | 40.7150 | 55.2913 | 20.8056 | 35.5831 | 22.7848 |
| | (11.3807) | (6.0613) | (16.8111) | (13.8014) | (12.7765) | (5.4125) | (9.2433) | (6.6282) |
| $b$ | 0.2636 | 0.4153 | 0.3030 | 0.4873 | 0.3052 | 0.3953 | 0.2340 | 0.4304 |
| | (0.0543) | (0.0456) | (0.0968) | (0.0532) | (0.0537) | (0.0449) | (0.0542) | (0.0462) |
| $\mu$ | 0.4875 | $1^*$ | 0.3763 | $1^*$ | 0.4537 | $1^*$ | 0.5223 | $1^*$ |
| | (0.0275) | | (0.0351) | | (0.0272) | | (0.0268) | |
| $\theta_R$ | 0.8534 | 0.8063 | 0.8709 | 0.8239 | 0.8757 | 0.7983 | 0.8345 | 0.8104 |
| | (0.0183) | (0.0254) | (0.0224) | (0.0284) | (0.0187) | (0.0263) | (0.0184) | (0.0249) |
| $\theta_\pi$ | 1.8626 | 1.6096 | 2.7538 | 2.2660 | 2.2157 | 1.6536 | 1.6340 | 1.5640 |
| | (0.2312) | (0.1550) | (0.4477) | (0.3065) | (0.3300) | (0.1584) | (0.1784) | (0.1504) |
| $\theta_{Y0}$ | 0.7004 | 0.5699 | 1.0504 | 0.7571 | 0.7934 | 0.5294 | 0.6525 | 0.5984 |
| | (0.1314) | (0.0953) | (0.2405) | (0.1628) | (0.1680) | (0.0870) | (0.1128) | (0.1028) |
| $\theta_{Y1}$ | −0.7200 | −0.5768 | −1.0336 | −0.7376 | −0.8251 | −0.5422 | −0.6641 | −0.5994 |
| | (0.1336) | (0.0959) | (0.2358) | (0.1557) | (0.1726) | (0.0885) | (0.1139) | (0.1022) |
| $\rho_z$ | 0.9482 | 0.9465 | $0.9999^\dagger$ | 0.9612 | 0.9565 | 0.9496 | 0.9423 | 0.9462 |
| | (0.0191) | (0.0236) | | (0.0333) | (0.0200) | (0.0214) | (0.0184) | (0.0248) |
| $\rho_g$ | 0.8873 | 0.8926 | 0.8887 | 0.8808 | 0.8808 | 0.8994 | 0.8927 | 0.8879 |
| | (0.0221) | (0.0341) | (0.0286) | (0.0604) | (0.0237) | (0.0335) | (0.0216) | (0.0337) |
| $\rho_a$ | 0.8866 | 0.9128 | 0.8829 | 0.8764 | 0.8700 | 0.9171 | 0.9013 | 0.9097 |
| | (0.0346) | (0.0299) | (0.0348) | (0.0368) | (0.0333) | (0.0297) | (0.0341) | (0.0295) |
| $\sigma_z$ | 0.0093 | 0.0131 | 0.0086 | 0.0130 | 0.0088 | 0.0130 | 0.0097 | 0.0126 |
| | (0.0008) | (0.0018) | (0.0010) | (0.0020) | (0.0008) | (0.0013) | (0.0009) | (0.0022) |
| $\sigma_g$ | 0.0221 | 0.0169 | 0.0311 | 0.0206 | 0.0250 | 0.0164 | 0.0197 | 0.0172 |
| | (0.0029) | (0.0026) | (0.0053) | (0.0046) | (0.0034) | (0.0027) | (0.0026) | (0.0026) |
| $\sigma_a$ | 0.0469 | 0.0279 | 0.0820 | 0.0457 | 0.0576 | 0.0263 | 0.0390 | 0.0289 |
| | (0.0130) | (0.0069) | (0.0193) | (0.0149) | (0.0151) | (0.0061) | (0.0104) | (0.0077) |
| $\sigma_\pi$ | 0.0057 | 0.0036 | 0.0048 | 0.0028 | 0.0073 | 0.0037 | 0.0049 | 0.0036 |
| | (0.0004) | (0.0002) | (0.0005) | (0.0002) | (0.0005) | (0.0003) | (0.0003) | (0.0002) |
| $\sigma_h$ | 0.0083 | 0.0302 | 0.0081 | 0.0348 | 0.0095 | 0.0300 | 0.0075 | 0.0303 |
| | (0.0010) | (0.0016) | (0.0018) | (0.0024) | (0.0012) | (0.0016) | (0.0009) | (0.0016) |
| $\sigma_R$ | 0.0020 | 0.0021 | 0.0019 | 0.0019 | 0.0019 | 0.0021 | 0.0020 | 0.0021 |
| | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) |
| $\log \mathcal{L}$ | 3135.44 | 3057.26 | 1837.75 | 1792.03 | 3092.11 | 3053.96 | 3162.34 | 3059.57 |
| $C^u/C^e$ | 0.6196 | $1^*$ | 0.5604 | $1^*$ | 0.6167 | $1^*$ | 0.6317 | $1^*$ |
| | (0.0317) | | (0.0620) | | (0.0304) | | (0.0311) | |

*Notes*: The superscript $^*$ denotes a parameter value that is imposed prior to estimation. The superscript $^\dagger$ denotes a value that converged to the boundary of the allowable parameter space during estimation. The term $\log \mathcal{L}$ denotes the maximized value of the log-likelihood function. The numbers in parentheses are standard errors. The standard errors for $C^u/C^e$ are obtained using the delta method.

Table 6: Maximum Likelihood Estimates of Alternative Models

| Parameter | $N = 0.57$ | $N = 0.9399$ | No Habit | | GDP Data | | Employment Data | |
|---|---|---|---|---|---|---|---|---|
| | Partial | Partial | Partial | Full | Partial | Full | Partial | Full |
| $\phi$ | 23.2882 | 44.0343 | 44.1927 | 9.9771 | 108.0848 | 44.2613 | 128.8620 | 133.3808 |
| | (5.0265) | (11.0279) | (11.6914) | (2.1057) | (19.7526) | (11.3006) | (18.2917) | (15.3826) |
| $b$ | 0.2408 | 0.2635 | $0^*$ | $0^*$ | 0.0164 | 0.3859 | 0.1931 | 0.1734 |
| | (0.0490) | (0.0543) | | | (0.0762) | (0.0450) | (0.0447) | (0.0394) |
| $\mu$ | 0.3819 | 0.4872 | 0.4889 | $1^*$ | 0.2709 | $1^*$ | 0.4832 | $1^*$ |
| | (0.0232) | (0.0274) | (0.0283) | | (0.0291) | | (0.0475) | |
| $\theta_R$ | 0.8120 | 0.8533 | 0.8403 | 0.6530 | 0.8586 | 0.8098 | 0.7312 | 0.6590 |
| | (0.0221) | (0.0183) | (0.0189) | (0.0460) | (0.0171) | (0.0262) | (0.0503) | (0.0581) |
| $\theta_\pi$ | 1.7476 | 1.8620 | 1.7946 | 1.2647 | 1.6678 | 1.7359 | 2.1640 | 2.0691 |
| | (0.1741) | (0.2310) | (0.2113) | (0.0671) | (0.2104) | (0.1847) | (0.2854) | (0.2319) |
| $\theta_{Y0}$ | 0.6558 | 0.7001 | 0.6550 | 0.4642 | 1.0922 | 1.0321 | 4.2375 | 3.2107 |
| | (0.1029) | (0.1313) | (0.1197) | (0.0641) | (0.2057) | (0.1759) | (0.7035) | (0.4403) |
| $\theta_{Y1}$ | −0.6657 | −0.7197 | −0.6676 | −0.4671 | −1.1061 | −1.0370 | −4.2192 | −3.2105 |
| | (0.1044) | (0.1334) | (0.1205) | (0.0623) | (0.2065) | (0.1746) | (0.6933) | (0.4336) |
| $\rho_z$ | 0.9192 | 0.9481 | 0.9284 | 0.9465 | $0.9999^\dagger$ | 0.9463 | 0.9849 | 0.9838 |
| | (0.0216) | (0.0191) | (0.0192) | (0.0219) | | (0.0276) | (0.0096) | (0.0155) |
| $\rho_g$ | 0.8797 | 0.8873 | 0.8969 | 0.9243 | 0.8786 | 0.9007 | 0.9156 | 0.9295 |
| | (0.0274) | (0.0221) | (0.0200) | (0.0261) | (0.0220) | (0.0267) | (0.0174) | (0.0175) |
| $\rho_a$ | 0.9076 | 0.8866 | 0.8886 | 0.9430 | 0.8461 | 0.8958 | 0.8579 | 0.9028 |
| | (0.0305) | (0.0343) | (0.0350) | (0.0242) | (0.0339) | (0.0289) | (0.0228) | (0.0164) |
| $\sigma_z$ | 0.0111 | 0.0093 | 0.0101 | 0.0113 | 0.0064 | 0.0104 | 0.0015 | 0.0012 |
| | (0.0011) | (0.0008) | (0.0008) | (0.0016) | (0.0005) | (0.0017) | (0.0003) | (0.0004) |
| $\sigma_g$ | 0.0178 | 0.0221 | 0.0206 | 0.0101 | 0.0270 | 0.0186 | 0.0170 | 0.0181 |
| | (0.0025) | (0.0029) | (0.0028) | (0.0016) | (0.0036) | (0.0028) | (0.0028) | (0.0037) |
| $\sigma_a$ | 0.0259 | 0.0468 | 0.0473 | 0.0135 | 0.0667 | 0.0322 | 0.0700 | 0.0756 |
| | (0.0056) | (0.0127) | (0.0133) | (0.0026) | (0.0137) | (0.0080) | (0.0094) | (0.0087) |
| $\sigma_\pi$ | 0.0058 | 0.0057 | 0.0058 | 0.0037 | 0.0038 | 0.0037 | 0.0046 | 0.0053 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0002) | (0.0002) | (0.0002) | (0.0003) | (0.0003) |
| $\sigma_h$ | 0.0066 | 0.0083 | 0.0063 | 0.0288 | 0.0048 | 0.0300 | 0.0267 | 0.0291 |
| | (0.0010) | (0.0010) | (0.0008) | (0.0015) | (0.0007) | (0.0016) | (0.0014) | (0.0015) |
| $\sigma_R$ | 0.0022 | 0.0020 | 0.0020 | 0.0028 | 0.0019 | 0.0022 | 0.0028 | 0.0029 |
| | (0.0002) | (0.0001) | (0.0001) | (0.0004) | (0.0001) | (0.0002) | (0.0004) | (0.0004) |
| $\log \mathcal{L}$ | 3143.16 | 3135.46 | 3126.83 | 3033.50 | 3604.83 | 3417.15 | 3493.82 | 3468.22 |
| $C^u/C^e$ | 0.4986 | 0.6192 | 0.4889 | $1^*$ | 0.2824 | $1^*$ | 0.5806 | $1^*$ |
| | (0.0290) | (0.0316) | (0.0283) | | (0.0664) | | (0.0391) | |

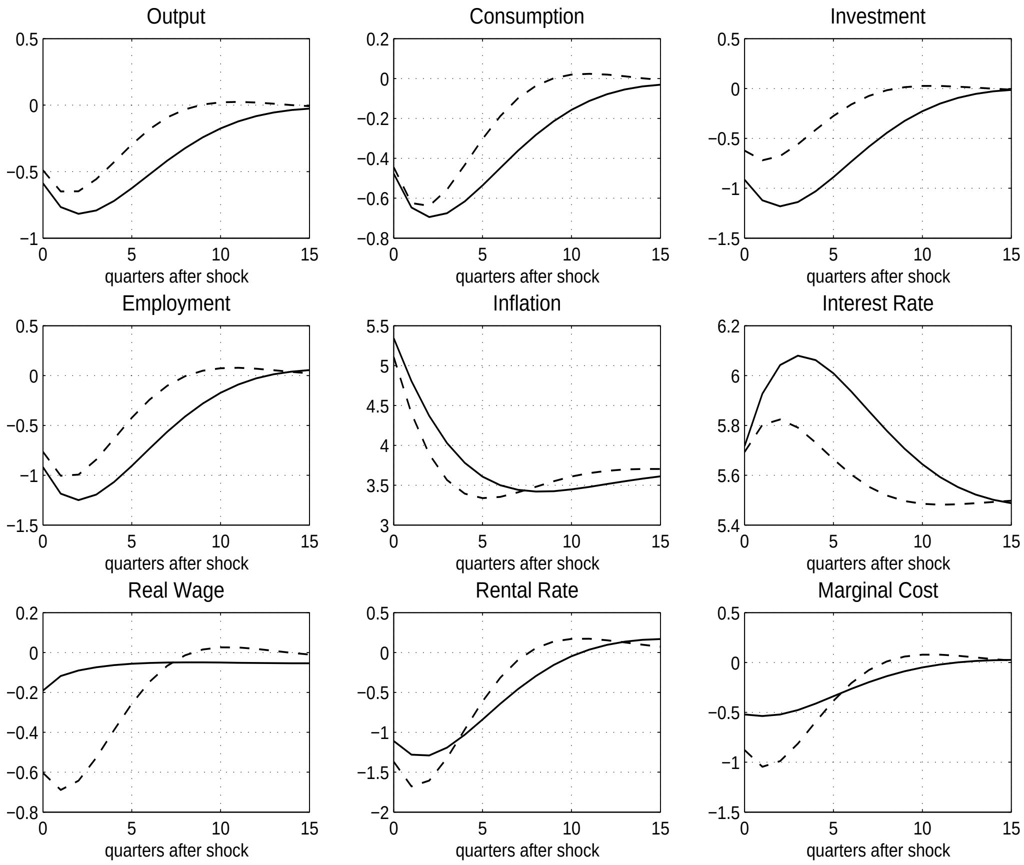
*Notes*: The superscript $^*$ denotes a parameter value that is imposed prior to estimation. The superscript $^\dagger$ denotes a value that converged to the boundary of the allowable parameter space during estimation. The term $\log \mathcal{L}$ denotes the maximized value of the log-likelihood function. The numbers in parentheses are standard errors. The standard errors for $C^u/C^e$ are obtained using the delta method.

Table 7: Maximum Likelihood Estimates of Alternative Models

| Parameter | Benchmark | | Measurement Error | | Basic Sticky-Price |
|---|---|---|---|---|---|
| | Partial | Full | Partial | Full | |
| $\phi$ | 44.1014 (11.3807) | 22.0684 (6.0613) | 169.2391 (25.6094) | 21.6074 (6.3363) | 39.9308 (5.0100) |
| $b$ | 0.2636 (0.0543) | 0.4153 (0.0456) | 0.0931 (0.0587) | 0.5759 (0.0447) | 0.6556 (0.0354) |
| $\mu$ | 0.4875 (0.0275) | $1^*$ | 0.1154 (0.0221) | $1^*$ | – |
| $\varphi$ | – | – | – | – | 0.9791 (0.1094) |
| $\theta_R$ | 0.8534 (0.0183) | 0.8063 (0.0254) | 0.8407 (0.0211) | 0.7741 (0.0261) | 0.7630 (0.0281) |
| $\theta_\pi$ | 1.8626 (0.2312) | 1.6096 (0.1550) | 1.0513 (0.0299) | 1.4352 (0.1211) | 1.8482 (0.2023) |
| $\theta_{Y0}$ | 0.7004 (0.1314) | 0.5699 (0.0953) | 0.6526 (0.2037) | 0.4416 (0.0787) | 0.3000 (0.0738) |
| $\theta_{Y1}$ | −0.7200 (0.1336) | −0.5768 (0.0959) | −0.6642 (0.2042) | −0.4546 (0.0797) | −0.3843 (0.0791) |
| $\rho_z$ | 0.9482 (0.0191) | 0.9465 (0.0236) | $0.9999^\dagger$ | 0.9378 (0.0194) | 0.9360 (0.0155) |
| $\rho_g$ | 0.8873 (0.0221) | 0.8926 (0.0341) | 0.8732 (0.0459) | 0.9423 (0.0232) | 0.9896 (0.0058) |
| $\rho_a$ | 0.8866 (0.0346) | 0.9128 (0.0299) | 0.9328 (0.0135) | 0.9202 (0.0305) | 0.9389 (0.0198) |
| $\sigma_z$ | 0.0093 (0.0008) | 0.0131 (0.0018) | 0.0048 (0.0003) | 0.0134 (0.0014) | 0.0215 (0.0015) |
| $\sigma_g$ | 0.0221 (0.0029) | 0.0169 (0.0026) | 0.0168 (0.0063) | 0.0125 (0.0028) | 0.1365 (0.0636) |
| $\sigma_a$ | 0.0469 (0.0130) | 0.0279 (0.0069) | 0.0322 (0.0060) | 0.0257 (0.0067) | 0.0288 (0.0042) |
| $\sigma_\pi$ | 0.0057 (0.0004) | 0.0036 (0.0002) | 0.0014 (0.0003) | $0.0000^\dagger$ | 0.0068 (0.0005) |
| $\sigma_h$ | 0.0083 (0.0010) | 0.0302 (0.0016) | $0^*$ | $0^*$ | – |
| $\sigma_L$ | – | – | – | – | $0.0000^\dagger$ |
| $\sigma_R$ | 0.0020 (0.0001) | 0.0021 (0.0002) | 0.0019 (0.0001) | 0.0020 (0.0001) | 0.0024 (0.0002) |
| $\varrho_c$ | $0^*$ | $0^*$ | $0.0000^\dagger$ | 0.0033 (0.0003) | $0^*$ |
| $\varrho_i$ | $0^*$ | $0^*$ | 0.0844 (0.0046) | 0.0100 (0.0061) | $0^*$ |
| $\varrho_w$ | $0^*$ | $0^*$ | $0.0000^\dagger$ | 0.0307 (0.0017) | $0^*$ |
| $\varrho_\pi$ | $0^*$ | $0^*$ | 0.0018 (0.0002) | 0.0020 (0.0001) | $0^*$ |
| $\log \mathcal{L}$ | 3135.44 | 3057.26 | 3253.00 | 3080.80 | 3122.43 |
| $C^u/C^e$ | 0.6196 (0.0317) | $1^*$ | 0.1939 (0.0544) | $1^*$ | – |

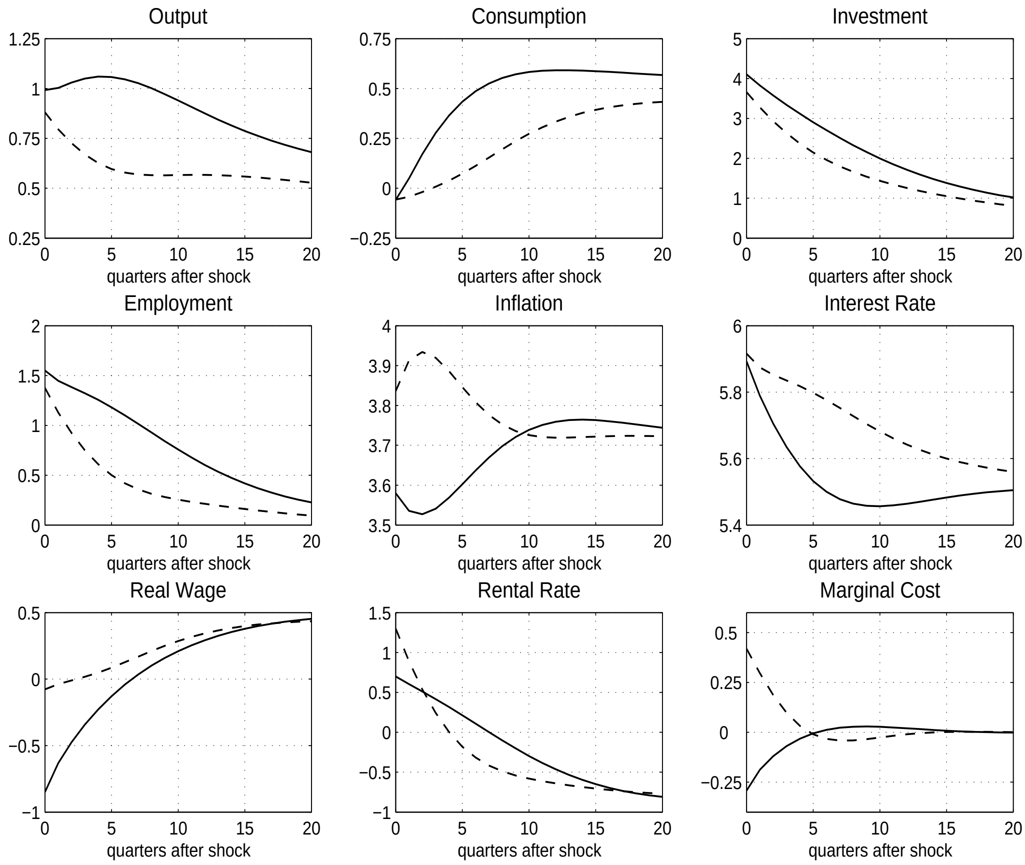
*Notes*: The superscript $^*$ denotes a parameter value that is imposed prior to estimation. The superscript $^\dagger$ denotes a value that converged to the boundary of the allowable parameter space during estimation. The term $\log \mathcal{L}$ denotes the maximized value of the log-likelihood function. The numbers in parentheses are standard errors. The standard errors for $C^u/C^e$ are obtained using the delta method.

Figure 1: Impulse Responses to a Cost-Push Shock



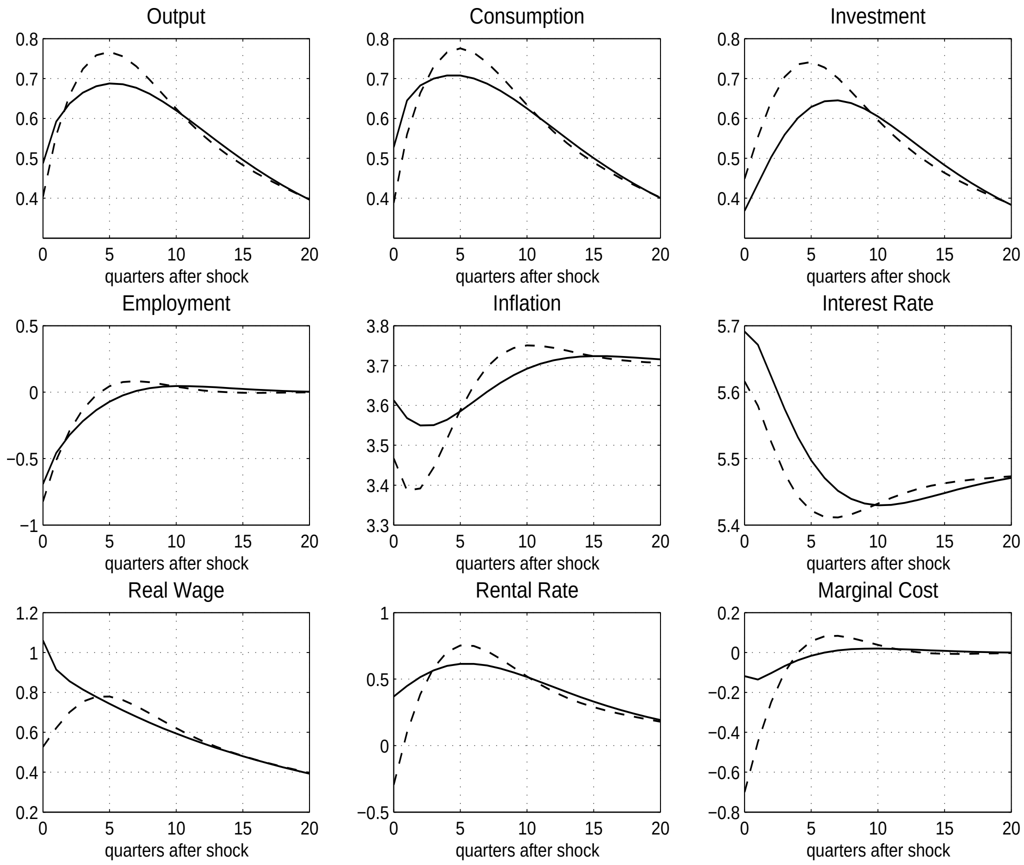

*Notes*: Each panel graphs the response of one of the model's variables to an estimated one-standard-deviation cost-push shock. Real variables are expressed as percentage point deviations from steady state. Inflation and the nominal interest rate are measured in percentage points at an annual rate. The solid lines correspond to the PI model and the dashed lines correspond to the FI model.

Figure 2: Impulse Responses to an Investment-Specific Technology Shock



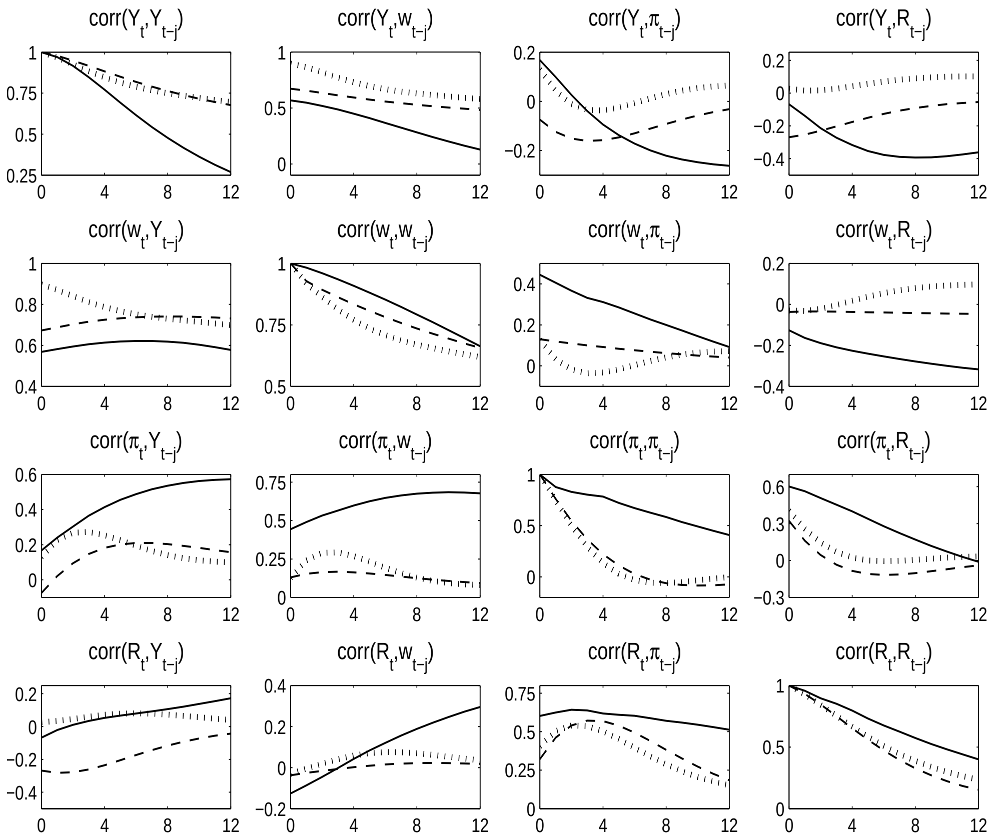

*Notes*: Each panel graphs the response of one of the model's variables to an estimated one-standard-deviation investment-specific technology shock. Real variables are expressed as percentage point deviations from steady state. Inflation and the nominal interest rate are measured in percentage points at an annual rate. The solid lines correspond to the PI model and the dashed lines correspond to the FI model.

Figure 3: Impulse Responses to a Neutral Technology Shock




*Notes*: Each panel graphs the response of one of the model's variables to an estimated one-standard-deviation neutral technology shock. Real variables are expressed as percentage point deviations from steady state. Inflation and the nominal interest rate are measured in percentage points at an annual rate. The solid lines correspond to the PI model and the dashed lines correspond to the FI model.

Figure 4: Vector Autocorrelation Functions




*Notes*: Vector autocorrelation functions for output $Y$, the real wage $w$, inflation $\pi$, and the nominal interest rate $R$ are drawn for the US data (solid line), the PI model (dashed line), and the FI model (dotted line). Output is defined in the model and the data as the sum of consumption and investment.

Figure 5: Relationship Between $s$ and $C^e/C^s$