

Long-Term Asset Price Volatility and Macroeconomic Fluctuations*

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We analyze a stochastic growth model with lags in the operation of new technologies. Stock values are impacted by news on technological innovations and some other external shocks affecting the economy. We assess the quantitative importance of various macroeconomic variables in accounting for both the observed volatility of stock values and the less pronounced volatility of real macroeconomic aggregates. Our analysis singles out price markups and leverage as key determinants of asset price volatility, and confers a rather limited role to technology shocks, adjustment costs, interest rate policies, input costs, taxes, and labor and financial frictions.

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1 Introduction

This paper is concerned with the main macroeconomic determinants of asset prices. Although in recent times a burgeoning literature has emerged in the frontier between macroeconomics and finance, there is no general consensus on the main driving forces of asset price volatility – which remain a puzzle to economists.

Dynamic equilibrium models have been fairly successful in accounting for comovements of real economic aggregates but have failed to offer plausible explanations for the volatility of stock values based on the variability of economic fundamentals. In the neoclassical growth model, changes in total factor productivity (TFP), the relative price of capital, taxes, and frictions in labor and capital markets hardly generate any volatility of stock values [see Rouwenhorst (1995) for some numerical exercises]. Indeed, these factors do not affect significantly the volatility and persistence of dividends and earnings under observable variations in consumption. Viewed in another way, capital is the only asset in the economy, and investment must fluctuate enormously to get desirable levels of volatility in stock values. The model's performance can be improved with adjustment costs [Christiano and Fisher (2003)], but these costs need to be implausibly high to attain reasonable levels of volatility in capital stock values.

A great deal of research has focused on the equity premium [e.g., Bansal and Yaron (2004), Boldrin, Christiano and Fisher (2001), Danthine and Donaldson (2002), Guvenen (2009) and Jinnai (2009)]. There is much less work intended to offer a joint explanation for the volatilities of the stock market and other macroeconomic variables [cf., Christiano and Fisher (2003), Gomme, Ravikumar and Rupert (2011) and Rouwenhorst (1995)]. Recent approaches to the equity premium should be complementary to our analysis to provide a full theory of the volatility of asset values and the risk-free rate.

We consider a stochastic growth model with lags in the operation of new technologies. Our model is a simplified variant of those in Romer (1990) and Comin and Gertler (2006), but our objectives are quite different. Romer (1990) is concerned with innovations and economic

growth, and Comin and Gertler (2006) with a quantitative analysis of real economic fluctuations.¹ Technological innovations arrive exogenously to the economy. These innovations, however, cannot be readily put into use and undergo a process of adoption embedded in the production of new varieties of intermediate goods. Asset prices incorporate the option value of technological innovations that remain to be adopted. We decompose the value of the stock market into the value of installed capital, the value of technology goods, and the option value of adopting present and future innovations. Then, episodes of technology innovation, changes in price markups, and financial shocks may generate sudden fluctuations in the aggregate value of stocks. This propagation mechanism is somewhat present in the partial equilibrium setting of Abel and Eberly (2005), in the tree economy of Gârleanu, Panageas and Yu (2009), and in the learning model of Pástor and Veronesi (2009). In all these papers the value of the firm may differ from the replacement value of the stock of capital. In contrast to these authors, we carry out a quantitative general equilibrium analysis of the volatility of asset prices along with other macroeconomic fluctuations. Hence, the challenge for our model is to generate observed levels of volatility in stock markets while preserving the less pronounced volatility of real macroeconomic aggregates.

Figure 1 plots the evolution of the S&P index and the corresponding price-earning (PE) ratio. The S&P index has been filtered by taking out our best fit for a deterministic exponential trend. All these series display similar long-term cyclical behavior; indeed, as discussed below stock prices are a main driving force of these fluctuations.² Note that peak values occur in 1900, 1929, 1965 and 2000. Therefore, the amplitude of these long-term cycles can be up to 35 years. Jovanovic and Rousseau (2001) associate these long fluctuations in the stock market with three technological revolutions: Electricity, World War II, and IT. These authors document long lags in the operation and diffusion of new technologies. Nicholas (2008) claims that innovation was a main driver of the stock market run-up of

¹In a later paper, Comin, Gertler and Santacreu (2009) build their analysis from our asset pricing equation of Proposition 2.1 below. Their empirical implementation, however, is fairly independent from ours. They do not include price markups and leverage.

²Since the early papers of Kleidon (1986), Marsh and Merton (1987) and others, researchers have emphasized the persistence and lower variability of dividends and earnings, which are highly correlated.

the late 1920s. Figure 2 is intended to illustrate the financial impact of the recent IT revolution. Market capitalization relative to GDP is decomposed into the values of three different groups of companies: (i) The incumbents, (ii) Companies originating in 1980-1990, and (iii) Companies originating after 1990. As one can see, most added stock value belongs to new corporations. These newcomers reflect the value added of local technology adopters. We use the market value of corporations (rather than the S&P index) to capture potential impacts of these new companies. The market value of corporations is the sum of the market value of corporate equity, and the book value of net debt. The joint consideration of equity and debt is convenient in our model and avoids the introduction of arbitrary corporate debt policies and dividends. As documented in Hall (2001), pay-outs to debt holders have been fairly erratic in recent decades. We will carry out some model simulations, and provide empirical estimates of the effects of corporate debt on the volatility of corporate equity which acts as the residual component.

But our story is not only a story of technology adoption. As a matter of fact, there seem to be other trends associated with these cycles coming from factors such as price markups, productivity, population, housing prices, and taxes. Price markups are substantial in the US economy [Hall (1988)], and depend on the degree of competition, cyclical forces, and the state of the global economy. Moreover, given the cost structure of the oil industry and of other raw materials, most international commodity prices may be driven by the volatility and persistency of price markups which again may be generated by global forces in demand and supply [Dvir and Rogoff (2009)]. Price markups are also prominent in the innovation and product cycles [Broda and Weinstein (2010) and Rotemberg and Woodford (1995)]. New technologies may display low elasticities of substitution and enjoy high markups. In our simple economy below, these changes will be reflected in increases of the aggregate price markup. As in some recent New-Keynesian models our price markup evolves exogenously, and our calibrations are in agreement with this literature [Smets and Wouters (2007)]. We estimate the price markup by a simulated moments estimator. The estimated values are actually quite close to the empirical estimates obtained from the dynamic evolution of oil

prices. Moreover, the volatility and persistence of the price markup in the model is compatible with the observed volatility and persistence of dividends and earnings, and the fluctuation of various macroeconomic aggregates such as investment and consumption.

Apart from price markups, we also perform a quantitative study of the effects of various macroeconomic variables. A notable feature of these numerical exercises is that adjustment costs for capital investment, interest rate policies, taxes, changes in input prices, and labor and financial frictions may only have a significant impact on the volatility of asset values at the expense of implausible fluctuations in some other variables. The introduction of some of these frictions, however, may help explain the evolution of price-earning ratios and the correlation of stock values with real macroeconomic aggregates.

The paper will proceed as follows. In Section 2 we lay out our model of technology adoption and derive some qualitative properties of the solution with emphasis on a fundamental asset pricing equation that decomposes the stock price into the value of physical capital and the value of adopted and unadopted technologies for the production of intermediate products. Section 3 is devoted to the computation and calibration of the model, and Sections 4 and 5 report various numerical experiments. We conclude in Section 6 with a further evaluation of our main findings.

2 The Model

The economy is populated by a continuum of identical households. At every time $t = 0, 1, \dots$, each agent demands quantities of the aggregate consumption good, supplies labor inelastically, and trades in the equity and bond markets. The aggregate consumption good is produced by a single firm with a constant returns to scale technology. Three inputs are involved in the production of this final commodity: Capital accumulated by the firm, labor, and a composite intermediate good. Both the firm and the consumer act competitively in all markets, but the sector of intermediate goods is composed of a continuum of monopolistic competitors. The range of available intermediate goods can be expanded by a fixed set of local adopters upon the arrival of new technologies. As in Romer (1990), an increase in

the varieties of intermediate goods allows for a more efficient use of resources and augments capital and labor productivity. The remaining source of change in productivity is an exogenous shock to the TFP of the final good production function which will also capture the variability of labor in the data. Proposition 2.1 below puts forward an asset pricing equation which will be the main building block in our empirical investigation.

2.1 The household

The representative household supplies one unit of labor inelastically, and has preferences over infinite streams of consumption. Preferences are represented by the expected discounted objective:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{(c_t - hc_{t-1})^{1-\sigma}}{1-\sigma} \right] \quad (1)$$

where c_t denotes the quantity of consumption at t , with $0 < \beta < 1$, $0 \leq h < 1$, and $\sigma \geq 0$. Observe that this utility function includes habit persistence for positive h [Boldrin, Christiano and Fisher (2001)].

The agent may participate in financial markets by trading shares of an aggregate stock a_t and units of a risk-free bond b_t . The aggregate stock yields a stochastic dividend d_t , and the bond sells at a predetermined gross interest rate R_t . For initial asset holdings a_0, b_0 , the optimization problem of the agent is to choose a stochastic sequence of consumption, shares of the aggregate stock, and units of the risk-free bond $\{c_t, a_{t+1}, b_{t+1}\}_{t \geq 0}$ to attain the maximum utility in (1) subject to the sequence of budget constraints

$$c_t + q_t a_{t+1} + b_{t+1} = \omega_t + (q_t + d_t) a_t + R_t b_t + T_t \quad (2)$$

$$q_t a_{t+1} + b_{t+1} \geq 0, \quad t = 0, 1, 2, \dots, \quad (3)$$

for given stock prices q_t , rates of interest R_t , exogenous wages ω_t , and lump-sum transfers T_t . Note that (3) is a simple borrowing limit which in this representative agent economy entails no loss of generality.

2.2 The production sector

The firm producing the final good accumulates capital and buys labor and intermediate goods. The firm's TFP is stochastic, and represented by a random variable θ_t . At every date t there is a mass A_t of intermediate goods that enter into the production of the final good. These intermediate goods are bundled together in a composite good M_t defined by a CES technology $M_t = [\int_0^{A_t} m_{s,t}^{\frac{1}{\vartheta_t}} ds]^{\vartheta_t}$ where $m_{s,t}$ denotes the amount of intermediate good s bought by the firm at time t and $\vartheta_t > 1$ follows an exogenous stochastic process to be specified below.

Given initial conditions k_0, B_0 , the firm chooses stochastic sequences of investment, labor, debt, and intermediate goods $\{i_t, l_t, B_{t+1}, (m_{s,t})_{s \in [0, A_t]}\}_{t \geq 0}$ so as to maximize the present value of dividends:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \eta_t d_t^f \right] \quad (4)$$

subject to

$$d_t^f \equiv (1 - \tau) \left[Y_t - \Omega_t \left(i_t + \omega_t l_t + \int_0^{A_t} p_{s,t} m_{s,t} ds \right) - R_t B_t + B_{t+1} \right] \quad (5)$$

$$Y_t \equiv \theta_t \left[\gamma (k_t^\alpha l_t^{1-\alpha})^\rho + (1 - \gamma) M_t^\rho \right]^{\frac{1}{\rho}}, \quad 0 < \gamma < 1, \quad -\infty < \rho < 1 \quad (6)$$

$$k_{t+1} = (1 - \delta) k_t + g(i_t/k_t) k_t, \quad \text{and } B_t \leq \bar{B}_t. \quad (7)$$

Here, η_t is a state price³ converting income of period t to period 0, and $p_{s,t}$ denotes the price of intermediate good s at time t . Our definition of dividends in (5) includes financial leverage. Observe that the amount of debt is bounded by \bar{B}_t . We include a tax on dividends τ and a friction Ω_t that we later explore in our numerical experiments. This friction may reflect trends in factor prices or financial costs, and can be made extensive to the sector of intermediate goods below; also, Ω_t may only apply to some inputs so that the quantitative impact of these distortions may be linked to the functional form of the aggregate production function (6). The physical capital stock depreciates at a constant rate $0 \leq \delta < 1$. Capital

³For our economy with a representative household, state price η_t will correspond to the shadow value of income at time t over the same quantity at time 0.

accumulation is also subject to adjustment costs which are represented by function g . This latter function is positive and concave with $g(\delta) = \delta$ and $g'(\delta) = 1$.

Besides stock prices, interest rates, wages, and the above distortions, the firm considers that TFP and price markups evolve exogenously. Stochastic variables θ_t and ϑ_t are governed by the following stationary first-order autoregressive processes

$$\ln(\theta_t) = \psi^\theta \ln(\theta_{t-1}) + \sigma_\theta \varepsilon_t^\theta \quad (8)$$

$$\ln(\vartheta_t) = \psi_0^\vartheta + \psi_1^\vartheta \ln(\vartheta_{t-1}) + \psi_2^\vartheta \varepsilon_t^\vartheta \quad (9)$$

where $\psi^\theta, \psi_1^\vartheta \in (0, 1)$, $\psi_2^\vartheta, \sigma_\theta > 0$, $\varepsilon_t^\theta \stackrel{iid}{\sim} N(0, 1)$, and $\ln(\varepsilon_t^\vartheta) \stackrel{iid}{\sim} N(0, \sigma_\vartheta)$.

Monopolistic competition prevails in the market for intermediate goods. Each variety s is supplied by an independent producer. For simplicity, the production process adopts the following form: One unit of good s requires only one unit of the final good. Then, producer of variety s picks an optimal pricing strategy $p_{s,t}$ and quantity $m_{s,t}$ from inspection of the downward-sloping demand for the product by the firm producing the aggregate commodity – after assuming a fixed set of prices and quantities for all other varieties. More precisely, for each time period t producer of variety s maximizes the amount of profits:

$$\pi_{s,t} \equiv \max_{m_{s,t}} \{p_{s,t} m_{s,t} - m_{s,t}\} \quad (10)$$

where $p_{s,t}$ should be viewed as a function of $m_{s,t}$, and can be read off from the inverse demand function

$$p_{s,t} = \left(\frac{m_{s,t}}{M_t} \right)^{\frac{1-\vartheta_t}{\vartheta_t}} p_t \quad (11)$$

with $p_t = \left(\int_0^{A_t} p_{s,t}^{\frac{1}{1-\vartheta_t}} ds \right)^{1-\vartheta_t}$.

Production of intermediate goods may be discontinued because of exogenous factors. Let ϕ be the probability of survival of a technology at every date t . Let $V_{s,t}$ be the present value of operating technology s from the beginning of time t :

$$V_{s,t} = \mathbb{E}_t \left[\sum_{r=t}^{\infty} \frac{\eta_r}{\eta_t} \phi^{r-t} \pi_{s,r} \right]. \quad (12)$$

By the symmetry embedded in our model, $\pi_{s,t}$ and $V_{s,t}$ are the same for all s .

2.3 Technology adoption

Technological innovations arrive exogenously to the economy. The average stock of technological innovations Z_t evolves according to the law of motion

$$Z_t = \phi Z_{t-1} + \mu x_{t-1} \quad (13)$$

with normalizing constant $\mu > 0$ and

$$\ln x_t = \psi^x \ln x_{t-1} + \sigma_x \varepsilon_t^x \quad (14)$$

where $\psi_x \in (0, 1)$, $\sigma_x > 0$, and $\varepsilon_t^x \stackrel{iid}{\sim} N(0, 1)$.

Technologies are put into use by local adopters. The adoption sector is composed of a continuum of agents $i \in [0, 1]$ that behave competitively. Each adopted technology sells at price V_t to a producer of intermediate goods. Let A_t^i be the stock of already adopted technologies by agent i , and $\lambda(H_t^i)$ the probability of adopting a new technology after investing the amount of resources H_t^i . An adopter can undertake a diversified menu of projects, and hence we assume that her aggregate productivity is not subject to uncertainty. The stock A_{t+1}^i follows the law of motion

$$A_{t+1}^i = \lambda(H_t^i) \phi [Z_t^i - A_t^i] + \phi A_t^i. \quad (15)$$

The optimal amount of expenditure H_t^i is derived from the following Bellman equation in which the value function is the option value J_t^i of a new technology:

$$J_t^i = \max_{H_t^i} \left\{ -H_t^i + \phi \mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t} (\lambda(H_t^i) V_{t+1} + (1 - \lambda(H_t^i)) J_{t+1}^i) \right] \right\}. \quad (16)$$

As is well known, this equation can be computed recursively by the method of successive approximations. It follows that the optimal amount of expenditure H_t^i is the same for all i . We then let the aggregate stock of adopted technologies $A_{t+1} = \int A_{t+1}^i di$.

2.4 Equilibrium and asset prices

In the present model, given the dividend tax τ and the sequence of frictions $\{\Omega_t\}_{t \geq 0}$, the exogenous state variables are the stock of available technologies Z_t , the addition of new

varieties x_t , the TFP index θ_t , and the price markup ϑ_t . The endogenous state variables are the capital stock k_t , the stock of adopted technologies A_t , and consumption c_{t-1} (if $h > 0$). The remaining variables are determined as solutions of the model from the above optimization problems, market clearing and feasibility conditions, and laws of motion of the exogenous state variables.

As suggested before, we adopt the convention that the stock market value includes all the above three production sectors. That is, $q_t a_{t+1}$ comprises the value of the objective (4) for the firm producing the final good, plus the discounted net value of profits over the set of intermediate goods and technology adoption. Hence, the aggregate dividend $d_t \equiv d_t^f + \pi_t A_t - H_t(Z_t - A_t)$. In what follows we assume that the aggregate net supply of the asset equals one (i.e. $a_{t+1} = 1$) so that q_t corresponds to the value of the stock market. Therefore, market clearing in the stock and bond markets requires $a_{t+1} = 1$, and $b_{t+1} = B_{t+1}$. For the aggregate commodity, market clearing holds if

$$YN_t \equiv Y_t - A_t m_t = c_t + i_t + H_t(Z_t - A_t) \quad (17)$$

where Y_t denotes gross production of the final good and m_t is the quantity of each variety of intermediate good produced. Hence, $A_t m_t$ is the cost of producing the composite intermediate good, and YN_t is the value added generated by this economy. This variable can be broken down into consumption, investment in physical capital, and investment in adopting new technologies.

The first-order conditions for the representative household correspond to the usual no-arbitrage conditions for the aggregate stock and the risk-free bond:

$$1 = \mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t} \left(\frac{d_{t+1} + q_{t+1}}{q_t} \right) \right] \quad (18)$$

$$1 = \mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t} R_{t+1} \right]. \quad (19)$$

The firm producing the final good will always demand positive amounts of each factor. Hence, the first-order conditions for the maximization of the objective in (4) will always hold with equality, and the imposed restriction on the amount of leverage should be taken

into consideration when such constraint is binding. In the adoption sector, optimal positive expenditure in new varieties requires:

$$1 = \lambda'(H_t)\phi\mathbb{E}_t\left[\frac{\eta_{t+1}}{\eta_t}(V_{t+1} - J_{t+1})\right]. \quad (20)$$

It follows that for a concave function $\lambda(H)$ the optimal expenditure H is positively correlated with the expected difference between the value of adopted and non-adopted varieties.

The next proposition is central to our study. It shows that the value of the stock market comprises the value of adopted technologies and the option value to adopt new technologies.⁴

Proposition 2.1 *The stock market value*

$$q_t = p_t^k k_{t+1} - B_{t+1} + V_t^+ A_t + J_t^+ (Z_t - A_t) + \xi_t \quad (21)$$

where $V_t^+ \equiv V_t - \pi_t$, $J_t^+ \equiv J_t + H_t$, $\xi_t \equiv \mathbb{E}_t\left[\sum_{r=t+1}^{\infty} \frac{\eta_r}{\eta_t} J_r (Z_r - \phi Z_{r-1})\right]$, and $p_t^k \equiv \frac{\Omega_t}{g_t}(1 - \tau)$.

Therefore, the value of the stock market incorporates five components: The value of installed capital, the amount of debt, the value of adopted technologies, the option value of inventions currently available but not yet implemented, and the present value of future inventions expected to happen. These latter components are further sources of volatility in the stock market over the value of capital and adopted technologies. We will analyze the dynamic evolution of these components – as well as their correlation with real macro aggregates – under perturbations of the exogenous state variables. For the purposes of our quantitative analysis, we consider $q_t + B_{t+1}$, which is termed the market value of corporations. This avoids modeling of corporate debt policies and pay-outs to debt holders. As already discussed, pay-outs to debt holders have been quite erratic in recent decades [Hall (2001)].

3 Computation and Calibration of the Model

The equilibrium is computed numerically using a high-order perturbation method [Schmitt-Grohé and Uribe (2004)] that takes into account the high volatility of stock market prices. To

⁴For a formal proof see our working paper version.

check for accuracy of the computed solution, we have combined this approximation method with a numerical dynamic programming algorithm [Santos (1999)] for the computation of Bellman’s equation (16).

Our purpose is to match different statistics of medium-term fluctuations observed in the data. Following Comin and Gertler (2006) we define medium-term cycles as those within a frequency band of 2 to 50 years. We use annual data from 1960 to 2007. Each nominal variable is transformed in real terms through the GDP implicit price deflator taken from NIPA Table 1.1.4. We also transform each aggregate variable in per-capita terms. Population is taken from NIPA Table 7.1. We take the logarithm of each variable and filter over various frequency bands using the band pass filter of Christiano and Fitzgerald (2003).⁵ Output (YN) is the corporate value added from the NIPA Table 1.14. Investment (I) is the sum of Investment in Private Nonresidential and Residential Fixed Assets of US Corporations (Standard Fixed Asset Tables 4.7 and 5.7). The replacement value of corporate capital is the sum of nonresidential and residential tangible corporate fixed assets (Standard Fixed Asset Tables 4.1 and 5.1). Consumption (C) is measured as the sum of non-durables and services (NIPA Table 1.1.5). The Solow residual (SR) is taken from the Bureau of Labor Statistics (BLS) private business sector. Wages are measured as compensation of employees from the NIPA Table 1.14. The number of patent applications (PT) is obtained from U.S. Patent and Trademark Office for 1970–2004, and from the Historical Statistics of the United States series W–99 for 1948 to 1970. The interest rate (R) is the short-term commercial paper rate from Robert Shiller’s web page: [http : //www.econ.yale.edu/ shiller/data.htm](http://www.econ.yale.edu/shiller/data.htm). The market value of corporations (MVC) has been computed following Peralta-Alva (2007). It is the sum of corporate’s market value of equity and book value of net debt. As discussed in McGrattan and Prescott (2003), market and book values of net debt are very close. Dividends (D) are defined from corporate value added by taking out both wages and investment. We should emphasize that stocks and dividends in the model are meant to include joint ventures and startups, which may account for some fraction of the option value of present and future inventions. The impact of these new companies may squarely be missed by some other

⁵This filtering method is appropriate for difference-stationary and deterministic-trend processes.

aggregate stock indexes like the S&P.

We start with a basic calibration of the model with no habit persistence (i.e., $h = 0$ in the above utility function), and without taxes and frictions (i.e., $\tau = 0$ and $\Omega = 1$). Our baseline calibration of parameter values is displayed in the first column of Table 1. There are several ingredients in this calibration exercise. First, various standard parameters are taken from the literature. We include here parameters defining the utility function and adjustment costs. Second, some parameters were selected in order to match some long-run ratios in the model's deterministic steady state. This obviously includes interest rates, the investment ratio, the ratio of intermediate goods in total production and the income share of wages. Third, regarding the sector of technology adoption [equation (16)], where there could be a wide range of microeconomic empirical estimates, parameter values are selected to match some macroeconomic data. As a matter of fact, to avoid a very high sensitivity of optimal expenditure H , we postulate an expenditure function that becomes fairly parsimonious with R&D expenditures. And fourth, for the estimation of the elasticity of substitution parameter ρ , and the laws of motion for TFP, markups, and technology innovation, we use a simulation-based estimation procedure along the lines of Santos (2010). This exercise yields an optimal estimation of the covariance matrix for these three shocks. The estimation of the covariance matrix may be of independent interest as it suggests how unobservable shocks to TFP, markups and technological innovations may be correlated in the data.

We assume an inelastic labor supply. It is well known that standard RBC models do not generate enough volatility in worked hours [see Cooley and Prescott (1995) and Kydland (1995)]. We could improve the performance of the model in this dimension by incorporating labor indivisibilities, or variable effort. However, these labor market refinements do not change significantly asset pricing volatility. Parameter σ in the utility function is set to 5, which is within the range of empirical estimates for many studies. We choose values for the set of parameters $(\beta, \alpha, \gamma, \delta)$ in line with the aforementioned business cycle literature. Parameter β is fixed at 0.95, leading to an annual interest rate of 5.26%. We make $\alpha = 0.26$ based on evidence of the average share of labor costs over corporate value added. The share

of materials in gross output is assumed to be 0.5; this is in accordance with estimates for the manufacturing sector [see Jaimovich and Floetotto (2008)]. In the corresponding model with no uncertainty, this income share implies a steady-state value for $\gamma = 0.7$.

We reproduce the average investment to capital ratio in the data by assuming an annual depreciation rate δ of 0.09 in (7). We specify the adjustment cost function as in Jermann (1998):

$$g(i/k) = \frac{\delta^{\frac{1}{\varsigma}}}{1 - \frac{1}{\varsigma}} \left(\frac{i}{k}\right)^{1 - \frac{1}{\varsigma}} + \frac{\delta}{1 - \varsigma} \quad (22)$$

where the positive parameter ς is the elasticity of the investment to capital ratio with respect to Tobin's q . We let $\varsigma = 8$, in line with empirical evidence [see Jermann (1998), Jinnai (2009) and references therein]. As discussed below, our results present low sensitivity to this parameter.

We assume that the data counterpart for the number of adopted technologies (i.e., $A_{t+1} - \phi A_t$) is the number of patent applications PT . Following empirical estimates in Hall (2007), parameter ϕ on the survival rate of each intermediate product is set to 0.98. The probability of adoption is determined by an exponential function

$$\lambda(H_t) = \Lambda H_t^\kappa \quad (23)$$

with $\Lambda > 0$ and $\kappa \in (0, 1)$. We assign parameter values in conjunction with the laws of motion for A and Z below to replicate the volatility and persistence of patents and the ratio of R&D expenditures over output. The steady-state value for probability $\lambda(H)$ is 0.166, which yields an average adoption time of six years. Parameter κ then determines the volatility of expenditures in technology adoption. We come close to this volatility for κ equal to 0.80. Under these parameter values, we then get that the mean value of the ratio of adoption expenditures over corporate value added is 2.33 percent. This figure is roughly the ratio found in the data for both corporate and non-corporate expenditures. In our simulated exercises the optimal law of motion for the ratio of adoption expenditures over output ($RH_t \equiv H_t(Z_t - A_t)/YN_t$) is approximated by the expression

$$RH_t = R_0 + R_1(Z_t - A_t) \quad (24)$$

where R_0 and R_1 are constants with $R_1 > 0$. This approximate policy function has low computational cost, and tracks down the volatility of R&D data in a more parsimonious way.

Parameter values for the exogenous stochastic processes (8)–(9) and (14), and parameter ρ are selected from a loss function defined over weighted second-order moments of output YN , investment I , market value of corporations MVC , Solow residual SR , and patent applications PT . The estimated value of ρ in the production function is -0.6. Krusell *et al.* (2000) provide some estimates for the elasticity of substitution between capital and skilled labor which are consistent with our estimation of ρ . In the model with no uncertainty, we get that the steady-state value for the intermediate producers' gross markup ϑ is equal to 1.18. This value is rather low as compared to the range of available estimates [Rotemberg and Woodford (1995) provide an overview of microeconomic evidence]. But as the markup shock stems from a log-normal distribution, by Jensen's inequality the simulated mean for parameter ϑ is 1.38 which seems a more reasonable value.

We can see from Table 1 that the markup shock seems highly persistent with autoregressive coefficient $\psi_1^\vartheta = 0.968$. This key autoregressive parameter is in line with estimated values of New-Keynesian models. For instance, Smets and Wouters (2007, Table 4, p. 597) report a mean autocorrelation parameter equal to 0.90 in a model with price stickiness. However, this parameter jumps to 0.97 when the degree of price stickiness is moved to a minimal value. Moreover, using data from Dvir and Rogoff (2009), we obtain similar persistence values from univariate estimations over various subperiods of the detrended price of oil.⁶ It is worth pointing out that our estimation of the volatility of the price markup shock uncovers a link to technological innovations – which may be reflected in changes in the elasticity of substitution of intermediate goods. This is confirmed in Table 1 for $Corr\{\varepsilon^x, \ln(\varepsilon^\vartheta)\} = 0.70$. Technological innovations are therefore associated with high price markups [Broda and Weinstein (2010)]. Moreover, $Corr\{\varepsilon^\theta, \ln(\varepsilon^\vartheta)\} = 0.81$, which suggests strong correlated

⁶Taking $\psi_0^\vartheta = 0$, our estimates for an univariate regression of oil prices are: $\psi_1^\vartheta = 0.93$ and $\sigma_\vartheta = 0.09$ for 1900–2008, with $\psi_1^\vartheta = 0.96$ and $\sigma_\vartheta = 0.10$ for the most recent subperiod 1950–2008, and $\psi_1^\vartheta = 0.93$ and $\sigma_\vartheta = 0.12$ for the shorter, recent subperiod 1970–2008. Note that in our baseline calibration of Table 1 we actually get $\psi_0^\vartheta = -0.145$ but for all our simulations we always obtain that ϑ_t is greater than 1.

effects between the Solow residual and price markups.

4 Numerical Experiments

This section contains several numerical experiments to assess the model's predictions. To learn about the influence of some external forces in the dynamics of the model, we have computed impulse-response functions⁷ for shocks in the TFP index θ , the stock of available technologies Z , and the price markup ϑ . For our benchmark calibration of the model, positive changes in θ and ϑ lead to extended increases in the market value of corporations $MVC_t = q_t + B_{t+1}$ and its components specified in Proposition 2.1, with more pronounced effects for changes in ϑ . Widening the range of available technologies Z may actually decrease MVC , as the arrival of new technologies depresses the price of existing ones. In a second set of experiments, we check the ability of the model to reproduce various second-order moments found in the data. We complete this analysis with some extensions: Taxes, frictions impacting labor costs, and leverage.

4.1 Second-order moments

The foregoing exercises should be helpful to gain some intuition for the simulated moments that we now pass to present. These moments are obtained from equilibrium paths with 3000 observations, where the first 1000 observations have been dropped to avoid influence of initial conditions. To isolate the effects of some variables we consider three model variations. *Model I (the basic model)*: Our benchmark calibration that excludes habit persistence (i.e., $h = 0$) and frictions impacting input costs (i.e., $\Omega = 1$).

Model II (changes in preferences): Our benchmark calibration does not generate enough volatility of the risk-free interest rate. As is well known [see Boldrin, Christiano and Fisher (2001)], this volatility can be increased thorough habit persistence. The calibration procedure goes along the lines of our previous calibration exercise. Parameter values for the

⁷Graphical illustrations of these impulse-response functions are available in our working paper version.

exogenous stochastic processes (8)–(9) and (14), and parameters ρ, h are chosen from a loss function which now incorporates the volatility of the risk-free interest rate. The second column of Table 1 contains the estimated parameter values.

Model III (input costs frictions): We capture shocks to input costs thorough variable Ω . This variable follows a first-order autoregressive process

$$\ln(\Omega_t) = \varphi^\Omega \ln(\Omega_{t-1}) + \varepsilon_t^\Omega \text{ with } \varepsilon_t^\Omega \stackrel{iid}{\sim} N(0, \sigma^\Omega). \quad (25)$$

This shock is modeled as a pecuniary friction: The proceeds of this distortion are rebated back to the consumer as a lump-sum transfer. As in our previous calibrations, we now perform a simulation-based estimation exercise for the exogenous stochastic processes (8), (9), (14) and (25), and parameters ρ, h . The estimated parameters are listed in the third column of Table 1.

In Table 2 we present volatilities for Models I, II and III. In Model I the volatility of MVC is 16.61 as compared to 23.96 in the data. Therefore, the model can provide over two-thirds of the actual volatility in the data. The volatilities of consumption C , and investment I are in line with the business cycle literature. The volatilities of SR , PT , MVC , the return RC of MVC and dividends D are pretty similar for the three models. Model II improves on the volatility of R and Model III *substantially* improves on the volatility of the price-dividend ratio PD . Should adjustment costs be taken out of Model I, then the volatility of investment goes from 11.27 percent to 11.99 percent, and the stock market volatility goes from 16.61 percent to 16.42 percent. Hence, the introduction of adjustment costs leads to a mild drop in the volatility of capital investment. This minor effect on the volatility of the stock market seems to occur because adjustment costs may crowd out expenditures in technology adoption.

Figure 3 decomposes the MVC in Model III as in our fundamental asset pricing equation (21). Roughly, the value of installed physical capital ranges between 15 and 50 percent of the corporate value, the value of the intermediate goods sector ranges between 25 and 65 percent of the corporate value, whereas the option value of adopting future technologies lies between 10 and 30 percent of the corporate value. These figures seem quite plausible, and it

should be understood that the relative weight of capital is simply affected by the volatility of all other components. That is, the replacement value of capital is fairly smooth. It is common in the macroeconomic literature [e.g., Hall (2001)] to see that the weight of capital in the total stock value may get down to one fourth of its peak value in periods of high activity or technological innovations.

Table 3 reports on the persistence of the variables. All three models can fairly well reproduce all the autocorrelations observed in the data for variables YN , C , I , SR , PT , MVC , and R . Model III, however, improves on the persistence of D , PD , and R . This seems key for Model III to account for the volatility of PD in Table 2. It follows from Table 3 that our results on the volatility of MVC and PD do not rely on undesirable high persistence of macro aggregates.

Table 4 displays contemporaneous correlations of output YN with other macro aggregates. Note that these empirical estimates are associated with high standard errors, and hence the confidence intervals are usually fairly wide. In most of the business cycle literature, YN is highly correlated with SR over the shorter term cyclical component, and YN is also too highly correlated with MVC . In our models, we still see a high correlation of YN with SR , but YN is more mildly correlated with MVC . Again, Model III *substantially* improves upon the correlations of YN with each of the following variables: C , MVC , D , PD and R .

Finally, Table 5 presents contemporaneous correlations between PD and remaining macro variables. By and large, we observe that the simulated moments are quite close to the empirical ones. Note that Model III exhibits a much better performance, since it *substantially* improves upon the correlations of PD with each of the following variables: YN , C , I , and SR . Still, Model III fails in regards to the correlation between PD and C , between PD and MVC , and between PD and R . In the following section we interpret these failures as a possible lack of monetary propagation mechanisms. Further, Campbell (1999) reviews the international evidence for some major countries, and finds no robust patterns between the risk-free rate R and some other macroeconomic aggregates.

In summary, all models generate a reasonable volatility of the market value of corporations

MVC along with the volatilities of real macroeconomic variables. The volatility of MVC is not driven by excessive high persistence (i.e., close to unit roots) of real macro aggregates. Autocorrelations of the variables are roughly the same in both the models and the data. The introduction of habit persistence generates a more desirable volatility of the risk-free interest rate R . Supply shocks given by pecuniary frictions in input costs lead to a better volatility of the price-dividend ratio PD and improved autocorrelations of dividends D and risk-free rate R . These latter two variables are also better correlated with output YN . None of the models yields good correlations between PD and C , between PD and MVC , and between PD and R . As pointed out below, additional financial frictions such as borrowing constraints may improve the performance of these latter statistics.

4.2 Extensions

Taxes: Taxes on corporate profits and dividends could greatly affect the stock market value as well as endogenous investment and dividends [cf. McGrattan and Prescott (2005) and Poterba (2004)]. We have considered an exogenous process for taxes that is meant to fit the evolution of taxes on dividends in the US as reported in McGrattan and Prescott (2003). This tax policy had a very small effect on the stock market. We should also remark that some activist fiscal policies on taxes and allowances for depreciation [Auerbach (2009)] have a damping effect on stock market values. After analyzing various arbitrary tax policies, we have concluded that taxes may strongly affect the volatility of asset values as they can change optimal dividend policies, but these desirable changes in the volatility of stock values are only obtained at the expense of excessive volatility in some real variables such as capital investment and consumption.

Labor frictions: The model with variable labor does not significantly improve upon the volatility of the stock market [see Rouwenhorst (1995)]. The introduction of variable labor brings the same problems encountered in the business cycle literature [e.g., Kydland (1995)]. Moreover, sticky wages, labor market rigidities and additional shocks to the labor markets seem to have a minor influence on the long-term volatility of the stock market. General

and nested CES production functions for capital and labor and intermediate goods did not lead to much improvement of the current results. As a proxy for labor distortions, we have experimented with a persistent shock in the shares of labor and capital income. This distortion generated too much volatility in capital investment. Figure 4 plots the evolution of the income share of labor, capital and intermediate goods for Model III. We can see that the income share of labor hovers around 60 percent and it is also reasonably volatile. This share seems in accord with casual observations [cf. Krusell *et al.* (2000)]. Finally, restricting the analysis to a Cobb-Douglas production function lowers slightly the volatility of MVC and generates much less fluctuations in the income share of labor and dividends.

Borrowing constraints, monetary policy, and leverage: As compared to the data, in our Model III the correlation between PD and C is too high, and the correlation between PD and MVC is too low. The correlation between PD and C may be improved by tighter borrowing limits. Kehoe and Levine (2001) illustrate how various types of borrowing arrangements may change the volatility of consumption and asset prices. Kehoe and Levine consider a model with two types of agents. The computation of asset pricing models with heterogenous agents is a complex topic that goes well beyond our original objectives. Similar considerations should apply to improve the correlation between PD and MVC . In the recent economic crisis we have seen low PD ratios associated with tighter borrowing limits, a lower quality of collateral, as well as higher credit risk. Hence, it seems that some monetary factors may be responsible for the low correlation between PD and MVC generated by our model.

Leverage – short-term and long-term debt – appears to be an important source of stock market volatility, and this is reflected in our model as we introduce arbitrarily debt policies for the aggregate firm that resemble actual data. In our complete markets setting these policies are easy to simulate since we just need to keep track of corporate debt and equity. We can also assess the relevance of corporate debt from the data: The volatility of corporate equity in our data set is 28.81 percent whereas the volatility of the market value of corporations is 23.96. The difference between these two figures seems a lower bound for the effects of debt on the volatility of stock prices. Indeed, by the Modigliani-Miller theorem in a frictionless

economy this difference would be ascribed to leverage. With financial frictions it is reasonable to expect that debt may have much bigger effects.

5 Variance Decomposition of PD

To further our understanding of the sources of stock market volatility, we now provide a variance decomposition of the price-dividend ratio. Numerical simulation of non-linear equilibrium models poses some challenges which are not present in traditional econometric estimation – concerned with sampling error. We shall introduce some techniques for numerical simulation that are of independent interest. Our analysis will proceed as follows: (1) *Numerical approximations*, based upon computation of variance decompositions using the model’s asset pricing equation (18), (2) *Testing the model*, based upon comparisons of variance decompositions over data analysis and equilibrium sample paths, and (3) *Evaluation of results*, based upon a sensitivity analysis and performance of related models.

A lot of research has been devoted to explore sources of volatility of stock prices, e.g., see Gilles and LeRoy (1991) and references therein. Some authors [Campbell and Shiller (1988) and Cochrane (1992, 2008)] argue that the price-dividend ratio can mainly be explained by expected future returns, whereas expected future dividend growth lacks explanatory power. Therefore, the empirical evidence seems to suggest that the volatility of PD is mainly determined by news related to the discounting factor. We should nevertheless remark that these results are not generally accepted. Some authors have questioned their econometric significance [see Ang (2002) and Ang and Bekaert (2007)] and others have found strong inconsistencies over data samples [see Boudoukh *et al.* (2007) and Larrain and Yogo (2008)]. This ongoing debate provides further motivation for our numerical work. We focus on the computation of the population moments of the invariant distribution of the model for asset prices and returns. These moments can be calculated either directly from an approximate solution or from arbitrarily long simulations; hence, the computed population moments may contain approximation errors but are not subject to the sampling error found in data analysis. We can also gain further intuition for these results by providing a sensitivity analysis

over the model's parameters or by comparisons to related models.

Following Campbell and Shiller (1988), we now derive an approximate expression for PD by a log linearization over an observed sample path. Let $pd_t \equiv \ln\left(\frac{MVC_t}{D_t}\right)$, $\Delta d_t \equiv \ln\left(\frac{D_t}{D_{t-1}}\right)$, $r_t \equiv \ln\left(\frac{MVC_t + D_t}{MVC_{t-1}}\right)$, where D_t refers to our definition of dividends from Section 2, and MVC_t is the market value of corporations at the end of t . Then, from these definitions, we get the following equation

$$pd_t = -r_{t+1} + \Delta d_{t+1} + \ln[1 + \exp(pd_{t+1})]. \quad (26)$$

By a first-order Taylor approximation for $\ln[1 + \exp(pd_{t+1})]$ at the expected value $\mathbb{E}[pd_t]$, it must hold that

$$pd_t \approx \nu - r_{t+1} + \Delta d_{t+1} + \rho pd_{t+1}, \quad (27)$$

where $\rho \equiv \exp(\mathbb{E}[pd_t]) / (1 + \exp(\mathbb{E}[pd_t]))$ and $\nu = \ln[1 + \exp(\mathbb{E}[pd_t])] - \rho \exp(\mathbb{E}[pd_t])$. Iterating forwards on this difference equation over pd_{t+1} for N periods, we must have

$$pd_t \approx \nu \frac{1 - \rho^N}{1 - \rho} - \sum_{s=1}^N \rho^{s-1} r_{t+s} + \sum_{s=1}^N \rho^{s-1} \Delta d_{t+s} + \rho^N pd_{t+N}. \quad (28)$$

Applying the conditional expectations operator \mathbb{E}_t , and multiplying both sides of (28) by $pd_t - \mathbb{E}[pd_t]$, we can then obtain the variance decomposition

$$\begin{aligned} Var(pd_t) \approx & -Cov \left\{ \mathbb{E}_t \left[\sum_{s=1}^N \rho^{s-1} r_{t+s} \right], pd_t \right\} \\ & + Cov \left\{ \mathbb{E}_t \left[\sum_{s=1}^N \rho^{s-1} \Delta d_{t+s} \right], pd_t \right\} \\ & + Cov \left\{ \mathbb{E}_t \left[\rho^N pd_{t+N} \right], pd_t \right\}. \end{aligned} \quad (29)$$

Accordingly, we can define the following ratios [e.g., see Cochrane (1992)]:

$$CVAR_{N,r} \equiv \frac{-Cov \left\{ \mathbb{E}_t \left[\sum_{s=1}^N \rho^{s-1} r_{t+s} \right], pd_t \right\}}{Var(pd_t)} \times 100, \quad (30)$$

$$CVAR_{N,d} \equiv \frac{Cov \left\{ \mathbb{E}_t \left[\sum_{s=1}^N \rho^{s-1} \Delta d_{t+s} \right], pd_t \right\}}{Var(pd_t)} \times 100, \quad (31)$$

$$CVAR_{N,pd} \equiv \frac{Cov \left\{ \mathbb{E}_t \left[\rho^N pd_{t+N} \right], pd_t \right\}}{Var(pd_t)} \times 100. \quad (32)$$

Observe that these ratios represent the fraction of the variance of pd that can be attributed to fluctuations of expected future returns, dividend growth, and the volatility of the terminal term pd_{t+N} , respectively. We now lay out various methods for the computation and estimation of these ratios. In the sequel, it is important to realize that the above variance decomposition is based upon the following assumptions: (i) Equation (26) considers the realized return r_{t+1} whereas our pricing equation (18) holds under the discounting operator $\mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t}(\cdot) \right]$, and (ii) Equation (27) comes from a first-order Taylor approximation. These two working assumptions will be circumvented in our numerical computations over asset pricing equation (18).

5.1 Numerical approximations

We are now concerned with a variance decomposition of pd based on the computation of our asset pricing equation (18). That is, the stock price is defined as the expected discounted value of future dividends, using the operator $\mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t}(\cdot) \right]$ rather than the realized return r_{t+1} . We provide variance decompositions of pd under the following two methods:

Method 1: Let us first recall that both $\frac{\eta_{t+1}}{\eta_t}$ and d_t are functions of the state variables, and both terms interact in a nonlinear way in the computation of pd . Hence, we propose the following numerical approximation of the variance decomposition based on the computation of two objects: A constant-dividend ratio pd^r and a constant-discounting ratio pd^d . More precisely, pd^r is computed from the exact pd ratio by letting $\Delta d_t = 0$, for all $t \geq 0$, and pd^d is computed from the exact pd ratio by letting $\frac{\eta_{t+1}}{\eta_t} = \beta$, so that expected future dividends are discounted by our calibrated value $\beta = 0.95$. We can then define the following ratios:

$$NCVAR_{1,r} \equiv \frac{-Cov\{pd_t^r, pd_t\}}{Var(pd_t)} \times 100, \quad (33)$$

$$NCVAR_{1,d} \equiv \frac{Cov\{pd_t^d, pd_t\}}{Var(pd_t)} \times 100. \quad (34)$$

These population values can be calculated by model simulation. For Model III, we get $NCVAR_{1,r} = 83.64$ and $NCVAR_{1,d} = 15.39$. Hence, almost 84 percent of the variance decomposition corresponds to changes in the expected value of future state prices, whilst

only 15 percent of the variance decomposition corresponds to changes in expected dividend growth.

Method 2: This procedure builds upon a linear approximation of the model's policy function explained in our working paper version. Then, $\mathbb{E}_t [\sum_{s=1}^{\infty} \rho^{s-1} \hat{r}_{t+s}]$ and $\mathbb{E}_t [\sum_{s=1}^{\infty} \rho^{s-1} \Delta d_{t+s}]$ can be expressed as linear functions of the state variables, where $\hat{r}_{t+1} \equiv -\ln \left(\frac{\eta_{t+1}}{\eta_t} \right)$. We likewise define the following ratios:

$$NCVAR_{2,r} \equiv \frac{-Cov \{ \mathbb{E}_t [\sum_{s=1}^{\infty} \rho^{s-1} \hat{r}_{t+s}], pd_t \}}{Var(pd_t)} \times 100, \quad (35)$$

$$NCVAR_{2,d} \equiv \frac{Cov \{ \mathbb{E}_t [\sum_{s=1}^{\infty} \rho^{s-1} \Delta d_{t+s}], pd_t \}}{Var(pd_t)} \times 100. \quad (36)$$

Again, these population values can be calculated by model simulation. For Model III, we get $NCVAR_{2,r} = 91.23$ and $NCVAR_{2,d} = 10.13$. Hence, about 91 percent of the variance decomposition corresponds to changes in the expected value of future state prices, whereas about 10 percent of the variance decomposition corresponds to changes in expected dividend growth.

As already stressed, these statistics do not depend on the Campbell-Shiller approximation (28) and are computed using the operator $\mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t} (\cdot) \right]$. Method 2 attributes more variability to asset returns, which may stem from computational errors of the linear approximation. Interestingly, for these two approximation methods the sum of the components $NCVAR_r$ and $NCVAR_d$ is very close to 100. Under both methods, the variance of pd is mainly explained by news associated with the discounting factor.

5.2 Testing the model

We now test the model using (30)-(32). Hence, we calculate $CVAR_{N,r}$, $CVAR_{N,d}$ and $CVAR_{N,pd}$ for both the data and arbitrarily long sample paths of Model III. For the data, these statistics are calculated over our annual set of observations for the time period 1960-2007. For model statistics, using the computed equilibrium function we generate a rather long equilibrium path, and calculate the associated sequence of asset returns r_t . Then, with all available information in place, we compute $CVAR_{N,r}$, $CVAR_{N,d}$ and $CVAR_{N,pd}$ for Model

III. The estimated values are presented in Table 6 for several terminal periods N . According to these estimates, for Model III the fraction of the variance of pd that can be associated with expected dividend growth is never greater than 15 percent. Observe from this table that actual data attaches a negative weight to expected dividend growth, which is manifested in an over-reaction of stock prices to changes in expected future returns with values around 120 percent. Although these estimates may change over data samples, they underscore the role of fluctuations of expected asset returns in the volatility of the price-dividend ratio.

5.3 *Evaluation of these results*

Both numerical approximations and testing of the model suggest that the variance of pd for Model III is mainly explained by changes in expected asset returns rather than by dividend growth. We actually get similar variance decompositions of Model III for the simulation of our model by method 1 and for the computation of $CVAR_{N,r}$ and $CVAR_{N,d}$ in Table 6 for $N \rightarrow \infty$. In both cases the variability attributed to expected asset returns in Model III is around 85 percent. As in Campbell and Shiller (1988) this confirms that the approximation errors for these empirical tests seem to be small. From a methodological point of view, it is therefore reassuring that we get similar variance decomposition results for both computational and commonly used econometric methods. As a matter of fact, our numerical procedures provide a further validation of empirical tests because our computations of the variance decomposition for Model III in Table 6 are not subject to sampling error.

We carried out the same analysis for Models I and II and found similar quantitative results. Hence, these variance decompositions do not seem to depend on the form of the utility function, and should be ascribed to the evolution of the price markup (9) and its effects on the dynamics of asset prices and dividends. This is most clearly seen when we perform a similar analysis of the neoclassical growth model. In the real business cycle model of Rouwenhorst (1995) with a log utility function, we find that 90 percent of the pd volatility is explained by expected dividend growth. In this latter model, it takes a coefficient of risk aversion $\sigma = 10$ for fluctuations of expected future returns to account for half of the volatility

of pd . Therefore, traditional business cycle models cannot generate desired levels of volatility of asset prices, and such volatility is basically driven by expected dividend growth.

6 Concluding Remarks

This paper explores macroeconomic determinants of asset price volatility in a general equilibrium model with lags in technology adoption. Technologies are embedded in the production of new varieties of intermediate goods. Stocks are impacted by the arrival of new technologies and other shocks affecting the economy. Our analysis builds on an asset pricing equation that decomposes the market value of corporations into the value of installed capital, the value of existing technologies, and the option value of adopting new technologies.

This general equilibrium setting imposes severe discipline in our numerical experiments: Desired levels of volatility of asset prices usually come with pronounced changes in macroeconomic fluctuations. To get an idea of related computations, in our simulations of the neoclassical growth model a volatility (i.e., a normalized standard deviation) of investment of the order of 9.71 percent translates into a volatility of the capital stock of the order of 5.72 percent. As the volatility of the market value of corporations is about 23.96 percent, it is then not surprising that many candidate variables will have a limited role in accounting for observed fluctuations of stock market prices, as they would require implausible fluctuations in other sectors. As documented in our comparisons of Model I–Model III, some frictions may nevertheless be useful to explain the correlation of the stock market with other macroeconomic variables.

We find that TFP shocks and the arrival of new technologies, interest rate policies, taxes, and real and financial frictions have minor effects on the long-term volatility of asset market values under various CES formulations of the aggregate production function for labor and capital. Technological innovations can have significant effects if they come along with high markups and TFP changes. Leverage – short-term and long-term debt – appears to be an important source of stock market volatility from both additional model simulations and a simple decomposition of our data into corporate equity and debt.

Overall, we get that in our model the volatility of the market value of corporations is of the order of 18.98 percent as opposed to 23.96 percent in the data. Hence, the model can deliver about 3/4 of the observed volatility. We then carry out a battery of tests on the volatility and correlation of various macroeconomic variables. We also perform a variance decomposition of the price-dividend ratio. We find that about 85 percent of the volatility of the price-dividend ratio can be explained by fluctuations of expected asset returns – leaving the remaining 15 percent to changes in expected dividend growth. These values are in line with our data estimates. In contrast, many variations of the neoclassical growth model predict low volatility for the price-dividend ratio, and such volatility is driven by dividend growth. In this latter model, sizable effects for the asset return component are only a possibility for close to unit-root behavior in the state variables and for rather high coefficients of risk aversion. In the traditional business cycle literature, stock values are strongly correlated with output, dividends and earnings are not sufficiently volatile, and the risk-free rate has almost zero variability. The good performance of our model can be understood by our decomposition of the asset pricing equation (21) in which the stock market may anticipate the value of technologies that need to be adopted, and news about future events, i.e., the expected path of all exogenous variables. In our model stock values are leading indicators which are only mildly correlated with output and other real variables [Campbell (1999)].

To conclude, let us briefly mention two extensions which are the current focus of our research. First, our calibration exercise can be improved to account for cross correlations over time. We have introduced inflation and various Taylor’s rules targeting nominal and real interest rates. Then, the volatility of the stock market is studied along with the variability of equilibrium yield curves [cf. Piazzesi and Schneider (2007)]. Second, our theory of markups and leverage as main determinants of stock market volatility can be tested using disaggregated data by industry. There is a considerable amount of variability of markups across sectors; moreover, leverage is more pronounced in industries with high fixed costs. The variability of price markups across sectors seems to be highly correlated with asset market volatility as

reflected in the various stock indexes under study.

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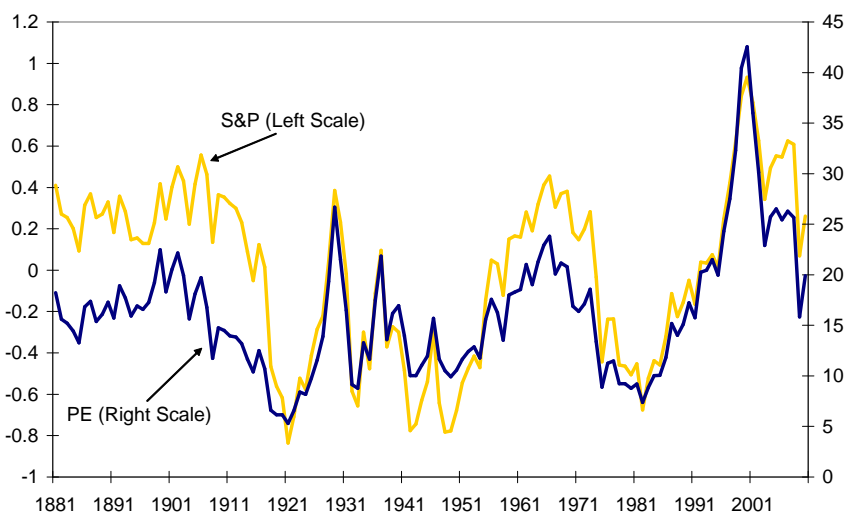
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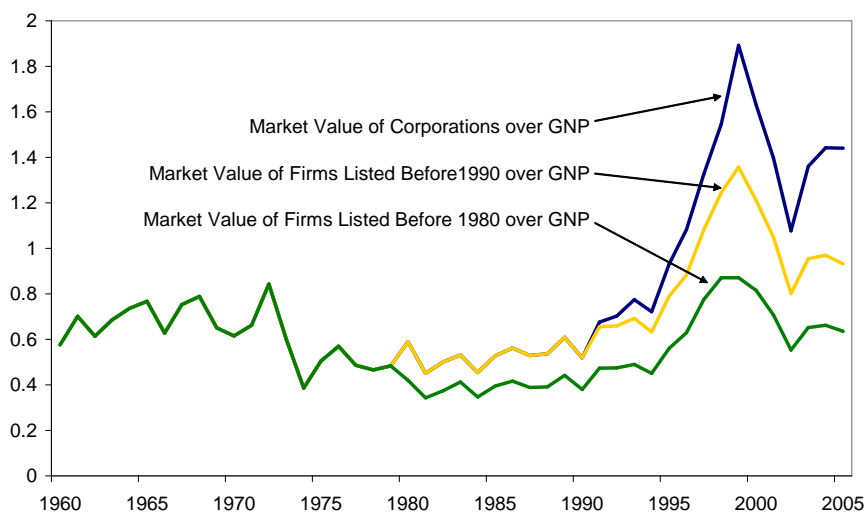
Figure 1: Evolution of S&P and PE



Source: Robert Shiller's web site: <http://www.econ.yale.edu/shiller/data.htm>.

Note: Detrended S&P price index and price-earning ratio. Annual data. The price-earning ratio is computed as current price over average earnings for previous ten years.

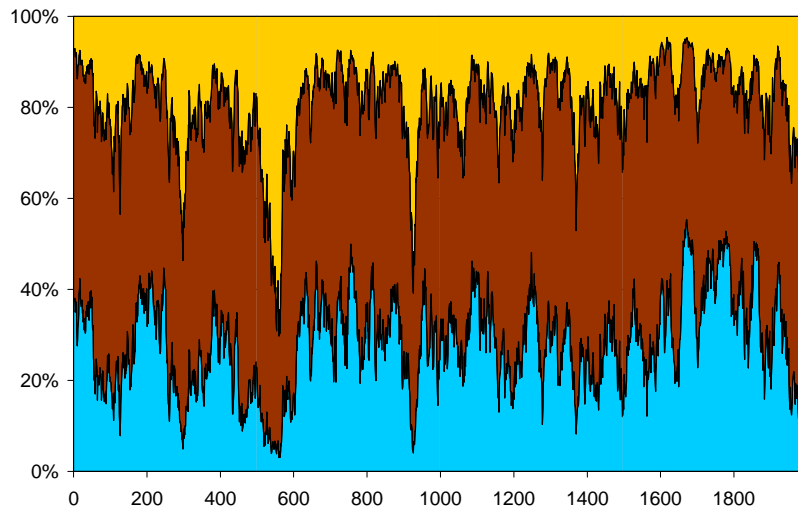
Figure 2: Market Value of Different Vintages



Sources: CRSP and NIPA.

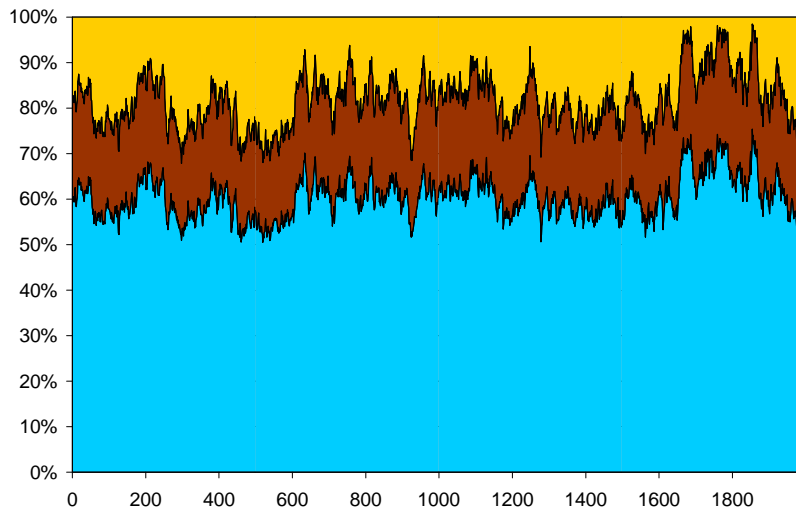
Note: Market value of corporations over GNP for different vintages. Annual data from 1960 to 2005.

Figure 3: Components of the Stock Market Value



Note: The bottom, blue area is the relative value of capital, the middle, red area is the relative value of adopted technologies, and the top, orange/yellow area is the relative value of unadopted technologies.

Figure 4: Factor Income Shares



Note: The bottom, blue area is the labor income share, the middle, red area is the capital income share, and the top, orange/yellow area is the share of intermediate sector's profits.

Table 1: Calibration of Parameter Values

Parameter	MI	MII	MIII
β	0.95	0.95	0.95
σ	5	2.75	5
h	0	0.5	0.5
α	0.26	0.26	0.26
γ	0.70	0.70	0.70
δ	0.09	0.09	0.09
ρ	-0.60	-0.60	-0.60
ς	8	8	8
κ	0.80	0.80	0.80
λ	0.166	0.166	0.166
ϕ	0.98	0.98	0.98
R_0	-0.0038	-0.0038	-0.0038
R_1	0.222	0.222	0.222
ψ^θ	0.87	0.91	0.91
ψ_0^ϑ	-0.145	-0.145	-0.145
ψ_1^ϑ	0.968	0.968	0.968
ψ_2^ϑ	0.1503	0.1503	0.1503
ψ^x	0.40	0.40	0.40
ψ^Ω	–	–	0.79
σ_θ	0.0133	0.013	0.0123
σ_ϑ	0.2135	0.1820	0.13
σ_x	0.21	0.21	0.20
σ_Ω	–	–	0.045
$Corr \{ \varepsilon^\theta, \ln(\varepsilon^\vartheta) \}$	0.81	0.81	0.81
$Corr \{ \varepsilon^\theta, \varepsilon^x \}$	0.45	0.45	0.75
$Corr \{ \varepsilon^x, \ln(\varepsilon^\vartheta) \}$	0.70	0.70	0.70
$Corr \{ \varepsilon^\Omega, \ln(\varepsilon^\vartheta) \}$	–	–	0.55

Table 2: Standard Deviations

	2-50				2-8				8-50			
	Data	MI	MII	MIII	Data	MI	MII	MIII	Data	MI	MII	MIII
<i>YN</i>	3.41 (2.77, 4.06)	3.01	3.02	2.78	1.68 (1.30, 2.07)	1.12	1.13	1.03	2.96 (2.21, 3.71)	2.79	2.80	2.58
<i>C</i>	1.88 (1.44, 2.31)	2.29	2.21	1.64	0.74 (0.59, 0.88)	0.76	0.57	0.38	1.73 (1.28, 2.19)	2.16	2.13	1.60
<i>I</i>	9.71 (7.76, 11.66)	11.27	9.57	11.65	4.29 (3.55, 5.03)	4.87	5.28	5.48	8.71 (6.86, 10.56)	10.15	7.98	10.27
<i>SR</i>	2.48 (2.04, 2.93)	2.57	2.74	2.51	1.06 (0.73, 1.40)	1.16	1.17	1.08	2.21 (1.88, 2.53)	2.30	2.48	2.27
<i>PT</i>	7.50 (6.04, 8.97)	8.00	8.61	8.83	2.80 (1.98, 3.63)	3.07	3.24	3.18	6.96 (5.49, 8.44)	7.39	7.98	8.24
<i>MVC</i>	23.96 (19.34, 28.58)	16.61	19.37	18.98	9.81 (6.93, 12.70)	6.41	8.56	8.08	21.78 (17.80, 25.76)	15.32	17.38	17.16
<i>RC</i>	14.80 (10.19, 19.41)	9.92	13.03	12.18	13.23 (9.36, 17.09)	8.71	11.75	10.83	6.45 (4.86, 8.05)	4.73	5.64	5.56
<i>D</i>	8.08 (5.96, 10.21)	10.59	9.32	12.21	4.34 (3.45, 5.23)	4.15	3.41	6.31	6.68 (5.10, 8.26)	9.74	8.67	10.45
<i>PD</i>	23.17 (17.85, 28.48)	8.13	13.53	24.00	9.32 (7.62, 11.03)	3.19	7.07	12.38	21.12 (16.59, 25.64)	7.48	11.53	20.56
<i>R</i>	2.48 (1.69, 3.26)	0.78	2.16	2.56	1.32 (0.94, 1.69)	0.30	1.49	1.39	2.06 (1.44, 2.68)	0.73	1.56	2.15

Note: Both data and model's simulations have been filtered for various frequency bands: 2-50 years, 2-8 years, and 8-50 years. *YN*: corporate value added; *C*: consumption; *I*: investment; *SR*: Solow residual; *MVC*: market value of corporations; *RC*: return of *MVC*; *D*: dividends; *PD*: price-dividend ratio; and *R*: risk-free interest rate. MI refers to Model I; MII refers to Model II; and MIII refers to Model III. 95-percent confidence intervals appear beneath sample statistics.

Table 3: Autocorrelations

	2-50				2-8				8-50			
	Data	MI	MII	MIII	Data	MI	MII	MIII	Data	MI	MII	MIII
<i>YN</i>	0.71 (0.54, 0.87)	0.83	0.83	0.83	0.18 (0.03, 0.32)	0.05	0.07	0.01	0.86 (0.75, 0.97)	0.95	0.95	0.96
<i>C</i>	0.80 (0.65, 0.95)	0.86	0.91	0.92	0.25 (0.11, 0.39)	0.07	0.24	0.26	0.89 (0.79, 0.99)	0.96	0.96	0.96
<i>I</i>	0.77 (0.63, 0.92)	0.78	0.64	0.73	0.25 (0.10, 0.40)	0.06	-0.02	-0.03	0.90 (0.78, 1)	0.94	0.93	0.95
<i>SR</i>	0.80 (0.68, 0.91)	0.76	0.78	0.77	0.18 (-0.01, 0.37)	0.04	0.05	0.00	0.92 (0.84, 1)	0.94	0.94	0.95
<i>PT</i>	0.85 (0.71, 0.99)	0.83	0.84	0.85	0.03 (-0.19, 0.26)	0.24	0.26	0.29	0.97 (0.86, 1)	0.94	0.94	0.94
<i>MVC</i>	0.79 (0.63, 0.95)	0.82	0.77	0.78	0.00 (-0.13, 0.13)	0.06	0.02	0.06	0.95 (0.86, 1)	0.95	0.95	0.95
<i>RC</i>	0.01 (-0.24, 0.25)	-0.02	-0.09	-0.04	-0.21 (-0.39, -0.04)	-0.28	-0.31	-0.29	0.89 (0.75, 1)	0.87	0.87	0.87
<i>D</i>	0.66 (0.48, 0.85)	0.82	0.84	0.68	0.09 (-0.05, 0.24)	0.04	0.08	0.00	0.90 (0.76, 1)	0.96	0.96	0.94
<i>PD</i>	0.78 (0.60, 0.95)	0.81	0.68	0.69	-0.03 (-0.17, 0.10)	0.07	-0.01	0.03	0.94 (0.82, 1)	0.95	0.94	0.93
<i>R</i>	0.67 (0.54, 0.80)	0.82	0.44	0.67	0.10 (-0.18, 0.39)	0.01	-0.07	0.04	0.91 (0.77, 1)	0.96	0.91	0.93

Note: Both data and model's simulations have been filtered for various frequency bands: 2-50 years, 2-8 years, and 8-50 years. *YN*: corporate value added; *C*: consumption; *I*: investment; *SR*: Solow residual; *MVC*: market value of corporations; *RC*: return of *MVC*; *D*: dividends; *PD*: price-dividend ratio; and *R*: risk-free interest rate. MI refers to Model I; MII refers to Model II; and MIII refers to Model III. 95-percent confidence intervals appear beneath sample statistics.

Table 4: Correlations with YN

	2-50				2-8				8-50			
	Data	MI	MII	MIII	Data	MI	MII	MIII	Data	MI	MII	MIII
C	0.72 (0.46, 0.98)	0.96	0.96	0.81	0.81 (0.68, 0.93)	0.95	0.90	0.66	0.71 (0.39, 1)	0.96	0.97	0.84
I	0.75 (0.55, 0.95)	0.82	0.89	0.85	0.78 (0.64, 0.92)	0.85	0.94	0.93	0.75 (0.56, 0.95)	0.82	0.90	0.84
SR	0.52 (0.20, 0.85)	0.94	0.97	0.92	0.70 (0.49, 0.90)	1.00	1.00	1.00	0.46 (0.10, 0.82)	0.94	0.96	0.91
PT	0.17 (-0.07, 0.42)	0.28	0.38	0.53	0.06 (-0.21, 0.35)	0.32	0.34	0.36	0.21 (-0.07, 0.49)	0.27	0.39	0.56
MVC	0.17 (-0.25, 0.60)	0.59	0.82	0.58	0.03 (-0.24, 0.30)	0.57	0.83	0.42	0.20 (-0.25, 0.67)	0.59	0.83	0.61
RC	-0.26 (-0.50, -0.03)	0.29	0.19	0.11	-0.46 (-0.72, -0.21)	0.42	0.50	0.25	-0.19 (-0.48, 0.09)	0.35	0.05	0.05
D	0.02 (-0.29, 0.34)	0.34	0.50	0.16	0.09 (-0.12, 0.30)	0.33	0.23	0.00	-0.02 (-0.38, 0.33)	0.34	0.54	0.20
PD	0.17 (-0.30, 0.64)	0.70	0.56	0.29	-0.01 (-0.29, 0.27)	0.12	-0.14	-0.05	0.22 (-0.27, 0.71)	0.80	0.74	0.37
R	-0.09 (-0.35, 0.16)	-0.52	-0.74	-0.10	-0.11 (-0.47, 0.23)	-0.33	-0.83	-0.07	-0.08 (-0.33, 0.16)	-0.55	-0.79	-0.11

Note: Both data and model's simulations have been filtered for various frequency bands: 2-50 years, 2-8 years, and 8-50 years. YN : corporate value added; C : consumption; I : investment; SR : Solow residual; MVC : market value of corporations; RC : return of MVC ; D : dividends; PD : price-dividend ratio; and R : risk-free interest rate. MI refers to Model I; MII refers to Model II; and MIII refers to Model III. 95-percent confidence intervals appear beneath sample statistics.

Table 5: Correlations with PD

	2-50				2-8				8-50			
	Data	MI	MII	MIII	Data	MI	MII	MIII	Data	MI	MII	MIII
YN	0.17 (-0.30, 0.64)	0.70	0.56	0.29	-0.01 (-0.29, 0.27)	0.12	-0.14	-0.05	0.22 (-0.27, 0.71)	0.80	0.74	0.37
C	-0.03 (-0.42, 0.35)	0.77	0.47	0.39	0.13 (-0.11, 0.38)	0.10	-0.33	-0.21	-0.06 (-0.47, 0.35)	0.87	0.62	0.50
I	0.06 (-0.36, 0.49)	0.39	0.58	0.09	-0.01 (-0.34, 0.33)	0.15	0.02	0.04	0.07 (-0.39, 0.53)	0.44	0.81	0.10
SR	0.04 (-0.39, 0.47)	0.63	0.59	0.26	0.25 (-0.02, 0.53)	0.13	-0.09	-0.04	0.01 (-0.53, 0.54)	0.74	0.79	0.35
PT	0.39 (0.02, 0.76)	0.34	0.29	0.30	0.03 (-0.25, 0.30)	-0.07	-0.12	-0.26	0.45 (0.02, 0.88)	0.42	0.40	0.44
MVC	0.94 (0.79, 1.00)	0.66	0.60	0.60	0.89 (0.72, 1.00)	0.04	-0.07	-0.01	0.95 (0.79, 1.00)	0.77	0.80	0.78
RC	0.17 (-0.09, 0.43)	0.28	0.28	0.28	0.60 (0.36, 0.83)	0.26	0.21	0.25	-0.11 (-0.51, 0.28)	0.44	0.48	0.41
D	-0.07 (-0.44, 0.29)	0.41	0.26	-0.42	-0.11 (-0.62, 0.39)	0.01	-0.15	-0.07	-0.05 (-0.52, 0.41)	0.49	0.36	-0.55
R	0.03 (-0.37, 0.44)	-0.61	-0.56	-0.61	-0.35 (-0.68, -0.02)	-0.03	-0.05	-0.05	0.12 (-0.38, 0.63)	-0.71	-0.88	-0.83

Note: Both data and model's simulations have been filtered for various frequency bands: 2-50 years, 2-8 years, and 8-50 years. YN : corporate value added; C : consumption; I : investment; SR : Solow residual; MVC : market value of corporations; RC : return of MVC ; D : dividends; R : risk-free interest rate; and PD : price-dividend ratio. MI refers to Model I; MII refers to Model II; and MIII refers to Model III. 95-percent confidence intervals appear beneath sample statistics.

Table 6: Variance Decomposition of PD

Time Horizon	$CVAR_{N,r}$		$CVAR_{N,d}$		$CVAR_{N,pd}$		Total	
	Data	Model	Data	Model	Data	Model	Data	Model
$N = 1$	19.37 (7.78, 30.95)	6.72	-1.37 (-8.42, 5.68)	4.33	81.22 (67.5, 94.94)	88.49	99.22	99.55
$N = 5$	58.70 (43.70, 73.69)	26.18	6.81 (-8.18, 21.80)	10.87	31.94 (18.90, 44.97)	60.85	97.45	97.91
$N = 10$	95.13 (62.28, 127.97)	41.11	-10.17 (-22.71, 2.37)	12.31	10.15 (-11.25, 31.55)	42.81	95.10	96.24
$N = 20$	128.58 (108.94, 148.21)	59.76	-16.41 (-34.52, 1.70)	12.42	-11.19 (-16.97, 5.40)	21.99	100.98	94.18
$N = 30$	118.27 (98.18, 138.36)	69.28	-16.86 (-35.83, 2.11)	12.42	0.59 (-1.37, 2.55)	11.53	101.99	93.24
$N = 100$		80.32		12.30		0.08		92.71

Note: Variance decomposition for different horizons N . 95-percent confidence intervals appear beneath sample statistics.