Asset Price Volatility, Price Markups, and Macroeconomic Fluctuations[☆]

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Abstract

A variant of the neoclassical growth model is considered to study the role of innovation, lags in technology adoption, total factor productivity *TFP*, and price markups as main determinants of asset price volatility. The model confers a prominent role to price markups as opposed to other macroeconomic sources of uncertainty. In the data, price markups are highly correlated with stock market values, whereas other financial measures of profitability exhibit much less volatility and are weakly correlated with stock market values.

Keywords: Technological innovations, price markups, stock market volatility, price-dividend ratio, taxes.

1. Introduction

A burgeoning literature in the frontier between economics and finance has emerged to study asset price volatility, but there is no general consensus on the driving forces of stock markets which remain a puzzle to economists. A variant of the neoclassical growth model is here proposed to analyze technology innovation, *TFP* shocks, and price markups as main determinants of stock market volatility. Conceptually, the aggregate asset value in our model should be identified as the market value of corporations (MVC): the sum of the market values of corporate equity and net debt. The joint consideration of these two components avoids the introduction of arbitrary policies for corporate debt and dividends.[1] Payouts to debt holders have been fairly erratic in recent decades (e.g., Hall, 2001). The volatility of MVC is mainly driven by stock values: the volatility of MVC is about 6 percent below that of equity. (In our data the volatility of equity is about 26.40 percent and the volatility of MVC is about 24.93 percent.) The volatility of MVC will be related to various macroeconomic aggregates as well as to the stock market return and the price-dividend ratio.

Our analysis focuses on medium and long-term volatility. That is, fluctuations of economic aggregates over a frequency band of 2 to 50 years. This volatility should be easier to study as it is isolated from noisy information. Still, the economics literature has struggled to come to terms with pronounced fluctuations in stock market values – commonly known as the *excess volatility puzzle.*

First, the observed volatility of stock market values and price-dividend ratios is about ten times greater than that of output and consumption, and about three times greater than that of real investment (e.g., see Gomme, Ravikumar and Rupert, 2011). Dynamic equilibrium models have failed to account for the volatility of stock values based on macroeconomic uncertainty – even after allowing for agent heterogeneity and market frictions. Second, asset market volatility is also disconnected from the real economy (Alburquerque *et al.*, 2016; Greenwald, Lettau and Ludvigson, 2014), and financial measures of profitability are weakly correlated with stock values. This poses a challenge for traditional consumption-based asset-pricing theories. And third, stock market returns are much more volatile than short-term interest rates. Most of the volatility of

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[1]Akin measures for the market value of US corporations were considered by Hall (2001), McGrattan and Prescott (2005), Peralta-Alva (2009), and Wright (2004).

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stock market returns stems from unexpected changes in future excess returns (Campbell and Ammer, 1993). Several models can generate reasonable equity premia, but are unable to account for plausible levels of asset price volatility. Our research should then complement theories of the equity premium.

Our model is a simplified variant of those in Romer (1990) and Comin and Gertler (2006). Technological innovations arrive exogenously to the economy and undergo a process of adoption embedded in the production of new varieties of intermediate goods. Changes in price markups arise exogenously, which may be due to fluctuations in economic conditions and variations in the elasticity of substitution or monopoly power after the creation of new goods. Episodes of technology innovation and shocks to productivity and price markups may produce persistent fluctuations in the aggregate value of stocks and $R\&D$ expenditure. Similar propagation mechanisms are considered in Gârleanu, Panageas and Yu (2012), who include "large" infrequent technological innovations embodied into new capital vintages. In contrast to these authors, we carry out a general equilibrium analysis of the volatility of financial variables along with other macroeconomic aggregates.

In our numerical experiments most of the volatility of financial variables comes from price markups, whereas technology innovation, lags in the adoption of new technologies, and TFP shocks may only have a significative impact at the expense of implausible fluctuations in the real economy. Our model generates about two-thirds of the observed volatility in the financial variables. Movements in the stock market value and the price-dividend ratio remain fairly isolated from changes in output, consumption, and investment.

Several recent contributions consider *long-run productivity risks* (e.g., Croce, 2014; Kaltenbrunner and Lochstoer, 2010; Kung and Schmid, 2015) and *time-varying financial risks* (e.g., Alburquerque *et al.*, 2016; Gourio, 2012). While all these papers get sizable equity premia and term premia they consistently fail to capture the long-term volatility of stock prices. Markups and technology innovation are of interest to account for the cross-section distribution of returns and the *value premium* (e.g., Gomes, Kogan and Zhang, 2003; Kogan and Papanikolaou, 2014).

The paper will proceed as follows. Section 2 documents that markups are positively correlated with stock market prices, and display great variation across company cohorts and over time. Section 3 lays down our two-sector model with technology adoption. Section 4 tests the performance of the model on the volatility of financial variables along with other macroeconomic aggregates. The various sources of volatility of the price-dividend ratio are presented in Section 5. We conclude in Section 6.

2. Stock Market Volatility and Markups

As already pointed out, to assess financial asset volatility our analytical framework relies on the market value of corporations (MVC). This is a consolidated measure of the market values of equity and net debt liabilities. Two data sources are considered. First, in this section all data are taken from US companies in Compustat North America over the 1950-2012 period. This will allow us to compare the volatility and correlation of MVC with various profitability measures at the micro level (i.e., across companies). Second, following Hall (2001) and McGrattan and Prescott (2005) we use the Financial Accounts of the US over the 1948-2007 period as our primary source to map our model to the data. This latter database incorporates both publicly and privately held corporations, which may pick up potential impacts of recently founded companies. Thus, companies are included since their foundation dates, e.g., Google was founded in 1998 and went public in 2004. Hence, Google is included in our database since 1998. In both data sets, the volatility of MVC is roughly ten times greater than that of output and consumption, and MVC is hardly correlated with output and consumption. Moreover, MVC is also uncorrelated with our measures of dividends, stock market returns, and interest rates, but it is fairly correlated with the price-dividend ratio.

Figure 1 decomposes MVC for different company cohorts in the recent IT revolution. Market capitalization relative to aggregate corporate value added is broken down into the following groups of companies: (i) Firms listed before 1970, (ii) Firms listed in 1970-1979, (iii) Firms listed in 1980-1989, and (iv) Firms listed since 1990. As one can see, most added value belongs to new corporations. Next, the financial performance of these cohorts will be assessed over various measures of profitability.

The finance literature has introduced several cash-flow and profitability measures to study stock-return predictability. The most common ones are dividends $D1$ and net income NI. As shown in Barsky and DeLong

(1993), both measures are reasonably correlated with stock market values at low frequencies. Although Fama and French (2006) find that *NI* has some predictive power for cross-section company returns, Novy-Marx (2013) argues that gross profitability *GP* seems more appealing. *GP* and earnings before extraordinary items *IB* are usually called clean accounting measures. Some popular profitability measures like *EBITDA*, *EBIT*, and operating income before and after depreciation, *OIBDP* and *OIADP*, may also be of some interest. All these financial measures are detailed in the Appendix.

Table 1 offers a broad evaluation of firms' financial performance. For each company cohort, this table is intended to compare the relative weight of *MVC* against commonly used financial measures by considering averages over three different time intervals: 1990-1994, 1995-1999, and 2000-2004. The price markup of a company is defined as the ratio between total revenue and total variable cost, i.e., entries *REVT* and *COGS* in the Compustat data set. The aggregate price markup is then obtained as a weighted average of company markups where the weights are the shares of company revenues. To obtain markup estimates, companies are ranked by *R&D* intensity at every given date. *MU50* refers to the average markup of the top 50% companies with the highest ratio of *R&D* expenditure over total revenue, *MU75* refers to the average markup of the top 75% companies with the highest ratio of *R&D* expenditure over total revenue, *MU100* refers to the average markup of all the companies reporting *R&D* activity, and *MU* refers to the average company markup in our sample.[2] Markups are reported as percentages of the average markup in the corresponding date. Hence, a value above 100 means that this cohort can secure a higher markup than the sample average. For every other measure, the table reports the percentage or relative value belonging to this cohort. For instance, on the first column under the dividends *D1* entry of the table one can read that the value is 69.88. This means that the companies originating before 1970 were able to secure 69.88 percent of the total sum of dividends in the sample of companies over the 1990-1994 period, whereas they only represent 66.70 percent of total *MVC*. The youngest cohorts command the highest markups, but appear to be indistinguishable in terms of every other profitability measure.

This lack of correlation at the cross-section level is also validated in a further time series analysis for our sample of companies over the 1960-2012 period.[3] Table 2 reports correlation coefficients between log differences of *MVC* and log differences of every aforementioned variable over various time frequencies. This table incorporates a new measure of aggregate income for shareholders and bondholders, *D2*, which is computed by taking investment, wages, and taxes out of aggregate corporate value added and so it is inclusive of interest payments to debt holders. Similar measures have been considered by various authors (cf. Boldrin and Peralta-Alva, 2009; Larrain and Yogo, 2008; McGrattan and Prescott, 2005). Growth rates for *MVC* and the financial accounting measures (excluding markups) are adjusted by the growth of aggregate corporate value added. While markups may display correlation coefficients of about 0.80 over the range of five- to thirty-year frequencies, financial accounting measures such as *D1* display correlation coefficients of about 0.10. Most correlation coefficients of the profitability measures are not statistically significant at conventional confidence levels, and their volatilities are rather small; see last column of Table 2.

Similar calculations with sectoral data are performed to check for the robustness of these findings. Sectors are defined following Fama and French's five-industry classification codes (Cnsmr, Manuf, HiTec, Hlth, and Other) from Kenneth French's web page. Two further categories for high-tech companies are identified: (*i*) Companies whose stocks are currently traded in the *NASDAQ* stock exchange, and (*ii*) Companies with *SIC* codes 281, 283, 284, 289, 357, 367, 381, and 384. Nearly all correlation coefficients between the log differences of *MVC* and the log differences of *MU50*, *MU75*, and *MU100* over five- and ten-year time intervals are statistically significant. Correlations over the ten-year frequency are slightly stronger with coefficients ranging between 0.60 and 0.80. Therefore, the robust correlation between changes in *MVC* and markup measures extends to sectoral data.

[2] Companies performing *R&D* activities in our sample represent about 39% of total market capitalization. The group of companies in *MU50* represents about 18% of total market capitalization, and the group of companies in *MU75* represents about 25% of total market capitalization. Several other methods have been proposed to measure markups (cf. Nekarda and Ramey, 2013).

[3] Because of our limited sample of companies in the Compustat data set at early dates, the 1950-1960 period is taken out of the sample.

The average price markup of the economy *MU* does not mimic so well the evolution of *MVC*. Our markup measure *MU50* usually displays the highest correlations with stock market values. It may be possible to construct some other related profitability measures over selected company groups that are highly correlated with stock market values.[4] But price markups can be microfounded and have become a basic ingredient of New Keynesian models. Markups may arise from optimal pricing rules and price rigidities, and can be related to changes in elasticities because of income and substitution effects, economic policies, and technology adoption.

3. A Simple Model of Technology Adoption

The economy is populated by a continuum of identical households. The aggregate consumption good is produced by a single firm under a constant-returns-to-scale technology. Three inputs are involved in final production: capital accumulated by the firm, labor, and a composite intermediate good of technological products. Both firm and consumers act competitively in all markets, but the sector of intermediate goods is composed of monopolistic producers. The range of available intermediate goods can be expanded by a fixed set of local adopters upon the arrival of new technologies.

3.1. The household

At each date $t = 0, 1, ...$, the representative household supplies one unit of labor inelastically. Preferences are represented by the following Epstein-Zin recursive formulation:

$$\mathcal{U}_t = \left[(1-\beta) c_t^{1-\sigma} + \beta \mathbb{E}_t \left\{ \mathcal{U}_{t+1}^{1-\chi} \right\}^{\frac{1-\sigma}{1-\chi}} \right]^{\frac{1}{1-\sigma}} \tag{1}$$

where $\mathbb{E}_t$ is the expectations operator at t, $0 < \beta < 1$ is the subjective discount factor, $0 < \sigma \neq 1$ is the inverse of the elasticity of intertemporal substitution, and $\chi > 0$ is the coefficient of relative risk aversion.

The agent may participate in financial markets by trading shares a_t of an aggregate stock. Let q_t be the price of a unit share, and d_t denote the stochastic dividend. For given stock prices q_t, exogenous wages ω_t, lump-sum transfers T_t, and initial asset holdings a_0, the optimization problem is to choose a stochastic sequence $\{c_t, a_{t+1}\}_{t\geq 0}$ to attain the maximum utility in (1) subject to the sequence of budget constraints:

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

where $c_t \geq 0$ and $q_t a_{t+1} \geq 0$, for all $t \geq 0$.

3.2. The production sector

The firm producing the final good accumulates capital and buys labor and intermediate goods. Final production Y_t is determined by a *CES* function subject to a *TFP* shock represented by a random variable A_t. At every date t there is a mass Ω_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* function $M_t = [\int_0^{\Omega_t} m_{s,t}^{\frac{1}{\vartheta_t}} ds]^{\vartheta_t}$ where $m_{s,t}$ denotes the amount of intermediate good s bought by the firm at time t, and $\vartheta_t > 1$. Given initial condition k_0, the firm chooses stochastic sequences of investment, labor, and intermediate goods $\left\{i_t, l_t, (m_{s,t})_{s\in[0,\Omega_t]}\right\}_{t\geq 0}$ so as to maximize the present value of dividends

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \eta_t d_t^f \right] \tag{3}$$

[4] On related research, Gabaix (2011) argues that investment decisions of the top capital spenders have a big impact on aggregate fluctuations. Capital expenditures of the top 100 firms make up for over 60% of the aggregate investment of the publicly traded firms (Grullon, Hund, and Weston, 2013). Using information on US public firm patenting, Bena and Garlappi (2013) document that in a given year about 303 firms are actively innovating, and these innovating firms account for about 40% of total market capitalization.

subject to

$$d_t^f \equiv (1-\tau^s)Y_t - \left(i_t + \omega_t l_t + \int_0^{\Omega_t} p_{s,t} m_{s,t} ds\right) - \tau^c AE_t - T_t^{LS} \tag{4}$$

$$Y_t \equiv A_t \left[\gamma \left(k_t^{\alpha} l_t^{1-\alpha}\right)^{\rho} + (1-\gamma) M_t^{\rho}\right]^{\frac{1}{\rho}}, 0 < \alpha, \gamma < 1,\ \rho < 1 \tag{5}$$

$$AE_t \equiv (1-\tau^s)Y_t - \left(\omega_t l_t + \int_0^{\Omega_t} p_{s,t} m_{s,t} ds + \delta_a k_t + T^{ded}\right) \tag{6}$$

$$k_{t+1} = (1-\delta)\, k_t + g(i_t/k_t) k_t. \tag{7}$$

Here, η_t is a state price converting income of period t to period 0, and $p_{s,t}$ is the price of intermediate good s at time t. Dividends in (4) include a sales tax τ^s, a corporate tax τ^c over accounting earnings AE_t, and a lump-sum tax $T_t^{LS} \equiv \tau^{ls} YN_t$ defined as a constant fraction of aggregate value added YN_t. Taxable accounting earnings allow for capital depreciation $\delta_a k_t$ and additional tax deductions defined as a constant fraction of the steady-state aggregate value added: $T^{ded} \equiv \tau^{ded} YN$. Taxes are rebated back to the representative household as a lump-sum payment, T_t. The capital stock k_t depreciates at a constant rate $0 \leq \delta < 1$. Physical investment i is subject to adjustment costs (Jermann, 1998):

$$g(i/k) = \frac{\delta^{\frac{1}{\varsigma}}}{1-\frac{1}{\varsigma}} (\frac{i}{k})^{1-\frac{1}{\varsigma}} + \frac{\delta}{1-\varsigma} \tag{8}$$

where $\varsigma > 0$ is the elasticity of the ratio i/k over Tobin's q.

Forcing variables A_t and ϑ_t are governed by stochastic processes:

$$\begin{aligned} ln(A_t) &= \psi^A ln(A_{t-1}) + \sigma_A \varepsilon_t^A && (9) \\ ln(\vartheta_t) &= \psi_0^{\vartheta} + \psi_1^{\vartheta} ln(\vartheta_{t-1}) + \varepsilon_{t-1}^{\vartheta} && (10) \end{aligned}$$

where $\psi^A, \psi_1^{\vartheta} \in (0,1)$, $\sigma_A > 0$, $\varepsilon_t^A \overset{iid}{\sim} N(0,1)$, and $ln(\varepsilon_t^{\vartheta}) \overset{iid}{\sim} N(\mu_{\vartheta}, \sigma_{\vartheta})$.

Monopolistic competition prevails in the technology sector for intermediate goods. Each variety s is supplied by a single producer under a linear cost function $c(m) = m$. Producer of variety s picks an optimal pricing strategy $p_{s,t}$ based on quantity $m_{s,t}$ 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 after-tax profits:

$$\pi_{s,t} \equiv \max_{m_{s,t} \geq 0} \left\{(1-\tau^c)\left(p_{s,t} m_{s,t} - m_{s,t}\right)\right\} \tag{11}$$

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

$$p_{s,t} = \left(\frac{m_{s,t}}{M_t}\right)^{\frac{1-\vartheta_t}{\vartheta_t}} p_t \tag{12}$$

of the aggregate firm, and $p_t = \left(\int\limits_0^{\Omega_t} p_{s,t}^{\frac{1}{1-\vartheta_t}} ds\right)^{1-\vartheta_t}$.

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:

$$V_{s,t} = \mathbb{E}_t \left[\sum_{r=t}^{\infty} \frac{\eta_r}{\eta_t} \phi^{r-t} \pi_{s,r}\right]. \tag{13}$$

3.3. Technology adoption

The average stock of technological innovations Z_t evolves according to the law of motion

$$Z_t = \phi Z_{t-1} + \mu x_{t-1} \tag{14}$$

with normalizing constant $\mu > 0$ and

$$lnx_t = \psi^x lnx_{t-1} + \sigma_x \varepsilon_t^x \tag{15}$$

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

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 monopolistic producer of intermediate goods. Let Ω_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. The stock Ω_{t+1}^i follows the law of motion:

$$\Omega_{t+1}^i = \lambda(H_t^i)\phi \left[Z_t^i - \Omega_t^i\right] + \phi\Omega_t^i. \tag{16}$$

The optimal 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:

$$J_t^i = \max_{H_t^i} \left\{ -H_t^i + \phi \mathbb{E}_t \left[\frac{\eta_{t+1}}{\eta_t} \left(\lambda(H_t^i) V_{t+1} + \left(1 - \lambda(H_t^i)\right) J_{t+1}^i \right) \right] \right\}. \tag{17}$$

Observe that the optimal amount of expenditure H_t^i is the same for all i. Without loss of generality, we assume $Z_t^i = Z_t$ for all i, and consider the aggregate stock of adopted technologies $\Omega_{t+1} = \int \Omega_{t+1}^i di$.

3.4. Equilibrium and asset prices

For the final good, market clearing holds if

$$YN_t \equiv Y_t - \Omega_t m_t = c_t + i_t + H_t(Z_t - \Omega_t) \tag{18}$$

where YN_t denotes aggregate value added, $\Omega_t m_t$ is the cost of producing the composite intermediate good, and m_t is the amount produced of each variety.

The next proposition is central to our study. Let us define the aggregate dividend $d_t \equiv d_t^f + \pi_t \Omega_t - H_t(Z_t - \Omega_t)$. Assume that the aggregate supply of the asset $a_t = 1$ for all $t \geq 0$. Then, from the first-order conditions of the representative household, one can obtain the following decomposition of stock market values:

Proposition 3.1 *The stock market value:*

$$q_t = p_t^k k_{t+1} - PVT_t + V_t^+ \Omega_t + J_t^+ (Z_t - \Omega_t) + \xi_t \tag{19}$$

where $p_t^k \equiv \frac{1}{g'(\frac{i_t}{k_t})}$, $PVT_t \equiv \mathbb{E}_t \left[\sum_{r=t+1}^{\infty} \frac{\eta_r}{\eta_t} \left(T_t^{LS} - \tau^c T^{ded} \right) \right]$, $V_t^+ \equiv V_t - \pi_t, J_t^+ \equiv J_t + H_t,$ *and* $\xi_t \equiv \mathbb{E}_t \left[\sum_{r=t+1}^{\infty} \frac{\eta_r}{\eta_t} J_r \left(Z_r - \phi Z_{r-1} \right) \right]$.

Therefore, the stock market incorporates the value of installed capital $p_t^k k_{t+1}$, the present value of lump-sum taxes PVT_t, the value of adopted technologies $V_t^+ \Omega_t$, the option value of inventions currently available but not yet adopted $J_t^+ (Z_t - \Omega_t)$, and the present value of future inventions expected to happen ξ_t. These latter components are further sources of asset price volatility.

From numerical experimentation, in all calibrations below the model appears to have a unique ergodic invariant distribution. It seems then adequate to simulate the model using a high-order perturbation method

(Schmitt-Grohé and Uribe, 2004) that takes into account the high volatility of stock market values. To check accuracy for the computed solution, this approximation method is combined with a numerical dynamic programming algorithm (Santos, 1999) for the computation of Bellman's equation (17).

4. Numerical Experiments

This section presents an easy-to-follow calibration with uncorrelated shocks as well as an extensive sensitivity analysis towards understanding the role of lags in technology adoption and stochastic markups. A good part of the variation of financial variables can be ascribed to fluctuations in exogenous markups, and hence the calibration of the law of motion (10) is most critical. Our tax structure is intended to match some first- and second-order moments observed in the data. Without taxes, the share of dividends in output will be too high. As before, definitions and data sources are gathered together in the Appendix. As in *D2* above, dividends are defined from corporate value added after taking out investment, wages, and corporate taxes. All values refer to annual data from 1948 to 2007.

4.1. Baseline calibration

The second column of Table 3 lists parameter values for our baseline calibration *BL*. Parameters σ and χ are set to 5, corresponding to the *CRRA* utility function, which falls within the range of empirical estimates for many studies. Parameter $\beta = 0.95$, leading to an annual interest rate of 5.26%.

Parameter α is set to 0.2, which implies a labor income share in aggregate value added equal to 0.63 in the deterministic steady state. From data in the manufacturing sector, the share of materials in final production is generally assumed to be around 0.50 (e.g., Comin and Gertler, 2006; Jaimovich and Floetotto, 2008). Letting $\gamma = 0.65$, this share becomes equal to 0.54 in the deterministic steady state. Our model matches the average investment to capital ratio in the data under an annual depreciation rate $\delta = 0.09$.

For the process of technology adoption, our calibration reproduces the volatility and persistence of the expenditure process $H(Z-\Omega)$ rather than the increment in the stock of adopted technologies (i.e., $\Omega_{t+1}-\phi\Omega_t$) which is harder to measure. Barlevy (2007) shows a high degree of correlation between *R&D* spending from the *NSF* and Compustat data. We use the *NSF* data. Following Hall (2007), the survival rate of each intermediate product ϕ is set to 0.98. The probability of adoption is determined by a simple function

$$\lambda(H_t) = \Lambda_0 + \Lambda_1 H_t^{\kappa} \tag{20}$$

with $\Lambda_0, \Lambda_1 > 0$ and $\kappa \in (0,1)$. Parameter $\Lambda_0 > 0$ is fixed so that the steady-state value for probability $\lambda(H)$ is equal to 0.166, i.e., an average adoption time of six years. Thus, our calibration imposes much less persistence than other studies such as Comin and Gertler (2006) in which this mean value equals 0.10. Parameters κ and Λ_1 along with the law of motion in (15) are adjusted to approximate the volatility and autocorrelation of *R&D* expenditure in the data. The simulated mean value for the ratio of adoption expenditures over net output is about 1.53 percent, which accords with the data. Indeed, the expenditure share of total *R&D* over corporate output for the period 1960-2007 is 2.14 percent, and the expenditure share of development is 1.56 percent.

Krusell *et al*. (2000) provide estimates for the elasticity of substitution between capital and skilled labor; our reported value $\rho = -0.6$ falls within their plausible range of estimates. The Cobb-Douglas specification would yield comparable levels of volatility for the financial variables. The volatilities of these financial variables also remain quite insensitive to changes in the elasticity parameter ς in the adjustment cost function (8). The *TFP* process (9) is adjusted to match the observed volatilities of output and investment.

The markup process (10) is estimated from Compustat data from six subsamples corresponding to all (100%) companies reporting *R&D* activities and the top 50%, 60%, 70%, 80%, 90% companies with the highest ratio of *R&D* expenditure over total revenue. After taking logs and detrending, the estimated persistence parameter $\widehat{\psi_1^{\vartheta}}$ in (10) lies within the range of values $[0.9434, 0.9827]$, and the estimated volatility parameter $\widehat{\sigma}_{\vartheta}$ lies within the range of values $[0.1413, 0.3862]$. These estimates roughly remain the same when considering the group of high-tech companies with *SIC* codes: 281, 283, 284, 289, 357, 367, 381, and

384. In light of all this evidence, let us fix $\psi_1^{\vartheta} = 0.968$, and $\sigma_{\vartheta} = 0.15$. These values[5] are also consistent with parameterizations of New Keynesian models with price rigidities. Smets and Wouters (2007, Table 4, p. 597) report an autocorrelation parameter $\psi_1^{\vartheta} = 0.90$, but this parameter jumps to $\psi_1^{\vartheta} = 0.97$ when the degree of price stickiness is moved to a minimal value.

The corporate income tax rate τ^c is set to 0.40. The final production tax rate τ^s is set to 0.035 to match the ratio of indirect taxes to value added in the corporate sector. The lump-sum tax rate τ^{ls} is set to 0.13, and the fraction for deductions $\tau^{ded} = 0.1625$. The depreciation allowance is set to $\delta_a = 0.1$. This tax structure approximates our *BL* model to the data in several dimensions: (*i*) a steady-state value of dividends over value added equal to 8 percent, (*ii*) a ratio of total taxes to (after-tax) dividends equal to 2.8, (*iii*) a volatility of taxes equal to 4.30 percent, and (*iv*) a correlation coefficient of taxes with corporate value added equal to 0.69.

4.2. Impulse-response functions

Figures 2 and 3 display impulse-response functions for the *TFP* index A, and the price markup ϑ for our baseline calibration *BL*. Changes in the stock of available technologies Z will be discussed later.

An increment of one standard deviation over the deterministic steady-state value of A has a more persistent effect on *MVC* than in the neoclassical growth model because of the extra investment in technology adoption *H*. An increase in *TFP* stimulates consumption C and investment *I*, and dividends D go down. The interest rate R goes down to accommodate convergence back to the steady state. The demand for intermediate goods is increased and profits per variety π go up. Higher profits along with lower interest rates lead to increases in all components of *MVC* in Proposition 3.1 (i.e., V, J, ξ). An increment of one standard deviation over the deterministic steady-state value of ϑ boosts *MVC* and D considerably, I and C go down slightly, and H increases. The aggregate firm purchases less intermediate goods, and C and I go down because of the decline in the productivities of capital and labor.

Note that the impact on *MVC* of ϑ is five times greater than that of A. The change in A has similar effects on *C*, *K* and *MVC*, whereas the change in ϑ leaves C and K almost unaffected. A positive change in A depresses *D*, and moves considerably the price-dividend ratio *PD* in spite of the minor change in *MVC*. The change in ϑ produces a positive strong move in *D*, and dampens *PD*. This strong effect of ϑ on D comes from our simplistic modeling of the production of intermediate goods, and will become evident in our further quantitative analysis.

4.3. Volatility

Simulated moments are obtained from equilibrium paths over 3,000 observations. Since all level variables are expressed in log values, the standard deviation corresponds to the (relative) volatility. Both data and equilibrium paths have been filtered with a band pass filter for a frequency band of 2-50 years, which is further decomposed into windows of 2-8 and 8-50 years.

Table 4 reports standard deviations for our baseline calibration *BL* and four other variants of this benchmark calibration. For *BL* the volatility of real macroeconomic variables is quite similar to the prototypical real business-cycle model (Cooley and Prescott, 1995). The standard deviations of financial variables *MVC* and *PD* are over two-thirds of those found in the data. Both in the data and in our model the volatility of *RC* (the return of *MVC*) is much higher than the volatility of the risk-free rate *R*. Hence, the volatility of the excess return *ER* is driven by *RC* rather than by *R*. Our model generates an adequate volatility for dividends *D*. In our *BL* calibration, the labor income share hovers around 63 percent and it is reasonably volatile. Perturbations of the markup process affect the labor income share because of profit swings in the production of intermediate goods. The model with variable labor does not significantly improve upon the volatility of financial variables. Total taxes are less volatile than in the data; alternative calibrations show that taxes are not a relevant source of volatility.

[5] In a recent paper, Corhay, Kung and Schmid (2015) present an estimation of the aggregate markup as an inverse function of the labor income share. This indirect procedure seems to yield more persistence than our computations of the markup measure.

Several variants of BL are included in Tables 3 and 4 to assess the importance of lags in technology adoption and exogenous markups. Production parameters α and γ, and tax parameter τ^{ded} are adjusted to keep an appropriate share of dividends in value added.

***IACM*: A model with instant technology adoption and a constant markup**. Lags in technology adoption are ruled out by letting $\lambda = 1$, and exogenous fluctuations in markups are ruled out by letting ϑ be equal to its steady-state value: $\vartheta = 1.18$. Note that in this case the volatility of financial variables is roughly the same as that of real variables. Only the volatilities of D and PD get sizable. As pointed out above, TFP shocks lead to a strong negative correlation of D with YN. The volatility of PD arises from countercyclical shifts in D rather than procyclical shifts in MVC.

***CM*: A model with a constant markup**. From our baseline calibration BL, let $\vartheta = 1.18$. From Table 4, there are no noticeable changes in the volatility of our economic variables for models $IACM$ and CM. Hence, innovation and lags in technology adoption do not contribute to increase the volatility of our financial variables.

***IA*: A model with instant technology adoption**. From baseline calibration BL, let $\lambda = 1$. In this case, standard deviations are also reported over frequency bands of 2-8 and 8-50 years. Lags in technology adoption contribute to a rather small increase in the volatility of financial variables of about 10 percent. The most noticeable change is the volatility of the risk-free rate R, which goes from 1.07 percent in the IA model to 1.44 percent in the BL model, whereas it is 2.48 percent in our data set. The volatility of R in the data is expected to be higher because of unexpected inflation.

***RA*: A model with higher risk aversion**. The coefficient of risk aversion now moves from $\chi = 5$ to $\chi = 15$, and the elasticity of intertemporal substitution $EIS \equiv 1/\sigma = 1/5$ remains unchanged. Also, we let $Corr\left\{\varepsilon^A, ln(\varepsilon^\vartheta)\right\} = 0.80$, as opposed to independent shocks in the BL calibration. Given that $\chi > \sigma$, the representative household has a preference for early resolution of uncertainty (cf. Kaltenbrunner and Lochstoer, 2010). As discussed in Subsection 4.2, the positive correlation between shocks A and ϑ is essential to match the correlations of YN with markups, which appear with a negative bias in the BL calibration; see Table 5. These changes do not substantially affect the volatility of our financial variables including the risk-free interest rate, but generate a more suitable risk premium of 1.59 percent as compared to 6.5 percent in our data (with a Newey-West corrected standard error of 1.92 percent).

In summary, product price markups generate a significant increase in the volatility of the financial variables without compromising the volatility of real aggregates. With instant technology adoption and constant markups the volatility of MVC is equal to 2.38 percent, as opposed to 24.93 in the data. The introduction of a stochastic markup process rises the volatility of MVC to 14.32 percent. Including lags in technology adoption increases the volatility of MVC to 16.30 percent, as well as the volatility of the risk-free rate. Sizable equity premia require markups to be correlated with TFP.

4.4. Correlations

Another dimension of the excess volatility puzzle is the lack of correlation between real and financial variables. These correlations do not differ significantly within the subgroup of models with stochastic markups, and hence the IA and RA models will be omitted. Models $IACM$ and CM lack economic interest because of their low volatility for the financial variables. Hence, Table 5 displays some representative correlations for our BL model for the wider frequency band of 2-50 years.

Correlations with YN: Real business-cycle models present high correlations of output with real and financial variables. Our baseline calibration BL inherits the high correlation of output with real variables, but recovers the low correlation of YN with financial variables; see Subsection 4.2. Markups are procyclical in the data, but negatively correlated with output in the model. This is because stochastic innovations are uncorrelated in our BL calibration.

Correlations with D: Changes in TFP produce a rather strong negative correlation of dividends D with both real economic activity and financial variables. As we can see from Table 5 these correlations are much milder under our baseline calibration BL. Still, there is a strong negative correlation between D and YN and between D and RC, which require a more suitable correlation of the TFP and markup processes; i.e., see our discussion of the $IACM$ and RA calibrations.

Correlations with MVC: While installed physical capital $p_t^k k_{t+1}$ and the present value of lump-sum taxes PVT_t can be highly correlated with YN, C, and I, the remaining portion $V_t^+ \Omega_t + J_t^+ (Z_t - \Omega_t) + \xi_t$ of MVC in Proposition 3.1 exhibits a much lower correlation.[6] Hence, MVC is mildly correlated with several other economic aggregates. Our BL model generates a rather low correlation of MVC with PD and a strong negative correlation of MVC with R. As seen in Table 5, in our model markups are strongly correlated with D, which in turn affects the correlation of MVC with PD.

Autocorrelations: For our purposes, the autocorrelation coefficient of dividends D is most critical. In both model and data, this coefficient is around 0.60. Our BL model captures well the autocorrelation of our economic variables, but fails for PD and R. Actually, the problem is the autocorrelations of PD and R for the frequency band of 2-8 years.

It follows that our BL model mimics quite well several second-order moments. The main issues come from the negative biases in the correlations of MVC with PD and MVC with R, and the autocorrelations of PD and R for the frequency band of 2-8 years. Apart from lessening the strong correlation between markups and dividends, this suggests the need for medium-term time-varying risk (cf., Greenwald, Lettau and Ludvigson, 2014), which may come from monetary and financial factors. In the recent economic crisis, market sentiment and increased financial risk along with a loss of collateral quality could be blamed for downward shifts in MVC, PD, and R.

5. Variance Decomposition of the Price-Dividend Ratio PD

A vast literature contends that the variance of PD can be explained by changes in expectations of future returns (e.g., Campbell and Shiller, 1988; Cochrane, 1992). These results are not generally accepted. Ang (2002) and Ang and Bekaert (2007) question their econometric significance, whereas Boudoukh *et al*. (2007) and Larrain and Yogo (2008) propose broader measures of profitability accounting for a larger fraction of the variance of PD.

Following Campbell and Shiller (1988), the price-dividend ratio PD can be approximated under a log-linearization over an observed sample path. Let $pd_t \equiv ln\left(\frac{MVC_t}{D_t}\right)$, $rc_t \equiv ln\left(\frac{MVC_t + D_t}{MVC_{t-1}}\right)$, and $\Delta d_t \equiv ln(\frac{D_t}{D_{t-1}})$. Then, for every horizon N the variance of pd can be decomposed into the following sources of volatility:

(i) Expected future returns: $CVAR_{N,rc} \equiv \frac{-Cov\left\{\mathbb{E}_t\left[\sum_{s=1}^{N} \rho^{s-1} rc_{t+s}\right], pd_t\right\}}{Var(pd_t)} \times 100$

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

(iii) Terminal price component: $CVAR_{N,pd} \equiv \frac{Cov\left\{\mathbb{E}_t\left[\rho^N pd_{t+N}\right], pd_t\right\}}{Var(pd_t)} \times 100$

where $0 < \rho < 1$. Table 6 provides a variance decomposition of pd for $N = 30$. As in Cochrane (1992), this table reports OLS estimations of the forecastable variation of future returns over 30-year windows. Data statistics are calculated over our annual set of observations for the time period 1948-2007, and model statistics are calculated over a simulated sample of 50,000 observations. Similar results are obtained when statistics are computed as averages over multiple simulated samples. In the data, about 50 percent of the volatility of pd is explained by predictable variations in dividend growth. This relatively high value seems quite reasonable for our broad measure of dividends (Larrain and Yogo, 2008). Note that our data estimates present large standard errors, which is usually ascribed to the high autocorrelation observed in financial variables (e.g., Ang, 2002; Ang and Bekaert, 2007; Cochrane, 2008). In our BL model, about three-fourths of the variance of pd is accounted by dividends; these values are close but lie outside the 95-percent confidence intervals reported in Table 6. Of course, some positive bias is to be expected since our model is just made

[6] In our simulations the value of installed physical capital $p_t^k k_{t+1}$ ranges between 22 and 63 percent of the tax-adjusted MVC (i.e., $q_t + PVT_t$), the value of existing technologies $V_t^+ \Omega_t$ ranges between 30 and 65 percent, whereas the option value of adopting future technologies $J_t^+ (Z_t - \Omega_t) + \xi_t$ is much smaller and lies between 10 and 25 percent. These figures seem quite plausible. Hall (2001) argues that in periods of high technological activity the weight of capital may get down to one fourth of its peak value.

up of a representative household, and is abstracting from some other sources of volatility. The other two models with stochastic markups (IA and RA) present similar variance decompositions. The models with constant markup ($IACM$ and CM) generate higher values for $CVAR_{30,rc}$, but they lack economic interest because the volatility of MVC is implausibly low.

Finally, Table 7 reports the predictive power of pd over future excess returns and dividend growth. Because of our broad measure of dividends, it is worth noting that in our data the price-dividend ratio pd has some explanatory power not only for future excess returns but also for dividend growth. Our BL and RA calibrations present similar patterns for dividends, and lack explanatory power for future excess returns; more precisely, the coefficients for future excess returns display the right sign but are not statistically significant. Again, this lack of predictability confirms that our BL calibration may be missing some sources of medium-term time-varying risk.

6. Concluding Remarks

From the Standard & Poor's Compustat database, popular accounting measures of profitability are weakly correlated with stock values, whereas product price markup measures exhibit more volatility and are highly correlated with stock values. The predictive power of markups is enhanced when companies are grouped by *R&D* intensity.

Our two-sector model has been instrumental to explore the influence of technology innovation, *TFP* shocks, and product price markups on asset price volatility. Overall, the model generates a volatility for the market value of corporations of about 16.30 percent as opposed to 24.93 percent in the data – without imposing further volatility on the real economy. As compared to *TFP* shocks, exogenous variations in product price markups lead to about a five-fold increase in long-term asset price volatility with relatively little impact on the real economy. Innovation and lags in technology adoption have rather mild effects on the volatility of our financial variables.

In our model, fluctuations in price markups are strongly correlated with dividends because of a simplistic modeling of the production of intermediate goods. This results in a low correlation between the stock market value and the price-dividend ratio, as well as a low autocorrelation of the price dividend-ratio. Also, our baseline calibration is unable to account for the equity premium. A sizable equity premium and suitable stock market predictability may be obtained with correlated shocks and high degrees of risk aversion. Finally, the model's performance may be improved by considering time-varying risk and monetary factors to generate higher correlation among financial variables and persistent interest rates.

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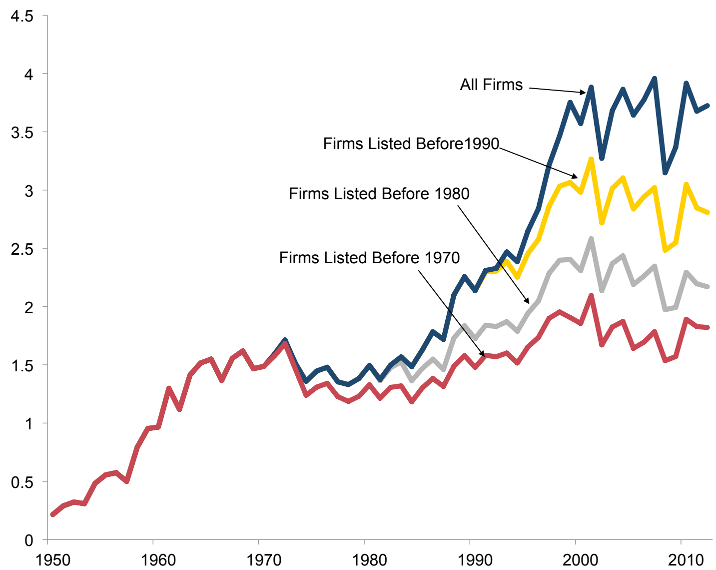
Figure 1: Market Value of Corporations over Corporate Value Added for Various Groups of Firms



Notes: See Appendix for definitions and data sources.

Table 1: Markups and Shares of *MVC* and Financial Accounting Measures across Company Cohorts

Year:	90–94			95–99				00–04			
Cohort:	70	70–80	80–90	70	70–80	80–90	90–00	70	70–80	80–90	90–00
MVC	66.70	11.24	19.98	57.97	12.00	18.35	11.68	51.00	13.77	17.81	16.62
MU50	80.44	73.42	158.92	57.69	56.42	87.07	164.71	43.26	41.93	70.07	121.47
MU75	98.87	88.31	121.68	94.30	83.67	104.18	168.16	88.70	74.98	101.35	165.62
MU100	97.83	90.26	123.32	98.38	89.18	109.55	116.33	97.95	95.35	86.57	108.71
MU	94.51	106.60	121.25	97.43	110.84	113.50	91.45	98.98	114.66	122.37	83.84
D1	69.88	12.29	16.30	65.50	11.47	13.12	9.90	60.20	9.86	12.85	14.78
NI	67.06	17.25	14.37	65.10	13.13	14.86	6.90	190.17	47.63	24.18	-159.86
GP	67.74	11.73	18.49	57.59	11.53	17.24	13.63	50.92	10.65	17.51	19.60
IB	69.36	14.94	14.43	64.59	13.82	15.42	6.17	102.38	25.42	25.29	-51.76
EBITDA	65.30	13.66	19.28	56.81	14.05	18.00	11.13	50.62	12.93	19.13	15.97
EBIT	62.70	15.15	20.09	55.23	14.92	18.18	11.66	51.62	13.75	19.41	13.98
OIBDP	65.30	13.66	19.28	56.81	14.05	18.00	11.13	50.62	12.93	19.13	15.97
OIADP	64.33	14.52	19.17	56.44	14.34	17.86	11.36	52.13	13.41	19.45	13.78

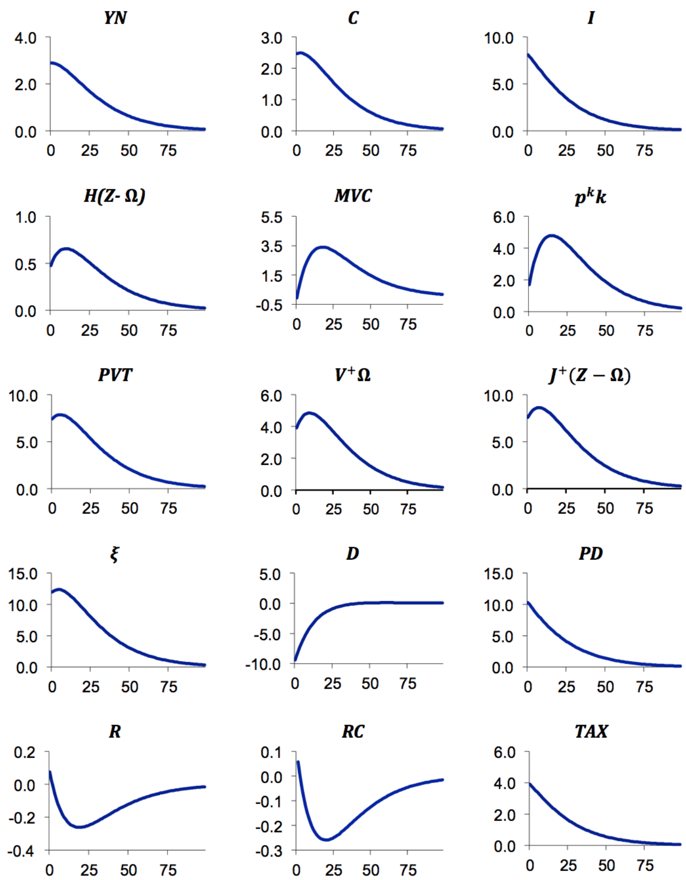
Notes: Reported values are averages for the various time intervals. *MVC*: market value of corporations. *MU50, MU75, MU100*: average markup for the top 50%, 75%, and 100% companies with the highest ratio of *R&D* expenditure over total revenue, respectively. *MU*: average markup. *D1*: dividends. *NI*: net income. *GP*: gross profit. *IB*: earnings before extraordinary items. *EBITDA*: earnings before interest, taxes, and depreciation. *EBIT*: earnings before interest and taxes. *OIBDP*: operating income before depreciation. *OIADP*: operating income after depreciation. See Appendix for definitions and data sources.

Table 2: Correlation Coefficients and Relative Volatilities

Time Interval:	1	3	5	7	10	20	30	VOL
MU50	0.00	0.35	0.50	0.65	0.70	0.83	0.74	0.62
	(0.09)	(0.11)	(0.10)	(0.09)	(0.09)	(0.06)	(0.08)	
MU75	0.14	0.36	0.39	0.49	0.51	0.72	0.80	0.21
	(0.11)	(0.13)	(0.14)	(0.13)	(0.15)	(0.11)	(0.06)	
MU100	0.46	0.46	0.53	0.62	0.68	0.82	0.80	0.21
	(0.14)	(0.14)	(0.13)	(0.12)	(0.14)	(0.08)	(0.06)	
MU	0.14	0.18	0.08	0.07	0.06	0.07	0.08	0.43
	(0.09)	(0.10)	(0.14)	(0.17)	(0.20)	(0.10)	(0.17)	
D1	0.14	0.05	-0.25	-0.50	-0.51	-0.56	0.42	0.31
	(0.14)	(0.12)	(0.13)	(0.14)	(0.13)	(0.13)	(0.16)	
D2	0.12	-0.01	-0.19	-0.15	-0.15	0.11	0.57	0.37
	(0.12)	(0.13)	(0.13)	(0.16)	(0.20)	(0.13)	(0.13)	
NI	0.35	0.29	0.13	-0.05	-0.07	-0.08	0.15	1.38
	(0.12)	(0.11)	(0.14)	(0.16)	(0.18)	(0.17)	(0.15)	
GP	0.47	0.35	0.21	0.02	-0.11	-0.42	-0.55	0.34
	(0.15)	(0.21)	(0.19)	(0.20)	(0.19)	(0.12)	(0.10)	
EBITDA	0.46	0.38	0.23	0.01	-0.08	-0.33	-0.38	0.39
	(0.13)	(0.18)	(0.21)	(0.24)	(0.22)	(0.14)	(0.10)	
EBIT	0.36	0.36	0.27	0.12	0.10	0.17	-0.01	0.58
	(0.13)	(0.15)	(0.17)	(0.20)	(0.21)	(0.17)	(0.12)	
OIBDP	0.46	0.38	0.23	0.01	-0.08	-0.33	-0.38	0.39
	(0.13)	(0.18)	(0.21)	(0.24)	(0.22)	(0.14)	(0.10)	
OIADP	0.40	0.36	0.19	-0.05	-0.11	-0.23	-0.25	0.52
	(0.14)	(0.17)	(0.20)	(0.22)	(0.22)	(0.17)	(0.09)	

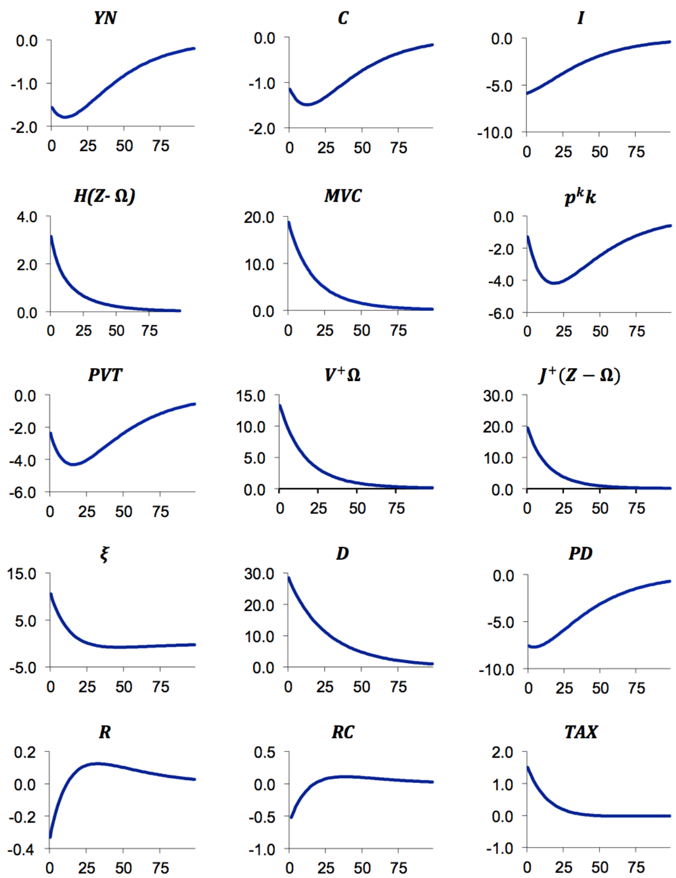
Notes: Contemporaneous correlations for log differences of MVC with markups and financial accounting measures over different time intervals. These growth rates for MVC and the financial accounting measures (excluding markups) are scaled down by growth of aggregate corporate value added. The last column, VOL, is the ratio of the standard deviation of each variable over the standard deviation of MVC for a frequency band of 2-50 years. MVC: market value of corporations. *MU50, MU75, MU100*: average markup for the top 50%, 75%, and 100% companies with the highest ratio of *R&D* expenditure over total revenue, respectively. MU: average markup. *D1*: dividends. *D2*: corporate value added less investment, wages, and taxes. NI: net income. GP: gross profit. IB: earnings before extraordinary items. $EBITDA$: earnings before interest, taxes, and depreciation. $EBIT$: earnings before interest and taxes. $OIBDP$: operating income before depreciation. $OIADP$: operating income after depreciation. Newey-West corrected standard errors are in parentheses. See Appendix for definitions and data sources.

Figure 2: Impulse–Response Functions to a Perturbation in A



Notes: Response to a positive perturbation of A by one standard deviation from the deterministic steady state. The y-axis measures percentage deviation from the deterministic steady-state value and the x-axis refers to annual dates. YN: corporate value added. C: consumption. I: investment. $H(Z-\Omega)$: adoption expenditures. MVC: market value of corporations. p^kK: value of installed capital. PVT: present value of lump-sum taxes. $V^+\Omega$: value of adopted technologies. $J^+(Z-\Omega)$: option value of inventions currently available but not yet adopted. ξ: present value of future inventions. D: dividends. PD: price-dividend ratio. R: risk-free rate. RC: return of MVC. TAX: total taxes.

Figure 3: Impulse–Response Functions to a Perturbation in ϑ



Notes: Response to a positive perturbation of ϑ by one standard deviation from the deterministic steady state. The y-axis measures percentage deviation from the deterministic steady-state value and the x-axis refers to annual dates. YN: corporate value added. C: consumption. I: investment. $H(Z-\Omega)$: adoption expenditures. MVC: market value of corporations. p^kK: value of installed capital. PVT: present value of lump-sum taxes. $V^+\Omega$: value of adopted technologies. $J^+(Z-\Omega)$: option value of inventions currently available but not yet adopted. ξ: present value of future inventions. D: dividends. PD: price-dividend ratio. R: risk-free rate. RC: return of MVC. TAX: total taxes.

Table 3: Calibration of Parameter Values

Parameters	*BL*	*IACM*	*CM*	*IA*	*RA*
			Preferences		
β	0.95	0.95	0.95	0.95	0.95
σ	5	5	5	5	5
χ	5	5	5	5	15
			Technology		
α	0.20	0.25	0.25	0.20	0.20
γ	0.65	0.70	0.70	0.65	0.65
δ	0.09	0.09	0.09	0.09	0.09
δ_a	0.10	0.10	0.10	0.10	0.10
ς	8	8	8	8	8
ρ	-0.60	-0.60	-0.60	-0.60	-0.60
λ	0.166	1	0.166	1	0.166
Λ_1	0.8833	–	0.8833	–	0.8833
κ	0.8	–	0.8	–	0.8
ϕ	0.98	0.98	0.98	0.98	0.98
			Taxes		
τ^s	0.035	0.035	0.035	0.035	0.035
τ^c	0.40	0.40	0.40	0.40	0.40
τ^{ls}	0.13	0.13	0.13	0.13	0.13
τ^{ded}	0.1625	0.15	0.15	0.15	0.15
δ_a	0.10	0.10	0.10	0.10	0.10
			Exogenous shocks		
ψ^A	0.95	0.95	0.95	0.95	0.95
ψ^x	0.40	0.40	0.40	0.40	0.40
ψ_0^ϑ	-0.145	–	–	-0.145	-0.145
ψ_1^ϑ	0.968	–	–	0.968	0.968
μ_ϑ	-1.8951	–	–	-1.8951	-1.8951
σ_A	0.0085	0.0108	0.0109	0.0093	0.0122
σ_x	0.20	0.20	0.20	0.20	0.20
σ_ϑ	0.15	–	–	0.15	0.15
$Corr\left\{\varepsilon^A, ln(\varepsilon^\vartheta)\right\}$	–	–	–	–	0.80

Notes: *BL*: baseline calibration. *IACM*: model with instant technology adoption and constant markup. *CM*: model with constant markup. *IA*: model with instant technology adoption. *RA*: model with higher risk aversion.

Table 4: Standard Deviations

	Data			*BL*			*IACM*	*CM*	*IA*			*RA*		
	2–50	2–8	8–50	2–50	2–8	8–50	2–50	2–50	2–50	2–8	8–50	2–50	2–8	8–50
YN	3.57 (2.98, 4.16)	2.06 (1.64, 2.48)	2.91 (2.21, 3.61)	3.44	1.28	3.19	3.42	3.47	3.48	1.29	3.23	3.45	1.72	2.99
C	1.84 (1.45, 2.23)	0.73 (0.61, 0.86)	1.68 (1.26, 2.10)	2.88	1.01	2.70	2.85	2.92	2.90	1.03	2.71	2.83	1.17	2.57
I	9.26 (7.53, 10.99)	4.65 (3.98 , 5.32)	7.97 (6.22, 9.72)	12.17	7.16	9.84	7.87	7.99	11.02	5.67	9.45	11.81	8.49	8.21
R&D	6.49 (4.99, 7.99)	2.27 (1.89, 2.65)	6.01 (4.68, 7.34)	8.02	3.14	7.37	–	7.27	–	–	–	8.39	3.37	7.69
MVC	24.93 (19.49, 30.37)	11.96 (8.08, 15.83)	21.83 (17.26, 26.40)	16.30	7.38	14.53	2.38	2.78	14.32	6.35	12.84	15.66	6.53	14.23
D	25.68 (18.76, 32.61)	17.64 (12.23, 23.05)	18.50 (14.72, 22.28)	28.37	15.04	24.05	13.29	15.49	25.73	12.21	22.65	24.57	15.89	18.73
PD	31.47 (23.67, 39.27)	16.86 (13.36, 20.36)	26.37 (18.62, 34.13)	24.77	18.48	16.48	12.89	14.27	21.07	14.73	15.07	23.79	19.89	13.03
RC	18.48 (11.94, 25.02)	17.22 (11.48, 22.95)	6.53 (4.59, 8.47)	11.05	10.12	4.42	0.78	1.35	9.51	8.67	3.88	9.52	8.68	3.91
R	2.38 (1.69, 3.06)	1.43 (1.06, 1.80)	1.87 (1.29, 2.44)	1.44	1.22	0.77	0.21	0.21	1.07	0.88	0.60	1.41	1.20	0.73
ER	18.69 (12.41, 24.98)	17.53 (12.00, 23.05)	6.27 (4.55, 7.99)	10.81	9.71	4.73	0.77	1.35	9.33	8.38	4.10	9.29	8.28	4.21
TAX	7.21 (5.52, 8.89)	4.44 (3.18, 5.70)	5.49 (4.35, 6.63)	4.30	1.67	3.96	4.64	4.69	4.68	1.83	4.31	6.29	2.23	5.88
MU75	5.35 (4.51, 6.18)	1.74 (1.40, 2.07)	5.03 (4.14, 5.91)	3.50	1.45	3.19	–	–	3.50	1.45	3.19	3.61	1.43	3.32

Notes: Standard deviations computed from log values for frequency bands of 2-50, 2-8, and 8-50 years. *YN*: corporate value added. *C*: consumption. *I*: investment. *R&D*: *R&D* expenditure. *MVC*: market value of corporations. *D*: dividends. *PD*: price-dividend ratio. *RC*: return of *MVC*. *R*: risk-free rate. *ER*: excess return of *MVC* over the risk-free rate. *TAX*: total taxes. *MU75*: average markup for the top 75% companies with the highest ratio of *R&D* expenditure over total revenue. The corresponding variable in the model is ϑ. *BL*: baseline calibration. *IACM*: model with instant technology adoption and constant markup. *CM*: model with constant markup. *IA*: model with instant technology adoption. *RA*: model with higher risk aversion. Newey-West corrected 95-percent confidence intervals are in parentheses. See Appendix for definitions and data sources.

Table 5: Correlations

	Correlation with YN		Correlation with D		Correlation with MVC		Autocorrelation	
	Data	Model	Data	Model	Data	Model	Data	Model
YN	1	1	-0.27 (-0.48, -0.06)	-0.55	0.15 (-0.18, 0.47)	-0.08	0.58 (0.41, 0.75)	0.83
C	0.70 (0.54, 0.84)	0.99	-0.23 (-0.47, 0.01)	-0.47	-0.04 (-0.36, 0.26)	-0.10	0.80 (0.70, 0.89)	0.85
I	0.73 (0.58, 0.88)	0.88	-0.56 (-0.76, -0.35)	-0.68	-0.06 (-0.43, 0.31)	-0.05	0.71 (0.57, 0.85)	0.56
$R\&D$	0.41 (0.05, 0.76)	0.01	0.06 (-0.33, 0.45)	0.19	0.51 (0.25, 0.78)	0.40	0.83 (0.75, 0.92)	0.83
MVC	0.15 (-0.18, 0.47)	-0.08	0.23 (-0.15, 0.61)	0.49	1	1	0.73 (0.57, 0.89)	0.74
D	-0.27 (-0.48, -0.06)	-0.55	1	1	0.23 (-0.15, 0.61)	0.49	0.55 (0.36, 0.77)	0.64
PD	0.34 (0.06, 0.62)	0.58	-0.63 (-0.77, -0.49)	-0.82	0.60 (0.34, 0.86)	0.09	0.69 (0.53, 0.86)	0.27
RC	-0.28 (-0.40, -0.16)	0.13	0.44 (0.14, 0.75)	-0.42	0.32 (0.10, 0.54)	0.37	-0.07 (-0.33, 0.17)	-0.15
R	-0.13 (-0.32, 0.06)	-0.06	0.03 (-0.17, 0.23)	0.18	-0.03 (-0.35, 0.29)	-0.50	0.60 (0.41, 0.78)	0.06
ER	-0.26 (-0.39, -0.13)	0.11	0.44 (0.12, 0.75)	-0.37	0.32 (0.10, 0.54)	0.42	-0.08 (-0.32, 0.14)	-0.08
TAX	0.61 (0.44, 0.77)	0.69	-0.14 (-0.35, 0.06)	0.11	0.20 (-0.03, 0.43)	0.39	0.53 (0.33, 0.73)	0.81
$MU75$	0.28 (-0.01, 0.58)	-0.45	0.19 (-0.07, 0.47)	0.86	0.37 (0.11, 0.64)	0.58	0.84 (0.76, 0.92)	0.79
$V^+\Omega_t$	–	0.13	–	0.39	–	0.96	–	0.75
$J^+(Z-\Omega)$	–	0.22	–	0.31	–	0.85	–	0.78
ξ	–	0.54	–	0.13	–	0.73	–	0.78

Notes: Selected correlations for model BL. These statistics are computed from log values for a frequency band of 2-50 years. YN: corporate value added. C: consumption. I: investment. $R\&D$: $R\&D$ expenditure. MVC: market value of corporations. D: dividends. PD: price-dividend ratio. RC: return of MVC. R: risk-free rate. ER: excess return of MVC over the risk-free rate. TAX: total taxes. $MU75$: average markup for the top 75% companies with the highest ratio of $R\&D$ expenditure over total revenue. The corresponding variable in the model is ϑ. $V^+\Omega_t$: value of adopted technologies. $J^+(Z-\Omega)$: option value of inventions currently available but not yet adopted . ξ: present value of future inventions. Newey-West corrected 95-percent confidence intervals are in parentheses. See Appendix for definitions and data sources.

Table 6: Variance Decomposition of pd

	$CVAR_{30,rc}$	$CVAR_{30,d}$	$CVAR_{30,pd}$	Total
Data	38.86 (24.65, 53.06)	49.84 (24.91, 74.78)	8.80 (-5.53, 23.13)	97.51
BL	20.16	73.99	6.15	100.32
$IACM$	41.43	42.95	10.54	94.92
CM	37.98	47.79	10.44	96.21
IA	18.98	72.18	7.20	98.36
RA	19.58	76.98	3.20	99.76

Notes: Data and model OLS estimates of $CVAR_{30,rc} \equiv \frac{-Cov\left\{\mathbb{E}_t\left[\sum_{s=1}^{30}\rho^{s-1}rc_{t+s}\right],pd_t\right\}}{Var(pd_t)} \times 100$, $CVAR_{30,d} \equiv \frac{Cov\left\{\mathbb{E}_t\left[\sum_{s=1}^{30}\rho^{s-1}\Delta d_{t+s}\right],pd_t\right\}}{Var(pd_t)} \times 100$, and $CVAR_{30,pd} \equiv \frac{Cov\left\{\mathbb{E}_t\left[\rho^{30}pd_{t+30}\right],pd_t\right\}}{Var(pd_t)}$. Total refers to the sum of these three statistics. Here, $rc_t \equiv ln\left(\frac{MVC_t+D_t}{MVC_{t-1}}\right)$, $\Delta d_t \equiv ln(\frac{D_t}{D_{t-1}})$, and $pd_t \equiv ln\left(\frac{MVC_t}{D_t}\right)$. MVC: market value of corporations. D: dividends. BL: baseline calibration. $IACM$: model with instant technology adoption and constant markup. CM: model with constant markup. IA: model with instant technology adoption. RA: model with higher risk aversion. Newey-West corrected 95-percent confidence intervals are in parentheses. See Appendix for definitions and data sources.

Table 7: Excess Return and Dividend Predictability

	Data		*BL*		*IACM*		*CM*		*IA*		*RA*	
	Δer	Δd	Δer	Δd	Δer	Δd	Δer	Δd	Δer	Δd	Δer	Δd
Horizon in Years: N=1												
β	-0.222 (-0.340, -0.104)	0.101 (-0.082, 0.286)	-0.007	0.288	0.000	0.053	0.001	0.057	-0.001	0.228	-0.017	0.520
R^2	0.168	0.021	0.000	0.225	0.000	0.032	0.001	0.032	0.000	0.180	0.003	0.396
Horizon in Years: N=3												
β	-0.124 (-0.183, -0.065)	0.137 (0.029, 0.245)	-0.003	0.126	0.000	0.049	0.002	0.055	0.000	0.110	-0.016	0.196
R^2	0.251	0.155	0.000	0.203	0.001	0.091	0.006	0.093	0.000	0.170	0.008	0.352
Horizon in Years: N=5												
β	-0.106 (-0.152, -0.060)	0.079 (0.021, 0.137)	-0.000	0.093	0.000	0.044	0.001	0.049	0.003	0.086	-0.012	0.125
R^2	0.357	0.155	0.000	0.220	0.001	0.135	0.009	0.140	0.000	0.192	0.008	0.321
Horizon in Years: N=7												
β	-0.085 (-0.122, -0.047)	0.052 (0.016, 0.089)	0.001	0.076	0.000	0.040	0.002	0.045	0.004	0.073	-0.011	0.092
R^2	0.352	0.109	0.000	0.228	0.001	0.170	0.010	0.178	0.002	0.209	0.009	0.289
Horizon in Years: N=10												
β	-0.087 (-0.122, -0.051)	0.033 (-0.018, 0.084)	0.001	0.062	0.000	0.036	0.001	0.040	0.004	0.061	-0.009	0.073
R^2	0.395	0.056	0.000	0.244	0.002	0.217	0.013	0.226	0.003	0.230	0.009	0.289

Notes: Excess returns and dividend growth are regressed on the price-dividend ratio. The table reports predictive coefficients β and R^2 statistics for regressions: $(1/N)\sum_{s=1}^{s=N} er_{t+s} = \alpha + \beta pd_t$ and $(1/N)\sum_{s=1}^{s=N} \Delta d_{t+s} = \alpha + \beta pd_t$. Here, $er_t \equiv ln(RC_t) - ln(R_t)$, $\Delta d_t \equiv ln(\frac{D_t}{D_{t-1}})$, and $pd_t \equiv ln\left(\frac{MVC_t}{D_t}\right)$. RC: return of MVC. R: risk-free rate. D: dividends. MVC: market value of corporations. BL: baseline calibration. $IACM$: model with instant technology adoption and constant markup. CM: model with constant markup. IA: model with instant technology adoption. RA: model with higher risk aversion. Newey-West corrected 95-percent confidence intervals are in parentheses. See Appendix for definitions and data sources.