Stock Price Fluctuations and Productivity Growth[1]

Diego Comin[2]   Mark Gertler[3]   Phuong Ngo[4]

Ana Maria Santacreu[5]

September 13, 2016

[2]Dartmouth University, NBER, and CEPR.
[3]New Your University and NBER.
[4]Economics Department, Cleveland State University.
[5]Federal Reserve Bank of St. Louis.

Abstract

This paper studies the relationship between stock prices and fluctuations in TFP. We document a strong predictability of lagged stock price growth on future TFP growth at medium horizons. To explore the sources of this co-movement, we develop a one-sector real business model augmented to allow for (i) endogenous technology through R&D and adoption, and (ii) exogenous shocks to the risk premium. Model simulations produce predictability patterns quantitatively similar to the data. A version of the model with exogenous technology produces no predictability of TFP growth. Decomposing historical TFP, we show that the predictability uncovered in the data is fully driven by the endogenous component of TFP. This finding suggests that fluctuations in risk premia impact TFP growth through their effect on the speed of technology diffusion instead of responding to exogenous fluctuations in future TFP.

Keywords: Endogenous Technology, Risk Premium Shocks, Stock Market, Business Cycles.

JEL Classification: E3, O3.

1   Motivation

There is a long tradition both in macroeconomics and finance exploring the empirical relationships between stock prices and economic activity.[1] Going back to Fama (1981, 1990), Barro (1990) and Cochrane (1991), the literature has observed that both stock returns and the growth in stock prices predict future investment and GDP growth at short horizons.[2]

In this paper, we present new evidence on the co-movement between stock prices and future economic activity. Specifically, we show that stock prices growth over the previous 20, 12 and 4 quarters predict future total factor productivity (TFP) growth.[3] The predictive power of stock prices over TFP increases with the horizon peaking at approximately 25 quarters and remaining large and significant even after 40 quarters.

This co-movement between stock prices and future TFP growth may admit various interpretations. One possibility is that it is just a manifestation of standard q-theory. Specifically, current investment in physical capital responds to future TFP growth and, due to adjustment costs, it may lead to higher current prices of installed capital.

A second hypothesis is that exogenous shocks to future TFP cause current risk premia rather than the other way around. Under this interpretation, agents demand a higher premium to hold risky assets when they expect future TFP to grow more slowly for exogenous reasons.

A third hypothesis is that stock prices are impacted by shocks that also drive the firms' incentives to develop and adopt new technologies. Because, it takes time for new technologies to be incorporated into production processes, shocks that drive current stock prices affect productivity measures over long-horizons.[4]

---

[1]See for example, Campbell (2003) and Cochrane (2008) for surveys that cover both directions of causation.

[2]This evidence is related to tests of Tobin's q theory of investment. See Tobin (1969), Hayashi (1982) and Abel and Blanchard (1986).

[3]Our measure of TFP growth comes from Fernald (2014) who purges the Solow residual from pro-cyclical biases due to increasing returns in production driven by imperfect competition, sunk costs and variable capacity utilization. Fernald interprets this corrected measure of TFP as true technology.

[4]Cochrane (1991) poses a related interpretation from a very different empirical exercise. Specifically, he studies how dividend-price ratios forecast future stock and investment returns. He finds that dividend price ratios forecast differentially stock versus investment return and interprets this finding as evidence that "this component of stock returns may reflect long-run movement in productivity, which is kept constant in [his] setting."

We investigate the sources of co-movement between stock prices and TFP with the help of a dynamic stochastic general equilibrium (DSGE) model. Ours is a one-sector, real business cycle model with adjustment costs to investment to allow for the q-theory mechanism. The model is extended with an endogenous determination of the evolution of technology and exogenous fluctuations in the risk premium.[5] We endogenize technology by introducing research and development activities that lead to the creation of new intermediate goods. Once intermediate goods are invented, they can be adopted and used in production raising total factor productivity.

Making technology endogenous leads to a richer notion of the stock market than in standard macro models where stock prices just reflect the value of physical capital.[6] In our setting, the market also prices in the value of the technologies developed and adopted. Increases in the market value of adopted technologies raise the return to adoption investments inducing companies to devote more resources to adoption activities which result in a faster diffusion of new technologies. Similarly, exogenous increases in the value of unadopted technologies induce agents to devote more resources to R&D activities leading to a faster rate of creation of intermediate goods.[7] These responses of R&D and adoption cause pro-cyclical movements in the growth rate of TFP which have (nearly) permanent effects in TFP levels. In this way, our model can account qualitatively for the co-movement patterns between stock prices and future TFP growth we document.

To investigate the source of the predictability of TFP growth we simulate our model and a neoclassical version that excludes the endogenous technology mechanism. In both cases, we use as exogenous disturbances shocks to TFP and to the risk premium that are calibrated to match their empirical volatility and autocorrelation.[8] The series

---

[5]See Comin and Gertler (2006) for a formulation that includes both of these margins. The previous version of this manuscript (Comin et al. (2009), and Iraola and Santos (2007) only have endogenous adoption.

[6]See for example Blanchard (1981). See Laitner and Stolyarov (2003, 2014) for models where knowledge embodied in corporations is also priced by the market.

[7]The pro-cyclicality of R&D and diffusion is consistent with the evidence. See Geroski and Walters (1995), Comin and Gertler (2006), Barlevy (2007) and Comin (2009). Broda and Weinstein (2010) also document the pro-cyclicality of a measure of new goods adoption by households. In particular they study new grocery, drugstore and mass merchandise goods.

[8]Following a common approach in finance (see, e.g., Cochrane, 1991, Campbell and Shiller (1988a,b) and Campbell (2008)) we construct measures of teh ex-ante risk premium by regressing excess returns on the lagged (log) dividend-price ratio.

simulated from the endogenous technology model produce predictability patterns of future TFP growth based on lagged stock price growth and lagged growth in the risk premium that are quantiattively similar to those observed in the data. In contrast, we find no predictability of future TFP growth in the exogenous technology model.

Using our model to decompose historical TFP into the endogenous and exogenous components, we study their contribution to the predictability of TFP growth documented in the data. Consistent with the endogenous technology mechanism, we find that the predictability of TFP growth is entirely driven by the endogenous component of TFP. Instead, we find no evidence of predictability of future exogenous TFP growth by lagged stock price or risk premia growth. Furthermore, our model simulations produce a predictability of the future growth of endogenous TFP that quantatively resembles the estimates from the data.

This evidence suggests that the predictability of TFP does not result from q-theory mechanisms or by endogenous risk premia movements that respond to expectations about future TFP growth. Instead, the evidence suggest that the development and adoption of new technologies respond to movements in risk premia and stock prices leading to protracted flcutuations in future productivity growth.

We conclude our analysis by exploring the historical relevance of this mechanism for the evolution of TFP in the U.S. over the period 1970-2008. We find that the high risk premium from the mid 1970s to the mid 1980s reduced the speed of diffusion of new technologies causing a decline in the endogenous component of TFP that fully accounts for the productivity slowdown from 1975 to 1990. Reassuringly, the elasticity of the speed of diffusion with respect to output induced by our model is in line with estimates from microeconomic studies.[9]

In addition to the papers cited above, there are various papers related to ours. The literature on general purpose technologies (GPTs)[10] has linked productivity dynamics to the adoption of new technologies. However, in contrast to our model, the GPT theories argue that the implementation of new technologies caused a decline in measured output and hence a productivity slowdown. The empirical evidence seems more in line with our model than with GPT theories of the productivity slowdown.

---

[9]See Anzoategui et al. (2015).

[10]See for example, Greenwood and Yorukoglu (1997), and Helpman and Trajtenberg (1996).

The speed of diffusion of technologies in the data is pro-cyclical.[11] Cross-sectional evidence is also consistent with our model since sectors that invested more intensively in adopting computers in the 60s and 70s experienced higher productivity growth in the 70s, as well as higher increases in productivity from the 60s to the 70s.[12]

Another related strand of work has studied how the exogenous arrival of new technologies affects stock prices. Iraola and Santos (2007, 2009) use a simplified version of Comin and Gertler (2006) with only technology adoption to study through simulation exercises the role of TFP, price markups and shocks to the arrival of technologies in producing stock price fluctuations. However, Iraola and Santos do not study productivity dynamics and do not have a risk premium. In the context of GPT frameworks, Hobijn and Jovanovic (2001) and Laitner and Stolyarov (2003) have argued that personal computers lowered the market value of incumbents during the 1970s. This approach is silent about why in the 1990s we did not see a similar pattern with the arrival of another disruptive technology, the internet. Motivated by the boom and bust in stock prices during the late 90s and early 2000s, Pastor and Veronesi (2009) build a model where the wide-spread adoption of a new technology enhances aggregate risk leading to a decline in stock prices. The argument posed by Pastor and Veronesi that technology adoption positively drives risk seems inconsistent with our estimates of a strong negative co-movement between the risk premium and the adoption rate.

The asset pricing literature has developed models to endogenize the risk premium that, in our model, is exogenous.[13] A recent strand on this literature has combined some of the preferences used in the asset pricing literature (e.g., Epstein-Zin, habit formation) with endogenous technology to produce sizable risk premia (see, Kung and Schmid (2015), Garleanu et al. (2012)). These papers are complementary to ours in the emphasis of endogenous technology mechanisms and risk premia for both macroeconomic and finance variables. However, rather than trying to explain the existence of some components of the risk premium, our goal is to explore the consequences of fluctuations in the ex-ante risk premium for the economy, regardless of its nature.[14]

---

[11]See Comin (2009) and Anzoategui et al. (2015).

[12]See Comin (2000).

[13]See, for example, Epstein and Zin (1989), Weil (1990), Constantinides and Duffie (1996), Campbell and Cochrane (1999), Bansal and Yaron (2004), Verdelhan (2010), and Bianchi et al. (2014).

[14]Additionally, our paper differs from this stream of work in the details of the endogenous tech-

4

Our analysis shows that the effect of risk premia on future TFP growth (also present in these papers) suffices to explain the predictability of future TFP growth documented in the data. This finding suggests a limited role for the feedback from future TFP growth on current risk premia towards explaining the predictability patterns in the data.

The rest of the paper is organized as follows. Section 2 documents the predictive power of stock prices and the risk premium over TFP future growth. Section 3 presents the model. Section 4 presents the exploration of the sources of predictability. Section 5 concludes.

2   Stock prices and future TFP

What is the relationship between stock prices and future TFP growth? Do stock prices forecast productivity growth? We start exploring these questions by plotting the evolution of the average (annual) growth rate of the S&P index deflated by the GDP deflator over the previous twenty quarters and the average (annual) TFP growth rate over the next 25 quarters (see Figure 1). The TFP measure comes from Fernald (2014) and removes the effects of cyclical capacity utilization and increasing returns in production. Basu et al. (2006) interpret this TFP measure as a proxy for true technology. Figure 1 shows a strong correlation (0.53) between lagged stock prices and future TFP. This correlation is significant at the 1% level.

We assess more generally the predictive power of stock prices on TFP by estimating the following specification:

$$TFP_{t,t+p} = \alpha + \gamma * Stock_{t-q,t} + \epsilon_t, \tag{1}$$

where $Stock_{t-q,t}$ is the average annual growth rate of real stock market value for the q quarters that precede period t; $TFP_{t,t+p}$ is the average annual growth rate of TFP between t and $t + p$.

Table 1 reports the estimates of coefficient γ for various horizons p (expressed in

---

nology mechanisms. In particular, they do not incorporate endogenous adoption of disembodied technologies which we find to be the critical channel to explain the co-movement between stock prices/risk premia and TFP documented in section 2.

quarters). The standard errors are constructed using a Monte Carlo procedure.[15] We also report the R^2 of each regression as a measure of the predictive power of lagged stock prices growth over future TFP growth.

The main finding from Table 1 is that past growth in stock prices forecasts positively future TFP growth.[16] The estimate for γ becomes statistically significant as we increase the forecasting horizon. The predictive power of stock prices over TFP at medium term horizons is high. For example, the estimate of γ when considering a horizon for TFP of 5 quarters and when computing stock market growth over the last 5 years is an insignificant 3.3% which accounts for 2% of the variance in TFP growth. As we increase the horizon for TFP growth (i.e., p) the estimate of γ increases and becomes significant, and the R^2 of the regression rises. For example, over a horizon of 25 quarters, $\hat{\gamma}$ is a significant 5.4%, with a R^2 of 28%.

These magnitudes are quantitatively important. They imply that an increase in lagged stock market growth by one standard deviation is associated with an increase in average TFP growth over the next 25 quarters by four tenths of one percentage point. That represents half of the average annual growth in TFP over our sample and half of one standard deviation in TFP growth. The estimated coefficients remain statistically and economically significant over horizons of up to 40 quarters.

---

[15]Specifically, the steps are: 1. estimate univariate AR(1) processes for TFP and stock prices; 2. simulate 10,000 time series, each 259 periods long; 3. compute the dependent and independent variables; 5. run regression (1); 6. compute the standard deviation of the 10,000 estimates of γ, $\hat{\gamma}$.

[16]We have obtained very similar results using (log) price-dividend ratios as forecasting variables as well as using future (log) TFP levels as dependent variables after controlling for initial (log) TFP.
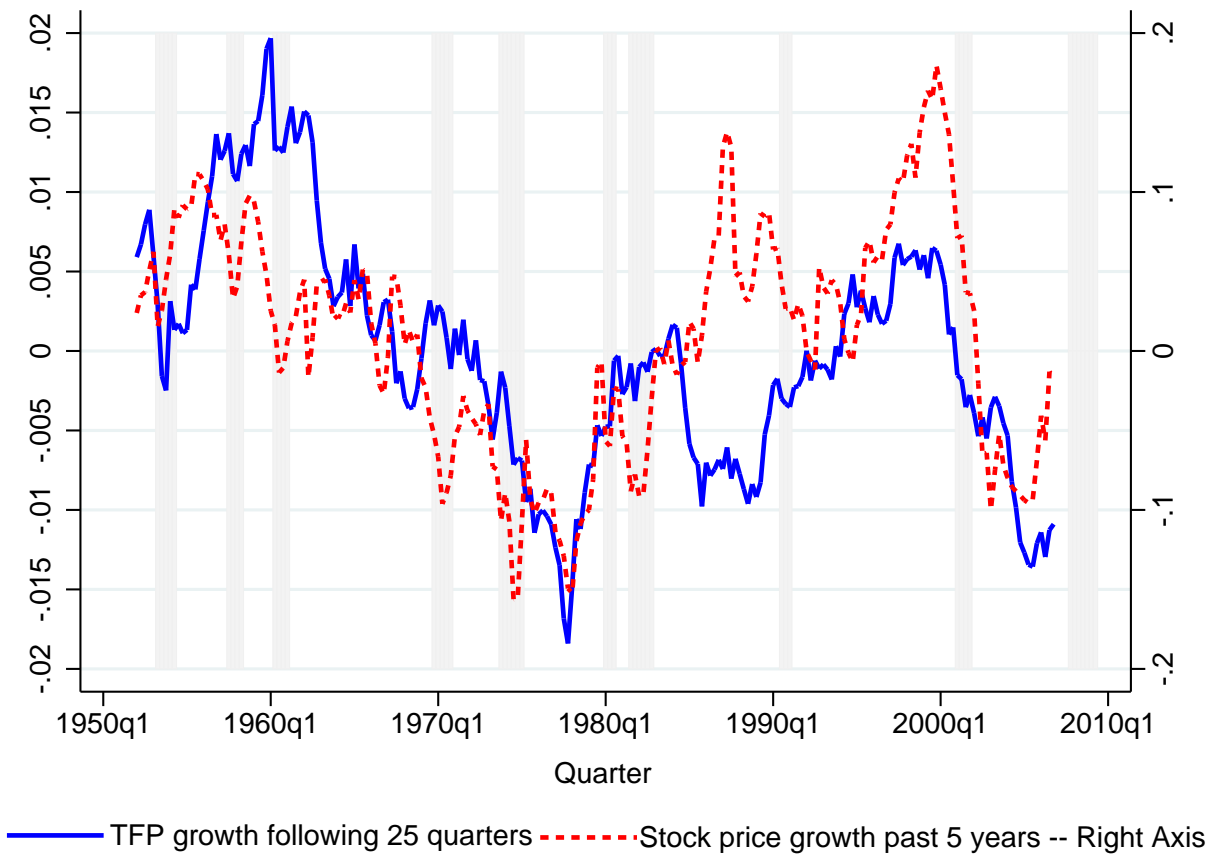
Figure 1: Past Stock Market Growth and Future TFP Growth

Table 1: FORECASTABILITY OF TFP WITH STOCK PRICES 1947-2013

Row	Dependent variable	Independent variable		Horizon (p)							
				5	10	15	20	25	30	35	40
1	$TFP_{t,t+p}$	$Stock_{t-20,t}$		0.033	0.048	0.046	0.051^*	0.054^{***}	0.049^{***}	0.046^{***}	0.042^{***}
			s.e.	0.034	0.032	0.03	0.027	0.025	0.023	0.021	0.019
			R^2	0.02	0.11	0.15	0.21	0.28	0.28	0.28	0.26
2	$TFP_{t,t+p}$	$Stock_{t-12,t}$		0.017	0.025	0.025	0.030^*	0.031^{**}	0.034^{**}	0.033^{**}	0.029^{**}
			s.e.	0.024	0.021	0.019	0.016	0.015	0.013	0.012	0.011
			R^2	0.01	0.05	0.06	0.10	0.14	0.19	0.22	0.19
3	$TFP_{t,t+p}$	$Stock_{t-4,t}$		-0.014	0.002	0.004	0.004	0.007	0.007^*	0.008^{**}	0.010^{**}
			s.e.	0.011	0.008	0.006	0.005	0.005	0.004	0.004	0.004
			R^2	0.02	0.00	0.006	0.005	0.02	0.03	0.04	0.07

Note: (i) Standard errors (s.e.) are computed by Monte Carlo simulation as explained in the text. (ii) TFP is corrected from variation in capital utilization, increasing returns and imperfect competition as in Basu et al. (2006); (iii) Stock is the value of the stock and bonds of the companies in the S&P 500 deflated by the GDP deflator; (iv) $TFP_{t,t+p}$ is the average annualized growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the average annualized growth rate of stock between quarters t-20 and t; *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.

As we reduce the window over which we compute lagged stock growth, the estimates for γ and the predictive power of the regression decline. When using stock price growth over the last three years the highest R^2 of the regressions is 22% (found for a TFP growth horizon of 35 quarters). For the growth in stocks over the last year the highest R^2 is 7% (at a 40 quarter horizon).

There is wide consensus in finance that a key driver of stock returns and stock price growth is the (ex-ante) risk premium (see e.g., Campbell and Shiller 88, 89). We explore the robustness of our predictability results to using as predicting variable a more fundamental proxy for stock price growth such as the growth in the risk premium. Figure 1 plots the evolution of the growth in the risk premium over the previous three years.[17] Lagged growth in the risk premium is negatively correlated with TFP growth over the next 5 years (-0.52) and with stock price growth over the past 5 years (-0.76). Both of these correlations are statistically significant.

The statistical relationships we have uncovered are reminiscent of those found by Fama (1981), Barro (1990) and Cochrane (1991). These authors document that lagged stock price growth and stock returns predict positively investment and GDP growth over the next year. They interpret these relationships in the context of neo-classical investment theory in the presence of adjustment costs (see, e.g., Cochrane (1991)). Despite the similarity, we consider that the patterns we have uncovered are distinct from those documented by Fama (1981), Barro (1990) and Cochrane (1991). First, the effect of investment in productivity growth (through capital accumulation) is removed from TFP growth measures by construction.[18] Second, the co-movement

---

[17]We construct the ex-ante risk premium series as a two-stage forecast of ex-post excess returns to corporate debt and equity based on the two regressions reported in Table 11. In the first stage we forecast excess equity returns with lagged price-dividend ratios (see Campbell and Cochrane (1999), Campbell (2008), and Cochrane (1991)). In the second stage, we forecast excess equity and bond returns. This two-stage procedure takes advantage of the longer time series of excess equity returns and log-dividend price ratios.

Excess equity returns are calculated as the difference between real quarterly returns to equity in the S&P 500 companies and the real quarterly yields of 3-month Bills. We compute returns using monthly data on stock prices and use the timing convention adopted by Cochrane (1991). The stock price and dividend data comes from Shiller's web-page. Price-dividend ratios are constructed as the log ratio of stock prices at $t-1$ over the average dividends over the previous year. From 1969 onwards when data on corporate debt is widely available, we compute a measure of quarterly excess returns that also includes the value of corporate and the associated interest payments.

[18]Basu et al. (2006) procedure, in principle, removes cyclical variation in utilization and increasing returns that may pollute the Solow residual.

between last year's growth in stock prices and next year growth in real investment and output are high-frequency phenomena.[19] Instead, the co-movement we have uncovered operates at significantly lower frequencies and manifests itself more strongly over horizons of 20-35 quarters. Therefore, the underlying mechanisms that drive it are likely to be more persistent than those responsible for the short run predictability of investment growth identified by the finance literature. CONNECT TO BEAUDRY AND POITIER (2006). HERE EFFECT ON GROWTH IN TFP NOT IN LEVEL. VERY DIFFERENT FINDINGS THEY FIND GROWTH OF A STOCK PRICE SHOCK ON TFP FOR 4 QUARTERS. NO EFFECT AFTER THEN. OUR FINDINGS SUGGEST VERY DIFFERENT PATTERN.

A Campbell-Shiller decomposition could provide an explanation for the co-movement in Table 1. Campbell and Shiller (1988, 1989) show that the log-price dividend ratio can be expressed as

$$p_t - d_{t-1} \simeq \sum_{j=0}^{\infty} \rho^j \left(\triangle d_{t+j} - r_{t+j} \right) + k/(1-\rho) \tag{2}$$

where p_t is log stock prices, d_t are log dividends, $\triangle$ denotes the first difference operator, r_t is the (log) gross stock return, and ρ and k are two constants.

By construction, the log price-dividend ratio is a linear transformation of our measure of the ex-ante risk premium, which in turn is highly correlated with stock price growth. Therefore, it may be possible that the estimates in Table 1 reflect the co-movement between future TFP growth and dividend growth which according to the accounting identity (2) is one of the drivers of the price-dividend ratio.

Some indirect evidence against this hypothesis comes from Campbell and Shiller (1988, 1989). They use VARS to estimate an expectational version of (2). Their estimates imply that revisions in expectations about future dividend growth account only for a small fraction of the observed variation in price-dividend ratios. That implies that the majority of the variation in the forecasting variable in (1) is not related to future divdiend growth. Therefore, it is not very likely that the co-movement documented in Table 1 is mediated by future dividend growth.

---

[19]We confirm this co-movement in our data. The coefficient of stock price growth over the last year on output growth over the next five quarters is 0.04 and is statistical significant.

Table 2: FORECASTABILITY OF OUTPUT, DIVIDENDS AND EARNINGS WITH STOCK PRICES 1947-2013

Row	Dependent variable	Independent variable		Horizon (p)							
				5	10	15	20	25	30	35	40
1	$Dividend_{t,t+p}$	$Stock_{t-20,t}$		0.05	-0.05	-0.05	0	0.05	0.06	0.05	0.03
			s.e.	0.09	0.08	0.08	0.08	0.07	0.07	0.06	0.06
			R^2	0	0	0.01	0	0.03	0.05	0.04	0.02
2	$Earning_{t,t+p}$	$Stock_{t-20,t}$		-0.81	-0.52	-0.2	-0.05	0.14	0.08	0.02	0.02
			s.e.	0.51	0.48	0.44	0.41	0.37	0.34	0.32	0.29
			R^2	0.04	0.04	0.01	0	0.04	0.02	0	0
3	$GDP/cap_{t,t+p}$	$Stock_{t-20,t}$		0.04	0.02	0.03	0.03	0.03	0.02	0.01	0.01
			s.e.	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12
			R^2	0.01	0	0.03	0.06	0.06	0.04	0.02	0.02

Note: (i) Standard errors (s.e.) are computed by Monte Carlo simulation as explained in the text; (ii) Stock is the value of the stock and bonds of the companies in the S&P 500 deflated by the GDP deflator; (iii) Dividend (Earning) is the total dividend (earning) of the companies in the S&P 500 deflated by the GDP deflator; GDP/cap is real GDP per capital; (iv) $Stock_{t-20,t}$ is the average annualized growth rate of stock between quarters t-20 and t; (v) $Dividend_{t,t+p}$ is the average annualized growth rate of dividend between quarters t and t+p; *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.
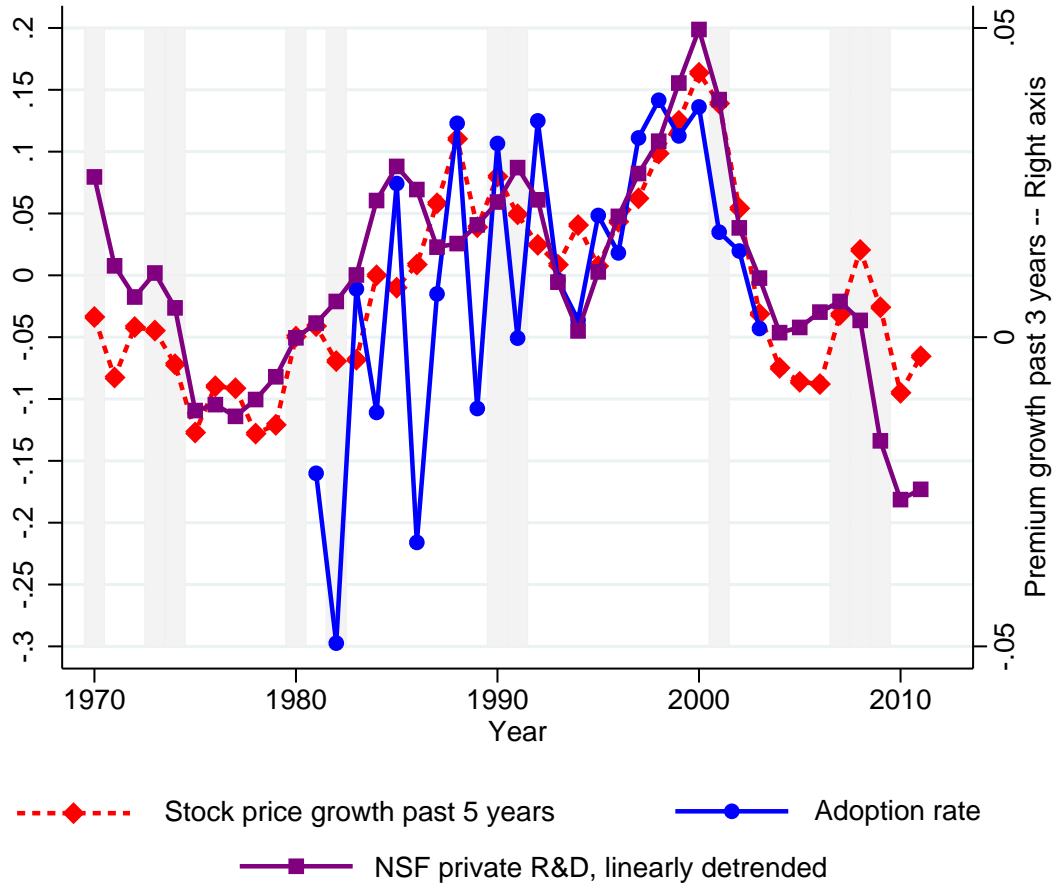
Figure 2: Evolution of Diffusion, R&D, and Risk Premium

To test more directly this hypothesis, we estimate a variation of our baseline regression (1) where the dependent variables are the growth of dividends. In addition to dividends growth, we consider two related dependent variables. The first is the growth rate of earnings, which unlike dividends should not be affected by the distribution policies of companies. The second is the growth rate of output which is relevant because the channel by which TFP growth could affect dividend growth is through output growth.

Table 2 presents the estimates. The predictive power of lagged stock price growth and premium growth for the growth of earnings, dividends and output are very lim-

ited. In particular, the R^2's are much smaller than for TFP growth, and the point estimates are far from significant.[20] The contrast between Tables 1 and 2 strongly suggests that the reason why stock price growth predicts future TFP is not because it predicts the growth in earnings/dividends/output which happen to be contemporaneously correlated with TFP growth.

A different rationalization of Table 1 is that growth in stock prices (or factors that drive stock price growth such as variation in the risk premium) affect future TFP growth. Movements in TFP growth (especially at long horizons) reflect improvements in production technology. Variation in the risk premium may impact the incentives of companies to invest in developing and adopting new technologies, and hence the growth of their TFP. Because, it may take time for new technologies to be brought in production, we should expect the co-movement between stock prices and future TFP growth to be evident in the data over long horizons.[21]

Why NO CO-MOVEMENT WITH DIVIDENDS OR OUTPUT? Two reasons why the endogenous technology channel leads to lower predictability of future dividend/output growth than of future TFP growth. First, risk premia shocks affect contemporaneously output and hence profitability. Therefore, the potential effect on the growth of these variables over long horizons is more limited than for a state variable such as endogenous technology which does not change upon impact. Second, shocks other than risk premia are important drivers of fluctuations in output and profitability. These shocks may introduce mean reversion dynamics in output, earnings and dividends which induce negative predictability over medium term horizons.

As shown by the Campbell-Shiller decomposition in (2), this effect would be consistent with the endogenous technology hypothesis because in our argument stock prices are predominantly driven by variation in risk premia. Hence, fluctuations in the growth of future profits have minor effects on current stock prices.

We conclude this section by exploring the co-movement between stock prices and direct measures of the firms' investments in developing new technologies and the speed

---

[20]In the few instances that they are significant or the R^2 is significant, the sign is the opposite of what would be expected to explain the resulst from Table 1.

[21]A complementary argument for why improvements in technology are harder to be detected at high frequencies is that, in the process of correcting TFP for cyclical variation in capacity, the Basu el at. procedure also filters the high frequency variation in technology which results from an endogenous response to the demand shocks they use as instrument.

at which new technologies diffuse. Figure 2 plots two proxies for these variables. The first is the log-linearly detrended real private R&D expenditures per capita.[22] The second variable we consider is the average speed of diffusion of four manufacturing technologies that improved automation and design.[23] Both series co-move strongly with lagged growth in stock prices and in the risk premia. In particular, the correlation with lagged stock price growth is 0.79 for R&D and 0.66 for the speed of diffusion of technologies. Similarly, the correlation with lagged growth in the risk premium is -0.75 for R&D and -0.47 for the speed of technology diffusion. All of these coefficients are significant at the 1% level. (See Table 3.)

Table 3: Stock Prices and Endogenous Technology Correlation

	Private R&D	Speed of Technology Diffusion
$Stock_{t-20,t}$	0.79***	0.66***

Note: (i) Stock is the value of the stock and bonds of the companies in the S&P 500 deflated by the GDP deflator; (ii) $Stock_{t-20,t}$ is the average annualized growth rate in the stock market past five years; (iii) Private R&D is the the log-linearly detrended real private R&D expenditures per capita, which is computed by the NSF; (iv) Speed of Technology Diffusion is the average speed of diffusion of four manufacturing technologies that improved automation and design. See Anzoategui et al. (2015) for details. The four technologies are computerized numerical controlled machines, automated inspection sensors, 3-D CAD, and flexible manufacturing systems.

This evidence is consistent with the view that lagged changes in the risk premium impact companies' investments in developing and adopting new technologies which affect future growth in TFP. Next, we formalize this hypothesis with a model of business cycles and endogenous technology.

3   Model

Our model is a one-sector, real business cycle model extended to allow for endogenous development and adoption of new technologies and for exogenous fluctuations in risk

---

[22]This series is computed by the NSF.

[23]See Anzoategui et al. (2016) for details. The four technologies are computerized numerical controlled machines, automated inspection sensors, 3-D CAD, and flexible manufacturing systems.

premia. We introduce a (time-varying) risk-premium by assuming that consumers dislike holding stocks and their aversion to stocks fluctuates stochastically. We endogenize technology by allowing agents to engage in research activities that result in the development of new intermediate goods. Invented, intermediate goods are adopted at an endogenous rate leading to higher total factor productivity. For simplicity, we abstract from many other mechanisms that are standard in business cycle and asset pricing models but that are not critical to explore our hypothesis on the co-movemnet between stock prices and future TFP growth.

3.1 Consumers

Consumers consume, supply labor and decide how to allocate their wealth. Each consumers supplies two types of labor: skilled, L_{st}, and unskilled, L_{ut}. The former is used in R&D and technology adoption activities, while the latter is used in production.[24] Agents hold two types of securities: risk-free bonds, B_t, that are in zero net supply, and claims to the portfolio composed by all the companies in the economy (i.e. the market portfolio). Each claim has a price of 1. So, the value of the claims held by the representative consumer is equal to the number of claims they demand, Q_t^d. Let R_t^f denote the gross return on risk-free bonds and R_t the gross return on a claim to the stock market. To introduce a risk premium, we assume that consumers derive disutility from holding claims to the market portfolio. In particular the flow of utility is

$$u_t = \log(C_t - \psi_h C_{t-1}) - \left[\mu^w \frac{L_{ut}^{1+\varphi_u}}{1 + \varphi_u} + \mu^s \frac{L_{st}^{1+\varphi_s}}{1 + \varphi_s} \right] - \zeta_t Q_t^d, \tag{3}$$

where ζ_t captures the stochastic disutility from holding stocks, μ^w is the disutility from supplying unskilled labor and μ^s is the disutility from supplying skilled labor.

[Relate to ambiguity aversion as in Bianchi, Ilut and Schenider (2015)]

The representative consumer maximizes the present discounted flow of utility given

---

[24]For the time being we treat workers as homogeneous. When estimating the model we introduce wage rigidities as in Erceg et al. (2000). This variation requires assuming that labor is differentiated, see the appendix for more details.

by equation (4), subject to the budget constraint (5) and a No-Ponzi game condition.

$$\underset{\left\{C_{t+i},\; L_{t+i},\; L_{st+i},\; B_{t+i},\; Q^d_{t+i}\right\}^{\infty}_{i=0}}{Max} \quad E_t \sum_{i=0}^{\infty} \beta^i \left\{u_{t+i}\right\} \tag{4}$$

$$B_{t+i+1} + Q^d_{t+i+1} + C_{t+i} + T_{t+i} = \sum_{v \in \{u,s\}} W^v_{t+i} L_{vt+i} + R^f_{t+i} B_{t+i} + R_{t+i} Q^d_{t+i} \tag{5}$$

The first order conditions that characterize the solution to the consumers problem are:

$$v_t W^u_t = \mu^w L^{\varphi_u}_{ut} \tag{6}$$

$$v_t W^s_t = \mu^s L^{\varphi_s}_{st} \tag{7}$$

$$E_t \left[\beta \Lambda_{t,t+1} R^f_{t+1}\right] = 1 \tag{8}$$

$$E_t \left[\beta \Lambda_{t,t+1} \left(R_{t+1} - \psi_{t+1}\right)\right] = 1 \tag{9}$$

where the stochastic discount factor, $\Lambda_{t,t+1}$, is given by

$$\Lambda_{t,t+1} = \frac{v_{t+1}}{v_t} \tag{10}$$

$$v_t = \frac{1}{C_t - \psi_h C_{t-1}} - \frac{\beta * \psi_h}{C_{t+1} - \psi_h C_t} \tag{11}$$

and

$$\psi_{t+1} = \zeta_{t+1} * v_{t+1}$$

Combining equations (8) and (9), we obtain the following expression for the risk premium $(R_t - R^f_t)$ in which it is clear that, to a first order, the risk premium is equal to ψ_{t+1}.

$$E_t \left[\beta \Lambda_{t,t+1} \left(R_{t+1} - R^f_{t+1}\right)\right] = E_t \left[\beta \Lambda_{t,t+1} \psi_{t+1}\right] \tag{12}$$

3.2 Production

There is a continuum A_t of intermediate goods available for production. Each intermediate good is produced by one producer with the following Cobb-Douglas production function:

$$Y_{it} = \chi_t K^\alpha_{it} \left(L^u_{it}\right)^{1-\alpha}, \tag{13}$$

16

where Y_{it} denotes the amount of the ith intermediate good produced, χ_t is an aggregate productivity shock, K_{it} is the capital rented by the ith producer, and L_{it}^u the amount of unskilled labor hired.

Let η_{it} be the marginal cost of production of the ith intermediate good producer, W_t^u the unskilled wage rate, D_t^K the rental rate of capital net of depreciation, δ the depreciation rate and P_t^K the cost of replacing one unit of capital. Cost minimization implies:

$$\eta_{it}\alpha\frac{Y_{it}}{K_{it}} = [D_t^K + \delta P_t^K] \tag{14}$$

$$\eta_{it}(1-\alpha)\frac{Y_{it}}{L_{it}^u} = W_t^u \tag{15}$$

Intermediate goods are bought by a competitive firm that combines them to produce aggregate output as follows:

$$Y_t = \left(\int_0^{A_t} Y_{it}^{1/\vartheta} di\right)^{\vartheta}, \ \vartheta > 1. \tag{16}$$

Normalizing the price of aggregate output to 1, we can express the demand faced by a intermediate good producer as

$$Y_{it} = Y_t\left(P_{it}\right)^{-\frac{\vartheta}{\vartheta-1}}. \tag{17}$$

Given this demand function, if intermediate producers were unconstrained, the prices would be a constant gross markup, ϑ, times the marginal cost of production, η_{it}.. Following Jones and Williams (2000) and Aghion and Howitt (1997), we disentangle markups from the elasticity of substitution among intermediate goods by recognizing that the threat of imitation by competitors may limit the mark up they can charge to $\bar{\mu}$. The equilibrium markup charged by intermediate goods producers , μ, is then given by

$$\mu = \min\{\vartheta, \bar{\mu}\}. \tag{18}$$

This yields the following expression for the profits of an intermediate good producer

$$\pi_t = (\mu - 1)\eta_{it}Y_{it} \tag{19}$$

Using the normalization of the price of output, the demand functions, pricing rules for intermediate and the intermediate production functions, we can derive expressions for the aggregate production function, aggregate factor demands and profit flows in the symmetric equilibrium. In particular, aggregate output is equal to

$$Y_t = \theta_t K_t^\alpha \left(L_t^u\right)^{1-\alpha} \tag{20}$$

where $K_t = \int_0^{A_t} K_{it} di$ is the aggregate capital stock, $L_t^u = \int_0^{A_t} L_{it}^u di$ is the number of unskilled hours employed in the economy and θ_t is the TFP level. As shown in equation (21) TFP has two components. The exogenous aggregate shock, χ_t, and the endogenous productivity gains associated with the adoption of new technologies, A_t.

$$\theta_t = \chi_t A_t^{\vartheta - 1} \tag{21}$$

The aggregate demands for capital and labor are

$$\alpha \frac{Y_t}{K_t} = \mu[D_t^K + \delta P_{t+1}^K] \tag{22}$$

$$(1-\alpha)\frac{Y_t}{L_t^u} = \mu W_t^u. \tag{23}$$

And the equilibrium profit flows for the representative producer of an adopted intermediate good are

$$\pi_t = \frac{(\mu - 1)Y_t}{\mu A_t}. \tag{24}$$

3.3   Capital producers

Capital is produced competitively by transforming final output into new investment. It takes one unit of output to produce one unit of capital. The production of capital is subject to adjustment costs. Producers of capital goods determine the flow of net investment by maximizing the present discounted value of the net revenues from renting capital, where the discount rate they face is the risky rate, R_t. Formally, they solve the following maximization problem:

$$\max_{\{I_{t+\tau}^n\}} E_t \sum_{\tau=0}^{\infty} \left(\Pi_{i=0}^{\tau} R_{t+i}^{-1}\right) \left\{ \left(D_{t+\tau} K_{t+\tau} - \frac{\gamma_k}{2} \left(\frac{I_{t+\tau}^n}{K_{t+\tau}} - g_y\right)^2 K_{t+\tau} - I_{t+\tau}^n \right\}$$

subject to

$$K_{t+\tau+1} = I_{t+\tau}^n + K_{t+\tau} \qquad (25)$$

where I_t^n is net investment, g_y is the growth rate of output in steady state, $D_{t+\tau}$ denotes the rental price of capital, $P_{t+\tau}^I$ is the shadow price of capital also known as the price of installed capital.

Optimal production of investment is given by the following conditions:

$$P_t^I = 1 + \gamma_k \left(\frac{I_{t+\tau}^n}{K_{t+\tau}} - gy\right) \qquad (26)$$

$$1 = E_t \left[R_{t+1}^{-1} \left\{ D_{t+1} + \gamma \left(\frac{I_{t+1}^n}{K_{t+1}} - gy\right) \left(\frac{I_{t+1}^n}{K_{t+1}}\right) - \frac{\gamma_k}{2} \left(\frac{I_{t+1}^n}{K_{t+1}} - g_y\right)^2 + P_{t+1}^I \right\} / P_t^I \right]. \qquad (27)$$

Equation (26) introduces a wedge between the cost of investment and the price of installed capital that as is common in teh adjustemnt costs literature is increasing in the level of net investment. Equation (27) states the arbitrage between the borrowing cost faced by capital goods producers and the rate of return from poducing one unit of capital. discount rate faced by cost of funds faced by the is an arbitrage condition that equalizes the return to capital to the retun of risky assets.

3.4   Technology

Technology is not manna from Heaven. Agents invest resources to develop and adopt new technologies that enhance the productive possibilities of the economy (A_t). Technology diffusion and development are not instantaneous processes. As in Comin and Gertler (2006), we capture the slow diffusion of technology by introducing two sequential investments. Agents first develop new prototypes through R&D. Then they

19

engage in stochastic investments that, if successful, make the resulting intermediate good usable for production. The stochastic nature of this second investment implies that, on average, there is a lag between the time of invention of the technology and the time in which it is used in production.

Formally, individual researchers perceive that a unit of skilled labor produces $\bar{\kappa}_t$ new technologies, where

$$\bar{\kappa}_t = \frac{\kappa Z_t}{S_t^{1-\rho}}. \tag{28}$$

κ pins down the productivity of R&D activities, S_t is total amount of research services employed in the economy, Z_t is the stock of all intermediate goods developed and $\rho \in (0,1)$. This formulation captures diminishing returns to aggregate R&D, and knowledge spillovers that ensure the existence of a balanced growth path.

A fraction $(1-\phi)$ of developed technologies becomes obsolete every period. The resulting law of motion for the technologies developed by researcher p, Z_t^p, is:

$$Z_{t+1}^p = \phi \bar{\kappa}_t S_t^p + \phi Z_t^p \tag{29}$$

Aggregating equation (29) among all researchers, we obtain the following law of motion for the stock of technologies is:

$$Z_{t+1} = (\phi \kappa S_t^\rho + \phi) Z_t. \tag{30}$$

Before being used in production, intermediate goods need to be adopted. Potential adoption firms competitively bid for the right to adopt each intermediate good. After gaining the right to adopt an intermediate good, an adoption firm, hires h_t hours of skilled labor to face a probability λ_t that the prototype is usable for production at time $t+1$. In particular,

$$\lambda_t = \lambda(Z_t h_t) \tag{31}$$

with $\lambda' > 0$, $\lambda'' < 0$.[25] This formulation assumes that past experience with technology, measured by the total number of intermediate goods developed Z_t, facilitates the adoption of new technologies. This assumption ensures the existence of a balanced

---

[25]In particular, we assume that

$$\lambda(Z * h) = \bar{\lambda}(Zh)^\varsigma$$

growth path where the speed of adoption is λ, and the average delay between the development and adoption of technologies (i.e., the adoption lag) is $1/\lambda$.

The law of motion for the aggregate number of adopted intermediate goods in the symmetric equilibrium is:

$$A_{t+1} = \phi A_t + \phi \lambda_t (Z_t - A_t). \tag{32}$$

The adoption and R&D intensities are driven by the value of adopted and unadopted intermediate goods. The value of an adopted intermediate good, v_t, is given by the present value of profits from commercializing the technology. Formally, v_t is defined recursively by the Bellman equation

$$v_t = \pi_t + E_t \left[\phi v_{t+1} / R_{t+1} \right], \tag{33}$$

where $1/R_{t+1}$ is the discount factor applied by intermediate good producers between t and $t+1$.

Adopters are willing to bid for prototypes up to the value of the option to adopt them, j_t, which is given by

$$j_t = \max_{h_t} -W_t^s * h_t + E_t\{\phi[\lambda_t v_{t+1} + (1 - \lambda_t)j_{t+1}]/R_{t+1}\}, \tag{34}$$

where W_t^s is the wage rate of skilled labor.

Free entry into R&D implies that the discounted value of intermediate goods created every period equals the cost of skilled labor engaged in R&D (35).

$$W_t^s S_t = E_t \left[R_{t+1}^{-1}(Z_{t+1} - Z_t)j_{t+1} \right]. \tag{35}$$

Optimal investment in adopting a new technology requires that the marginal cost of adoption services equals their expected marginal benefit (36).

$$W_t^s = E_t \left[R_{t+1}^{-1} Z_t \phi \lambda' \left(Z_t h_t \right) \left(v_{t+1} - j_{t+1} \right) \right] \tag{36}$$

A market clearing condition ensures that the supply of research labor equals its demand for R&D and adoption activities.

$$L_t^s = S_t + h_t * (Z_t - A_t) \tag{37}$$

Equations (35) and (36) illustrate the cyclical properties of aggregate R&D and adoption expenditures. In general, there are two sources of cyclicality. On the one hand, the pro-cyclicality of profits accrued by intermediate goods producers (19) makes both the value of unadopted goods (j_{t+1}) and the capital gains from adoption ($v_{t+1} - j_{t+1}$) pro-cyclical. On the other, the cyclicality of the research wage rate makes the cost of R&D and adoption pro-cyclical. These two forces have opposing effects on the cyclicality of R&D and adoption. The first force tends to make them pro-cyclial while the second tends to make them counter-cyclical. Thus, in principle, the sign of the co-movement between output and adoption and R&D investments is ambiguous.[26] Empirically, however, wages are significantly less pro-cyclical that what the flexible wage model predicts. To match the cyclicality of wages, we will introduce wage rigidities when we estimate the model. Once we have a realistic wage profile, the pro-cyclicality of the value of unadopted technologies and the capital gains from adoption dominates leading to pro-cyclical adoption and R&D investments as we shall see below.

In addition to these two channels, risk premium shocks affect the R&D and adoption decisions through two additional ones. For a given flow of profits, risk premium shocks affect the rate at which future profits are discounted and hence the value of adopted and unadopted technologies (See equations 33 and 34). Furthermore, for a given j_{t+1} and on ($v_{t+1} - j_{t+1}$), risk premium shocks affect the return required by researchers and adopters from their investments. (See equations 35 and 36.) These two forces strengthen the cyclicality of R&D and adoption when the economy is hit by risk premium shocks.[27]

---

[26]The literature on endogenous growth has struggled to reconcile the labor intensity of R&D with the pro-cyclicality of R&D investments (see, e.g., Aghion and Saint-Paul (1994), Aghion and Howitt (1992). Other approaches to reconcile these two facts are to introduce financial frictions (Aghion et al. (2011) and short term biases of innovators (Barlevy (2007)). To the best of our knowledge, the first model that resorted to wage rigidities to produce pro-cyclical R&D in a setting with labor intensive R&D was Anzoategui et al. (2015).

[27]Indeed, these investments are always pro-cyclical with risk premium shocks even in the absence of wage rigidities as we shall see below.

3.5 The value of corporations

The market value corporations, Q_t, reflects the value of all their assets. This includes the value of the stock of capital accumulated by capital goods producers, as well as intangible assets such as the right to produce adopted intermediate goods and the option to adopt developed intermediate goods. Formally,

$$Q_t = \overbrace{P_t^I K_t}^{\text{Value of installed capital}} + \overbrace{A_t(v_t - \pi_t)}^{\text{Value of adopted technologies}} + \overbrace{(Z_t - A_t)(j_t + h_t * W_t^s)}^{\text{Value of unadopted technologies}} \quad (38)$$

It is important to note that the stock market value is quite different in our model from standard macro models. In models where technology is exogenous, the only asset corporations own is their physical capital. Therefore, the stock market value is just given by the first term in equation (38). In contrast, in our model, stock prices are affected by factors that impact the stream of profits from commercializing new technologies (and the rates at which those are discounted). In addition to providing a richer theory of stock price fluctuations, recognizing the market value of technology allows us to account for the significant wedge that exists between stock prices and the book value of capital (see, e.g., Hall (2001), McGrattan and Prescott (2001)).

Another feature of equation (38) that is worth noting is that Q_t does not include the value of technologies that have not been developed yet. This is the case because the arrival of intermediate goods in the future is not a free lunch. The free entry condition (35), implies that, in equilibrium, the expected present discounted value of profits accrued by the producers of future intermediate goods equals the cost of developing them. Therefore, their net value is zero.[28]

(DEFINE THEM TO INCLUDE AMORTIZATION/SMOOTHING)

We can also compute the aggregate dividends distributed in the economy, D_t as

$$D_t = \overbrace{D_t^K K_t}^{\text{Rental of K}} + \overbrace{A_t \pi_t}^{\text{Profits from A}} - \overbrace{AC_t}^{\text{Amortized adoption costs}} \quad (39)$$

---

[28]Conversely, if new technologies arrive exogenously as in Comin et al. (2009) and Iraola and Santos (2007), the expression for the stock market has an additional term that captures the value of all technologies that will arrive in the future to the economy.

Adoption costs:

$$AC_t = (Z_t - A_t) * h_t * W_t^s \tag{40}$$

$$\overline{AC}_t = \frac{\sum_{i=0}^{T} AC_{t-i}}{T} \tag{41}$$

Akin to the expression for stock prices, dividends have three components. The first is the revenues from renting capital. The second corresponds to the operating profits from commercializing intermediate goods. The third, are the costs of adopting intermediate goods.

Without loss of generality, we assume that the price of a claim on the stock market is equal to one. Therefore, the number of claims held by the households, Q_t^d, is equal to the stock market value, Q_t.

$$Q_t^d = Q_t \tag{42}$$

3.6 Government

To match the model production structure to the National Income and Product Accounts we introduce a passive government that finances an exogenous expenditure flow, G_t, with lump sum taxes, T_t, levied on households. We assume that the government runs a balanced budget every period:

$$G_t = T_t \tag{43}$$

3.7 Equilibrium

The economy has a symmetric sequence of markets equilibrium. The equilibrium is characterized by the following conditions:

1. Consumers optimally supply both types of labor and determine their consumption and portfolio allocation as described in equations (6-9).

2. Intermediate goods producers demand capital and labor optimally according to equations (22) and (23), and charge a markup given by (18).

3. Investment in physical capital satisfies the optimality condition (26).

4. R&D expenditures satisfy the free entry condition (35).

5. Adoption expenditures maximize the expected value of adopters by satisfying equation (36).

6. The endogenous state variables, K_t, Z_t and A_t evolve according to equations (25), (30) and (32).

7. The resource constraint of the economy is:

$$Y_t = C_t + G_t + I_t$$

8. The markets for skilled (37) and unskilled labor (equations 23 and 6) clear.

9. The market for claims on stocks clears (42).

4 Empirical exploration

Next, we use our model as a laboratory to explore the potential role of various mechanisms as drivers of the predictability patterns documented in section 2. In the first three subsections we discuss the calibration strategy, present the theoretical moments and the impulse response functions. After these preliminaries, we focus on the exploring the potential drivers of predictability. To this end, we first evaluate the model's ability to reproduce the patterns observed in the data. We contrast this with versions of an exogenous technology model with different specifications for the TFP shock processes. Finally, we conduct a battery of robustness analyses where we vary the calibrated values of parameters and enrich our laboratory model.

4.1 Calibration

Table 4 presents the calibrated parameters and the values we use in the baseline simulation. In section 4.5, we discuss how the predictability patterns change as we vary the valeus used for some of the parameters as well as when we introduce some additional mechanisms in our laboratory model.

There are four types of parameters. Those that parameterize (i) the preferences, (ii) the production and markups, (iii) the endogenous technology mechanisms, and (iv) the shocks. The parameters in the groups (i) and (ii) are fairly standard in the literature and we postpone their dicussion to the Appendix. Here we focus on the calibration for the endogenous technology parameters and the processes followed by the shocks.

Five parameters pin down the endogenous technology mechanisms. The value of κ is set to match the long-run growth rate of the economy which we assume it to be 2% per year. The elasticity of the number of intermediate goods with respect to R&D labor, ρ, is set to 0.6 which lies in the low part of the range of estimates of the elasticity of patents with respect to R&D spending (e.g. Griliches, 1990). $\bar{\lambda}$ is set to produce an average adoption lag of 7 years which is consistent with the estimates in Comin and Hobjin (2010) and Cox and Alm (1996). The elasticity of λ with respect to adoption efforts, ζ, is set to 0.85 to induce a ratio of private R&D to GDP consistent with the U.S. post-1970 experience (of approximately 1.5% of GDP). Finally, the obsolescence rate $(1 - \phi)$ is set to 4% annual following the estimate of Caballero and Jaffe (1993).

There are two parameters that measure markups and elasticities of substitution. We set the elasticity of substitution between intermediate goods to 3 so that the unconstrained gross markup ϑ is 1.5, which is consistent with the estimates of Broda and Weinstein (2010). We set the constrained gross markup charged by intermediate goods producers, μ, to 1.25 as suggested by the estimates of Norrbin (1993) and Basu and Fernald (1997). This calibration yields a share of physical capital value in the total stock market value of 48% which is close to the average for the S&P 500 between 1970 and 2008, which is 42%.[29] The value of adopted technologies account for 48.5% of stock prices in steady state, while unadopted technologies account for the remaining 3.5%.

We consider three exogenous disturbances: the risk premium, the exogenous TFP and the labor supply shocks. This setting allows us to explore the co-movement patterns between stock prices, TFP and output with a minimum set of shocks. We set the standard deviation and autocorrelation of the risk premium shock to match

---

[29]Note that, counter-factually, the value of installed capital fully accounts for stock prices in standard macro models with exogenous technology.

Table 4: CALIBRATED PARAMETERS

Parameter	Description	Value
Preferences		
β	Discount factor	0.995
ψ_h	Habit formation	0.7
φ_s	Inverse labor supply elasticity for skilled workers	1/3
φ_u	Inverse labor supply elasticity for unskilled workers	1
ψ	Steady state risk premium	0.07/4
Production/markup		
α	Share of capital in GDP	0.33
δ	Depreciation rate	0.015
$f''(1)$	Investment adjustment cost parameter	20
ϑ	Gross markup for differentiated intermediate goods	1.5
$\bar{\mu}$	Constrained gross markup	1.25
G/Y	Government spending-output ratio	0.16
Endogenous technology		
κ	The average productivity of R&D, set to match the steady state growth rate of 2% per year	
$\bar{\lambda}$	Set to produce the average adoption rate of 0.15 annually	
ρ	Elasticity of succesfully developing a new tech wrt the stock of developed intermediate goods	0.6
ζ	Elasticity of adoption	0.85
ϕ	Survival probability for intermediate goods	0.99
Shocks		
σ_ψ^2	Variance of risk premium shocks	0.158^2
σ_χ^2	Variance of exogenous TFP shocks	0.8^2
$\sigma_{\mu^w}^2$	Variance of labor supply shocks	2^2
ρ_ψ	AR1 coefficient of risk premium shocks	0.987
ρ_χ^1	AR1 coefficient of exogenous TFP shocks	0.8
ρ_χ^2	AR2 coefficient of exogenous TFP shocks	0.1
ρ_{μ^w}	AR1 coefficient of labor supply shocks	0.9

those of the proxy we have built by forecasting the ex-post excess return by the lagged log-price-dividend ratio (See section 2). The exogenous TFP (χ_t) and labor supply shock (μ_t^w) processes are set by first identifying the actual realizations of these shocks necessary to generate the TFP growth and hours growth series (1970:I - 2008:III) from Fernald (2014) with our model. Then we set the model parameters to match those in the identified exogenous TFP series. The autocorrelation of the labor supply shock is 0.9; for exogenous TFP, the first order autocorrelation is 0.8, and the second order is 0.1.

4.2 Theoretical moments

Before studying the dynamics induced by our model, we report the univariate moments of the key variables and the relative contribution to their variance of the three shocks. Given the very limited array of shocks and amplification mechanisms considered, we do not intend to reproduce the empirical volatility of the key variables.

Columns 2 and 3 of Table 5 report the standard deviation of the H-P filtered variables in the model and the data. Recall that we have calibrated the shocks to match the volatility and autocorrelation of the growth in the risk premium, TFP and hours worked. Hence it is not surprising that the volatility of the H-P series in the model and data coincide for these three variables.

The model produces fluctuations in output that represent roughly two thirds of the volatility of output in the data. The volatility of dividends in the model is roughly one third of what we see in the data.[30] As a result, stock prices in the model have a standard deviation that is 45% of the volatility in the data. Table 5 also reports the volatility of R&D expenditures in the model which is approximately twice as large as in the data. This discrepancy surely reflects the lack of adjustment costs in the

---

[30]The discrepancy in the relative volatility of dividends is magnified by the measures of dividends used in the data and in the model. The empirical measure of dividends is real quarterly S&P dividends per capita from Shiller. An alternative measure of profitability is earnings which are significantly more volatile than dividends.

The reported dividend measure in the model is given by equation (39) and is net of adoption costs. If adoption costs are not netted, the relative volatility of dividends in the model is 1.31. In reality, we do not know how much of the costs of adopting new technologies are passed to shareholders in the form of lower dividends. But it is reassuring that the empirical volatility of dividends falls within the model volatilities in the two polar cases.

R&D employment decision in the model.[31,32] Our simulations suggest that the excess volatility of R&D in the model is not key for the predictability of TFP. They point to a more important role of the speed of diffusion. Unfortunately, we do not have precise measures of the volatility of the speed of diffusion. The estimates in Comin (2009) and Anzoategui et al. (2016) suggest that its volatility is approximately four times greater than output. In our model, the theoretical standard deviation of the speed of diffusion is 1.6, which is 20% of the implied volatility in the data.

Table 5: THEORETICAL MOMENTS

Variable	Standard deviation		Variance decomposition		
	Data	Model	Risk premium	Exogenous TFP	Labor supply
Risk premium	0.21	0.21	100	0	0
TFP	0.88	0.96	1	99	0
Hours worked	1.76	1.76	28	8	64
Y	2	1.32	20	28	52
Stock Prices	7.6	3.38	69	11	20
Dividends	6	1.90	22	28	51
Adoption rate	8.7	1.36	99.7	0.1	0.2
R&D expenditures	4.7	6.32	100	0	0

Note: All variables are HP filtered.

Columns 6 to 8 of Table 5 decompose the variance of the HP-filtered variable between the contribution of the three shocks. The labor supply shock is the key driver of fluctuations in hours worked (64%), output (52%), and dividends (51%). The risk premium shock is the main driver of stock prices (69%),[33] R&D expenditures (96%), and the speed of diffusion (100). It is therefore the driver of fluctuations in the endogenous component of TFP. However, because technology is a state variable, its volatility at high frequencies is much smaller than the volatility of TFP. Hence, the predominant role of exogenous TFP shocks in the variance of TFP.

---

[31]One of our robustness checks in section XX incorporates adjustment costs to R&D activity.

[32]Labor hoarding in R&D activities might also explain part of teh discrepancy. The greater volatility of non-labor than labor costs in R&D supports this hypothesis.

[33]This finding is consistent with the estimates in Campbell and Shiller (1988a).

4.3   Impulse response functions

To gain a better understanding of the workings of our model, we study its impulse response functions. Figure 3 plots the impulse response functions in our model to a one standard deviation to the three shocks we consider: risk premium (column one), exogenous TFP (column two), and the cost of labor supply (column three). For comparison purposes, we also plot (in dashed red) the response of the exogenous technology version of model, where there is no adoption or R&D.

The risk premium shock raises the rate of return required to invest in physical capital causing a significant drop in investment. Conversely, the increased demand for riskless bonds reduces the risk free rate and causes a slight increase in consumption. The responses of investment and consumption lead to a significant contemporaneous decline of output (panel 1). Because the profits of intermediate goods producers and the marginal product of capital are initially approximately proportional to output, dividends decline by approximately the same as output (panel 3).

The higher risk premium causes both directly and indirectly (though lower profits) an immediate drop in the value of adopted and unadopted technologies (see panel 2). Potential adopters and intermediate good developers respond to the decline in the value of technologies and to the higher discount rates by cutting the number of skilled hours devoted to R&D and adoption. Hence, the large drop in S and λ (see panel 5a).

The slowdown in R&D and adoption causes a gradual decline (relative to trend) in the number of adopted intermediate goods. Note that, because the number of adopted technologies, A_t, is a state variable, endogenous technology ($A_t * (\vartheta - 1)$) does not decline upon impact but only gradually. Forty quarters after the shock, the endogenous component of TFP has declined by 0.55%, while output has dropped by 1.3%.

In the short term, output evolves similarly in the endogenous and exogenous technology models suggesting that the endogenous technology mechanisms do not produce much amplification of business cycle shocks. Over time, our model produces a significantly larger drop in output. The response of investment is very similar in the endogenous and exogenous technology models throughout. Therefore, the gap in output is driven by the effect of the premium shock on the stock of adopted technologies.
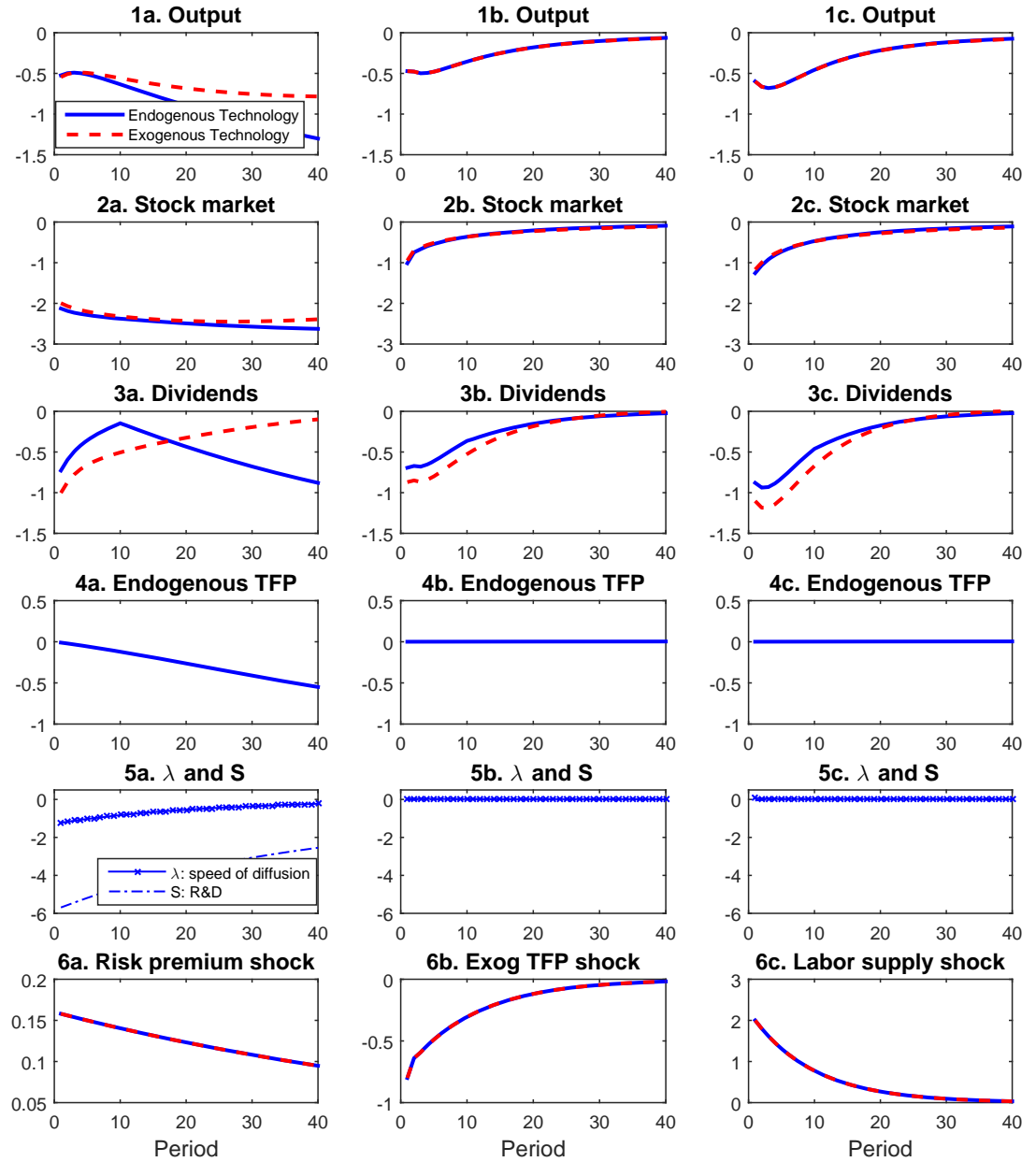
Figure 3: IMPULSE RESPONSE FUNCTIONS TO SHOCKS

Stock prices drop by 2.1% upon the increase in the risk premium (panel 2a). While this drop is similar in the exogenous technology model, the mechanisms at work are very different in both models reflecting the differences in the assets priced by the market. In the exogenous technology model, stock prices just reflect the value of installed capital. Therefore, the decline in stock prices reflects the drop in the price of installed capital and the gradual decline in the stock of physical capital. In the endogenous technology model, the value of corporations also reflects the market value of the technology companies develop and adopt. The majority of the decline in stock prices reflects the drop in the market value of the stock of developed and adopted technologies in response to the higher risk premium. This result is consistent with literature on the value of corporate intangibles (e.g., Hall, 2001, and Prescott and McGrattan XX).

The drop in stock prices is very persistent. This in part reflects the impact that the decline in the speed of diffusion and R&D have on the stocks of adopted, and unadopted technologies (See panels 2a and 5a). This co-movement between stock prices and technology diffusion in our model contrast with that in Pastor and Veronesi (2009). In their model, once a revolutionary technology reaches a certain diffusion level, it moves from being an idiosyncratic risk to an aggregate risk causing a collapse in stock prices. In our model, instead, diffusion is endogenous and responds negatively to risk premium shocks. This co-movement pattern between risk premia and speed of technology diffusion is consistent with the evidence presented in Figure 2 and Table 3.

The responses of stock prices and endogenous TFP in panels 2a and 4a are qualitatively consistent with the predictability of future TFP growth presented in Table 1. In particular, because of the protracted impact of the risk premia shock on the growth rate of newly adopted technologies (i.e., A_t), a contemporaneous increase in the premium (or drop in stock prices) leads to lower future TFP growth. Furthermore, the impulse response function clearly shows that these effect is still at work 40 quarters after the shock (see panel 4a). The root cause for this protracted effect on TFP is the slow diffusion of new technologies that is central to our model.

Interestingly, the predictability of future output and dividend growth in response to a premium shock in the model is more muted than the the predictability of TFP. This is the case because, unlike endogenous TFP, output and dividends are significantly

impacted contemporaneously by the premium shock, and their subsequent growth is smaller than that of TFP.

The second column of Figure 3 plots the impulse response function to a one standard deviation increase in exogenous TFP. The increase in TFP immediately raises output (panel 1b), consumption and investment. The increase output is mimicked by dividends which reflect both the higher marginal product of capital and the higher profits accrued from selling adopted intermediate goods. Higher current and future dividends lead to a contemporaneous increase in stock prices.

It is important to note that stock prices respond very differently to the risk premium and the TFP shocks. TFP shocks have a smaller and more transitory impact on stock prices than risk premia shocks. This is the case because risk premia shocks affect the rate at which future profits are discounted in addition to the flow of profits. TFP shocks only affect stock prices by affecting the flow of dividends.[34] One consequence of this difference is that stock prices are initially impacted more by a risk premium than by a TFP shock. A second consequence is that risk premia shocks have very significant effects on the companies investments in adopting and developing new technologies. In contrast, the impact that TFP shocks have on adoption and R&D investments is much more muted (panel 4b). As a result, risk premia shocks trigger protracted fluctuations in the stock of adopted technologies and, since those are valuable assets, also on stock prices.

Figure 3 helps us understand whether exogenous TFP shocks can produce the observed predictability patterns. As we have discussed, the increase in current and future dividends drives the contemporaneous increase in stock prices. Because TFP shocks have a small effect on endogenous TFP, the overall response of TFP closely resembles the evolution of the TFP shock. After the initial increase in TFP, the mean reversion of the shock leads to a decline in TFP. Therefore, exogenous TFP shocks induce negative co-movement between current stock prices and future TFP growth. That is the opposite of the pattern documented in Table 1.

TFP shocks only impact stock prices through their effect on current and future dividends. Furthermore, as illustrated in Figure 3, the evolution of output and dividends resembles the TFP shock itself. Therefore, exogenous TFP shocks will produce

---

[34]They have a minor effect on discount rates through their effect on the riskless rate which declines slightly in response to a positive TFP shock.

similar predictability patterns for the future growth of TFP, output and dividends. That is inconsistent with the different predictability patterns we have observed for TFP, output and dividends.

The third column of Figure 3 reports the impulse response functions to the labor supply shock (μ_t^w). An increase in μ_t^w contracts labor supply causing a reduction in hours worked and a decline in output and dividends. As with the TFP shock, stock prices are impacted by movements in μ_t^w through their effect on current and future dividends. Therefore, in response to a prospect for lower current and future dividends, stock prices drop upon impact. Because shocks to μ_t^w are mean reverting, they induce negative predictability of the future growth rate of output and dividends by lagged stock prices. μ_t^w have a small effect on adoption and R&D. Therefore, they do not induce any significant predictability of future TFP growth.

4.4 Predictability

We can now proceed to study the drivers of predictability patterns uncovered in section 2. First we investigate what drives the predictability of TFP growth, and later turn our attention to the predictability of output and dividend growth. Methodologically, we simulate 10,000 times the model and, for each run, we estimate the predictability regressions (1). Our estimate of the theoretical predictability in the model is the average point estimate across the 10,000 simulations.[35]

---

[35]Each run is 556 periods long, and we discard the first 400 periods before running the regressions.

Table 6: PREDICTABILITY ESTIMATES FOR TFP GROWTH

Row	Dependent variable	Independent variable		Horizon (p)							
				5	10	15	20	25	30	35	40
1	$TFP_{t,t+p}$	$Stock_{t-20,t}$	Data	0.033	0.048	0.046	0.051*	0.054***	0.049***	0.046***	0.042***
			s.e.	0.034	0.032	0.029	0.027	0.025	0.023	0.021	0.019
			R^2	0.02	0.11	0.15	0.21	0.28	0.28	0.28	0.26
2	$TFP_{t,t+p}$	$Stock_{t-20,t}$	Model	0.011	0.023	0.030	0.033	0.034	0.034	0.032	0.029
			R^2	0.101	0.198	0.284	0.356	0.414	0.463	0.505	0.542
3	Endogenous $TFP_{t,t+p}$	$Stock_{t-20,t}$	Model	0.065	0.064	0.063	0.060	0.057	0.054	0.050	0.045
			R^2	0.651	0.670	0.686	0.700	0.712	0.723	0.733	0.743
4	Exogenous $TFP_{t,t+p}$	$Stock_{t-20,t}$	Model	-0.054	-0.041	-0.033	-0.027	-0.023	-0.020	-0.018	-0.016
			R^2	0.030	0.058	0.083	0.107	0.125	0.142	0.160	0.180
5	$TFP_{t,t+p}$	$Stock_{t-20,t}$	Exogenous Technology Model	-0.052	-0.040	-0.032	-0.027	-0.023	-0.020	-0.017	-0.016
			R^2	0.029	0.057	0.083	0.108	0.127	0.145	0.164	0.184

Note: (i) Note: (i) Standard errors (s.e.) are computed by Monte Carlo simulation as explained in the text. (ii) TFP data is corrected from variation in capital utilization, increasing returns and imperfect competition as in Basu et al. (2006); (iii) Stock data is the value of the stock and bonds of the companies in the S&P 500 deflated by the GDP deflator; (iv) $TFP_{t,t+p}$ is the average annualized growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the average annualized growth rate of stock between quarters t-20 and t; (vi) Our estimate of the theoretical predictability in the models is the average point estimate across the 10,000 series (runs); Each run is 556 periods long, and we burn in the first 400 periods before regression; *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.

35

4.4.1 TFP Growth

Table 6 reports the estimates of the predictability regressions for TFP growth.[36] Row 1 reproduces the estimates from the actual data, and Row 2 from our endogenous technology model. They show that the co-movement between stock price growth and future TFP growth in the model is similar to what we have found in the data. For example, the coefficient of stock price growth over the previous five years on future TFP growth over a 25 quarter horizon is 0.034 in the model and 0.054 in the data. When increasing the TFP horizon to 40 quarters the model's estimate is 0.029 while the data counterpart is 0.042. The model produces a greater predictability at long than short horizons. This is a feature we have observed in the data. The predictive power of stock price growth is very high, more so than in the data. For example, the R^2 of the predicting regression for TFP growth over the next 25 quarters is 0.41 vs. 0.28 in the data.

To understand the mechanism that drives the predictability of TFP in our model, we decompose the simulated TFP series into the endogenous and exogenous components. We re-run the predictability regressions for each of these components. Rows 3 and 4 report the point estimates and R^2's. These estimates show that the predictability of TFP is entirely driven by the endogenous component. Indeed, the predictability of exogenous TFP growth is negative. In other words, in our model, exogenous fluctuations in TFP generate the opposite co-movement patterns between lagged stock price growth and future TFP growth that we observe in the data. In contrast, fluctuations in future endogenous TFP growth strongly co-move positively with lagged growth in stock prices.

To understand the different predictability patterns for endogenous and exogenous TFP growth, recall that virtually all the variation in endogenous TFP in our model originates from the risk premium shock. Risk premia shocks generate large contemporaneous pro-cyclical responses of stock prices. Furthermore, risk premia shocks trigger procyclical responses in adoption and R&D activity which have a protracted effect on TFP growth. The estimates in row 3 show that the co-movement induced by risk premia shocks between stock prices and future endogenous TFP growth accounts for a significant portion of the actual co-movement between these variables in the

---

[36]Given the sample size, the precision of the average point estimate is very high (and we do not report it).

data.

Exogenous TFP shocks induce a negative predictability because they are mean reverting (See panel 5b of Figure 3).[37] As a result, current increases in stock prices induced by positive TFP shocks are followed by declines in the growth rate of TFP. Hence, the negative estimates in the predicting regressions. This intuition also explains why in the exogenous technology model there is a negative co-movement between lag stock price growth and future TFP growth (See row 5 of Table 6). Therefore, the take away is that teh endogenous technology model can produce the predictability of future TFP growth documented in the data while the baseline exogenous technology model cannot.

4.4.2 Output and dividend growth

---

[37]Recall that we have allowed for a AR(2) process for exogenous TFP that we have estimated in the data to match the actual evolution of TFP.

Table 7: Predictability estimates for output and dividend growth

Row	Dependent variable	Independent variable		Horizon (p)							
				5	10	15	20	25	30	35	40
1	$Y_{t,t+p}$	$Stock_{t-20,t}$	Data	0.04	0.02	0.03	0.03	0.03	0.02	0.01	0.01
			s.e.	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12
			R^2	0.01	0	0.03	0.06	0.06	0.04	0.02	0.02
2	$Y_{t,t+p}$	$Stock_{t-20,t}$	Model	0.007	0.014	0.020	0.023	0.021	0.017	0.012	0.006
			R^2	0.125	0.213	0.286	0.345	0.393	0.434	0.472	0.507
3	$Y_{t,t+p}$	$Stock_{t-20,t}$	Exogenous technology model	-0.038	-0.033	-0.027	-0.025	-0.025	-0.026	-0.028	-0.031
			R^2	0.062	0.115	0.165	0.211	0.253	0.293	0.333	0.374
4	$Dividends_{t,t+p}$	$Stock_{t-20,t}$	Data	0.05	-0.05	-0.05	0	0.05	0.06	0.05	0.03
			s.e.	0.09	0.08	0.08	0.08	0.07	0.07	0.06	0.06
			R^2	0	0	0.01	0	0.03	0.05	0.04	0.02
5	$Dividends_{t,t+p}$	$Stock_{t-20,t}$	Model	-0.225	-0.114	-0.051	-0.022	-0.008	-0.002	0.000	0.000
			R^2	0.094	0.153	0.216	0.276	0.329	0.377	0.420	0.461
6	$Dividends_{t,t+p}$	$Stock_{t-20,t}$	Exogenous technology model	-0.342	-0.292	-0.248	-0.213	-0.187	-0.166	-0.149	-0.135
			R^2	0.081	0.138	0.184	0.223	0.257	0.289	0.319	0.347

Note: (i) Standard errors (s.e.) are computed by Monte Carlo simulation as explained in the text; (ii) Stock data is the value of the stock and bonds of the companies in the S&P 500 deflated by the GDP deflator; (iii) Dividend data is the total dividend of the companies in the S&P 500 deflated by the GDP deflator; Y data is real GDP per capital; (iv) $Stock_{t-20,t}$ is the average annualized growth rate of stock between quarters t-20 and t; (v) $Dividend_{t,t+p}$ is the average annualized growth rate of dividend between quarters t and t+p; (vi) Our estimate of the theoretical predictability in the models is the average point estimate across the 10,000 series (runs); Each run is 556 periods long, and we burn in the first 400 periods before regression; *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.

A surprising finding from section 2 is the difference in the predicting patterns found for TFP growth (on the one hand) and output and dividend growth (on the other). Next we explore why this may be the case. We start by running the predictability regressions for output and dividend growth in the data simulated from our endogenous technology model. Table 7 presents the estimates together with those from the data. The main observation is that both for output and dividend growth, the estimates in the model and data are quite similar. For example, the coefficient of stock price growth on the average growth of TFP over the next 25 quarters is 0.03 in the data vs. 0.02 in our model. At a 40 quarter horizon, the coefficient is 0.01 in both data and model. For dividend and earnings growth the data coefficients are more volatile but always far from significant. In our model generated data, the estimated coefficients are close to zero, especially over longer horizons. For example, the point estimate is -0.01 over a 25 quarter horizon and 0 over the 40 quarter horizon. Hence, we conclude that the model is consistent with the predictability pattern documented in the data for output and divivend growth and especially with the higher estimated coefficients of stock price growth on future TFP growth than on future growth in output, dividends and earnings.

To explore the mechanisms behind the lack of association in the model between stock prices and future output and dividend growth we decompose the simulated stock price movements into three additive components which correspond to the variation induced by the three shocks in the model. Then, we reestimate equation (1) using as dependent variable the lagged growth rate of the stock prices series induced by each of the three shocks. Table 8 reports the point estimates from this exercise. The main finding is that, conditional on risk premium shocks, stock price growth is positively associated with future (overall) output and dividend growth. Conversely, conditional on exogenous TFP and labor supply shocks, stock price growth are negatively associated with future (overall) output and dividend growth.[38] The predictability for output and dividend growth results from combining these three patterns.

---

[38]The impulse response functions illustrate that this follows from the mean reverting nature of output and dividends after shocks to exogenous TFP and labor supply. For the risk premium shock, output continues to growth after the initial impact while dividends follow an inverted U-shape.

Table 8: CONDITIONAL PREDICTABILITY ESTIMATES IN MODEL FOR OUTPUT AND DIVIDEND GROWTH

Row	Dependent variable	Independent variable		Horizon (p)							
				5	10	15	20	25	30	35	40
1	$Y_{t,t+p}$	$Stock(premium)_{t-20,t}$	Model	0.091	0.100	0.096	0.089	0.079	0.068	0.057	0.046
			R^2	0.135	0.232	0.310	0.370	0.417	0.455	0.489	0.521
2	$Y_{t,t+p}$	$Stock(TFP)_{t-20,t}$	Model	-0.017	-0.012	-0.010	-0.010	-0.013	-0.016	-0.019	-0.023
			R^2	0.062	0.115	0.166	0.213	0.256	0.297	0.336	0.375
3	$Y_{t,t+p}$	$Stock(muw)_{t-20,t}$	Model	0.006	0.012	0.010	0.006	0.001	-0.004	-0.009	-0.014
			R^2	0.063	0.117	0.168	0.215	0.257	0.297	0.335	0.375
4	$Dividends_{t,t+p}$	$Stock(premium)_{t-20,t}$	Model	-0.787	-0.678	-0.549	-0.456	-0.390	-0.340	-0.300	-0.266
			R^2	0.117	0.222	0.301	0.362	0.412	0.454	0.491	0.524
5	$Dividends_{t,t+p}$	$Stock(TFP)_{t-20,t}$	Model	-0.190	-0.078	-0.019	0.007	0.017	0.020	0.020	0.017
			R^2	0.085	0.145	0.211	0.275	0.330	0.379	0.423	0.463
6	$Dividends_{t,t+p}$	$Stock(muw)_{t-20,t}$	Model	-0.154	-0.042	0.012	0.033	0.040	0.040	0.038	0.034
			R^2	0.077	0.139	0.211	0.278	0.335	0.384	0.429	0.468

Note: We simulate the models 10,000 times (runs). Each run has 556 periods. We discard the first 400 periods to avoid initial value problems. Output and dividends data are computed by feeding all the three shocks, while Stock(premium), Stock(TFP) and Stock(muw) are computed by feeding only risk premium shocks, exogenous TFP shocks, and labor supply shocks, respectively. The estimates of coefficients and R^2 are the average results of 10,000 runs.

The weaker predictability for these variables than for TFP growth is a consequence of two factors. 1. Conditional on risk premium shocks, the predictability of TFP is greater than the predictability of output. 2. The labor supply shock has no effect on TFP but it is the main driver of output fluctuations. Therefore the mean reversion that it induces in output reduces the estimates of the coefficient for the predictability of output in equation (1).

Next, we explore the predictability of output and dividend growth in the alternative model with exogenous technology. Rows 3 and 6 of Table 7 report the average point estimates from the simulated data. The main observation is that in the exogenous technology model, the predictability patterns for output and dividend growth are qualitatively the same as for TFP growth. That is, we observe that an increase in stock prices predicts future declines in the growth of output divdiends and TFP. The intuition is as follows. In all three shocks, stock prices jump pro-cyclically upon inpact. In the shocks to exogenous TFP and labor supply, this reflects expectations about current and future dividends. In the risk premium shock, they also reflect higher current and future discount rates. For the TFP and labor supply shocks, output and dividends are mean reverting because these shocks are mean reverting. Therefore, an increase in current stock prices is associated with a future decline in the growth rate of output and dividends. For risk premium shocks, dividends are also mean reverting but output is not. This helps explain the stronger negative predictability estimated for dividends than for output growth under the exogenous technology model.

4.5   Robustness

We next study how the co-movement between stock price and future growth in the three variables of interest is affected by the values assigned to several key parameters. We conduct this battery of sensitivity analyses with three goals in mind. First, to illustrate the robustness of the findings. Second, to shed light on what are the key parameters in driving the co-movement between risk premia and endogenous TFP growth. Finally, to explore whether there are other versions of the exogenous technology model that can be reconciled with the predictability patterns documented in the data.

We take on the first two goals by substituting on some of the parameter values

used in our baseline calibration of the endogenous technology model. Afterwards, we focus on the exogenous technology model and reexamine the predictability regressions under alternative specifications for the TFP shock processes.

4.5.1 Parameter values

Consider the sensitivity to values set for parameters with less consensus in the literature.

Table 9: ROBUSTNESS OF PREDICTABILITY ESTIMATES IN ENDOGENOUS TECHNOLOGY MODEL

Row	Data/Model predictability	TFP growth		Output growth		Dividend growth	
		t,t+25	t,t+40	t,t+25	t,t+40	t,t+25	t,t+40
1	Data	.054***	.042***	0.030	0.010	0.050	0.030
2	Baseline model	0.034	0.029	0.021	0.006	-0.008	0.000
3	Lower adjustment cost to investment, $f''(1) = 10$	0.038	0.031	-0.007	-0.021	-0.092	-0.069
4	Lower habit, $\psi_h=0.3$	0.038	0.032	0.023	0.009	-0.039	-0.029
5	Higher habit $\psi_h=0.9$	0.030	0.026	0.002	0.007	-0.043	-0.031
6	Higher markup of intermediate good producers $\bar{\mu}= 1.3$	0.034	0.029	0.024	0.010	-0.031	-0.024
7	With variable capacity utilization	0.028	0.025	-0.025	-0.021	0.014	0.002
8	Higher elasticity adoption, $\zeta= 0.95$	0.046	0.036	0.033	0.014	-0.029	-0.025
9	Higher skill labor supply elasticity, $\varphi_s = 1/2$	0.068	0.053	0.050	0.027	-0.009	-0.009
10	Lower elasticity of adoption, $\zeta=0.5$	0.015	0.018	0.005	-0.001	-0.052	-0.038
11	With adjustment costs to R&D	0.027	0.023	0.017	0.004	-0.046	-0.036
12	Lower elasticity of R&D, $\rho=0.4$	0.017	0.014	0.013	-0.001	-0.051	-0.042

Note: We simulate the models 10,000 times (runs). Each run has 556 periods. We discard the first 400 periods to avoid initial value problems. The estimates of coefficients are the average point estimate results of 10,000 runs. The independent of the regressions is the average growth of stock price in the past 5 years, $Stock_{t-20,t}$.

Robustness to lowering adjustment costs to investments. Indeed, predictability of TFP growth increases, while coefficients in equation () predictability of output and dividends decline (intuition).

Robustness to varying habit formation parameter (h).

Robustness to higher markup for intermediate good producers (μ).

Robustness to introducing variable capacity utilization. Little effect on predictability of TFP growth, but it reduces association between stock price growth and future output growth. This is teh case because it raises initial output response and causing greater subsequent mean reversion.

Two ways to increase the volatility of the speed of diffusion: increase the elasticity of adoption, ς, and to increase the elasticity of supply of skilled labor. (Why do they help)?

Lower elasticity of adoption seems key to lowering the effect. Why is it unreasonable? very high R&D lower adoption investments than R&D.

Two ways to lower volatility of R&D: lower elasticity, introduce adjustment costs. Overall.

4.5.2   Alternative specifications of exogenous TFP shock

Before concluding our exploration of predictability, we revisit the alternative hypothesis by considering variour specifications of the shocks to exogenous TFP. Recall that in our baseline calibration we introduce shocks to teh level of TFP that follow an AR(2) process. The autocorrelation coefficients are estimated from the Fernald (2014) capacity corrected TFP data from 1970:I to 2008:III. Now we consider shocks to the growth rate rather than the level of exogenous TFP. We model these shocks as an AR(1) process and follow two different approaches to calibrate them.

The first approach consists in estimating an AR(1) process on the first difference of the Fernald TFP series. This yields an autocorrelation coefficient of -0.15 and a standard deviation for the innovations of the shock of 0.81. A potential concern with this approach is that, despite the efforts to correct for cyclical variation in capacity utilization, markups and increasing returns, the Fernald TFP series may still be polluted by high-frequency factors orthogonal to technology that induce mean reversion in measured TFP. To address this concern, we filter out fluctuations in the Fernald TFP growth series with periods smaller than two years. Obviously, the

resulting series are more persistent. The AR(1) coefficient is 0.89 and the standard deviation for the innovation is 0.15. Note that, the persistence of exogenous TFP growth implies that upon impact of the shock, agents learn that exogenous TFP will be higher in the future. In this sense, this specification is similar to a news shock as in Beaudry and Poitier (xx).

Table 10: Robustness of predictability estimates in exogenous technology model

Row	Data/Model predictability	TFP growth		Output growth		Dividend growth	
		t,t+25	t,t+40	t,t+25	t,t+40	t,t+25	t,t+40
1	Data	0.054***	0.042***	0.03	0.01	0.05	0.03
2	Baseline model with AR(2) shock to TFP $AR(1)=0.80$, $AR(2)=0.12$	-0.023	-0.016	-0.025	-0.031	-0.187	-0.135
3	Model with shock to TFP growth $AR(1)=-0.15$, $\sigma_{\epsilon_A} = 0.81$	-0.015	-0.014	-0.017	-0.029	-0.179	-0.134
4	Model with shock to TFP growth $AR(1)=0.90$, $\sigma_{\epsilon_A} = 0.15$	-0.034	-0.034	-0.010	-0.033	-0.181	-0.143

Note: We simulate the models 10,000 times (runs). Each run has 556 periods. We discard the first 400 periods to avoid initial value problems. The estimates of coefficients are the average point estimate results of 10,000 runs. The independent of the regressions is the average growth of stock price in the past 5 years, $Stock_{t-20,t}$.

Table 9 reports the estimates of the predictability regressions from the simulations of the exogenous technology model under the alternative specifications of the exogenous TFP process. For comparison purposes, we also report the predictability estimates from the actual data (row 1) and from the exogenous technology model in the baseline calibration (row 2).

Our estimates show that the failure of the exogenous technology model to account for the predictability patterns persists with the alternative specifications for the TFP shock process. In particular, the model fails to produce a positive association between current stock price growth and future TFP growth. Similarly, in all specifications there is a strong negative association with future output and dividends growth which is inconsistent with the lack of association we document in the data.

To provide the intuition for these findings, Figure 4 plots the impulse response functions to the three exogenous TFP shocks in the exogenous technology model. In particular, the first column corresponds to the AR(2) shock to the TFP level, the second column to the mean reverting AR(1) shock to TFP growth and the third column to the persistent shock to TFP growth. Though the estimates in the predictability regressions are similar, the mechanisms that drive them differ across the specifications. In both the baseline and the mean reverting shock to TFP growth (second column) there is a contemporaneous increase in stock prices and a mean-reverting increase in TFP. This explains the negative co-movement between stock price growth and future TFP growth. In the TFP growth (second column) TFP is less mean reverting than in the baseline. As a result, stock prices are less negatively associated with future TFP growth.

The responses to the persistent shock to TFP growth (column 3) are quite different. Despite its persistence, TFP growth is still mean reverting. That means that it grows faster shortly after the shock than at longer horizons. Stock prices, drop initially, but then start growing in response to the higher dividends and declining riskless rates. As a result, a period of fast stock price growth precedes the phase where TFP growth is slower. This co-movement produces the negative predictability reported in Table 9.[39]

---

[39]It is important to emphasize that this co-movement is not driven by the initial drop in investment which causes the initial drop in stock prices. Similarly, the negative predictability is not a consequence of the preferences we use. To show this we have replaced our preferences by those in Greenwood, Herzcowitz and Huffman (1988) that do not display wealth effects in labor supply. In
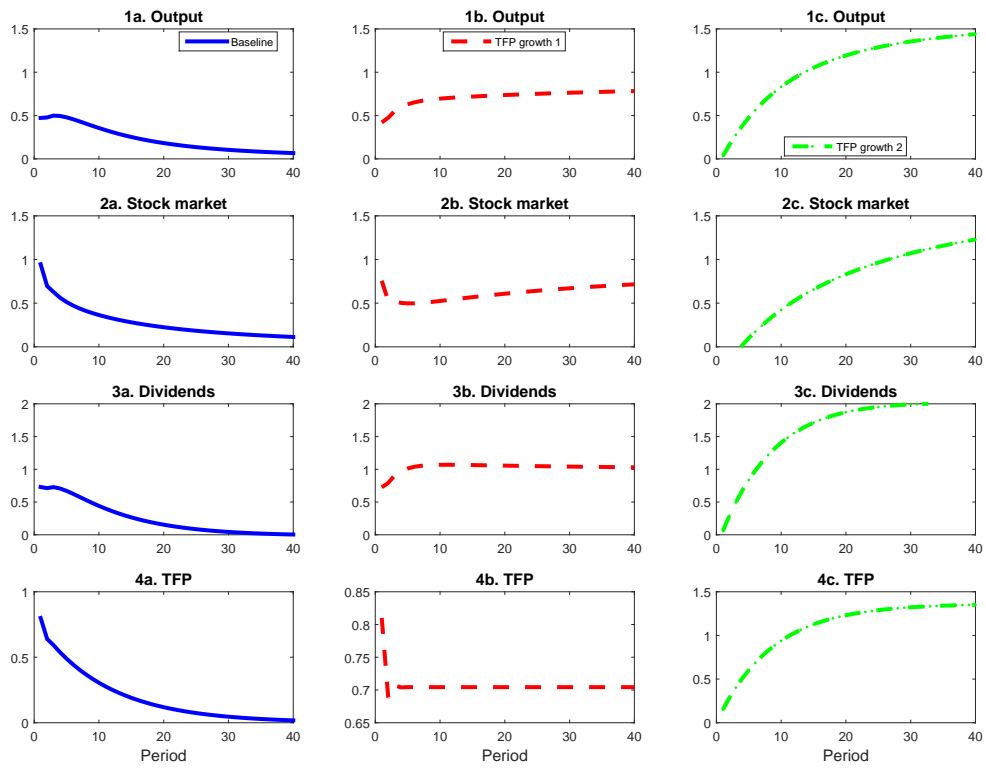
Figure 4: IMPULSE RESPONSE FUNCTIONS TO SHOCKS IN EXOGENOUS TFP MODELS

48

As for TFP growth, the estimates of the predictability of future output and dividend growth are robust to the alternative specifications for the TFP shocks. In particular, the exogenous technology model still produces a negative association between current stock price growth and future growth of output and dividends. This co-movement pattern is generated by all three shocks. Therefore we conclude that the different versions we have explored of the exogenous technology model are not consistent with the predictability patterns uncovered in the data.

5   Evolution of TFP

We conclude our analysis by illustrating the historic relevance of the mechanism highlighted in this paper. To this end, we present the historic decomposition of TFP by our model for the period that covers the so-called productivity slowdown of th 1970s and 1980s. This is a period where the risk premium was high. Figure 5 plots the evolution of TFP detrended with a linear trend of 1.33% (consistent with a steady state growth of output of 2% per year). TFP has fluctuated quite significantly . The most significant development was the productivity which supposed a decline in TFP (relative to trend) of ten percentage points from 1975 until 1990.

Figure 5 also decomposes the evolution of TFP into the endogenous and exogenous components. The two components are not only distinct in nature but evolve very differently. The exogenous component of TFP fluctuates significantly over the business cycle with drops during the 1973, 1980, 1982, and 2008 recessions.[40] While the endogenous component is smoother and does not fluctuate much at high frequencies but fluctuates very significnatly over the medium term. For example, endogenous TFP declined by 10 percentage points between the first quarter of 1975 and the first quarter of 1990. This magnitude represents the overall decline in total TFP. Exogenous productivity instead shows no trend over this fifteen years-period.

---

this case, stock prices increase a bit upon impact rather than decline. However, the estimates of the predictability regressions are very similar to those in Table 9. The coefficient of lagged stock price growth over the previous five years on TFP growth over the next 25 quarters is -0.0257 vs. -0.034 in Table 9, and over 40 quarters it is -0.0414 vs. -0.0335 with standard King, Plosser and Rebelo (1988) preferences.

[40]There is also a drop in the initial stages of the 2008 recession for the three quarters covered by our sample.
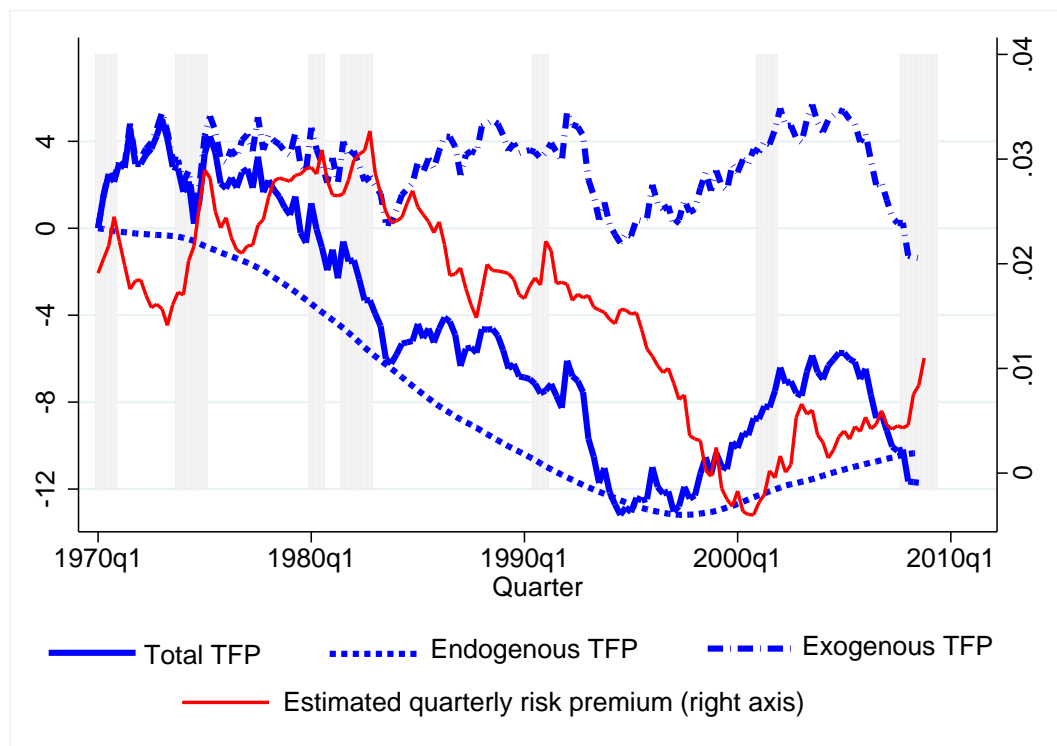
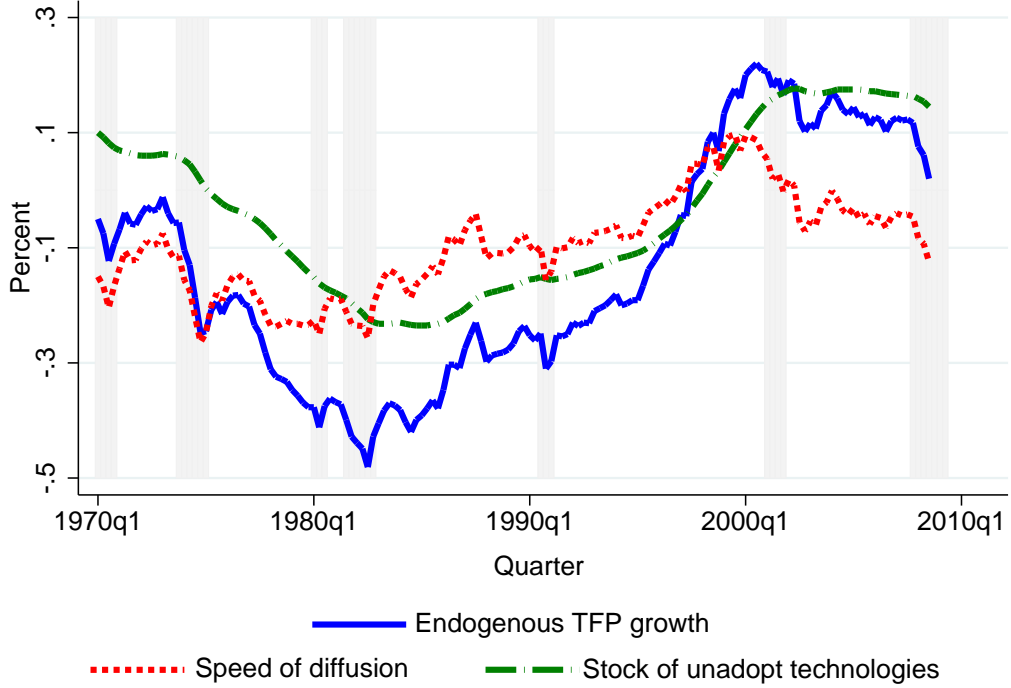Figure 5: TFP: TOTAL, ENDOGENOUS, AND EXOGENOUS

50

Figure 6: Decomposition of endogenous TFP Gowth by Speed of adoption vs. Stock of Unadopted Technologies Components

Next, we explore the channel responsible for the fluctuations in endogenous productivity growth. From equation (32), we derive the following expression for the log-linear gross growth of A:

$$\widehat{g_{At+1}} = \hat{\lambda}_t * \overline{\phi\lambda\left(Z/A - 1\right)/(1 + g_A)} + \left(\hat{Z}_t - \hat{A}_t\right) * \overline{\phi\lambda Z/A/(1 + g_A)}, \qquad (44)$$

where $\hat{x}$ denotes the log-deviation of x from the steady state, and $\bar{x}$ is the value of x in steady state. Equation (44) shows that fluctuations in endogenous TFP growth may originate from fluctuations in the speed of adoption (λ_t) and in the ratio of total technologies to unadopted technologies (Z_t/A_t). Note that the stock of unadopted technologies grows when R&D accelerates and declines when the rate of technology adoption accelerates.

Figure 6 plots the evolution of the growth of A_t and its two components. Our first

observation is that the growth rate of A fluctuates pro-cyclically, something that was not evident from the evolution of endogenous TFP in Figure 5. In particular, we find large drops in the growth rate of A in each of the recessions that hit the U.S. economy during our sample period. Figure 6 clearly shows that the channel responsible for the cyclical variation in the growth of A is the speed of technology diffusion.

The relevance of the speed of diffusion for fluctuations in the growth of endogenous TFP is not circumscribed to high frequencies. For example, the decline in the speed of diffusion contributed to a decline in endogenous TFP between 1975 and 1990 that fully accounts for the productivity slowdown. Conversely, variation in the stock of unadopted technologies (and hence its main driver: R&D) played no role in the slowdown of endogenous TFP. This conclusion is consistent with Griliches (1988) who denoted R&D as a "non-explanation" for the puzzling productivity slowdown of the 70s and 80s. Our analysis not only confirms Griliches' conclusion but it resolves the long-standing puzzle. The slowdown was the result of a protracted reduction in the speed of diffusion of technologies.

6 Conclusions

In this paper, we have uncovered a strong empirical relationship between lagged stock price growth and future TFP growth over medium-term horizons (25-40 quarters). To explore the nature of this relationship, we have developed a DSGE model. The model features endogenous technology through R&D and adoption as in Comin and Gertler (2006), and introduces shocks to risk premia.

Simulations from our model produce TFP growth predictability from lagged stock price growth and premium growth similar to those documented in the data both in terms of the magnitude of the coefficients and its R^2. A version of the model with exogenous technology fails to replicate the empirical predictability of TFP growth. Furthermore, using the historical decomposition of TFP, we have documented that the empirical association between TFP growth and lagged stock price growth fully operates through the endogenous component of TFP. We conclude from this analysis that the predictability of TFP growth is a consequence of the effect that risk premium shocks have on stock prices, the speed diffusion of technologies and TFP growth,

instead of a manifestation of the q-theory of investment or a feed-back from exogenous future TFP shocks to current risk premia.

We have also documented the historical relevance of the mechanisms in our model. Risk premium shocks have been the main driver of fluctuations in technology adoption investments and R&D over the period 1970-2008. In particular, the high risk premia of the second half of the 1970s and 1980s reduced the speed of diffusion of technologies causing *the* productivity slowdown. It was not until the second half of the 1990s, when the decline in the risk premia led to an acceleration in R&D and adoption that also caused the productivity revival of the late 1990s and early 2000s.

Future work may explore the possibility for further amplification of our mechanisms by making the risk premium (partly) endogenous.

References

Abel, B. A. and O. J. Blanchard (1986). The present value of profits and the cyclical variability of investment. *Econometrica 54 (2)*, 249–273.

Aghion, P., M. Angeletos, A. Banerjee, and K. Manova (2011). Volatility and growth: Financial development and the cyclical composition of investment. *Journal of Monetary Economics*.

Aghion, P. and P. Howitt (1992). A model of growth through creative destruction. *Econometrica 60 (2)*, 323–351.

Aghion, P. and P. Howitt (1997). *Endogenous Growth Theory*. MIT Press.

Aghion, P. and G. Saint-Paul (1994). Uncovering some casual relationships between productivity growth and the structure of economic fluctuations. *NBER and Labor*.

Anzoategui, D., D. Comin, M. Gertler, and J. Martinez (2015). Endogenous technology adoption and r&d as sources of business cycle persistence. *Working Paper*.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance 59 (4)*, 1481–1509.

Barlevy, G. (2007). On the cyclicality of research and development. *American Economic Review 97 (4)*, 1131–1164.

Barro, J. R. (1990). The stock market and investment. *Review of Financial Studies 3 (1)*, 115–131.

Basu, S. and J. G. Fernald (1997). Returns to scale in u.s. production: Estimates and implications. *Journal of Political Economy 105 (2)*, 249–283.

Basu, S., M. S. Kimball, and J. G. Fernald (2006). Are technology improvements contractionary? *American Economic Review 96*, 1418–1448.

Bianchi, F., C. Ilut, and M. Schneider (2014). Uncertainty shocks, asset supply and pricing over the business cycle. *Working Paper*.

Blanchard, J. O. (1981). Output, the stock market, and interest rates. *American Economic Review 71 (1)*, 132–143.

Broda, C. and D. E. Weinstein (2010). Product creation and destruction: Evidence and price implications. *American Economic Review 100 (3)*, 691–723.

Caballero, J. R. and A. B. Jaffe (1993). How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. *NBER Macroeconomics Annual 8*, 15–86.

Campbell, Y. J. (2003). Consumption-based asset pricing. *Handbook of Economics of Finance, Chapter 13, Edited by G.M. Constantinides, M. Harris and R.Stulz*, 801–885.

Campbell, Y. J. (2008). Viewpoint: Estimating the equity premium. *The Canadian Journal of Economics 41 (1)*, 1–21.

Campbell, Y. J. and J. H. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy 107 (2)*, 205–251.

Campbell, Y. J. and R. J. Shiller (1988a). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies 1 (3)*, 195–228.

Campbell, Y. J. and R. J. Shiller (1988b). Stock prices, earnings, and expected dividends. *The Journal of Finance, Papers and Proceedings of the Forty-Seventh Annual Meeting of the American Fnanance Associations December 28-30, 1987 43 (3)*, 661–676.

Cochrane, H. J. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance 46 (1)*, 209–237.

Cochrane, H. J. (2008). Financial markets and the real economcy. *Handbook of the Equity Risk Premium, Chapter 7*, 237–330.

Comin, D. (2000). An uncertainty-driven theory of the productivity slowdown: Manufacturing. *Working Paper*.

Comin, D. (2009). On the integration of growth and business cycles. *Empirica 36*, 165–176.

Comin, D. and M. Gertler (2006). Medium-term business cycles. *American Economic Review 96 (3)*, 523–551.

Comin, D., M. Gertler, and A. M. Santacreu (2009). Technology innovationt and diffusion as sources of output and asset price fluctuations. *Working Paper, Harvard University*.

Comin, D. and B. Hobjin (2010). An exploration of technology diffusion. *American Economic Review 100 (5)*, 2031–2059.

Constantinides, M. G. and D. Duffie (1996). Asset pricing with heterogeneous consumers. *Journal of Political Economy 104 (2)*, 219–240.

Cox, W. M. and R. Alm (1996). The economy at light speed: Technology and growth in the information age and beyond. *Federal Reserve Bank of Dallas Annual Report*, 2–17.

Epstein, G. L. and S. E. Zin (1989). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica 57 (4)*, 937–969.

Erceg, J. C., D. W. Henderson, and A. T. Levin (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics 46*, 281–313.

Fama, F. E. (1981). Stock returns, real activity, inflation, and money. *American Economic Review 71 (4)*, 545–565.

Fama, F. E. (1990). Stock returns, expected returns, and real activity. *Journal of Finance 45 (4)*, 1089–1108.

Fernald, G. J. (2014). Productivity and potential output before, during, and after the great recession. *Working Paper*.

Garleanu, B. N., S. Panageas, and J. Yu (2012). Technological growth and asset pricing. *Journal of Finance LXVII (4)*, 1265–1293.

Geroski, P. A. and C. F. Walters (1995). Innovative activity over the business cycles. *Economic Journal 105 (431)*, 916–928.

Greenwood, J. and M. Yorukoglu (1997). 1974. *Carnegie-Rochester Conference Series on Public Policy 46*, 49–95.

Griliches, Z. (1988). Productivity puzzles and r&d: Another nonexplanation. *Journal of Economic Perspective 2 (4)*, 9–21.

Hall, E. R. (2001). Stock market and capital accumulation. *American Economic Review 91 (5)*, 1185–1202.

Hayashi, F. (1982). Tobin's marginal q and average a: A neoclassical interpretation. *Econometrica 50 (1)*, 213–224.

Helpman, E. and M. Trajtenberg (1996). Diffusion of general purpose technologies. *NBER Working Paper N. 5773*.

Hobijn, B. and B. Jovanovic (2001). The information-technology revolution and the stock market: Evidence. *American Economic Review 91 (5)*, 1203–1220.

Iraola, A. M. and M. Santos (2007). Productivity and stock returns. *Work in progress*.

Iraola, A. M. and M. Santos (2009). Long-term asset price volatility and macroeconomic fluctuations. *ITAM Working Paper*.

Jones, I. C. and J. C. Williams (2000). Too much of a good thing? the economics of investment in r&d. *Journal of Economic Growth 5*, 65–85.

Kung, H. and L. Schmid (2015). Innovation, growth, and asset prices. *Journal of Finance 70 (3)*, 73–1037.

Laitner, J. and D. Stolyarov (2003). Technological change and the stock market. *American Economic Review 93 (4)*, 1240–1267.

Laitner, J. and D. Stolyarov (2014). Low-frequency technology shocks, creative destruction, and the equity premium. *Working Paper*.

McGrattan, E. and E. Prescott (2001). Taxes, regulations, and asset prices. *NBER Working Paper No. 8623*.

Norrbin, C. S. (1993). The relation between price and marginal cost in u.s. industry: A contradiction. *Journal of Political Economy 101 (6)*, 1149–1164.

Pastor, L. and P. Veronesi (2009). Technological revolutions and stock prices. *American Economic Review 99 (4)*, 1451–1483.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit, and Banking 1 (1)*, 15–29.

Verdelhan, A. (2010). A habit-based explanation of the exchange rate risk premium. *Journal of Finance 65 (1)*, 123–146.

Weil, P. (1990). Nonexpected utility in macroeconomics. *Quarterly Journal of Economics 105 (1)*, 29–42.

7 Appendix

7.1 Construction of risk premia series

In section 2, we report two measures of the ex-ante risk premium. The first follows Campbell and Cochrane (1999), Campbell (2008), and Cochrane (1991) and is computed by regressing excess stock returns on (lagged) log price-dividend ratios. Excess stock returns are calculated as the difference between real quarterly returns to equity in the S&P 500 companies and the real quarterly yields of 3-month Bills. We compute returns using monthly data on stock prices and use the timing convention adopted by Cochrane (1991). The stock price and dividend data comes from Shiller's web-page. Price-dividend ratios are constructed as the log ratio of stock prices at $t-1$ over the average dividends over the previous year.

Column I of Table 11 reports our estimate over the sample period 1932:I to 2008:IV. The coefficient on the price-dividend ratio is negative (and significant at the 1% level) indicating the presence of mean reversion in stock prices.[41]

The second measure of the risk premium incorporates corporate debt in the value of corporations. Specifically, from 1969 onwards, we compute a measure of quarterly excess returns that also includes the value of corporate debt and the associated interest payments.[42] Column II of Table ?? shows the relation between the excess returns of debt and equity and the excess return of equity. As one would expect, the two are highly correlated with R^2 of 0.93, but including debt reduces the volatility of excess returns.

We construct the ex-ante equity premium series as a two-stage forecast of ex-post excess returns to corporate debt and equity based on the two regressions reported in Table ??. In the first stage we forecast excess equity returns with lagged price-dividend ratios, and in the second stage, we forecast excess equity and bond returns. This two-stage procedure takes advantage of the longer time series of excess equity returns and log-dividend price ratios. The resulting series for the risk premium is the observable used in the estimation of the model.

---

[41]Standard errors are corrected using the Newey-West method with four lags.

[42]The data on corporate data is only widely reported after 1969.

Table 11: FORECASTING EXCESS RETURNS

	I	II
	Excess Equity Return t,t+1	Excess Equity and Debt Return t,t+1
log P-D(t-1)	-0.029***	
	(0.01)	
Excess Equity Return t,t+1		0.726***
		(0.02)
Number of observations	300	157
R^2	0.03	0.93

Note: (i) Standard errors computed using Newey-West method with 4 lags; (ii) Excess Equity return is the difference between real return on equity and real 3 month T-Bill yields; (iii) Excess Equity and Debt is the difference between the real return to the combined value of equity and corporate debt and real 3 month T-Bill yields; (iv) Log P-D(t-1) is the (log of) stock prices at (t-1) over the average real dividend over the previous year.

7.2   Calibration

The discount factor, β, and the average aversion to risky assets, ψ, are set so that the annual riskless rate is 2% and the risk premium is 7%. These values are consistent with the estimates in Cochrane (2001), Campbell, Lo and MacKinlay (1996), and Campbell (2008). The habit formation parameter, ψ_h, is set to 0.3 following the macro estimates of Anzoategui et al. (2015). This is consistent with the micro estimates of Durham and Dale (1991). We set the inverse labor supply elasticities for skilled and unskilled labor, φ_s and φ_u, to 0.5 following Kydland and Prescott (1978) and Kydland (2004). The capital share and depreciation rate are, respectively, set to standard values of 1/3 and 0.02 (quarterly). The government spending to output ratio is set to the post-war average of 16%. The magnitude of the adjustment costs to investment (f'(1)) is set to 3 following the estimates of Christiano, Eichenbaum, and Evans (2005) who estimate a value of 3.1 in a flexible price model.