Stock price fluctuations and Productivity growth[1]

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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]

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[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-

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.

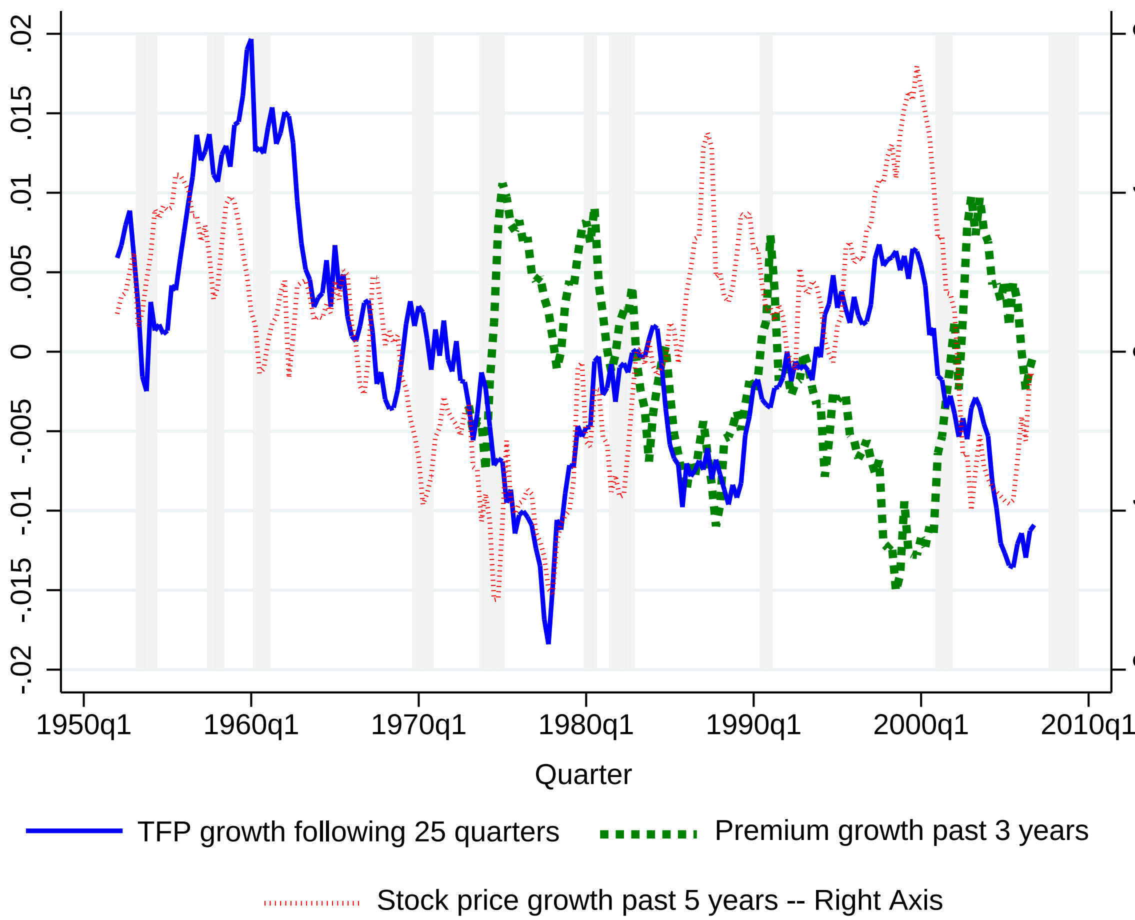

Figure 1: Past Stock Market Growth, Past Risk Premium Growth, and Future TFP Growth

Table 1: Forecastability of TFP with Stock Prices 1947-2013

Dependent variable	Independent variable		Horizon (p) 5	10	15	20	25	30	35	40
$TFP_{t,t+p}$	$Stock_{t-20,t}$		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
$TFP_{t,t+p}$	$Stock_{t-12,t}$		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
$TFP_{t,t+p}$	$Stock_{t-4,t}$		-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
$TFP_{t,t+p}$	$Premium_{t-13,t-1}$		-0.54	-0.58	−0.64**	−0.58***	−0.48**	−0.41*	−0.32*	−0.19
		s.e.	0.39	0.35	0.31	0.27	0.24	0.22	0.20	0.19
		R^2	0.06	0.16	0.28	0.29	0.27	0.28	0.23	0.10

Note: (i) Standard errors (s.e.) are computed by a Monte Carlo procedure as explained in the text. R^2 is the R-squared from the regression. Period is 1947-2013 for Stock prices and 1970-2013 for risk premium; (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 growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the annual growth rate in the stock market between quarters t-20 and t; (vi) TFP_{t+p} is linearly detrended TFP. *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level; (vi) Row 2 and 3 controls for initial TFP (i.e. TFP_t)

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 bottom panel of Table 1 shows that future TFP growth is also predictable with the growth in the lagged risk premium. The predictive power peaks around 20 quarters and the R^2 is 29%. Therefore, the risk premium and stock price growth have a similar predicting power over future TFP growth.

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 neoclassical 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

[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 8. 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.

effect of investment in productivity growth (through capital accumulation) is removed from TFP growth measures by construction.[18] Second, the co-movement 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.

One possible way to rationalize the source of the co-movement in Table 1 is by considering a Campbell-Shiller decomposition of the log dividend-price ratio. 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 might be possible that the estimates in Table 1 reflected the co-movement between future TFP growth and dividend growth which according to the accounting identity (2) should be related to the past 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.

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

[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

Dependent variable	Independent variable		Horizon (p) 5	10	15	20	25	30	35	40
$Dividend_{t,t+p}$	$Stock_{t-20,t}$		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
$Earning_{t,t+p}$	$Stock_{t-20,t}$		-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
$GDP/cap_{t,t+p}$	$Stock_{t-20,t}$		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
$Dividend_{t,t+p}$	$Premium_{t-13,t-1}$		-0.11	1.53	1.57	0.7	-0.37	-0.56	-0.2	0.14
		s.e.	0.78	0.72	0.66	0.60	0.55	0.52	0.50	0.47
		R^2	0	0.04	0.08	0.03	0.02	0.08	0.01	0.01
$Earning_{t,t+p}$	$Premium_{t-13,t-1}$		12.67***	10.07***	5.96	1.67	-2.51	-0.65	1.18	0.71
		s.e.	4.75	4.29	3.82	3.42	3.09	2.83	2.63	2.45
		R^2	0.05	0.08	0.07	0.01	0.07	0.01	0.02	0.01
$GDP/cap_{t,t+p}$	$Premium_{t-13,t-1}$		-0.05	-0.09	-0.01	-0.15	-0.13	0.1	0.39	0.41
		s.e.	1.11	1.09	1.08	1.06	1.04	1.03	1.02	1.01
		R^2	0	0	0	0.01	0.01	0.01	0.15	0.27

Note: (i) Standard errors (s.e.) are computed by a Monte Carlo procedure as explained in the text. R^2 is the R-squared from the regression. Period is 1947-2013 for Stock prices and 1970-2013 for risk premium; (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 growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the annual growth rate in the stock market between quarters t-20 and t; (vi) TFP_{t+p} is linearly detrended TFP. *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level; (vi) All regressions in levels (rows 2 and 3) controlling for initial TFP (i.e. TFP_t)

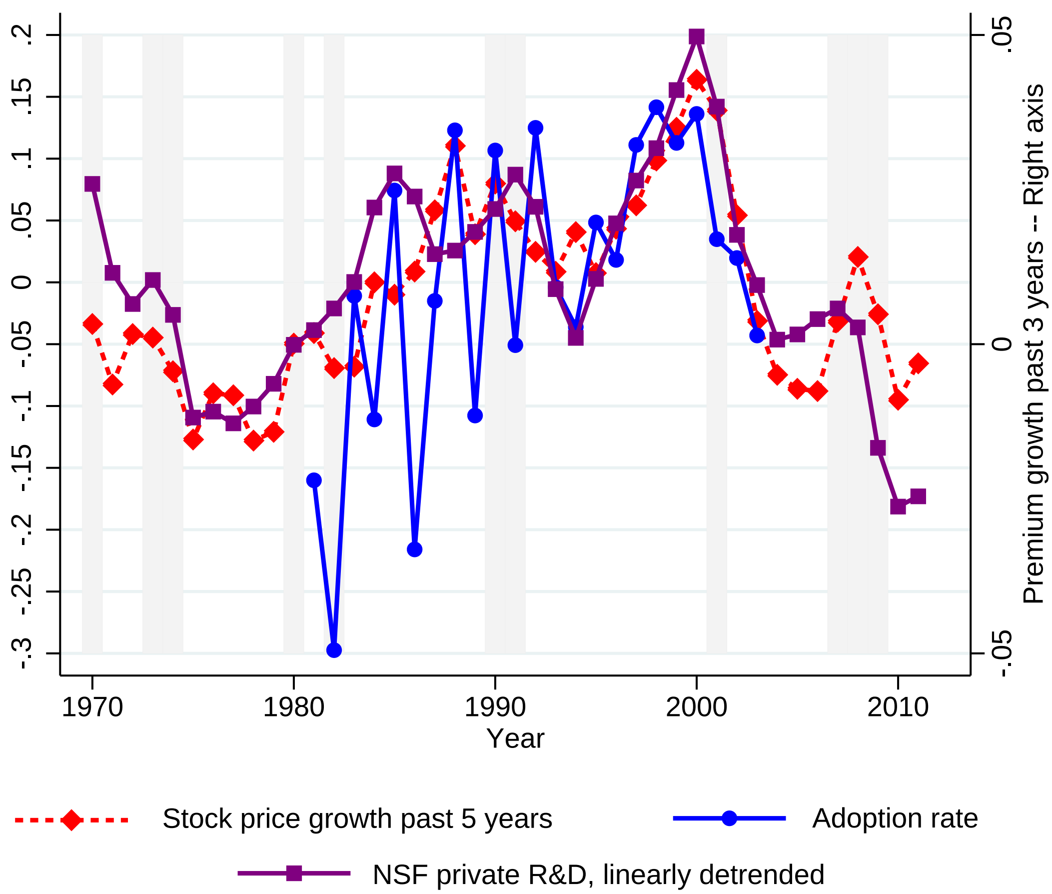

Figure 2: Evolution of Diffusion, R&D, and Risk Premium

To test more directly this hypothesis, we estimate a variation of our baseline regression (1) where the dependent variables are the growth in dividends, earnings and output instead of TFP growth. Table 2 presents the estimates from this exercise. The predictive power of lagged stock price growth and premium growth for the growth of earnings, dividends and output are very limited. In particular, the R^2's are much smaller than for TFP growth, and the point estimates are not significant.[20] The contrast between Tables 1 and 2 suggests that the reason why stock price growth predicts

[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.

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 growth in the risk premium) affect the incentives of companies to invest in developing and adopting new technologies. Movements in TFP growth (especially at long horizons) reflect improvements in production technology. Because, on average, it takes time for new technologies to be brought in production, measures of TFP growth over longer horizons will reflect better the actual variation in technology experienced by companies.[21]

To start exploring these mechanisms, we consider the evolution of direct measures of the firms' investments in developing new technologies and the speed 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.)

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.

[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.

[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.

Table 3: Stock Prices and Endogenous Technology Correlation

	Private R&D	Speed of Technology Diffusion
$Stock_{t-20,t}$	0.79***	0.66***
$Premium_{t-13,t-1}$	-0.75***	-0.47**

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 annualized growth rate in the stock market past five years; (iii) $Premium_{t-13,t-1}$ is the annualized growth rate in risk premium past three years; (iv) Private R&D is the the log-linearly detrended real private R&D expenditures per capita, which is computed by the NSF; (v) 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.

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 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.

The representative consumer maximizes the present discounted flow of utility given by equation (4), subject to the budget constraint (5) and a No-Ponzi game condition.

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

$$B_{t+i+1} + Q_{t+i+1}^d + C_{t+i} + T_{t+i} = \sum_{v \in \{u,s\}} W_{t+i}^v L_{vt+i} + R_{t+i}^f B_{t+i} + R_{t+i} Q_{t+i}^d \tag{5}$$

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

$$\begin{aligned} \upsilon_t W_t^u &= \mu^w L_{ut}^{\varphi_u} && (6)\\ \upsilon_t W_t^s &= \mu^s L_{st}^{\varphi_s} && (7)\\ E_t\left[\beta \Lambda_{t,t+1} R_{t+1}^f\right] &= 1 && (8)\\ E_t\left[\beta \Lambda_{t,t+1}\left(R_{t+1} - \psi_{t+1}\right)\right] &= 1 && (9) \end{aligned}$$

[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.

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

$$\Lambda_{t,t+1} = \frac{\upsilon_{t+1}}{\upsilon_t} \quad (10)$$

$$\upsilon_t = \frac{1}{C_t - \psi_h C_{t-1}} - \frac{\beta * \psi_h}{C_{t+1} - \psi_h C_t} \quad (11)$$

and

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

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

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

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:

$$Y_{it} = \chi_t K_{it}^{\alpha} \left(L_{it}^u \right)^{1-\alpha}, \quad (13)$$

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

Let η_{it} be the marginal cost of production of the i^{th} 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:

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

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

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. In particular, it takes one unit of output to produce one unit of capital. As in Gertler and Karadi (2011), we assume that the production of net investment is subject to flow adjustment costs. Specifically, capital goods producers solve the following maximization problem:

$$\max_{\{I_{nt+\tau}\}} E_t \sum_{\tau=0}^{\infty} \Lambda_{t,\tau} \left\{ (P_{t+\tau}^I - 1) I_{nt+\tau} - f\left(\frac{I_{nt+\tau} + \bar{I}_{t+\tau}}{\gamma_y (I_{nt+\tau-1} + \bar{I}_{t+\tau-1})} \right) (I_{nt+\tau} + \bar{I}_{t+\tau}) \right\}$$

where $P_{t+\tau}^I$ denotes the price of installed capital, $\bar{I}_t$ is the steady state level of (gross) investment in period t, γ_y is the gross growth rate of output in the steady state, and I_{nt} is net investment:

$$I_{nt} = I_t - \delta K_t \tag{25}$$

Furthermore, we assume that $f(1) = f'(1) = 0$, and $f''(1) > 0$.

Optimal production of investment is given by the following condition:

$$P_t^I = 1 + f\left(.\right) + \frac{I_{nt} + \bar{I}_t}{\gamma_y(I_{nt-1} + \bar{I}_{t-1})} f'(.) - E_t \left[\Lambda_{t,t+1} \left(\frac{I_{nt+1} + \bar{I}_{t+1}}{\gamma_y(I_{nt+} + \bar{I}_t)} \right)^2 f'(.) \right] \tag{26}$$

The law of motion for the capital stock in the economy is

$$K_{t+1} = K_t + I_{nt}. \tag{27}$$

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 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 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

[25] In particular, we assume that

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

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

[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).

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]

3.5 The value of corporations

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

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

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

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

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]

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

$$D_t = \overbrace{D_t^K K_t}^{\text{Rental of K}} + \overbrace{A_t \pi_t}^{\text{Profits from A}} - \overbrace{(Z_t - A_t) * h_t * W_t^s}^{\text{Adoption costs}} \tag{39}$$

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.

$$Q_t^d = Q_t \tag{40}$$

The realized return from holding stocks is then given by:

$$R_t = \frac{D_t + Q_t}{Q_{t-1}} \tag{41}$$

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 govern-

[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.

ment runs a balanced budget every period:

$$G_t = T_t \tag{42}$$

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 (27), (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 (40).

4 Empirical evaluation

We next evaluate the model's ability to produce the predictability patterns unocovered in section 2. To this end, we conduct two types of exercises. The first uses data simulated from the model after calibrating the volatility of risk premium and exogenous TFP shocks to their empirical volatilities. The second uses the historical series of TFP and risk premium to identify the model-consistent shocks series. With the simulated data we evaluate the model's ability to produce the predictability of TFP growth observed in the data. The historical analysis of the sources of predictability provides further evidence to identify our mechanisms from others. In particular, it allows to explore whether stock prices and risk premia growth predict the historical endogenous or exogenous components of TFP growth. Before presenting these exercises, we describe the model calibration and present its impulse response functions and theoretical moments.

4.1 Calibration

Table 4 presents the calibrated parameters and their values. 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. Since first two types of parameters are fairly standard in the literature, we postpone the dicussion of their calibration to the Appendix. Here we mostly focus on explaining 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 0.35 following the estimates of Anzoategui et al. (2015).[29] $\bar{\lambda}$ 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). Section 4.7 conducts a robustness analysis to alternative calibrations of the values of ρ and ζ.

[29] Unlike the rest of the literature, this paper estimates the curvature of R&D in the context of a quarterly model like ours. Because of greater diminishing returns in R&D at the high frequency, the point estimate of ρ is lower than in the rest of the literature (e.g., Griliches, 1990).

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	0.5
φ_u	Inverse labor supply elasticity for unskilled workers	0.5
ψ	Steady state risk premium	0.07/4
Production/markup		
α	Share of capital in GDP	0.33
δ	Depreciation rate	0.02
$f''(1)$	Investment adjustment cost parameter	3
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	0.35
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	0.81^2
ρ_ψ	Persistence of risk premium shocks	0.987
ρ_χ	Persistence of exogenous TFP shocks	0.92

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 45% which virtually coincides with the average for the S&P 500 over our sample period of 42%.[30] The value of adopted technologies account for 52% of stock prices in steady state, while unadopted technologies account for the remaining 3%.

In our model we restrict exogenous disturbances to only the risk premium and the exogenous TFP shocks. With this strategy we do not intend to disregard the relevance of other shocks but rather to focus on the minimal set of shocks that allows us to study meaningfully the co-movement between stock prices and TFP. This perspective also guides our approach to calibrate the volatility and persistence of our two shocks. We set the standard deviation and autocorrelation of the risk premium shock to match those of the proxy we have built by forecasting the ex-post excess return by the lagged log-price-dividend ratio (See section 2). To calibrate the parameters in the exogenous TFP process, we first identify the actual realizations of this shock necessary to generate the TFP growth series (1970:I - 2008:III) from Fernald (2014) with our model. Then we set the autocorrelation of exogenous TFP (χ_t) and the standard deviation of its innovations to match those in the identified exogenous TFP series.

4.2 Impulse response functions

To gain a better understanding of the workings of our model, we next study its impulse response functions. Figure 3 plots the impulse response functions to a one standard deviation positive shock to the risk premium. For comparison purposes, we also plot (in dashed red) the response of a version of the model with the same parameter values but without adoption and R&D (i.e. with exogenous technology).

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

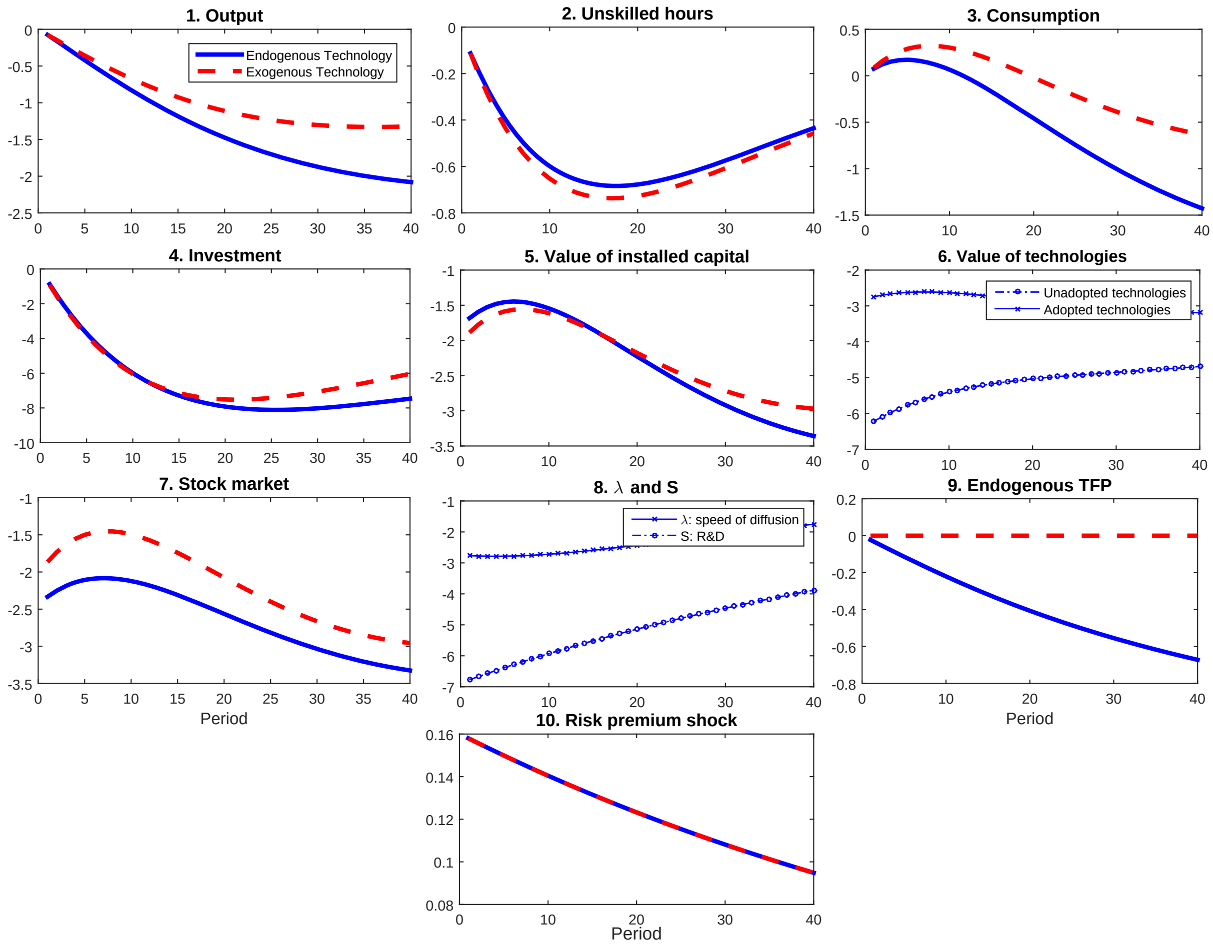

Figure 3: Impulse Response Functions to a Risk Premium Shock

The risk premium shock raises the rate of return required to invest in physical capital causing a decline in investment. Consumption, instead, increases slightly. As a result, the risk premium shock causes an initial decline in output.

The higher premium causes an immediate drop in the value of adopted and unadopted technologies (see panel 6). Potential adopters and intermediate good developers respond to this decline in the value of technologies by cutting the number of skilled hours devoted to R&D and adoption. Hence, the large drop in S and λ (see panel 8). The slowdown in R&D and adoption causes a gradual decline (relative to trend) in the number of adopted intermediate goods, and hence in the endogenous component of TFP (i.e., $A_t * (\vartheta - 1)$). This protracted effect is mirowed by output (and capital). Forty quarters after the shock, output has dropped by almost 3 percentage points and the endogenous component of TFP has declined by almost 1 percentage point.

In the short term, output evolves very similarly in the endogenous and exogenous technology models sugegsting 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. Note that 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.

Stock prices drop by almost three percentage points upon the increase in the risk premium (by one standard deviation). This drop is nearly 50% larger than in the model with exogenous technology. This wedge reflects the different notions of the stock market in both models. While stock prices just reflect the value of installed capital in the exogenous technology model, once technology is endogenized, the value of corporations also includes the value of the technology they develop and adopt. Because the risk premium affects more the values of adopted and unadopted technologies than the installed price of capital (see panels 5 and 6), stock prices drop more in the endogenous technology model. The gradual drop in the stock of adopted and developed technologies, together with the decline in the capital stock, lead to a subsequent decline in stock prices which level of at around 4%.

The evolution of stock prices 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 to being an aggregate risk causing a collapse in stock prices. In our model, instead, the risk premium shock contemporaneously impacts the diffusion rate pro-cyclically. This co-negative movement pattern between risk premia and speed of technology diffusion is consistent with the evidence presented in section 2.

The response of the speed of technology diffusion and R&D to the premium shock cause a pro-cyclical evolution in the growth rate of TFP which results in a permanent shift in the level of TFP. These dynamics are consistent with the predictability patterns documented in section 2.

Figure 4 plots the impulse response function to one standard deviation increase

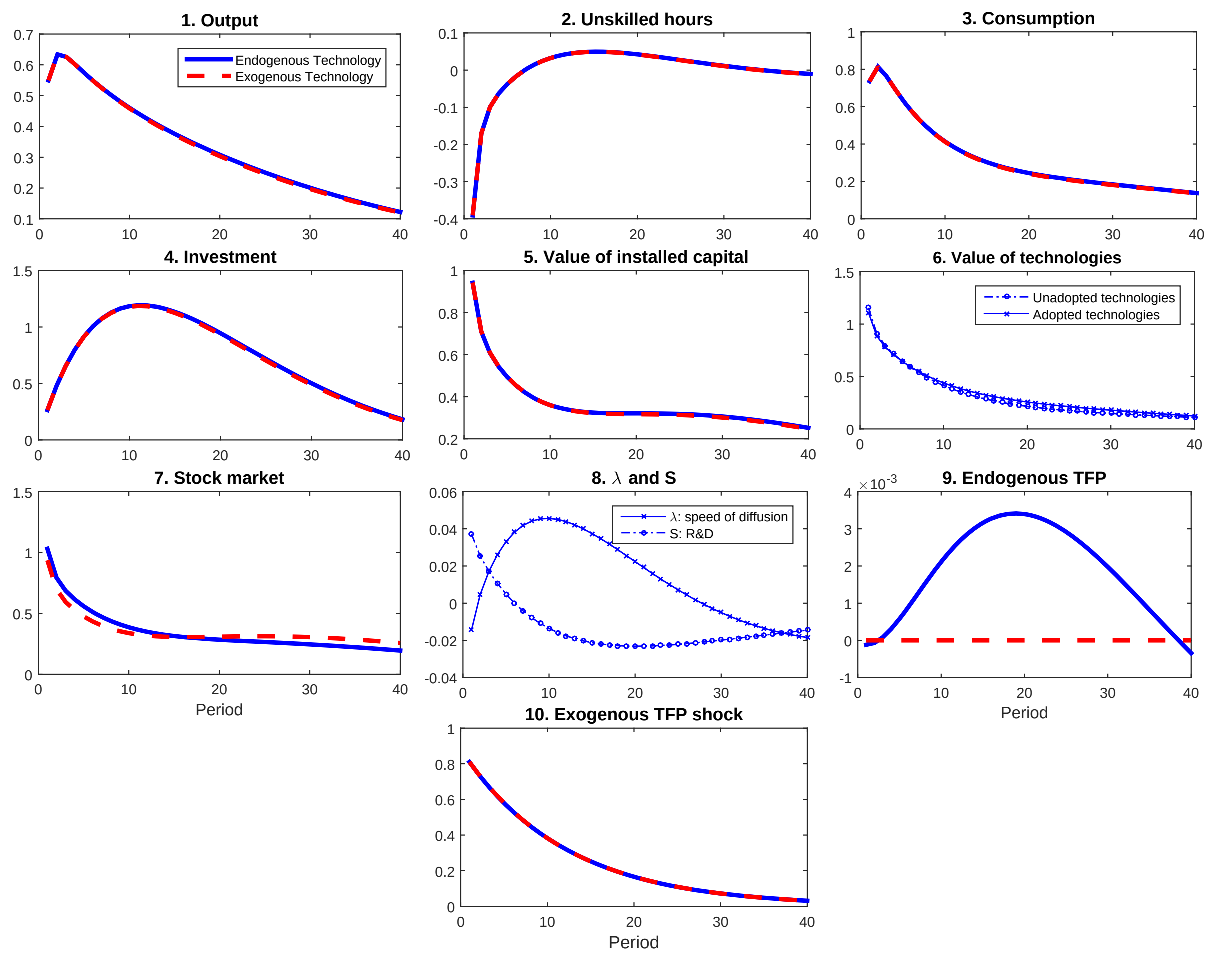

Figure 4: Impulse Response Functions to a TFP Shock

in exogenous TFP. The higher productivity immediately raises output, consumption and investment. Hours worked decline because the income effect dominates the substitution.[31] Stock prices increase reflecting the greater value of installed capital and of newly developed and adopted technologies. The greater value of technologies tends to induce greater investments in adoption and R&D. These are partially mitigated by the increase in the wage for skilled workers. Upon impact, the value effect dominates the wage effect for R&D. For adoption they nearly cancel out. As a result the number of adopted technologies does not increase initially. Slowly the effect on the value of adopted technologies dominates the increase in skilled wages, leading to a gradual increase in the number of adopted technologies and in the endogenous component of TFP. This effect is considerable smaller than the effect induced by the premium shock.

Figure 4 also illustrates the inconsistency of exogenous TFP with the predictability patterns uncovered in section 2. As mentioned above, stock prices increase upon impact of a positive TFP shock. After that moment, the mean reversion of the shock leads to a decline in TFP that the endogenous TFP component cannot mitigate. Therefore, exogenous TFP shocks cause a negative predictability of lagged stock price growth on future TFP growth. Furthermore, because in our model risk premia are exogenous, TFP shocks do not play any role in the predictability reported in Table (1) of risk premia on future TFP growth.

4.3 Theoretical moments

Before evaluating the predictability of TFP growth in the model, we explore the theoretical moments it produces (see Table 5).[32] Columns 1 and 2 report the standard deviation of variables relative to the standard deviation of output (in the model and the data).[33] The relative volatility of stock prices, dividends and the speed of adoption

[31] This is the case because of the habit and the higher persistence induced by the endogenous technology mechanisms. The effect of TFP shocks on hours worked is consistent with teh VAR evidence from Gali (1999).

[32] All variables are HP filtered.

[33] We try to preserve the simplicity of our model by limiting the number of shocks and propagation mechanisms. The standard deviation of HP-filtered output in the model is 0.8 while in the data it is 1.55.

is in the ballpark of the data.[34] The most significant deviation from the data is that the model greatly overpredicts the volatility of R&D expenditures.[35] This surely reflects the lack of adjustment costs in the R&D employment decision in the model. In reality, the volatility of R&D expenditures is lower than what our model predict due to the presence of planning costs and labor hoarding.[36] In section 4.6, we present evidence that suggests that the excess volatility of R&D in the model is not key for the predictability of TFP.

Table 5: Theoretical moments

Variable	Standard deviation		Autocorrelation		Variance Decomposision	
	Data	Model	Data	Model	Risk premium	TFP
Y	1	1	0.83	0.90	31.84	68.16
			(0.73, 0.92)			
St	4.92	4.15	0.77	0.63	77.64	22.36
			(0.66, 0.89)			
Dt	1.74	2.83	0.94	0.69	85.71	14.29
			(0.87 , 1)			
Adoption rate*	5.68	4.02	-0.46	0.16	99.89	0.11
			(-0.78, -0.14)			
RD expenditure*	3.05	9.60	0.91	0.14	99.99	0.01
			(.74, 1.08)			

Note: All variables are HP filtered. Standard deviations are relative to output.
* Annual Data

The autocorrelation and cyclicality of the variables is roughly in line with the data. The main deviation is the speed of adoption which in our series appears mean

[34]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.

[35]We compute R&D expenditures as R&D labor times the skilled wage rate (i.e., $S_t * W_t^S$).

[36]The greater volatility of non-labor than labor costs in R&D suggests the prevalence of labor hoarding in R&D.

reverting at the high frequency due to the small sample of technologies we use to construct it.

Columns 7 and 8 of Table 5 decompose the variance of the HP-filtered variable between the contribution of risk premium and TFP shocks. TFP shocks account for approximately twice as much variance of output as risk premium shocks. For the rest of the variables, the risk premium shock accounts for a much greater variance than the TFP shock. In particular, the variance share attributable to risk premium shocks are 78% for stock prices,[37,38] 88% for dividends, 100% for the adoption rate and 97% for R&D expenditures. The importance of risk premium shocks in the volatility of adoption and R&D is a consequence of the dual effect of the risk premium on the marginal benefit from developing and adopting a technology. While the effect of standard macro shocks is mostly operating through their impact on the profit flows, risk premium shocks have an additional effect through the rate at which these profit flows are discounted. This second effect makes risk premia a powerful driver of fluctuations in the technology upgrading margins.

4.4 Predictability

We can now proceed to evaluate the model's ability to account for the predictability of future TFP growth with lagged stock price growth uncovered in the data. To this end, we simulate 10,000 times the model and, for each one, we run the predictability regressions (1).[39]

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

[38] For comparison purposes, we have conducted a similar decomposition in a version of our model with the same parameter values and shocks but without the endogenous technology mechanisms. The risk premium shock accounts for 57% of the stock market variance.

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

Table 6: PREDICTABILITY OF TFP WITH STOCK PRICES AND RISK PREMIA: MODEL VS. DATA

Dependent variable	Independent variable		Horizon (p)							
			5	10	15	20	25	30	35	40
$TFP_{t,t+p}$	$Stock_{t-20,t}$	Data	0.033	0.048	0.046	0.051*	0.054***	0.049***	0.046***	0.042***
		s.e.	0.034	0.0316	0.0294	0.0271	0.0247	0.0226	0.0208	0.0192
		R^2	0.02	0.11	0.15	0.21	0.28	0.28	0.28	0.26
		Model	0.057	0.055	0.052	0.047	0.041	0.035	0.028	0.022
		R^2	0.094	0.182	0.257	0.321	0.373	0.418	0.458	0.495
		Exogenous Technology Model	-0.094	-0.078	-0.065	-0.054	-0.046	-0.040	-0.035	-0.032
		R^2	0.030	0.057	0.084	0.112	0.139	0.167	0.195	0.223
$TFP_{t,t+p}$	$Premium_{t-13,t-1}$	Data	-0.54	-0.58	−0.64**	−0.58***	−0.48**	−0.41*	−0.32*	-0.19
		s.e.	0.39	0.35	0.31	0.27	0.24	0.22	0.20	0.19
		R^2	0.06	0.16	0.28	0.29	0.27	0.28	0.23	0.1
		Model	-0.894	-0.830	-0.777	-0.724	-0.668	-0.608	-0.546	-0.484
		R^2	0.09	0.18	0.25	0.30	0.35	0.39	0.43	0.47
		Exogenous Technology Model	0.039	0.036	0.023	0.012	0.003	-0.001	-0.001	0.002
		R^2	0.028	0.053	0.069	0.082	0.094	0.108	0.124	0.140

Note: (i) Standard errors (s.e.) are computed by a Monte Carlo procedure as explained in the text. R^2 is the R-squared from the regression. Period is 1947-2013 for Stock prices and 1970-2013 for risk premium; (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 growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the annual growth rate in the stock market between quarters t-20 and t; (vi) TFP_{t+p} is linearly detrended TFP. *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6 reports the average point estimates of the predictability regressions in the simulated data and compares them with those in the actual data. [40] The top panel uses lagged growth in stock prices over the last 5 years as forecasting variable. Our main finding is that the predictability of TFP growth by lagged stock price growth in the model is very similar to what we have found in the data. For example, the coefficient of lagged stock price growth (over five years) on future TFP growth over a 20 quarter horizon is 0.047 in the model and 0.051 in the data. When increasing the TFP horizon to 35 quarters the model's estimate is 0.028 while the data counterpart is 0.046. Over short horizons, the model produces higher estimates than the data although the difference is not statistically significant. In terms of predictive power, the model matches the high predictability observed in the data of lagged growth in both stock rices and risk premia on future TFP growth.

The bottom panel of Table 6 uses the growth in the risk premium over the previous three years as forecasting variable. We find that in the model the lagged premium growth also predicts future TFP growth. In particular, both the average coefficient and predictive power from the simulated data are in line with the data. For example, at a 20 quarter horizon, the coefficient of lagged premium growth on future TFP growth is -0.58 in the actual data vs. -0.72 in the model-simulated data. The respective R^2s are 0.29 vs. 0.3.[41] We conclude from these exercises that our model accounts quantitatively for the predictability of TFP growth documented in section 2.

For comparison purposes, we study the predictability of TFP in a version of our model with exogenous technology.[42] This exercise allows us to evaluate whether exogenous TFP shocks in a q-theory model of investment can produce the co-movement patterns between stock prices and TFP growth documented in the data.

One immediate limitation of neoclassical investment models is that they cannot produce any TFP growth predictability with risk premia. This follows from the fact that, in q-theory models, both TFP and risk premia are exogenous independent processes that, by construction are independent. Therefore in the simulated data

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

[41] All estimates are statistically significant.

[42] The model parameters and shocks processes are set to the same values as in the estimated endogenous technology model.

there will be no co-movement between TFP growth and risk premia.[43]

Accordingly, we focus on the power of the exogenous technology model to produce the TFP-growth predictability with lagged stock price growth over the past 5 years as predicting variable. The sixth row in Table 6 presents the average point estimates. In contrast to the empirical evidence, in the simulations from the exogenous technology model, lagged stock price growth is associated with lower future TFP growth. The intuition behind this result is as follows. A positive TFP shock leads to higher future dividends and, therefore, to higher stock prices. Because TFP shocks are mean reverting, an increase in stock prices triggered by a positive TFP shock is associated with negative TFP growth in the future. Hence the impossibility of the exogenous technology model to account for the empirical predictability of future TFP growth.

Another way to interpret the estimates in Table 6 are in terms of the sources of TFP growth that cause the predictability. Equation (21) implies that TFP can be decomposed between endogenous and exogenous components. This decomposition motivates the question of which of the two components is actually predictable by lag growth in stock prices and risk premium. To answer this question, we can compare the estimates from the forecasting regressions run on the simulations from the models with only exogenous TFP and our model that has both exogenous and endogenous TFP components. Because only in our model we find TFP predictability patterns similar to those in the data, we conclude that it is the endogenous TFP component the one that allows our model to produce the right co-movement patterns between TFP and stock price growth.

4.5 Sources of predictability

The simulations of the model with exogenous TFP from section 4.4 have shown that the neoclassical model is unable to account for the predictability patterns uncovered in section 2. There may be, however, other mechanisms by which exogenous movements in TFP might drive the co-movement between TFP and risk premia observed in the data. Consider, for example, that agents demanded a higher premium on risky assets when they expected exogenous declines of TFP in the future as in long-run risk models (e.g., Bansal and Yaron, 2004). This mechanism might rationalize the predictability

[43] This claim is confirmed in the last row of Table 6.

of future TFP growth by the risk premia.[44] Furthermore, the increase in risk premia will reduce current stock prices generating a positive co-movement between current stock price growth and future TFP growth.

These dynamics differ in two important respects from our model. First, the direction of causation runs from exogenous TFP growth to the risk premium (or stock prices) and not the other way around. Second, the TFP component that is relevant for predictability regressions is the exogenous component. In contrast, our model only produces predictability of *endogenous* future TFP growth. This stark difference provides a testable prediction. Next, we use the historical evolution of the endogenous and exogenous TFP components to investigate which of the two have co-moved with lagged risk premia and stock prices.

[44] One theory that could produce a risk premium that was linked to expectations about future TFP growth is the long-run risk of Bansal and Yaron (2004).

Table 7: FORECASTABILITY OF ENDOGENOUS AND EXOGENOUS TFP

Dependent variable	Independent variable		Horizon (p)							
			5	10	15	20	25	30	35	40
Endogenous $TFP_{t,t+p}$	$Stock_{t-20,t}$		0.037	0.037	0.041	0.044**	0.047***	0.046***	0.046***	0.048***
		s.e.	0.034	0.032	0.029	0.027	0.025	0.023	0.021	0.019
		R^2	0.35	0.38	0.45	0.55	0.64	0.65	0.65	0.63
Exogenous $TFP_{t,t+p}$	$Stock_{t-20,t}$		0.005	0.011	0.004	-0.008	-0.010	-0.017	-0.017	-0.019
		s.e.	0.024	0.021	0.019	0.016	0.015	0.013	0.012	0.011
		R^2	0	0.01	0	0	0.04	0.15	0.18	0.31
Endogenous $TFP_{t,t+p}$	$Premium_{t-13,t-1}$		-0.410	-0.430	−0.46**	−0.51***	−0.56**	−0.52*	−0.49*	-0.460
		s.e.	0.011	0.008	0.006	0.005	0.005	0.004	0.004	0.004
		R^2	0.23	0.27	0.38	0.45	0.43	0.43	0.37	0.31
Exogenous $TFP_{t,t+p}$	$Premium_{t-13,t-1}$		-0.240	-0.400	-0.390	-0.190	-0.150	0.100	0.140	0.190
		s.e.	0.388	0.350	0.307	0.272	0.245	0.223	0.205	0.189
		R^2	0.01	0.09	0.16	0.06	0	0.03	0.07	0.19

Note: (i) Standard errors (s.e.) are computed by a Monte Carlo procedure as explained in the text. R^2 is the R-squared from the regression. Period is 1947-2013 for Stock prices and 1970-2013 for risk premium; (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 growth rate of TFP between quarters t and t+p; (v) $Stock_{t-20,t}$ is the annual growth rate in the stock market between quarters t-20 and t; (vi) TFP_{t+p} is linearly detrended TFP. *** denotes significant at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7 shows that the predictability of TFP growth is entirely driven by the endogenous component of TFP. This finding is consistent with the hypothesis that risk premia drive endogenous TFP fluctuations. Conversely, the estimates in rows 2 and 4 of Table 7 are inconsistent with the alternative hypothesis that exogenous movements in future TFP growth drive current risk premia.

Kung and Schmid (2015) develop a version of the long-run risk theory where exogenous TFP shocks drive endogenous fluctuations in TFP as well as in risk premia.[45] Because fluctuations are driven by TFP shocks, this theory still implies that risk premia should predict future exogenous TFP growth, and hence would not be consistent with Table 7. In more general models, shocks other than exogenous TFP could trigger endogenous TFP mechanisms and create a feed back from endogenous TFP to the risk premium. This mechanism would work in addition to our effect of the (now endogenous) risk premium on endogenous TFP. Note that, both of these mechanisms contribute to the predictability of future TFP growth. However, the fact that the amount of co-movement in our model (with an exogenous premium) is already in the ballpark of the estimate in the data may suggest that this feed back (from TFP to the risk premium) is not quantitatively important. A formal assessment of this hypothesis requires the use of a model that both endogenizes the risk premium and incorporates the endogenous technology mechanisms. Exploring this avenue goes beyond the scope of this paper.

4.6 Evolution of TFP

We continue our analysis of the relationship between risk premia and TFP growth by exploring its historical relevance for the evolution of TFP and stock prices over the period 1970:I to 2008:III.

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 over the last 40 years. The most significant development was the productivity which supposed a decline in TFP (relative to trend) of ten percentage

[45]In particular, the model in Kung and Schmid (2015) features endogenous R&D. Both the analyses in this paper and in Anzoategui et al. (2015) suggests that once adoption lags are properly accounted for, exogenous TFP shocks do not produce significant propagation through endogenous technology mechanisms.

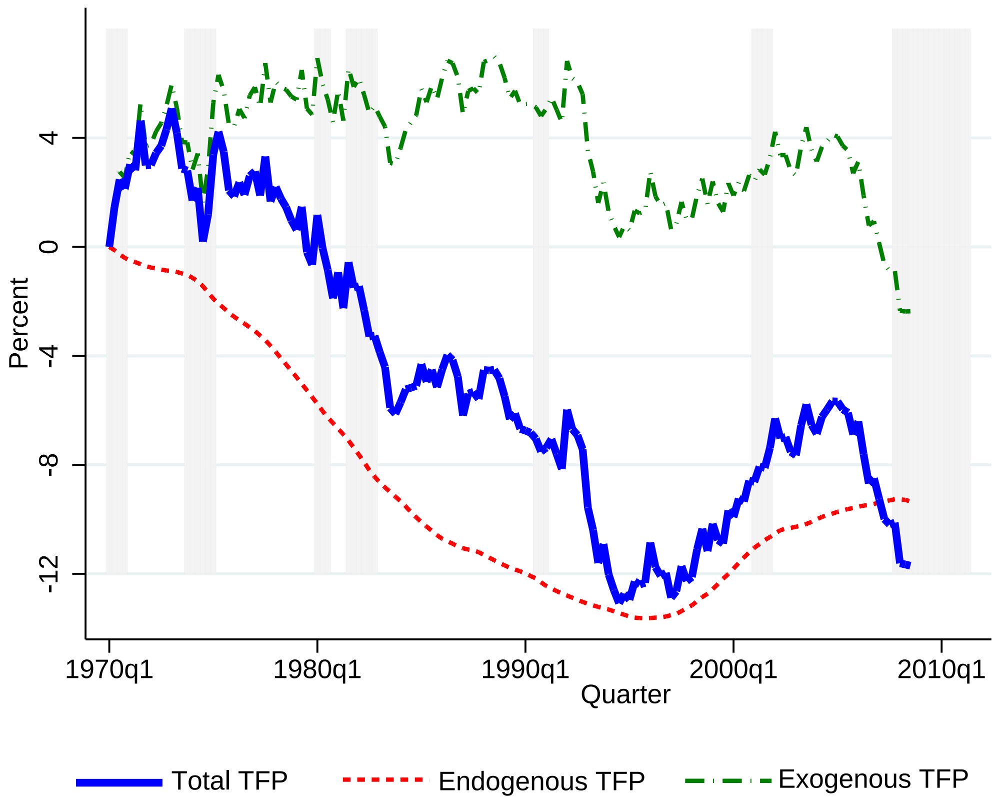

Figure 5: TFP: Total, Endogenous, and Exogenous

points from 1975 until 1990. During the second half of the 1990s and early 2000s, TFP recovered by 4 percentage points but during the second half of the 2000s, it deteriorated again.[46]

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.[47] While the en-

[46]See Fernald (2014).

[47]There is also a drop in the initial stages of the 2008 recession for the three quarters covered by our sample.

dogenous 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. The endogenous component is also relevant for the TFP acceleration during the second half of the 90s and the mid 2000s. In particular, between 1995 and the end of 2004, it increased by 3.8 percentage points which represents roughly half of the increase in total TFP over this period. However, the decline in detrended productivity between 2005 and the end of our sample is due to exogenous TFP.[48] This conclusion is a consequence of the limited type of shocks considered in our analysis. Anzoategui et al. (2015) introduce shocks to liquidity and to the productivity of R&D in a model with similar endogenous technology mechanisms to ours. They show that the endogenous TFP dynamics produced by these shocks accounts for much of the evolution of total TFP between 2004 and 2013.

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:

$$\widehat{g_{At+1}} = \hat{\lambda}_t * \overline{\phi\lambda\left(Z/A-1\right)/(1+g_A)} + \left(\hat{Z}_t - \hat{A}_t\right) * \overline{\phi\lambda Z/A/(1+g_A)}, \tag{43}$$

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 (43) 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 acclerates.

Figure **??** 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

[48] This may be a consequence of the shocks introduced in our analysis. Anzoategui et al. (2015) introduce liquidity shocks in a model similar to ours and show that they can account for much of the endogenous evolution of TFP between 2004 and 2012.

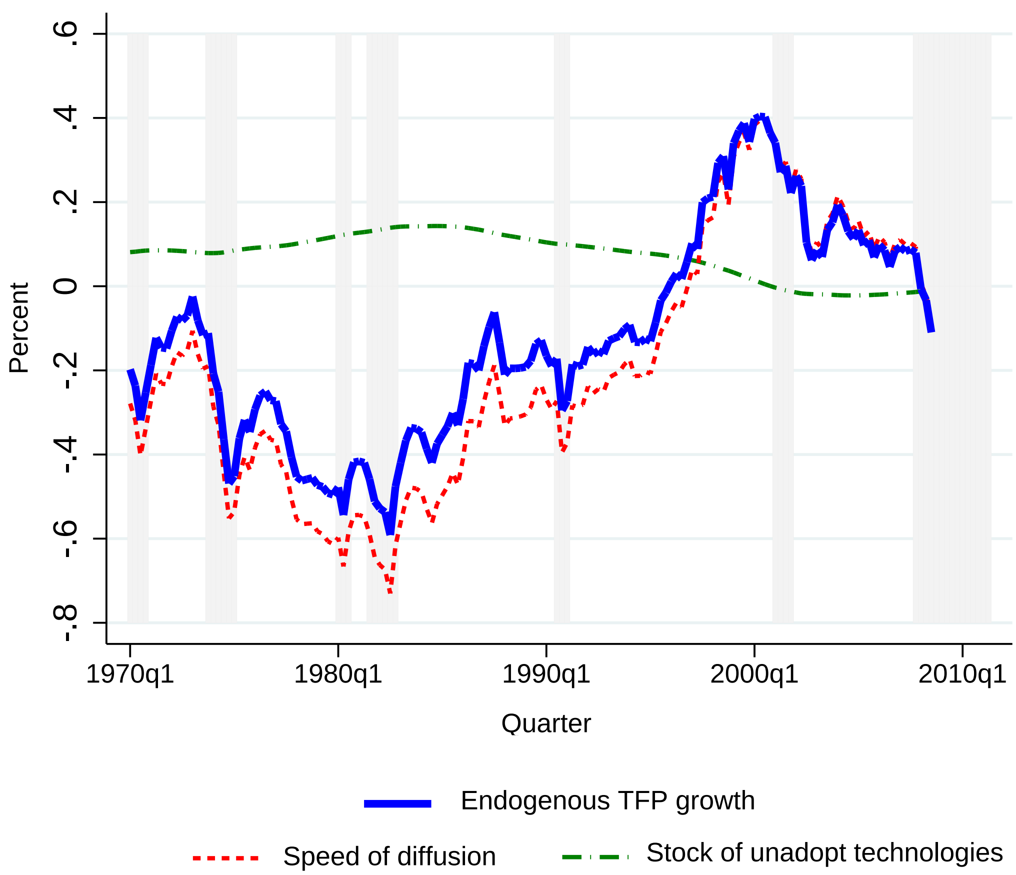

Figure 6: Decomposition of endogenous TFP Gowth by Speed of adoption vs. Stock of Unadopted Technologies Components

U.S. economy during our sample period. Figure **??** 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.

The increase in the speed of diffusion of technologies was also responsible for the acceleration of TFP during the second half of the 90s. Starting in 2000, its contribution to TFP growth declined but it was not until the 2008 recession that it led to a decline in TFP. In contrast, variation in the stock of unadopted technologies led to almost no movements in TFP during the 2000s.

The importance our historical analysis attributes to the speed of diffusion of new technologies begs for the question of whether the fluctuations in the speed of adoption, λ_t, induced by our model are realistic. The empirical evidence on the cyclicality of the speed of diffusion suggests that, indeed, it is reasonable. Anzoategui et al. (2015) studies the cyclicality of the diffusion of 26 specific technologies in the UK and U.S. over the post-war period.[49,50] They find that the speed of diffusion of technologies is

[49] The sample of technologies includes special presses, foils, wet suction boxes, gibberellic acid, automatic size boxes, accelerated drying hoods, basic oxygen process, vacuum degassing, vacuum melting, continuous casting, tunnel kilns, process control by computer, tufted carpets, computer typesetting, photo-electrically controlled cutting, shuttleless looms, numerical control printing presses, numerical control turning machines, numerical control turbines, CT scanners, computerized numerical controlled machines, automated inspection sensors, 3-D CAD, and flexible manufacturing systems.

[50] Specifically, they introduce a term that that captures the economic conditions of the economy in a standard specification of the speed of diffusion of technologies as in Mansfield (1961). Our interest here is just to establish the volatility and co-movement between diffusion and the cycle. However, one may think that, because the technologies in the sample are not general purpose, the potential for reverse causality is negligible.

pro-cyclical and that its elasticity with respect to medium term fluctuations in GDP is four. The relative theoretical volatilities of diffusion and output presented in Table 6 is consistent with this estimate.

To ascertain the plausibility of the historical evolution of the adoption rate in our model, we plot the series of the adoption rate in the model and for the sample of four U.S. technologies (see Figure 7).[51] The correlation between the model and historical series is 0.6. The speed of diffusion was low during the 80s in both model and data. It gradually increased, peaked around 2000 and declined until the end of the series in 2003. This pattern is captured by both model and data. The two main discrepancies between the series are that the empirical measure of the speed of diffusion is less smooth and that the 2000 peak in the model is higher than in the data. Overall, the speed of diffusion series produced by the model are empirically plausible.

Figure 8 presents the historical decomposition of the adoption rate. The figure confirms that risk premium shocks are the fundamental driver of fluctuations in the rate at which new tecnologies diffuse in the economy.[52] The significance of the risk premium shock for productivity dynamics opens a new channel by which risk premia drive output. Previous research on the business cycle consequences of risk premia (e.g., Cochrane (1991)) has emphasized the investment channel as a potential mechanism by which fluctuations in risk premia may affect output. This channel is present in our analysis and is responsible for 31% of the fluctuations in HP-filtered output produced by our model. Through its effect on the firms' decisions to develop and especially to adopt new technologies, risk premium shocks drive the evolution of out-

[51] Specifically, we plot the log-deviations from steady state of λ_t in the model vs. the log-deviations from the (technology-specific) average diffusion rate in the data. See Anzoategui et al. (2015) for details on the data series.

[52] For completeness, Figure A1 in the Appendix plots the historical evolution of R&D expenditures in the model and the data. The model does a poor job in reproducing the evolution of R&D. It fails to account for the strong upward trend in private R&D that occurred in the 70s and early 80s. Furthermore, despite the strong co-movement between model and data, the actual R&D expenditure series are less volatile than in the model. This may partly reflect the possibility of labor hoarding in R&D activities as suggested by the greater cyclicality of non-labor than labor R&D expenditures. It may also be indicative of the relevance of other shocks to explain R&D investments. For example, Anzoategui et al. (2015) show the importance of shocks to the productivity of R&D. Despite this excessive volatility of R&D in the model, Figure 6 has shown that it plays a minor role in explaining the dynamics of TFP and its endogenous component. Figure A2 presents the historical decomposition of R&D expenditures. As for the speed of diffusion, premium shocks are responsible for all variation in R&D in our model.

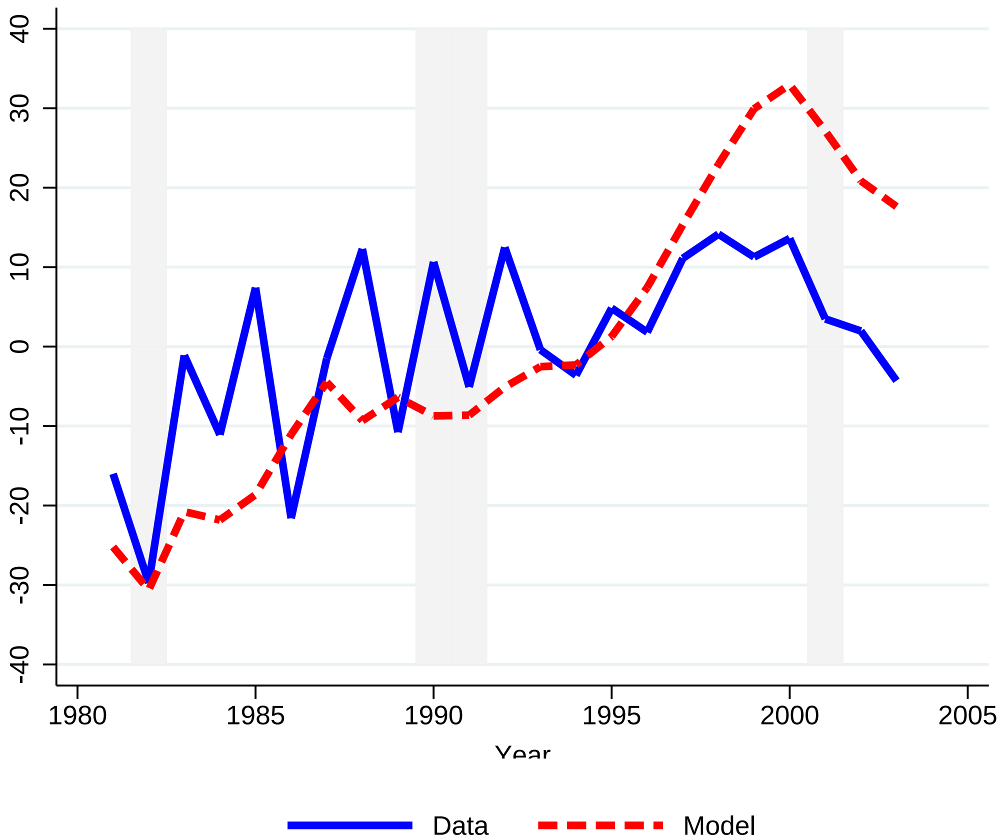

Figure 7: Evolution of Speed of Diffusion

put at lower frequencies. This channel is quantitatively more important for output volatility than the traditional investment channel.

4.7 Robustness

To be added

5 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.

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6 Appendix

6.1 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 8 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.[53]

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.[54] 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.

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

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

Table 8: 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.

6.2 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.

6.3 Appendix exhibits

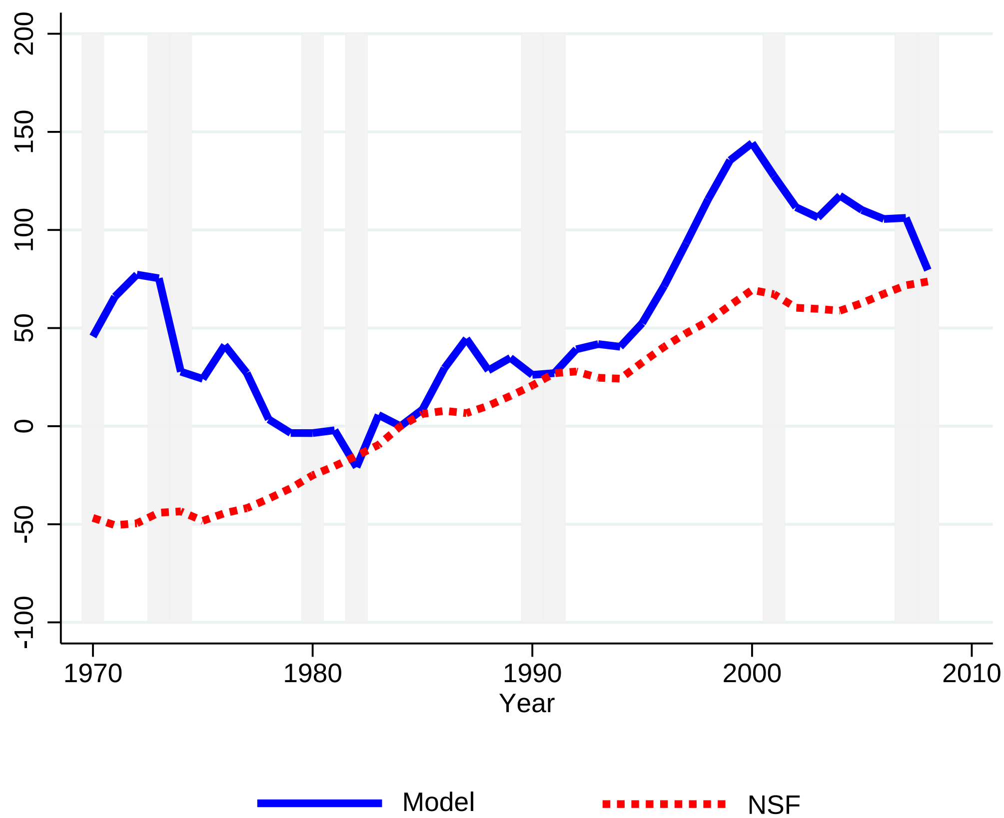

Figure 8: Evolution of R&D expenditure