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The Real Side of Financial Exuberance: Bubbles, Output and Productivity at the Industry Level

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The Real Side of Financial Exuberance: Bubbles, Output and Productivity at the Industry Level

Francisco Queirós*

Abstract
There has been a growing interest in the theory of rational bubbles. Recent theories predict that bubbles are expansionary, but differ in the underlying mechanisms. This paper provides empirical evidence that help us assess different theories, and documents four main findings: stock market overvaluation is associated with (i) faster output and input growth, (ii) declining TFP growth, (iii) a greater contribution of labor for output growth, with no change in the contribution of capital, (iv) an increase in the number of firms. Overall, these findings suggest that bubbly expansions are driven by increased factor accumulation (in particular labor), and not from higher productivity growth.

JEL classification: E44, G12, G31, G32

Keywords: Stock prices, fundamentals, bubbles, productivity growth.

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1 Introduction

There has been a revived interest, in recent years, in theory of rational bubbles. Motivated by the large fluctuations in stock markets and in wealth-to-GDP ratios observed in recent years, a new generation of models has been developed to explain how surges in asset prices can be a source of business cycle fluctuations and boost economic growth. Although most of the recent literature shares the common prediction that bubbles stimulate production, there is substantial disagreement about the underlying mechanisms. For example, several theories suggest that bubbles can be expansionary by triggering a reallocation of resources from unproductive to productive (but constrained) entrepreneurs, thereby resulting in greater aggregate TFP (Martin and Ventura (2012), Miao and Wang (2012), Hirano and Yanagawa (2017), Hashimoto et al. (2020), Clain-Chamosset-Yvrad et al. (2021)). A different class of models yields, however, a different prediction — the possibility of issuing overvalued assets (such as stocks) provides firms with a subsidy and allows unproductive firms to enter (or inefficient incumbents to remain active). This can result in a deterioration of aggregate productivity, and in the possibility for inefficient booms, with too many firms entering (Queirós (2021), Tang and Zhang (2021)).

In this paper, I aim to provide an empirical characterization of stock market overvaluation, and study its comovement with real economic variables. I seek to answer the following questions: when firms become overvalued in one industry, what happens to the dynamics of productivity? Does it grow faster or slower? And what happens to output growth? And to its sources?

To answer these questions, I proceed in two parts. First, I construct measures of stock market overvaluation at the industry level. The baseline measure I build is based on Campbell and Shiller (1988) and consists in calculating the difference between stock prices and an estimate of the NPV of dividends. Importantly, this measure is consistent with the definition of a rational bubble. The results of this paper can thus be used to assess different theories in the rational bubble literature.

Second, I combine these measures with industry-level data on output, inputs and productivity from the BLS Multifactor Productivity Database, as well as data on the number of firms and establishments from the US Census Bureau. I document four main findings. In particular, when the estimated bubble component of one industry increases, we observe

Fact 1: faster output and input growth (capital and labor)

Fact 2: declining TFP growth

Fact 3: when looking at growth accounting decompositions, there is a higher contribution of labor, with no change in the contribution of capital and a decline in the contribution of TFP

Fact 4: an increase in the number of active firms and establishments

Several conclusions can be drawn from these findings, which have important implications for the recent bubble literature. First, during a stock market bubble, growth does not seem to come from an increase in allocative efficiency, as several models suggest. Rather, growth appears to be driven by increased factor accumulation, and to happen in spite of a deterioration in productivity growth (facts 1 and 2). Second, when looking at the importance of each factor of production, growth seems to come mostly from a rising contribution of labor, and not so much from a greater contribution of capital; the growth contribution of TFP experiences a significant decline (fact 3). This finding is also relevant to the recent developments in the theory of rational bubbles. In particular, several models have emphasized how asset bubbles can alleviate credit market imperfections, allowing constrained firms to expand.[1] While this finding does not deny the importance of credit market considerations, it indicates that understanding growth during an stock market boom requires a better understanding of the interactions between asset bubbles

[1]See Farhi and Tirole (2012), Martin and Ventura (2012) or Hirano and Yanagawa (2017), among many others.

and labor markets. Finally, stock market bubbles seem to be associated with a change in the industry market structure, in particular with an increase in the number of active firms (fact 4). This last fact is consistent with recent models studying the interaction between bubbles and firm dynamics (Queirós (2021), Tang and Zhang (2021)).

The findings of this paper are shown to be robust to alternative indicators of stock market overvaluation, and to hold at different time intervals. Taken together, they offer a novel perspective on the interactions between bubbles and production variables, and highlight potential downsides of stock market overvaluation. I conclude by discussing possible policy implications and hints for future research.

Related Literature This paper is connected to the literature studying *mispricing* in stock markets. The hypothesis that stock prices can deviate from fundamentals was the object of a strand of research that started in the 1980s. This includes the variance bound tests of Shiller (1981), LeRoy and Porter (1981) and West (1988), and the statistical tests of the present value model pioneered by Campbell and Shiller (1987, 1988). A common conclusion of this literature is that stock prices exhibit volatility levels that cannot be explained by standard present value relationships.[2]

The real consequences of stock market mispricing has been also studied by previous research. A robust finding in the literature is that there is a strong correlation between proxies for overvaluation and investment at the firm level (Baker, Stein and Wurgler (2003), Goyal and Yamada (2004), Gilchrist et al. (2005), Polk and Sapienza (2009), Chirinko and Schaller (2011), Campello and Graham (2013)). An exception is Bakke and Whited (2010), who find no correlation between

[2]See also Ofek and Richardson (2002) and Lamont and Thaler (2003) for specific evidence of the dotcom bubble. Brunnermeier and Nagel (2004) and Griffin et al. (2011) have shown that overvaluation in this episode cannot be exclusively attributed to irrational traders.

mispricing and investment when correcting for measurement error in Tobin's Q. Contrarily to the majority of these studies, I do not rely on proxies for overvaluation (such as market-to-book ratios or dispersion in earnings forecasts); instead, I make use of a precise definition of fundamentals and overvaluation, which is consistent with the definition of a rational bubble. Furthermore, I conduct my analysis at the industry level, and can hence study the comovement between overvaluation and industry-level aggregates such as total factor productivity.[3]

Finally, this paper is related to the recent macroeconomic literature studying rational bubbles.[4] I contribute to this literature by identifying the channels through which bubbles can lead to higher growth. Some papers have used the Campbell and Shiller (1988) methodology to obtain aggregate estimates of the bubble component of the US stock market, and characterize its response to monetary policy shocks (Galí and Gambetti (2015)), or its impact on aggregate output (Tang and Zhang (2021)). Contrarily to these papers, I conduct my analysis at the industry level and, among other things, study the comovement between bubbles and productivity growth.

This article is organized as follows. Section 2 describes the measures of stock market overvaluation that I construct. Section 3 studies the correlation between overvaluation, productivity and other industry variables. Section 4 concludes.

2 Measuring Stock Market Overvaluation

I start by describing the two indicators of stock market overvaluation that I construct. The main indicator I use is based on Campbell and Shiller (1988), and consist in calculating the different between stock prices and an estimate of the NPV of future dividends; I shall refer to

[3]Related to this paper, Bennett et al. (2020) show that firm-level productivity increases in the degree of stock price informativeness.

[4]See Martin and Ventura (2018) for a summary of the literature.

it as the *Campbell and Shiller price-fundamental deviation*. While this measure is consistent with the definition of a rational bubble, its construction requires different assumptions. Therefore, I complement the analysis with a simpler indicator, which is often used in the literature, namely the *Shiller CAPE ratio*. I explain each of these measures below. Before doing so, I make a brief description of the data used to construct these two indicators.

2.1 Data description

To construct the measures of stock market overvaluation, I use annual data from COMPUSTAT for the period 1975-2019. Companies with annual revenue or market capitalization of $10,000 or less are excluded. Apart from this selection criteria, the panel contains all firm-year observations with nonmissing data on sales, earnings (EBITDA), stock prices, common shares outstanding and industry classification (see Appendix A.1 for data definitions). Firms are grouped in 3-digit industries, consistent with the classification used in the BLS *Multifactor Productivity Database* (which will be also used in this paper). The full sample includes 218,167 observations, for an average of 4,848 firms per year. Online Appendix B.1 provides details on the industry classification, as well as the number of firms and total stock market capitalization of each industry.

2.2 Indicators of stock market overvaluation

The Shiller CAPE ratio The first measure of stock market overvaluation I construct is the Shiller CAPE ratio. This is a popular indicator of overvaluation and is simply constructed as the ratio of total stock market capitalization to a 10-year moving average of past earnings (used as a proxy for fundamentals).[5] In this paper, I compute this ratio at the industry level. I construct industry indexes for stock market capitalization and earnings, correcting for entry/exit in the dataset (see Appendix A.2 for details). For each industry I then construct

$$\text{cape}_{it} = p_{it} - \bar{e}_{it}^{10}$$

where p_{it} is the real stock price (in logs and at the end of t) and $\bar{e}_{it}^{10} \equiv \log\left[\left(E_{it-9} + \cdots E_{it}\right)/10\right]$ is a 10-year moving average of log real earnings. The earnings metric I use is the EBITDA.

The Campbell and Shiller price-fundamental deviation Despite being a simple and intuitive indicator of overvaluation, the CAPE ratio has two main disadvantages: it is backward looking (fundamentals are proxied with past earnings) and does not make use of a formal definition of fundamentals (i.e. the discounted value of future dividends). To address these concerns, I construct a second measure based on Campbell and Shiller (1988). This consists in calculating the difference between stock prices and an estimate of the value of discounted future dividends, where the latter are predicted by means of a VAR. This will require more assumptions than the CAPE ratio, but its outcome is consistent with the definition of a rational bubble.

Suppose that an industry i pays a stochastic sequence of dividends $\left\{D_{it+j}\right\}_{j=1}^{\infty}$ to be discounted at rates $\left\{R_{it+j}\right\}_{j=0}^{\infty}$. Then the fundamental value of the industry (i.e. the expected discounted value of its future dividends) can be written as

$$F_t = E_t\left\{\sum_{k=1}^{\infty} \frac{D_{t+k}}{\prod_{j=0}^{k-1} R_{it+j}}\right\} \tag{1}$$

[5] Robert Shiller provides a monthly version of this measure for the S&P Composite index, from January 1871 to now; this features a historical maximum in December 1999, at the peak of the dotcom bubble.

As shown by Campbell and Shiller (1988), we can write (1) in log-linear form as

$$f_{it} \approx d_{it} + \sum_{j=0}^{\infty} \rho_i^j E_t \left\{ \Delta d_{it+j+1} - r_{it+j} \right\} + c_i \tag{2}$$

where c_i is a constant and $\rho_i = \exp\left(\bar{g}_i - \bar{r}_i\right)$, and $\bar{g}_i$ and $\bar{r}_i$ denote the growth rate of dividends and the discount rate along a balanced growth path.[6] Equation (2) can be used to estimate the fundamental f_{it}, given assumptions about the required rate of return r_{it}. In what follows, I will assume that it can be approximated by a market return r_t^M (e.g. the return on the SP composite index) plus some industry-specific component σ_i so that

$$E_t \left\{ r_{it} \right\} = E_t \left\{ r_t^M \right\} + \sigma_i$$

Although σ_i is introduced to keep the framework general, I will set $\sigma_i = 0$.[7] As I show in Online Appendix B.3, σ_i essentially pins down the level of the fundamental, but does not affect its time series patterns. Since in all the regressions that follow I exploit within-industry variation (i.e. I include industry fixed effects), the exact level of the fundamental will not be important.

Given these assumptions, the right-hand side of (2) can be computed once we estimate a process for $\Delta d_{it+1} - r_t^M$. Following Campbell and Shiller (1988) I consider the following VAR

[6] In particular, $c_i = (1-\rho_i)^{-1} \log(1/\rho_i) - \log(1/\rho_i - 1)$.

[7] Note that r_t^M is market return (not a risk-free rate), and will incorporate a time-varying risk-premium.

$$\underbrace{\begin{bmatrix} \Delta d_{it+1} - r_t^M \\ \\ p_{it+1} - d_{it+1} \\ \\ \text{cape}_{it+1}^{10} \end{bmatrix}}_{\mathbf{z_{it+1}}} = \underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ \\ a_{21} & a_{22} & a_{23} \\ \\ a_{31} & a_{32} & a_{33} \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} \Delta d_{it} - r_{t-1}^M \\ \\ p_{it} - d_{it} \\ \\ \text{cape}_{it}^{10} \end{bmatrix}}_{\mathbf{z_{it}}} + \underbrace{\begin{bmatrix} u_{it+1}^1 \\ \\ u_{it+1}^2 \\ \\ u_{it+1}^3 \end{bmatrix}}_{\mathbf{u_{it+1}}} \tag{3}$$

In this VAR all variables are in deviation from their industry-specific mean (hence the exclusion of a constant term). Both the price-dividend ratio $(p_{it} - d_{it})$ and the CAPE ratio $\left(\text{cape}_{it}^{10}\right)$ are included as predictors of discounted dividend growth $\left(\Delta d_{it+1} - r_t^M\right)$. As shown by Campbell and Shiller (1988), the inclusion of the price-dividend ratio is important and is theoretically justified: it provides a statistical summary of all the information that market participants have about future dividends and discount rates (which can be partially unobservable to the econometrician). Indeed, in the absence of overvaluation, p_{it} is itself the present discounted value of future dividends.

The VAR in (3) is estimated with OLS and the results are shown in Table 5 (Online Appendix B.2). Dividends are the sum of common dividends and net stock repurchases.[8] Both the price-dividend ratio and the Shiller CAPE ratio are shown to be significant predictors of discounted dividend growth. Given these estimates, we can compute the fundamental defined in (2) as

$$\hat{f}_{it} = d_{it} + \mathrm{e}_1 \hat{\mathrm{A}} \left(I_3 - \rho \hat{\mathrm{A}}\right)^{-1} \mathbf{z_{it}} + c$$

where $\mathrm{e}_1 = [1 \;\; 0 \;\; 0]'$. Using $\bar{r}^M = 0.071$ (the average annual real return on the S&P composite

[8]See Appendix A.1 for details. The inclusion of (net) stock repurchases is of special importance, given that firms increasingly distribute cash flows through stock buybacks (Fama and French (2001)).

index in the period), $\sigma_i = 0$ (as explained above) and $\bar{g}_i = 0.03$ (the long-run dividend growth rate), I obtain $\rho = 0.960$ and $c = 4.194$. I then measure the degree of stock market overvaluation as the difference between the log stock price and the log fundamental

$$\text{pdev}_{it} = p_{it} - \hat{f}_{it}$$

I shall refer to this difference as the Campbell and Shiller price-fundamental deviation.

Figure 1 shows the evolution of observed prices and estimated fundamentals in two industries: 'Food, Beverage and Tobacco Manufacturing' and 'Broadcasting and Telecommunications'. In the first case, stock prices exhibit relatively mild fluctuations around the estimated fundamental. In the second case, it is possible to observe a larger price-fundamental deviation around the year 2000 (coinciding with the dotcom bubble). I next investigate how these two measures of stock market overvaluation comove with industry-level aggregates, in particular total factor productivity.

3 The Real Side of Stock Market Overvaluation

I now proceed by analyzing the relationship between overvaluation and real industry variables. As explained below, all production and productivity data come from official statistics (namely, the Bureau of Labor Statistics). They therefore comprise all firms in the economy and not just the set of public companies. This fact is important, since there is typically a time lag between the creation of a firm and its possible addition to the stock market.[9] Thus, the results include the effects of firms that are created during a stock market boom (maybe in reaction to overvalued

[9] According to Ritter (2021), within the 1980-2020 period, firms going public had a median age of 8 years.

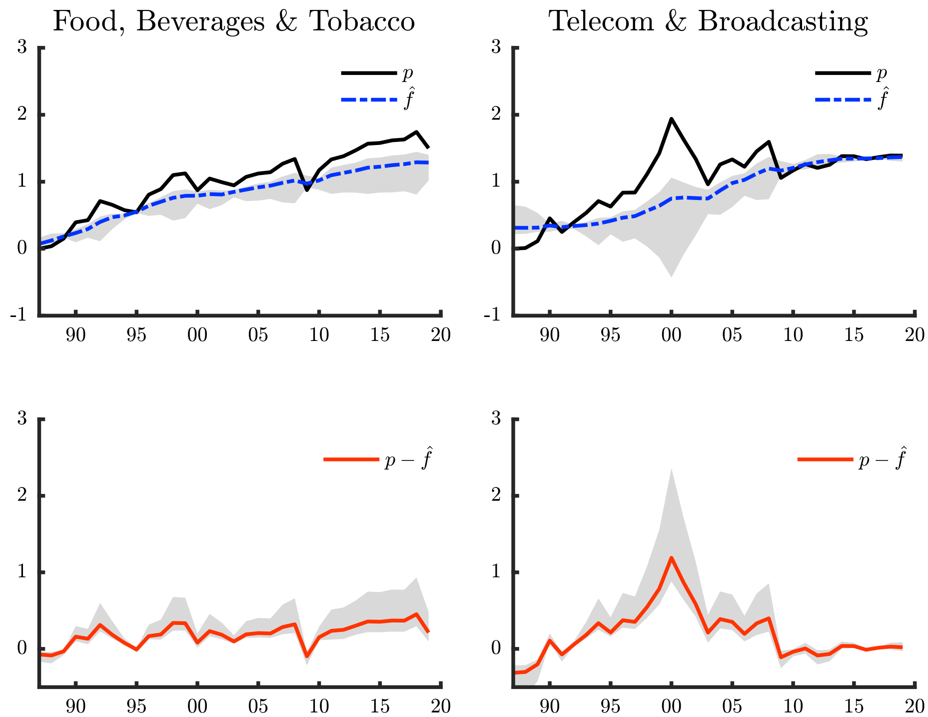

Figure 1: Price-fundamental deviations

This figure shows price-fundamental deviations for two industries: 'Food, Beverage and Tobacco Manufacturing' (NAICS 311-312) and 'Broadcasting and Telecommunications' (NAICS 515-517). All variables are measured at the beginning of the year. Fundamentals are estimated using the VAR explained above. Appendix A.1 provides details on variable definitions. Prices and fundamentals are rescaled so that $p_{i,90} = 0$. Shaded areas represent 99% bootstrap confidence bands (see Appendix B.4 for details).

stocks), but which do not become immediately listed. For example, despite having been created during the dotcom boom in 1998, Google only had its IPO in 2004 (i.e. after the dotcom crash). In an ideal exercise, overvaluation would also be computed for the universe of all firms in an industry (and not just for the set of public companies). This is however not possible, given the absence of data on market prices for private firms.

3.1 Data description

Output, Inputs and Productivity Data on output, inputs and productivity comes BLS *Multifactor Productivity Database*. This is a dataset containing industry-level data for production variables and estimates for total factor productivity. Total factor productivity is estimated as a Solow residual, using estimates on the growth rates of output, labor and capital, as well as of the shares of each input in total output. The data is disaggregated at 3-digit NAICS industries and covers the period 1987-2019.[10]

Number of Firms and Establishments I use data from the *Statistics of U.S. Businesses* (from the US Census Bureau). This contains data on the number of firms and establishments per industry. Contrarily to the previous dataset, these data are only available for the period 1998-2018.

3.2 Baseline Results

I am interested in how stock market overvaluation at the end of year $t-1$ predicts an industry level outcome at t (e.g. TFP growth). The model I consider is

$$y_{it} = \lambda_i + \eta_t + \beta \text{ overvaluation}_{it-1} + u_{it} \tag{4}$$

where y_{it} is the outcome of interest of industry i and year t and overvaluation$_{it-1}$ is the indicator for stock market overvaluation in the industry at the end of year $t-1$. λ_i and η_t represent industry and year fixed effects. The inclusion of time fixed effects is important, since it allows me to control for time-varying macro variables that can be correlated with overvaluation, such as interest rates.

Fact #1: greater output and input growth

I start by studying the comovement between overvaluation and the growth rates of output, capital and employment. The results are shown in Table 1. Columns (1) to (3) use the Shiller CAPE

[10] Data is available at https://www.bls.gov/TFP/mprdload.htm.

Overvaluation and Production Variables						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δ log Y_{it}	Δ log K_{it}	Δ log L_{it}	Δ log Y_{it}	Δ log K_{it}	Δ log L_{it}
Shiller CAPE$_{i,t-1}$	0.0167***	0.0138***	0.0224***			
	(0.00381)	(0.00392)	(0.00346)			
Campbell-Shiller PD$_{i,t-1}$				0.0184***	0.0146***	0.0242***
				(0.00323)	(0.00303)	(0.00323)
Observations	1,584	1,584	1,584	1,584	1,584	1,584
R-squared	0.410	0.545	0.459	0.409	0.543	0.456
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 1

This table shows the estimates of equation (4) for three different dependent variables: the log differences of output, capital and labor (between $t-1$ and t). Data on overvaluation is from COMPUSTAT (1975-2019) and data on production variables are from the BLS Multifactor Productivity Database (1987-2019). To control for outliers, all three dependent variables are trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped-clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

ratio, while columns (4) to (6) use instead the Campbell and Shiller price-fundamental deviation. The estimates indicate a strong positive correlation between stock market overvaluation at the end of year $t-1$ and output and input growth at t. Comparing the results between columns (2) and (3), and between (5) and (6), we see that employment seems to increase faster than capital during a stock market boom. To assess the economic significances, I consider a one-standard deviation increase to the price-fundamental deviation. This predicts a 0.009 increase in log output growth (17% of its standard deviation), a 0.007 increase in log capital growth (20% of its standard deviation) and a 0.012 increase in employment (27% of its standard deviation).

Fact #2: declining TFP growth

The previous results suggest that episodes of stock market overvaluation are accompanied by faster output growth and input usage. What is the behavior of productivity? Does it grow or decline during a stock market boom? To address this question, I repeat the regression exercise,

Overvaluation and TFP Growth				
	(1)	(2)	(3)	(4)
VARIABLES	Δ log TFP_{it}	$\mathbb{1}\{\Delta\text{TFP}_{it} > 0\}$	Δ log TFP_{it}	$\mathbb{1}\{\Delta\text{TFP}_{it} > 0\}$
Shiller $\text{CAPE}_{i,t-1}$	-0.00497**	-0.109***		
	(0.00219)	(0.0398)		
Campbell-Shiller $\text{PD}_{i,t-1}$			-0.00375**	-0.0911***
			(0.00183)	(0.0312)
Observations	1,584	1,584	1,584	1,584
R-squared	0.153	0.119	0.152	0.116
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 2
This table shows the estimates of equation (4) for two dependent variables: Δ log TFP (between $t-1$ and t) and $\mathbb{1}\{\Delta\text{TFP} > 0\}$ (an indicator variable that takes value one if TFP growth between $t-1$ and t is positive, and zero otherwise). Data on overvaluation is from COMPUSTAT (1975-2019) and data on productivity is from the BLS Multifactor Productivity Database (1987-2019). To control for outliers, Δ log TFP is trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** p<0.01, ** p<0.05, * p<0.1

but now use (log) TFP growth as the dependent variable. The results are shown in Table 2. Column (1) uses the Shiller CAPE ratio, while column (3) uses the Campbell-Shiller price-fundamental deviation. Both estimates point to a negative and significant correlation between overvaluation and productivity growth: an increase in overvaluation at the end of year $t-1$ predicts weaker productivity growth in the subsequent year. In terms of economic magnitudes, a one-standard deviation increase to the price-fundamental deviation predicts a 0.002 decline in productivity growth, which represents 6% of its standard deviation.

These results indicate that productivity growth slows down when overvaluation is high. However, they do not necessarily imply an actual decline of productivity, i.e. *negative* productivity growth. But do we actually observe a higher propensity for negative productivity growth when overvaluation is high? To answer this question, I change the dependent variable and use an indicator variable that takes value one whenever TFP growth is positive (and zero otherwise).

The results are shown in columns (2) and (4) of Table 2. They indicate a strong negative correlation between industry overvaluation and the likelihood of positive TFP growth. Looking again at economic magnitudes, a one standard deviation increase to the price-fundamental deviation predicts a 4.6 pp decline in the probability of positive TFP growth (9% of its standard deviation).

To illustrate these findings, Figure 3 in Online Appendix C shows the dynamics of TFP in two industries that were at the center of the dotcom bubble: 'Telecommunications' and 'Data Processing & Internet Publishing'. As shown, TFP declines from 1995 until the peak of the bubble, and starts to increase after the stock market crash.

Fact #3: declining contribution of TFP for output growth, with a rising labor contribution and no change in the capital contribution

The evidence discussed so far suggests that output growth during stock market booms is driven entirely by greater factor accumulation. But what happens to the relative growth contributions of labor and capital during a bubbly expansion? The BLS provides a decomposition of sectoral output growth into three different components: capital, labor and and TFP growth[11]

$$\Delta \ln \mathrm{Y}_{it} = \underbrace{\alpha_i^K \Delta \ln \mathrm{K}_{it}}_{\text{capital contribution}} + \underbrace{\alpha_i^L \Delta \ln \mathrm{L}_{it}}_{\text{labor contribution}} + \underbrace{\Delta \ln \mathrm{MFP}_{it}}_{\text{MFP contribution}}$$

To assess the relative contribution of each component, I construct the ratio

$$\mathrm{K}_{it}^{\text{cont}} \equiv \frac{\alpha_i^K \Delta \ln \mathrm{K}_{it}}{\Delta \ln \mathrm{Y}_{it}}$$

[11] Data is available at https://www.bls.gov/TFP/contributions-to-output.htm.

Contributions to Output Growth						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	K_{it}^{cont}	L_{it}^{cont}	TFP_{it}^{cont}	K_{it}^{cont}	L_{it}^{cont}	TFP_{it}^{cont}
Shiller CAPE$_{i,t-1}$	0.0242	0.302**	-0.407***			
	(0.0450)	(0.122)	(0.137)			
Campbell-Shiller PD$_{i,t-1}$				-0.000846	0.326***	-0.417***
				(0.0417)	(0.108)	(0.127)
Observations	1,082	1,082	1,082	1,082	1,082	1,082
R-squared	0.281	0.201	0.208	0.281	0.201	0.206
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 3
This table shows the estimates of equation (4) where the dependent variables are the relative contribution of capital, labor and TFP for output growth (as defined in the main text). Data on overvaluation is from COMPUSTAT (1975-2019) and data on growth contributions is from the BLS Multifactor Productivity Database (1987-2019). To control for outliers, the dependent variables are trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** p<0.01, ** p<0.05, * p<0.1

which is defined only if $\Delta \ln Y_{it} > 0$. Identical ratios are constructed for labor and TFP. I then estimate equation (4), using each one of these ratios as the dependent variable. The results are shown in Table 3. The higher is the degree of stock market overvaluation, the higher is the labor contribution for output growth, while the lower is the contribution of total factor productivity. The capital contribution does not seem to change significantly. Note that this result does not mean that capital does not contribute for output growth during a stock market boom. It means that, during a boom accompanied by overvalued stocks, the fraction of growth driven by capital accumulation is identical to that of a normal boom (i.e. a boom not characterized by high overvaluation). The relative contribution of labor is, however, significantly higher.

Fact #4: higher growth in the number of firms and establishments

Some models in the recent bubble literature do predict a negative comovement between overvaluation and aggregate productivity (Queirós (2021), Tang and Zhang (2021)). In these models, when firms issue overvalued assets (such as stocks) they obtain a rent or subsidy. The existence of such a subsidy has an impact on the extensive margin of firms, since it allows both for the entry of new unproductive firms, and for the permanence of low productivity incumbents (which would exit otherwise). What is the relationship between overvaluation and the extensive margin of firms? To answer this question, I estimate equation (4) using the log growth rate of the number of establishments and firms in the industry. The results are shown in Table 4. There is a strong positive correlation between overvaluation and the number of establishments and firms in the industry. This suggests that high valuation can make it more attractive for new firms to enter, and that stock market bubbles can be accompanied by changes in the market structure.

3.3 Additional Results

The results reported in this paper pertain to the correlation between overvaluation at the end of $t-1$ and the growth rate of some variable in the subsequent year t. In Online Appendix C, I show that the results also hold when looking at cumulative growth rates over 5 years. In particular, higher stock market overvaluation at the end of year $t-1$ predicts faster growth for output, capital and labor in the following 5 year horizon (Table 6). It also predicts weaker productivity growth, and again a greater propensity for an actual decline of TFP (Table 7).

Two conclusions can be drawn from these findings. First, they suggest that stock market overvaluation can have long-lasting consequences at the industry level. Second, they question the common view that overvalued stocks mostly reflect expectations about future technological

Overvaluation and the Number of Firms				
	(1)	(2)	(3)	(4)
VARIABLES	Δ log est$_{it}$	Δ log firm$_{it}$	Δ log est$_{it}$	Δ log firm$_{it}$
Shiller CAPE$_{i,t-1}$	0.0105***	0.00790**		
	(0.00324)	(0.00370)		
Campbell-Shiller PD$_{i,t-1}$			0.0102***	0.00720**
			(0.00280)	(0.00323)
Observations	956	956	956	956
R-squared	0.335	0.307	0.332	0.304
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 4

This table shows the estimates of equation (4) where the dependent variables are the log differences in the number of establishments and firms in the industry. Data on the number of firms and establishments is from the US Census Bureau (1998-2018). To control for outliers, the dependent variables are trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** p<0.01, ** p<0.05, * p<0.1

developments (which could boost productivity in the future). These findings suggest that, on the contrary, overvaluation predicts a weaker productivity growth over medium-run horizons.

3.4 Summary and discussion

The results suggest that periods of stock market overvaluation are characterized by faster output growth. This increase in output growth is driven entirely by greater input usage (mostly labor), and happens in spite of weaker TFP growth. As shown, relative to an average output boom, an expansion that is accompanied by rising overvaluation is characterized by a significantly higher contribution of labor for output growth, and a significant lower contribution of TFP. The contribution of capital does not significantly change.

Overall, these results indicate that stock market booms are periods of declining productivity growth. This seems consistent with recent models studying the interactions between bubbles and firm dynamics (Queirós (2021), Tang and Zhang (2021)). An implication of these theories is that bubbles can lead to inefficient booms, with too many firms entering or growing excessively. The results of this paper point to some downsides associated with stock market overvaluation. Can bubbly expansions, by lower aggregate TFP, be detrimental for welfare? Should regulatory authorities aim to control bubbles? Should they limit access to IPOs during episodes of high overvaluation? The answer to these questions is outside the scope of this paper, but they should be addressed in quantitative models.

This paper also suggests that more emphasis should on the interactions between bubbles and labor markets. There is theory work studying the interactions between bubbles and unemployment in models with labor market frictions (Miao et al. (2016), Biswas et al. (2020), Hashimoto et al. (2020), Vuillemey and Wasmer (2020)). However, more research should study the implications of bubbles on firms' hiring decisions and individuals' incentives for human capital accumulation. For example, do firms lower their hiring standards during a stock market boom? And do bubbles have an impact on individuals' education decision, such as the decision to attend or to leave college? Research has shown that booms in real estate and construction, by leading to an increase in male wages, can have a negative impact on college enrollment of men (Aparicio-Fenoll (2016)). Are there similar effects associated with stock market bubbles?

4 Conclusion

This paper provides a characterization of the empirical comovement between stock market bubbles and real economic variables. To this end, I construct indicators of stock market overvaluation at the industry level, which are consistent with the concept of rational bubble. The findings indicate that stock market overvaluation is associated with higher output growth. Such an additional growth is driven by increased factor accumulation (in particular labor), and happens in spite of a decline in productivity growth. As discussed, these findings can be used to test different models, and can also guide future theory work on the topic. For example, what are the threats posed by declining productivity growth during a stock market boom? Should they be a concern for regulatory authorities? Do firms lower they hiring standards during a stock market boom? Why is the contribution labor for output growth higher in bubbly times?

In spite of growing theoretical research in the topic of asset bubbles, existing empirical work has been scarce. This is in part understandable, given that bubbles and fundamentals are not directly observable, which makes estimates dependent on necessary assumptions. These challenges are, however, common to the estimation of several economic objects, such as markups, marginal costs or total factor productivity. They should not, for this reason, discourage future empirical work on the topic. On the contrary, they highlight the need for more research, and the importance of alternative and complementary approaches.

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A Appendix

A.1 Variable definitions

- Stock market capitalization: end-of-year stock price (COMPUSTAT item #199) times common shares outstanding (COMPUSTAT item #25).
- Dividends: common dividends (COMPUSTAT item #21)
- Net stock repurchases: net purchases of common and preferred stock (COMPUSTAT item #115 - item #108) minus change in preferred stock/redemption value (Δ item #56).
- Sales (COMPUSTAT item #12)
- EBITDA: earnings before interest, taxes, depreciation and amortization (COMPUSTAT item #13)

Nominal variables are deflated by the Consumer Price Index (obtained from the Bureau of Labor Statistics).

A.2 Industry Aggregates

Let sale_{jt} be the sales of firm j in year t. Let S_t^0 be the set of active firms in a given industry at year t that already existed in $t-1$. Let S_t^1 be the set of active firms at year t that are also active in year $t+1$ (in the same industry). The correction factor applied at year t is denoted by γ_t and is recursively defined as[12]

$$\gamma_t = \gamma_{t-1} \frac{\sum_{j \in S_t^0} \text{sale}_{jt}}{\sum_{j \in S_t^1} \text{sale}_{jt}}$$

Given this definition, for any firm level variable x_{jt} the corresponding aggregate variable X_t is constructed as

$$X_t = \gamma_t \sum_{j \in S^1} x_{jt}$$

I construct industry aggregates for stock market capitalization, earnings, dividends and net stock repurchases. Aggregate net stock repurchases are set to zero when negative.

[12]Note that the set of firms that transition from t to $t+1$ corresponds to the set of firms existing at $t+1$ that were active in the previous period, i.e. $S_t^1 = S_{t+1}^0$.

Online Appendix to

"Asset Bubbles and Product Market Competition"

B Data and Additional Results

B.1 Industry Classification

			Number of Firms			Market Capitalization		
	Name	NAICS	Median	Min	Max	Median	Min	Max
1	Farms	111, 112	20	8	27	18.6	3.3	67.6
2	Forestry, Fishing, and Related Activities	113-5	6	1	10	2.8	0.7	9.5
3	Oil and Gas Extraction	211	303	60	363	340.4	68.0	1,168.6
4	Mining (except oil and gas)	212	147	73	244	307.2	60.9	1,294.9
5	Support Activities for Mining	213	59	32	83	130.9	16.2	368.8
6	Construction	23	101	45	149	65.4	9.5	176.3
7	Wood Products	321	40	16	57	33.6	13.1	79.0
8	Non Metallic Mineral Products	327	36	13	59	48.2	5.9	120.3
9	Primary Metals Products	331	78	24	116	110.7	42.2	434.8
10	Fabricated Metal Products	332	86	32	131	86.3	25.2	169.3
11	Machinery	333	242	102	350	381.3	87.4	926.5
12	Computer and Electronic Products	334	706	252	972	1,969.1	205.5	4,673.1
13	Electrical Equipment	335	102	31	130	185.9	66.2	403.9
14	Transportation Equipment	336	144	66	189	711.6	156.5	1,796.6
15	Furniture	337	32	10	45	17.7	3.0	36.6
16	Miscellaneous Manufacturing	339	158	49	234	165.0	15.4	411.1
17	Food and Beverage and Tobacco Products	311, 312	155	53	206	937.2	161.5	2,439.9
18	Textile Mills and Textile Product Mills	313, 314	20	5	45	8.6	3.8	25.2
19	Apparel and Leather and Applied Products	315, 316	78	20	117	96.7	15.2	400.9
20	Paper Products	322	60	20	99	171.7	71.5	329.3
21	Printing Activities	323	31	8	50	16.5	8.8	23.9
22	Petroleum and Coal Products	324	43	23	54	1,163.9	236.9	2,797.5
23	Chemical Products	325	598	241	676	2,525.8	337.9	4,799.6
24	Plastics and Rubber Products	326	67	13	88	33.5	11.5	70.9
25	Wholesale Trade	42	227	91	359	215	43.7	471.1
26	Retail Trade	44-45	287	76	421	1,131.1	154.8	2,826.2

Data is from COMPUSTAT for the period 1987-2019. Stock market capitalization is reported in millions of USD.

	Name	NAICS	Number of Firms			Market Capitalization		
			Median	Min	Max	Median	Min	Max
27	Air Transportation	481	37	17	44	68.1	13.8	272.7
28	Rail Transportation	482	14	6	21	83.1	29.4	374.9
29	Water Transportation	483	28	16	63	45.1	4.5	122.2
30	Truck Transportation	484	29	19	52	22.6	2.5	82.0
31	Transit and Ground Passenger Transportation	485	3	2	6	8.5	2.4	101.1
32	Pipeline Transportation	486	22	17	51	133.1	7.7	548.1
33	Other Transportation and Support Activities	487, 488, 492	21	8	26	12.1	1.2	34.8
34	Publishing Industries	511	234	76	564	634.0	43.1	2,046.7
35	Motion Picture and Sound Recording Industries	512	35	6	124	91.3	10.4	411.2
36	Broadcasting and Telecommunications	515, 517	207	61	377	2,109.4	242.1	4,366.6
37	Data Processing, Internet Publishing, Scientific, and Other Information Services	518, 519	198	36	318	568.5	59.4	3,660.1
38	Real Estate	531	223	127	307	216.1	12.9	1219.8
39	Rental and Leasing Services and Lessors of Intangible Assets	532, 533	94	33	142	62.3	11.1	205.9
40	Computer Systems Design and Related Services	5415	134	33	263	190.3	39.0	637.5
41	Miscellaneous Professional, Scientific, and Technical Services	5412-4 5416-9	135	43	213	152	11.6	339.7
42	Administrative and Support Services	561	89	38	168	87.3	20.4	246.4
43	Waste Management and Remediation Services	562	40	12	67	38.2	18.8	120.9
44	Education	610	27	16	39	22.7	4.1	56.5
45	Ambulatory Health Care Services	621	82	25	125	44.8	2.4	144.5
46	Hospitals and Nursing and Residential Care Facilities	622, 623	35	13	62	49.5	10.5	86.1
47	Performing Arts, Spectator Sports, Museums, and Related Activities	711, 712	10	5	22	5.0	0.4	32.5
48	Amusements, Gambling, and Recreation Industries	713	36	8	53	18.2	2.3	48.7
49	Accommodation	721	43	18	73	63.9	6.9	241.5
50	Food Services and Drinking Places	722	81	32	139	106.7	17.1	419.5

Data is from COMPUSTAT for the period 1987-2019. Stock market capitalization is reported in millions of USD.

B.2 Campbell and Shiller VAR: Estimates

Campbell-Shiller VAR: 1987-2019			
	(1)	(2)	(3)
VARIABLES	$\Delta d_{it+1} - r_t^M$	$p_{it+1} - d_{it+1}$	cape_{it+1}^{10}
$\Delta d_{it} - r_{t-1}^M$	-0.120***	0.133***	0.0105
	(0.0442)	(0.0438)	(0.0138)
$p_{it} - d_{it}$	0.429***	0.599***	0.0360***
	(0.0393)	(0.0383)	(0.0133)
cape_{it}^{10}	-0.146***	-0.0536	0.795***
	(0.0452)	(0.0468)	(0.0203)
Observations	1,650	1,650	1,650
R-squared	0.251	0.302	0.666

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5
This table shows the results for the panel VAR defined in equation (3). Data is from COMPUSTAT (1975-2019) and the estimation is done for the period 1987-2019. Industry variables are aggregated from firm data and a correction factor is applied to adjust for listing/delisting. See Appendix A.2 for details.

Table 5 shows the estimates of the VAR defined in equation (3). From column (1), we see that both the price-dividend ratio $(p_{it} - d_{it})$ and the CAPE ratio (cape_{it}^{10}) happen to be strong predictors of discounted dividend growth $(\Delta d_{it+1} - r_t^M)$.

B.3 The industry discount factor σ_i

In the construction of the Campbell and Shiller price-fundamental deviation, I assume that industries dividends are discounted at rate $R_{it} = 1 + r_{it}$ such that

$$E_t \{r_{it}\} = E_t \left\{r_t^M\right\} + \sigma_i$$

where r_t^M denotes a market return (e.g. the return on the SP composite index). In my baseline measure, σ_i is set to zero. Figure 2 shows the estimated fundamental and price-fundamental deviations for one particular industry under different values for σ_i. As one can see, σ_i essentially pins down the level of the fundamental (and hence the long-run average of the price-fundamental deviation) but not its time series patterns. In a previous working paper version (Queirós (2020)), I discuss alternative ways of obtaining σ_i. For example, the theory of rational bubbles states that bubbles cannot be negative; using this condition, one can pin down σ_i by imposing a lower bound on the price-fundamental deviation so that $\min_t \left\{p_{it} - \hat{f}_{it}\right\} = 0$.

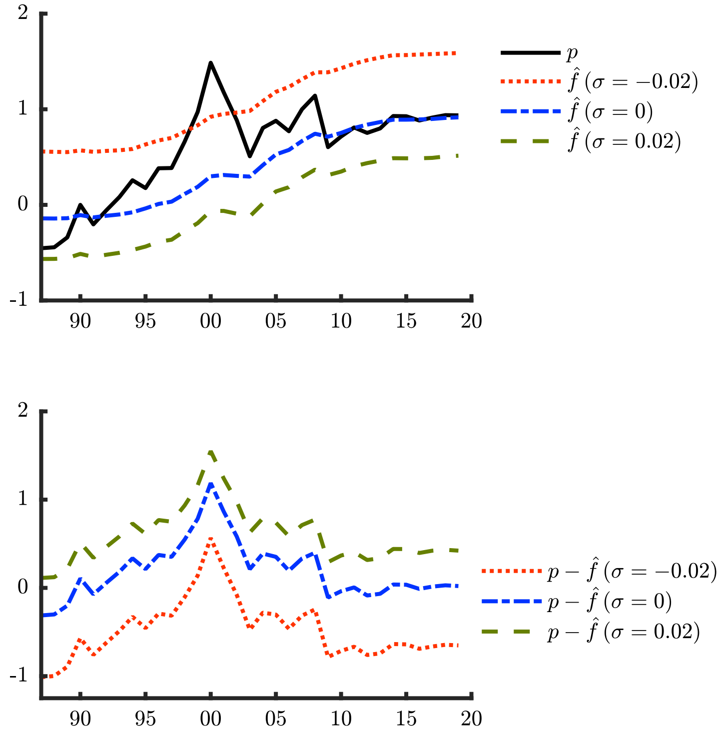

Figure 2: Price-fundamental deviations

This figure shows different estimates for the fundamental of 'Broadcasting and Telecommunications' (NAICS 515, 517) for different values of σ_i. All variables are measured at the beginning of the year. Appendix A.1 provides details on variable definitions. Prices and fundamentals are rescaled so that $p_{i,90} = 0$.

B.4 Standard Errors

Price-Fundamental Deviations

To obtain standard errors for the price-fundamental deviation I implement a block bootstrap method (Horowitz (2019)). It allows for both serial and cross-industry correlation in the error terms. The bootstrap procedure is as follows.

1. I use the VAR estimates in Table 5 to obtain the series of error terms for each industry i

$$\left\{ \underset{[3\times1]}{\hat{\mathbf{u}}_{\mathbf{i,0}}}\ ,\ \underset{[3\times1]}{\hat{\mathbf{u}}_{\mathbf{i,1}}}\ ,\ \underset{[3\times1]}{\hat{\mathbf{u}}_{\mathbf{i,2}}}\ , \ldots,\ \underset{[3\times1]}{\hat{\mathbf{u}}_{\mathbf{it}}} \right\}$$

2. Error terms will be picked in blocks with $n = T^{1/3} = 29^{1/3} \approx 3$ observations (Horowitz (2019)). This allows the error terms to be serial correlated. For example,

$$\mathbf{b}_{\mathbf{i,8}} = \{\hat{\mathbf{u}}_{\mathbf{i,8}}\ ,\ \hat{\mathbf{u}}_{\mathbf{i,9}}\ ,\ \hat{\mathbf{u}}_{\mathbf{i,10}}\}$$

and

$$\mathbf{b}_{\mathbf{i,10}} = \{\hat{\mathbf{u}}_{\mathbf{i,10}}\ ,\ \hat{\mathbf{u}}_{\mathbf{i,11}}\ ,\ \hat{\mathbf{u}}_{\mathbf{i,12}}\}$$

are two possible blocks. Note that the blocks can be overlapping.

3. I start by picking a random time period $s \in \{1, 2, \ldots, T\}$ and keep all N blocks starting in that period (where N is the number of industries)

$$\mathbf{B_s} = \left\{ \begin{array}{c} \mathbf{b_{1,s}} \\ \\ \mathbf{b_{2,s}} \\ \\ \vdots \\ \\ \mathbf{b_{N,s}} \end{array} \right\}$$

4. For each industry i, I pick a random block $\mathbf{b_{j,s}}$ (with replacement) from $\mathbf{B_s}$ above. Note that we can have $j = i$ (the block is drawn from the same industry) or $j \neq i$ (the block is drawn from a different same industry).

5. I repeat steps 3 and 4 until I have a new vector of $T = 29$ error terms for each industry.

For example, if in step 3 I first obtain $s = 8$ and then $s = 15$ the new sequence of error terms for the first two industries can be

$$\mathbf{\tilde{u}_1} = \{\underbrace{\mathbf{\hat{u}_{23,8}}\ ,\ \mathbf{\hat{u}_{23,9}}\ ,\ \mathbf{\hat{u}_{23,10}}}_{\mathbf{b_{23,8}}}\ ,\ \underbrace{\mathbf{\hat{u}_{11,15}}\ ,\ \mathbf{\hat{u}_{11,16}}\ ,\ \mathbf{\hat{u}_{11,17}}}_{\mathbf{b_{11,15}}}, \ldots\}$$

and

$$\mathbf{\tilde{u}_2} = \{\underbrace{\mathbf{\hat{u}_{44,8}}\ ,\ \mathbf{\hat{u}_{44,9}}\ ,\ \mathbf{\hat{u}_{44,10}}}_{\mathbf{b_{44,8}}}\ ,\ \underbrace{\mathbf{\hat{u}_{7,15}}\ ,\ \mathbf{\hat{u}_{7,16}}\ ,\ \mathbf{\hat{u}_{7,17}}}_{\mathbf{b_{7,15}}}, \ldots\}$$

This procedure allows for both serial correlation (errors are picked in blocks with $T = 3$ observations), and cross sectional dependence (blocks are picked together at the same s).

6. Then I use the estimates $\mathbf{\hat{A}}$ in Table 5 and new generated errors to construct a new sample

$$\mathbf{\tilde{y}_{it}} = \mathbf{\hat{A}}\ \mathbf{\tilde{y}_{it-1}} + \mathbf{\tilde{u}_{it}}$$

7. I estimate a VAR on the new generated data $\tilde{\mathbf{y}}_{\mathbf{t}}$ and compute price-fundamental deviations $p_{it} - \tilde{f}_{it}$

8. I do 10,000 repetitions of steps 1 to 7 and obtain the distribution of $p_{it} - \tilde{f}_{it}$ for all industries and time periods.

Regression Estimates

The regressions defined in (4) are estimated with OLS and standard errors are bootstrapped clustered at the industry level. The bootstrap is as follows. I generate $T = 400$ samples of data by drawing $n = 47$ industry blocks from the original dataset (with replacement). I reestimate the model for each of the new generated samples and compute the standard deviation of each coefficient estimate.

When the Campbell and Shiller price-fundamental deviation is used as a regressor, I need to correct for the fact that pdev_{it} is a generated regressor. To do so, when generating a new sample of data, I also pick a new sequence of price-fundamental deviations using the method described in (B.4) (points 1 to 7).

C Additional Results and Figures

C.1 5-Year Growth Rates

Overvaluation and Production Variables						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\Delta_{t-1,t+4}$ log Y_i	$\Delta_{t-1,t+4}$ log K_i	$\Delta_{t-1,t+4}$ log L_i	$\Delta_{t-1,t+4}$ log Y_i	$\Delta_{t-1,t+4}$ log K_i	$\Delta_{t-1,t+4}$ log L_i
Shiller CAPE$_{i,t-1}$	0.00980**	0.0143***	0.0123***			
	(0.00396)	(0.00392)	(0.00382)			
Campbell-Shiller PD$_{i,t-1}$				0.0113***	0.0153***	0.0138***
				(0.00334)	(0.00298)	(0.00311)
Observations	1,386	1,386	1,386	1,386	1,386	1,386
R-squared	0.539	0.663	0.562	0.539	0.661	0.562
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 6

This table shows the estimates of equation (4) for different dependent variables (the log differences of output, capital and labor between $t-1$ and $t+4$). Data on overvaluation is from COMPUSTAT (1975-2019) and data on production variables are from the BLS Multifactor Productivity Database (1987-2019). To control for outliers, the dependent variables are trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped-clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** p<0.01, ** p<0.05, * p<0.1

Overvaluation and TFP Growth				
	(1)	(2)	(3)	(4)
VARIABLES	$\Delta_{t-1,t+4}$ log TFP$_i$	$\mathbb{1}\{\Delta_{t-1,t+4}\text{TFP}_i > 0\}$	$\Delta_{t-1,t+4}$ log TFP$_i$	$\mathbb{1}\{\Delta_{t-1,t+4}\text{TFP}_i > 0\}$
Shiller CAPE$_{i,t-1}$	-0.00438*	-0.139**		
	(0.00234)	(0.0564)		
Campbell-Shiller PD$_{i,t-1}$			-0.00435**	-0.124**
			(0.00222)	(0.0552)
Observations	1,386	1,386	1,386	1,386
R-squared	0.213	0.337	0.210	0.336
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 7

This table shows the estimates of equation (4) for two dependent variables: $\Delta_{t-1,t+4}$ log TFP (log TFP growth between $t-1$ and $t+4$) and $\mathbb{1}\{\Delta_{t-1,t+4}\text{TFP} > 0\}$ (an indicator variable that takes value one if cumulative TFP growth between $t-1$ and $t+4$ is positive, and zero otherwise). Data on overvaluation is from COMPUSTAT (1975-2019) and data on productivity is from the BLS Multifactor Productivity Database (1987-2019). To control for outliers, Δ log TFP is trimmed at the 0.5% and 99.5% percentiles. Standard errors in parentheses are bootstrapped clustered at the industry level. When the Campbell and Shiller price-fundamental deviation is used, the bootstrap also accounts for the fact that this is a generated regressor (see Appendix B.4 for details). *** p<0.01, ** p<0.05, * p<0.1

C.2 TFP during the dotcom bubble

Figure 3 shows the dynamics of TFP in two industries that were at the center of the dotcom bubble: 'Telecommunications and Broadcasting' and 'Data Processing & Internet Publishing'. These are shown against the Campbell and Shiller price-fundamental deviation. A common pattern can be detected in these industries — TFP declines from 1995 until the peak of the bubble, and starts to increase after the stock market crash.

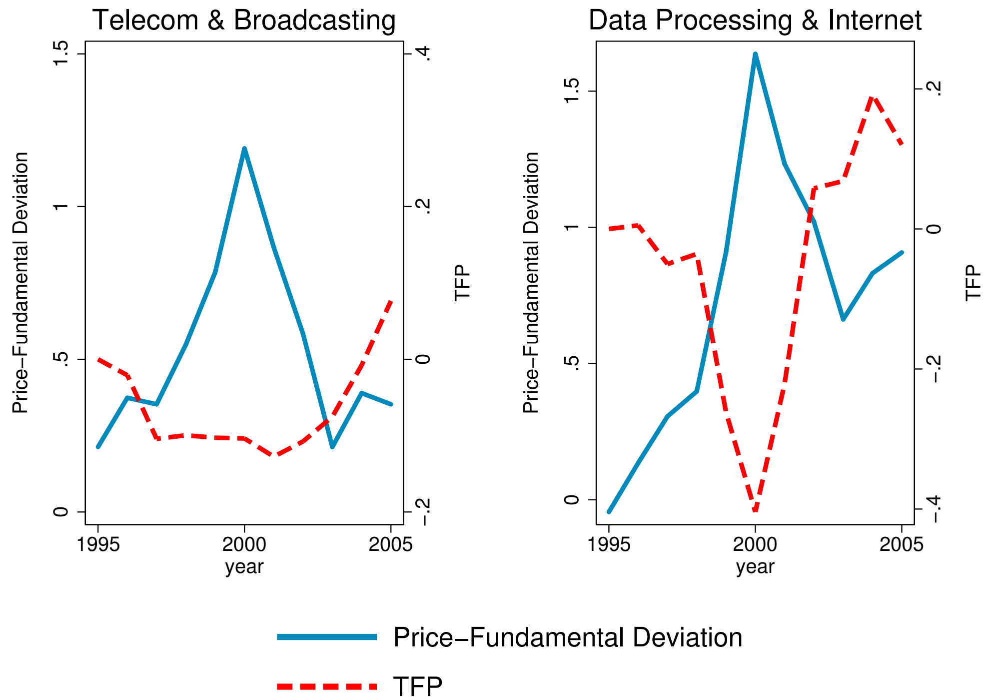

Figure 3: Multifactor productivity in the dotcom bubble

This figure shows the Shiller CAPE ratio and industry MFTP for two industries during 1995-2005: 'Telecommunications and Broadcasting' (NAICS 517), and 'Data Processing, Internet Publishing and Other Information Services' (NAICS 518-519). The CAPE ratio is the ratio of total stock market capitalization to a 10–year moving average of past earnings (EBITDA); the ratio is in logs and is measured at the beginning of the year (see Appendix A.2 for more details). TFP refers to industry multifactor productivity from the BLS multifactor productivity database.