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King of the Mountain: *The Shiller P/E and Macroeconomic Conditions*

Robert D. Arnott, Denis B. Chaves, and Tzee-man Chow

Robert D. Arnott
is the chairman and CEO at Research Affiliates, LLC, in Newport Beach, CA.
Arnott@rallc.com

Denis B. Chaves
is a portfolio manager at Vanguard's Quantitative Equity Group in Malvern, PA.
Denis_chaves@vanguard.com

Tzee-man Chow
is a senior vice president at Research Affiliates, LLC, in Newport Beach, CA.
chow@rallc.com

One of the most common misattributions in finance is Ben Graham's almost certainly apocryphal remark that "in the short run the market is a voting machine and in the long run it is a weighing machine."[1] The history of financial analysis is, in part, a quest for metrics that can help us better predict the voting and more accurately gauge the weight (i.e., fair value) of an investment. Robert Shiller and John Campbell introduced one of the most powerful measures of value when they developed the cyclically adjusted price/earnings ratio (CAPE) or Shiller P/E.[2] The Shiller P/E divides the current real price of a broad market index by a 10-year average of its inflation-adjusted earnings. Peak earnings no longer create an illusion of low P/E ratios; trough earnings no longer create artificially elevated P/E ratios. The Shiller P/E is a powerful predictor for long-horizon capital market returns all over the world. This result is expected, as long as markets exhibit long-horizon mean reversion toward the historical average for the Shiller P/E ratio.

The Shiller P/E is a much less powerful predictor of short-term returns. Can we fix this? Building on the work of Leibowitz and Bova [2007], we find that the average Shiller P/E ratio (hereafter, the "P/E") varies with both real interest rates and inflation. Moderate levels of inflation and real interest rates coincide with the highest average valuation multiples. Unusually high or low real yields—or inflation rates—tend to coincide with much lower average valuation multiples, creating a valuation "mountain." This relationship spans the developed world.

Suppose we measure the abnormal P/E by comparing the current P/E with a conditional normal P/E adjusted to reflect current inflation and real yields. If P/E mean reverts toward levels suggested by macroeconomic conditions, rather than toward long-term averages, the conditional abnormal P/E may be a better predictor of short-term market returns. We find this to be the case, to an extent that is statistically significant and economically meaningful. P/E is an excellent predictor of long-term returns over spans of 3 to 10 years (and even better over longer spans). P/E, relative to a normal P/E that is conditioned to reflect current inflation and real yields, proves to be the better predictor of shorter-term returns of one month to one year.

What levels of inflation and real interest rates are more favorable to stock markets? Many investors, commentators, and policymakers seem to believe that rock-bottom levels of inflation and real interest rates provide the best economic conditions for stock prices to soar. Their logic is straightforward. Consider the textbook valuation formula relating the current price of a stock or portfolio, P_t, to the sum of discounted expected future dividends, D_t:

$$P_t = \sum_{\tau=1}^{\infty} \frac{\mathrm{E}[D_t]}{(1+r_{t\to t+\tau})^{\tau}} \tag{1}$$

Given that the discount rate, $r_{t\to t+\tau}$, is the sum of expected inflation, real interest rates, and an equity risk premium, it seems obvious that a reduction in any of those three variables should reduce the discount rate and consequently raise stock prices. In this reasoning, the relationship between stock prices and either inflation or real interest rates is *monotonically inverse*.

Yet this straightforward logic is not supported by the data. In the messy real world, market participants appear to value stocks based on the Goldilocks principle: The levels of inflation and of real interest rates have to be "just right" to sustain high valuations. When either deviates from its "sweet spot"—*in either direction*—valuations tend to fall. The relationship between stock prices and inflation, and between stock prices and real interest rates, can be simplistically described as a mountain. It peaks at medium levels of inflation and real interest rates and slopes downward from that point in any direction.

How can we explain this mountain-shaped relationship? Where does the logic described above break down? To answer these questions, notice that the relationship is monotonic only if all other variables remain constant when the inflation rate or real interest rate changes. Why should they not be interconnected? It turns out that cash flows, measured here as earnings, and risk premiums exhibit nonlinear and nonmonotonic interrelationships with inflation and real interest rates.

For instance, using data starting in 1871, we consider a monthly regression of three-year nominal earnings growth ($\Delta E_{t\to t+36}$) on concurrent three-year inflation rates ($\pi_{t\to t+36}$).[3] We find that they are interconnected in a manner that is not helpful to the conventional narrative:

$$\begin{aligned} \Delta E_t &= 0.03 + 1.04 \cdot \pi_t + \varepsilon_t \;\; (R^2 = 8\%) \\ &\quad (1.72)\;\; (2.50) \end{aligned} \tag{2}$$

It gets even more interesting when we include the square of those same inflation rates.[4]

$$\begin{aligned} \Delta E_t &= 0.04 + 1.72 \cdot \pi_t - 12.4 \cdot (\pi_t)^2 + \varepsilon_t (R^2 = 16\%) \\ &\quad (2.82)\;\; (5.34) \qquad (-4.24) \end{aligned} \tag{3}$$

According to the logic presented earlier, very low inflation rates would drive the discount rate down and stock prices up. However, this regression shows that the growth rate in profits falls even faster, given the highly negative quadratic term. At times of very low—even negative—inflation rates, market participants evidently should worry about the economy and reduce their expectations of *real* earnings growth. The negative quadratic term creates a mountain-like relationship between earnings growth—the numerator in Equation 1—and inflation rates, influencing stock prices to display a similar relationship with inflation rates.

Similar arguments can be made about real interest rates. A prolonged period of low real interest rates may suggest a market expectation of slow macroeconomic growth, or increased fear, which might require a higher equity risk premium, hence lower valuations.[5] For instance, consider a forecasting regression of future three-year inflation volatility ($\sigma^{\pi}_{t\to t+36}$), a measure of price uncertainty, on current real yields (y_t) and the square of current real yields:

$$\begin{aligned} \sigma^{\pi}_t &= 0.02 + 0.23 \cdot y_t + 1.23 \cdot (y_t)^2 + \varepsilon_t (R^2 = 27\%) \\ &\quad (14.1)\;\; (5.27) \qquad (3.41) \end{aligned} \tag{4}$$

According to the logic presented earlier, very low real interest rates would drive the discount rate down and stock prices up. However, the strongly positive quadratic term shows that abnormally low (or high) real interest rates tend to indicate higher uncertainty in prices. It seems reasonable that market participants actually increase the discount rate—reduce the valuation multiples—as inflation volatility rises, causing stock prices to go down and not up. The positive quadratic term creates a U-shaped relationship between inflation volatility and real interest rates, again influencing stock prices to display a mountain-like relationship with real interest rates.

In this study, we formalize the mountain-shaped relationship between the stock market valuation and inflation rates and real yields. Under the right conditions—that is, moderate levels of inflation and real yields—the market P/E empirically tends to reside well above the unconditional long-term historical average of 16.7. In contrast, when either the inflation rate or the real yield is at an extreme, we observe a markedly lower valuation.

We define a continuous nonlinear Gaussian model to estimate the normal P/E ratio—hence, the short-term P/E mean-reversion target, given the inflation rate and the real yield.[6] It is widely accepted that the deviation of the current stock market valuation from its long-term unconditional average is a good predictor of the long-horizon (10-year) return. Our model of a short-term mean-reversion target significantly enhances the predictability of stock market returns at short horizons (1 year or less). Our observations are robust within the U.S. market as well as across the global developed markets.

LITERATURE REVIEW AND OUR CONTRIBUTIONS

The relationship between stock prices and nominal or real interest rates is well understood. Leibowitz and Bova [2007, p. 84], for instance, introduce the "intriguing conjecture that P/E in the U.S. market may decline in times of both significantly lower, as well as significantly higher, real interest rates." We extend their study in two directions before turning to the core goal of improving the efficacy of P/E as a predictor of shorter-term market returns.

First, we show that the same nonmonotonic, mountain-shaped relationship between P/E and real interest rates also holds between P/E and inflation. Second, we show that this relationship is found not only in the U.S. market but also in a sample including numerous developed markets. We then create a bell-shaped "mountain" that describes this relationship, and finally test the markets' tendency to mean revert toward this new variable normal P/E, conditioned on current inflation and real interest rates, as a predictor of future returns.

This article contrasts with the literature on what is commonly referred to as the inflation or money illusion. Modigliani and Cohn [1979], Ritter and Warr [2002], Asness [2003], and Campbell and Vuolteenaho [2004], among others, argue that investors extrapolate *past* trends in nominal cash flow growth when forming their expectations about *future* nominal growth, failing to adjust them for changes in inflation. As a consequence, in times of low inflation their cash flow growth assumptions are too high, resulting in inflated P/E; and in times of high inflation, their cash flow growth assumptions are too low, resulting in depressed P/E. This "inflation illusion," or "money illusion," generates long periods of a negative relationship between P/E and inflation. If cash flow growth expectations were correctly adjusted for inflation, P/E should not move as much with inflation.

A clear example of the inflation illusion took place during the late 1990s and early 2000s when a rule of thumb dubbed the "Fed model" became pundits' preferred argument to justify extremely high stock prices (debunked by Asness [2003]).[7] According to this simple rule, one need only compare the stock market earnings yield (E/P) with nominal interest rates to know whether stocks are fairly priced: Buy when E/P is above nominal interest rates and sell when it is below them. Because nominal interest rates were relatively low during that time, and inflation expectations have historically been the major driver of nominal interest rates, supporters of the Fed model failed to lower their nominal cash flow growth expectations. Using low nominal interest rates to discount those prospective cash flows resulted in high P/E.

We are not proponents of this simple trading rule. Yields, growth rates, and inflation are intertwined with nonlinear connections that make the Fed model an exercise in folly. We propose a more sophisticated model to assess market levels and forecast returns.

A growing literature shows that stock market return forecasts can be significantly improved by deviating from static mean-reversion targets. The most common approach, exemplified by Lettau and Van Nieuwerburgh [2008] and Pettenuzzo and Timmermann [2011], is to assume that the markets suffer structural breaks and thus mean-reversion targets are dependent on some unobservable state of the economy that needs to be inferred using advanced econometric techniques. We adopt a more direct and practical approach: Because P/E declines when either the inflation rate or the real yield deviates from moderate levels, conditioning P/E on inflation and real yield forms a sensible short-term mean-reversion target. We define a three-dimensional parametrized continuous bell curve to model the relationship between the expected P/E and both the inflation and the real yield. The difference between the observed and modeled P/E is more powerfully—and significantly—related to near-term future stock market returns than a simple P/E relationship. We hope that this work stimulates further research into the linkage between macroeconomic conditions and equilibrium valuation levels and that our parametrized Gaussian model helps others extract more statistical significance from these linkages.

PRACTICAL IMPLICATIONS

Leibowitz and Bova [2007] framed their analysis within the practical considerations of pension funding ratios. When real interest rates rise, the value of pension funds' liabilities decreases in the same proportion that the value of their assets decreases. When real interest rates fall, however, the value of pension fund liabilities and fixed-income assets increases, but the value of equity assets decreases. This perverse relationship between stock prices and interest rates can create a stark and economically important mismatch between the value of assets and liabilities.

In the wake of the financial crisis of 2008 and the ensuing Great Recession, it is more important to grasp the relationship between interest rates and stock prices. Slow to no macroeconomic growth, accompanied by high unemployment, has driven central banks in many developed countries (including the United States, Japan, the Eurozone, and the United Kingdom) to cut interest rates to near-zero and even negative rates, and to engage in assorted forms of unconventional monetary policy. In particular, varieties of quantitative easing—buying long-term government or asset-backed bonds with the goal of lowering long-term interest rates—became a common remedy in the medicine cabinet of many central banks. Where these policies have led to negative real interest rates, we should understand the implications for market valuation.

In the words of former Fed chairman Ben Bernanke [2010],

> This approach [quantitative easing] eased financial conditions in the past and, so far, looks to be effective again. *Stock prices rose* and long-term interest rates fell when investors began to anticipate the most recent action... And *higher stock prices* will boost consumer wealth and help increase confidence, which can also spur spending.[8] (emphasis added)

As the evidence we present suggests, reducing inflation or real interest rates can be helpful to market valuations, to a point. But beyond a certain threshold, it may cause the opposite of the intended effect on stock markets: in the long run, valuation multiples could actually fall. At the time of this writing, the P/E of the U.S. stock market has stayed above 24 for almost three years. Our model indicates the U.S. market is expensive—priced to offer anemic real returns, or worse, if the P/E reverts toward historical norms. That said, the Fed has done an admirable job in keeping the inflation rate (and, to a lesser extent, real interest rates) at levels that are favorable to stock prices. From these "Goldilocks" conditions, any positive shock to inflation and further reduction in real yield could be the catalyst for a serious reversal.

DATA

All data are from Global Financial Data. The U.S. sample starts in 1880; the international sample starts in 1972, when the requisite data are first available for three other countries: Canada, Japan, and the United Kingdom. We use the yield on 10-year sovereign bonds as our measure of nominal interest rates. We use one-year inflation from the consumer price index as our measure of inflation, but we calculate real yields by subtracting trailing three-year inflation.[9] Because we are interested in using a valuation ratio that is not subject to short-term earnings volatility, we rely on the Shiller P/E. Summary statistics of data are presented in Appendix A.

U.S. RESULTS

We start our analysis by examining the univariate relationship between P/E and either real yields or inflation. Using data from 1978 to 2004, Leibowitz and Bova [2007] find that stock market prices, as a multiple of earnings, tend to peak when real yields are situated between 2% and 3%. Using a far longer sample spanning 137 years, we show *very* similar results in Exhibit 1.[10] The tent-shaped chart indicates that U.S. stock market valuation multiples tend to be at their highest when real yields range from 3% to 4%. Outside this narrow interval, median P/Es fall rather quickly from a peak of 19.6 to 10.7 when real yields are below −1% and to 10.5 when real yields are above 6%. The whisker plots on the top of each bar show plus and minus one standard error around the median, estimated with the Newey–West approach to adjust for overlapping observations. These standard errors confirm that the median P/E is statistically different across different intervals of real yields. For instance, the difference between the top P/E of 19.6

EXHIBIT 1

Median P/E at Different Real-Yield Regimes (United States, 1880–2016)

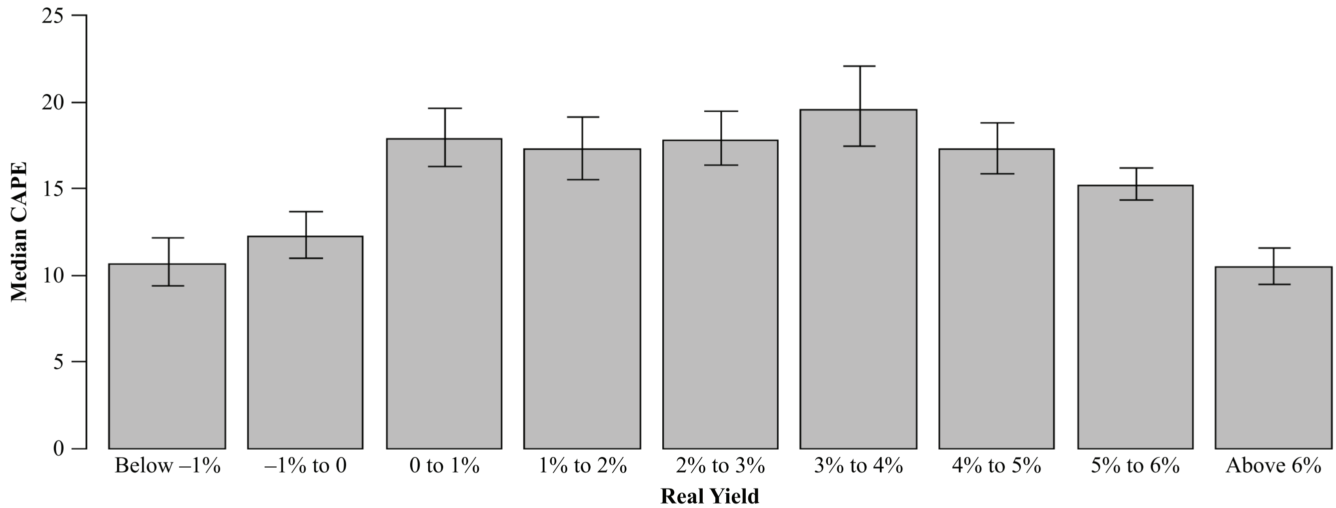
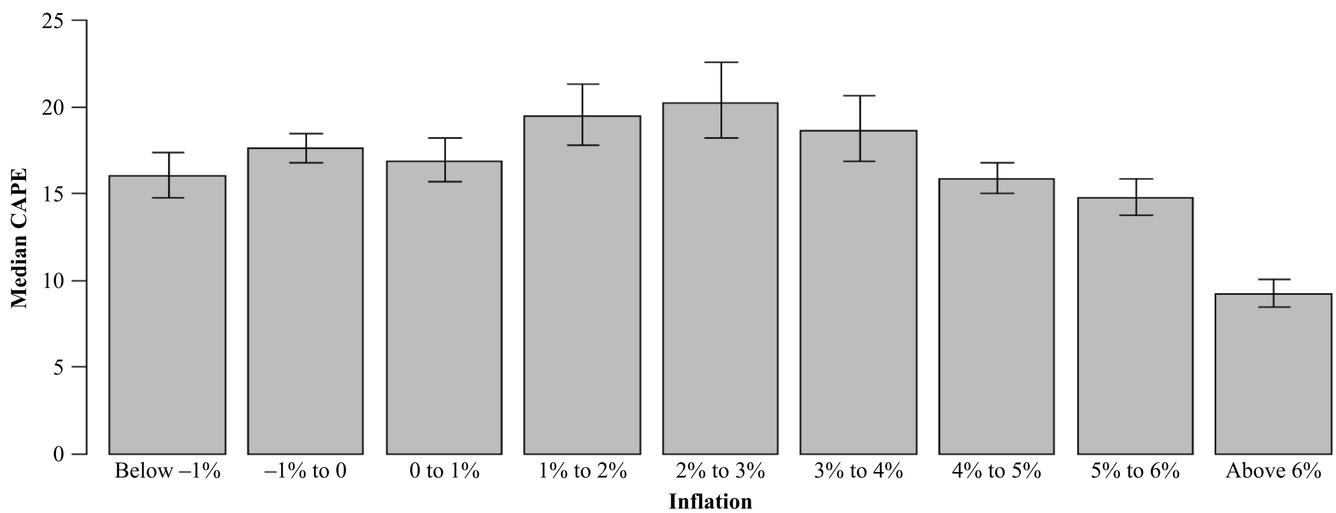


EXHIBIT 2

Median P/E at Different Inflation Regimes (United States, 1880–2016)



and the rightmost P/E of 10.5 has a *t*-statistic of 4.07, whereas the difference between the top P/E of 20.0 and the leftmost P/E of 10.7 has a *t*-statistic of 3.86.

Exhibit 2 shows a very similar pattern between median P/E and inflation rates. The "sweet spot" for the stock market lies between 2% and 3% inflation rates, with a median P/E of 20.3. The P/E represented by the bars on the right side of the chart decline faster—as inflation rates increase—than those on the left side—as inflation rates decrease. This fact might surprise supporters of the thesis that stocks offer sufficient protection against inflation. The difference between the top P/E of 20.3 and the rightmost P/E of 9.2 has a *t*-statistic of 6.53, whereas the difference between the top P/E of 19.4 and the leftmost P/E of 16.0 has a *t*-statistic of 1.78.

Finally, Exhibit 3 shows the joint relationship of the median P/E with real yields and inflation—a three-dimensional (3-D) valuation mountain. Because the peak of the 3-D chart hides some details on its far side, we also present a heat map, along with the number of

EXHIBIT 3

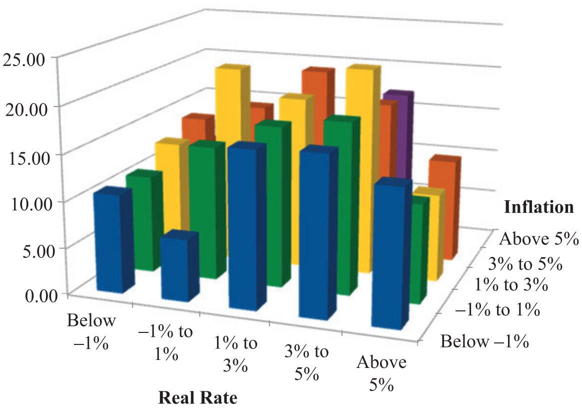
Median P/E at Different Inflation and Real-Yield Regimes (United States, 1880–2016)

CAPE

	Real Rate				
Inflation	**Below –1%**	**–1% to 1%**	**1% to 3%**	**3% to 5%**	**Above 5%**
Below –1%	10.67	6.69	16.75	17.00	14.42
–1% to 1%	10.66	14.58	17.39	18.46	10.65
1% to 3%	12.58	21.60	18.80	22.51	9.56
3% to 5%	13.91	15.81	20.48	17.22	11.37
Above 5%	9.53	10.59	9.19	16.91	

Count

	Real Rate				
Inflation	**Below –1%**	**–1% to 1%**	**1% to 3%**	**3% to 5%**	**Above 5%**
–100% to –1%	13	4	49	50	82
–1% to 1%	10	41	110	83	14
1% to 3%	34	111	257	118	22
3% to 5%	16	89	143	35	53
5% to 100%	118	69	80	26	0



observations used in each bin or "regime." To head off any criticism that the boundaries of the regimes were picked to enhance the results, we use equal increments of two percentage points. The peak median P/E of 22.5 is observed at what are considered "normal" levels of inflation between 1% and 3%, but at a relatively high level of real yields between 3% and 5%.

The objective of the 3-D chart is not to pinpoint the location of the peak but to show that further reductions in real yields or inflation rates do not help boost stock prices. Moving to the next lower regime in terms of inflation—less than 1% annual inflation—reduces the median P/E by 16% to 18.8%, while moving to regimes of still lower real yields reduces the median P/E all the way to 12.6 when real yields are below –1%.

Most of the regimes on the circumference of the matrix have a very low median P/E of about 10. It is important to emphasize that these regimes have fewer observations than those in the middle of the matrix, whose levels of inflation and real interest rates can be considered more normal. Some readers might infer that this distribution is a desirable characteristic for the U.S. economy because it translates into fewer moments of low stock market valuations. We counter that periods of low valuations are wonderful for investors who are *entering* the stock market.[11]

Let's now turn to our findings showing that the relationship between current P/E and future returns can be strengthened by incorporating information on real yields and inflation rates.

A Better Mountain

The charts presented thus far provide an interesting description of the data. Their discrete nature implies, however, that small variations in real yields or inflation result in no change or, alternatively, in sudden jumps in P/E when moving from one regime to another. The bucketing approach is also vulnerable to few samples and noisy data. In this section, we address these shortcomings by estimating the continuous function $f(i,\pi)$ that provides a reasonable and accurate description of P/E given any level of real yield and inflation.[12]

In our search for the most useful function, we evaluated the tradeoff between simplicity and the capacity to describe the data. Polynomials score very high on simplicity, but they have one important flaw: as real yields or inflation move to extremely high or low values, P/E tends to do the same, resulting in implausible numbers. Even if we could find a polynomial that would provide a good fit to the data in our sample, it would likely fail miserably outside this domain. Our proposed solution is to use a two-dimensional Gaussian function to model ln(P/E):

$$\ln\left(\frac{P}{E}\right) = f(i,\pi) = a + b \cdot \exp\left\{-[i-\mu_i \quad \pi-\mu_\pi] \begin{bmatrix} \sigma_i^2 & \rho\sigma_i\sigma_\pi \\ \rho\sigma_i\sigma_\pi & \sigma_\pi^2 \end{bmatrix}^{-1} \begin{bmatrix} i-\mu_i \\ \pi-\mu_\pi \end{bmatrix}\right\} \quad (5)$$

Exhibit 4

Gaussian ln(P/E) Model: Parameter Estimates (United States, 1880–2016)

Parameter	a	b	μ_i	μ_π	σ_i^2	σ_μ^2	ρ
Value	2.09	0.93	2.92%	1.36%	0.00308	0.00492	–0.391

Because of its technical nature, we relegate to Appendix B our method for fitting the Gaussian mountain to the P/E data. Exhibit 4 shows the in-sample parameter estimates for the United States, and Exhibit 5 plots curves of constant P/E.[13] A peak P/E of $\exp(a+b) \approx 20$ can be observed at a real yield of 2.92% and inflation of 1.36%. The lowest possible P/E would be $\exp(a) \approx 8$ at real yield and/or inflation levels far removed from these figures.

The most interesting question, however, is how well this model fits the data. To find the answer, we measure the statistical fit of the model using the adjusted R-squared formula,

$$R^2 = 1 - \frac{\sigma_e^2}{\sigma_{\ln(P/E)}^2} \frac{n-1}{n-p-1} \tag{6}$$

where σ_e^2 and $\sigma_{\ln(P/E)}^2$ are the variances of the model residuals and ln(P/E) are calculated over the entire sample of about 1,600 monthly observations. Calculating the statistical fit over the entire sample imposes a high hurdle on the model and simplifies the comparison with the linear regression models we present next.

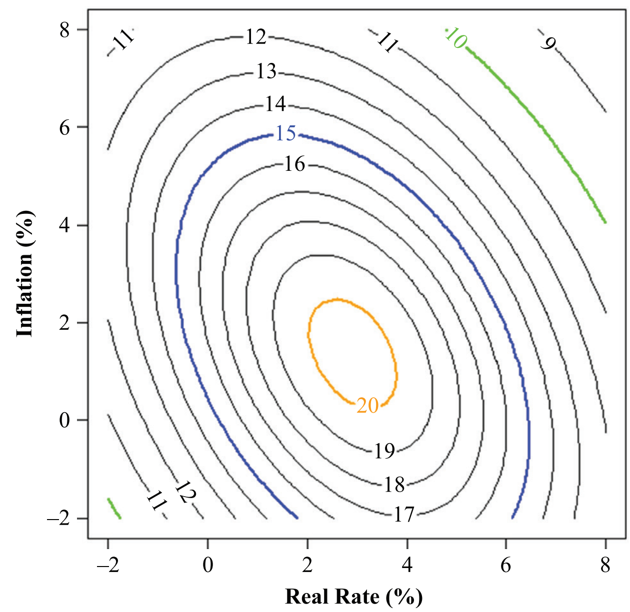
The first row of Exhibit 6 shows that the Gaussian model has an impressive adjusted R-squared of 51.1%. Skeptics may argue that a function with seven parameters ought to do a good job of fitting the data, but our use of an *adjusted* measure of statistical fit should partially alleviate this objection. For additional perspective, we also report the statistical fit of three simple linear regressions that encompass real yields, inflation, and a combination of both:

$$\ln\left(\frac{P_t}{E_t}\right) = a + b_1 i_t + b_2 \pi_t + \varepsilon_t \tag{7}$$

The results of Regressions 1 to 3 are shown in Exhibit 6. All three have very low statistical fits with R-squareds of 9% to 12%, one-fifth as good as the Gaussian model. Further, the coefficients on real yields

Exhibit 5

Level Sets for the Gaussian P/E Model (United States, 1880–2016)



in Regressions 2 and 3 are perversely positive, indicating that valuation levels should rise—not fall—as real interest rates rise.

Can We Enhance the Predictive Power of the Shiller P/E?

We submit that the foregoing insights about stock market valuations are sufficiently interesting by themselves. But can we use them to enhance our understanding of prospective stock market returns? To provide a reference point, we start by reporting results for the traditional forecasting regressions commonly found in the literature, using the natural logarithm of P/E to forecast subsequent annualized returns at horizons from one month to 10 years (and lagging the earnings by three months to reflect actual practice):

$$r_{t+k} = \alpha + \beta \ln\left(\frac{P_t}{E_{t-3}}\right) + \varepsilon_{t+k} \tag{8}$$

It is important to underscore that all of our regressions have a monthly frequency. For this reason, we report two sets of t-statistics to correct for

Exhibit 6

Statistical Fit of Various Models Used to Explain P/E (United States, 1880–2016)

Model	Inflation: Coefficient	Inflation: Newey-West *T*-stat	Real Yield: Coefficient	Real Yield: Newey-West *T*-stat	Adjusted R^2
Gaussian*					51.1%
Regression 1**	–2.95	(–2.38)			10.4%
Regression 2**			3.56	(1.86)	8.9%
Regression 3**	–2.05	(–1.22)	1.95	(0.81)	12.3%

**Equation 6.*

***Equation 7.*

heteroskedasticity and serial correlation in the residuals caused by overlapping returns. The first set uses the well-known approach developed by Newey and West [1987]. The second set uses the same coefficients as the original ordinary least squares (OLS) regressions but calculates their standard errors using separate regressions estimated with reduced and nonoverlapping data samples. This approach eliminates any serial correlation in the residuals and yields significantly lower t-stats, especially at longer horizons.

Exhibit 7 shows that all coefficients are negative; lower valuation multiples indicate depressed prices, which in turn signal subsequent higher returns. Our results confirm findings in the existing literature (e.g., Cochrane [2008]) that the statistical power of return forecasting increases with horizon. For instance, going from one month to 10 years raises the R-squared from less than 1% to more than 30% and the magnitude of the t-stat from 1.79 to 3.12.[14]

How can we use the information gained thus far to enhance stock market forecasts? We propose a simple idea. Traditional forecasting regressions, such as Equation 8, compare the current P/E with a single full-sample historical average. Instead, given that inflation and real yields provide valuable information about the median P/E, we should be able to enhance forecasting power by comparing the current P/E with the Gaussian model P/E, conditional on current levels of inflation and real yields. For instance, when real yields and inflation are both very low, a relatively low average P/E of about 10 might be normal. Therefore, if the current P/E was above 10, this would suggest a lower future return. By contrast, in a traditional regression, if the current P/E was below the full-sample average, we would

Exhibit 7

Return Forecasting Regression—Equation 8 (United States, 1880–2016)

Horizon	Coefficient	Newey–West *T*-stat	Nonoverlapping *T*-stat	Adjusted R^2
120	–0.07	–6.66	–2.07	32.4%
60	–0.08	–3.62	–3.12	19.1%
36	–0.09	–2.84	–2.18	11.8%
12	–0.10	–2.93	–2.58	4.4%
6	–0.09	–2.70	–2.16	1.9%
1	–0.08	–1.79	–1.79	0.2%

erroneously expect a higher future return. Translating this logic into a regression equation, we have

$$r_{t+k} = \alpha + \beta\left[\ln\left(\frac{P_t}{E_{t-3}}\right) - f(i_t, \pi_t)\right] + \varepsilon_{t+k} \tag{9}$$

where $f(i_t, \pi_t)$ denotes the natural logarithm of P/E, predicted by the Gaussian function stated in Equation 5, conditional on the current levels of inflation and real yield.[15]

Exhibit 8 shows the results of using Equation 9 to forecast returns. The most notable improvements come at the short-horizon forecasts for which the coefficients almost double from those in Exhibit 7, followed by an increase in the magnitudes of t-stats from borderline significance in Exhibit 7 to high significance in Exhibit 8.

Interestingly, the results are reversed at longer horizons; coefficients are reduced, especially for 10-year results, and the statistical significance of P/E disappears. These patterns are unsurprising. because the real yield and inflation change over time, today's levels are likely to differ substantially from those a decade into the future. Hence, conditioning our *long-term* forecasts on *current* inflation or real rates is a serious mistake. The crossover point for the coefficient is between three and five years in the future. Accordingly, conditioning P/E on these two current macroeconomic measures would appear to be ill advised for spans of three years or more, beyond which the basic Shiller P/E shows its impressive merit.

To further investigate our claim that current macroeconomic conditions are not very important for long-term forecasts because the real yield and inflation change significantly over time, we adopt a slightly different specification for the regression in Equation 9. Imagine that a genie informs us of future real yields and inflation rates, but not of future P/Es. If we substitute our expected P/E at the end of the forecasting window, $f(i_{t+k}, \pi_{t+k})$, for our expected P/E at the beginning of the forecasting window, $f(i_t, \pi_t)$, we obtain significantly higher statistical significance and fit across all forecasting horizons—but especially at five- and 10-year windows. For the sake of brevity, we do not report these unsurprising results here, but they are available on request.

EXHIBIT 8

Return Forecasting Regression—Equation 9 (United States, 1880–2016)

Horizon	Coefficient	Newey–West *T*-stat	Nonoverlapping *T*-stat	Adjusted R^2
120	–0.05	–2.17	–0.42	7.9%
60	–0.08	–1.88	–1.54	7.6%
36	–0.10	–2.13	–1.65	7.7%
12	–0.15	–3.15	–2.45	4.4%
6	–0.16	–3.60	–3.20	2.7%
1	–0.17	–3.23	–3.23	0.6%

GLOBAL (DEVELOPED MARKETS) RESULTS

How does this method fare "out of sample" when we apply it outside the United States? The results for global developed markets are similar to the U.S. results, with a few small differences due to data availability. We comment only briefly on the similarities and discuss the differences in greater detail. Throughout the discussion of our global market results, keep in mind that we pooled all available data starting in 1972.

The 3-D valuation mountain in Exhibit 9 shows that the joint relationship of median P/E with real yields and inflation also holds in international markets. The univariate relationship between P/E and inflation, illustrated along the vertical dimension of the heat map, differs in minor ways from the comparable relationship in the U.S. stock market. The reason for the global sample's more gradual slope from the peak to the foot of the mountain with decreasing inflation can be traced to fewer episodes of very low inflation in international countries after 1972. As the bottom half of the exhibit shows, the majority of inflation rate observations are

EXHIBIT 9

Median P/E at Different Inflation and Real-Yield Regimes (developed countries, 1972–2016)

CAPE

	Real Rate				
Inflation	**Below –1%**	**–1% to 1%**	**1% to 3%**	**3% to 5%**	**Above 5%**
Below –1%		19.05	24.03	7.20	14.99
–1% to 1%	13.06	14.70	21.88	24.35	16.82
1% to 3%	12.10	14.45	23.61	21.44	18.61
3% to 5%	14.21	17.18	16.72	17.18	14.81
Above 5%	11.60	9.78	13.19	9.60	11.00

Count

	Real Rate				
Inflation	**Below –1%**	**–1% to 1%**	**1% to 3%**	**3% to 5%**	**Above 5%**
Below –1%	0	8	22	10	83
–1% to 1%	21	355	654	244	119
1% to 3%	51	542	1552	1061	411
3% to 5%	91	265	535	369	380
Above 5%	151	187	308	343	412

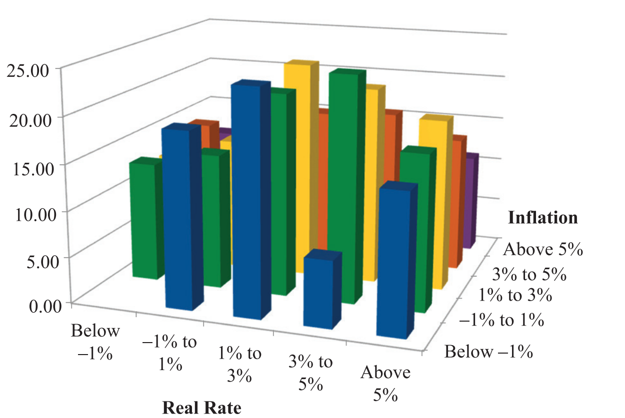


EXHIBIT 10

Gaussian ln(P/E) Model: Parameter Estimates (developed countries, 1972–2016)

Parameter	a	b	μ_i	μ_π	σ_i^2	σ_μ^2	ρ
Value	2.21	0.941	3.05%	1.89%	0.00290	0.00226	–0.176

zero or higher. Furthermore, because in the late 1980s Japan experienced a stock market bubble with extremely high P/E—in excess of 100!—and very low inflation, the middle-to-left sections of the chart might be overstated.[16] Nevertheless, the pattern is similar to that represented in Exhibit 3, with peak median P/E falling in the moderate range of real yields and inflation around zero.

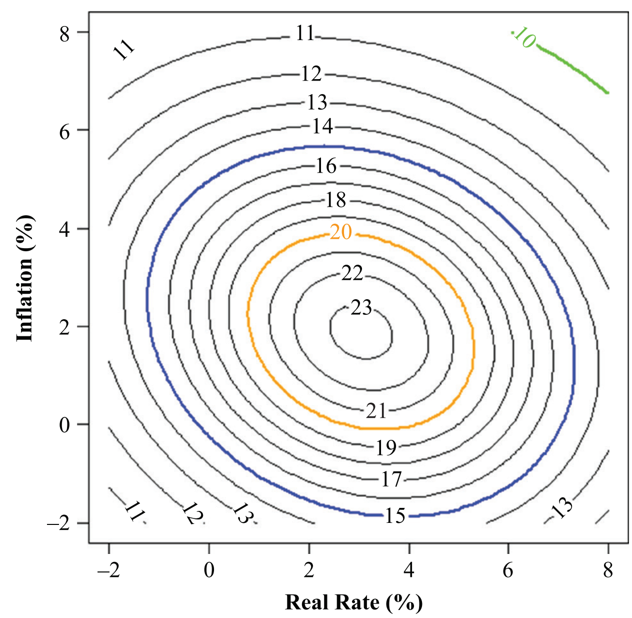
Using the developed country sample to estimate the parameters for Equation 5 results in numbers very similar to those obtained for the United States. Exhibit 10 shows a marginally higher parameter *a* and an almost identical parameter *b*, jointly indicating a slightly higher peak P/E of about 23. The location of the international peak P/E is very close to the location of the U.S. peak P/E, at a real yield of 3.05% and an inflation rate of 1.89%. (The U.S. peak is at 2.92% and 1.36%, respectively.) Though the near-identical location of the peak is likely to be coincidence, we believe that the broad similarity of the peaks is not. These developed country data provide a powerful out-of-sample ratification of the U.S. findings. Exhibit 11 also confirms the similarity between the level sets obtained from the two distinct samples.[17]

The Gaussian model does not perform as well in terms of statistical fit for the international sample as for the U.S. market. Exhibit 12 shows the 28.0% adjusted R-squared of the developed market sample, which is smaller than the 51.1% adjusted R-squared of the U.S. market. We are not troubled by this, however, because a single model faces a significant challenge in its ability to fit the multinational data in the international sample: it has to explain P/E in more than 20 countries as different, for example, as Canada and Japan, with different accounting standards, different investor risk aversion, and so forth.

When using linear regressions to explain P/E, we observe some similar results but also some differences. Unlike the U.S. sample, the coefficient on real yields has the expected negative sign, but the statistical fit of less than 1% is very poor. The picture is reversed when inflation is included in the regressions. The R-squareds jump to 18.6% (univariate) and 19.1% (multivariate),

EXHIBIT 11

Level Sets for the Gaussian P/E Model (developed countries, 1972–2016)



twice the numbers in the U.S. sample. These relatively higher statistical fits can be explained by the lack of observations in low inflation periods. With fewer observations on the left half of the chart, the regression does a good job in fitting only on the right half.

Finally, Exhibits 13 and 14 report results for return-forecasting regressions using Equations 8 and 9, respectively. As in the U.S. sample, we observe a significant increase in forecasting power when we include inflation and real yields. The short-horizon *t*-stats move from being marginally significant to strongly significant, and the R-squareds very nearly double. The improvements are especially important at the one-month horizon, with the coefficient moving from −0.09 to −0.16 and the R-squared from 0.2% to 0.4%. In this case, however, long-horizon coefficients and R-squareds are very similar across the two regressions.

CONCLUSION

Our work on the relationship between stock prices and the levels of both inflation and the real interest rate has been gratifying on two levels. First, we and many others have long believed that valuation is an important determinant of real asset class returns. But the poor

EXHIBIT 12

Statistical Fit of Various Models Used to Explain P/E (developed countries, 1972–2016)

	Inflation		Real Yield		
Model	**Coefficient**	**Newey–West *T*-stat**	**Coefficient**	**Newey–West *T*-stat**	**Adjusted R^2**
Gaussian*					28.0%
Regression 1**	–7.08	(–6.41)			18.6%
Regression 2**			–1.04	(–0.58)	0.2%
Regression 3**	–7.15	(–7.02)	–1.57	(–0.95)	19.1%

**Equation 6.*

***Equation 7.*

linkage with short-term returns has always been an Achilles' heel for valuation measures. The Shiller P/E has customarily been a favorite of the valuation community because of its demonstrated correlation with long-horizon real returns for U.S. and international stock markets. We are pleased to see that conditioning the "normal" P/E on current macroeconomic conditions can lead to an impressive step-up in its efficacy as a predictor of near-term capital market returns. Valuations do matter—and not just in the long term, but also in the short term. We need only recognize that on a short-term basis, depending on current macroeconomic conditions, a stock's valuation may gravitate toward a level that is different from its long-term historical average.

Second, our work suggests a rich path for further research. Many macroeconomic and market measures have been found to be linked to near-term capital market returns—including corporate issuances and the price-to-dividend, price-to-book, investment-to-capital, and consumption-wealth-income ratios.[18] Our technique demonstrates that there are more powerful ways to integrate macroeconomic measures with stock valuation methods than the linear combinations that predominate in quantitative research. As in the example we have presented, the efficacy of valuation is increased (in this specific case, *doubled*) by assuming that the equilibrium level for P/E varies with the macroeconomic state. We need no longer rely on long-term historical averages to infer near-term mean-reversion targets. This result suggests that valuation, always a powerful tool for long-term investors, can also become useful for assessing short-term market prospects. We are hopeful that our work opens the door to others who will explore new ways to think about valuation measures and the manner in which we can use them.

EXHIBIT 13

Return Forecasting Regression—Equation 8 (developed countries, 1972–2016)

Horizon	Coefficient	Newey–West *T*-stat	Nonoverlapping *T*-stat	Adjusted R^2
120	–0.06	–15.63	–1.88	21.4%
60	–0.11	–6.74	–4.80	20.5%
36	–0.12	–3.82	–2.56	13.0%
12	–0.13	–2.22	–1.88	3.7%
6	–0.12	–2.29	–1.98	1.6%
1	–0.09	–1.74	–1.74	0.2%

EXHIBIT 14

Return Forecasting Regression—Equation 9 (developed countries, 1972–2016)

Horizon	Coefficient	Newey–West *T*-stat	Nonoverlapping *T*-stat	Adjusted R^2
120	–0.07	–7.23	–2.50	16.0%
60	–0.14	–6.43	–6.51	19.7%
36	–0.16	–4.71	–3.77	14.2%
12	–0.20	–3.51	–2.64	5.8%
6	–0.20	–3.63	–3.25	2.9%
1	–0.16	–2.66	–2.66	0.4%

APPENDIX A

DATA SOURCE AND SUMMARY STATISTICS

Summary statistics for individual countries are displayed in Exhibit A1. Although the U.S. sample starts in 1880, the international sample starts in 1972, the first year the requisite data are available for at least three countries: Canada, Japan, and the United Kingdom. Other countries

Exhibit A1
Summary Statistics

	Start Date	CAPE		Inflation		Real Yield	
		Median	Std. Dev.	Median	Std. Dev.	Median	Std. Dev.
USA	12/31/1880	16.43	6.64	2.3%	4.4%	2.1%	3.4%
Australia	6/30/1979	16.12	7.25	3.1%	3.1%	3.4%	2.0%
Austria	9/30/1991	25.46	14.43	1.9%	0.9%	2.4%	1.7%
Belgium	6/30/1979	15.64	5.66	2.4%	2.1%	3.6%	2.3%
Canada	12/31/1965	18.65	8.46	3.2%	3.1%	3.2%	2.0%
Denmark	6/30/1979	23.18	11.05	2.4%	3.0%	3.4%	2.8%
Finland	12/31/1997	24.85	22.02	1.5%	1.1%	2.3%	1.6%
France	3/31/1989	20.90	7.41	1.8%	0.9%	2.8%	1.9%
Germany	6/30/1979	19.31	6.90	1.8%	1.5%	3.3%	1.9%
Greece	12/31/1986	10.57	8.21	3.6%	5.3%	2.2%	5.6%
Hong Kong	10/31/1996	17.52	4.42	2.0%	3.1%	1.5%	3.9%
Ireland	4/30/2000	14.41	6.27	2.5%	2.5%	1.1%	2.9%
Italy	12/31/1990	16.11	8.99	2.4%	1.6%	2.5%	2.1%
Japan	12/31/1965	32.09	26.60	1.8%	4.2%	1.7%	2.5%
Netherlands	6/30/1979	13.66	7.01	2.2%	1.5%	3.1%	2.2%
New Zealand	12/31/1997	16.02	4.73	2.2%	1.1%	3.3%	1.3%
Norway	6/30/1979	14.09	5.74	2.4%	3.2%	3.4%	1.9%
Portugal	12/31/1997	15.85	7.02	2.5%	1.3%	2.0%	2.6%
Singapore	6/30/1998	16.05	5.31	1.1%	1.9%	1.7%	2.0%
Spain	11/30/1989	17.22	6.93	3.1%	1.8%	2.2%	2.0%
Sweden	6/30/1979	17.66	7.95	2.4%	3.7%	2.7%	2.0%
Switzerland	6/30/1979	20.81	8.12	1.2%	1.9%	1.8%	1.1%
UK	3/31/1972	14.81	5.70	4.0%	5.2%	2.1%	2.9%

Source: Global Financial Data.

included in the international sample, with later start dates, are Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, and Switzerland.

Median P/Es are mostly in the 15–25 range, with a few exceptions. Most notably, Japan had a median P/E of 32, while the Netherlands' value was close to 14. The United Kingdom had the highest median inflation rate at 4.0%, while Singapore's was just 1.1%. The median real yield was lowest in Ireland (1.1%) and Japan (1.7%), and highest in Belgium (3.6%) and Denmark (3.4%).

Appendix B

FITTING THE GAUSSIAN BELL CURVE TO THE CAPE DATA

We construct a two-dimensional Gaussian (bell-shaped) function to model ln(P/E)s:

$$\ln\left(\frac{P}{E}\right) = f(i,\pi) = a + b \cdot exp\left\{-[i-\mu_i \quad \pi-\mu_\pi] \begin{bmatrix} \sigma_i^2 & \rho\sigma_i\sigma_\pi \\ \rho\sigma_i\sigma_\pi & \sigma_\pi^2 \end{bmatrix}^{-1} \begin{bmatrix} i-\mu_i \\ \pi-\mu_\pi \end{bmatrix}\right\} \quad \text{(A-1)}$$

The first parameter, a, describes the minimum ln(P/E) when $i \to \infty$ and $\pi \to \infty$. The sum of the first two parameters, $a + b$, describes the maximum ln(P/E), a value attained when $i = \mu_i$ and $\pi = \mu_\pi$, which represent the location of the maximum ln(P/E). Finally, the remaining three parameters—σ_i, σ_π, and ρ—guide the "width" of the mountain along each dimension as well as its orientation (east, west, north, south), and have a similar interpretation as the volatilities and correlation in a two-dimensional normal distribution.

Because this function has seven parameters that need to be estimated, using the matrix in Exhibit 3, which has 25 (or fewer) observations, could result in imprecise estimates. Accordingly, for estimation purposes, we create a 10 × 10 grid by dividing the real-yield/inflation domain into equally sized squares with the same boundaries ({−2%, −1%, 0%, 1%, 2%, 3%, 4%, 5%, 6%}) along both dimensions. Then we minimize the weighted sum of squared errors by using the median values of P/E, i, and π within each of the regimes delineated by these boundaries:

$$\min \sum_{j=1}^{100} \frac{\sqrt{N_j}}{\sigma_j} e_j^2 = \min \sum_{j=1}^{100} \frac{\sqrt{N_j}}{\sigma_j} \left[\ln\left(\frac{P}{E}\right)_j - f(i_j, \pi_j) \right]^2 \tag{A-2}$$

The weights in Equation A-2 are directly proportional to the square root of the number of observations and inversely proportional to the standard deviation of ln(P/E), both measured within the confines of each regime. This choice of weights forces the optimization to pay more attention to areas on the grid that have more observations and less variability.

ENDNOTES

The views and opinions expressed herein are those of the author and do not necessarily reflect the views of The Vanguard Group, its affiliates or employees.

[1]In their seminal book, *Security Analysis*, Graham and Dodd actually say, "In other words, the market is not a weighing machine, in which the value of each issue is registered by an exact and impersonal mechanism, in accordance with its specific qualities. Rather we should say that the market is a voting machine, whereon countless individuals register choices which are partly the product of reason and partly the product of emotion" (Graham and Dodd [2008], p. 70).

[2]John Y. Campbell and Robert Shiller used 10-year average earnings in the earnings-to-price ratio in Campbell and Shiller [1988] and tested its predictive strength in Campbell and Shiller [1998]. Shiller adopted the term CAPE in the third edition of *Irrational Exuberance* (Shiller [2015], p. xv).

[3]A precise notation would be $\Delta E_{t\to t+36}$ and $\pi_{t\to t+36}$. To minimize clutter, we simplify this to ΔEt and πt.

[4]Standard errors are corrected for heteroskedasticity and time-series correlation in the residuals using the methodology of Newey–West. See the data section for sources and details.

[5]One of the authors (Arnott) has frequently posed a thought experiment: Suppose the "equity risk premium" had been labeled as a "fear premium" from the early days of the concept. After all, there's little empirical evidence of the correct linkage between objective measures of risk—such as volatility or beta—and return. And investors in an inefficient market may demand a higher reward, hence a lower starting price, for investing where others fear to tread. Had finance theory begun with a fear premium, rather than a risk premium, many of the anomalies of modern finance would have been unsurprising, even expected.

[6]This is analogous to the method used in Arnott and Chaves [2012] in finding polynomial linkages between demographic profiles and capital market returns.

[7]It bears mention that the "Fed model" was developed based on market data from the 1960s to the 1990s. Before the 1960s and after the 1990s, the model fails. Data from before the 1960s were readily available when the "Fed model" was in its heyday, but were conveniently ignored. It has subsequently failed miserably post-2000, yet the model retains many adherents.

[8]The frequent central bank assertions that quantitative easing is not contributing to the much-vaunted wealth gap are at odds with this stated intent for quantitative easing. Who has assets? Overwhelmingly, it's the affluent. Therefore, seeking to create a wealth effect, ipso facto, drives wealth inequality—but we digress.

[9]We use a three-year inflation window when calculating the real yield in order to reduce the risk of having two variables—inflation and real yields—that are simple mirror images of each other during periods of stable nominal interest rates. In addition, Arnott and Bernstein [2002] find that long-term bond yields were better correlated with three-year inflation than with longer or shorter spans.

[10]We focus our attention on median P/Es to reduce the influence of outliers, especially in international markets, but our results are qualitatively the same if we use average P/Es.

[11]We find the cheerleading for bull markets to be interesting; as Arnott and Bernstein [1997] observe, bull markets are good for those who are about to sell and bear markets are good for those who are still accumulating and investing.

[12]In the interest of brevity, from this point on we denote the inflation rate by π, and the real interest rate (or yield) by i.

[13]The model is defined on ln(P/E), but Exhibit 5 plots P/E directly because the P/E ratio is most commonly quoted in linear numbers.

[14]Low R-squareds on short-term results are deceptive; they're often much more useful than they seem. For instance, the R-squared of 32% on 120-month real returns implies a correlation of 0.57, while the R-squared of 4.4% on 12-month real returns implies a correlation of 0.21. A very crude analogy is that the P/E is approximately 57% as useful as a genie telling us the exact 10-year future real return for the stock market or 21% as useful as perfect foresight on the 1-year future real return for stocks. Given a choice, would you rather have 57% correlation with perfect 10-year foresight on the real return, or 10 snapshots, each with 21% correlation with 1-year perfect foresight? We would probably choose the

latter, but it would be a tough call. In other words, the 32% R-squared on 10-year real returns is not necessarily better than the 4.4% R-squared on 1-year real returns.

[15]One possible concern is that our Gaussian function is estimated using the full sample, but this is also a concern for regular forecasting regressions because they use the full sample to estimate averages of dependent and independent variables.

[16]Even if we use ln(P/E), these outliers can dominate the analysis.

[17]We have also applied the Gaussian model to smaller samples including Europe or Asia (including Australia and New Zealand, but excluding Japan) with success. These results are available from the authors by request. The case of Japan is interesting; the Gaussian model fails to identify a peak given the extremely high valuations at times of very low inflation.

[18]See Goyal and Welch [2008] for a review and summary of those variables.

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