Table 1 (*Continued*)

Study	Issue	Method	Specialties/conditions	Results
Kim (1995, 2010)	CAPM test	MLE	Closed form adjustment; for individual stocks or groups	– MLE method can effectively adjust the errors-in-variables bias and CAPM holds – Support CAPM
Kim (1997)	CAPM test	MLE	Closed form adjustment; for individual stocks or groups; for multifactor estimation	– Linear relationship between beta and expected return – Book-to-market ratio has significant explanatory power for expected return, but size has not
Lewbel (1997)	Elasticity of patent applications to R&D expenses	Instrumental variable method	Applicable if no outside data available for use as instruments	– TSLS estimator can mitigate the effects of measurement error – The estimated elasticity of patent applications with respect to R&D expenditures yields very close to one
Erickson and Whited (2000)	Test *q* theory	GMM	For balanced panel data	– Cash flow does not affect firms' financial decision, even for financially constrained firms – Support the *q* theory if measurement error is taken into account
Pastor et al. (2008)	Determinants of cost of capital	Implied cost of capital	Use earnings forecasts to compute implied cost of capital	– The implied cost of capital can capture time variation in expected stock returns
Chang et al. (2009)	Determinants of capital structure	MIMIC model	Allow several observable variables as indicators without multicollinearity problem	– Seven constructs, growth, profitability, collateral value, volatility, non-debt tax shields, uniqueness, and industry, as determinants of capital structure have significant effects on capital structure decision
Yang et al. (2009)	Determinants of capital structure	LISREL model	Jointly determine capital structure and return	– Stock returns, expected growth, uniqueness, asset structure, profitability, and industry classification are main determinants of capital structure – Leverage, expected growth, profitability, firm value, and liquidity can explain stock returns – The capital structure and stock return, in addition, are mutually determined by each other
Almeida et al. (2010)	Test *q* theory	GMM and instrumental variables method	Simple instrumental variable – lagged variable	– Estimators from GMM are unstable across different specifications and not economically meaningful – Estimators from a simple instrumental method are robust and conform to *q* theory
Davis (2010)	CAPM test	Bayesian approach	One-step estimation	– Positive relationship between excess return and market risk – Support CAPM
Jagannathan et al. (2010)	CAPM tests	Three-stage cross-sectional regression	Adjust for rolling window betas	– Dealing with measurement error in rolling window betas – Support CAPM
Guay et al. (2011)	Determinants of cost of capital	Corrected implied cost of capital	Sluggish analyst forecasts may result measurement error on implied cost of capital	– The corrected implied cost of capital can improve the ability to explain cross-sectional variation in future stock returns
Da et al. (2012)	CAPM tests	Three-stage cross-sectional regression	Adjust for rolling window betas	– Dealing with measurement error in rolling window betas – Support CAPM
Erickson and Whited (2012)	Test *q* theory	GMM	For unbalanced panel data	– Instrumental variables, dynamic panel estimators, and high-order moment estimators can perform well under correct specification – Developing a minimum distance technique allowing high-order moment estimators be used in unbalanced panel data

Table 1 (*Continued*)

Study	Issue	Method	Specialties/conditions	Results
Ortiz-Molina and Phillips (2014)	Determinants of cost of capital	Implied cost of capital	Use earnings forecasts to compute implied cost of capital	– The implied cost of capital can mitigate measurement error problem on determine the cost of capital
Lee and Tai (2014)	Determinants of capital structure	SEM with CFA approach	Jointly determine capital structure and return	– SEM with CFA approach outperforms MIMIC model and 2SLS method in terms of the joint determinants of capital structure and stock return

improve the ability to explain cross-sectional variation in future stock returns.

4.2. Capital asset pricing model

The capital asset pricing model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966) implies that the expected returns on securities and their market risks (β) are positively and linearly correlated and that market risks have sufficient power to explain expected returns of securities. Black et al. (1972), Fama and MacBeth's (1973), and others use the two-step method to test CAPM. In the first step, estimated betas are obtained by time-series market model for each security. In the second step, the estimated betas are used in testing the linear relationship between betas and expected returns on securities. Because estimated betas are subjected to a measurement error (estimation error) problem, there exists an EIV problem in the second step. The EIV problem will result in estimating the explanatory power of beta and the estimated rate of return on beta risk. More specifically, the EIV problem leads to an underestimation of the coefficient associated with beta risk. Although the EIV problem exists in the two-step method of the asset pricing test, most researchers do not carefully use sophisticated econometric and statistical methods to deal with this kind of problem. Roll (1969, 1977) shows that the testing asset pricing model suffers an EIV problem, concluding that (i) no correct and unambiguous test of the theory has appeared in the literature, and (ii) practically no possibility exists that such a test can be accomplished in the future. Roll and Ross (1994) show that the measurement error problem of market rate of return can bias the empirical test of CAPM.

Several studies focus on beta estimation in the first step to solve the EIV problem in testing CAPM. Brennan (1970), Lee and Jen (1978) and Roll (1977) show that the possible measurement error in market beta risk is the unobserved market rate of return and risk-free rate of return.[5] To improve the beta estimator, Fabozzi and Francis (1978) and Lee and Chen (1979) use the random coefficient procedure to estimate random coefficient betas. Brennan and Schwartz (1977), Brennan (1979) and Brown and Warner (1980) also provide different types of market models which can produce different results in predicting rates of return, testing efficient market hypotheses, and measuring security price performance.

To reduce the impact of the measurement error problem in the second step, Black et al. (1972) use the grouping method in the capital asset pricing model test. Although the results support the linear relationship between the systematic risk and expected return, CAPM cannot hold because of the non-zero intercept term and the lower market premium in the cross-sectional regression. Blume and Friend (1973) and Fama and MacBeth (1973) also use the grouping method in testing CAPM and show that the CAPM is valid. However, Jagannathan, Skoulakis, and Wang (2009) show that the time series average of the cross-sectional estimators converges in probability to the true value of the estimator. Although their results support CAPM indicating a linear relationship between the systematic risk and the expected return, the lower value of time-series average of the market premium shows that the measurement error problem still exists after Fama and MacBeth's (1973) grouping method.

Considering the measurement errors of the market rate of return and risk-free rate of return, Lee (1977) uses two EIV estimation methods, Wald's two-group grouping method and Durbin's instrumental variable method, to adjust the estimated beta risk in the first step of the capital asset pricing test. Although correcting the measurement errors induced from the unobservable market rate of return, Lee (1977) finds that the predictive ability of the capital asset pricing model is still poor.

Litzenberger and Ramaswamy (1979) derive an after-tax version of CAPM and show that, in the equilibrium, the before-tax expected return on a security is linearly related to its systematic risk and its dividend yield. Litzenberger and Ramaswamy (1979) further empirically test both the before tax and the after-tax versions of CAPM. Instead of grouping method, Litzenberger and Ramaswamy (1979) use maximum likelihood estimation in the second-step regression to test the before-tax and the after-tax versions of capital asset pricing model. Although maximum likelihood estimators are consistent, the average risk premium is small and not significantly different from zero.

Given the EIV bias in the two-step CAPM test, Gibbons (1982) introduces a one-step Gauss-Newton procedure and uses the maximum likelihood method to obtain the estimated price of systematic risk. Because the one-step Gauss-Newton procedure does not use estimated beta as an explanatory variable in a regression model, the measurement errors problem of estimated beta can be avoided. Shanken (1992) shows that using generalized least square (GLS) on the second step of CAPM test can yield an estimator identical to the Gauss-Newton estimator obtained by Gibbons' (1982) maximum likelihood method. Gibbons (1982) shows that the Gauss-Newton procedure increases the precision of estimated risk premium, but rejects the mean-variance efficiency of the market portfolio.

Shanken (1992), who provides a modified version of the two-step estimator by using maximum likelihood estimation, finds that Fama and MacBeth's two-step procedure overstates the precision of the estimator in the second-step and therefore provides an adjusted standard error for the estimator in the second-step regression. Jagannathan and Wang (1998a, 1998b) further

[5] Roll (1969), Roll (1977) and Lee and Jen (1978) show that the observed market rate returns in terms of stock market index are measured with errors since the stock market index does not include all assets which investors can invest. Lee and Jen (1978) have theoretically shown how beta estimate and Jensen performance measures can be affected by both constant and random measurement errors of R_m and R_f. Diacogiannis and Feldman (2011), Green (1986), Roll and Ross (1994) and Gibbons and Ferson (1985) have argued that market portfolio measure with errors is an inefficient portfolio and show how the inefficient benchmark can affect theoretical CAPM derivation. Diacogiannis and Feldman (2011) provide a pricing model that uses inefficient benchmarks, a two beta model, one induced by the benchmark, and one adjusting for its inefficiency.

release Shanken's assumption that asset returns are conditional homoscedasticity to derive a more general standard error for the second-step estimator by generalized least squares.

Fama and French (1992) use a two-way sort grouping method to control for size effect, and find a weak relationship between beta risk and expected return. Before reaching the conclusion that the capital asset pricing has not been valid in the recent years, one possible reason that may be considered is that the measurement error problem cannot be fully eliminated by the grouping method, and results of CAPM test may vary depending on the portfolio formation technique (e.g. Ahn et al., 2009).

To deal with the problem of EIV in testing CAPM, Kim (1995) provides a maximum likelihood method, extracting information associated with the relationship between the measurement error variance and idiosyncratic error variance and incorporating such information into the maximum likelihood estimation in the second step of the capital asset pricing model test. Given the assumption that the disturbance term of the market model is homoscedasticity, the corrected factors for the traditional least squares estimators of the cross-sectional regression coefficients can be obtained. Although Kim's (1995) maximum likelihood method can only deal with the EIV problem of the estimated beta in the first pass, the maximum likelihood method can test, besides the capital asset pricing model, the multifactor asset pricing models. Kim (1995) uses maxima likelihood method to reexamine CAPM and multi-factor asset pricing model and finds more support for the role of market beta risk and less support for the role of firm size. His results show that the prominent risk factors (e.g. size, book-to-market ratio, and momentum factors) might result a different explaining power for cross-sectional stock returns after correcting the EIV problem.

MacKinlay and Richardson (1991) use generalized method of moments (GMM) to test the mean–variance efficiency. They theoretically show that the estimator from GMM and the estimator from maximum likelihood method are equivalent when stock returns are conditionally homoscedasticity, but GMM can avoid the EIV problem by estimating coefficients in one step. Empirical and simulation results show that the conclusion mean–variance efficiency of market indexes is sensitive to the model settings.

Chen (2011) offers an empirical examination of various EIV estimation methods in the testing of CAPM, including the grouping method, the instrumental variable method, and the maximum likelihood method. Both potential measurement error problems of market return in the first pass and estimated beta in the second pass are corrected by either the grouping method or the instrumental variable method. Chen (2011) shows that empirical results support the role of market beta in the capital asset pricing model after correcting the EIV problem.

To deal with the measurement error problem associated with testing both CAPM and APT, Lee and Wei (1984) and Wei (1984) use the MIMC model to test whether APT outperformed CAPM. Betas are obtained from simultaneous equation system, and a cross-sectional regression of the security return against its β will be used to test the CAPM. They conclude that the beta estimated from the MIMC model by allowing measurement error on the market portfolio does not significantly improve the OLS beta estimate, and MLE estimator does a better job than the OLS and GLS estimators in the cross-sectional regressions because the MLE estimator takes care of the measurement error in beta.

More recently, Jagannathan, Kim, and Skoulakis (2010) and Da, Guo, and Jagannathan (2012) use three-stage cross-sectional regression to correct the errors-in-variables problem from the rolling-window betas. Their empirical findings support CAPM in explaining option-adjusted stock returns at the individual stock level.

4.3. Capital structure

Titman and Wessels (1988), Chang et al. (2009) and Yang et al. (2009) use structure equation models (e.g. LISREL model and MIMIC model) to mitigate the measurement problems of proxy variables when working on capital structure theory. Titman and Wessels (1988) use LISREL method to investigate determinants of capital structure. In the structure equation model, they use 15 indicators associated with eight latent variables and set 105 restrictions on the coefficient matrix. Empirical results, however, do not support four of eight propositions on the determinants of capital structure. Specifically, their results show that a firm's capital structure is not significantly related to its non-debt tax shields, volatility of earnings, collateral value of assets, and future growth. One possible reason for the poor results is that the indicators used in the empirical study do not adequately reflect the nature of the attributes suggested by financial theory.

Chang et al. (2009) apply a Multiple Indicators and Multiple Causes model (MIMIC) with refined indicators to reexamine Titman and Wessels (1988) work on determinants of capital structure. Chang et al. (2009) examine the seven indicator factors as follows: growth, profitability, collateral value, volatility, non-debt tax shields, uniqueness, and industry. Their empirical results show that the growth is the most influential determinant on capital structure, followed by profitability, and then collateral value. Under a simultaneous cause–effect framework, their seven constructs as determinants of capital structure have significant effects on capital structure decision.

Yang et al. (2009) apply a LISREL model to find determinants of capital structure and stock returns, and estimate the impact of unobservable attributes on capital structure decisions and stock returns. Using leverage ratios and stock returns as two endogenous variables and 11 latent factors as exogenous variables, Yang et al. (2009) find that stock returns, expected growth, uniqueness, asset structure, profitability, and industry classification are main determinants of capital structure, while leverage, expected growth, profitability, firm value, and liquidity can explain stock returns. In addition, the capital structure and stock return are mutually determined by each other.

Lee and Tai (2014) develop a simultaneous determination model to identify the joint determinants of capital structure and stock returns. The structural equation model with confirmatory factor analysis shows that stock return, asset structure, growth rate, industry classification, uniqueness, volatility and financial rating, profitability, government financial policy, and managerial entrenchment are key factors in determining a firm's capital structure. Such results are robust in the MIMIC and two-stage least square methods.

4.4. Measurement error in investment equation

Modern q theory, developed by Lucas and Prescott (1971) and Mussa (1977), shows that the shadow value of capital, marginal q, is the firm manager's expectation of the marginal contribution of new capital goods to future profits. Marginal q, therefore, should summarize the effects of all factors relevant to the investment decision. Lucas and Prescott (1971) and Hayashi (1982) show that the equality of marginal q with average q is under the assumptions of constant returns to scale and perfect competition. Because the marginal q is unobservable in the real world, most of empirical studies adopt Lucas and Prescott (1971) and Hayashi's (1982) assumption and use average q instead of marginal q to test q theory. In addition, if financial markets' valuation of the capital will be equal to the manager's valuation, average q, should equal an observable value, Tobin's q, defined as the ratio of the market value to the replacement value. Most empirical studies use Tobin's q as a proxy for marginal q to test the q theory of investment. However, their empirical results are inconsistent to the q theory (e.g. Blundell, Bond, Devereux, and Schiantarelli, 1992; Fazzari, Hubbard, and Petersen, 1988; Gilchrist & Himmelberg, 1995; Schaller, 1990).[6]

The model introduced by Fazzari et al. (1988) is

$$\frac{I_{it}}{K_{it}} = \eta_i + \beta q_{it}^* + \alpha \frac{CF_{it}}{K_{it}} + u_{it}, \tag{51}$$

where I_{it} represents the investments of firm i at time t, K_{it} is capital stock of firm i at time t, q_{it}^* is the marginal q_{it}, CF_{it} is cash flow of firm i at time t, η_i is the firm-specific effect, and u_{it} is the innovation term.

Almeida et al. (2010) show that OLS estimated coefficient of independent variable with measurement error, q_{it}^*, will be biased downward, and OLS estimated coefficient of the independent variable without measurement error, CF_{it}/K_{it}, will be biased upward. Following Eq. (51), if one of independent variables has measurement error and the other independent variables has no measurement error; the asymptotic biases of estimated coefficients can be defined as:

$$\text{p}\lim \hat{\beta} - \beta = \frac{-\beta\sigma_\varepsilon^2}{\sigma_{CF/K}^2 - b_{CF/K,q^*} + \sigma_\varepsilon^2}, \tag{52}$$

and

$$\text{p}\lim \hat{\alpha} - \alpha = \beta b_{CF/K,q^*} \left(\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_{CF/K}^2 (1 - R_{CF/K,q^*}^2)} \right), \tag{53}$$

in which $\sigma_{CF/K}^2$ is the variance of CF/K, σ_ε^2 is the variance of error term between unobserved marginal q and observable average q^*, $b_{CF/K,q^*}$ is the auxiliary regression coefficient of a regressing q^* on CF/K, and $R_{CF/K,q^*}^2$ is the correlation coefficient between q^* and CF/K. We know that $\sigma_{CF/K}^2 - b_{CF/K,q^*} + \sigma_\varepsilon^2$ is generally positive, so the estimated coefficient of q^* is downward biased. In addition, the direction of bias of estimated coefficient of CF/K will depend on the signs of β and $b_{CF/K,q^*}$. Given that q and cash flow are positively correlated, we can get the conclusion of Almeida et al. (2010) that $\hat{\beta}$ is downward biased and $\hat{\alpha}$ is upward biased.

Erickson and Whited (2000) argue that the measurement error of marginal q can result in different implications in empirical q models. They incorporate an EIV model to reexamine the empirical work done by Fazzari et al. (1988). By using generalized method of moments (GMM), Erickson and Whited (2000) obtain consistent estimators that the information contained in the third- and higher-order moments of the joint distribution of the observed regression variables. The estimator precision and consistency can be increased by exploit the information afforded by an excess of moment equations over parameters. Results show that cash flow does not affect a firms' financial decision, even for financially constrained firms, and the q theory is held if measurement error is taken into account.

Almeida et al. (2010) use Monte Carlo simulations and real data to compare the performance of generalized method of moments and instrumental variables approach dealing with measurement error problems in investment equations. In Monte Carlo simulations, they find estimators of GMM proposed by Erickson and Whited (2000) are biased for both mismeasured and well-measured regressors when the data have individual-fixed effects, heteroscedasticity, or no high degree of skewness. In contrast, the instrumental variable method results fairly unbiased estimators under those same conditions. Almeida et al. (2010) further empirically examine the investment equation introduced by Fazzari et al. (1988) by using GMM and instrumental variable method. Almeida et al. (2010) adopt Biorn's (2000) method using the lags of the variable as instruments in testing the investment equation. Empirical results show that estimators from generalized method of moments are unstable across different specifications and not economically meaningful, while estimators from a simple instrumental method are robust and conform to q theory. Almeida et al. (2010) conclude that instrumental method yields more consistent estimators and support the q theory in the investment equation.

In contrast, Erickson and Whited (2012) compare the ability of three errors-in-variables models, instrumental variables, dynamic panel estimators, and the high-order moment estimators in investment equation. They conclude that all of three models can perform well under correct specification, while the high-order moment estimators often outperform the instrumental variables and dynamic panel estimators in terms of bias and dispersion. Erickson and Whited (2012) also demonstrate a minimum distance technique to extend the high-order moment estimators used on unbalanced panel data.

5. Conclusion

In this paper, we investigate theoretical issues related to errors-in-variables (EIV) problem, and review how existing EIV estimation methods deal with measurement error problem. We first show how EIV problems affect the coefficients of independent variables in the regression model. We then discuss how classical method, mathematical programming method, grouping method, instrumental variable method, maximum likelihood method, and LISREL method deal with EIV problems. We further investigate how alternative EIV models have been used in empirical finance research. We find that the empirical research of cost of capital, asset pricing, capital structure, and investment equation have used alternative EIV methods to improve the empirical results. Not only can the reader of this paper understand the important research topics in finance, but also can the reader realize how measurement error problems affect the results of empirical work in such research topics. Finally, we suggest that future empirical studies on finance related issues should pay more efforts to deal with EIV problems and obtain more robust empirical results.

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Decomposing the Size Premium

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Abstract

We decompose firm size into four components: the lagged 5-year component that represents size five years ago, and the long-run, intermediate-run, and short-run components that capture changes in size in each horizon. Our analyses indicate that while the lagged 5-year component explains about 80% of the cross-sectional variation in size, it has little return predictability. In contrast, the long-run change in size component explains only 18% of size, but it completely captures the size premium. Our decomposition also sheds light on the January effect, the disappearance of the size premium since early 1980s, and the return behaviors of new entrants.

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1 Introduction

Size premium, the empirical finding that small stocks (measured by market capitalization) outperform big stocks on average, is one of the most well-known investment strategies in the stock market. In the asset pricing literature, besides the market factor, the small-minus-big (SMB) size factor is the only factor that is included in all leading multi-factor asset pricing models, including Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and more recent Hou, Xue, and Zhang (2015) four-factor model based on q theory of investment and Fama and French (2015) five-factor model. In this paper, we examine the size premium from a different perspective from many existing studies in the literature. We decompose the firm size into four components and study how each component contributes to current firm size and to the size premium.

Our decomposition is motivated by the well-known cross-sectional stock return patterns at various horizons, namely, long-term contrarian (De Bondt and Thaler (1985)), intermediate-term momentum (Jegadeesh and Titman (1993)), and short-term reversal (Jegadeesh (1990)). The first component in our size decomposition is the (log) firm size five years ago, capturing the extremely persistent component of firm size. The second component, the long-run component, measures the cumulative change in (log) firm size during prior 13-60 months, following the timing of long-term contrarian strategy. The third component, the intermediate-run component, captures the cumulative change in (log) firm size during prior 2-12 months, corresponding to the timing of the price momentum strategy. The last component is the short-run component, defined as the prior 1-month change in (log) firm size, consistent with the timing of the short-term reversal.

Our empirical analyses suggest that despite being the most important determinant of current firm size, the lagged 5-year component has little predictive power for future stock returns. Compared with the 4.93% annual size premium, the premium based on the lagged 5-year component is only 1.53% per year with a t-statistic of 0.63. Controlling for the market factor further reduces the magnitude of the lagged 5-year size premium to -0.59% per year. Given that firm size is highly persistent, this result indicates that the size premium does not originate from the *level* of firm size; instead, it is the *changes* in firm size during past years that possess the predictive power for future stock returns. The second component is the long-run change in size, which explains an average of 18.4% of the cross-sectional variation in firm size. However, this component strongly predicts stock returns. In decile portfolios sorted by this long-run component, the difference in stock returns between firms with the most decrease in market value and firms with most increase in market value in the prior 13-60 months is 7.33% per year with an annual Sharpe ratio of 0.5. As a comparison, the Sharpe ratio for the size premium based on the same sample is only 0.3. The intermediate-run component is also a strong return predictor, with stocks with most increase in market value in the prior 2-12 months outperforming stocks with most decrease in market value by 8.64% per year, which has a similar magnitude to the momentum profit. All else being equal, small firms tend to have worse past stock performance than big firms, so the size strategy contains a short position in momentum which contributes negatively to the size premium. Despite its large premium, the intermediate-run component explains only about 2.6% of firm size, so its overall effect on the size premium is small. For the same reason, the short-run component only explains less than 1% of the cross-sectional variation in size.

The relative performances of the strategies based on size components suggest that the size premium is mainly driven by the long-run component, which we further confirm in several ways. First, in an independent double sort by firm size and its long-run component, we find that conditional on firm size, the average premium based on the long-run component is 5.42% with a t-statistic of 3.84, whereas the average size premium conditional on the long-run component is only 2.65% per year with a t-statistic of 1.31. Controlling for the market factor further amplifies the difference, generating a capital asset pricing model (CAPM) alpha of 6.11% and 1.41%, respectively. Second, we conduct linear factor model time series regressions tests. When size portfolio returns are regressed on the long-run size component factor (together with the market factor), none of these portfolios has a statistically significant abnormal return, including the long-short size portfolio. On the other hand, when returns of portfolios sorted by the long-run component are regressed on the size premium factor (together with the market factor), we find a significant abnormal return of more than 3 standard errors from zero for the long-short spread portfolio. Our last test is Fama-MacBeth regressions. Although firm size and its long-run component are both significant predictors for the future stock returns in univariate regressions, the coefficient on firm size becomes insignificant once controlling for its long-run component. Taken together, our results suggest that for size premium investors, a strategy that is based on its long-run component consistently dominates the traditional size strategy in terms of risk-return tradeoff.

Our decomposition is simple and straightforward. It also sheds lights on several other aspects of the size premium. For instance, the close link between changes in the firm size and stock returns provides a natural explanation for the negative (positive) correlation between momentum (long-term contrarian) profits and size premium. More interestingly, our decomposition uncovers a novel seasonality of the size premium in its exposure to the momentum factor due to the standard Fama and French (1992) timing. In Fama and French (1992), size portfolios are rebalanced at the end of every June, and firm size in June of year t is used to create size portfolios from July of year t to June of year $t+1$. This timing implies that the relative weight of the intermediate-run component decreases monotonically from July of current year to June of next year. If a large portion of the change in market equity is due to stock returns, we expect a similar seasonality in the momentum factor exposure of the Fama and French (1992) size premium. Indeed, in the time series regressions of the long-short Fama and French (1992) size portfolio returns on the market and momentum factors, we find the negative momentum factor loading peaks in the third quarter (-0.17 with a t-statistic of -2.72) and bottoms in the second quarter (0.05 but statistically insignificant). As a comparison, when we repeat the same analysis using the size portfolios sorted by the market value from the previous month, the seasonality in momentum betas disappears.

Our decomposition also provides insights into the January effect, the empirical finding that the size premium is concentrated in January (e.g., Keim (1983)). Two leading explanations for the January effect in the literature are the tax-loss selling hypothesis and institutional investor window dressing hypothesis, both of which posit that shortly before year-end, investors sell stocks that have had losses during the year. Since the stock performance within the past year is closely related to the intermediate-run and short-run components, our decomposition provides a quantitative evaluation of these two hypotheses. Our empirical analyses suggest that although all size components positively contribute to the strong performance of size strategies in January, the intermediate-run and short-run components combined only explain less than 20% of the January effect. In contrast, we find a surprisingly large January effect based on the lagged 5-year and the long-run components, which contribute about 60% and 30%, respectively, to the overall January effect. The results for the long-run component, and especially for the lagged 5-year component, pose a challenge to both leading hypotheses of the January effect, as neither interpretation traces firm performance for such a long horizon. Therefore, our analysis indicates that a large portion of January effect remains puzzling.

Size premium is found to have disappeared since its discovery in early 1980s. In a review paper on anomalies and market efficiency, Schwert (2003) writes that "it seems that the small-firm anomaly has disappeared since the initial publication of the papers that discovered it". Indeed, the average size premium between 1982 and 2002 is only 1.55% per year (t-statistic = 0.39) in our sample. However, we find that the long-run size component remains a significant return predictor during the same sample period. When firms are sorted into decile portfolios based on the long-run component, the long-short portfolio generates an average return of 8.22% per year (t-statistic = 2.16). Therefore, although the traditional size premium indeed disappears between early 1980s and early 2000s, the premium based on the component that is driving the size premium (i.e., the long-run component) was still alive and remains quite strong. Our analysis also suggests that the disappearance of the size premium is primarily due to the bad performance of the lagged 5-year component, which produces an average annual excess return of -2.19% in that sample period.

Lastly, we apply our decomposition to uncover a novel phenomenon among new entrants, which are excluded from our benchmark analyses. We find a positive relation between the size premium and firm age for firms that enter the CRSP dataset within the past 5 years. In the Fama-MacBeth univariate regressions of one-month ahead stock returns on the log firm size, the size coefficient decreases in magnitude from -0.22 for stocks of 4-5 years old to -0.03 (statistically insignificant) for stocks younger than one year old. Our decomposition provides a natural explanation for this interesting pattern. Since young firms do not have a long history, the long-run component, the component that drives the size premium, becomes less important in explaining the cross-sectional size variation, whereas the intermediate-run component that drags down the size premium becomes relatively more important. Our analysis indicates that although the premiums based on each size component remain quantitatively similar and stable across age groups, the change in the size composition with firm age implies a smaller size premium among younger firms.

The paper adds to the large literature on the firm size effect. Beginning with Banz (1981), size premium has been studied extensively in the past three decades. Fama and French (1995) find that size premium can be related to financial distress. Fama and French (1996) use the size premium factor to mimic the underlying risk factor that size premium represents. Studies most closely related to us are Berk (1995, 1996). Berk (1995) argues that size-related regularities should not be regarded as anomalies if size is measured by market value. All else being equal, a firm with higher discount rate has a smaller firm value and higher expected return, so even without specifying the underlying data generating process for stock returns, the negative relation between firm size and future stock returns should always be observed. Berk (1996) uses alternative non-market based measures of firm size, including book value of assets, book value of un-depreciated property, plant, and equipment, total value of annual sales, and total number of employees, but finds no return predictive power. The result of our analyses is consistent with Berk (1995, 1996). Instead of studying non-market based size measures, we find the lagged 5-year market value also doesn't predict stock returns, which suggests that it is not the level of market value, but its changes in recent years that predict stock returns. In addition, because past changes in market value have no direct relation with the current level of book asset, annual sale, or number of employees, the lack of return predictability of these variables that is documented in Berk (1996) should not be surprising.

Our decomposition and its implication for return predictability are motivated by the cross-sectional stock return regularities at various horizons, including long-term contrarian, intermediate-term momentum, short-term reversal, and equity issuance. The objective of this paper is not to explain these patterns.[1] Instead, we take these phenomena as given and study how the composition of these size components quantitatively affects the overall size premium. In terms of the methodology of variable decompositions, our paper is similar to Gerakos and Linnainmaa (2016) who decompose the book-to-market ratio to understand the value premium.

The paper proceeds as follows. Section 2 describes the data. In Section 3, we provide detailed discussions on how to decompose firm size into four components. Section 4 explores the return predictability of each size component. We document that the size premium is mainly driven by the component that captures the change in firm size in prior 13-60 months. In Section 5, we apply our size decomposition to other aspects of the size premium, including a novel seasonality in the momentum factor exposure, the January effect, the disappearance of size premium since early 1980s, and the behaviors of new entrants. Section 6 concludes.

[1]There is large literature on these phenomena in the cross section. For long-term contrarian and value premium, see, for instance, De Bondt and Thaler (1985), De Bondt and Thaler (1987), Lakonishok, Shleifer, and Vishny (1994), Zhang (2005), Lettau and Wachter (2007), Da (2009), Ai, Croce, and Li (2013), Ai and Kiku (2015), Kogan and Papanikolaou (2014). For intermediate-term momentum, see Jegadeesh and Titman (1993), Jegadeesh and Titman (2001), Johnson (2002), Liu and Zhang (2008), Liu and Zhang (2014). For short-term reversal, see Lehmann (1990), Jegadeesh (1990), Jegadeesh and Titman (1995), Nagel (2012), Da, Liu, and Schaumburg (2013). For equity issuance, see, Daniel and Titman (2006), Pontiff and Woodgate (2008), Lyandres, Sun, and Zhang (2008). A small line of research focuses on a joint explanation for these phenomena, especially for intermediate-term momentum, long-term contrarian, and value premium. See, for example, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Sagi and Seasholes (2007), Li and Zhang (2017), and Li (2016). See Fama and French (2008) and Nagel (2013) for excellent literature reviews on the cross-sectional stock returns.

2 Data and Summary Statistics

Our data come from several sources. Stock data are from the monthly CRSP database. Accounting data are from Compustat Annually database. The Fama and French factors are from the Fama/French data library. Our sample include NYSE/AMEX/NASDAQ common stocks (with a share code of 10 or 11) with nonmissing market value at the end of June. Our sample period covers 630 months from July 1963 to December 2015. We use size and market value interchangeably unless specified otherwise. In addition, we follow Shumway (1997) to correct for the delisting bias.

Panel A of Table 1 presents the mean (R^e), standard deviation (Std), Sharpe ratio (SR), Skewness (Skew), and Kurtosis (Kurt) of the value-weighted excess returns, as well as the CAPM alpha (α^{CAPM}), of size decile portfolios and the spread portfolio that buys small firms and short-sells big firms (S-B). Panel B reports the firm characteristics of these portfolios. Following Fama and French (1992), at the end of each June, we form ten portfolios based on the market equity at June using NYSE breakpoints. The portfolios are then held for one year. Panel A of Table 1 confirms the finding in previous literature that small firms have higher average returns than big firms. The return difference between small and big firms is 3.28% per year, with an annualized Sharpe ratio of 0.2. The long-short portfolio return has large positive skewness and kurtosis, indicating that the size strategy has a small chance of gaining large positive returns. CAPM captures a portion of the size premium. After controlling for the market factor, the average abnormal return of the S-B portfolio becomes only 2.21% per year with a t-statistic of 0.89. The latter finding is consistent with Israel and Moskowitz (2013), who document that CAPM captures a sizable portion of the size premium.

[Insert Table 1 Here]

Panel B reports the characteristics of a typical firm in each size decile. These characteristics include the log market cap (ME), the book-to-market equity ratio (BM), prior 2-12 month stock returns (MOM), and the prior 13-60 month stock return (LTCON). This panel shows that there is a large cross-sectional dispersion in firm size. For instance, the average market value for a typical firm in the small size decile (Decile S) is only 20 million dollars, compared with 6.6 billion dollars in the big size decile (Decile B). Small (big) firms tend to be value (growth) firms, and the book-to-market ratio decreases monotonically from the small decile to the big decile. More importantly, big firms tend to have better past stock performance than small firms. Specifically, the average prior 2-12 month return (MOM) is 0.44% for small firms and 11.54% for big firms, and the average prior 13-60 month return (LTCON) is 6.66% for small firm and 69.72% for big firms.

The pattern above suggests that the size strategy contains a long position in long-term contrarian strategy that buys long-term losers and short-sells long-term winners, and a short position in the momentum strategy that buys momentum winners and short-sells momentum losers. The large profitability of the long-term contrarian and intermediate-term momentum strategies documented in the literature motivates us to decompose firm size into components over corresponding horizons.

3 Decomposing firm size

Based on the results from the previous section, we decompose the log firm size into four components. The first component, ΔME(SR), captures the change in firm size during the past 1-month, consistent with the timing of short-term reversal effect. As we will see later in this paper, although this short-run component may not be crucial for the Fama and French (1992) size strategy, it is an important component for the size strategy based the market value of the previous month, especially for its unique role in January effect. The second component, ΔME(IR), captures the change in firm size during prior 2-12 months, consistent with the timing of intermediate-term momentum effect. The third component, ΔME(LR), captures the changes in firm size during prior 13-60 months, consistent with the timing of the long-term contrarian effect. The last component, ME(lag5), measures the firm size five years ago and captures the extremely persistent component of firm size. For the benchmark analysis, we focus on the Fama and French (1992) timing in creating size portfolios using the market value at the end of June.[2] We also restrict our benchmark sample to only include firms that have non-missing market value in previous June and June 5 years ago. In Section 5.4, we apply our decomposition to understanding the behaviors of these new entrants.

With the Fama and French (1992) timing, the size portfolios are created at the end of June of year t, and the firm size at June and the resulting size decile is assigned to every month from July of year t to June of year $t+1$. In contrast, the short-run, intermediate-run, and long-run windows that correspond to the timing of short-term reversal, momentum, and long-term contrarian strategies are moving with the calendar month even within the twelve months following the rebalancing of size portfolios at the end of June. With this difference taken into consideration, each month, we decompose market equity as follows. For firms in July of year t, the (log) firm size contains all four components, because the size change from the beginning to the end of June of year t represents the short-run component. As a result, our decomposition is based on the following three cross-sectional regressions:

$$ME_{t,6} = a_{0t} + b_{0t} \times ME_{t,5} + \epsilon_{0t} \equiv \widehat{ME}_{0t} + \Delta\text{ME(SR)}_t \tag{1.1}$$
$$\widehat{ME}_{0t} = a_{1t} + b_{1t} \times ME_{t-1,6} + \epsilon_{1t} \equiv \widehat{ME}_{1t} + \Delta\text{ME(IR)}_t \tag{1.2}$$
$$\widehat{ME}_{1t} = a_{2t} + b_{2t} \times ME_{t-5,6} + \epsilon_{2t} \equiv \text{ME(lag5)} + \Delta\text{ME(LR)}_t, \tag{1.3}$$

where $ME_{t,6}$, $ME_{t,5}$, $ME_{t-1,6}$, $ME_{t-5,6}$, are the log market equity (in million dollars) at the end of June in year t, the end of May in year t, the end of June in year $t-1$, and the end of June in year $t-5$, respectively. In the cross-sectional regression equation (1.1), we regress the log size at the end of June of year t on the log size at the end of May of year t, and the residual component $\Delta\text{ME(SR)}_t$ is the short-run component for the size in July of year t. The predicted values $\widehat{ME}_{0t}$ from (1.1) are then used as the dependent variables in equation (1.2) to extract the intermediate-run component. Specifically, we regress $\widehat{ME}_{0t}$ on the log size at the end of June of year $t-1$, and

[2]In some analyses of this paper, we also consider an alternative size strategy that is based on the market value from the end of previous month.

the residual $\Delta\text{ME(IR)}_t$ is the intermediate-run component. Lastly, we regress the predicted values from equation (1.2), $\widehat{ME}_{1t}$, on the log size at the end of June of year $t-5$ in equation (1.3). The residual is the long-run component $\Delta\text{ME(LR)}_t$, whereas the predicted value is our lagged 5-year component ME(lag5).

For all other months from August of year t to June of year $t+1$, there are only three components, because the information about the change in size from the previous month is absent in the size at the end of June.[3] For each of these months, we first regress the log firm size onto the log size twelve months ago. The residual is the intermediate-run component $\Delta\text{ME(IR)}_t$, and the predicted values from the first step are then regressed onto the log size at the end of June of year $t-5$. For example, for size in August of year t, we perform the following decomposition:

$$ME_{t,6} = a_{1t} + b_{1t} \times ME_{t-1,7} + \epsilon_{1t} \equiv \widehat{ME}_{1t} + \Delta\text{ME(IR)}_t \tag{2.1}$$

$$\widehat{ME}_{1t} = a_{2t} + b_{2t} \times ME_{t-5,6} + \epsilon_{2t} \equiv \text{ME(lag5)} + \Delta\text{ME(LR)}_t, \tag{2.2}$$

The residuals from equations (2.1) and (2.2), $\Delta\text{ME(IR)}_t$ and $\Delta\text{ME(LR)}_t$, are the intermediate-run and long-run size components for firms in August year t, whereas the predicted value from equation (2.2), ME(lag5), represents the lagged 5-year component.

The decomposition implies that even though the firm size is a constant (fixed to be the market value at the end of previous June) within the twelve months following size portfolio rebalancing, its components do change from one month to the next. The change in the composition has novel implications on the factor loadings and the performance of new entrants, which we discuss in later sections. We also realize that there are other ways to decompose firm size in a similar spirit. We choose the current procedure because, by construction, it guarantees that: 1) the components add up to the (log) firm size in June; and 2) these components are orthogonal to each other.[4]

Figure 1 shows the time series variation of the relative importance of these size components in explaining the cross-sectional variance of firm size. Each month, we run cross-sectional univariate regressions of log size in June on each of these four components (or three components if not in July) and collect the adjusted R^2. The R^2 for year t is then calculated as the average R^2 from July year $t-1$ to June year t to remove the seasonality of the size components. The figure shows that among all four size components, the lagged 5-year component, ME(lag5), is the most important determinant that explains about 80.5% of the cross-sectional variance of firm size.[5] This result is expected because firm size is highly persistent over time – a big firm today is very likely to remain a big firm five years later. The next important component is the long-run component ΔME(LR), which explains an average of 18.4% of current size. Between late 1980s and early 2000s, we observe

[3]However, this short-run component is present every month for the size measure based on the market value at the end of the previous month.

[4]We repeat our analysis based on alternative decomposition procedures and find very similar results. For instance, when we construct size components by directly taking the difference in log size between the beginning and end of each horizon, instead of running regressions, the main finding is quantitatively similar. These results are available upon requests.

[5]These R^2s are reported in Panel A of Table 7 under Group 0.

an increase in the stock return idiosyncratic volatility, which could drive the increase in the R^2 of the long-run component relative to the lagged 5-year component. The last two components, the intermediate-run ΔME(IR) and short-run ΔME(SR), explain an average of 2.6% and 0.4%, respectively, of the cross-sectional size distribution. Given that the short-run component is only available in July, we ignore it in most discussions on the Fama and French (1992) size strategy.

[Insert Figure 1 Here]

Table 2 reports the firm characteristics of deciles sorted by the size components. Since our benchmark sample now imposes the restriction of non-missing size components, which differs from Table 1, we also report the characteristics of size deciles using this benchmark sample in Panel A. Besides properties of log size (ME), book-to-market (BM), prior 2-12 month returns (MOM), and prior 13-60 month returns (LTCON), we also report the results for size components– ME(lag5), ΔME(IR), and ΔME(LR). Panel A shows that the components display an increasing pattern from the small decile to the big decile size portfolios. For ΔME(IR), it is -0.06 for small firms and 0.05 for big firms. For ΔME(LR), it increases from -0.36 for small firms to 0.43 for big firms. Interestingly, the dispersion in lagged 5-year firm size is only slightly smaller than that in the current firm size, again indicating that firm size is highly persistent. This finding is also consistent with the large explanatory power of the lagged 5-year component for the cross-sectional variation in firm size plotted in Figure 1.

[Insert Table 2 Here]

Panels B, C, and D of Table 2 report the characteristics of the decile portfolios sorted by the size components. Since our decomposition procedure enforces an orthogonal condition among these components, sorting by one component does not create dispersions in other components, as shown in the last three rows of each panel. In Panel B, the intermediate-run component sorts create a large spread in the prior 2-12 month return. Firms with high ΔME(IR) have an average momentum (MOM) of 57.03%, in contrast with -27.19% for firms with low ΔME(IR). In Panel C, firms with high ΔME(LR) have a large long-term contrarian (LTCON) of 271.58%, compared with that among firms with low ΔME(LR) (-45.78%). Therefore, the strategies based on intermediate-run and long-run components are closely related to momentum and long-term contrarian strategies, respectively.[6] Similar to the patterns for the size portfolio in Panel A, Panel D also shows that firms with large lagged 5-year size have higher current size and lower book-to-market ratio than those with small lagged 5-year size.

[6]Changes in firm size can be due to both stock returns and net issuance. The existing studies document both variables predict future stock returns. We could have further decomposed the change in firm size at each horizon into the change in price and change in number of shares outstanding. We choose not to do this for the sake of parsimony.

4 Decomposing the Size Premium

Based on the size decomposition from the previous section, we study the return predictability of these components and quantitatively estimate their contributions to the overall size premium.

Table 3 reports the mean (R^e), standard deviation (Std), and Sharpe ratio (SR) of the value-weighted excess return, as well as CAPM alpha (α^{CAPM}), of decile portfolios sorted by size (Panel A), ΔME(IR) (Panel B), ΔME(LR) (Panel C), and ME(lag5) (Panel D). By restricting non-missing size components, the size premium becomes stronger: the average size premium is 4.93% per year (t-statistic = 2.02) with a Sharpe ratio of 0.3. However, controlling for the market factor reduces the size premium to 4.01% and the corresponding t-statistic becomes 1.68.

[Insert Table 3 Here]

Panel B reports the results for the intermediate-run component ΔME(IR). Stocks with the largest increase in firm size in the intermediate run (Decile Hi) have an average excess return of 10.32% per year (t-statistic = 3.36), compared with only 1.69% for the firms with the largest decrease in size (Decile 1) in the same horizon. The difference in average returns between the two extreme decile portfolios is 8.64%, which is more than 3.6 standard errors from zero. A long-short investment strategy that buys high ΔME(IR) firms and short-sells low ΔME(IR) generates a Sharpe ratio of 0.51. In addition, CAPM fails to explain the strategy returns; controlling for market exposures creates an abnormal return of 9.1% per year with a t-statistic of 3.85. This strategy performance is consistent with the momentum strategy that past intermediate-term winners have higher future returns than intermediate-term losers. Unfortunately, size premium investors do not benefit from its good performance at all, because the size strategy effectively takes a short position in it. In fact, this exposure consistently drags down the profitability of the size strategy over time.

Panel C reports the stock performance of the long-run component ΔME(LR). Opposite to the intermediate-run component, firms with the largest increase in size in the long run underperform firms with the largest decrease in firm size by 7.33% per year (t-statistic = 3.23). The long-short investment strategy based on ΔME(LR) generates a Sharpe ratio of 0.5, and this strong profitability is not captured by CAPM. The CAPM abnormal return is 7.76% with a t-statistic of 3.41. The result for the portfolios sorted by the lagged 5-year component is reported in Panel D. In contrast to the other two components from Panel B and Panel C, the return displays a hump shape from the low ME(lag5) decile to the high ME(lag5) decile. The long-short portfolio generates an insignificant average return of only 1.53% with a Sharpe ratio of 0.1. Controlling for the market factor further reduces this premium to a negative value (-0.59% per year).

The result in Table 3 indicates that among all components of firm size from our decomposition, only the long-run component, ΔME(LR), contributes positively to the overall size premium in an statistically and economically significant way. In other words, the size premium is likely to be mainly driven by this long-run component. To test this conjecture, we perform three different analyses. In the first analysis, we compare the performance of portfolios double sorted by size and its long-run component. In particular, we create 5-by-5 portfolios double-sorted independently by size and ΔME(LR). Panel A.1 of Table 4 reports the conditional size premium within each ΔME(LR) quintile and the average conditional size premium across ΔME(LR) quintiles. Among all ΔME(LR) quintiles, the conditional size premium is only significant in ΔME(LR) quintile 2. In the high ΔME(LR) quintile, the conditional size premium is negative at -1.24% per year, even though it is not statistically significant from zero. The average conditional size premium across ΔME(LR) quintiles is insignificant at 2.65%. The unconditional CAPM further reduces the abnormal conditional size premium to 1.41% per year. In sharp contrast, the conditional ΔME(LR) premium is significant in 4 out of 5 size quintiles. It ranges from 8.92% (t-statistic = 6.37) among small firms to 3.65% (t-statistic = 1.50) among big firms. The average conditional ΔME(LR) premium is 5.42% per year, which is more than 3.85 standard errors from zero. The CAPM alpha for the conditional ΔME(LR) premium is even higher at 6.11% per year, with a t-statistic of 4.33.

[Insert Table 4 Here]

The second test is a linear factor model test between size premium and ΔME(LR) premium. In Panel B.1 of Table 4, we test a two-factor model on size decile portfolios with the market factor and the ΔME(LR) premium factor as the factors. The ΔME(LR) premium factor is calculated as the return difference between the low ΔME(LR) decile and the high ΔME(LR) decile. Compared with the CAPM result from Panel A of Table 3, none of the ΔME(LR) deciles has a significant abnormal return in the two-factor model, and the long-short portfolio (L-H) has an abnormal return of -0.54% per year (t-statistic = -0.29). The reduction in abnormal returns is mainly due to the exposure to the ΔME(LR) factor, which decreases monotonically from 0.49 for small firms to -0.09 for big firms, and the difference is 12.6 standard errors from zero.

When we switch the order and regress the ΔME(LR) decile excess returns on a two-factor model with the market factor and size premium factor as the factors, the result looks quite different. In Panel B.2, we find that despite the strong decreasing pattern of the size factor exposures across ΔME(LR) portfolios, the abnormal return remains large in many portfolios. In addition, the long-short ΔME(LR) portfolio (L-H) has an abnormal return of 5.8% per year, which is more than 3.18 standard errors from zero. Adding the ΔME(IR) premium factor does not alter the result in a significant way (Panel C). If anything, the abnormal return of the long-short ΔME(LR) portfolio becomes even bigger (7.72% per year with a t-statistic = 4.38).

Our third test is Fama-MacBeth regressions. Compared to the value-weighted portfolio approach in the first two tests, Fama-MacBeth regressions put relatively more weights on small firms. Each month, we run a cross-sectional regression of one-month ahead stock returns on log size and its components ΔME(IR), ΔME(LR), and ME(lag5), and the time series average of these coefficients are reported in Table 5. Columns (1)-(4) report the univariate regression results. Consistent with the results from Table 3, we find that although size (ME) is a strong predictor for future stock returns, the coefficient on ME(lag5) is only -0.05 with a t-statistic of -1.43. In contrast, the other two components ΔME(IR) and ΔME(LR) have much stronger predictive power. The coefficient on ΔME(IR) is 0.73, which is more than 4 standard errors from zero. The coefficient on ΔME(LR) is

-0.41 with an even stronger t-statistic of -5.52. These results confirm the relative performance of the corresponding long-short portfolios reported in Table 3.

[Insert Table 5 Here]

Columns (5)-(7) present the horse race results from the Fama-MacBeth regressions using log size and one of its components as the return predictors. In Column (5), when both size and size 5 years ago are included into the same regression, the coefficient on size becomes more significant at -0.32 with a t-statistic of -4.4, compared with the univariate specification. On the other hand, the coefficient on ME(lag5) is now positive. This finding is intuitive from our decomposition: if the lagged 5-year component has no predictive power for stock return and is adding noise to the size premium, controlling this component would make the size premium stronger. We find a similar pattern when we control for the ΔME(IR) component (Column (7)). As we discussed earlier, the size premium strategy contains a short position in the ΔME(IR) premium, so controlling ΔME(IR) would enhance the performance of size strategies. In column (6), the horse race between size and its long-run component ΔME(LR), controlling for ΔME(LR), firm size has little predictive power for returns. Its coefficient decreases from -0.11 in the univariate regression in Column (1) to an insignificant value of -0.04 (t-statistic $= -1.12$). Interestingly, the coefficient on the ΔME(LR) becomes more statistically significant.

One advantage of the Fama-MacBeth regressions over the portfolio approach is that we can quantify the contribution of each size component to the overall size premium. If one component explains an average of X (or $100X$ percent) of the cross-sectional variation in size, and the Fama-MacBeth regression coefficient on this component is Y, its contribution to the coefficient on size in the Fama-MacBeth regression would be $X \times Y$. We use the coefficient estimates from Specifications (2)-(4) and the explanatory power of each component for the cross-sectional variation in firm size in Section 3 to estimate their contributions. For the lagged 5-year component, its percentage contribution is approximately 39.9% ($0.054 \times 80.5\%/0.109$), and this is compared with 69.4% ($0.411 \times 18.4\%/0.109$) for the long-run component and -17.5% ($-0.734 \times 2.6\%/0.109$) for the intermediate-run component.[7] This result indicates that although the 5-year component captures more than 80% of the firm size, it only contributes less than 40% of the size premium.[8] In contrast, the long-run component ΔME(LR) captures only 18% of firm size but contributes almost 70% of the size premium. In untabulated analyses, we find the ΔME(LR) premium is not driven by extremely small and illiquid firms, which is a criticism for the implementability of size strategies (Horowitz, Loughran, and Savin (2000)). For example, when we exclude from our sample firms with market value of less than 5 million dollars, or firms with end-of-June price lower than $5 per

[7]The fact that the contributions from these components do not exactly add up to one can be due to: 1) we did not include the short-run component in this calculation; 2) there are seasonality in the size components within a year; and 3) the panel data is not balanced; we have more observations in later years than earlier years.

[8]The contribution from the lagged 5-year component is driven by its correlation with the premium based on the long-run component. In an untabulated analysis, we find that the ME(lag5) premium changes sign and becomes positive after controlling for the market factor and a ΔME(LR) premium factor.

share, the long-short ΔME(LR) portfolio still produces an average return of more than 7% per year with a t-statistic greater than 3.

Taken together, our analyses suggest that the size premium is driven by its long-run component ΔME(LR). Once controlling for this long-run component, firm size does not have significant predictive power for future stock returns. These findings are consistent with Berk (1995, 1996). Berk (1995) argues that size-related regularities should not be regarded as anomalies if size is measured by market value. All else being equal, a firm with a higher discount rate has a smaller firm value and higher expected return, so even without specifying the data generating process of stock returns of a firm, the negative relation between firm size and future stock returns should always be observed. Our findings can be consistent with this argument: firms that experience a large decrease in market value in the prior 13-60 months (i.e., in the long run) could have experienced positive shocks to discount rate (either rationally or irrationally). Their realized returns are negative but expected returns increase. However, we find the similar argument does not hold for the horizon of prior 2-12 months. Instead, this intermediate-run change in firm size, which is related to the momentum strategies, positively predicts future stock returns. Berk (1996) studies the size premium using alternative measures of firm size including book value of assets, book value of un-depreciated property, plant, and equipment, total value of annual sales, and total number of employees, but find no return predictive power. Our decomposition provides a natural interpretation for his findings. Particularly, it is not the level of market value, but its recent change, that predicts stock returns. Because the recent changes in market value have no direct relation with the level of these alternative size measures, it is not surprising these variables have no return predictive power. For size premium investors, our findings also suggest that investing in its long-run component is far better than investing in firm size itself from the perspective of risk-return tradeoff.

5 Further Implications

In this section, we explore additional implications of our size decomposition. In Section 5.1, we uncover an interesting seasonality in the momentum factor loading of size portfolios that is due to the Fama and French (1992) timing. In Section 5.2, we use our decomposition to evaluate leading explanations for the January effect in the existing literature. In Section 5.3, we discuss the disappearance of the size premium between early 1980s and early 2000s. We study how our decomposition can be applied to new entrants in Section 5.4.

5.1 Seasonality in momentum beta

Our size decomposition is performed at each month, so these components change from one month to the next. The rolling horizons of the intermediate-run and long-run components indicate that there is a seasonality of the intermediate-run and long-run components in the twelve months following the portfolio rebalancing at the end of each June. For instance, in July of year t, the intermediate-run component is based on the change in log market value from July of year $t-1$ to May of year t.

As time moves forward by one month, the horizon shrinks by one month, and the intermediate-run component in August of year t is based on the change in log market value from August of year $t-1$ to May of year t. In June of year $t+1$, although the firm size still corresponds to the market value at the end of June of year t, its intermediate-run component is only based on the change in size from May of year t to June of year t. Since the intermediate-run change in size is highly correlated with the price momentum, the size premium should also show a seasonality in its momentum factor exposure. Figure 2 presents this seasonality.

[Insert Figure 2 Here]

In Panel A of Figure 2, we plot the average quarterly momentum factor beta of the size premium following portfolio rebalancing at the end of June according to the Fama and French (1992) timing. For each quarter, we estimate the momentum beta by running time series regressions of the monthly long-short size portfolio excess return on the market excess return and the winner-minus-loser portfolio return from momentum deciles. We test this at the quarterly frequency to avoid even higher frequency seasonality such as the January effect. Panel A shows that for Quarter 3 (Q3) from July to September, i.e., the first quarter following portfolio rebalancing, the size premium has a large negative momentum factor loading of -0.174 (t-statistic $= -2.72$). This negative sign is consistent with the short position of the size premium in the momentum strategies. The momentum beta increases monotonically over time, and by Quarter 2 (Q2) from April to June, i.e., the last quarter of the 12-month holding period, it becomes positive at 0.05 but statistically insignificant (t-statistic $= 0.56$). As a comparison, we also estimate the momentum beta across quarters for the size premium based on the market value from the end of the previous month, and the result is plotted in Panel B of Figure 2. With this alternative timing, size deciles are rebalanced every month, and the horizon for the intermediate-run component is constant. Therefore, we do not expect a strong seasonality in momentum beta for this size strategy. Indeed, from Panel B of Figure 2, the size premium has a negative momentum exposure in all quarters: the momentum beta is -0.176 for Q3, -0.114 for Q4, -0.194 for Q1, and -0.13 for Q2. This confirms that the seasonality of momentum beta from Panel A is due to the Fama and French (1992) timing.

5.2 The January effect

The size premium itself is also highly seasonal. Banz (1981) and Reinganum (1983) document that the good stock market performance in January is mainly driven by small stocks. Keim (1983) finds that half of the size premium over the 1963 to 1979 period occurs during January, whereas Blume and Stambaugh (1983) show that all of the size effect occurs in January after adjusting for the "bid-ask spread" bias. Among alternative hypotheses explaining the puzzling January effect, two leading explanations are tax-loss selling hypothesis (see, e.g., Branch (1977), Dyl (1977), Givoly and Ovadia (1983), Starks, Yong, and Zheng (2006)) and the institutional investor window dressing hypothesis (see, for instance, Haugen and Lakonishok (1988), Musto (1997), and Ritter and Chopra (1989)). Both hypotheses argue that investors tend to sell stocks that have had bad performance, and this selling pressure depresses year-end stock prices which rebound in January. In the tax-loss selling hypothesis, investors sell losing stocks in order to lower taxes on net capital gains. In the institutional investor window dressing hypothesis, portfolio managers sell losing stocks to avoid revealing that they have held poorly performing stocks.

To evaluate these two hypotheses, we decompose the size premium in January in the same way as we decompose the overall size premium. Table 6 reports the result. We consider both the Fama and French (1992) size strategy, and the size strategy based on the previous-month-end market value to fully capture the stock performance during the previous year. Panel A presents the average explanatory power of each size component for the cross-sectional variation in firm size. For the Fama and French (1992) size strategy, there are three size components because the short-run component only exists in July. The lagged 5-year, long-run, and intermediate-run components explain 80.6%, 18.6%, and 2.3% of firm size, respectively. The composition looks very similar for the size premium based on the previous-month market value, except for the intermediate-run component, which doubles its explanatory power to 4.7%. Furthermore, the short-run component now shows up and explains about 0.6% of firm size.

[Insert Table 6 Here]

Panel B of Table 6 reports the results from Fama-MacBeth regressions. For the Fama and French (1992) timing, the coefficient on the log firm size in January is -1.62, which is 14.9 times greater than the estimate for all months (Column (1) of Table 5), confirming the January effect in our sample. In addition, these values suggest that the average size premium estimated from the Fama-MacBeth regression for non-January months is negative. The three size components all contribute positively to January effect. The estimated coefficient on ME(lag5) is -1.29, which is 23.9 times greater than that from Table 5, suggesting that even the lagged 5-year component displays a strong January effect. The coefficient on ΔME(LR) is -3.04, which is 7.4 times greater than that from Table 5. This result indicates that although the ΔME(LR) premium is significantly higher in January, it also exists in other months.[9] The coefficient on that ΔME(IR) is -3.27, which is 4.5 times greater than that for all months in magnitude but with an opposite sign. The latter pattern is consistent with the momentum literature that find the average momentum profit to be negative in January (e.g., Jegadeesh and Titman (1993)). The predictive power of the short-run and intermediate-run components for the January return is also consistent with Branch (1977)'s observation that stocks that had negative returns during the prior year also have high returns in January, a finding that motivates the tax-loss selling hypothesis.

In order to quantify the contribution of each size component to the January effect, we multiply the estimated R^2 from Panel A of Table 6 with the corresponding Fama-MacBeth regressions coefficients from Panel B. In the case of the Fama and French (1992) timing, the contributions from the lagged 5-year, long-run, and intermediate-run components are 64.0%, 34.8%, and 4.6%,

[9] Indeed, in an untabulated analysis, we find that the average value-weighted return of the long-short ΔME(LR) portfolio for non-January months is 4.5% with a t-statistic of 2.06.

respectively. In the case of the size strategy based on the market value from previous month, the intermediate-run component becomes more important and these three components contribute to 58.0%, 29.2%, and 11.5%, respectively. In addition, the short-run component appears in January and has a large negative predictability for the January return. The estimated coefficient of ΔME(SR) is -17.22 with a t-statistic of -7.23, indicating that stocks that perform poorly in previous December rebounds strongly in January. This pattern is consistent with the selling pressure on losing stocks in the tax-loss selling hypothesis and institutional investor window dressing hypothesis. Despite its significance, this component only explains about 5.8% of the overall January effect, due to its low explanatory power for firm size from Panel A.

Our quantitative results pose a challenge for both leading hypotheses for the January effect. Both hypotheses rely on investors' behaviors in reaction to the stock performance from the previous year. Our estimates suggest that the contribution from the stock performance in the previous year is well below 20%. The significant coefficient on the long-run component is consistent with De Bondt and Thaler (1985) and Chan (1986), and suggests that investors may wait for years before realizing losses. Still, there is about 60% the January size premium that comes from the lagged 5-year component. Therefore, a large portion of the January effect remains puzzling.[10]

5.3 The disappearance of size premium

It has been documented that the size premium has disappeared since its discovery. For example, Schwert (2003) reports an average CAPM alpha of 0.2% per month with a t-statistic of 0.67 between 1982 and 2002 for the Dimensional Fund Advisors (DFA) US 9-10 Small Company Portfolio, which closely mimics the size strategy described in Banz (1981). Several studies have proposed potential explanations for this disappearance. Hou and van Dijk (2014) argue that it is the large negative profitability shocks that drives the poor performance of small firms after early 1980s. Asness, Frazzini, Israel, Moskowitz, and Pedersen (2015) document that size premium is robust after controlling for quality. Shi and Xu (2015) emphasize the importance of the delisting bias. They document that there is a positive size premium for firms close to be delisted, and once excluding these observations, the size premium reappears. Ahn, Min, and Yoon (2016) find that the size effect is significantly positive at the bottom of the business cycles.

Our decomposition provides an alternative explanation for this phenomenon. Figure 3 plots the cumulative returns of the long-short portfolio based on firm size and its components. The figure shows that the strategy based on the long-run component outperforms the size strategy, whereas the intermediate-run and the lagged 5-year components perform poorly. For the full sample period from July 1963 to December 2015, the cumulative return is about 190.5% for the size premium, which is smaller than 327.3% for the ΔME(LR) premium. On the other hand, the cumulative return is only 14.4% for the lagged 5-year component, and -531.1% for the intermediate-run component.

[10] In untabulated analyses, we extend the horizon back further and find that the premium based on the lag 10-year or even 20-year market values still displays a strong January effect. This pattern is unlikely to be explained by the delayed realization of long-run losses by investors.

The large negative loss for the intermediate-run component is consistent with its strong return predictability documented in Section 4.

[Insert Figure 3 Here]

Narrowing the sample period down to 1982-2002 during which Schwert (2003) documents the disappearance of the size effect, we find that the average size premium is indeed only 1.55% per year, which is about 0.39 standard errors from zero. However, the premium based on the long-run component, ΔME(LR), is 8.22% per year with a t-statistic of 2.16. These results suggest that although the size premium has disappeared between early 1980s and early 2000s, the premium based on the component that drives the size premium (i.e., the long-run component) was still alive and remained quite strong. But what makes the overall size premium disappeared? Our analysis indicates that one main reason is the poor performance of the lagged 5-year component. When focusing on the pattern of the cumulative returns of the size premium and the lagged 5-year size premium between 1982 and early 2000s in Figure 3, we can see a strong comovement between these two time series. More importantly, the average premium of this lagged 5-year component is -2.19% per year during this sample period. This bad performance, together with its large explanatory power for the cross-sectional variation in size (Figure 1), drags down the average size premium.[11,12]

5.4 New entrants

Our analysis in previous sections focuses solely on firms that have non-missing size components from the decomposition. In particular, we exclude firms that entered the CRSP database within the previous 5 years. Fama and French (2004) document that firms that obtain public equity financing expands dramatically in the 1980s and 1990s. The cross section of the profitability of these firms are highly left skewed but their growth rates are highly right skewed. Therefore, the behavior of the size premium among these new entrants could potentially be different from those in our benchmark sample.

In this subsection, we apply our size decomposition to these new entrants. Different from a relatively mature firm in our benchmark sample, the composition of a newly entered young firm depends on the number of years since its entry. For example, a firm that enters the CRSP database 4 years ago has both the long-run and intermediate-run components. In contrast, for a firm that enters 11 months ago, the long-run component is absent. To control this cohort effect, we separate these new entrants into five groups. Group 1 includes stocks younger than 1 year, Group 2 includes

[11] One possible explanation for the negative ME(lag5) premium is the increased idiosyncratic volatility. In untabulated analyses, we notice that the level of common idiosyncratic volatility (CIV) (Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016)) doubled from early 1980s to early 2000s. Furthermore, we find a strong negative exposure of the ME(lag5) premium to the CIV shock, so unexpected increases in CIV lower the ME(lag5) premium in this sample period. A comprehensive exploration of these historically small firms can be interesting for future studies.

[12] Another explanation for the disappearance of size premium since early 1980s is the bad performance of the newly entered firms. See, for example, Fama and French (2004), Hou and van Dijk (2014). We discuss the implication of our decomposition on the performance of these firms in Section 5.4.

stocks older than 1 year but younger than 2 years, Group 3 includes stocks older than 2 years but younger than 3 years, Group 4 includes stocks older than 3 years but younger than 4 years, and Group 5 includes stocks older than 4 years but younger than 5 years. As a comparison, we also include stocks in our benchmark sample as Group 0. Since these new entrants do not have a long history up to 5 years, we define ME(lag) as the initial log market value when firms enter the CRSP database for firms in all groups other than Group 0.

Panel A of Table 7 reports the explanatory power (R^2) of each component for the cross-sectional variation in firm size. For all groups, the persistent component, ME(lag), has the most explanatory power, followed by ΔME(LR), ΔME(IR), and ΔME(SR). More importantly, there are clear patterns for these component R^2 across these age groups. The R^2 for ME(lag), ΔME(IR), and ΔME(SR) decreases monotonically from Group 2 to Group 5, whereas the R^2 for ΔME(LR) displays an opposite increasing pattern. Intuitively, compared to a relatively older firm, the probability for a young firm to have a big change in market value since its entry is small, so its entry size explains the majority of its current size. In addition, the short-run and intermediate-run components carry less weight as firms get older, because the long-run component gradually plays a more important role. For firms younger than 1 year old, the long-run component is absent, whereas the intermediate-run component may only cover a fraction of the 11-month horizon. Interestingly, the monotonic patterns do not extend to the benchmark sample (Group 0) that consists of more mature stocks. For example, the R^2 for ME(lag) is 80.5% in Group 0, which is higher than 55% in Group 5. Similarly, the R^2 for ΔME(LR) is only 18.4% for Group 0, even lower than 28.3% for Group 3. This break in monotonicity can be due to higher stock return volatility and more frequent equity issuance for these young firms, resulting a greater cumulative change in firm size within the past few years. This effect can be so strong that it dominates the effect from the horizon changes so that the mature firms in Group 0 is more predicted by their ME(lag).[13]

[Insert Table 7 Here]

In Panel B, we run univariate Fama-MacBeth regressions of one-month ahead stock returns on log firm size and its components. When the predictive variable is log firm size (ME), the estimated coefficient is negative for all age groups, but it is much smaller in magnitude for younger firms. For instance, the coefficient is -0.22 for firms that are 4 years old, compared with only -0.03 for firms younger than 1 year old. Therefore, we find a positive relation between size premium and firm age. To understand this pattern, the last four columns report the coefficients of the size components. Surprisingly, the estimated coefficients are very stable across age groups. For the ME(lag) component, it ranges from -0.049 to -0.092, but none of these estimates are statistically significant. This finding is consistent with what we documented in the benchmark sample that lagged 5-year size has no predictive power for future stock returns. Similar patterns are found for the other components. The estimated coefficient for firms in Groups 1-5 is between -0.56 and -0.69

[13] Indeed, we find the cross-sectional standard deviations of the monthly change in firm size in the intermediate-run and long-run horizons are 13.4% and 15.4% for firms in Group 5, significantly larger than the corresponding values of 10.4% and 11.6% for firms in Group 0.

for ΔME(LR), between 0.61 and 0.78 for ΔME(IR), and between -4.4 and -7.7 for ΔME(SR). Therefore, the relation between size premium and firm age for these new entrants must be mainly driven by the variation in the size components. In particular, for firms younger than 1 year old, the ME(lag) and ΔME(LR) components dominate, so the size premium is small and insignificant. As firms get older, the long-run component becomes more important and the corresponding R^2 is increased to 43.7% when firms are 4 years old (Group 5). As a result, the implied size premium among these firms is much stronger than firms in Group 1.

6 Conclusion

In this paper, we analyze the size effect by decomposing firm's market value into four components. Our result indicates that despite explaining about 80% of the cross-sectional variation in firm size, the lagged 5-year component, which measures firm size 5 years ago, has little predictive power for future stock returns. In contrast, the intermediate-run and long-run components, which measure the changes in firm size in the prior 2-12 and 13-60 month horizons, only capture 3% and 18% of firm size. However, they are strong return predictors: firms with the largest increase in size in the intermediate-run (long-run) outperform (underperform) firms with the largest decrease in size in intermediate-run (long-run) by 8.64% (7.33%). Therefore, the standard size strategy effectively takes a long position in the premium based on the long-run component and a short position in the intermediate-run component. These results also suggest that the size premium is mainly driven by this long-run component, which we confirm using double-sorted portfolios, linear factor time series regressions, and Fama-MacBeth cross-sectional regressions.

We apply this decomposition to several aspects of the size premium. First, we uncover an interesting seasonality in momentum factor beta of the size premium with Fama and French (1992) timing. Since a large fraction of change in firm size in the intermediate-run horizon is due to stock returns, the seasonality of the intermediate-run component from the decomposition procedure also implies a momentum exposure seasonality. Second, our size decomposition sheds light on the January effect quantitatively. Leading explanations such as the tax-loss selling hypothesis and the institutional investor window dressing hypothesis are based on the stock performance in the previous year. Our analysis suggests that the previous-year change can only explain less than 20% of the January effect. Instead, firm size 5 years ago captures more than 60% of the January effect, which poses a challenge to these explanations. Third, we relate our decomposition to the disappearance of size premium between early 1980s and early 2000s. Our result suggests that although the traditional size premium disappeared in this sample period, the premium from the long-run component that drives the size premium was still alive and quite strong. Lastly, we study the performance of new entrants, that is, firms that enter the CRSP database within the previous 5 years. We document a positive relation between size premium and firm age among these new entrants, and find that the change in the composition of size components with firm age is mainly responsible for this positive correlation.

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Table 1: Characteristics of size portfolios

This table reports the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe Ratio (SR), Skewness (Skew), Kurtosis (Kurt), and intercepts from CAPM model (α^{CAPM}) of the decile Size portfolios in Panel A, and the time-series average of the cross-sectional median firm characteristics in Panel B. At the end of June each year, we sort NYSE/AMEX/NASDAQ common stocks by market equity into Size deciles. ME is log of market equity in million dollars. BM is the book value of equity divided by market value at the end of the last fiscal year. MOM is momentum, defined as prior 2-12 month returns, LTCON is long-term contrarian, defined as prior 13-60 month returns. The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample period is from July 1963 to December 2015.

Panel A: Size portfolio excess returns

Port.	S	2	3	4	5	6	7	8	9	B	S-B
R^e	8.54	8.00	9.15	8.55	8.72	7.64	7.94	7.58	6.72	5.27	3.28
	(2.43)	(2.44)	(3.01)	(2.88)	(3.06)	(2.87)	(3.00)	(3.05)	(2.88)	(2.57)	(1.28)
Std	21.99	21.93	20.79	20.26	19.37	18.25	17.88	17.34	15.99	14.67	16.65
SR	0.39	0.36	0.44	0.42	0.45	0.42	0.44	0.44	0.42	0.36	0.20
Skew	-0.15	-0.25	-0.45	-0.45	-0.51	-0.56	-0.45	-0.48	-0.45	-0.36	0.73
Kurt	2.48	2.12	2.02	2.18	2.27	1.95	2.16	1.81	2.00	1.72	4.20
α^{CAPM}	1.91	0.76	2.02	1.53	1.81	0.99	1.32	1.08	0.65	-0.30	2.21
	(0.91)	(0.47)	(1.50)	(1.20)	(1.74)	(1.08)	(1.60)	(1.51)	(1.20)	(-0.63)	(0.89)

Panel B: Size portfolio characteristics

Port.	S	2	3	4	5	6	7	8	9	B
ME	3.00	4.48	5.03	5.47	5.88	6.29	6.72	7.21	7.83	8.80
BM	0.92	0.72	0.70	0.67	0.64	0.62	0.60	0.60	0.59	0.50
MOM	0.44	7.71	9.78	10.89	11.38	11.73	11.78	11.65	11.46	11.54
LTCON	6.66	41.07	52.69	56.19	61.98	64.68	64.43	61.88	64.41	69.72

Table 2: Characteristics of size and component portfolios

This table reports the time-series average of the cross-sectional median firm characteristics in the decile portfolios sorted by log size (ME, Panel A), intermediate-run change in log size (ΔME(IR), Panel B), long-run change in log size (ΔME(LR), Panel C), and lagged 5-year log size (ME(lag5), Panel D). At the beginning of each month, firms are sorted into deciles based on the sorting variables. ME is logarithms of market equity at June in million dollars following the timing in Fama and French (1992). BM is the book value of equity divided by market value at the end of the last fiscal year. MOM is momentum, defined as prior 2-12 month returns, LTCON is long-term contrarian, defined as prior 13-60 month returns. The size decomposition is described in Section XXX. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from the size decomposition from July 1963 to December 2015.

Panel A: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.05	4.49	5.07	5.54	5.98	6.40	6.84	7.35	7.94	8.90
BM	1.06	0.82	0.77	0.73	0.70	0.66	0.62	0.62	0.59	0.48
MOM	2.34	8.48	10.31	10.88	11.41	11.67	11.76	11.41	11.47	11.54
LTCON	7.58	41.58	53.05	56.56	62.82	63.84	63.39	63.47	64.35	70.23
ΔME(IR)	-0.06	0.00	0.02	0.02	0.03	0.03	0.04	0.03	0.04	0.05
ΔME(LR)	-0.36	0.02	0.13	0.18	0.24	0.26	0.29	0.30	0.32	0.43
ME(lag5)	3.36	4.45	4.91	5.33	5.70	6.10	6.53	7.02	7.58	8.49

Panel B: Portfolios sorted by intermediate-run change in size (ΔME(IR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.65	4.46	4.84	5.08	5.24	5.36	5.41	5.40	5.24	4.67
BM	0.80	0.81	0.80	0.79	0.78	0.78	0.77	0.75	0.75	0.73
MOM	-27.19	-9.79	-2.39	3.11	7.86	12.18	17.11	23.13	32.05	57.03
LTCON	25.68	37.08	41.09	43.13	44.82	46.00	46.18	47.13	45.71	29.41
ΔME(IR)	-0.38	-0.19	-0.11	-0.06	-0.01	0.04	0.08	0.14	0.21	0.40
ΔME(LR)	-0.07	0.00	0.04	0.05	0.07	0.08	0.08	0.09	0.07	-0.08
ME(lag5)	4.18	4.64	4.90	5.07	5.14	5.19	5.19	5.13	4.90	4.27

Panel C: Portfolios sorted by long-run change in size (ΔME(LR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.09	4.00	4.53	4.96	5.24	5.46	5.59	5.67	5.74	5.71
BM	1.28	1.06	0.95	0.86	0.81	0.75	0.69	0.62	0.53	0.41
MOM	8.29	8.81	8.82	9.19	9.03	8.87	8.66	8.10	7.31	3.60
LTCON	-45.78	-7.44	13.91	31.06	46.95	63.78	82.43	107.21	147.88	271.58
ΔME(IR)	0.00	0.00	-0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.00
ΔME(LR)	-1.10	-0.53	-0.27	-0.09	0.06	0.21	0.36	0.53	0.78	1.31
ME(lag5)	4.33	4.53	4.80	5.03	5.16	5.23	5.22	5.11	4.93	4.23

Panel D: Portfolios sorted by lagged 5-year size (ME(lag5))

Port.	Lo	2	3	4	5	6	7	8	9	Hi
ME	3.19	4.50	5.03	5.46	5.88	6.30	6.74	7.24	7.83	8.83
BM	0.92	0.82	0.80	0.78	0.74	0.72	0.69	0.67	0.66	0.57
MOM	5.80	8.21	8.98	9.70	9.44	9.88	9.72	10.45	9.51	9.39
LTCON	41.84	37.45	40.56	41.82	42.19	44.41	44.40	43.64	42.54	39.95
ΔME(IR)	-0.02	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02	0.02
ΔME(LR)	-0.03	-0.03	0.02	0.04	0.05	0.08	0.12	0.12	0.13	0.16
ME(lag5)	3.31	4.53	5.00	5.41	5.81	6.20	6.62	7.10	7.67	8.57

Table 3: Returns and asset pricing tests of size and component portfolios

This table reports the value-weighted average excess returns (R^e), standard deviation (Std), Sharpe Ratio (SR), and intercepts from CAPM model (α^{CAPM}) of decile portfolios sorted by log size (ME, Panel A), intermediate-run change in log size (ΔME(IR), Panel B), long-run change in log size (ΔME(LR), Panel C), and lagged 5-year log size (ME(lag5), Panel D). The size decomposition is described in Section XXX. At the beginning of each month, firms are sorted into deciles based on the sorting variables. The returns and CAPM alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Panel A: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	10.22	9.51	10.19	9.82	9.89	8.45	8.51	7.75	6.72	5.29	4.93
	(3.05)	(3.05)	(3.55)	(3.53)	(3.67)	(3.36)	(3.41)	(3.25)	(2.99)	(2.61)	(2.02)
Std	21.42	21.17	19.92	19.16	18.32	17.37	17.19	16.83	15.50	14.58	16.33
SR	0.48	0.45	0.51	0.51	0.54	0.49	0.49	0.46	0.43	0.36	0.30
α^{CAPM}	3.79	2.61	3.43	3.21	3.44	2.14	2.19	1.46	0.89	-0.22	4.01
	(1.88)	(1.60)	(2.51)	(2.55)	(3.06)	(2.23)	(2.37)	(1.93)	(1.34)	(-0.45)	(1.68)

Panel B: Portfolios sorted by intermediate-run change in size (ΔME(IR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	1.69	3.95	5.62	4.61	6.29	5.78	6.68	8.21	8.54	10.32	-8.64
	(0.49)	(1.5)	(2.48)	(2.17)	(3.13)	(2.89)	(3.29)	(3.96)	(3.54)	(3.36)	(-3.64)
Std	23.05	18.01	16.14	15.20	14.84	14.46	14.80	15.40	16.88	20.47	16.65
SR	0.07	0.22	0.35	0.30	0.42	0.40	0.45	0.53	0.51	0.50	-0.51
α^{CAPM}	-5.95	-2.08	0.04	-0.77	0.99	0.58	1.30	2.62	2.42	3.16	-9.10
	(-3.46)	(-1.41)	(0.04)	(-0.80)	(1.12)	(0.74)	(1.67)	(3.65)	(2.85)	(2.39)	(-3.85)

Panel C: Portfolios sorted by long-run change in size (ΔME(LR))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	11.88	8.43	8.26	8.19	7.48	7.03	5.95	5.66	5.46	4.54	7.33
	(3.77)	(3.48)	(3.76)	(3.84)	(3.77)	(3.39)	(2.89)	(2.67)	(2.42)	(1.59)	(3.23)
Std	20.67	17.33	15.85	14.81	14.14	14.55	14.73	15.13	16.44	19.57	14.81
SR	0.57	0.49	0.52	0.55	0.53	0.48	0.40	0.37	0.33	0.23	0.50
α^{CAPM}	5.17	2.54	2.80	3.01	2.47	1.80	0.62	0.15	-0.58	-2.60	7.76
	(2.99)	(1.94)	(2.47)	(2.90)	(3.07)	(2.22)	(0.81)	(0.20)	(-0.69)	(-2.61)	(3.41)

Panel D: Portfolios sorted by lagged 5-year size (ME(lag5))

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
R^e	7.02	8.95	8.25	8.67	8.51	7.97	7.42	7.50	6.62	5.49	1.53
	(2.02)	(2.77)	(2.71)	(2.91)	(3.17)	(3.04)	(2.99)	(3.09)	(2.99)	(2.82)	(0.63)
Std	22.56	21.82	20.30	20.08	18.23	18.06	17.33	16.71	15.66	14.14	15.99
SR	0.31	0.41	0.41	0.43	0.47	0.44	0.43	0.45	0.42	0.39	0.10
α^{CAPM}	-0.41	1.46	1.10	1.53	1.91	1.35	1.00	1.18	0.71	0.18	-0.59
	(-0.23)	(1.03)	(0.91)	(1.37)	(1.88)	(1.51)	(1.31)	(1.99)	(1.40)	(0.35)	(-0.27)

Table 4: Relation between size and ΔME(LR) component

This table reports the relation between firm size and ΔME(LR) components. In Panel A, each month we construct 5-by-5 portfolios independently double-sorted by firm size and ΔME(LR) component. Panel A.1 reports the size premium (the annualized value-weighted excess returns and CAPM alphas difference between bottom and top size quintile portfolios) within and across ΔME(LR) quintiles. Panel A.2 reports the ΔME(LR) premium (the annualized value-weighted excess returns and CAPM alphas difference between bottom and top ΔME(LR) quintile portfolios) within and across size quintiles. Panel B reports the time series regression coefficients of size (Panel B.1) and ΔME(LR) (Panel B.2) decile portfolios in a two-factor model, with the market factor and the ΔME(LR) premium factor as the risk factors. Panel B.1 reports the intercept (α), the market beta (β_1), and the ΔME(LR) factor beta (β_2). Panel B.2 reports the intercept (α), the market beta (β_1) and the size factor (β_2). Panel C reports the time series regression coefficients of size (Panel C.1) and ΔME(LR) (Panel C.2) decile portfolios in a three-factor model with the addition of a ΔME(IR) premium factor. The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Panel A: Double sorts and conditional premium

Panel A.1: Conditional size premium across ΔME(LR) quintiles

ΔME(LR)	Lo	2	3	4	Hi	Average
R^e	4.02	4.06	3.35	3.06	-1.24	2.65
	(1.40)	(2.03)	(1.81)	(1.37)	(-0.5)	(1.31)
α^{CAPM}	2.46	2.91	2.11	1.82	-2.26	1.41
	(0.90)	(1.53)	(1.19)	(0.85)	(-0.91)	(0.74)

Panel A.2: Conditional ΔME(LR) premium across size quintiles

Size	Lo	2	3	4	Hi	Average
R^e	8.92	5.50	4.24	4.80	3.65	5.42
	(6.37)	(3.34)	(2.51)	(2.64)	(1.50)	(3.85)
α^{CAPM}	9.29	5.99	5.04	5.65	4.57	6.11
	(6.63)	(3.57)	(3.00)	(3.13)	(1.88)	(4.33)

Panel B: Size and ΔME(LR) portfolios in two-factor models

Panel B.1: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	-0.04	-0.88	0.48	0.71	1.24	0.66	0.99	0.41	0.47	0.50	-0.54
	(-0.03)	(-0.71)	(0.45)	(0.67)	(1.32)	(0.76)	(1.17)	(0.64)	(0.75)	(1.08)	(-0.29)
β_1	1.11	1.18	1.16	1.13	1.10	1.07	1.07	1.06	0.98	0.91	0.20
	(31.41)	(43.10)	(47.04)	(43.64)	(45.01)	(51.78)	(55.62)	(75.20)	(63.40)	(90.75)	(4.67)
β_2	0.49	0.45	0.38	0.32	0.28	0.19	0.15	0.14	0.05	-0.09	0.59
	(12.56)	(14.30)	(14.33)	(12.28)	(10.94)	(8.77)	(7.18)	(7.40)	(3.34)	(-8.62)	(12.60)
R^2	0.71	0.80	0.84	0.85	0.87	0.90	0.91	0.94	0.94	0.95	0.30

Panel B.2: ΔME(LR) portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	3.39	1.83	2.51	2.95	2.42	1.82	0.96	0.63	-0.13	-2.41	5.80
	(2.68)	(1.55)	(2.25)	(2.88)	(2.97)	(2.26)	(1.28)	(0.88)	(-0.16)	(-2.44)	(3.18)
β_1	1.05	0.96	0.90	0.86	0.83	0.87	0.90	0.94	1.02	1.20	-0.15
	(33.38)	(31.30)	(30.77)	(32.69)	(36.29)	(41.22)	(36.32)	(41.53)	(38.94)	(51.86)	(-3.22)
β_2	0.44	0.18	0.07	0.01	0.01	0.00	-0.09	-0.12	-0.11	-0.05	0.49
	(10.22)	(4.88)	(1.49)	(0.47)	(0.38)	(-0.19)	(-3.16)	(-5.63)	(-5.51)	(-1.96)	(8.52)
R^2	0.82	0.79	0.79	0.81	0.83	0.85	0.88	0.89	0.90	0.88	0.29

Panel C: Size and ΔME(LR) portfolios in three-factor models

Panel C.1: Size portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	-0.04	-0.76	0.83	0.98	1.59	1.05	1.36	0.90	0.73	0.61	-0.65
	(-0.02)	(-0.58)	(0.76)	(0.91)	(1.62)	(1.15)	(1.54)	(1.37)	(1.07)	(1.26)	(-0.33)
β_1	1.11	1.18	1.15	1.12	1.09	1.06	1.06	1.05	0.97	0.91	0.20
	(30.92)	(42.53)	(46.74)	(43.71)	(44.80)	(50.88)	(53.93)	(75.42)	(61.36)	(90.76)	(4.64)
β_2	0.49	0.45	0.37	0.31	0.27	0.18	0.14	0.12	0.05	-0.10	0.59
	(11.51)	(12.38)	(12.87)	(11.33)	(10.53)	(8.48)	(6.85)	(6.82)	(3.05)	(-7.96)	(11.41)
β_3	0.00	0.01	0.03	0.02	0.03	0.03	0.03	0.04	0.02	0.01	-0.01
	(0.01)	(0.29)	(0.99)	(0.85)	(1.24)	(1.47)	(1.57)	(2.93)	(1.60)	(0.70)	(-0.16)
R^2	0.71	0.80	0.84	0.85	0.87	0.90	0.91	0.94	0.94	0.95	0.30

Panel C.2: ΔME(LR) portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi	L-H
α	4.62	2.68	3.70	3.71	2.86	2.23	1.45	0.72	-0.32	-3.11	7.72
	(3.70)	(2.29)	(3.19)	(3.41)	(3.25)	(2.83)	(1.93)	(0.98)	(-0.37)	(-3.14)	(4.38)
β_1	1.05	0.95	0.89	0.86	0.83	0.87	0.90	0.94	1.03	1.20	-0.16
	(37.14)	(30.79)	(29.99)	(31.76)	(35.12)	(41.21)	(36.81)	(41.34)	(38.63)	(52.50)	(-3.77)
β_2	0.42	0.16	0.05	0.00	0.00	-0.01	-0.09	-0.12	-0.11	-0.04	0.46
	(10.70)	(4.80)	(1.15)	(0.08)	(0.13)	(-0.57)	(-3.49)	(-5.55)	(-5.36)	(-1.56)	(9.01)
β_3	0.13	0.09	0.12	0.08	0.05	0.04	0.05	0.01	-0.02	-0.07	0.20
	(4.58)	(3.81)	(3.92)	(2.89)	(1.78)	(2.02)	(2.12)	(0.54)	(-0.81)	(-3.31)	(4.99)
R^2	0.83	0.80	0.80	0.81	0.83	0.86	0.88	0.89	0.90	0.88	0.34

Table 5: Fama-MacBeth regressions

This table reports the results from Fama-MacBeth regressions of returns (in percentages) on firm characteristics, including the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	1.724	1.460	1.234	1.229	1.442	1.406	1.788
	(4.49)	(3.91)	(5.07)	(5.05)	(3.89)	(3.77)	(4.67)
ME	-0.109				-0.323	-0.041	-0.123
	(-2.77)				(-4.4)	(-1.12)	(-3.11)
ME(lag5)		-0.054			0.273		
		(-1.43)			(4.24)		
ΔME(LR)			-0.411			-0.371	
			(-5.52)			(-6.15)	
ΔME(IR)				0.734			0.862
				(4.06)			(4.86)
R^2(%)	1.48	1.14	0.78	0.74	2.04	1.95	2.16

Table 6: January effect

This table analyzes January effect for two size strategies. The first strategy follows Fama and French (1992) timing and defines firm size as the market value at the end of previous June. The second strategy defines firm size as the market value at the end of previous month. Panel A reports the fraction of the cross-sectional variance of log firm size that is explained by its components. Panel B reports the coefficients from the univariate Fama-MacBeth regressions of returns (in percentages) on the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes all January from 1964 to 2015.

Panel A: Adj R^2 of size regressions

Size timing	ME(lag5)	ΔME(LR)	ΔME(IR)	ΔME(SR)
End of previous June	0.806	0.186	0.023	
End of previous month	0.790	0.171	0.047	0.006

Panel B: Fama-MacBeth regressions

Size timing	ME	ME(lag5)	ΔME(LR)	ΔME(IR)	ΔME(SR)
End of previous June	-1.62	-1.29	-3.04	-3.27	
	(-6.79)	(-6.13)	(-6.14)	(-4.50)	
End of previous month	-1.81	-1.32	-3.08	-4.39	-17.22
	(-6.91)	(-6.43)	(-6.00)	(-5.08)	(-7.23)

Table 7: New entrants

This table analyzes new entrants, defined as all NYSE/AMEX/NASDAQ common stocks that enter the CRSP database within the past five years but have non-missing market value at the end of previous June. At each month, Group 1 includes stocks younger than 1 year, Group 2 includes stocks older than 1 but younger than 2 years, Group 3 includes stocks older than 2 but younger than 3 years, Group 4 includes stocks older than 3 but younger than 4 years, and Group 5 includes stocks older than 4 years. As a comparison, we also report the result for the sample of firms used in Table 2 (Group 0). ME(lag) is the log market value 5 years ago for Group 0. For the other groups, ME(lag) is the log market value when firms enter the CRSP database. Panel A reports the fraction of the cross-sectional variance of log firm size that is explained by its components. Panel B reports the coefficients from the univariate Fama-MacBeth regressions of returns (in percentages) on the logarithm of the firm size and its components. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample is monthly from July 1963 to December 2015.

Panel A: Adj R^2 of size regressions

Group	ME(lag)	ΔME(LR)	ΔME(IR)	ΔME(SR)
1	0.936		0.100	0.029
2	0.818	0.140	0.129	0.014
3	0.698	0.283	0.085	0.009
4	0.618	0.367	0.071	0.007
5	0.550	0.437	0.063	0.006
0	0.805	0.184	0.026	0.004

Panel B: Fama-MacBeth regressions

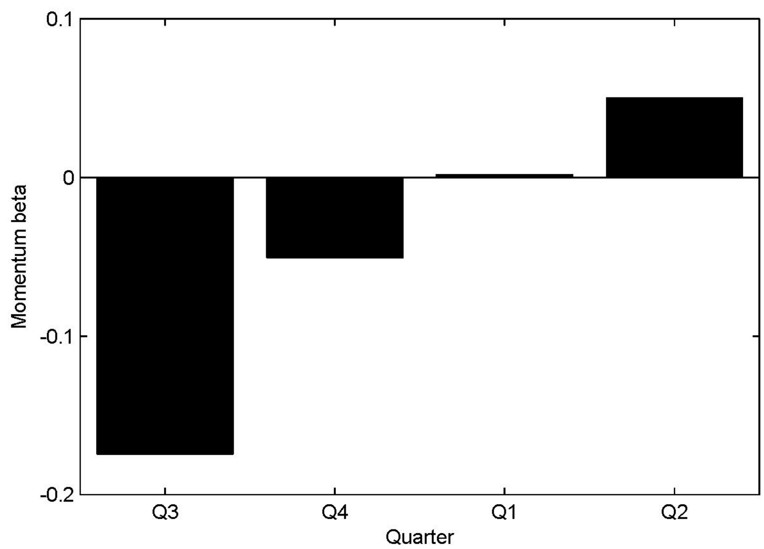
Group	ME	ME(lag)	ΔME(LR)	ΔME(IR)	ΔME(SR)
1	-0.030	-0.066		0.612	-4.390
	(-0.40)	(-0.86)		(1.28)	(-2.35)
2	-0.053	-0.074	-0.687	0.675	-6.105
	(-0.84)	(-1.06)	(-3.56)	(2.19)	(-2.92)
3	-0.219	-0.092	-0.639	0.779	-4.668
	(-3.27)	(-1.35)	(-4.10)	(2.87)	(-2.01)
4	-0.227	-0.049	-0.584	0.653	-7.701
	(-3.53)	(-0.72)	(-4.63)	(2.26)	(-3.45)
5	-0.223	-0.075	-0.558	0.658	-5.363
	(-3.75)	(-1.28)	(-5.48)	(2.62)	(-2.50)
0	-0.109	-0.054	-0.411	0.734	-6.010
	(-2.77)	(-1.43)	(-5.52)	(4.06)	(-4.24)

Figure 1: Fractions of cross-sectional variance of firm size explained by its components
This figure plots the fractions of cross-sectional variance of firm size explained by its components over time. At each month, we run a cross-sectional regression of log market equity from the previous June on each of its components (ME(lag5), ΔME(LR), ΔME(IR), and ΔME(SR)). For each component, the adjusted R^2 for year t is calculated as the average R^2 from July, year $t-1$ to June, year t. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.

Figure 2: Seasonality in momentum beta

This figure plots the seasonality in momentum beta of the Fama and French (1992) size premium (Panel A) and the size premium based on the market value of the previous month (Panel B). In each quarter, we estimate the momentum beta of the long-short size decile portfolios in a two-factor model with the market excess return and the winner-minus-loser portfolio return from momentum deciles as the risk factors. The sample includes all NYSE/AMEX/NASDAQ common stocks from July 1963 to December 2015.

Panel A: Size strategy based on Fama and French (1992) timing



Panel B: Size strategy based on the size of previous month

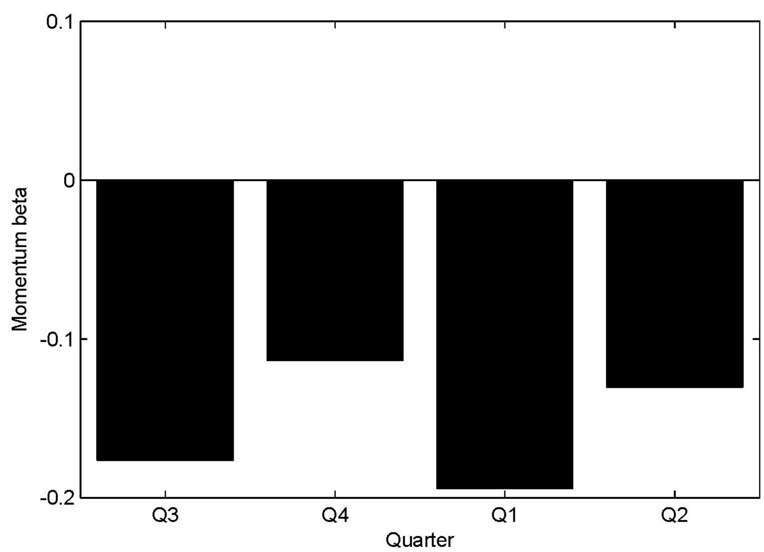
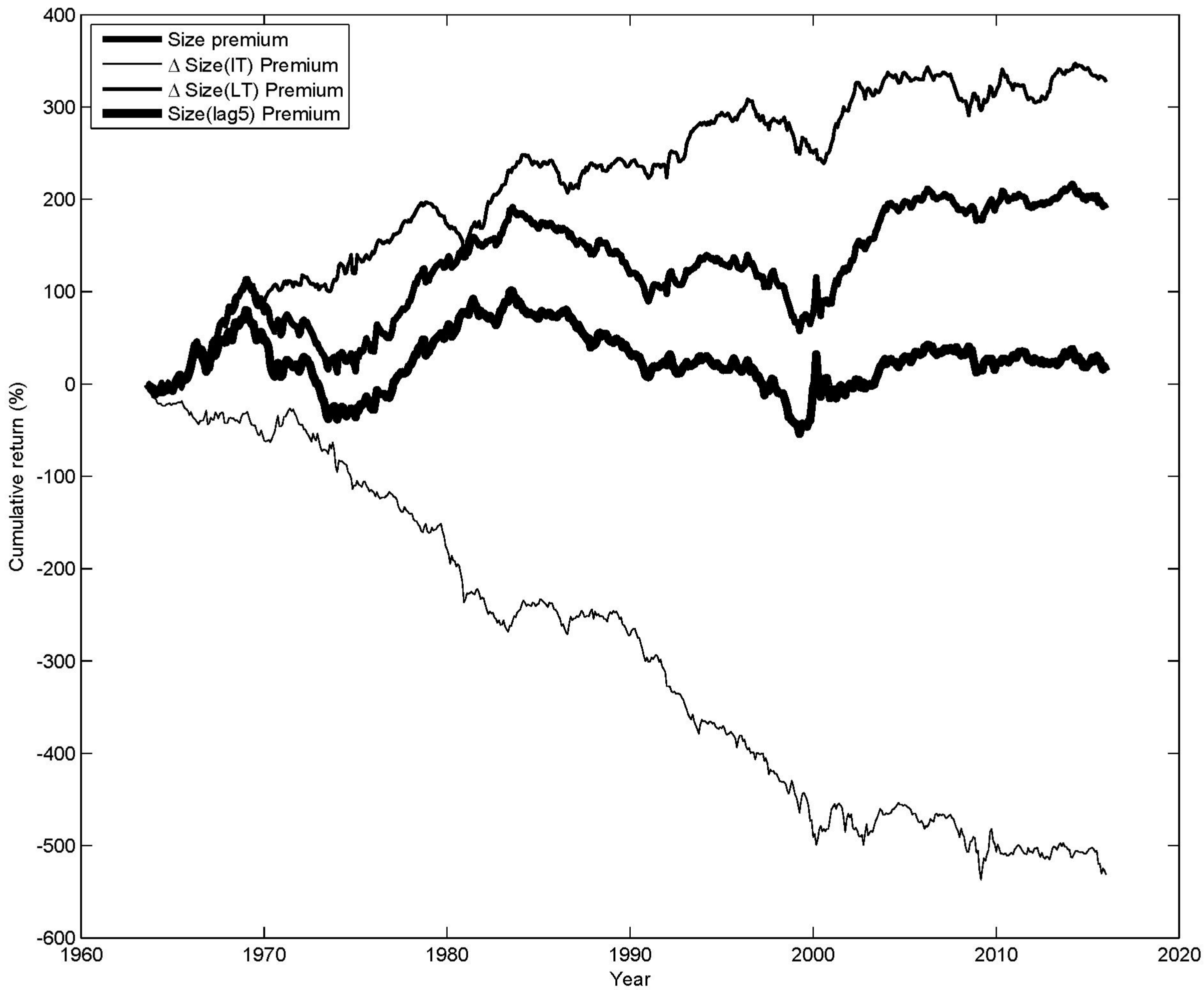


Figure 3: Cumulative returns of size and components strategies

This figure plots the cumulative returns of the long-short portfolio based on standard size and its components. To be consistent with the sign of the size premium, the long-short portfolio for each sorting variable is the difference between the bottom and top decile portfolios. The sample includes all NYSE/AMEX/NASDAQ common stocks with nonmissing size components from size decomposition from July 1963 to December 2015.



Why So Much Error in Analysts' Earnings Forecasts?

Vijay Kumar Chopra

Wall Street analysts tend to be too optimistic about the earnings prospects of companies they follow. The average consensus 12-month EPS growth forecast is 17.7 percent, which is more than twice the actual growth rate. In aggregate, forecasts are 11.2 percent above actual earnings at the start of a year and are revised downward continuously in the course of the year. For the full study period reported here, the percentage of 12-month earnings estimates revised downward exceeded the percentage revised upward, on average, by 4.4 percent every month. Since 1993, however, the quality of analyst forecasts seems to have improved. This article provides an intuitive explanation of the change and suggests ways in which analysts can use the explanation to improve portfolio performance.

Use of earnings estimates is an integral part of equity valuation by fundamental and quantitative analysts, and the estimates have even become an integral part of financial reporting in the popular press. The behavior and uses of earnings estimates have been widely studied. I/B/E/S International has published an excellent bibliography of earnings expectation research (Brown 1996). Studies that have shown that analysts tend to overestimate earnings include Clayman and Schwartz (1994), Dreman and Berry (1995), and Olsen (1996). Clayman and Schwartz attributed the positive bias to analysts' tendency to "fall in love" with their stocks. In addition, they proposed that investment banking relationships of investment houses and the prospect of being cut off from access to company managers make issuing negative or critical reports on companies difficult for analysts. Dreman and Berry examined quarterly earnings estimates and found that the average forecast errors tend to be high; in their study, only a small percentage of estimates fell into an acceptable error range. Olsen ascribed the positive bias and lack of accuracy in earnings estimates to herding behavior among forecasters. Francis and Philbrick (1993) argued that analysts make optimistic forecasts to maintain relationships with company managers.

The data for the studies reported here are from the I/B/E/S Global Aggregates database, which aggregates bottom-up analyst earnings forecasts to create forecasts at the market level. The specific forecasts analyzed were for the earnings of the S&P 500 Index. I/B/E/S uses market-capitalization weights to combine the mean earnings forecasts for each company in the S&P 500 into an index of earnings estimates. The data are available on a monthly basis beginning with January 1985; the cutoff point for this study is December 30, 1997.

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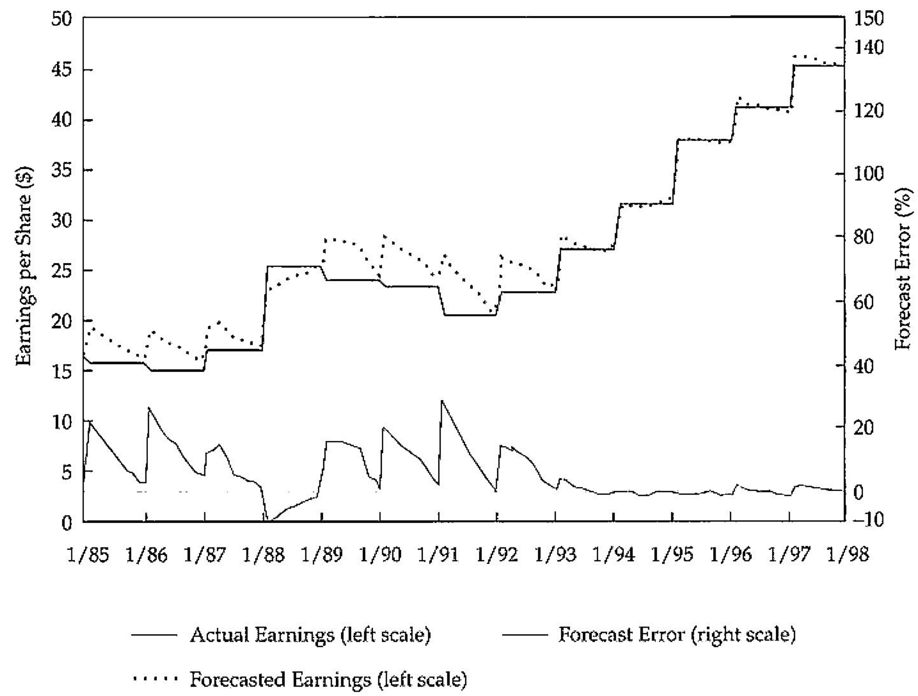
Forecast Changes during a Year

This study focused on how the forecasts for the S&P 500 earnings for the current fiscal year vary over the course of the year. **Figure 1** shows the "calendarized" current fiscal year (Calendar FY1 in I/B/E/S terminology) forecasts and actual earnings per share for the entire study period, January 1985 through December 1997.[1] Because of the delay in reporting earnings, the actual earnings are not known until after the year has ended. To make sure that all companies have reported, I used the actual earnings for a calendar year from the I/B/E/S computation made in July of the following year. Therefore, the July 1996 calculation of calendarized 1995 earnings is taken to be the actual earnings for calendarized 1995.

The calendarized actual earnings follow a stair-step pattern. The long-term upward trend and the cyclicality in actual earnings are both evident from Figure 1: Earnings tend to increase over the long run. The cumulative annualized growth rate in earnings for the period is 8 percent, but earnings

Figure 1. Calendarized FY1 Actual Earnings, Forecasted Earnings, and Forecast Errors for the S&P 500: 1985–97



have declined in some periods, such as 1986 and 1989–1991. The earnings recovery since 1992 has produced a steady step-up pattern.

In general, Figure 1 shows that earnings forecasts are very optimistic at the start of the year and decline toward actual values as the year progresses. The decline in full-year forecasts occurs as quarterly numbers are released and an increasing portion of the fiscal-year earnings becomes known. In addition, as the year progresses, company managers comment on the outlook for their companies in future quarters and analysts gather additional information that may lead them to revise their estimates. On rare occasions, analysts underestimate earnings, such as in 1988. For most years, however, analysts revise their initial estimates downward. Future research will have to separate the effect of time from the effect of better visibility for the late quarters of each year.

On average, the Street overestimated current-year earnings by 6.1 percent in the 1985–97 period. In some periods, such as around February 1991, the overestimation was as high as 30 percent, and in other periods, such as February 1988, earnings were underestimated by more than 8 percent. The average overestimation in the 1985–92 period was 9.4 percent.

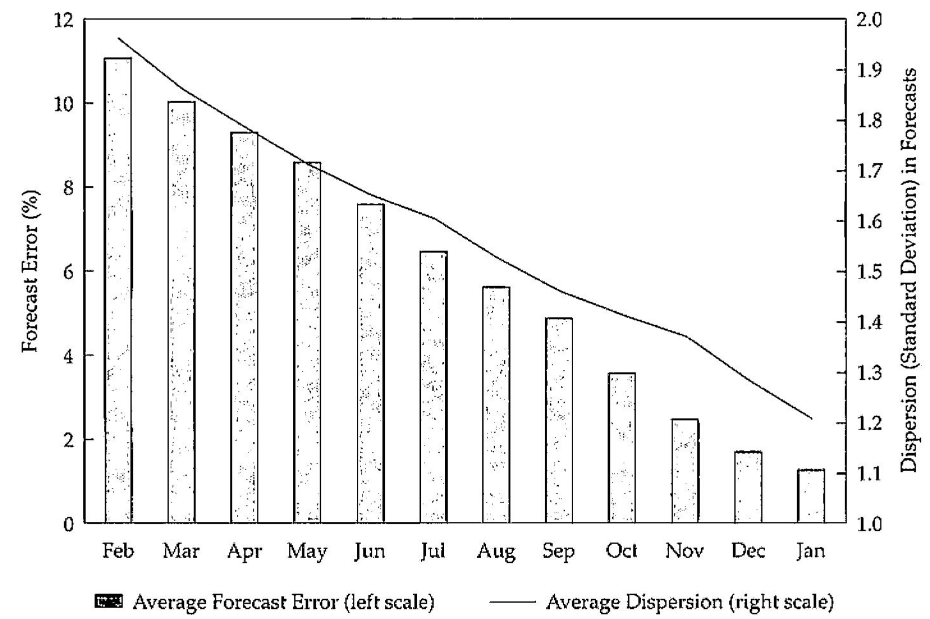
Since 1993, analyst forecasts have been much closer than in the past to actual earnings. The average forecast error since January 1993 has been remarkably small, an average overestimation of less than 1 percent.

Overestimations typically correct in the course of a year. **Figure 2** shows the decline toward reality of analyst optimism. On average, earnings are overestimated by about 11.2 percent at the start of the fiscal year. (The largest forecast errors occur in February because of the I/B/E/S convention of rolling over a calendar year at the end of January instead of at the end of December.) The overestimation declines to 8.7 percent three months later. Another quarter later, the estimate declines to only 6.6 percent above the actual. By the end of the third quarter, the overoptimism is only 3.6 percent. With attention shifting to the next fiscal year, the final overestimation is only slightly more than 1 percent on average. (Complete convergence does not occur at year end because of the delay in reporting earnings.)

The pattern of declining overestimation was more pronounced before 1993; in the pre-1993 period, the average forecast errors in February were almost 17 percent. At the end of July, they were still well over 10 percent. Since 1993, the error has been as low as 2 percent in February, fading to small negative values from September on.

Another perspective on analyst optimism can be gained by looking at the percentage of estimates of 12-month-forward earnings that are revised upward or downward every month.[2] **Figure 3**

Figure 2. Analyst Overoptimism and Dispersion in EPS Estimates: Monthly Pattern, Averages for 1985–97



Note: Estimates are from February of a calendar year to January of the following year because of the I/B/E/S February rollover. The initial estimate for Calendar FY1 is made in February, and the final estimate is made in January of Calendar FY2.

Figure 3. Net EPS Estimate Revisions

shows the net positive revisions of 12-month-forward earnings.[3] This series is volatile, but its overall trend is important. Most of the net revisions are negative, which is to be expected; analysts are constantly adjusting their estimates downward because the initial estimates are too optimistic. The average net revision for the entire period, indicated by the shaded line in Figure 3, is –4.4 percent—that is, the percentage of estimates revised downward exceeds the percentage revised upward by 4.4 percent each month. Since 1994, however, net revisions have been close to zero, which confirms the other evidence that analyst forecasts have improved in accuracy since that time.

Consider now another interesting aspect of analyst forecasts—the degree of disagreement among the estimates. Figure 2 shows the decline in the dispersion of estimates over the course of a typical year. The dispersion is greatest in February and declines systematically to its lowest value the following January. This decline can be attributed to quarterly earnings releases and the resulting increase in the visibility of the company's prospects. For the whole study period, dispersion in estimates at the level of the S&P 500 exhibits the sawtooth pattern shown in **Figure 4**. Analyst estimates of Calendar FY1 earnings show the greatest disagreement at the start of the year. As companies report interim quarterly results, the proportion of the fiscal year for which earnings have to be forecasted declines, which reduces the divergence in Calendar FY1 estimates as the year proceeds. This pattern has been particularly strong since 1988 and does not show any signs of fading in recent years. Although analysts may have gotten better at estimating the year's overall level of earnings, the disagreement among analysts over earnings estimates has not diminished over the years.

Forecasted versus Actual EPS Growth

Analysts' earnings growth rate forecasts provide another perspective on the overoptimism evident in their forward estimates of EPS. **Figure 5** shows the rolling 12-month-forward actual and forecasted growth in S&P 500 earnings. For example, the 12-month forecasted growth rate in March 1986 was 16.6 percent whereas the actual growth rate for the subsequent 12 months was –2 percent.

Figure 5 provides three key insights into analyst behavior. First, earnings growth forecasts are always positive. The forecasts lie roughly in the 10–30 percent range, with an average of 17.7 percent, whereas actual growth averages 8.6 percent, almost 9 percent below the forecasts on an annual basis. Therefore, on average, analysts' forecasts are double the actual growth rate in earnings.

Second, actual earnings growth rates vary a lot more than the forecasted rates. Actual earnings growth varies between –15 percent and 40 percent, whereas the forecasts lie within a much narrower range, 10–30 percent. The standard deviation of forecasted growth rates is only 5.4 percent, compared with a 12 percent standard deviation for actual earnings growth rates. Note that, in aggregate, analysts never forecast an absolute decline in earnings, but actual earnings have fallen for extended periods of time (e.g., January 1985 to June 1986, which coincided with a rapid decline in the pace of economic activity and a collapse in the price of oil, and again from January 1989 through June 1991, which was a time of brief economic recession).

Third, Figure 5 shows that, as with EPS levels, actual and forecasted EPS growth rates have been much closer since January 1993. **Table 1** summarizes the forecasting behavior of analysts for the

Figure 4. Dispersion in Analyst EPS Estimates over Time

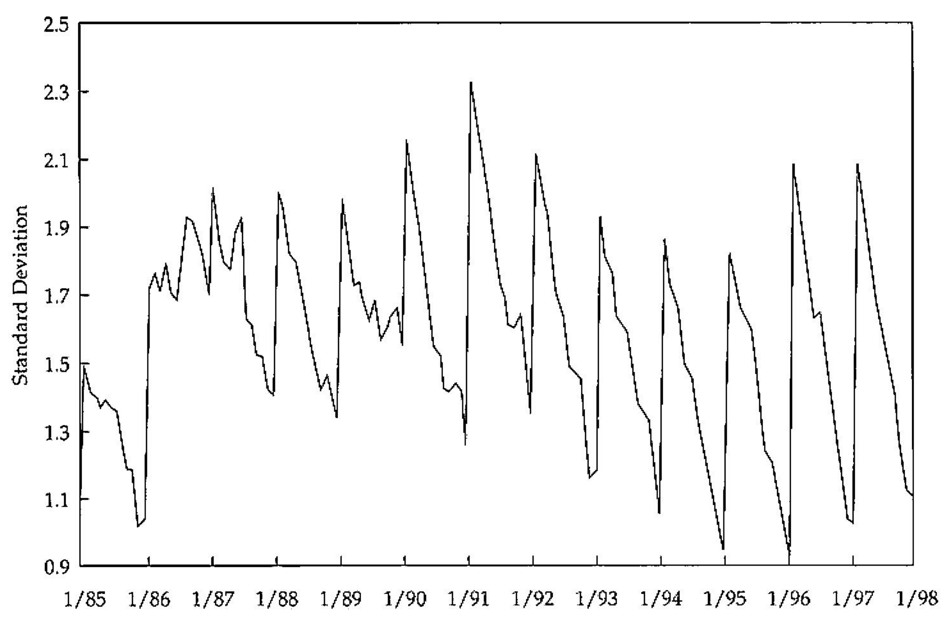
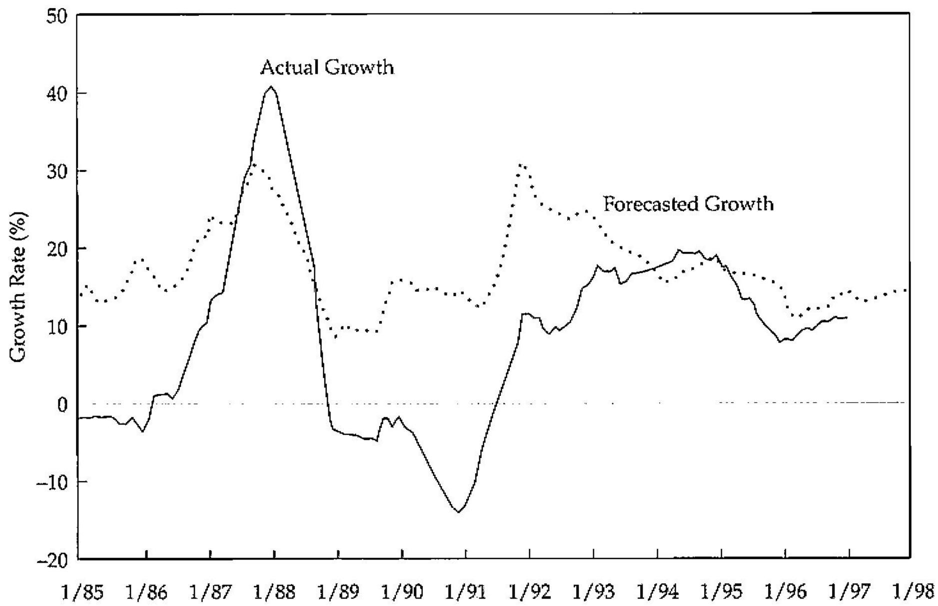


Figure 5. Forecasted versus Actual EPS Growth Rates



Note: The actual growth rates end in December 1996, whereas the forecasted growth rates are available through the end of 1997 because the actual growth rate is not known until 12 months after a given month-end. For example, the actual growth rate for March 1986 comes from March 1987 data.

Table 1. Twelve-Month-Forward Forecasted and Actual Earnings Growth Rates: Summary Statistics

Period/Statistic	Forecasted Growth Rate	Actual Growth Rate	Difference in Rates
January 1985 to December 1996			
Mean	17.7%	8.6%	9.1%
Standard deviation	5.4	12.0	9.3
Maximum	31.2	41.0	28.7
Minimum	8.4	−14.0	−13.1
January 1993 to December 1996			
Mean	16.5	14.4	2.1
Standard deviation	3.2	3.9	2.8
Maximum	24.3	19.5	8.3
Minimum	10.9	7.7	−2.9

Note: The difference between forecasted and actual growth rates is a new series. The last column shows the mean, standard deviation, maximum, and minimum for this series.

whole study period and the post-1993 periods. The average forecasted growth rate of 16.5 percent since January 1993 reported in Table 1 is only about 2 percent higher than the actual increase of 14.4 percent. The standard deviations have also been closer, at 3.2 for the forecast versus 3.9 for the actual.

The correlation between average forecasted and actual EPS growth rates for the total period is 0.67, which indicates that analysts have done a moderately good job of capturing changes in EPS growth rates over time. The correlation for the 1993–97 period was 0.70.

Does the recent convergence between analyst forecasts and actual EPS indicate a sudden increase in analyst forecasting ability? Possibly, but the more likely explanation is that analysts have continued to predict optimistic growth rates but those predictions turned out to be in line with actual rates that were high by historical standards. That is, because of restructurings during the previous decade, when the economy started strengthening in 1992, earnings per share grew strongly to match the usual analyst optimism. This explanation is supported by a comparison of rates since January 1993 with rates for the whole period. The forecasted growth rates are very close, 16.5 for the recent period and 17.7 for the whole period, which indicates that analyst optimism did not decline; the actual growth rate for the recent period, however, was almost 6 percentage points higher than growth for the whole period. In short, the actual growth rate for January 1993 through December 1997 has been close to the long-term average growth forecast in what has been one of the longest economic expansions in the history of the United States.

Economic Growth and Earnings Growth

At the aggregate level, company earnings are likely to be tied to the state of the economy. Strong economic growth should, therefore, lead to strong growth in EPS, and indeed, a comparison of growth in industrial production with earnings growth for the S&P 500 supports that expectation.[4]

Figure 6 provides plots of the year-on-year growth in industrial production and the year-on-year growth in actual earnings. Earnings growth lags industrial production growth by between 9 and 18 months, with an average of about 12 months. In order to highlight the close link between growth in industrial production and EPS growth, the earnings growth has been shifted back by 12 months; that is, for example, the June 1996 growth in industrial production is the growth for June 1995 to June 1996 and the June 1996 earnings growth is the growth from June 1996 to June 1997.

Figure 6 suggests that investment analysts could predict aggregate earnings using industrial production data. The correlation between the growth of the two series is 0.77. When industrial production is lagged by one additional month to account for the late release of the data, the correlation is still very high, 0.73. In comparison, the correlation between forecasted and actual earnings growth rates has been averaging 0.67.

An exploration of the link between the strength of the economy and earnings growth estimates will shed considerable light on why earnings estimates are consistently off the mark and why they have been closer to actual earnings since 1993. **Figure 7** shows the year-on-year growth in industrial production and plots the error in the 12-month-forward earnings growth forecast (the difference between the 12-month-forward forecasted earnings growth and actual earnings growth). The clear inverse relationship between the two series indicates that forecast errors are greatest when industrial production growth is at a peak or trough. Furthermore, when industrial production growth accelerates, forecast errors decline, and when industrial production decelerates, forecast errors increase. When growth in industrial production accelerates, earnings grow strongly and the gap between the optimistic growth forecasts and actual earnings growth narrows, which results in more-accurate forecasts. When growth in industrial production decelerates, earnings growth declines

Figure 6. Industrial Production Growth and Aggregate EPS Growth

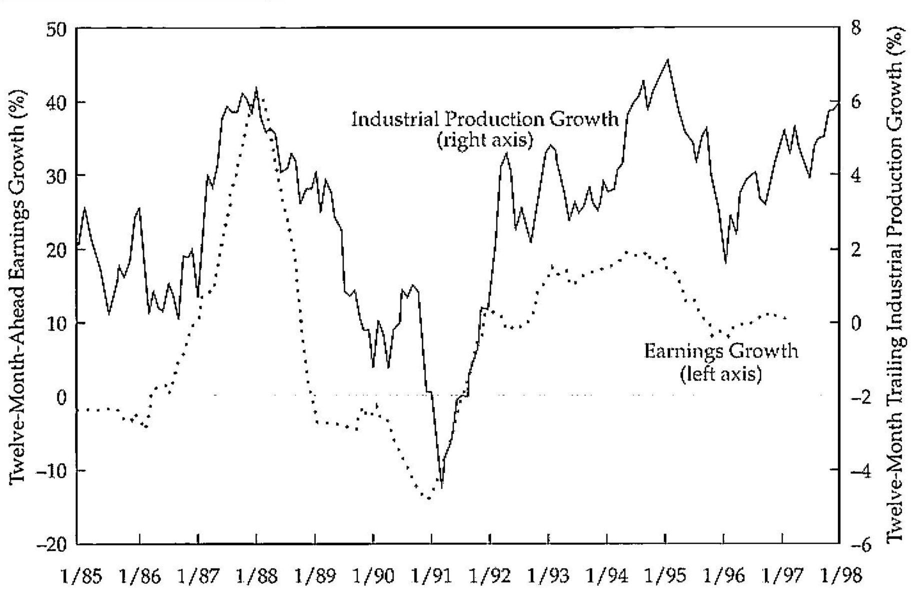
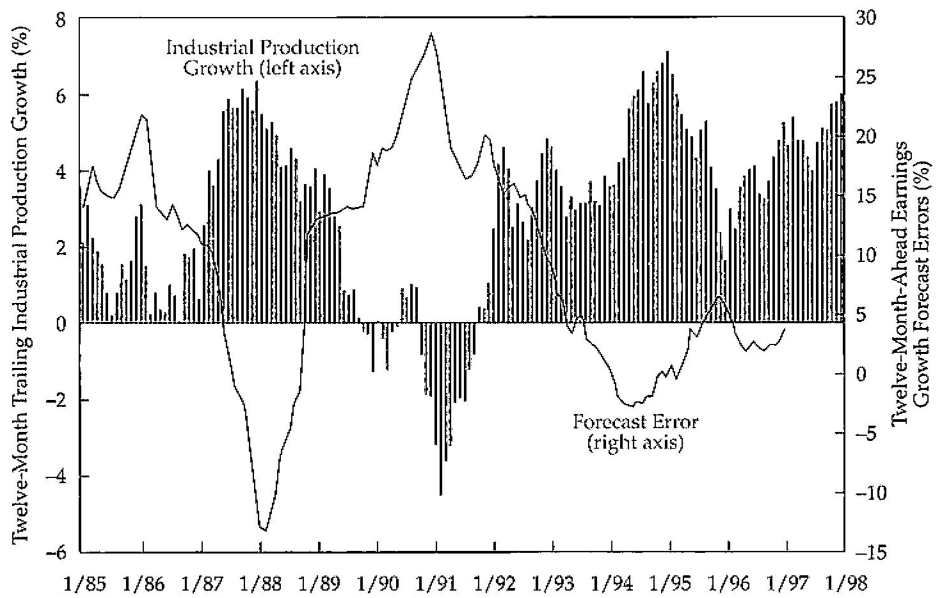


Figure 7. Industrial Production Growth and Errors in EPS Growth Forecasts



(with a 12-month lag) and the gap between the optimistic forecasts and actual earnings growth widens, which results in inaccurate forecasts. When industrial production growth is at its peak, the forecast errors overshoot on the downside and are large but negative. An example is the fourth quarter of 1987 through the first quarter of 1988. On the other hand, when the growth in industrial production started declining in January 1988 from 6.4 percent down to –4.5 percent in March 1991, the forecast errors went from –13 percent to almost 29 percent.

In light of this evidence on growth in the economy and analysts' forecasts, the aggregate behavior of analysts can be described as follows: They are normally very optimistic. When economic growth strengthens, actual earnings accelerate toward the normally optimistic forecasts, so forecast errors decline. If economic growth is very strong, earnings rise well beyond the forecasts, so analysts end up underforecasting earnings for a while. When the economy slows down, earnings start declining but the analysts' optimism prevents them from reducing their estimates far enough. Therefore, the size of forecast errors increases. If forecast errors are negative when the economy starts to slow down, as in January 1988, the errors become less negative at first; then, as the economy continues to decelerate and moves into a recession, the forecast errors move into the positive range and continue to grow. In December 1990, the errors hit a peak of almost 29 percent.

This behavior implies that analysts are likely to be most accurate in an environment of continuing strong economic growth, when earnings growth will approach the analysts' usually bullish forecasts—as has been the case since early 1992. The worst economic environment for aggregate analyst forecasts is one of an accelerating or decelerating economy, and the faster the pace of acceleration or deceleration, the greater the deviation between forecasts and actual earnings growth. The bottom line is that analysts will continue to forecast inaccurately as long as business cycles exist.[5]

Investment Implications

Users of EPS estimates will clearly benefit from recognizing the extent of analyst optimism. Valuation models that rely on earnings forecasts are likely to be biased, but if the extent of optimism is similar across industries and sectors, these valuation models will still be useful in evaluating stocks relative to each other.

The finding that forecast errors vary systematically with the business cycle suggests that analysts may focus too much on firm-specific issues and not enough on the overall macroeconomic environment. Portfolio managers could improve portfolio performance, therefore, by adjusting consensus earnings for systematic biases in forecasts.

One of the uses of aggregate estimate data is in global asset allocation, and conventional asset allocation approaches rely on comparing earnings yields with interest rates. Emanuelli and Pearson (1994) described an approach to global asset allocation that relies on estimate revisions. Recognizing that biases in earnings forecasts are linked to the business cycle and adjusting earnings forecasts to reduce the bias will improve the performance of such global asset allocation strategies.

Conclusion

Analysts' forecasts of EPS and growth in EPS tend to be overly optimistic. Calendarized earnings estimates overstate actual earnings by about 11 percent at the start of the year. These estimates are revised downward monotonically as a typical year unfolds. On average, the percentage of 12-month earnings estimates revised downward exceeds the percentage revised up by 4.4 percent a month. Analyst forecasts of 12-month earnings growth rates average 17.7 percent, more than twice the actual growth rate in the past 13 years.

Industrial production is a good predictor of earnings growth for a year in the future; the correlation is 0.77 percent. The analyst forecast for aggregate EPS growth is also a good predictor of actual growth (with a correlation of 0.67), but the forecasted growth rates are generally too optimistic and lie in a narrow (10–30 percent) range whereas the actual growth rates have varied from –10 percent to 40 percent.

Analysts' usual optimism, their tendency to forecast in a narrow and comfortable range, and the business cycle prove to be the bane of their forecasts. Acceleration or deceleration in economic growth tends to catch analysts off-guard. The forecasts are most accurate in an environment of continued strong growth, such as the one the U.S. economy has been in since 1992. Therefore, although the quality of forecasts has improved since 1992, it will deteriorate if and when the U.S. economy slows down and reverts to its historical cyclical pattern.

Notes

1. I/B/E/S uses the "Compustat rule" to calendarize company-level data prior to aggregation. Data for fiscal years ending between January and May are included in the aggregate for the prior calendar year. Data for the fiscal years ending between June and December of the current calendar year are included in the current calendar-year aggregate (Calendar FY1). For example, data for a company with a fiscal year ending in March 1996 are in the 1995 aggregate; data for a company with a fiscal year ending August 1996 are in the 1996 aggregate. I/B/E/S applies a February "rollover"; that is, when the calendar year ends and a new calendar year begins, the data for Calendar FY1 should shift or roll over from the year just ended to the new year, but I/B/E/S lags the shift by one month. Therefore, the current calendar year is not considered Calendar FY1 until February. The rationale for the lag is, presumably, that a majority of the companies with fiscal years ending in December do not report by the end of January.
2. I/B/E/S calculates 12-month-forward estimates for a company by prorating the current and next fiscal year estimates using the formula [(*a*/12)(Current fiscal year EPS] + [(12 – *a*)]/[12(Next fiscal year EPS)], where *a* is the number of months remaining in the current year. I/B/E/S then aggregates 12-month-forward company estimates to the index level.
3. Net revisions are defined as (Number of estimates revised upward – Number of estimates revised downward)/Total estimates, over the preceding four weeks, in percentage terms.
4. I used industrial production as a measure of economic activity instead of GDP because of the monthly availability of production data. Using GDP produced qualitatively similar results.
5. This link between forecast errors and the business cycle contrasts with the findings of Dreman and Berry, who found that forecast errors are not meaningfully affected by the business cycle.

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Trends in analyst earnings forecast properties

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Abstract

Forecast dispersion, error, and optimism are computed using 120,022 quarterly observations from 1990 to 2001. Forecast dispersion, error, and optimism all decrease steadily over the sample period, with loss firms showing an especially striking decrease. By the end of the sample period, dispersion and error differences between profit and loss firms are relatively minor, optimism for loss firms is around an unbiased 50%, and pessimism dominates profit firms. Additionally, loss firm earnings appear more difficult to forecast. The reduction in dispersion, error, and optimism does not appear fully attributable to earnings management, earnings guidance, or earnings smoothing. The trends are consistent with increased litigation concerns.

JEL classification: D84; G14; G24
Keywords: Earnings forecasts; Analysts; Earnings management; Forecast dispersion; Forecast accuracy

1. Introduction

A major responsibility of analysts is to make earnings forecasts. Professionals, such as investment bankers, financial advisors, and stockbrokers, rely on these forecasts to make their decisions, as do many individual investors. The forecasts serve as critical inputs into stock valuation models. Earnings announcement period returns are influenced by the forecasts (e.g., Imhoff & Lobo, 1992), and forecast dispersion is even related to monthly or annual stock returns (Ang & Ciccone, 2001; Diether, Malloy, & Scherbina, 2002; Dische, 2002). Forecasts are now publicly available on many investment-related web sites, providing free access to millions of investors all over the world.

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For a long period of time, the ability of analysts to forecast earnings was questioned. Analysts were biased some argued, optimistic and unresponsive to earnings changes (Abarbanell & Bernard, 1992; DeBondt & Thaler, 1990). They tended to herd, making forecasts or recommendations similar to other analysts (Hong, Kubik, & Solomon, 2000; Olsen, 1996; Stickel, 1990; Trueman, 1994; Welch, 2000). They were better than time-series earnings estimates, but only slightly (Fried & Givoly, 1982; O'Brien, 1988).

Recent studies have found that analyst forecasts have changed, perhaps even improved. Analysts have reduced both the size of their forecast errors and their optimism (Brown, 1997; Matsumoto, 2002; Richardson, Teoh, & Wysocki, 2001). Unfortunately for the analysts, many attribute this trend, not to better forecast accuracy, but to increases in earnings guidance, management, or smoothing (e.g., Degeorge, Patel, & Zeckhauser, 1999; Matsumoto, 2002).

The purpose of this study is twofold, both to document trends in forecast properties and to differentiate among theories as to why the trends exist. Several trends are investigated; some revisited, some new: (1) the trends of dispersion, error, and optimism; (2) the trend of wrongly forecasted profits or losses; (3) the trend of naïve forecast performance versus analyst forecast performance; (4) the trend of earnings volatility; and (5) the trend of Street versus GAAP earning differences. In addition, the influence of Regulation FD on the trends is examined. Quarterly data is used during a 1990 to 2001 sample period. As previous research has shown that analysts have greater difficulty forecasting the earnings of firms with losses (Brown, 2001; Butler & Saraoglu, 1999; Ciccone, 2001; Dowen, 1996; Dreman & Berry, 1995), firms with profits and losses are separated and examined independently in much of the testing.[1]

There are several possible explanations for changes in forecast properties: legal liability (e.g., Skinner, 1994), earnings guidance (e.g., Matsumoto, 2002), earnings management (e.g., Degeorge et al., 1999), earnings smoothing (consistent with Bartov, 1993), or information flow improvements (consistent with Asthana, 2003). The testing investigates the validity of these reasons.

The results are quite remarkable. Forecast properties have undergone an extraordinary change, perhaps best called a transformation, during the sample period. Forecast dispersion and error both decrease throughout the sample period, with most of the decrease due to loss firm forecasts. Although analysts still do not forecast loss firms with the same degree of accuracy as profit firms, the differences in forecasting performance are steadily eroding.

Optimism also decreases as analysts moved from being optimistically biased to being pessimistically biased during the sample period. The pessimism associated with profit firms is astonishing. Near the end of the sample period, almost three quarters of the

[1] Several related studies exist. Brown (1997), Richardson et al. (2001), and Matsumoto (2002) all show a decreasing trend in signed earnings surprise or optimism, although they do not separate firms by profitability. Gu and Wu (2003) evaluate forecast differences between profit and loss firms but do not examine trends in performance. Dreman and Berry (1995) and Butler and Saraoglu (1999) do separate firms by profitability while examining trends, but both rely on sample periods ending in 1991. Brown (2001) uses the signed, earnings surprise of the last forecast made prior to the earnings release date to examine shifts in the trend of the median surprise for profit and loss subsamples.

quarterly forecasts for profit firms are pessimistic. Analysts still tend to be optimistic toward loss firms, but this optimism has decreased dramatically over the sample period, hovering around an unbiased 50% at the end of the period. The decrease in the optimistic biases is so pronounced that the still-lingering legend of analyst earnings optimism (e.g., Easterwood & Nutt, 1999; Gu & Wu, 2003) is clearly no longer true, even for loss firms. If anything, analysts have a new concern: earnings pessimism for profit firms.

Additional results show that analysts have gotten much better at predicting the sign of earnings when firms report losses. Moreover, forecasting loss firm earnings appears to be much more difficult than forecasting profit firm earnings. Given this difficulty, analysts actually seem to provide greater value to the market when forecasting for loss firms.

Finally, the results suggest that the trends in forecast properties are unlikely to be fully attributable to earnings guidance, management, or smoothing. Firms unlikely to manage earnings—those with negative surprises, earnings declines, and losses—experience similar reductions in dispersion and error as the sample of all firms. So do firms considered unlikely to be guiding firms toward a specific earnings target, those with high dispersion. Furthermore, Street versus GAAP earnings differences and earnings volatility do not affect the results. The trends in forecast properties are consistent with litigation concerns, especially those surrounding loss reporting. In addition, although not specifically tested, analysts, aided by new information technology, may have simply improved in their forecasting abilities.

2. Forecast property changes

One of the most prominent explanations for the changing trends in forecast properties centers on earnings management. In the financial press, managers are often thought to play an "earnings game," manipulating reported earnings (and hence the surprise) to reap various benefits: increased stock prices, favorable publicity, and bonuses (Vickers, 1999). Fox (1997) tells of a Microsoft 1997 quarterly earnings release in January, the 41st time in 42 consecutive quarters that Microsoft met or beat the Wall Street consensus. The earnings game is often considered dangerous: when played long-term prospects are sacrificed by concern with short-term profits. Corporate decisions are altered, accounting rules are stretched, and investors lose faith in both financial statements and stock prices (Collingwood, 2001).

Academics have intensively investigated the issue of earnings management. Burgstahler and Dichev (1997) and Degeorge et al. (1999) find that firms manage earnings to meet analyst expectations, avoid losses, and avoid earnings declines. These studies mention several reasons why executives manage earnings, including increased job security, increased bonuses, and bolstered investor interest. Furthermore, anecdotal evidence suggests that firms like the favorable publicity of positive surprises, profits, and earnings increases. Of the three objectives identified by Degeorge, Patel, and Zeckhauser, the positive profit objective proves predominant. However, missing a consensus earnings estimate can be very costly to a firm. For example, Skinner and Sloan (2002) find that, all else equal, the price decline after a negative surprise is greater than the price increase following a positive surprise.

Another way of managing earnings entails "smoothing" or making earnings less volatile through time (e.g., Bartov, 1993). There are several theories that attempt to explain this behavior. Healy (1985) and Holthausen, Larcker, and Sloan (1995) find smoothed earnings are related to management bonus arrangements. Degeorge et al. (1999) use these findings to argue that managers may reduce high earnings levels to make future earnings objectives easier to meet. Fudenberg and Tirole (1995) argue that managers will boost earnings in bad times to increase the probability of retaining their jobs. Trueman and Titman (1988) believe that firms smooth earnings to lower their perceived bankruptcy risk and thus lower their cost of debt.

A cheaper way of playing the earnings game involves forecast guidance. Firms guide analysts toward a pessimistic target and then beat that target (Matsumoto, 2002), an easy way to garner favorable publicity.

An additional perspective on earnings guidance is rooted in legal liability issues. Firms face scrutiny when reporting large, unexpected losses. The consequent stock price decrease angers investors, who then might sue the firm for damages, consistent with Skinner (1994, 1997). Kasznik and Lev (1995) provide support for this argument by showing that firms increased their tendency to warn investors of impending losses. By warning of losses, firms are not necessarily playing an earnings game. As such, guiding analysts toward pessimistic targets and warning analysts of losses, although related, are considered two distinct concepts in this study.

Simpler explanations also exist to explain forecasting trends. For example, an alternative viewpoint looks at data availability and the information revolution, consistent with Asthana (2003). Forecasting techniques might be improving, aided in part by more precise and timelier economic information. Communications channels between firm managers and analysts may be better. Perhaps even the recent proliferation of freely available financial information on the Internet makes analysts more careful as they strive to add value and provide information above and beyond what is known by individual investors.

3. Data and methodology

The First Call summary database is used to obtain the forecast properties. Quarterly forecasts are used to present all results. The results using annual forecasts are similar to the quarterly results and do not require separate analysis. The last mean forecast available prior to the fiscal period end is used as the consensus forecast. All conclusions are similar if median forecasts are used instead of the mean forecasts or if the last mean forecasts prior to the earnings release are used instead of the last mean forecasts prior to fiscal period end.

Forecast dispersion is defined as the standard deviation of the forecasts divided by the absolute value of the mean forecast. This measure requires at least two forecasts.[2] Forecast error is defined as the difference between the actual earnings and the mean forecasted

[2] Although the procedure sharply reduces the sample size, the results for dispersion are similar if only companies with five or more analysts are included.

earnings, divided by the actual earnings. The absolute value is taken to obtain the final error number. A "raw error" is also computed as the absolute value of the difference between actual and forecasted earnings (i.e., the error is not deflated).[3] A forecast is considered optimistic if the mean forecast is greater than the corresponding actual earnings. The error and optimism measures require at least one forecast.

Many studies deflate the forecast properties by the stock price rather than the deflators described above. Thus, as a check, trends in dispersion and error are reexamined using price at the beginning of the fiscal year as the deflator. These results are qualitatively similar to the presented results, although the trends are not quite as obvious.[4]

Forecast dispersion is sometimes thought to signify herding. With this interpretation, low dispersion would be undesirable as it suggests greater herding. However, in this study, low dispersion is considered a desirable property. At least two reasons suggest this is true: (1) firms with losses or earnings declines, potential candidates to hide bad information, tend to have highly dispersed forecasts in previous studies (Ciccone, 2001), and (2) the high positive correlation between dispersion and error.[5]

An important component of this research is the separation of firms with losses and profits. A loss is defined as when the actual earnings per First Call are less than zero. A profit is defined as when actual earnings are greater than or equal to zero. First Call earnings, frequently referred to as "Street" or "operating" earnings (among other names), are often different from earnings under generally accepted accounting principles or GAAP (Abarbanell & Lehavy, 2000; Bradshaw & Sloan, 2002). The results are similar if GAAP earnings are used to determine profitability. The Compustat database is used to obtain GAAP earnings.

To alleviate problems with small denominators, a firm with a divisor less than US$0.02 in absolute value terms has the problem divisor set to US$0.02. Two procedures are used to reduce the influence of large observations. Firms with dispersion or error numbers greater than 10 and firms with earnings per share greater than an absolute value of US$20 are eliminated from their respective sample. Combined, the two procedures eliminate a total of 220 quarterly observations with no effect on the conclusions.

The final sample includes the years 1990 through 2001, a 12-year or 48-quarter period.[6] The total sample includes 120,022 firm quarters: 94,194 with profits and 25,828 (21.5%) with losses. The number of observations varies by the forecast property being examined.

[3] The raw error, often called the "earnings surprise" (although usually with the sign or direction of the error), is important because this number is often reported by the news media. It is important to note that "error" and "raw error" have two distinct meanings in this study.

[4] Using price as a deflator, average profit firm dispersion decreases from 0.0027 in the early (1990–1995) sample period to 0.0015 in the later sample period (1996–2001). Loss firm dispersion decreases from 0.0128 to 0.0069. Profit firm error decreases from 0.0052 to 0.0041, while loss firm error decreases from 0.0409 to 0.0333. All differences are significant with 99% confidence.

[5] To illustrate the latter point, the correlation between the dispersion and error is computed as 0.22 (0.24 if a log transform is performed). In a related test, every quarter each firm is placed into 1 of 10 portfolios based on its ranking of dispersion and 1 of 10 portfolios based on its ranking of error. The correlation between the group placement (1–10) is then computed. The correlation between the dispersion and error groupings is .47.

[6] The year 1990 contains considerably less sample firms than the other 11 years. Caution is thus recommended when evaluating the 1990 data.

The dispersion measure has the fewest number of observations: 84,919 quarterly observations.

Portfolio analyses are used to communicate the results in an easily accessible manner. The included tables present the results year-by-year and also during two sample periods: an "early" sample period from 1990 through 1995 and a "later" sample period from 1996 through 2001. Each period contains half the sample years. In addition, regression models controlling for size and book-to-market ratio are used to support the major conclusions reached.

4. Forecasting trends

Table 1 presents, by year, the forecast properties and maximum number of observations (recall there are sample size differences among the various properties). Dispersion, error, raw error, and optimism all steadily decrease throughout the sample period. The trend for optimism is interesting as the forecasts changed from being optimistic more than 50% of the time in the first couple of sample years to being optimistic less than 50% of the time after 1992. The amount of optimism continues to decrease during the sample period, reaching a low of 34.27% in 2000.

Table 1
Forecast dispersion, error, and optimism

	Quarterly forecasts				
	Maximum number of observations	Dispersion	Error	Raw error	Percent optimistic
All years	120,022	0.22	0.44	0.09	40.27
1990–1995	40,949	0.27	0.48	0.11	45.90
1996–2001	79,073	0.20	0.42	0.09	37.36
Difference		0.07*	0.06*	0.02*	8.54*
1990	1373	0.31	0.58	0.16	57.70
1991	2929	0.38	0.59	0.15	53.77
1992	6497	0.30	0.46	0.11	46.36
1993	8411	0.26	0.46	0.12	46.64
1994	10,249	0.25	0.46	0.10	43.33
1995	11,490	0.24	0.47	0.09	43.88
1996	14,002	0.23	0.44	0.09	39.27
1997	14,942	0.19	0.41	0.08	38.86
1998	15,184	0.20	0.41	0.08	38.71
1999	13,638	0.20	0.43	0.09	34.95
2000	12,314	0.17	0.42	0.10	34.27
2001	8993	0.21	0.42	0.09	37.46

This table reports mean analyst quarterly forecast properties over the sample period 1990 through 2001. Dispersion is defined as the standard deviation of the quarterly forecasts divided by the absolute mean forecast. Raw error is defined as the absolute value of the actual earnings less the forecasted earnings. Error is defined as the absolute value of the actual earnings less the forecasted earnings, divided by the absolute actual earnings. A firm's forecast is considered optimistic if the mean forecast is greater than the corresponding actual earnings. As the sample size varies by the forecast property in question, the maximum number of observations is reported.

* Difference is significantly different from zero with 99% confidence.

Table 2 shows the same forecast properties after separating firms by profitability. The dispersion and error of loss firms is considerably greater than the dispersion and error of profit firms. This occurs in every sample year and, although not tabulated, in every sample quarter. However, loss firms show greater reductions in dispersion and error throughout the sample period. The average dispersion of loss firms decreases from a high of 1.12 in 1990 to 0.30 in 2000 and 0.33 in 2001. Thus, the typical forecast dispersion of a loss firm today is roughly a quarter of what it was just 10 years ago. The story is similar for forecast error. The mean forecast error of loss firms decreases from a high of 1.16 in 1990 to 0.63 in 2000 and 0.55 in 2001. The error reduction for profit firms is not nearly as large, decreasing from a high of 0.48 in 1991 to 0.33 in 2000 and 0.35 in 2001.

The first two charts in Fig. 1 show the forecast dispersion and error by year and profitability. The figure provides a nice illustration of the eroding dichotomous forecasting ability of analysts. Clearly, analysts are narrowing the gap in their performance between profit and loss firms.

Table 2 also presents statistics for the mean raw error. Similar to the previous results, improvement in the raw error numbers occurs regardless of profitability, but the improvement is especially large for loss firms. For example, the raw error of loss firms decreases by more than half, from an average of US$0.48 in 1991 to US$0.21 in 2000 and US$0.16 in 2001.

The last columns of Table 2 show the percentage of optimistic forecasts. In the early sample period, analysts are overwhelmingly optimistic toward loss firms, more than 75% of time. The optimism remains above 70% until 1997 when it drops to 67.66%. From

Table 2
Forecast dispersion, error, raw error, and optimism by profitability

	Dispersion		Error		Raw error		Percent optimistic (negative surprise)	
	Profit	Loss	Profit	Loss	Profit	Loss	Profit	Loss
All quarters	0.15	0.53	0.35	0.78	0.06	0.23	33.63	64.48
1990–1995	0.18	0.88	0.37	1.02	0.07	0.33	40.32	75.93
1996–2001	0.13	0.43	0.33	0.70	0.05	0.20	29.76	60.70
Difference	0.05*	0.45*	0.04*	0.32*	0.02*	0.13*	10.56*	15.23*
1990	0.19	1.12	0.47	1.16	0.10	0.49	52.97	85.42
1991	0.24	1.11	0.48	1.09	0.08	0.48	48.40	78.44
1992	0.21	0.94	0.37	0.95	0.07	0.34	40.91	76.43
1993	0.17	0.91	0.37	0.96	0.08	0.34	41.67	74.80
1994	0.17	0.80	0.36	0.99	0.06	0.30	37.82	73.54
1995	0.16	0.81	0.35	1.11	0.06	0.28	37.54	76.75
1996	0.15	0.70	0.34	0.86	0.05	0.26	32.06	70.90
1997	0.12	0.50	0.32	0.78	0.05	0.22	31.58	67.66
1998	0.13	0.47	0.32	0.71	0.04	0.19	30.68	65.21
1999	0.14	0.39	0.33	0.70	0.05	0.20	26.84	58.42
2000	0.13	0.30	0.33	0.63	0.05	0.21	26.63	51.97
2001	0.15	0.33	0.35	0.55	0.05	0.16	29.44	53.12

This table reports mean analyst quarterly forecast properties sorted by profitability over the sample period 1990 through 2001. A profit occurs when actual quarterly earnings are greater than or equal to zero. A loss occurs when actual quarterly earnings are less than zero. See Table 1 for variable definitions.

* Difference is significantly different from zero with 99% confidence.

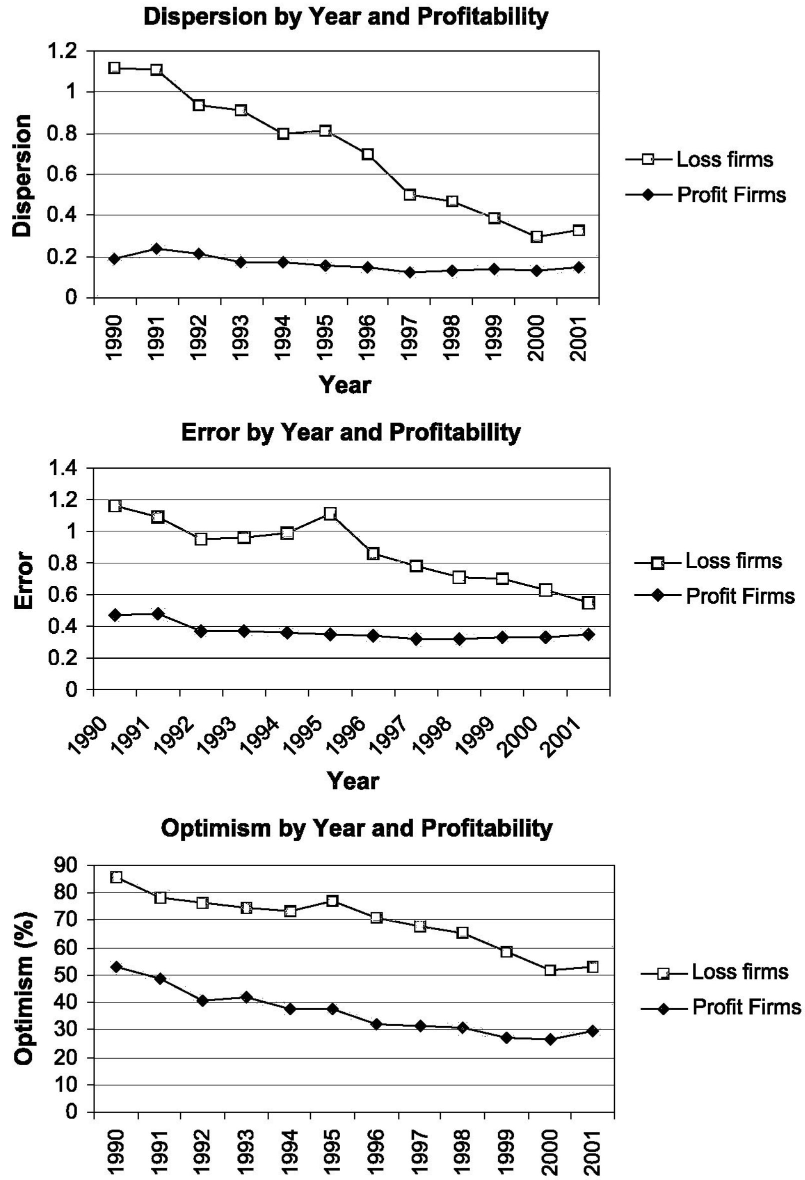

Fig. 1. Forecast properties by year and profitability.

there, the optimism continues to decrease, dropping to an almost unbiased 51.97% in 2000 and 53.12% in the 2001. For profit firms, optimism on average vanishes in 1991 and continues to decrease steadily throughout the sample period. By the end of the sample period, optimism is under 30%. The last chart in Fig. 1 illustrates this trend of decreasing optimism for both profit and loss firms.

Although the testing focuses on realized actual earnings to determine profitability, the results from Table 2 are repeated using expected earnings to determine profitability. Firms are resorted into profit and loss portfolios based on the mean forecast at fiscal year end. These results (not tabulated) are qualitatively similar to the Table 2 results, although average dispersion, error, and optimism are higher for expected profit firms (versus actual profit firms) and lower for expected loss firms. Optimism actually drops below 50% for expected loss firms during the last three sample years: 1999, 2000, and 2001. Related testing is performed on Table 6.

Regression models are utilized next to control for variables aside from profitability that influence forecasts. Previous studies have shown that size and growth prospects (growth indicated by book-to-market ratio) affect the information environment (e.g., Atiase, 1985; Ciccone, 2001).[7]

To test, two sets of regression models are used. The first set of regressions is employed to confirm the trend of lower dispersion and error during the sample period. These models use dispersion and error as the dependent variables and size, book-to-market ratio, a loss dummy variable, and year dummy variables as the independent variables. The Compustat database is used to gather the size and book-to-market ratio data. Size is defined as price times shares, computed at the beginning of the fiscal year. Book-to-market ratio is defined as beginning of fiscal year equity (Compustat item A216) divided by size. Logarithms of size and book-to-market ratio are used in the regressions. The loss dummy variable equals one if the actual First Call earnings are negative and zero otherwise. The year dummy variables equal one if the forecast is from the corresponding year and zero otherwise. The first year dummy variable corresponds to 1991, leaving 1990 as the base year. This specification is as follows for firm i during year t, quarter q.

$$\begin{aligned}\text{Forecast property}_{i,t,q} = {} & a + b_1 \log(\text{size})_{i,t} + b_2 \log(\text{b/m})_{i,t} \\ & + b_3 \text{ loss dummy}_{i,t,q} + b_4 \text{ year 1991 dummy}_{i,t} + \ldots \\ & + b_{14} \text{ year 2001 dummy}_{i,t} + e_{i,t,q} \end{aligned} \tag{1}$$

Table 3 presents the results of these regressions. Although size, book-to-market ratio, and especially losses affect the forecasts, the significant, negative values on the year dummy variables tend to increase in magnitude over the sample period. For example, using error as the dependent variable, the coefficient of the 1992 year dummy is -0.11 (indicating an average decrease of -0.11 relative to the 1990 base year), while that of the 2001 year dummy is -0.23 (indicating an average decrease of -0.23 relative to the 1990 base year). These results confirm the trends revealed in the portfolio results.

In the second set of regressions, models are employed annually from 1990 through 2001 to confirm the erosion of differences between profit and loss firm forecasts.

[7] The size of the analyst following is also included in separate regressions with no effect on the conclusions. Analyst following is not included in the presented results because of its strong correlation to size, thus blurring the relation between size and the forecast properties.

Table 3
Regression results using year dummy variables

	Dispersion		Error	
	Coefficient	*t* Value	Coefficient	*t* Value
Intercept	0.24	9.21	1.09	30.61
log (size)	0.01	2.17	− 0.04	− 22.61
log (book/market)	0.06	21.55	0.06	15.95
Loss dummy	0.42	82.48	0.43	61.21
1991	0.07	2.78	− 0.02	− 0.60
1992	0.00	0.21	− 0.11	− 3.71
1993	− 0.03	− 1.21	− 0.13	− 4.42
1994	− 0.04	− 1.99	− 0.13	− 4.47
1995	− 0.05	− 2.33	− 0.12	− 4.33
1996	− 0.05	− 2.45	− 0.15	− 5.34
1997	− 0.11	− 5.40	− 0.19	− 6.86
1998	− 0.11	− 5.44	− 0.19	− 6.82
1999	− 0.13	− 6.23	− 0.19	− 6.67
2000	− 0.15	− 7.61	− 0.20	− 7.31
2001	− 0.17	− 8.27	− 0.23	− 8.29
N	75,337		105,287	

This table reports the results of a regression model. Either forecast dispersion or error is the dependent variable. The independent variables are the logarithm of size (price times shares) in thousands, the logarithm of book-to-market value (equity/size), a loss dummy equal to one if the actual quarterly First Call earnings are below zero and equal to zero otherwise, and year dummy variables spanning 1991 through 2001 equal to one if the quarterly forecast is from the corresponding year. The regression model is below:

$$\text{Forecast property}_{i,t} = a + b_1 \log(\text{size})_{i,t} + b_2 \log(\text{b/m})_{i,t} + b_3 \text{ loss dummy}_{i,t} + b_4 \text{ year 1991 dummy}_{i,t} + \ldots + b_{14} \text{ year 2001 dummy}_{i,t} + e_{i,t}$$

Dispersion and error are the dependent variables, while size, book-to-market ratio, and a loss dummy variable are the independent variables. The annual model appears below:

$$\text{Forecast property}_{i,q} = a + b_1 \log(\text{size})_i + b_2 \log(\text{b/m})_i + b_3 \text{ loss dummy}_{i,q} + e_{i,q} \tag{2}$$

The results of these regressions appear on Table 4. Once again, the portfolio results are confirmed. For example, using dispersion as the dependent variable, the coefficient on the loss dummy variable decreases sharply over the sample period, dropping from 0.83 and 0.86 in 1990 and 1991, respectively, to 0.20 in 2001.

Table 5 shows the percentage of analysts forecasting the wrong sign. In the early sample period using the annual earnings, analysts forecast profits for firms with actual losses 33.95% of the time. This number is far greater than the reverse. In the early sample period, analysts forecast losses for firms with actual profits just a little over 1% of the time. Although over the sample period, there is no improvement in predicting profits for actual profit firms (profit prediction actually gets worse), the improvement for loss firms is rather extraordinary. At the end of the sample period, profits are forecasted for loss firms only 14.24% of the time in 2000 and 12.20% of the time in 2001, consistent with the increasing tendency of firms to warn of losses.

Table 4
Annual regression results using loss dummy variables

Year	Dispersion									
	Coefficient				t Value				F value	R^2 (adjusted)
	Intercept	Size	B/M	Loss dummy	Intercept	Size	B/M	Loss dummy		
1990	−0.14	0.03	0.12	0.83	−0.76	2.22	3.41	12.94	65.43	0.21
1991	0.14	0.01	0.12	0.86	0.88	1.11	4.97	17.19	115.18	0.18
1992	0.10	0.01	0.11	0.73	1.80	0.96	6.86	22.20	189.14	0.14
1993	0.20	0.00	0.06	0.73	2.61	0.10	4.29	27.04	258.12	0.14
1994	0.20	0.00	0.07	0.63	2.93	0.31	6.51	27.26	268.99	0.12
1995	0.15	0.00	0.04	0.66	2.39	0.65	4.10	31.80	354.31	0.13
1996	0.37	−0.01	0.04	0.62	6.81	−3.34	5.02	35.40	455.72	0.14
1997	0.25	−0.01	0.04	0.38	5.85	−2.05	5.95	29.54	324.43	0.09
1998	0.13	0.00	0.05	0.34	3.08	1.08	6.67	28.82	299.31	0.08
1999	0.08	0.01	0.06	0.29	1.73	2.43	10.13	23.20	218.10	0.07
2000	0.16	−0.00	0.04	0.22	3.66	−0.09	7.17	18.48	126.99	0.05
2001	−0.08	0.02	0.04	0.20	−1.77	5.29	6.51	16.95	103.18	0.05

Year	Error									
	Coefficient				t Value				F value	R^2 (adjusted)
	Intercept	Size	B/M	Loss dummy	Intercept	Size	B/M	Loss dummy		
1990	0.77	−0.02	0.09	0.51	3.09	−0.88	1.93	5.80	14.98	0.04
1991	1.16	−0.05	0.09	0.50	6.97	−3.71	3.12	8.96	45.28	0.05
1992	0.81	−0.03	0.07	0.60	7.77	−3.71	4.01	17.03	118.41	0.06
1993	1.02	−0.05	0.09	0.54	10.88	−6.21	5.40	17.58	146.80	0.06
1994	1.18	−0.06	0.07	0.58	13.82	−8.91	4.86	21.00	213.69	0.07
1995	1.06	−0.05	0.04	0.68	12.83	−8.18	2.41	25.27	285.53	0.08
1996	1.13	−0.06	0.04	0.54	16.23	−10.77	3.72	24.18	287.19	0.07
1997	0.95	−0.05	0.03	0.41	14.56	−9.22	3.10	21.17	228.30	0.05
1998	0.86	−0.04	0.08	0.35	13.78	−7.35	7.46	19.78	214.93	0.05
1999	0.78	−0.03	0.07	0.37	11.79	−5.87	6.69	19.09	192.21	0.05
2000	0.76	−0.03	0.06	0.35	11.29	−5.70	7.11	18.84	168.52	0.04
2001	0.70	−0.02	0.06	0.19	8.91	−3.94	4.90	9.36	58.84	0.02

This table reports the results of an annual regression model, run every sample year from 1990 through 2001. Either forecast dispersion or error is the dependent variable. The independent variables are the logarithm of size (price times shares) in thousands, the logarithm of book-to-market value (equity/size), and a loss dummy equal to one if the actual quarterly First Call earnings are negative and zero otherwise. The regression model is below:

$$\text{Forecast property}_i = a + b_1 \log(\text{size})_i + b_2 \log(\text{b/m})_i + b_3 \text{ loss dummy}_i + e_i$$

To directly examine forecast performance when actual profitability differs from forecasted profitability, firms are separated into four portfolios based on actual versus expected profits or losses. For example, one portfolio includes firms with expected profits that report actual losses, while another includes firms with expected losses reporting actual losses. Mean dispersion and error are computed for each of the four portfolios. The results are presented in Table 6.

In an unsurprising result, firms with expected and actual profits have the lowest dispersion and error. Interestingly, however, firms with expected and actual losses have the

Table 5
Percentage of firms with wrong sign mean forecasts

	Quarterly forecasts	
	Forecasted loss, actual profit (%)	Forecasted profit, actual loss (%)
All years	1.79	23.31
1990–1995	1.22	33.95
1996–2001	2.11	19.80
Difference	− 0.89*	14.15*
1990	0.89	44.79
1991	1.58	35.11
1992	1.38	30.79
1993	1.04	31.85
1994	1.18	32.15
1995	1.27	37.08
1996	1.72	29.57
1997	1.73	24.28
1998	1.86	21.42
1999	2.52	19.59
2000	2.49	14.24
2001	2.89	12.20

This table reports the percentage of analysts forecasting the wrong sign (e.g., forecasting a profit when an actual loss is eventually reported) over the sample period 1990 through 2001. All numbers are in percent.
* Difference is significantly different from zero with 99% confidence.

second lowest dispersion and error, while the two portfolios containing firms with actual profitability different from expected profitability have the highest dispersion and error. In addition, although error does decrease in the portfolio of expected loss, actual loss firms throughout the sample period, the trend is not nearly as clear and the differences not nearly as large compared with the Table 2 results. These results, combined with the results from Table 5, suggest that a large portion of the decrease in loss firm error comes from two sources: (1) improvement in the error of expected profit, actual loss firms and (2) the higher percentage of losses being predicted (i.e., less expected profit, actual loss firms).

The final testing in this section examines the error and optimism of the mean analyst forecast versus the error and optimism of a "naïve" forecast, the actual First Call earnings in the prior fiscal period.[8] This test addresses several important issues. It provides a measure of the amount of value that analysts provide over and above a forecasting method simple enough to be employed by even the most unsophisticated of individual investors. The test also provides a standard by which to measure earnings predictive difficulty. Firms with accurate naïve forecasts can be thought of as having earnings that are relatively easy to predict. Related to prediction difficulty, the test also somewhat controls for earnings

[8] For the tabulated quarterly results, the naïve model compares the current quarter earnings with the prior quarter earnings (e.g., third quarter 1992 compared with second quarter 1992). To control for earnings seasonality, the prior year quarterly earnings are also used to compute naïve forecasts (e.g., second quarter 1993 compared with second quarter 1992). However, because these naïve forecasts are less accurate than the naïve forecasts using the prior quarter earnings, the results are presented using the more accurate prior quarter naïve forecasts. (Using all sample firms, the average naïve error is 0.82 using prior year quarterly earnings and 0.72 using prior quarter earnings.) The results using the prior year naïve forecasts are similar although analyst superiority is greater.

Table 6
Dispersion and error by expected and actual profitability

Expected	Quarterly forecasts							
	Dispersion				Error			
	Profit	Profit	Loss	Loss	Profit	Profit	Loss	Loss
Actual	Profit	Loss	Profit	Loss	Profit	Loss	Profit	Loss
All years	0.13	0.93	1.07	0.42	0.31	1.97	2.38	0.42
1990–1995	0.16	1.17	1.37	0.74	0.35	2.06	2.59	0.50
1996–2001	0.12	0.82	0.98	0.35	0.29	1.91	2.31	0.40
Difference	0.04*	0.35*	0.39*	0.39*	0.06*	0.15*	0.28*	0.10*
1990	0.19	1.31	0.67	0.98	0.47	2.01	2.09	0.49
1991	0.23	1.30	0.99	1.01	0.44	1.97	2.90	0.62
1992	0.19	1.38	2.00	0.76	0.34	2.06	2.76	0.46
1993	0.16	1.24	1.33	0.76	0.35	2.03	2.44	0.46
1994	0.15	1.08	1.30	0.68	0.33	2.07	2.57	0.49
1995	0.14	1.04	1.26	0.69	0.32	2.12	2.55	0.51
1996	0.13	1.04	1.22	0.57	0.30	1.89	2.25	0.43
1997	0.11	0.84	1.00	0.40	0.28	1.94	2.42	0.41
1998	0.11	0.75	1.08	0.40	0.28	1.88	2.11	0.39
1999	0.12	0.73	0.94	0.32	0.28	1.90	2.38	0.41
2000	0.11	0.68	0.84	0.24	0.28	1.98	2.18	0.41
2001	0.13	0.77	0.77	0.27	0.29	1.93	2.54	0.37

This table reports mean analyst quarterly forecast properties sorted by expected and actual profitability over the sample period 1990 through 2001. An actual profit occurs when actual quarterly earnings are greater than or equal to zero, while an actual loss occurs otherwise. A forecasted profit occurs when mean forecasted earnings are greater than or equal to zero, while a forecasted loss occurs otherwise. See Table 1 for variable definitions.

* Difference is significantly different from zero with 99% confidence.

volatility or earnings management (see also next section). Firms with managed or less volatile earnings would probably have more accurate naïve forecasts.

Error, raw error, and optimism are computed using both the analyst forecasts and the naïve forecasts for all sample firms having the required prior period actual earnings information. The sample size is 103,778 firm-quarter observations: 82,203 with profits and 21,575 (20.8%) with losses.

Table 7 reports the results for two forecast properties: error and raw error. For each sample firm, the analyst forecast error is subtracted from the naïve forecast error. For example, if the naïve forecast error is 0.90 and the analyst forecast error is 0.40, then the difference is 0.50. The mean of these differences is computed and reported in the table. Note that in the table, positive numbers indicate analyst superiority, and the larger the difference, the more accurate analyst forecasts are versus naïve forecasts.

Several findings are important. Analyst forecasts are considerably more accurate in every sample year indicating that analysts provide a great deal of value in forecasting earnings versus a simple naïve model. However, they provide more value when forecasting the earnings of loss firms. For example, for all years, the difference between the naïve and analyst error is on average 0.26 for profit firms and 0.45 for loss firms.

Analysts have also slightly increased the value of their forecasting during the sample period, particularly for loss firms. For example, in the early sample period, the analysts are

Table 7
Differences between naïve and analyst forecasts: error and raw error

	Quarterly forecasts					
	Error differences (naïve error − analyst error)			Raw error (RE) differences (naïve RE − analyst RE)		
	All	Profit	Loss	All	Profit	Loss
All years	0.30	0.26	0.45	0.08	0.07	0.08
1990–1995	0.26	0.24	0.39	0.07	0.07	0.07
1996–2001	0.32	0.27	0.47	0.08	0.08	0.08
Difference	−0.06*	−0.03*	−0.08*	−0.01*	−0.01*	−0.01
1990	0.27	0.23	0.48	0.07	0.05	0.18
1991	0.19	0.17	0.32	0.08	0.08	0.11
1992	0.29	0.26	0.45	0.08	0.08	0.06
1993	0.26	0.24	0.38	0.05	0.05	0.06
1994	0.27	0.25	0.35	0.07	0.07	0.06
1995	0.26	0.24	0.40	0.08	0.08	0.08
1996	0.32	0.28	0.55	0.08	0.08	0.07
1997	0.30	0.27	0.46	0.08	0.08	0.07
1998	0.36	0.29	0.59	0.09	0.09	0.10
1999	0.33	0.30	0.44	0.09	0.09	0.08
2000	0.31	0.29	0.39	0.08	0.09	0.07
2001	0.25	0.17	0.38	0.08	0.08	0.08

This table reports the difference between naïve forecast errors and analyst forecast errors over the sample period 1990 through 2001. Analyst forecast error and raw error are defined as in Table 1. Naïve forecast raw error is defined as the absolute value of actual quarterly earnings less the previous quarter's actual earnings. Naïve forecast error deflates this number by the absolute actual quarterly earnings. The reported differences are computed as the naïve error less the analyst error. Thus, positive differences indicate analyst superiority (i.e., lower errors): the higher the difference, the greater the analyst superiority.

* Difference is significantly different from zero with 99% confidence.

superior by 0.39 in predicting error. In the later sample period, this superiority increases to 0.47.

Although not tabulated, naïve forecasts for loss firms are markedly less accurate versus naïve forecasts for profit firms. The mean quarterly naïve forecast error is 0.60 for profit firms and 1.22 for loss firms. The differences remain fairly stable across the sample period. This suggests that loss firm earnings are much more difficult to predict. Thus, considering both the inherent difficulties and the trends of reduced error, analysts seem to be doing an adequate job when forecasting loss firm earnings.

Table 8 presents the results for differences in optimism. With respect to the percentage of optimism, it is assumed that the goal when forecasting is to achieve a systematically unbiased 50%. Therefore, the comparison of analyst forecast optimism versus naïve forecast optimism is computed using 50% as a reference. For example, if analysts are optimistic 45% of the time and naïve forecasts are optimistic 65% of the time, then analyst forecasts are superior by 10% with respect to the 50% goal [(65% − 50%) − (50% − 45%) = 10%]. A positive sign indicates better analyst performance; a negative sign indicates better naïve performance.

The results are fascinating. Naïve forecasts for loss firms are primarily optimistic (63.75%) while naïve forecasts for profit firms are primarily pessimistic (35.58%). Thus,

Table 8
Differences between naïve and analyst forecasts: optimism

	Quarterly forecasts					
	Profit			Loss		
	Percent optimistic, analysts	Percent optimistic, naïve	Analyst superiority versus unbiased 50%	Percent optimistic, analysts	Percent optimistic, naïve	Analyst superiority versus unbiased 50%
All years	33.42	35.58	− 2.16	64.43	63.75	− 0.68
1990–1995	40.29	35.63	4.66	76.70	68.10	− 8.60
1996–2001	29.78	35.56	− 5.78	60.69	62.43	1.74
Difference	10.51*	0.07	− 10.44	16.01*	5.67*	10.34
1990	53.13	35.78	11.09	84.07	69.91	− 14.16
1991	51.88	37.62	10.50	78.77	68.49	− 10.28
1992	41.32	35.84	5.48	77.97	65.85	− 12.12
1993	41.90	36.01	5.89	75.00	66.67	− 8.33
1994	37.95	35.23	2.72	74.69	68.19	− 6.50
1995	37.75	35.29	2.46	77.92	70.13	− 7.79
1996	32.50	33.78	− 1.28	72.67	69.16	− 3.51
1997	31.95	33.86	− 1.91	67.54	64.96	− 2.58
1998	30.53	37.15	− 6.62	64.97	65.22	0.25
1999	26.86	35.30	− 8.44	58.83	60.38	1.55
2000	26.18	34.90	− 8.72	52.21	60.58	8.37
2001	29.11	40.99	− 11.88	51.36	55.75	4.39

This table reports the difference between naïve forecast optimism and analyst forecast optimism over the sample period 1990 through 2001. Optimism is present if the mean forecast is greater than the corresponding actual earnings. As 50% is considered the unbiased target, analyst superiority is determined using 50% as the benchmark. Positive numbers in the "analyst superiority versus unbiased 50%" column indicate analyst superiority, while negative numbers indicate naïve forecast superiority. The analyst superiority column is computed as follows:

$$\text{Analyst superiority} = (\,|\%\text{ optimistic naïve} - 50\%|\,) - (\,|\%\text{ optimistic analysts} - 50\%|\,)$$

*Difference is significantly different from zero with 99% confidence.

the optimism analysts show toward loss firms and the pessimism analysts show toward profit firms is perhaps a natural reflection of an easy starting point. For profit firms, in the early sample period, analysts are nearly unbiased. However, as analyst pessimism increases during the sample period for profit firms, analyst superiority with regard to systematic biases steadily changes to inferiority. As an example, analysts are superior relative to the 50% reference for profit firms by 11.09% in 1990 and 10.50% in 1991. However, these numbers decrease to − 8.72% in 2000 and − 11.88% in 2001, indicating a decline in analyst performance. In contrast, for loss firms, analysts move steadily from inferior performance to superior performance. Fig. 2 shows the trends graphically. Like the corresponding table, positive numbers in the figure indicate superior analyst performance.

5. Earnings management, smoothing, and guidance issues

The increase in forecast pessimism (positive surprises) and decrease in forecast error seen in this and other studies is consistent with earnings management, guidance, and

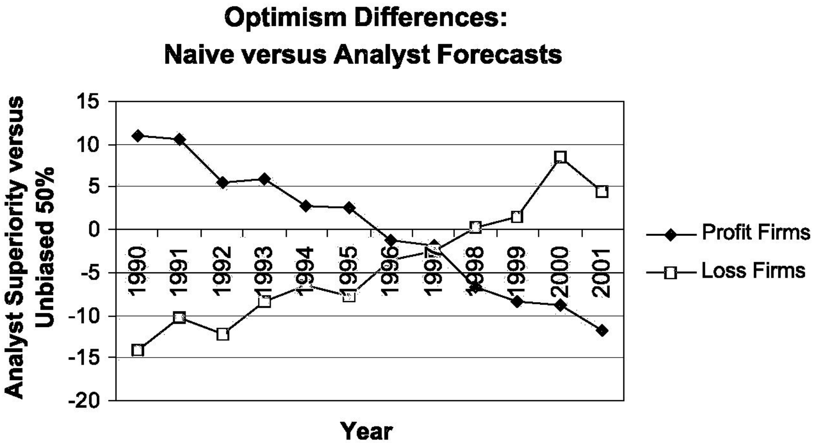

Fig. 2. Analyst versus naïve forecast differences in optimism by year. Note: positive numbers indicate analyst superiority; negative numbers indicate naïve superiority.

smoothing. Various tests are performed to see whether the trends are related to these issues and to differentiate among the potential explanations.

The first procedure examines the subset of firms that failed to meet all three incentives mentioned by Degeorge et al. (1999) when managing earnings: incentives of avoiding losses, avoiding earnings declines, and meeting analyst expectations. Thus, these firms are considered unlikely to be managing earnings as none of the incentives is reached.

Table 9 reports the results. Although the average dispersion, error, and raw error are all higher for this sample of firms versus the full loss firm subsample, similar degrees of improvement in each property are seen. As an example, the average error of these firms drops from 1.23 in the early sample period to 0.93 in the later sample period. This compares with the results for loss firms with either type of surprise from Table 2: 1.02 in the early sample period, decreasing to 0.70 in the later sample period.

To investigate smoothing, trends in earnings volatility are examined. If the decrease in forecasting performance is attributable to increased smoothing, earnings volatility should decrease as well. Earnings volatility is computed as the standard deviation of earnings from the eight most recent quarters. The sample of firms with eight quarters of earnings begins in 1992 and consists of 51,965 firms: 42,543 with profits and 9422 (18.1%) with losses. The trends in earnings volatility are reported in Table 10. Although loss firm earnings volatility decreases, profit firm volatility remains fairly stable across the sample period. Thus, earnings smoothing does not explain trends in profit firm forecasts. For loss firms, the magnitude of the decrease in earnings volatility is far less than the magnitude of the decrease in error and dispersion. Therefore, earnings volatility probably does not explain a large proportion of the trends in loss firm forecasts.

Related testing looks at forecasting trends in a set of firms considered unlikely candidates to smooth earnings, those firms with high earnings volatility. Thus, in each sample year, firms with high earnings volatility are separately analyzed. Both absolute and relative measures of high volatility are used. Absolute measures specify an arbitrary

Table 9
Forecast dispersion, error, and raw error: firms with optimistic forecasts (negative surprises), earnings declines, and losses

	Quarterly forecasts		
	Dispersion	Error	Raw error
All years	0.71	1.01	0.36
1990–1995	1.00	1.23	0.46
1996–2001	0.61	0.93	0.33
Difference	0.39*	0.30*	0.13*
1990	0.87	1.28	0.52
1991	1.20	1.27	0.65
1992	1.12	1.19	0.46
1993	1.03	1.14	0.52
1994	0.94	1.21	0.44
1995	0.93	1.31	0.39
1996	0.87	1.08	0.38
1997	0.66	0.99	0.34
1998	0.63	0.95	0.29
1999	0.54	0.94	0.33
2000	0.47	0.85	0.35
2001	0.50	0.74	0.25

This table reports mean analyst quarterly forecast properties for firms with optimistic forecasts, earnings declines, and losses over the sample period 1990 through 2001. An earnings decline is when actual quarterly earnings are less than the previous quarter's actual earnings. See Table 1 for the other variable definitions.

* Difference is significantly different from zero with 99% confidence.

earnings volatility number to which each firm's earnings volatility is compared, thus controlling for any changes in average volatility during the sample period. Quarterly earnings volatility is considered high if the standard deviation of the actual Street earnings is greater than US$0.50 per share over the prior eight quarters.[9] Under the relative measures of volatility, a firm is considered to have high earnings volatility if its volatility is in the top 10% during the year. Although the results are not tabulated, the same trends of decreasing dispersion, error, and optimism throughout the sample period still exist for the high earnings volatility sample of firms using either the absolute or relative volatility measures.

The next test investigates earnings guidance by isolating firms with high dispersion. These firms are often considered to have a greater disparity of opinion (e.g., Krishnaswami & Subramaniam, 1999) and are, therefore, unlikely to be guiding analysts toward a specific earnings target.

Similar to the volatility tests, absolute and relative measures are used. Under the absolute method, firms are considered to have high dispersion if their dispersion measure is greater than or equal to 0.50.[10] This sample contains 8225 firms (9.7% of the full dispersion sample), 4028 with profits and 4197 (51.0%) with losses. Under the relative measure, firms are considered to have high dispersion if their dispersion measure is in the top 10% during the relevant year.

[9] Other arbitrary cutoff points are employed with similar results.

[10] Other arbitrary cutoff points are employed with similar results.

Table 10
Earnings volatility by year

	Eight quarter earnings volatility		
	All	Profit	Loss
All years	0.17	0.14	0.28
1992–1996	0.17	0.14	0.36
1997–2001	0.16	0.14	0.25
Difference	0.01*	0.00	0.11*
1992	0.18	0.16	0.32
1993	0.18	0.15	0.35
1994	0.18	0.16	0.35
1995	0.18	0.14	0.43
1996	0.16	0.13	0.33
1997	0.16	0.14	0.29
1998	0.15	0.13	0.23
1999	0.16	0.14	0.24
2000	0.16	0.14	0.26
2001	0.18	0.15	0.26

This table reports mean quarterly earnings volatility over the sample period 1992 through 2001. Quarterly earnings volatility is defined as the standard deviation of actual earnings from the eight previous quarters. As 2 years of earnings are needed before the volatility can be computed, the sample period does not include 1990 and 1991.

* Difference is significantly different from zero with 99% confidence.

Table 11
Forecast error, raw error, and optimism by profitability: firms with dispersion greater than 0.50

	Quarterly forecasts								
	Error			Raw error			Percent optimistic		
	All	Profit	Loss	All	Profit	Loss	All	Profit	Loss
All years	1.09	1.14	1.04	0.23	0.13	0.33	64.61	39.95	88.28
1990–1995	1.21	1.24	1.17	0.30	0.19	0.42	69.24	49.36	90.93
1996–2001	1.01	1.07	0.96	0.19	0.08	0.28	61.76	33.51	86.81
Difference	0.20*	0.17*	0.21*	0.11*	0.11*	0.14*	7.48*	15.85*	4.12*
1990	1.35	1.60	1.09	0.55	0.37	0.74	73.85	58.82	90.32
1991	1.15	1.18	1.13	0.38	0.17	0.60	68.05	48.77	88.74
1992	1.11	1.13	1.09	0.32	0.21	0.45	66.73	47.71	90.00
1993	1.20	1.27	1.12	0.26	0.19	0.34	69.06	49.37	91.43
1994	1.23	1.21	1.25	0.30	0.21	0.40	67.97	48.56	90.12
1995	1.26	1.30	1.22	0.24	0.12	0.35	71.90	50.00	92.65
1996	1.12	1.13	1.11	0.24	0.11	0.38	66.83	41.83	91.40
1997	1.01	1.06	0.97	0.20	0.08	0.31	63.19	36.77	87.94
1998	0.97	1.03	0.93	0.17	0.07	0.26	64.15	35.50	86.82
1999	0.98	1.08	0.90	0.18	0.08	0.27	56.75	25.67	85.02
2000	1.02	1.09	0.96	0.16	0.08	0.22	56.10	29.21	80.94
2001	0.90	0.95	0.87	0.16	0.08	0.22	60.13	25.95	86.47

This table reports mean analyst quarterly forecast properties for firms with forecast dispersion greater than 0.50 over the sample period 1990 through 2001. See Table 1 for variable definitions.

* Difference is significantly different from zero with 99% confidence.

Table 11 presents the results using the absolute measure. (The results using the relative measure are similar.) There is a clear reduction in forecast error and raw error during the sample period for both profit and loss firms. Optimism also decreases dramatically for profit firms, starting around 50% in the first few sample years, but reaching below 30% for the last three sample years. Loss firms, however, are dominated by overwhelming optimism throughout the sample period (an average of 88.28%), the lack of improvement indicating a problem area that analysts should address. Thus, although analysts have reduced the size of their errors for firms with high dispersion, they still tend to overestimate the earnings of high dispersion, loss firms. This testing suggests that systematic profit firm pessimism occurs regardless of whether the forecasts are guided. However, the reduction of loss firm optimism occurs when firms warn analysts of the impending loss.

Overall, the improved forecasting ability of analysts occurs regardless of increases in earnings management, guidance, or smoothing. The trends are consistent with concerns of legal liability as most of the reduction in dispersion and error is due to loss firms. The trends are also consistent with improved analyst forecasting abilities. The increase in pessimism for profit firms may be partly attributed to an overreliance on the previous period's earnings.

6. GAAP versus Street earnings and Regulation FD

Another issue is related to the Street versus GAAP earnings debate. Abarbanell and Lehavy (2000) suggest that using forecast provider databases, such as First Call, to obtain earnings data might impact conclusions reached in earnings-related studies. First Call collects data based on the earnings that firms publicize to the market, often known as Street earnings, which may be different from GAAP earnings. Therefore, following the procedure of Brown (2001), the sample of firms in which GAAP earnings from Compustat equal Street earnings from First Call are examined separately. The earnings are considered equal if the absolute value of the difference is less than US$0.02 to control for rounding differences and materiality. The results (not shown) are similar to the previous results for the reduced sample. Moreover, the difference in Street versus GAAP earnings has not increased over the sample period (not shown).

Finally, the passage of Regulation FD in August 2000 and its subsequent implementation on October 23, 2000 might affect forecasts made during the surrounding time periods. To investigate this issue, the quarterly forecast properties from the beginning of 1999 through the end of 2001 are computed for only firms that have fiscal quarters on a March, June, September, December cycle. This provides a sample with three distinct, easily identifiable subperiods: (1) a pre-Regulation FD period, from the first quarter of 1999 through the second quarter of 2000; (2) a period during the implementation of Regulation FD, the third and fourth quarters of 2000; and (3) a post-Regulation FD period, the first quarter of 2001 through the fourth quarter of 2001. The second period, during the implementation, includes the quarter in which the regulation was passed.

Table 12
Forecast dispersion, error, raw error, and optimism surrounding implementation of regulation FD

Year: month	Profit firms				Loss firms			
	Dispersion	Error	Raw error	Percent optimistic	Dispersion	Error	Raw error	Percent optimistic
Pre								
1999: 3	0.15	0.35	0.05	27.35	0.39	0.66	0.15	56.36
1999: 6	0.13	0.33	0.05	26.49	0.40	0.67	0.16	57.89
1999: 9	0.14	0.34	0.05	27.96	0.41	0.66	0.19	56.41
1999: 12	0.15	0.34	0.06	25.42	0.37	0.74	0.28	59.95
2000: 3	0.13	0.35	0.05	23.89	0.34	0.59	0.17	50.55
2000: 6	0.13	0.32	0.05	24.49	0.28	0.64	0.19	49.63
During								
2000: 9	0.13	0.31	0.06	28.71	0.23	0.60	0.19	47.68
2000: 12	0.14	0.32	0.06	29.63	0.30	0.64	0.26	56.54
Post								
2001: 3	0.14	0.33	0.05	30.90	0.33	0.51	0.17	52.74
2001: 6	0.16	0.35	0.05	27.40	0.30	0.53	0.14	51.75
2001: 9	0.16	0.37	0.06	34.47	0.34	0.56	0.18	54.89
2001: 12	0.15	0.33	0.05	22.41	0.32	0.54	0.13	47.02

This table reports mean analyst quarterly forecast properties for the quarters surrounding the implementation of Regulation Free Disclosure (Reg FD). Reg FD was passed in August 2000 and implemented in October 2000. See Table 1 for variable definitions. Only firms with fiscal quarters ending in March, June September, and December are included in the sample.

After evaluating the results, presented in Table 12 for profit and loss subsamples, there are no identifiable differences in the forecast property trends during the three periods surrounding Regulation FD implementation regardless of whether the sample includes all firms, profit firms, or loss firms.

7. Conclusions

This study documents almost continuous reductions in analyst forecast dispersion, error, and optimism during the time period 1990 through 2001. The reductions, however, primarily come about due to staggering advances in forecasting loss firm earnings. At the end of the sample period, differences in forecasting performance between profit and loss firms are relatively small. Attempts are made to control for various issues that might affect the conclusions, such as earnings management, guidance, and smoothing, Street versus GAAP earnings, or Regulation FD. None of those issues can wholly explain the trends.

In addition, it appears that loss firm earnings are more difficult to predict. Given the prediction difficulties, the value provided to the market by analysts appears to be greater for loss firms versus profit firms.

While this study does not contradict prior studies showing increases in earnings management or guidance, it does shed additional light on the issue. Analysts are undoubtedly not as optimistic, their incentives to get investment banking clients or private information perhaps no longer as important as the notoriety they receive when they mislead investors.

Future studies can examine trends in analyst buy, sell, or hold recommendations, another area in which the media and academic research (and also the Securities and Exchange Commission) have criticized analysts. Analysts are known to frequently make buy recommendations but rarely make sell recommendations, often preferring to drop coverage of a firm rather than issue a sell recommendation (e.g., Barber, Lehavy, McNichols, & Trueman, 2001; McNichols & O'Brien, 1997; Stickel, 1995).

Acknowledgements

This paper has benefited from the comments of Afshad Irani, Ahmad Etebari, Werner DeBondt, John Becker-Blease, participants at the 2003 Financial Management Conference (especially the discussant Larry Wall), participants at a University of New Hampshire Seminar, and the referee. The author would like to thank Pamela Grant and Chuck Hill of Thomson Financial Services, who have generously provided the First Call data.

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Citi Global Wealth

Investments

WEALTH OUTLOOK 2023

Roadmap to recovery: Portfolios to anticipate opportunities

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Foreword

JIM O'DONNELL
CEO of Citi Global Wealth

Welcome to Outlook 2023, our annual publication that sets out our expectations and key investment themes for the coming year and beyond. This edition, "Roadmap to recovery: Portfolios to anticipate opportunities," highlights steps that we believe you should consider to help seek returns.

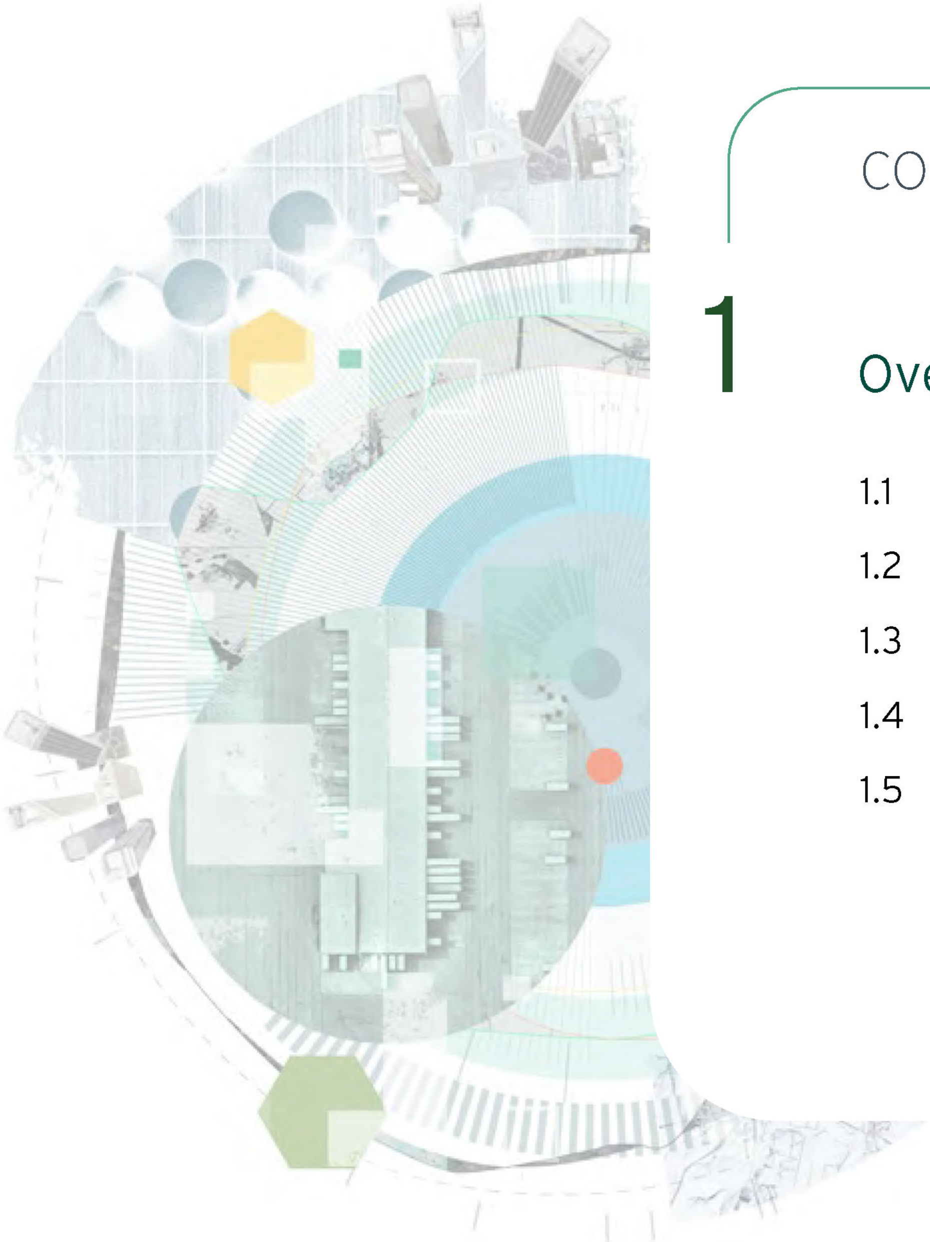
Investing over the past year has come with its challenges and uncertainties due to inflation, monetary tightening, slowing growth, international conflict and an intensified US-China tech rivalry. For the first time in decades, equities and fixed income suffered significant falls simultaneously, alongside alternative asset classes.

While 2023 will still have its share of challenges, we also see it as a year of change and opportunity. In the US, we expect a mild recession, with regions such as the eurozone being more heavily impacted. As inflation subsides, we see the US Federal Reserve pivoting from interest rate hikes to cuts and markets shifting focus to 2024 recovery, unlocking more potential opportunities for investors.

As the markets continue to swing, timely guidance has become even more valuable. Our insights help us engage in deeper client conversations and create strategies that achieve your investment objectives. The value of keeping portfolios fully invested remains increasingly important – market timing can come at a great cost, as turning points often arrive with little warning.

For your convenience, we have also created helpful summaries, including Findings & Opportunities and a new version of this publication in just two sides.

We look forward to continued partnership and success in the new year.



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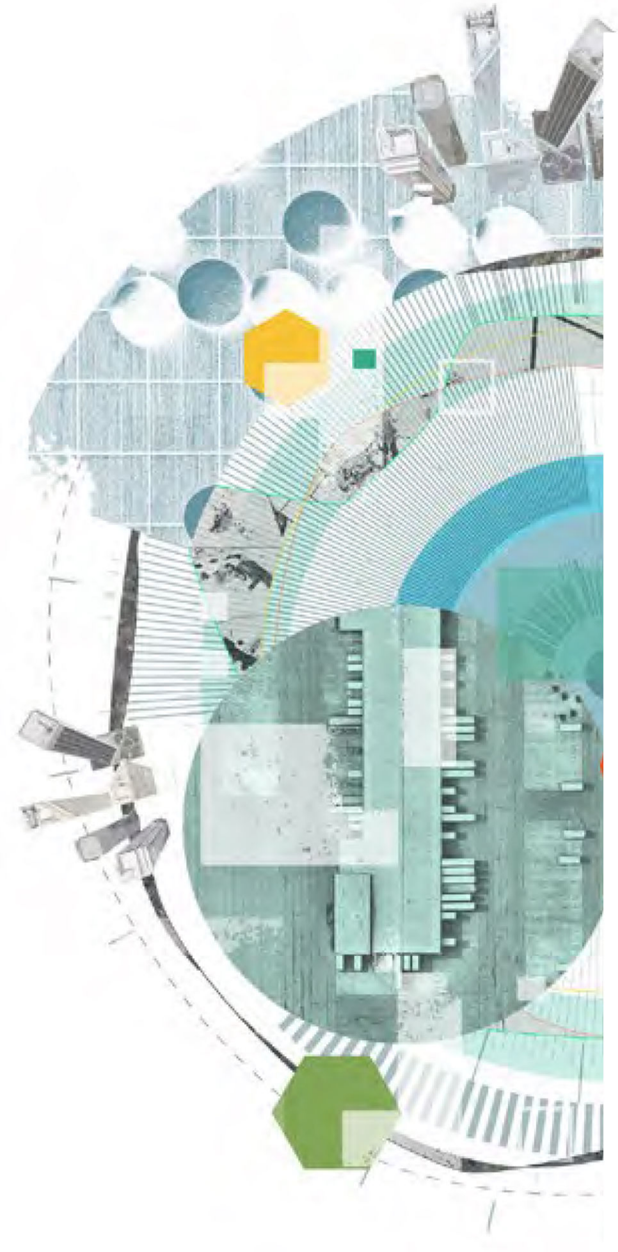
1 Overview



1.1

FROM THE DESK OF THE CIO:

Our Wealth Outlook 2023

DAVID BAILIN
Chief Investment Officer
and Global Head of Investments
Citi Global Wealth

For investors, 2022 will not be missed. The year presented a series of firsts and worsts. The tragic war in Ukraine hugely distorted global food and energy supply chains, further emphasized the divide between the US and China – see **A greater separation between East and West: G2 polarization intensifies** – and accelerated the onshoring of critical business infrastructure. The Fed instigated its fastest set of interest rate increases ever. In doing so, it responded to the inflation it caused by adding excessive liquidity to counteract the effects of the pandemic. As the safe-haven US dollar strengthened, goods almost everywhere else became more expensive, adding to global central bank tightening pressures. These are all sources of instability.

In this environment, equities and bonds declined in tandem by the most ever in 2022, with joint losses of about 20% at the low point. Cash outperformed almost every asset class. As we look ahead, however, we need to remember that markets lead economies. The poor market returns of 2022 anticipate the economic weakness we expect in 2023 – see **Roadmap to recovery: Markets lead, the economy follows.**

We believe that the Fed's rate hikes and shrinking bond portfolio have been stringent enough to cause an economic contraction within 2023. And if the Fed does not pause rate hikes until it sees the contraction, a deeper recession may ensue. The most recent inflation data and Fed minutes suggest that the Fed is aware of these risks. Yet Fed policymakers' tendency toward excess gives us pause as we plan for 2023.

With perfect hindsight, sitting out 2022 would have been worthwhile. But to think that way is dangerous for wealth preservation and creation. One year is just a "moment" in the lifetime of a portfolio. Sidestepping the pandemic and war-laden past three years would have been a major mistake for equity investors. Between December 2019 and November 2022, the S&P 500 Index rose 25% and the MSCI World 15.4%. For 2023, we reiterate the fundamental wisdom of keeping fully invested portfolios – see for example, **It is time to put excess cash to work**.

Remember, the world economy is highly adaptive and resilient. So too are markets.

Thinking about 2023

Markets in 2023 will lead the economic recovery we foresee for 2024. Therefore, we expect that 2023 may ultimately provide a series of meaningful opportunities for investors who are guided by relevant market precedents.

First, though, we need to get through a recession in the US that has not started yet. We believe that the Fed's current and expected tightening will reduce nominal spending growth by more than half, raise US unemployment above 5% and cause a 10% decline in corporate earnings. The Fed will likely reduce the demand for labor sufficiently to slow services inflation just as high inventories are already curtailing goods inflation.

The relative health of corporate and personal balance sheets has delayed an economic downturn, for now. Household borrowing is sustaining growth presently, but this dissaving is likely unsustainable, especially given financial market and real estate price deflation. Also, when short-term rates are higher, there is a natural bias to deferring purchases.

We remind investors that over the past 100 years, no bear market associated with a recession has bottomed before the recession has even begun. (Of course, there is a first time for everything.) We believe that the current bear market rally is based on premature hopes that the recession will not occur – a so-called "soft landing" – and that there will not be a meaningful decline in corporate earnings.

Second, we need to get through a deeper recession in Europe as it struggles through a winter of energy scarcity and inflation. We also need to see a sustained economic recovery in China, whose prior regulatory policies and current COVID policies curtail domestic growth.

Third, we need to see the Fed truly pivot. Ironically, when the Fed does finally reduce rates for the first time in 2023 – an event that we expect after several negative employment reports – it will do so at a time when the economy is already weakening. We think this will mark a turning point that will portend the beginning of a sustained economic recovery in the US and beyond over the coming year.

Higher returns may be on the horizon

After the big drop in valuations in 2022, our 10-year return forecasts – or "strategic return estimates" (SREs) – have risen. A year ago, our strategic asset allocation methodology pointed to annualized returns for Global Equities over the coming decade of 6.1%. Today, that stands at 10%. SREs for Private Equity and Real Estate are higher still. Likewise, the Global Fixed Income SRE has climbed from 3.7% to 5.1%. Even Cash now has an SRE of 3.4%, up from 1.5% – see **Better long-term returns ahead**.[1]

A "sequence of opportunities"

While no one can know the precise timing and sequence for selecting investments globally at a time of significant uncertainty, we think that there are numerous data points to suggest that a potential set of opportunities will arise in 2023.

Ahead of the expected recession, we are committed to selectivity and quality. This begins with fixed income, which we believe offers genuine portfolio value now for the first time in several years. Short-duration US Treasuries present a compelling alternative to holding cash. For US investors, municipal bonds also seek better risk-adjusted after-tax returns. Broader investment-grade bonds offer a range of higher yields at every maturity. And loans in private markets – think private equity lending – offer larger yield premiums with lower loan-to-value ratios than at any time since 2008-09.

If the economy does go into a mild recession, the US yield curve will initially invert more deeply. We can imagine thus that longer duration bonds may perform well at the stage. After this stage, we would look to redeploy assets more widely.

Broadening equity exposures

In the near term, we believe equities in companies with strong balance sheets and healthy cash flows will provide investors with greater portfolio resilience – see **Why dividend grower "tortoises" may be core holdings**.

We expect that as 2023 progresses, opportunities to increase portfolio risk will evolve. Once interest rates peak, we will likely shift toward non-cyclical growth equities. These have already repriced lower, and we expect them to begin performing once more before cyclicals. Among non-cyclical growth equities are many exposed to our Unstoppable Trends – see **Deepening digitization**. Subsequently, early in the recovery period, we will also seek a reentry opportunity in cyclical growth industries, as value equities may prosper when supply pipelines are unable to meet revived demand.

The dollar could continue rallying for longer than fundamentals justify. Overshoots have been a characteristic of prior periods of dollar strength. Around a durable dollar peak, we will look to add more non-US equities and bonds.

---

[1] Source: Citi Private Bank Global Asset Allocation team.
2023 SREs are based on data as of 31 Oct 2022. Global Equity consists of Developed and Emerging Market Equity. Global Fixed Income consists of Investment-Grade, High-Yield and Emerging Market Fixed Income. Strategic Return Estimates are in US dollars; all estimates are expressions of opinion, are subject to change without notice and are not intended to be a guarantee of future events. Strategic Return Estimates are no guarantee of future performance. Citi Private Bank Global Asset Allocation Team. SREs for Mid-Year 2022 are based on data as of 30 Apr 2022. Returns estimated in US dollars. Strategic Return Estimates (SRE) based on indices are Citi Private Bank's forecast of returns for specific asset classes (to which the index belongs) over a 10-year time horizon. Indexes are used to proxy for each asset class. The forecast for each specific asset class is made using a proprietary methodology that is appropriate for that asset class. Equity asset classes utilize a proprietary forecasting methodology based on the assumption that equity valuations revert to their long-term trend over time. The methodology is built around specific valuation measures that require several stages of calculation. Assumptions on the projected growth of earnings and dividends are additionally applied to calculate the SRE of the equity asset class. Fixed Income asset class forecasts use a proprietary forecasting methodology that is based on current yield levels. Other asset classes utilize other specific forecasting methodologies. Each SRE does not reflect the deduction of client advisory fees and/or transaction expenses. Past performance is not indicative of future results. Future rates of return cannot be predicted with certainty. The actual rate of return on investments can vary widely. This includes the potential loss of principal on your investment. It is not possible to invest directly in an index. SRE information shown above is hypothetical, not the actual performance of any client account. Hypothetical information reflects the application of a model methodology and selection of securities in hindsight. No hypothetical record can completely account for the impact of financial risk in actual trading. See Glossary for definitions.

Alternative investments

In our view, 2023 will potentially be a great vintage for alternative investments. Higher interest rates have caused a repricing of private assets amid much higher borrowing costs. As such, specialist managers will be able to deploy capital into areas of distress and illiquidity – see **Alternative investments may enhance cash yields**. Across the venture capital industry, capital is now being deployed more judiciously and at more favorable valuations for investors – see **Digitization and the growth in alternative investments**.

For real estate, a higher bar is now in place for new investment across almost all markets and property types. We see this as a favorable backdrop for real estate investors in 2023 – see **How unstoppable trends are redefining real estate**. Our strategic return estimates in these areas are now materially higher than they were just a year ago when interest rates were much lower, indicative of how much value may be earned over time by taking illiquidity risk when others are less willing to do so.

Toward a new normal with new risks

Over the past six months, we have written about the “little fires” burning across the globe.[2] No one knows how or when the war in Ukraine will end. We cannot be sure of China’s trajectory given its election of like-minded leadership. And we certainly do not know what political events will unfold in response to the recession itself, as governments will lack the resources needed to support individuals and companies as they did through the pandemic. In short, markets today are assuming that none of these little fires grow bigger or come together in an untimely way – see **Expect the unexpected: How we might be wrong**. That itself means that investors need to think of “sequencing” as a useful investing discipline.

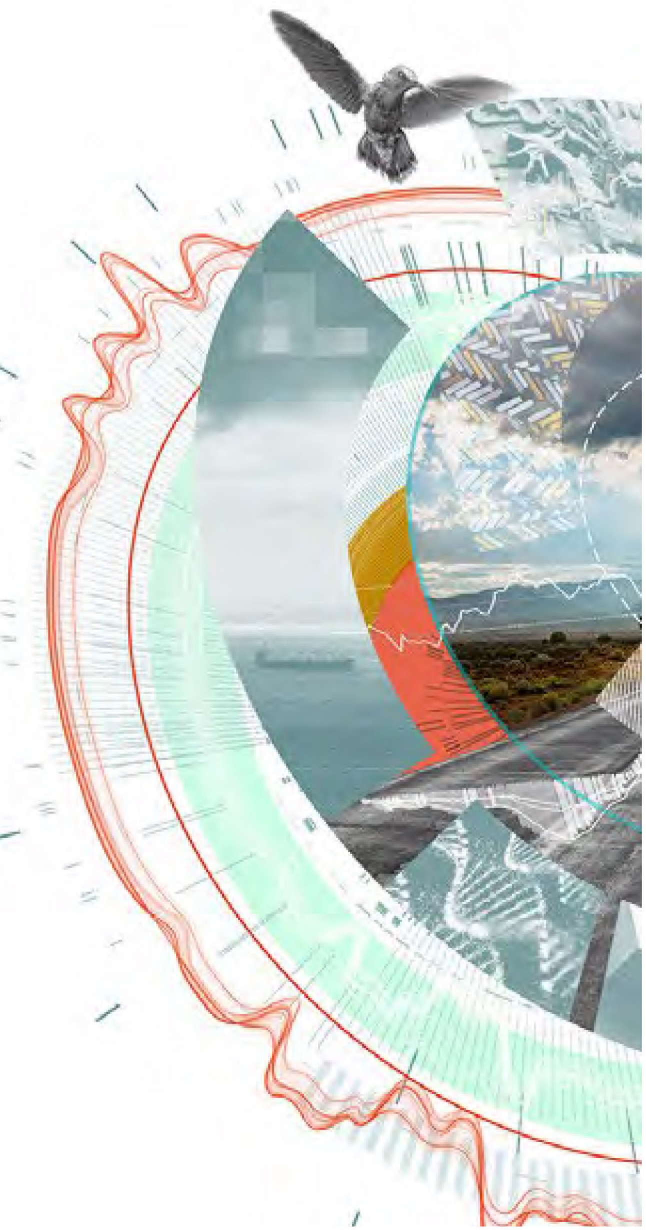
As we look ahead to 2023, it is a time for pragmatism and practicality. There has been no economic period like this one, buffeted by the collective impact of a pandemic, a war and a highly reactive Fed. That said, we maintain our realistic view that the world will see businesses improve the lives of customers across the world. For example, we believe that the climate challenges will ultimately be addressed and provide fuel for profits along the way – see **Energy security is vital**. We believe that the post-pandemic period will accelerate the development of new treatments for disease and new tools to prevent future calamities – see **Seeking to boost portfolio immunity with healthcare**. We believe that new global macro realities will present opportunities to reshape supply chains and alliances. And we also believe that a return to a “new normal” is the likeliest outcome for the global economy – though not the only one.

It has been a great honor to work with a highly capable team in our Office of the CIO these last years as we provide you, our valued clients, with insights designed to make your lives better as we make your portfolios more resilient.

Wishing us all a better, healthier and peaceful 2023.

DAVID BAILIN
Chief Investment Officer and
Global Head of Investments
Citi Global Wealth

[2] The Squeeze Is On - CIO Strategy Bulletin, Citi Global Wealth Investments, 9 Oct 2022



1.2

Roadmap to recovery: Markets lead, the economy follows

We expect global growth will deteriorate for some of 2023. Markets will then increasingly focus on the recovery that lies beyond. We enter the year defensively positioned but expect to pivot as a sequence of potential opportunities unfolds.

STEVEN WIETING
Chief Investment Strategist and Chief Economist

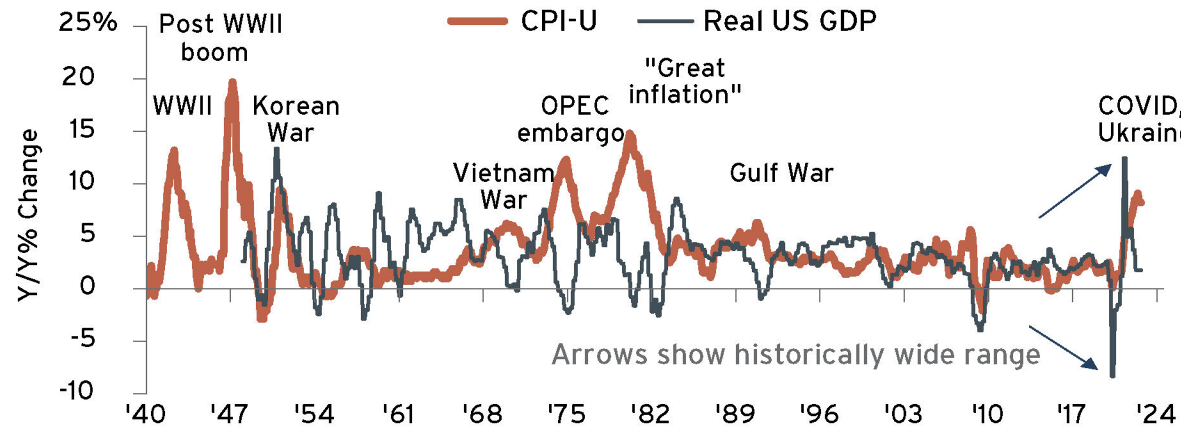
- The Fed's cumulative monetary tightening will likely stifle the world economy no later than mid-2023
- For portfolios now, we remain cautious, seeking returns through high-quality equities and bonds, as well as capital markets and alternative strategies for suitable investors
- Markets will start focusing on 2024's recovery sometime in 2023, enabling us to take greater investment risks across a variety of asset classes
- As interest rates peak, we would expect to shift first to quality growth equities in non-cyclical industries
- A 10% decline in broad corporate profits in 2023 should hit many cyclical industries before any recovery takes hold
- As unemployment rises, we expect the Fed to reverse course by the second half of 2023, with fixed income yields dropping
- The US dollar's bull market could overshoot even higher, but chances are building of non-US assets and currencies finding a "deep value bottom" in 2023
- While Fed drama has distracted many investors, we call for renewed attention on the unstoppable trends transforming the world economy

The post-COVID economic boom of 2021 has given way to a bad "hangover" as we head into 2023. As with any day-after pain, today's headache will not last. But many investors find it difficult even to imagine recovery. We believe change for the better will come in 2023, even as markets face challenges along the way.

Growth and inflation were never destined to stay in their previous narrow ranges given the COVID shock and war in Ukraine – **FIGURE 1**. Much of today's economic distortion derives from unusual disruptions to supply and vast, unpredictable swings in demand. Aggregate demand stimulus was not the right medicine for these problems. Stimulating demand without stimulating supply generates painfully high inflation.

One way to avoid compounding a hangover is to stop drinking. Tightening fiscal and monetary policy is the economic equivalent of that. US federal spending has fallen 11% year to date, for example – **FIGURE 2**. Real consumer goods spending has fallen about 1% in 2022 to date with the bulk of Fed monetary tightening's impact yet to come. The slowdown in consumer spending and the sharp rise in goods inventories will put the brakes on global trade growth and corporate profits in 2023 – **FIGURE 3**.

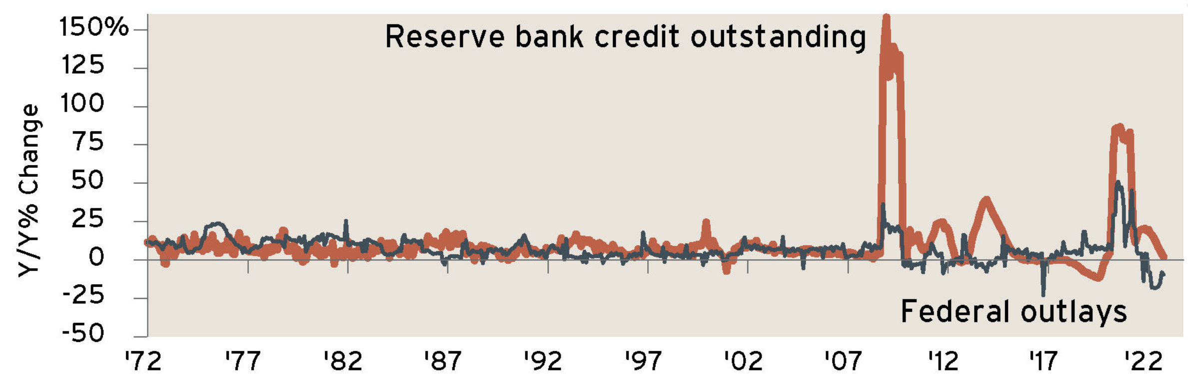
FIGURE 1. HOW THE COVID SHOCK HAS DISTORTED GROWTH AND INFLATION



Source: Haver, as of 29 Sep 2022.

Chart shows year-on-year (%) changes in consumer price inflation and real US GDP, with arrows around the 2020-2023 period to denote historically wide ranges in real GDP.

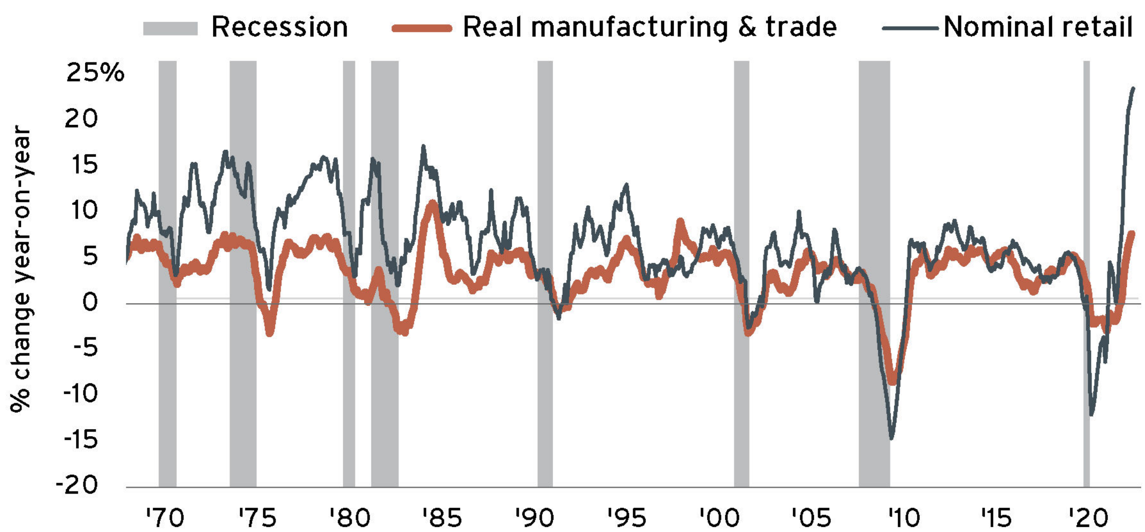
FIGURE 2. FISCAL AND MONETARY RESTRAINT RETURN



Source: Haver, as of 29 Sep 2022.

Chart shows US Federal spending and Federal Reserve credit Y/Y%.

FIGURE 3. SOARING INVENTORIES, WEAKENING TRADE AHEAD



Source: Haver, as of 29 Sep 2022.

Chart shows year-on-year percentage changes in real manufacturing and trade inventories and nominal changes in retail inventories. Gray shaded areas are recessions.

FIGURE 4. REAL GDP AND CITI GLOBAL WEALTH INVESTMENTS' FORECASTS

Citi Global Wealth Investments Real GDP Forecasts (Updated as of August 2022)					
	2020	2021	2022	2023	2024
China	2.4	7.5	3.5	4.5	4.0
US	−3.4	5.7	1.6	0.7	2.0
EU	−6.5	5.3	3.0	−0.5	1.0
UK	−9.3	7.4	3.4	−1.0	1.0
Global	−3.2	5.7	3.3	1.7	2.3

Source: Citi Global Wealth Office of the Chief Investment Strategist assumptions, as of June 24, 2022.

Chart shows real GDP changes in percentage for China, the US, EU, UK and world between 2020 and 2024, with forecast data from 2022 onward. All forecasts are expressions of opinion, are subject to change without notice are not intended to be a guarantee of future events. Indices are unmanaged.

We expect a global recession in 2023 – **FIGURE 4**. Indeed, the 1.7% annual global growth we expect is likely to be weakest in forty years outside of the Global Financial Crisis year of 2009 and the COVID shutdown year of 2020. Among the major economies, the eurozone and the UK are likely to come out worst, with full-year contractions of 0.5% and 1% respectively as they contend with sky-high energy costs, as well as policy tightening.

China looks to be one year ahead of the US and may provide some diversification to portfolios in the years to come. Amid weak labor markets and a real estate crisis, the world's second-largest economy is already in monetary easing mode. After two dismal years, we expect low Chinese profits to rise along with expanding money supply, just as US profits and money supply contract. However, its near-term prospects rely on the ongoing relaxation of its strict COVID measures and continued support for its nascent real estate recovery – see **Asia: Broader re-opening to enable regional recovery**.

With the US likely entering a mild recession and unemployment probably exceeding 5%, we see the greatest surge in inflation as largely behind us in 2022. That said, US inflation is unlikely to reach pre-COVID norms in 2023. We see it retreating to 3.5% by end-2023 and 2.5% by end-2024, while averaging higher during those calendar years. Our estimates are unchanged despite our reduced economic growth forecasts since June 2022 and slow recovery expectation for 2024.

The Fed has not been able to end recessions quickly once underway. However, it does have a history of frequent policy reversals. In the past 45 years, peak policy rates have been sustained for only seven months on average before cutting rates. If the Fed can soon find a balance between the excessive easing of 2021 and the rapid tightening it has "rhetorically" encouraged in 2022, it might avoid amplifying financial and economic excesses.

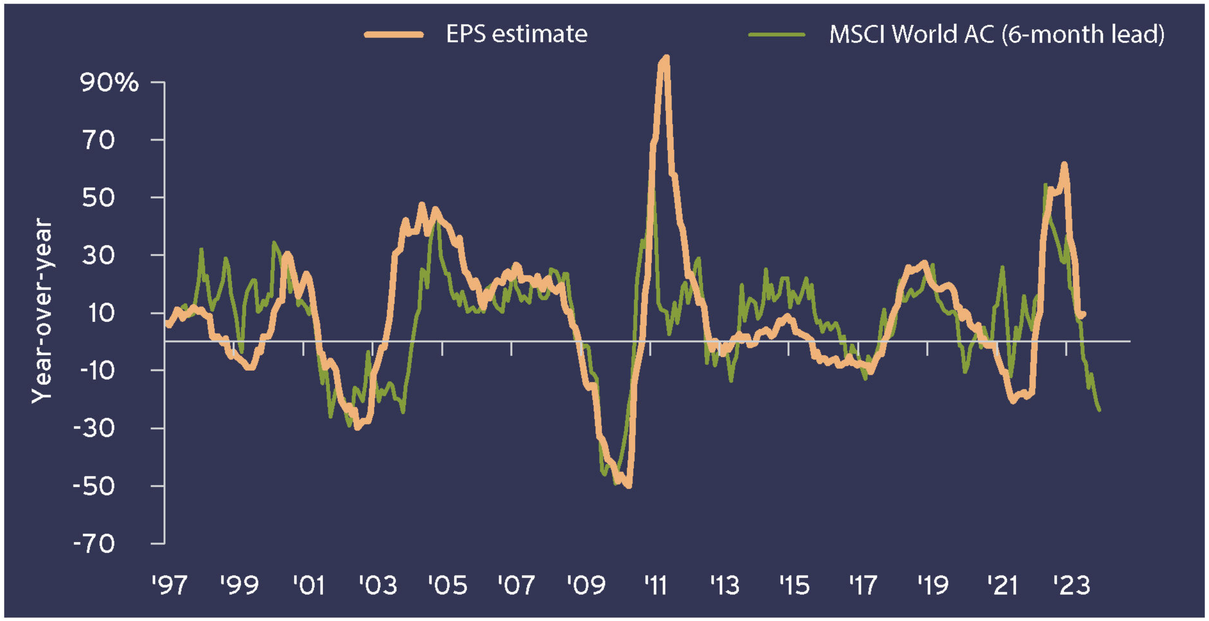
Positioning for a year of challenges and change

Across 2022, investors braced for the forecast 2023 recession. The resulting bear market is well underway, although incomplete. A new bull market has never begun before a recession has even started. Most typically, a bull market begins at around the mid-way stage of a recession. The very strong communications of the Fed's intentions and a year of bearish anticipation may see markets bottom somewhat sooner than usual. However, as of late November 2022, a recessionary decline in employment and corporate profits has not even begun.

Within 2023, we expect investors to start discounting 2024's recovery. Only twice in the past century – including the Great Depression – did US equities take more than two calendar years to find a lasting bottom. But further losses might still come first.

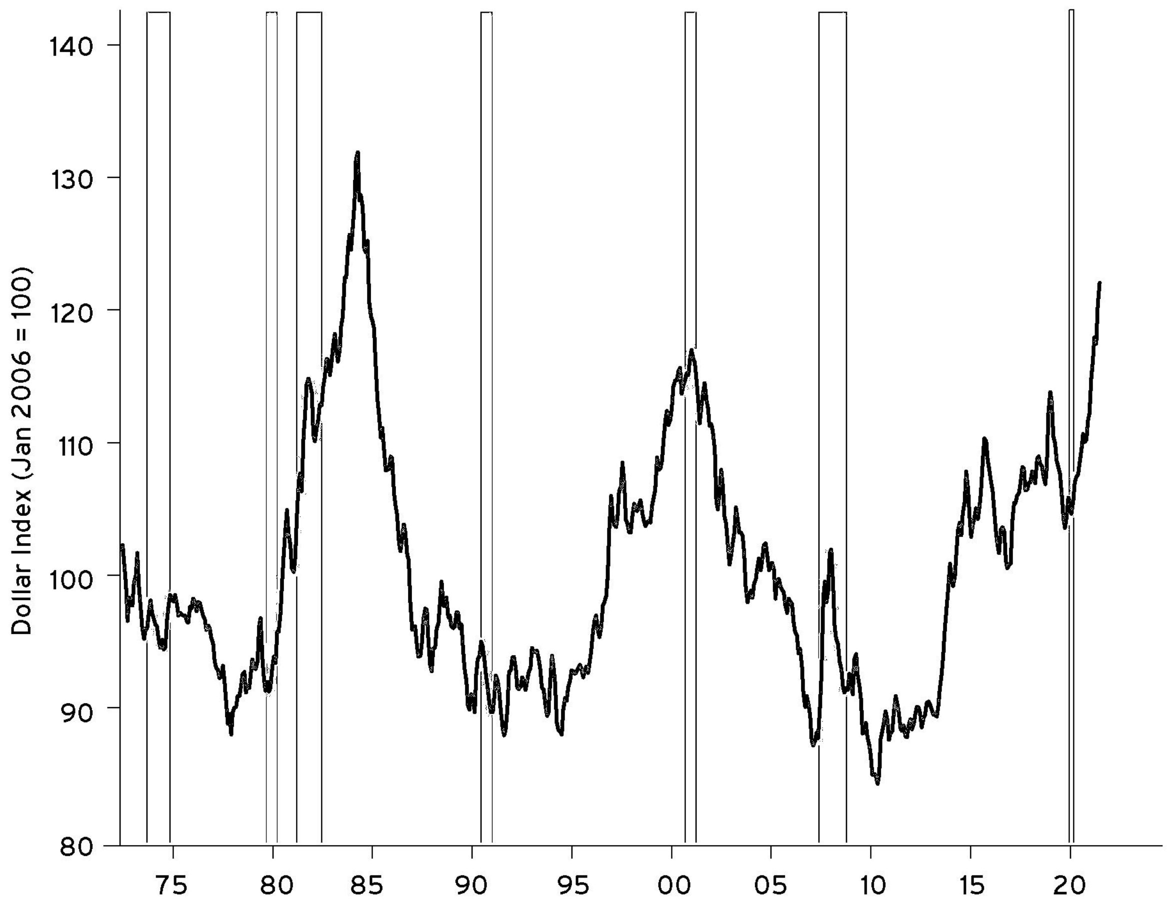
What might mark the bottom for markets amid the coming recession? As usual, producers will overreact to demand weakness, cutting output too far. Within several months of that moment, the "excessive caution" will be followed by reports of falling inventories. Such datapoints will be among the preconditions for recovery. Earnings per share will likely only follow equities higher, with the past lag having been about six months – **FIGURE 5.**

FIGURE 5. EARNINGS PER SHARE BOTTOM LATER THAN MARKETS



Source: Haver, as of 30 Nov 2022. Indices are unmanaged. An investor cannot invest directly in an index. They are shown for illustrative purposes only and do not represent the performance of any specific investment. Past performance is no guarantee of future results. Real results may vary. All forecasts are expressions of opinion, are subject to change without notice, and are not intended to be a guarantee of future events.

FIGURE 6. DOLLAR REACHING HISTORIC EXTREMES



Source: Haver, as of 30 Oct 2022. Indices are unmanaged. An investor cannot invest directly in an index. They are shown for illustrative purposes only and do not represent the performance of any specific investment. Past performance is no guarantee of future results. Real results may vary.

Chart shows US dollar index between 1973 and 2022. Gray areas represent US recessions.

The US dollar may overshoot

In the coming environment, we look for an end to the US dollar's mighty ascent. This period of strength has been its third such secular bull market since it began floating freely in 1971 – **FIGURE 6**. However, there is a risk that it will overshoot, rising for longer than is justified by fundamental drivers.

There are precedents for such an overshoot. While the Fed began easing during the 1982 recession, the dollar continued rising sharply until 1985. And the currency's strength persisted through much of 2002, despite the 2001 tech bubble burst.

The US experienced an asset bubble-induced recession in 2001. Despite sharp declines in real interest rates and a dramatic drop in equity valuations during the period, the US dollar continued to rise through much of 2002.

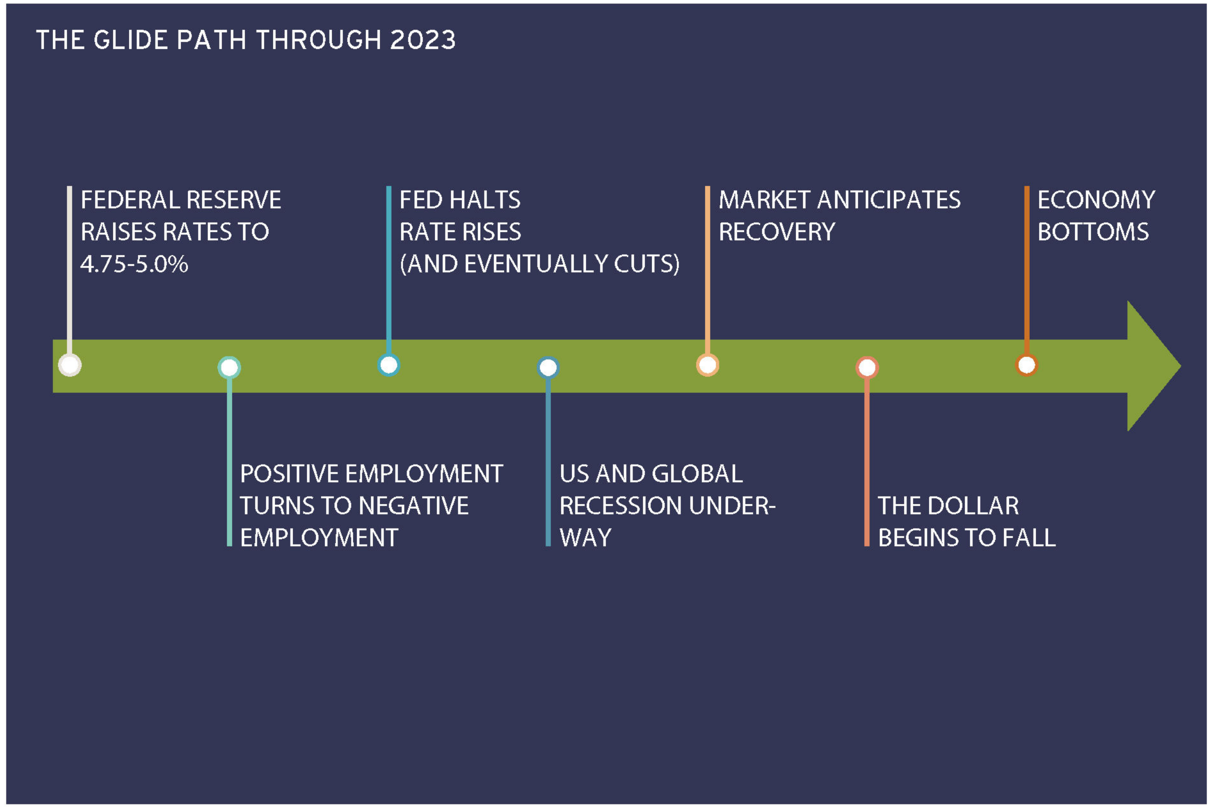
Given this, predicting a peak in the US dollar is tricky. We feel confident in our view that US and global equities will find a bottom and US rates a peak. Nevertheless, present circumstances suggest a peak value for the dollar – and trough values for major currencies – will be reached in the coming year. This will have lasting positive implications for returns in non-US assets for many investors for years to come.

A possible path through: opportunities now, opportunities later

In the year of challenges and change that we expect, we see various potential opportunities for investors. A sharp fall in valuations across many markets have driven up our ten-year strategic return estimates – see **The brighter long-term outlook for asset classes.** On a tactical view, the opportunities may present themselves in a sequence, some sooner and others later. In early 2022, rapidly rising interest rates created uncertainty for valuing any financial asset. The rough doubling in government bond yields over the past year has boosted higher quality fixed income yields to a more appropriate level for the first time in several years. Given a slowing cyclical backdrop, we see a stronger potential opportunity for fixed income assets within overall portfolio construction and to earn income on excess cash – see **Pursuing portfolio income with short-term bonds.** In the environment we expect, US 10-year Treasury yields may end 2023 at 3.0%.

Heading into 2023, we believe defensive equities may perform best near term and we remain overweight US dollar assets. By contrast, we remain cautious on Europe and Japan. However, we note that most non-US equities' poor performance in 2022 was owing to collapsing local currencies rather than local returns falling. This may start correcting in 2023 as peak fear and peak policy divergence with the US sets in – **FIGURE 8.**

FIGURE 7. OUR POTENTIAL "GLIDE PATH" FOR 2023



Source: CGWI Office of the Chief Investment Strategist, as of October 11, 2022. All forecasts are expressions of opinion, are subject to change without notice, and are not intended to be a guarantee of future events. Indices are unmanaged. An investor cannot invest directly in an index.

If so, long-lasting income-producing assets in Europe, Japan and others might be bought at unusually depressed values – see **Europe: Bracing for winter recession** and **Asia: Broader re-opening to enable regional recovery**. Just as a single example, German REITs have returned negative 40% in US dollar terms in 2022 and now yield 12%. If Europe were to recover half of its losses of the past two years, the annualized return would be 19% in US dollars, even assuming no change in REITs' price.

For many cyclical industries, however, a bottom may occur late in 2023. Before then, economic weakness will depress interest rates. Industry-leading growth equities may bottom before cyclicals, however. We also look for the recessionary conditions to create potential opportunities for certain alternative strategies – see **Alternative investments may enhance cash yields.**

We continue to focus on what drives economic growth over time and generates real investment returns. Apart from population growth, real economic growth is entirely determined by innovation. Developing new tools or better processes leaves us with means to create more output per person. Money – what central banks give and take away – provides us none of it. In general, the information technology and healthcare sectors have capitalized most on innovation and enjoyed the most potent demographic forces to drive superior long-run returns – **FIGURES 9 AND 10**. We explore these in **How unstoppable trends are redefining real estate** and **Digitization and the growth in alternative investments.**

Although the valuations of many innovative companies and sectors are under pressure, there is no fundamental change in their prospects. While there were many distortions in the COVID economy, we do not expect a global reduction in expenditures in essential areas such as cybersecurity and green tech – **Energy security is vital.** By contrast, at the end of the "dot-com" bubble in the early 2000s, both valuations and fundamentals unwound very sharply together.

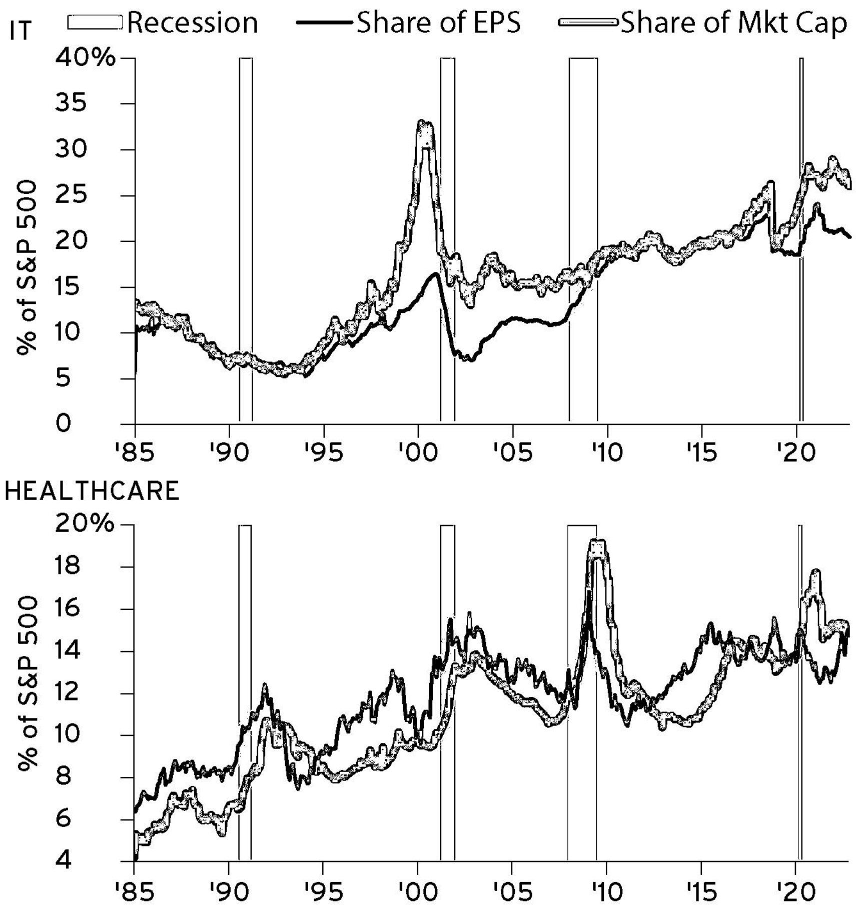
FIGURE 8. US DOLLAR SURGE COULD REVERSE AFTER OVERSHOOT

Country/region	YTD return (local ccy)	YTD return (USD)	YTD FX return (vs USD)
Brazil	7.7	12.5	4.8
US	−15.9	−15.9	0.0
Switzerland	−13.7	−17.7	−4.0
Canada	−3.3	−9.1	−5.8
China (A shares)	−22.1	−30.9	−8.8
Europe	−7.3	−16.7	−9.4
Australia	4.8	−5.0	−9.8
Korea	−19.1	−29.2	−10.1
India	3.5	−5.7	−9.1
Taiwan	−18.6	−27.8	−9.2
UK	5.6	−8.0	−13.6
Japan	0.5	−18.6	−19.0

Source: Haver, as of 24 Nov 2022.

Table shows the performance of various national equity markets in local currency terms, US dollar terms and the contribution to return of foreign exchange movements. Indices are unmanaged. An investor cannot invest directly in an index. They are shown for illustrative purposes only and do not represent the performance of any specific investment. Past performance is no guarantee of future results. Real results may vary.

FIGURES 9 AND 10. IT AND HEALTHCARE'S GROWING IMPORTANCE



Source: FactSet, as of 21 Nov 2022.

Charts show the rising trend of the market capitalization and earnings per share for the IT and healthcare sectors, expressed as a % of the total S&P 500 Index. Indices are unmanaged. An investor cannot invest directly in an index. They are shown for illustrative purposes only and do not represent the performance of any specific investment. Past performance is no guarantee of future results. Real results may vary.

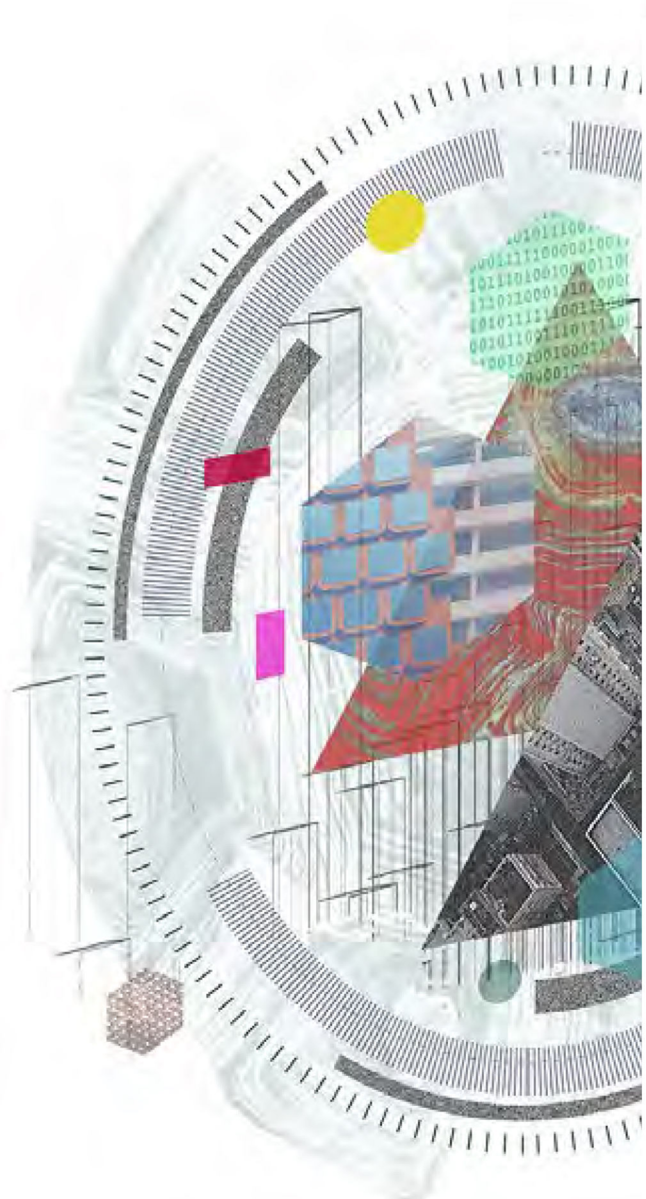
WHAT TO DO NOW?

While investing in 2022 was deeply challenging, any one year represents a mere "moment" in the lifetime of a portfolio. And even though the economic environment in 2023 may prove to be difficult, the greatest risk at times like these comes not from enduring the turbulent conditions but from trying to avoid them by market timing.

Given the high probability of recession in the US and elsewhere in 2023, we enter the year with a defensive asset allocation, albeit fully invested. However, as 2023 unfolds we will take a dynamic approach to tactical asset allocation. As markets ultimately find a bottom, our positioning is set to evolve toward equities and alternatives that anticipate a recovery.

As a first step toward building portfolios for the year ahead and beyond, investors should assess their present positioning. To help our existing clients in this review, our Outlook Watchlist report can review your exposure to key sources of potential risk and return, including our long-term investment themes. We can then discuss actionable strategies to help you adjust your allocation for the coming year and beyond. Please note this is not available to prospective clients at this time.

Outlook 2023 is your roadmap to understanding the route to economic recovery. Let us be your partner and guide on this road to recovery.



1.3

Expect the unexpected: How we might be wrong

While we expect recession in 2023, it could be deeper than we expect – or not happen at all. We consider this and other risks to our views in both directions.

STEVEN WIETING
Chief Investment Strategist and Chief Economist

- Monetary tightening amid ongoing supply shocks will likely hurt economic growth in 2023, albeit with inflationary pressure diminishing
- Self-reinforcing, 1970s-style inflation would force key central banks to drive a much harder economic landing than we expect
- But if inflation fades quickly, the US economy particularly has a small chance of avoiding recession
- US-China military escalation or a complete breakdown of trade relations are major if improbable risks for the world economy
- Issues over Russia's oil exports and Ukraine's agricultural exports could still cause disruptions
- A large-scale cyberattack also could potentially create widespread economic damage
- In the face of all these and other risks, we advocate globally diversified asset allocation, in line with your specific investment objective

The past three years have seen both the fastest pace of economic contraction on record and the fastest recovery. The period has also seen a new ground war in Europe on a scale not seen since World War II, with nuclear warnings from global leaders for the first time since the 1980s. Relations between the US and China are critically important to both sides yet precarious. In short, this is not an environment in which to have overly confident views.

In response to nuclear rhetoric from Russia, President Biden drew parallels with the Cuban Missile Crisis. The 35-day standoff in October-November 1962 arose when the USSR sought to station nuclear weapons on the island just 90 miles (145 km) from the US mainland. It stands as a powerful example of binary geopolitical risk. It is widely regarded as the closest the world has come to nuclear warfare since the end of World War II.

The leaders of the US and USSR pulled back from the doomsday scenario. Subsequently, the world economy grew strongly between 1963 and 1969. The US economy grew an average 4.3% annually during the period, including a recession that began fully eight years later. With one short bear market to endure, investors enjoyed strong equity market returns over most of the remaining decade.

Within the short period of grave nuclear risk that could have ended very differently for all of humanity, US equities dropped less than 10% before regaining it all and more. So, what is the lesson of the Cuban Missile Crisis for investors? Among many conclusions, we would highlight that 90% of geopolitical shocks since and including WWII have not caused turning points in economic activity – **FIGURE 1**.

But what about the exceptions? World War II was a grave catastrophe for humanity that deserves special consideration. That conflict aside, the OPEC oil embargo of late 1973 catalyzed a world-wide recession and higher consumer prices at the same time.

The present Russia-Ukraine war – along with the first Gulf War of 1990 and Iraq-Iran war beginning in 1980 – has strong similarities to the OPEC embargo shock. Each of these events had significant negative regional impacts and some notable global effects. Importantly, central banks have never been able immediately to offset the inflationary impact of supply shocks no matter what their hoped-for inflation targets might have been.

The risk of overlapping shocks

Today, we worry about overlapping shocks and the willingness of the US to pursue multiple problems at the same time, creating "joint probability risk." Monetary tightening, strategic competition with China and isolating Russia are all being pursued simultaneously, raising the likelihood that a trigger event will cause a cascade of impacts that ripple across world markets and the economy.

The decision of the US administration to limit US content in China's computing industry – particularly advanced semiconductor equipment – was expected. However, the extent of the US' actions went much further than most investors ever expected. It included prohibitions on "unlicensed" US citizens from working for Chinese firms in producing advanced chips.

As COVID-related supply chain disruptions highlight, there are acute vulnerabilities in the trade of intermediate products such as semiconductors. Disruptions could hamper a much larger share of the economy than the value of individual components might imply. The world's vast dependency on Taiwan-sourced semiconductors represents such a concentrated supply risk in our view – **FIGURE 2**.

November 2022's meeting between Presidents Biden and Xi helped boost confidence that neither side seeks immediate escalation – see **Asia: Broader re-opening to enable regional recovery**. The world can only hope that the G2 superpowers continue to prevent their strategic competition from evolving into conflict.

If inflation persists

Massive fiscal and monetary stimulus in response to the COVID shock tested the global economy's "speed limit." Policymakers took too much for granted, and inflation surged worldwide. Large shifts in demand within the economy led to shortages of goods. Some consumers were willing to purchase these goods at much higher prices.

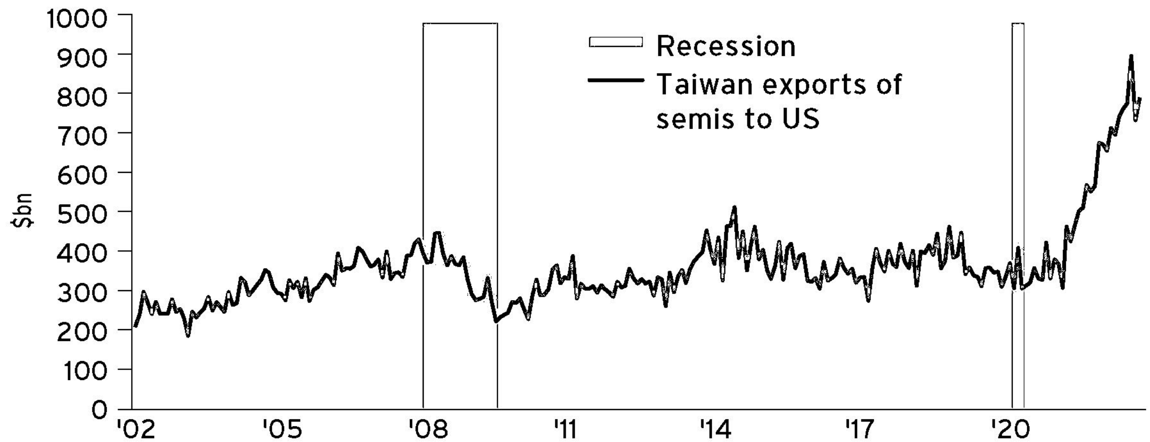
Following a surge in goods prices and a temporary drop in employment, US consumers turned their sights on labor-intensive services. Demand persistence – and a labor force still suffering from COVID distortions – has had second-order impact on wages. These have risen by the most on a per-person basis since the early 1980s.

FIGURE 1. SELECTED HISTORY OF GEOPOLITICAL CONFLICTS, SHOCKS AND MARKET REACTIONS

Geopolitical event	Date	S&P 500 (% since event date)			Nikkei (% since event date)			MSCI World ex USA (% since event date)			DXY Dollar Index		
		Initial Reaction	30 days	90 days	Initial Reaction	30 days	90 days	Initial Reaction	30 days	90 days	Initial Reaction	30 days	90 days
Cuban Missile Crisis	19 Oct 1962	−3.78	7.61	17.16									
JFK assasination	21 Nov 1963	−2.81	3.06	8.28									
US bombs Cambodia	29 Apr 1970	−15.30	−6.43	−4.94	−15.93	−12.49	−7.64	−10.45	−17.01	−16.07	−0.20	−0.23	−0.51
Arab oil embargo	18 Oct 1973	−16.23	−8.45	−13.04	−1.81	−1.44	−4.47	−14.68	1.96	−18.53	7.48	5.28	14.04
USSR invades Afghanistan	24 Dec 1979	−2.27	5.37	−7.78	0.57	2.63	0.68	3.94	3.94	11.85	−1.06	−0.71	5.91
US bombs Libya	15 Apr 1986	2.95	−1.39	0.16	3.09	3.73	16.08	0.00	6.19	8.16	−4.15	−4.80	−5.30
US invades Panama	15 Dec 1989	−2.06	−3.73	−3.43	0.63	−3.71	−14.63	0.00	3.67	−7.04	0.31	−1.69	−0.44
Gulf War	24 Dec 1990	−4.16	0.09	12.10	−6.95	−4.43	10.47	1.75	1.75	15.97	−0.21	−3.61	4.90
World Trade Center bombing	26 Feb 1993	−0.31	1.67	2.04	−0.44	12.36	23.00	0.00	8.52	18.62	0.18	−1.15	−4.79
911	11 Sep 2001	−11.60	0.45	4.34	−6.28	1.48	3.68	−8.48	3.24	5.48	−1.08	0.29	1.85
US invades Iraq	20 Mar 2003	2.49	2.06	15.57	4.77	−1.02	12.94	1.53	4.58	22.05	0.84	−1.85	−7.89
NORTH KOREA–RELATED													
Korean War	23 Jun 1950	−12.80	−8.67	1.20									
Operation Paul Bunyan	18 Aug 1976	−3.15	1.64	−4.32	−0.75	−0.21	−4.52	0.00	−0.26	−7.60	0.07	−0.57	−0.12
2009 nuclear test	25 Apr 2009	−1.28	5.09	13.05	−2.46	6.92	14.20	−2.32	12.28	21.21	0.52	−5.54	−7.04
2016 nuclear test	9 Sep 2016	−2.55	−0.81	2.97	−2.03	0.39	10.65	−2.06	−0.81	−0.72	−0.01	1.36	6.05
2017 escalation	7 Jul 2017	−0.24	−0.64	4.44	−0.30	−3.89	12.43	−0.26	−0.49	3.60	0.23	−1.22	1.62
POLITICAL EVENTS													
Nixon/Watergate	15 Mar 1974	−1.72	−7.28	−8.04	−1.80	1.05	4.42	0.00	−2.57	−6.12	−1.04	−1.57	−2.12
Clinton intern scandal	20 Aug 1998	−12.30	−6.20	5.59	−8.34	−11.66	−6.74	−12.75	−12.75	−6.37	−1.76	−5.18	−6.58
Brexit	23 Jun 2016	−2.30	4.30	3.72	−6.93	3.50	4.62	−5.31	−0.37	1.70	1.85	4.00	2.46

Source: Haver, as of 14 Oct 2022. Table lists select geopolitical events since the Pearl Harbor attacks of 1941 until Russia's invasion of Ukraine, and the associated initial, 30–day and 90–day performances of the S&P 500 Index, crude oil, the MSCI World Index ex USA and US dollar Index. Past performance is no guarantee of future results. Real results may vary. Indices are unmanaged. An investor cannot invest directly in an index. Index returns do not include any expenses, fees or sales charges, which would lower performance. They are shown for illustrative purposes only.

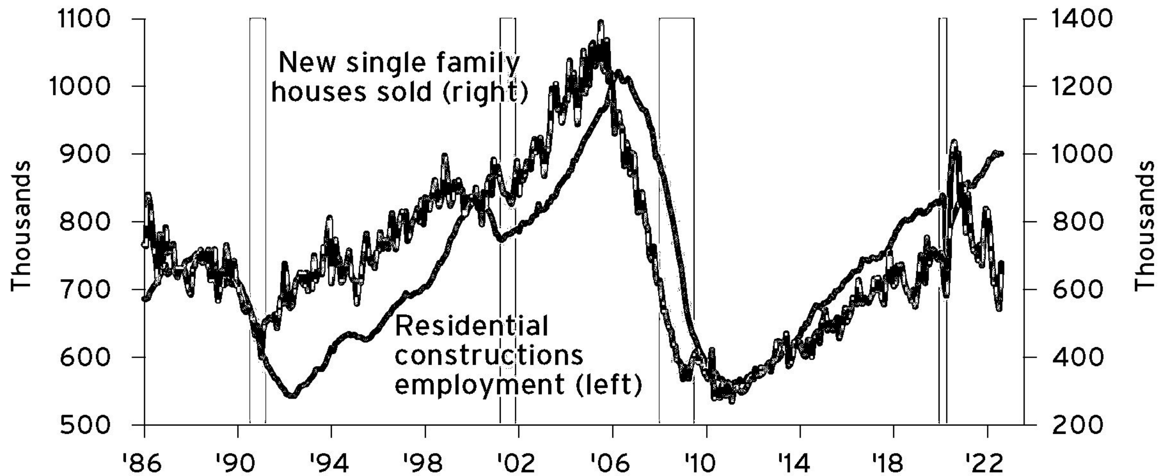
FIGURE 2. US DEPENDENCY ON IMPORTS OF TAIWANESE SEMICONDUCTORS



Source: Haver, through 10 Nov 2022.

Chart shows US imports of advanced technology from Taiwan, including semiconductors. Gray shaded periods denote recessions.

FIGURE 3. FEWER HOUSES SOLD, FEWER CONSTRUCTION WORKERS NEEDED



Source: Haver, as of 24 Nov 2022.

Chart shows new home sales in thousands compared to residential US construction employment in thousands, both series seasonally adjusted Gray shaded periods denote recessions.

US labor markets today are more competitive and the economy is more open than in the 1960s-1980s period. Nonetheless, many Fed policymakers fear inflation will develop "a life of its own" and persist beyond the initial sources of instability. Indeed, if wages and services prices beyond shelter costs fail to decelerate, the Fed would likely maintain a restrictive monetary policy deep into a US economic contraction and with little regard for wider global impact. This is the most likely path to a deeper economic contraction than we expect, and one that does not depend on any new external shocks.

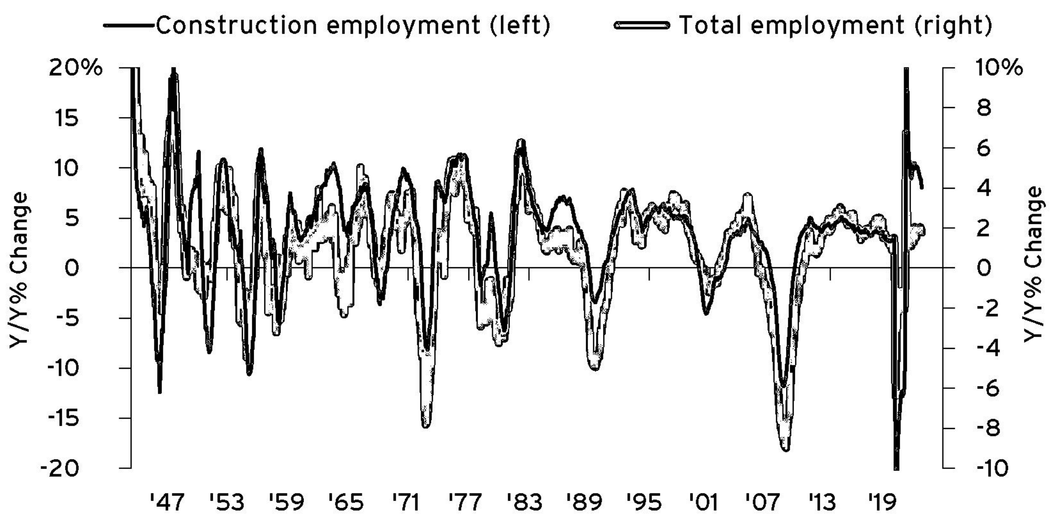
If inflation slows quickly

Given our pessimistic near-term outlook, we must acknowledge upside risk to our views. Since early 2020, US employment has only grown 0.7%, far from a boom. Exogenous inflation – arising from a variety of outside shocks including pandemic impact and conflict-driven trade disruptions – held the economy back but this drag on consumer incomes is already diminishing. While the most reliable long-term leading indicator of the US economy – the yield curve – is signaling recession for the coming year, no indicator is flawless. The near-term outlook is one of still-rising US employment and falling inflation. This is a brief window for the Fed to "de-escalate" its tightening campaign. After all, unlike the 1970s-1980s period, inflation expectations remain very contained. Price-resistant consumers are likely to help the Fed by reining in demand and will not assume wages will accelerate.

Unfortunately, the most likely case for the economy is one of both weakening growth and slowing inflation. We believe the lagged impact of the Fed's very potent action to date will find its way into economic activity and trigger an employment contraction within 2023.[1] The Fed is also tightening further and will continue shrinking its balance sheet until something changes its policy.

After a more than doubling of mortgage rates in the US in 2022 – and even more in some other economies with heavy reliance on adjustable rates – the housing market of 2023 doesn't support the same level of employment – **FIGURE 3**. While we do not have the same detailed history of construction categories, since the end of WWII, all periods of at least a year or more of broad construction employment decline have seen total private employment drop – **FIGURE 4**.

FIGURE 4. WHEN CONSTRUCTION EMPLOYMENT FALLS, SO DOES THE OVERALL JOBS MARKET



Source: Haver, as of 24 Nov 2022. Chart shows percentage year–on–year changes in construction employment and total private industry employment between 1947 and 2022.

WHAT TO DO NOW?

There are various major risks to the world economic outlook. The future could involve many different outcomes, not just the one best expressed in our existing asset allocation or where we expect to take it. As the COVID pandemic so brutally reminded us, major but improbable risks are always with us. We thus seek to preserve and grow wealth by way of a diversified asset allocation rather than taking highly concentrated risks in pursuit of the highest returns. While there are specific hedging techniques that your relationship team may recommend based on your suitability and objectives, our analysis shows that strong risk-adjusted returns over the past 80 years have been earned from investment allocations including lowly correlated or negatively correlated assets.[2] Such an allocation can be constructed around suitable risk and return objectives.

[1] Haver, as of 20 Nov 2022

[2] Our analysis is based on Adaptive Valuation Strategies, the Private Bank's proprietary strategic asset allocation methodology that has a historical database dating back to 1926. Our analysis was performed at an asset class level using indices as a proxy for each asset class. For more details, please see https://www.privatebank.citibank.com/insights/a-new-approach-to-strategic-asset-allocation. All forecasts are expressions of opinion, are subject to change without notice are not intended to be a guarantee of future events. Past performance is not indicative of future returns.

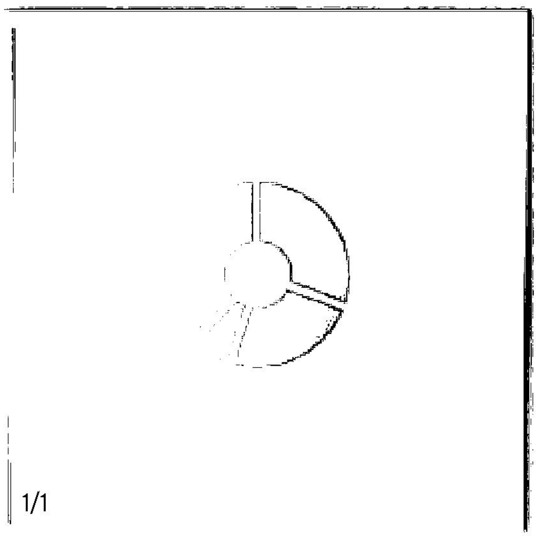
Is your portfolio ready for a year of change and opportunity?

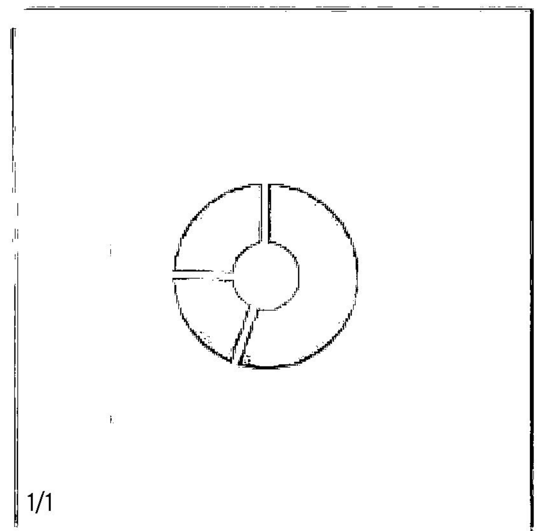
While global growth is set to worsen for some of 2023, we also expect markets to start focusing on the recovery that lies beyond.

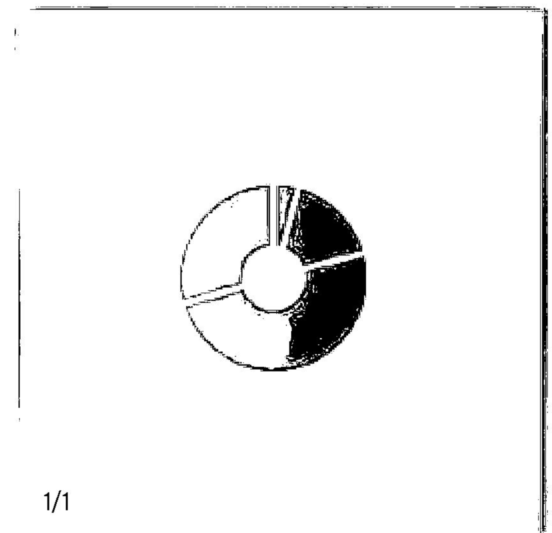
We believe this calls for dynamic portfolios that are ready to pivot as a sequence of potential opportunities unfolds. This includes quality investments amid the present uncertainty and exposure to the sources of long-term growth.

For current clients, our personalized Outlook Watchlist compares your portfolio to the allocation we recommend for you. And our Global Investment Lab's wider range of tools can highlight other potential opportunities to prepare your portfolio for the years ahead.

Please request your personalized Watchlist report from your relationship team today.







OUR POSITIONING

	DECEMBER 2021	DECEMBER 2022
GLOBAL EQUITY	6.0%	-2.0%
Developed Equities	1.7%	-6.6%
Large US	1.5%	0.5%
Large Developed ex-US	1.2%	-2.1%
Developed Small- and Mid-Cap	-1.0%	-5.0%
Thematic Equities	4.0%	3.0%
Emerging Market Equities	0.3%	1.6%
GLOBAL FIXED INCOME	-5.0%	1.0%
Developed Investment Grade	-8.0%	1.3%
US Investment Grade	1.9%	11.7%
Developed High Yield	-1.5%	-1.5%
Thematic Fixed Income	4.0%	2.0%
Emerging Market Debt	0.5%	-0.8%
Cash	-1.0%	-1.0%
Thematic Commodities: Gold	0.0%	2.0%

Overweight

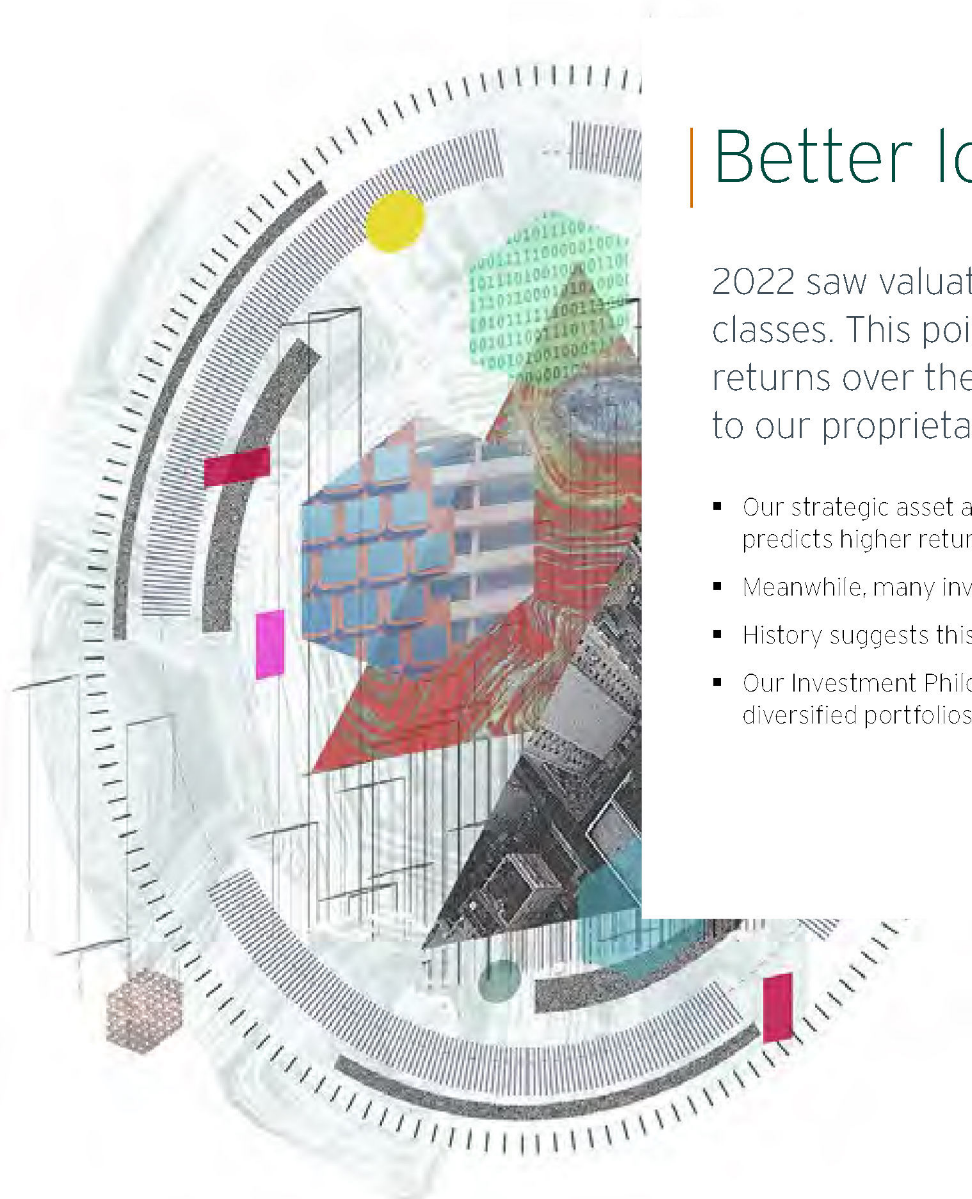
Underweight

Neutral

Figures are active over- and underweights on our GIC Risk Level 3 Portfolio.
Source: Office of the Chief Investment Strategist, as of 1 Dec 2022.

Opportunities

- More defensive equities for the near term, including dividend growers
- Quality short- to intermediate-term US dollar fixed income, such as Treasuries and investment-grade rated corporates/munis/preferreds
- Various "deep value" non-US dollar assets (such as income-producing real estate) once the US dollar peaks
- Tailored investments that take advantage of higher rates and volatility to provide yield and/or market participation with embedded downside hedges
- Tailored investments delivering immediate yield or exposure to markets at entry points below current spot prices
- Digitization, such as robotics, semiconductor equipment, cyber security, fintech and real estate
- Strategies around e-commerce logistics, multifamily homes and quality, sustainable offices
- Alternative strategies positioned for distressed lending/ recapitalization
- Companies driving the transition to secure cleaner sources of energy
- Healthcare equities, including pharmaceutical biologics, life science tools, value-based care and agetech
- Potential beneficiaries of G2 polarization as supply chains are reconfigured, including sectors in India, Southeast Asia and Mexico



1.5

Better long-term returns ahead

2022 saw valuations fall across asset classes. This points to potentially higher returns over the coming decade, according to our proprietary methodology.

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- Our strategic asset allocation methodology predicts higher returns over the decade
- Meanwhile, many investors are sitting on excess cash in their portfolios
- History suggests this is likely to prove a costly mistake over time
- Our Investment Philosophy calls for fully invested, globally diversified portfolios throughout economic cycles

Being an investor was very tough in 2022. A rare simultaneous selloff across many risk assets and the highest quality government bonds meant diversification failed for a time. Put simply, there was almost nowhere to hide, as the final column in **FIGURE 1** shows. However, this cloud has a long-term silver lining. The broad-based declines have driven many asset valuations down to levels that imply more rewarding future returns, according to our proprietary strategic asset allocation methodology.

Adaptative Valuation Strategies (AVS) looks out over a ten-year horizon. It uses current asset class valuations to produce annualized return forecasts or "Strategic Return Estimates" (SRE) for the decade ahead. This is based on the insight that lower current valuations have given way to higher returns over time, whereas higher valuations have been followed by lower returns. It then allocates to each asset class according to its outlook for returns.

For Global Equities, AVS has an SRE of 10.0% out to 2033 – **FIGURE 1**. Within this, Emerging Market Equities – shares from economies such as China, India and Brazil – have an SRE of 13.6%. Developed Market Equities – shares from economies such as the US, most of Europe and Japan – have an SRE of 9.5%. For context, the SRE for Global Equities in the middle of 2022 was 8.3%.

Cheaper bond valuations also point to higher returns. Investment-Grade Fixed Income – which includes bonds from the most creditworthy sovereign and corporate issuers – now has an SRE of 4.6%. This is up from 3.4% in mid-2022, mainly due to interest rate hikes which pushed bond yields up globally. Despite selling off alongside equities in 2022, this asset class has been less correlated to equities over time, helping investors to build diversified portfolios.

The SRE for High-Yield (HY) Fixed Income – bonds issued by less creditworthy corporate borrowers – has increased to 7.4%. Similarly, the SRE for Emerging Market Fixed Income – bonds issued by emerging country governments and companies – has increased to 7.8%. The SRE for Cash has risen to 3.4%, meanwhile.

In alternative asset classes, the SRE for Hedge Funds has risen to 9.5%. As at the mid-year stage, Private Equity remains the asset class with the highest SRE at 18.6%. This SRE is derived from small-cap public equity valuations, which are at historically cheap levels. By contrast, the SRE for Real Estate has only edged up to 10.6%.

FIGURE 1. AVS' LONG–TERM OUTLOOK FOR ASSET CLASSES

	2023 SRE *	2022 Mid–Year SRE	2022 return
Global Equities	10.0%	8.3%	
Global Fixed Income	5.1%	3.7%	
Developed Market Equities	9.5%	8.0%	–19.22%
Emerging Market Equities	13.6%	10.5%	–30.86%
Investment–Grade Fixed Income	4.6%	3.4%	–14.57%
High–Yield Fixed Income	7.4%	5.2%	–12.35%
Emerging Market Fixed Income	7.8%	6.0%	–23.32%
Cash	3.4%	1.5%	1.42%
Hedge Funds	9.5%	6.5%	–6.68%
Private Equity	18.6%	15.7%	–15.50%
Real Estate	10.6%	9.4%	–27.89%
Commodities	2.4%	2.0%	17.65%

Source: Citi Global Wealth Investments Global Asset Allocation team.

2023 SREs are based on data as of 31 Oct 2022. Global Equity consists of Developed and Emerging Market Equity. Global Fixed Income consists of Investment–Grade, High–Yield and Emerging Market Fixed Income. Strategic Return Estimates are in US dollars; all estimates are expressions of opinion, are subject to change without notice and are not intended to be a guarantee of future events. Strategic Return Estimates are no guarantee of future performance. Citi Private Bank Global Asset Allocation Team. SREs for Mid–Year 2022 are based on data as of 30 Apr 2022. Returns estimated in US dollars. Strategic Return Estimates (SRE) based on indices are Citi Private Bank's forecast of returns for specific asset classes (to which the index belongs) over a 10–year time horizon. Indices are used to proxy for each asset class. The forecast for each specific asset class is made using a proprietary methodology that is appropriate for that asset class. Equity asset classes utilize a proprietary forecasting methodology based on the assumption that equity valuations revert to their long–term trend over time. The methodology is built around specific valuation measures that require several stages of calculation. Assumptions on the projected growth of earnings and dividends are additionally applied to calculate the SRE of the equity asset class. Fixed Income asset class forecasts use a proprietary forecasting methodology that is based on current yield levels. Other asset classes utilize other specific forecasting methodologies. Each SRE does not reflect the deduction of client advisory fees and/or transaction expenses. Past performance is not indicative of future results. Future rates of return cannot be predicted with certainty. The actual rate of return on investments can vary widely. This includes the potential loss of principal on your investment. It is not possible to invest directly in an index. SRE information shown above is hypothetical, not the actual performance of any client account. Hypothetical information reflects the application of a model methodology and selection of securities in hindsight. No hypothetical record can completely account for the impact of financial risk in actual trading. See Glossary for definitions.

* AVS SRE methodology was enhanced in 2022 and mid–year SREs reported reflect this enhancement.

FIGURE 2: GLOBAL MULTI–ASSET CLASS DIVERSIFICATION VS A CASH–HEAVY ALLOCATION SINCE 1985

31 Dec 1985 to 31 Oct 2022	AVS Risk Level 3 allocation	Cash–heavy allocation
Developed Market Equity	27%	34%
Emerging Market Equity	5%	–
Investment–Grade Fixed Income	33%	33%
High–Yield Fixed Income	3%	–
Emerging Market Fixed Income	3%	
Cash	2%	33%
Hedge Funds	12%	
Private Equity	10%	
Real Estate	5%	
Commodities	0%	
ANNUALIZED MEAN RETURN	6.2%	3.9%
ANNUALIZED VOLATILITY	9.0%	5.5%

Source: Citi Global Wealth Investments Global Asset Allocation team, as of 31 Oct 2022.

The performance of the AVS Global USD Risk Level 3 and the cash–heavy portfolio was calculated on an asset class level using indices to proxy for each asset class.

1 Net performance results for both portfolios reflect a deduction of 2.5% maximum fee that can be charged in connection with advisory services that covers advisory fees and transaction costs. Individuals cannot directly invest in an index. The performance is for illustrative purposes only.

2 These are preliminary asset allocations for 2023. All performance information shown above is hypothetical, not the actual performance of any client account. Hypothetical information reflects the application of a model methodology and selection of securities in hindsight. No hypothetical record can completely account for the impact of financial risk in actual trading. For example, there are numerous factors related to the equities, fixed income or commodities markets in general which cannot be and have not been accounted for in the preparation of hypothetical performance information, all of which can affect actual performance. The returns shown above are for indices and do not represent the result of actual trading of investable assets/securities. The asset classes used to populate the allocation model may underperform their respective indices and lead to lower performance than the model anticipates.

Having been the top performing asset class in 2022, Commodities are not expected to do so well over the next ten years. Indeed, its SRE of 2.4% is the lowest of the ten asset classes that AVS addresses, even below Cash.

The perils of hoarding cash

The turmoil in 2022 has left many investors in a highly cautious mode. A common reaction we encounter is holding large amounts of cash, perhaps as much as one-third of a total portfolio, with equal proportions in equities and fixed income. And in fact, certain financial professionals, influenced by clients' behavior, may be tempted to recommend such an allocation in the wake of market shocks. How would such an allocation have performed over time compared to one created by AVS?

FIGURE 2 shows an AVS Global US dollar allocation at Risk Level 3. This is intended for an investor seeking modest capital appreciation and capital preservation. Given this investor's moderate appetite for risk, some allocation to alternative and illiquid asset classes are suitable.

The bottom two rows in **FIGURE 2** show the hypothetical performance of these two allocations over the past 37 years. Over the entire period, the AVS Risk Level 3 allocation would have outperformed the cash-heavy allocation portfolio by an annualized 2.3%. Hypothetically in dollar amounts, an initial investment of $1 million would have become $7.5 million for the Level 3 allocation, while the "cash-heavy" allocation would have grown to just $3 million. That said, its volatility is also lower, at 5.5% versus 9.0%. However, this is less risk than an investor at Risk Level 3 could take. As a result, they are inappropriately sacrificing performance potential by having too little risk exposure.

At moments of crisis, a cash-heavy approach has tended to outperform, but this can come at great cost. For example, consider these two sets of allocations in August 2008, just before the major selloff in risk assets – **FIGURE 3**. By the subsequent market lows seven months later (March 2009), the cash-heavy approach would have declined only by 17%, compared to 27% for the AVS Risk Level 3 allocation. However, after this point, both began to recover and reached breakeven in 20 and 13 months respectively. Thus, the AVS Risk Level 3 allocation recovered much faster than the cash-heavy allocation. Ten years later, the cash-heavy allocation would have returned only 21%, compared to 50% for the AVS Risk Level 3 allocation.

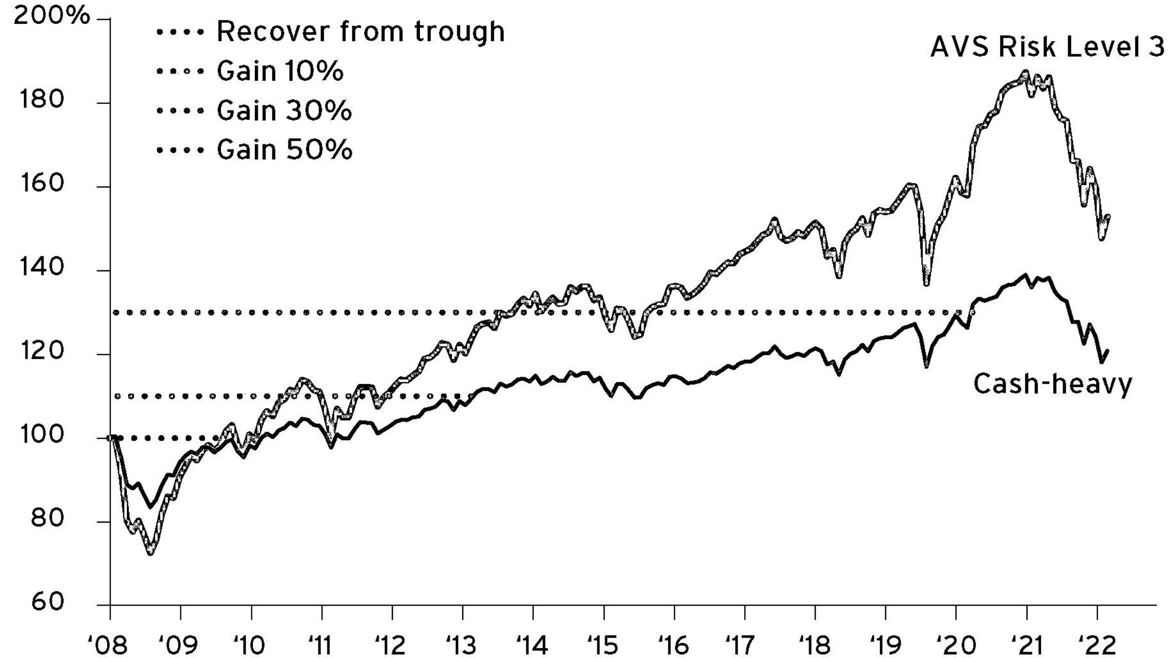
WHAT TO DO NOW?

Forecast 10-year returns have risen across all asset classes, albeit in some cases more than others. Nevertheless, many investors are sitting on excess cash, whose outlook has also improved from very low to modest levels. Our Investment Philosophy suggests this will prove an expensive mistake over time. We advocate fully invested, globally diversified portfolios for the long term, aligned to an appropriate strategic asset allocation.

Is your portfolio following a customized long-term plan?

FIGURE 3. GLOBAL MULTI–ASSET DIVERSIFICATION VS CASH–HEAVY ALLOCATION AFTER THE GLOBAL FINANCIAL CRISIS

CUMULATIVE RETURN AFTER GFC 2008



Source: Citi Global Wealth Investments Global Asset Allocation team, as of 31 Oct 2022.

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