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A LOOK INTO THE CROSS-SECTION OF INDUSTRY STOCK RETURNS

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ABSTRACT

Average stock returns on industry portfolios are related to industry total market equity and industry market equity concentration. Small industries outperform large industries marginally, while high-concentration industries outperform low-concentration industries significantly. The industry concentration premium persists after controlling for firm size and book-to-market equity ratio. A three-factor model using risk factors associated to industry size and industry concentration compares well to the Fama-French three-factor model, capturing return variation of portfolios formed on industry size, concentration, book-to-market equity, debt-to-equity, dividend-to-price, and earnings-to-price. My results are consistent with traditional economic theory and industry strategic analysis.

Key words: Industry size; Industry concentration; Risk premium; Three-factor model

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INTRODUCTION

Different industries generate different returns. Although every industry is unique for the value of the goods or services it produces and for its manufacturing characteristics, the overall profitability of each industry results from a systematic interplay between the sources of competitive pressure: customers, suppliers, and competing firms. Moreover, industries evolve continuously over time, not only in terms of competitive structure but also in size, driven by economic growth, consumer preferences shifts, and technological advances. The size and competition of an industry are thus key factors behind strategic decisions of individual firms, affecting revenues, costs, and cash flows, and ultimately influencing growth prospects and potential profitability of the industry as a whole.

The purpose of this Work Project is to explore the relationship between the average stock returns of industry portfolios, and both industry size and industry concentration, using equity market data to estimate the two industrial structure dimensions. My main findings are that high-concentration industries outperform low-concentration industries by 2.40% per year, whereas there is only a marginal albeit positive difference of 0.34% between the average stock returns of small industries and that of large industries. The premium associated to industry concentration persists even after controlling for Fama-French size and value risk factors, while the industry size premium does not.

I propose a three-factor model (1) to explain the expected excess returns $E(R_i - R_f)$ on an industry portfolio i against a risk-free rate R_f, using the excess return on the market portfolio $(R_m - R_f)$ with two industry risk premia: the difference between the returns on small industries and the returns on large industries (Small minus Large, or SML), and the difference between the returns on high-concentration industries and the returns on low-concentration industries (Concentrated minus Dispersed, or CMD).

$$E(R_i - R_f) = \beta_i \, E(R_m - R_f) + m_i \, E(SML) + c_i \, E(CMD) \qquad (1)$$

The slope coefficients β_i, m_i, and c_i are the factor loadings to the expected market risk premium, the expected industry size risk premium, and the expected industry concentration risk premium, respectively. In its ex-post format, the Industry Risk Factor Model (IRFM) has an intercept coefficient α_i, which is the abnormal average return that is not captured by the model, and e_i as an error term, in the time-series regression

$$R_i - R_f = \alpha_i + \beta_i \, (R_m - R_f) + m_i \, SML + c_i \, CMD + e_i \qquad (2)$$

I find that the IRFM compares well against Fama-French (1996) three-factor model in the explanation of excess returns on portfolios sorted on the basis of industry size and industry concentration, with statistically insignificant intercepts and adjusted R^2 above 80% across portfolios. Finally, I find that the IRFM also captures a similar amount of variability of excess returns on portfolios formed on book-to-market equity, debt-equity, dividend-to-price, and earnings-to-price ratios, at the industry level. Industries with high B/M, high D/E, low D/P, or low E/P averages are more sensitive to the industry size risk factor, while industries with high average values for B/M, D/E, D/P, or E/P display the higher loadings to the risk factor associated with industry concentration.

MOTIVATION

Between the extremes of monopoly and perfect competition, market imperfections are the main determinants of industry performance. On standard supply and demand models under long-run equilibrium, a monopolist firm has the power to set higher prices than firms in perfectly competitive markets, as the latter are price takers. Consequently, monopolists are able to obtain higher economic profits, in contrast to purely competitive markets where economic profits tend to zero in the long-run (Cabral (2000)).

However, the vast majority of markets (or industries) differ from either monopoly or pure competition classifications. For instance, there are Bertrand or Cournot duopolies, monopolistic competition, among a variety of oligopolistic scenarios. Thus, in addition to demand elasticity and productive technology, the number and competitive behavior of firms drive their market power: the extent to which firms are able to set and maintain prices above cost. The Structure-Conduct-Performance paradigm (SCPP) developed by Chamberlin (1933) and Bain (1954) states a causal and positive link between market concentration (structure), firm behavior (conduct), and market power (performance). Concentration refers to the size distribution of firms within a market: low concentration is a characteristic of industries with many firms that are similar in size, while industries with a small number of relatively large firms are highly concentrated.

Schumpeter (1911, 1942) adds innovation to the analysis of industrial organization, arguing that technological advances and market power are interconnected: it is under the existence of market imperfections that firms have enough incentive to innovate, because only then they can sustain the abnormal profits from product and process innovations. As such, Schumpeter advocates that the dynamic creative destruction process resulting from market imperfections is the ultimate disruptive force beneath economic progress.

Porter (1980) also establishes a simple but powerful qualitative relationship between industry structure and potential industry profitability that is deeply rooted to the field of industrial organization. He argues that there are five sources of competitive pressure: the bargaining power of buyers and suppliers, the threats of substitute products and new entrants, and the rivalry intensity – the Five Forces framework (5F). Still, the stage of development of an industry is an important element as well (Grant (2008)). The Industry Life Cycle (ILC) consists of four stages: introduction, growth, maturity, and decline.

The intersection of the 5F and ILC models states that price competition is intense if the 5F are strong, and if the industry is on the later stages of the ILC. As a consequence, industry size typically decreases from maturity to decline. Contrarily, price competition is less intense if the 5F are lax, and if the industry is on the earlier stages of the ILC: the competitive focus is in product development and advertising. Likewise, industry size increases from the introduction to the growth stage. The bottom-line is that competition erodes profitability, whereas the link between profits and industry size is ambivalent.

Despite extensive theoretical foundations, Schmalensee (1989) finds that empirical evidence point to a weak relationship between structure (measured as the concentration of sales) and performance (measured as returns on capital, on sales, on assets, on equity, and stock returns). He suggests the possibility of a reverse causal relationship between variables and the lack of data on actual price-cost margins as limitations of the results.

Hou and Robinson (2006) use sales concentration as a proxy for entry barriers and show evidence that concentrated industries earn lower stock returns. They derive a risk-based interpretation in line with the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965): the cash flows of firms operating in concentrated industries are less risky, because firms have lower distress risk or lower innovation risk, having thus lower expected returns. They find that the lower returns of concentrated industries persist after controlling for the Fama-French (1996) firm size and value risk factors.

I argue that, under the Efficient Market Hypothesis of Fama (1965), equity market prices should reflect not only entry barriers but also price-cost margins more robustly than sales. The usage of equity market data rather than accounting data also prevents forward-looking bias. Finally, I argue that the link between industry concentration and industry size must also be included in the analysis of the cross-section of stock returns.

METHODOLOGY

A. Data Sample

My sample includes all securities listed in NYSE, AMEX and NASDAQ that are included in the intersection between the CRSP Monthly Stock File, the COMPUSTAT Fundamentals Annual File, and the COMPUSTAT Security Monthly File, from January 1987 to December 2011. Equity market monthly data consisting of prices or bid-ask averages, number of common shares outstanding, and returns including dividends are retrieved from CRSP. Fiscal year fundamental data including book value per share, market price, dividends per share, common shares outstanding, preferred dividends, net income, and long-term debt are gathered from COMPUSTAT Fundamentals. Historical Standard Industry Classification (SIC) codes are from COMPUSTAT Security File.

The three datasets are merged using the unique 8-digit CUSIP firm identification code, which is provided by both CRSP and COMPUSTAT Files. In order to be included in the sample, each firm is required to have a price or a bid-ask average and a number of shares outstanding, in month t and $t-1$ simultaneously, and a historical SIC code in month t. Since my main result is derived from equity market data alone, there are no restrictions for firm fundamental data, although the possibility of forward-looking bias induced by the use of accounting information is prevented in further tests.

Monthly returns including dividends on a value-weighted portfolio comprising the NYSE, AMEX and NASDAQ are also retrieved from CRSP Monthly Stock File, from January 1987 to December 2011. Finally, monthly returns on mimicking portfolios for Fama and French (1996) size and value risk factors – Small minus Big (SMB) and High minus Low (HML), respectively – and on the one-month Treasury bill rate are obtained from the Fama-French Portfolios datasets, for the same time period.

B. Industry Definition and Classification

An industry is defined as a large-scale business activity, comprising firms engaged in the production of a good or a service. Depending on the scope of the analysis, industries can have a narrow range as in railroad operators, trucking services, water transporters, and air couriers, or a broader span that aggregates the former industries into a single transportation industry. The circumscription of firms within certain boundaries is a key step for measuring both industry size and industry concentration. In order to properly control for industry membership and obtain meaningful results, I pursue a principle of substitutability from the demand side: industries producing goods or services that are not perceived as substitutes by costumers should be segregated. This principle avoids, for instance, the grouping of frozen desserts and processed meat products in a large food industry, although they may be taken as substitutes by suppliers: the manufacturing plants and the distribution channels to produce and market them are similar enough.

Bhjoraj, Lee and Oler (2003) compare the four most used industry classification schemes in equity data research: the Standard Industrial Classification (SIC); the North American Industry Classification System (NAICS) that will replace the SIC; the Global Industry Classification Standard (GICS); and an alternative developed by Fama and French (1997) using the SIC at a 2-digit level (FF). They show evidence that GICS are significantly better at explaining the cross-sectional variance of industry stock returns, whereas SIC, NAICS and FF do not differ much from each other: while GICS uses a scheme based on business activity that is designed specifically for financial research, SIC and NAICS are maintained by governmental agencies to gather industrial statistics, and are grounded on manufacturing technology differences instead. Likewise, GICS should be better aligned with the principle of substitutability among different industries.

However, due to its shorter existence compared to the SIC, historical information regarding GICS is sparser both in time and firm coverage. In unreported tables, I find that from the intersection of CRSP and COMPUSTAT datasets described initially, an average of 18.4% of the listed securities have a historical GICS code, while SIC covers an average of 68.6% of the same firms, from January 1987 to December 2011. Previous to 1987, historical SIC coverage is virtually non-existent in COMPUSTAT Files. This implies that the definition of industries using historical GICS would lack completeness, affecting the robustness of the results. On the other hand, I favor the usage of SIC over NAICS for its simplicity and wider adoption of its classification scheme, despite almost 80% of the listed firms being covered by historical NAICS codes: the SIC scheme has a constant 4-digit classification that comprises around 440 industry denominations, while the NAICS varies between 2 and 6-digits for over 2200 industry denominations. This difference makes the uniform treatment of industries easier under the SIC scheme.

For the principle of substitutability, I establish industry boundaries using 3-digit SIC classifications. The choice between 1-digit (broad industrial groups) to 4-digit (narrow industry divisions) poses a trade-off between the industry specificity and the number of firms that is included: tightening the industry boundaries increases the meaningfulness of the industrial concentration and size measurements, but too few firms may also create statistical unreliableness. Nonetheless, it is the substitutability that matters: for instance, due to its manufacturing focus, 2-digit SIC codes enclose Agricultural Chemicals (SIC 2870) and Soap, Detergents, Cleaning Preparations, Perfumes, Cosmetics (SIC 2840) in the same industry, but the 4-digit level questionably breaks the latter from Perfumes, Cosmetics & Other Toilet Preparations (SIC 2844). Therefore, I find that 3-digit SIC codes provide a robust middle-ground for industrial classification.

C. Industry Size and Industry Concentration Measurement

Firstly, I measure industry size M_i as the sum of the market capitalization m_{ki} of all n firms included in industry i, corresponding to a given 3-digit SIC classification,

$$M_i = \sum_{k=1}^{n} m_{ki} \tag{3}$$

and where the market capitalization of firm k is the product of its number of common shares outstanding and its closing stock price, from the last trading date of a month.

Moreover, I measure industry concentration H_i with the Herfindahl-Hirschman Index (HHI), defined as the sum of the squared market shares s_{ki} of all n firms in industry i,

$$H_i = \sum_{k=1}^{n} (s_{ki})^2 = \sum_{k=1}^{n} \left(\frac{m_{ki}}{M_i}\right)^2 \tag{4}$$

where the market share of firm k refers to its market capitalization m_{ki} divided by the total market capitalization of the industry M_i, as above. The HHI takes values between zero (minimum concentration or perfect competition) and one (maximum concentration or monopoly). An alternative to the HHI is the Concentration Ratio (CR), which is the sum of the market shares of the largest q firms, with q being a positive integer, typically four or eight. Cabral (2000) argues that the HHI is a better measure of concentration as it always gives more weight to larger firms, producing a picture of how market shares are distributed that is particularly useful to distinguish industries with few firms.

Weaknesses of relying on equity market data from the NYSE, AMEX and NASDAQ to estimate industrial size and concentration are caused by the presence of private firms, public foreign firms that are only listed in their domestic stock exchange, importers and exporters, and conglomerates or highly diversified firms, with the latter issue being a common pitfall affecting current industry classification schemes.

D. Industry Portfolio Characteristics

Industry portfolios corresponding to each 3-digit SIC code include every firm that is listed under the same 3-digit SIC code, for a given month. These portfolios are value-weighted to better proxy the equity market returns of an industry as a whole, and they are automatically rebalanced on a monthly basis. Firms becoming listed in the NYSE, AMEX or NASDAQ are included in the portfolio returns in the following month. The implications of a delisting bias in CRSP Stock Files described by Shumway (1997) are also minimized by the usage of value-weighted portfolios and a buy-and-hold method, although the robustness of the empirical results may remain susceptible to this effect.

EMPIRICAL RESULTS

A. Industry Size, Industry Concentration and Average Stock Returns

For the simultaneous cross-section analysis of the average stock returns in terms of industry size and concentration, I rank and group industries into six portfolios based on their market capitalization M_i and concentration H_i. In January of year t, industries are sorted in two Size groups – Large (L) or Small (S) – depending on whether their market capitalization M_i of December of year $t-1$ is respectively above or below the median industry market capitalization. In January of year t, industries are also sorted in three Concentration groups – Concentrated (C), Medium (M), or Dispersed (D) – depending on their concentration H_i of December of year $t-1$. The Concentrated group includes the industries in the top 20 percent of the values for H_i, the Medium group includes the industries in the middle 60 percent, and the Dispersed group includes the industries in the bottom 20 percent. Industries corresponding to a 3-digit SIC code that contains zero firms in December of $t-1$ are not included in the ranking and grouping process.

I build six Size-Concentration portfolios using the intersection of the two Size groups with the three Concentration groups: Large and Concentrated (L/C), Large and Medium (L/M), Large and Dispersed (L/D), Small and Concentrated (S/C), Small and Medium (S/M), and Small and Dispersed (S/D). In order to avoid over-weighting few industries into the results, the returns on the six Size-Concentration portfolios are equal-weighted averages of the returns on the industry portfolios that compose them. The simultaneous industry grouping in terms of size and concentration, as well as weighing industries equally in each portfolio, produces a useful degree of orthogonality for both the average industry size and the average industry concentration, which allows a reasonable ceteris paribus comparison between the six Size-Concentration portfolios.

Panel A of Table 1 reports the annualized averages and standard deviations of the returns on the Size-Concentration portfolios in excess of the one-month Treasury bill rate, as well as the average number of industries, number of firms, industry size, and industry concentration, for the six portfolios. The panel shows that high-concentration industries tend to have higher average returns than low-concentration industries, with this result being more prominent in small industries: annual returns decline from 9.84% per year in S/C to 5.60% in S/D, while the difference between L/C and L/D is slightly above 0.50%. It is not clear whether a relationship between industry size and average returns exists, beyond small industries having higher standard deviations of returns than large industries – a pattern that seems to be separate from industry concentration.

Moreover, I find that most of the listed firms included in the sample operate in L/M, L/D or S/M industries: more than 4600 firms from a total of around 5000, on average. Nevertheless, there are close to as many S/C industries as there are L/D industries, with L/C and S/D forming the fringes in terms on number of industries.

Panel B and Panel C of Table 1 show time-series regression estimates of the CAPM and Fama-French three-factor model (FF), respectively, including slopes and intercepts, their t-statistics, and the R^2 adjusted for degrees of freedom, for the excess returns on the six Size-Concentration portfolios. The OLS results for the CAPM indicate that the slope coefficient $\hat{\beta}_i$ for the excess return on the market portfolio is highly significant in the six regressions, with t-statistics always above 20 standard errors. Moreover, none of the intercept coefficients $\hat{\alpha}_i$ are statistically significant, despite S/C industries carrying an average abnormal monthly return of 0.30%, or 3.53% in annualized terms. However, the R^2 of the regressions vary between 59.1% for S/C portfolio and 92.4% for the L/D portfolio: there is much variation, particularly in the excess returns on the portfolios of Small industries and of Concentrated industries, that is not captured by the CAPM.

On the other hand, the FF improves the significance of the slope coefficient $\hat{\beta}_i$ for the excess return on the market portfolio, and the magnitude of the adjusted coefficients of determination R^2, the latter with figures above 77.4%. The OLS results for the FF show that the slope coefficients $\hat{s}_i$ and $\hat{h}_i$ for Fama-French size and value risk factors, respectively, are positive and statistically significant for five of the Size-Concentration portfolios, the exception being L/C industries for which $\hat{s}_i$ is statistically insignificant: it has a t-statistic of -0.90. Furthermore, the slope coefficients $\hat{s}_i$ and $\hat{h}_i$ are higher for the three Small industry portfolios, while there is no discernible difference between the same slope coefficients across the Concentration groups. The intercept coefficients $\hat{\alpha}_i$ for the FF remain statistically insignificant, but only marginally for S/M and S/D: with t-statistics of -1.86 and -1.92, the hypotheses that the intercepts are different from zero are rejected by two-sided tests at 90% confidence. On average, the S/M portfolio has an abnormal return of -2.43%, and S/D has -2.93%, both in annualized terms.

B. Industry Size and Industry Concentration Risk Factors

Using the six Size-Concentration portfolios, I build one mimicking portfolio for the industry size risk factor (SML, or Small minus Large) and one mimicking portfolio for the industry concentration risk factor (CMD, or Concentrated minus Dispersed). SML is the monthly difference between the average of the returns on the three Small industries portfolios (S/C, S/M, S/D) and the average of the returns on the three Large industries portfolios (L/C, L/M, L/D); CMD is the monthly difference between the average of the returns on the two Concentrated industries portfolios (L/C, S/C) and the average of the returns on the two Dispersed industries portfolios (L/D, S/D). I use SML and CMD, with the excess return on the market portfolio $(R_m - R_f)$, as explanatory variables of the excess return on a portfolio $(R_i - R_f)$, in an ex-post three-factor model analogous to FF

$$R_i - R_f = \alpha_i + \beta_i \left(R_m - R_f\right) + m_i \, SML + c_i \, CMD + e_i \qquad (5)$$

where the factor loadings β_i, m_i, and c_i are the slope coefficients, the abnormal return α_i is the intercept coefficient, and e_i is an error term, in the time-series regression.

Panel D of Table 1 shows estimates of the Industry Risk Factor Model (IRFM) from (5) applied to the Size-Concentration portfolios. The adjusted R^2 of the IRFM compare well against the FF, capturing between 81.2% and 96.1% of the variation of the excess returns. The reported estimates indicate a negative relationship between industry-size factor loadings $\hat{m}_i$ and average industry size, whereas there is a positive relationship between industry-concentration factor loadings $\hat{c}_i$ and average industry concentration. The two slope coefficients $\hat{m}_i$ and $\hat{c}_i$ are statistically significant in the six portfolios, at 90% confidence. I find that the slope coefficients $\hat{\beta}_i$ are similar across the two models, but the estimated $\hat{\alpha}_i$ are statistically insignificant in the IRFM: the six portfolios do not display abnormal average returns when controlling for industry size and concentration.

Panel A of Table 2 presents descriptive statistics of the industry risk factors SML and CMD, and of the Fama-French risk factors SMB and HML, for the entire sample period (1987-2011) and for two sub-periods (1987-1999 and 2000-2011). The figures include annualized averages and t-statistics for the monthly returns on each risk factor. SML has an almost zero annualized average return (0.34%) for the entire sample, that varies from -3.82% in the first sub-period to 4.84% in the second. Consequently, it has no statistical significance for the entire sample. CMD displays a total average of 2.40% per year that is more stable through time (3.19% from 1987 to 1999, and 1.55% from 2000 to 2011), and has a t-statistic of 1.77, being statistically significant at a 90% level of confidence. On the other hand, SMB and HML generate 1.68% and 2.77% per year, respectively, but they are both statistically insignificant at 90% confidence.

Panel B of Table 2 shows time-series regression estimates of FF on the two industry risk factors. I find that the slope coefficients $\hat{s}_i$ and $\hat{h}_i$ are statistically significant for both regressions, with the two factor loadings being positive in the regression on SML, whereas $\hat{s}_i$ is negative in the regression on CMD. The relationship between SML and SMB is particularly strong: $\hat{s}_i$ of 0.556 and a t-statistic of 18.57. Contrarily, the slope coefficient $\hat{\beta}_i$ is insignificant for SML and CMD. With a t-statistic of 2.01, the estimated intercept $\hat{\alpha}_i$ of 2.47% per year for CMD is also statistically significant: after controlling for size and value, there is still a premium associated to concentration. Moreover, 55.2% of the variation of SML is captured by FF, against 21.1% of the variation of CMD.

Furthermore, Panel C of Table 2 shows time-series regression estimates of the IRFM on the two Fama-French risk factors, SMB and HML. I find that, after controlling for industry size and industry concentration, the size and value risk factors do not display any abnormal returns: the two estimated intercepts $\hat{\alpha}_i$ are statistically insignificant.

C. Industry Size and Average Industry Stock Returns

For the cross-section analysis of the average stock returns in terms of industry size, I rank and group industries into deciles in January of year t, based on their total market capitalization M_j of December of year $t-1$. The returns on the ten decile portfolios are equal-weighted averages of the included industry portfolio returns. Panel A of Table 3 shows the annualized averages and standard deviations of returns on decile portfolios, in excess of the one-month Treasury bill rate. I find that the lower industry size deciles tend to have higher average excess returns and standard deviations than the higher size deciles: a result that is intuitively close to the relationship between firm size and returns. Annual averages and standard deviations of excess returns increase from 7.03% and 16.37% in the top decile to 10.95% and 22.11% in the bottom decile.

Panel B and Panel C of Table 3 show time-series regression estimates of the FF and IRFM, respectively. The slope coefficients $\hat{s}_i$ and $\hat{h}_i$ indicate a cross-sectional negative relationship between industry size and both size and value factor loadings. The largest unexplained excess return belongs to the lowest industry size decile: 61.98%. Overall, the average adjusted R^2 is 85.49%. The IRFM slope coefficients $\hat{m}_i$ and $\hat{c}_i$ display a similar negative relationship between industry size and the factor loadings associated to industry size and industry concentration. The IRFM improves the adjusted R^2 of the lowest industry size decile to 86.54%, with the average adjusted R^2 for the deciles being marginally above that of FF, at 85.95%. Despite one of the deciles having a negative and statistically significant abnormal monthly return of -0.42%, the FF regressions produce an average estimated intercept of -0.092% per month, which is reasonably close to zero. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant in the IRFM regressions, and the average intercept coefficient is 0.000% per month.

D. Industry Concentration and Average Industry Stock Returns

For a similar cross-section analysis of the average stock returns in terms of industry concentration, I rank and group industries into deciles in January of year t, based on their industry concentration H_j of December of year $t-1$. The returns on the ten decile portfolios are equal-weighted averages of the included industry portfolio returns. Panel A of Table 4 reports the annualized averages and standard deviations of returns on decile portfolios, in excess of the one-month Treasury bill rate. I find that the higher industry concentration deciles tend to have higher average excess returns than the lower concentration deciles. Annual averages of excess returns decline from 9.98% in the top decile to 6.97% in the bottom decile. I find no discernible cross-sectional pattern linking industry concentration to the standard deviation of excess returns.

Panel B and Panel C of Table 4 show time-series regression estimates of the FF and IRFM, respectively. The slope coefficients $\hat{s}_i$ and $\hat{h}_i$ indicate a cross-sectional positive relationship between industry concentration and both size and value factor loadings. The largest unexplained excess return belongs to the highest industry concentration decile: 69.33%. Overall, the average adjusted R^2 is 85.88%. The IRFM slope coefficients $\widehat{m}_i$ and $\hat{c}_i$ also suggest a positive relationship between industry concentration and the factor loadings associated to industry size and industry concentration. The IRFM improves the adjusted R^2 of the top industry concentration decile to 90.62%, and the average adjusted R^2 for the deciles is marginally above that of FF, at 86.20%. FF regressions produce an average estimated intercept of -0.091% per month, which is reasonably close to zero, although there is another decile with a negative and statistically significant abnormal monthly return. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant in the IRFM regressions, and the average intercept coefficient is 0.001% per month.

E. Industry Risk Factors and Industry Book-to-Market Equity (B/M)

I compute industry book value as the sum of the book value of the equity of all firms included in an industry corresponding to a given 3-digit SIC classification. Industry market value is the sum of the market capitalization of all firms included in the same industry, using the number of shares outstanding and closing stock prices of the fiscal year. Thus, industry B/M is industry book value divided by industry market value. For the analysis of the interaction between industry B/M and the industry risk factors SML and CMD, I rank and group industries into quintiles in January of year $t+1$, based on their B/M for fiscal year $t-1$. The lag between the fiscal year data and stock returns ensures that equity market prices incorporate past accounting information. The returns on B/M portfolios are equal-weighted averages of the industry portfolio returns.

Panel A of Table 5 shows a positive relation between industry B/E and annualized average and standard deviation of excess returns: a result that is intuitively close to the relationship between firm book-to-market and returns. Industries in the top quintile produce an average of 9.80% per year with 19.66% standard deviation, while industries in the bottom quintile produce an average of 7.21% with 16.32% standard deviation.

Panel B of Table 5 reports time-series regression estimates of the IRFM on the B/E quintile portfolios. The OLS slope coefficients $\hat{m}_i$ and $\hat{c}_i$ are statistically significant in the five regressions, and they indicate a cross-sectional positive relationship between industry B/E and industry size and industry concentration factor loadings: $\hat{m}_i$ and $\hat{c}_i$ decline, respectively, from 0.997 and 0.526 in the top quintile to 0.437 and 0.199 in the bottom quintile. Moreover, the IRFM explains between 83.76% and 89.08% of the variation of B/E quintile excess returns. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant, and the average intercept coefficient is -0.038% per month.

F. Industry Risk Factors and Industry Debt-to-Equity (D/E)

I compute industry debt as the sum of the long-term debt of all firms included in an industry corresponding to a given 3-digit SIC classification. Industry equity is the sum of the market capitalization of all firms included in the same industry, as previously. Thus, industry D/E is industry debt divided by industry equity. For the analysis of the interaction between industry D/E and the industry risk factors SML and CMD, I rank and group industries into deciles in January of year $t+1$, based on their D/E for fiscal year $t-1$. The lag between the fiscal year data and stock returns ensures that equity market prices incorporate past accounting information. The returns on D/E portfolios are equal-weighted averages of the industry portfolio returns.

Panel A of Table 5 shows a U-shaped pattern between industry D/E and annualized average excess returns, and a positive relation between that financial ratio and standard deviation. Industries in the top and bottom quintile produce an average of 8.20% and 8.98% per year, while the middle quintile has an average excess return of 6.85%. On the other hand, the standard deviation of excess returns declines from 20.11% in the top D/E quintile to 17.10% in the bottom quintile.

Panel B of Table 5 reports time-series regression estimates of the IRFM on the D/E quintile portfolios. The OLS slope coefficients $\hat{m}_i$ and $\hat{c}_i$ are statistically significant in the five regressions, and they indicate a cross-sectional positive relationship between industry D/E and industry size and industry concentration factor loadings: $\hat{m}_i$ and $\hat{c}_i$ decline, respectively, from 0.965 and 0.461 in the top quintile to 0.507 and 0.166 in the bottom quintile. Moreover, the IRFM explains between 83.73% and 89.87% of the variation of D/E quintile excess returns. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant, and the average intercept coefficient is -0.037% per month.

G. Industry Risk Factors and Industry Dividend-to-Price (D/P)

I compute industry dividends as the sum of the difference between total dividends and preferred dividends paid by all firms included in an industry corresponding to a given 3-digit SIC classification. Industry price (market value) is obtained as previously. Thus, industry D/P is industry dividends divided by industry market value. For the analysis of the interaction between industry D/P and the industry risk factors SML and CMD, I rank and group industries into deciles in January of year $t+1$, based on their D/P for fiscal year $t-1$. The lag between the fiscal year data and stock returns ensures that equity market prices incorporate past accounting information. The returns on D/P portfolios are equal-weighted averages of the industry portfolio returns.

Panel A of Table 6 shows a U-shaped pattern between industry D/P and annualized average excess returns, and a negative relation between that financial ratio and standard deviation. Industries in the top and bottom quintile produce an average of 8.40% and 8.70% per year, while the second quintile has an average of 6.93%. Standard deviations of excess returns increase from 16.23% in the top to 21.41% in the bottom quintile.

Panel B of Table 6 reports time-series regression estimates of the IRFM on the D/P quintile portfolios. The OLS slope coefficients $\widehat{m}_i$ and $\hat{c}_i$ are statistically significant in the five regressions, and they display a similar cross-sectional U-shaped pattern with industry D/P, as that of excess returns. The relationship between SML and the bottom D/P quintile is particularly strong though: $\widehat{m}_i$ of 1.228 and a t-statistic of 27.42. On the other hand, the highest factor loading for CMD is for the top quintile portfolio: 0.421. Moreover, the IRFM explains between 81.04% and 91.95% of the variation of D/P quintile excess returns. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant, and the average intercept coefficient is -0.037% per month.

H. Industry Risk Factors and Industry Earnings-to-Price (E/P)

I compute industry earnings as the sum of the difference between the net income and preferred dividends paid by all firms included in an industry corresponding to a given 3-digit SIC classification. Industry price (market value) is obtained as previously. Thus, industry E/P is industry earnings divided by industry market value. For the analysis of the interaction between industry E/P and the industry risk factors SML and CMD, I rank and group industries into deciles in January of year $t+1$, based on their E/P for fiscal year $t-1$. The lag between the fiscal year data and stock returns ensures that equity market prices incorporate past accounting information. The returns on E/P portfolios are equal-weighted averages of the industry portfolio returns.

Panel A of Table 6 shows a U-shaped relationship between industry E/P and both annualized average excess returns and standard deviation. The annual average of 8.62% (18.78% standard deviation) in the top E/P quintile declines to 7.35% per year (16.44% standard deviation) in the middle quintile, while industries in the bottom quintile have an average of 8.44% with a 20.55% standard deviation.

Panel B of Table 6 reports time-series regression estimates of the IRFM on the E/P quintile portfolios. The OLS slope coefficients $\widehat{m}_i$ and $\hat{c}_i$ are statistically significant in the five regressions, and they display a similar cross-sectional U-shaped pattern with industry E/P, as that of excess returns. The relationship between SML and the bottom quintile is again particularly strong: $\widehat{m}_i$ of 1.103 and a t-statistic of 23.18. On the other hand, the highest factor loading for CMD is for the top E/P quintile: 0.467. Moreover, the IRFM explains between 82.50% and 90.13% of the variation of E/P quintile excess returns. I find that none of the estimated intercepts $\hat{\alpha}_i$ are statistically significant, and the average intercept coefficient is -0.037% per month.

CONCLUSION

Different industries generate different returns. Using market equity data to estimate industry size and industry concentration, I find evidence that the average stock returns on high-concentration industries are higher than those on low-concentration industries, whereas the average stock returns on small industries do not differ significantly from those on large industries. The impact of industry concentration is more pronounced in the smaller industries. My results are not without weaknesses, namely issues with the industry classification system and the delisting bias in stock return data. Nonetheless, the evidence is in line with traditional economic theory and industry strategic analysis.

I use this finding to build two industry risk factors associated to industry size and industry concentration, which are included in a novel three-factor model for returns on industry portfolios: the Industry Risk Factor Model. The IRFM compares well to the Fama-French three-factor model in the explanation of returns on portfolios formed on industry size and industry concentration. Finally, I show that the IRFM is a robust model for the returns on portfolios sorted on industry book-to-market equity, debt-to-equity, dividend-to-price, and earnings-to-price, suggesting that industry size and industry concentration can also be taken as sources of variance in stock returns.

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TABLES AND FIGURES

Table 1: Six Industry Size-Concentration Portfolios (87/01 – 11/12)

Industry Size	Large			Small		
Industry Concentration	Concentrated	Medium	Dispersed	Concentrated	Medium	Dispersed
Legend	L/C	L/M	L/D	S/C	S/M	S/D

Panel A – Descriptive Statistics							
	L/C	L/M	L/D	S/C	S/M	S/D	Sum
Annualized Mean Excess Return	7.50%	7.24%	6.94%	9.84%	7.24%	5.60%	
Annualized Standard Deviation	17.07%	17.47%	17.98%	20.76%	20.23%	19.66%	
Average Number of Industries	13	78	43	40	81	11	266
Average Number of Firms	90	1329	2805	85	523	171	5003
Mean M_i (in Million $)	25649	44013	124523	1167	2731	4413	
Mean H_i	0.841	0.379	0.126	0.893	0.421	0.166	

Panel B – Capital Asset Pricing Model: $R_i - R_f = \alpha_i + \beta_i\,(R_m - R_f) + e_i$							
	L/C	L/M	L/D	S/C	S/M	S/D	Average
α_i	0.139%	0.065%	0.009%	0.295%	0.030%	-0.077%	0.077%
t-statistic	0.963	0.623	0.103	1.320	0.173	-0.428	
β_i	0.912	1.010	1.069	0.987	1.076	1.021	
t-statistic	29.57	45.29	60.26	20.73	29.05	26.63	
Adjusted R^2	74.59%	87.32%	92.42%	59.06%	73.90%	70.41%	76.28%

Table 1: Six Industry Size-Concentration Portfolios (87/01 – 11/12) (cont.)

Panel C – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\ SMB + h_i\ HML + e_i$

	L/C	L/M	L/D	S/C	S/M	S/D	Average
α_i	0.045%	-0.043%	-0.084%	0.038%	-0.203%	-0.244%	-0.082%
t-statistic	0.331	-0.472	-1.358	0.228	-1.864	-1.923	
β_i	0.973	1.055	1.068	0.993	1.080	0.976	
t-statistic	32.111	52.088	76.835	26.464	44.337	34.314	
s_i	-0.039	0.077	0.262	0.672	0.617	0.678	
t-statistic	-0.901	2.680	13.275	12.589	17.796	16.770	
h_i	0.292	0.317	0.246	0.688	0.624	0.416	
t-statistic	6.376	10.359	11.747	12.136	16.966	9.701	
Adjusted R^2	78.16%	90.69%	95.86%	77.36%	89.95%	85.51%	86.26%

Panel D – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\ SML + c_i\ CMD + e_i$

	L/C	L/M	L/D	S/C	S/M	S/D	Average
α_i	-0.012%	0.001%	0.022%	0.037%	-0.029%	0.002%	0.004%
t-statistic	-0.098	0.008	0.295	0.529	-0.234	0.022	
β_i	0.976	1.030	1.055	1.036	1.067	0.957	
t-statistic	35.719	47.113	64.356	68.106	39.963	38.537	
m_i	-0.177	0.138	0.257	1.379	0.894	0.945	
t-statistic	-3.394	3.305	8.211	47.442	17.524	19.909	
c_i	0.612	0.250	-0.067	0.962	0.193	-0.360	
t-statistic	9.394	4.795	-1.702	26.523	3.033	-6.078	
Adjusted R^2	81.24%	88.54%	93.91%	96.07%	87.25%	88.32%	89.22%

Table 2: Industry Risk Factors and Fama-French Risk Factors (87/01 – 11/12)

Panel A – Descriptive Statistics

	Industry Risk Factors		Fama-French Risk Factors	
	SML	CMD	SMB	HML
Annualized Mean Excess Return	0.34%	2.40%	1.68%	2.77%
t-statistic	0.203	1.766	0.727	1.261
Ann. Mean Excess Return (87/01 – 99/12)	-3.82%	3.19%	-1.85%	-0.58%
Ann. Mean Excess Return (00/01 – 11/12)	4.84%	1.55%	5.51%	6.40%

Panel B – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\ SMB + h_i\ HML + e_i$

	SML	CMD	SMB	HML
α_i	-0.109%	0.206%	-	-
t-statistic	-1.159	2.009	-	-
β_i	-0.015	-0.038	-	-
t-statistic	-0.737	-1.679	-	-
s_i	0.556	-0.154	-	-
t-statistic	18.566	-4.713	-	-
h_i	0.291	0.158	-	-
t-statistic	9.167	4.572	-	-
Adjusted R^2	55.17%	21.10%	-	-

Panel C – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\ SML + c_i\ CMD + e_i$

	SML	CMD	SMB	HML
α_i	-	-	0.155%	0.191%
t-statistic	-	-	1.156	1.149
β_i	-	-	0.108	-0.141
t-statistic	-	-	3.704	-3.897
m_i	-	-	0.853	0.239
t-statistic	-	-	15.306	3.456
c_i	-	-	-0.481	0.540
t-statistic	-	-	-6.920	6.268
Adjusted R^2	-	-	53.44%	20.43%

Table 3: Excess Returns on Portfolios sorted on Industry Size (87/01 – 11/12)

Deciles	Large	2	3	4	5	6	7	8	9	Small
Panel A – Descriptive Statistics										
Ann. Mean	7.03%	7.06%	6.90%	6.82%	7.89%	7.70%	7.74%	8.20%	5.05%	10.95%
Ann. St. Dev.	16.37%	16.94%	18.14%	18.37%	19.15%	19.37%	21.25%	21.05%	22.08%	22.11%
Panel B – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\, SMB + h_i\, HML + e_i$										
α_i	0.036%	-0.042%	-0.080%	-0.117%	-0.059%	-0.104%	-0.197%	-0.129%	-0.416%	0.183%
t-statistic	0.822	-0.476	-0.766	-1.107	-0.469	-0.852	-1.551	-0.967	-2.685	0.790
β_i	1.022	1.036	1.065	1.057	1.084	1.090	1.147	1.100	1.060	0.843
t-statistic	103.336	52.216	45.776	44.605	38.674	39.851	40.351	36.840	30.545	16.280
s_i	-0.071	-0.006	0.154	0.270	0.276	0.338	0.564	0.624	0.818	0.853
t-statistic	-5.028	-0.220	4.647	8.017	6.918	8.680	13.937	14.691	16.566	11.578
h_i	0.066	0.345	0.284	0.366	0.435	0.511	0.657	0.600	0.683	0.696
t-statistic	4.410	11.517	8.091	10.236	10.285	12.385	15.316	13.306	13.035	8.905
Adjusted R^2	97.47%	90.50%	88.61%	88.49%	85.16%	86.19%	87.59%	86.05%	82.89%	61.98%
Panel C – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\, SML + c_i\, CMD + e_i$										
α_i	0.034%	0.002%	-0.025%	-0.017%	0.020%	0.011%	-0.032%	0.046%	-0.242%	0.199%
t-statistic	0.744	0.018	-0.220	-0.143	0.145	0.086	-0.227	0.310	-1.593	1.444
β_i	1.009	0.995	1.051	1.040	1.071	1.062	1.127	1.091	1.071	0.903
t-statistic	102.179	44.098	43.164	39.507	35.356	37.144	36.464	33.902	32.476	30.119
m_i	-0.098	0.056	0.175	0.280	0.321	0.575	0.842	0.859	1.224	1.721
t-statistic	-5.186	1.298	3.769	5.571	5.552	10.536	14.266	13.974	19.425	30.050
c_i	0.088	0.274	0.173	0.118	0.291	0.245	0.268	0.161	0.288	0.920
t-statistic	3.761	5.090	2.981	1.875	4.025	3.593	3.635	2.105	3.669	12.877
Adjusted R^2	97.34%	87.00%	86.81%	84.97%	81.69%	84.06%	84.52%	82.90%	83.68%	86.54%

Table 4: Excess Returns on Portfolios sorted on Industry Concentration (87/01 – 11/12)

Deciles	High	2	3	4	5	6	7	8	9	Low
Panel A – Descriptive Statistics										
Ann. Mean	9.98%	8.91%	6.49%	6.99%	8.03%	7.61%	6.70%	7.74%	6.01%	6.97%
Ann. St. Dev.	19.84%	20.31%	19.16%	19.47%	19.52%	18.30%	18.74%	19.08%	19.42%	17.07%
Panel B – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\, SMB + h_i\, HML + e_i$										
α_i	0.130%	-0.047%	-0.197%	-0.167%	-0.079%	-0.065%	-0.146%	-0.076%	-0.215%	-0.050%
t-statistic	0.698	-0.322	-1.518	-1.261	-0.625	-0.614	-1.278	-0.777	-2.346	-0.792
β_i	0.900	1.110	1.078	1.073	1.082	1.022	1.063	1.077	1.098	1.000
t-statistic	21.543	34.023	37.151	36.229	38.414	42.976	41.576	49.055	53.490	70.196
s_i	0.608	0.366	0.281	0.368	0.382	0.386	0.308	0.406	0.413	0.292
t-statistic	10.234	7.882	6.807	8.729	9.535	11.413	8.478	12.981	14.137	14.417
h_i	0.595	0.636	0.537	0.545	0.511	0.437	0.413	0.391	0.318	0.249
t-statistic	9.442	12.913	12.248	12.203	12.019	12.181	10.715	11.802	10.254	11.576
Adjusted R^2	69.33%	82.13%	84.11%	83.98%	85.57%	88.30%	87.12%	90.83%	92.26%	95.18%
Panel C – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\, SML + c_i\, CMD + e_i$										
α_i	0.083%	-0.015%	-0.068%	-0.074%	0.050%	0.067%	-0.066%	0.025%	-0.057%	0.064%
t-statistic	0.805	-0.111	-0.478	-0.528	0.358	0.552	-0.540	0.229	-0.560	0.855
β_i	0.957	1.107	1.034	1.056	1.058	1.004	1.052	1.077	1.083	0.988
t-statistic	42.597	36.647	33.230	34.683	34.891	38.074	39.673	44.880	49.015	60.673
m_i	1.276	0.701	0.518	0.608	0.559	0.502	0.460	0.515	0.479	0.317
t-statistic	29.747	12.149	8.708	10.460	9.654	9.956	9.074	11.220	11.341	10.196
c_i	1.017	0.741	0.218	0.383	0.200	0.092	0.257	0.157	-0.162	-0.092
t-statistic	18.991	10.293	2.945	5.278	2.764	1.467	4.063	2.746	-3.079	-2.375
Adjusted R^2	90.62%	83.81%	80.69%	82.10%	82.33%	84.80%	85.35%	88.42%	90.52%	93.34%

Table 5: Excess Returns on Portfolios sorted on Industry Book-to-Market Equity ratio and on Industry Debt-to-Equity ratio (89/01 – 11/12)

	Industry Book-to-Market Equity					Industry Debt-to-Equity				
Quintiles	High	2	3	4	Low	High	2	3	4	Low
Panel A – Descriptive Statistics										
Ann. Mean	9.80%	7.33%	7.14%	7.90%	7.21%	8.20%	7.50%	6.85%	7.85%	8.98%
Ann. St. Dev.	19.66%	18.90%	18.09%	17.63%	16.32%	20.11%	18.78%	17.52%	17.08%	17.10%
Panel B – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\ SML + c_i\ CMD + e_i$										
α_i	0.028%	-0.142%	-0.059%	-0.003%	-0.012%	-0.104%	-0.099%	-0.112%	0.011%	0.118%
t-statistic	0.196	-1.087	-0.491	-0.030	-0.121	-0.712	-0.728	-0.955	0.095	1.215
β_i	1.020	1.058	1.036	1.032	0.960	1.056	1.048	1.002	0.999	0.999
t-statistic	32.216	36.203	38.721	41.076	44.550	32.408	34.604	38.325	39.428	45.922
m_i	0.997	0.694	0.525	0.444	0.437	0.965	0.651	0.561	0.401	0.507
t-statistic	17.079	12.871	10.629	9.580	10.995	16.048	11.658	11.633	8.575	12.627
c_i	0.526	0.427	0.175	0.236	0.199	0.461	0.355	0.328	0.246	0.166
t-statistic	7.342	6.453	2.889	4.147	4.087	6.246	5.181	5.550	4.291	3.365
Adjusted R^2	83.76%	85.04%	86.30%	87.29%	89.08%	83.55%	83.73%	86.07%	86.22%	89.87%
Panel C – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\ SMB + h_i\ HML + e_i$										
α_i	-0.031%	-0.180%	-0.126%	-0.023%	0.023%	-0.180%	-0.160%	-0.133%	0.000%	0.141%
t-statistic	-0.254	-1.590	-1.198	-0.210	0.225	-1.444	-1.435	-1.225	0.005	1.374
Adjusted R^2	87.75%	88.55%	89.14%	88.09%	87.56%	87.71%	88.69%	87.69%	87.22%	88.53%

Table 6: Excess Returns on Portfolios sorted on Industry Dividend-to-Price ratio and on Industry Earnings-to-Price ratio (89/01 – 11/12)

	Industry Dividend-to-Price					Industry Earnings-to-Price				
Quintiles	High	2	3	4	Low	High	2	3	4	Low
Panel A – Descriptive Statistics										
Ann. Mean	8.40%	6.93%	7.70%	7.75%	8.70%	8.62%	8.37%	7.35%	6.65%	8.44%
Ann. St. Dev.	16.23%	16.76%	17.53%	18.93%	21.41%	18.78%	16.72%	16.44%	18.01%	20.55%
Panel B – Industry Risk Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + m_i\ SML + c_i\ CMD + e_i$										
α_i	0.048%	-0.066%	-0.015%	-0.042%	-0.108%	-0.034%	0.054%	0.001%	-0.126%	-0.081%
t-statistic	0.384	-0.521	-0.124	-0.368	-0.996	-0.240	0.443	0.008	-1.177	-0.701
β_i	0.901	0.959	1.017	1.103	1.128	1.037	0.961	0.962	1.056	1.090
t-statistic	31.901	33.650	38.775	42.928	46.459	33.026	35.018	40.411	44.260	42.249
m_i	0.522	0.393	0.446	0.521	1.228	0.678	0.409	0.398	0.504	1.103
t-statistic	10.023	7.474	9.219	10.998	27.418	11.699	8.077	9.073	11.448	23.177
c_i	0.421	0.327	0.242	0.171	0.404	0.467	0.315	0.208	0.233	0.344
t-statistic	6.585	5.068	4.071	2.933	7.359	6.566	5.068	3.858	4.317	5.884
Adjusted R^2	81.04%	81.92%	85.97%	88.47%	91.95%	82.50%	83.15%	86.88%	89.01%	90.13%
Panel C – Fama-French Three-Factor Model: $R_i - R_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i\ SMB + h_i\ HML + e_i$										
α_i	0.012%	-0.109%	-0.075%	-0.085%	-0.072%	-0.061%	0.025%	-0.025%	-0.153%	-0.119%
t-statistic	0.117	-1.052	-0.773	-0.792	-0.480	-0.491	0.233	-0.246	-1.542	-0.929
Adjusted R^2	88.20%	87.71%	90.33%	89.85%	84.29%	85.99%	86.87%	88.12%	90.34%	87.64%