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A Deeper Look Into Value investing's Future Prospects

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Master In Finance

Supervisor
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BUSINESS SCHOOL

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Dedico esta dissertação aos meus avós, a quem devo tanto, e os quais tanto anseiam por poder dizer que já têm um mestre na família.

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Resumo

Desde a era de ouro da teoria do investimento em valor, muitas coisas mudaram: desde a forma como os indivíduos investem as suas poupanças, até à diversidade de produtos financeiros disponíveis no mercado, desde a estrutura hierárquica e financeira da maioria das empresas até à forma como se fazem negócios, desde a regulamentação que rege as empresas e o mercado, até à economia mundial em geral e, finalmente, como não poderia deixar de ser: a própria filosofia do investimento em valor também tem vindo a sofrer alterações. Apenas uma coisa parece não ter mudado: os critérios de desempenho usados para avaliar esta teoria de investimento.

Nos últimos anos, quando aplicados esses critérios de *performance*, a academia reparou que o investimento em valor apresentava um desempenho medíocre comparativamente àquilo a que tinha habituado o mercado e os investidores. Mas será que estes resultados podem ser cegamente aceites? Quando tudo parece ter mudado, fará sentido esperar resultados válidos, aplicando o mesmo critério a realidades completamente diferentes? É isso o que nos propomos descobrir.

No presente trabalho forneceremos uma *framework* alternativa àquela que tem vindo a ser utilizada pela academia ao longo dos anos. Iremos expor alguns dos motivos que podem motivar esse (aparente) baixo desempenho, e alternativas para superar essas dificuldades. A nossa intenção é clara: avaliar se o investimento em valor realmente perdeu seu *hedge*, ou se, por outro lado, os académicos medem o desempenho desta teoria de investimento com critérios desatualizados e desajustados à realidade atual.

Palavras-chave: Investimento em Valor, Ativos Intangíveis; Investigação e Desenvolvimento; Capitalização de Intangíveis; Dados em Painel

Abstract

Since value investing's golden era, many things have changed: from the way individuals invest their savings, to the diversity of financial products available on the market, from the hierarchical and financial structure of the majority of the firms to the way how business is done, from the regulations that rule firms and the market, to the world economy in general, and finally, of course: the very philosophy behind value investing has also progressively changed. Only one thing does not seem to have changed: the performance criteria used to evaluate this investment theory.

In recent years, when applied these criteria, the academia noticed value investing releveled relatively poor performance compared to what investors and the market were used to. But can these results be blindly trusted? When everything does seem to have changed, does it make sense to expect valid results applying the same criteria to completely different realities? That is what we propose ourselves to find out.

In the present work we will provide an alternative framework to the one used by the academia over the years. We will expose some of the reasons that may motivate this (apparent) underperformance, and alternatives to overcome these difficulties. Our intention is clear: to evaluate if value investing has really lost its hedge, or if on the other hand, academics have just been measuring performance with outdated and unfitted criteria to the current reality.

Keywords: Value Investing, Intangible Assets; Research and Development; Capitalization of Intangibles; Panel Data

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List of abbreviations

PBV – Price-to-Book-Value

PE – Price-Earnings

R&D – Research and development

SG&A – Sales, General and administrative

FASB – Financial Accounting Standards Board

IASB – International Accounting Standards Board

PPE – Property, Plant and Equipment

GAAP – Generally Accepted Accounting Principles

NASDAQ – National Association of Securities Dealers Automatic Quotation System

AR&D – Adjusted R&D

ASG&A – Adjusted SG&A

AL – Adjusted Liabilities

AE – Adjusted Equity

ANS – Adjusted Nº of Shares

ANI – Adjusted Net Income

BVS – Book Value per Share

EPS – Earnings per Share

DPS – Dividends per Share

ADPS – Adjusted DPS

AEPS – 5-year Average EPS

IA – Intangibles to Assets

LA – Liabilities to Assets

EPSAG – 5 Year EPS Average Growth

EPSG – 5 Year EPS Compound Growth

ROA – Return on Assets

ROE – Return on Equity

AVGPE – Average PE

DY – Dividend Yield

Net Income – Net Income Before Extraordinary Items and Preferred Dividends

BLUE – Best Linear Unbiased Estimators

OLS – Ordinary Least Squares

LSDV – Least-Squares Dummy Variable

GLS – Generalized Least-Squares Dummy Variable

F test – Fischer Test

LM –Lagrange Multiplier

NYSE – New York Stock Exchange

CHAPTER 1

Introduction

In recent years, value investing has been questioned with criticism and doubts raised by the academia, including some of the most prominent experts in finance around the globe.

In fact, these academics provide powerful insight in their studies, regarding the reasons that led to this situation. Their approaches may differ in some matters, but their conclusions are unanimous: value investing is either "dead" or it requires a great reinvention, to remain competitive.

Charlie Munger commented that "You are looking for a mispriced gamble. That is what investing is. And you have to know enough to know whether the gamble is mispriced. That is value investing". But so, what has changed since the golden days (or rather, decades) of this approach? Is Investing no longer about seeking for mispriced gambles, or is it no longer enough to make good analyst work in identifying this mismatch between price and value? In our opinion, neither one nor the other.

Since this theory arose, its performance has been evaluated in what we consider an extremely simplistic manner: Value stocks have been being defined as low Price-to-Book-Value (PBV) and/or low Price-Earnings (PE) ratios stocks. And this might even had been reasonable on the beginning, but progress has been in charge of adapting the original formulation to keep up with the changes that capital markets, firms, investors, and the global economy have been suffering. If both the philosophy and the surrounding environment have changed, we believe it is fair at least to try to understand if our performance criteria should be revised too.

This matter is particularly important in our opinion since value investing is one of the most widespread investment theories, partly because of the tremendous and consistent success of some of its adopters and declaring it as being "dead" is something we need to be cautious, since this is a powerful message we are sending to the market, and that affects an astonishing number of investors' savings and future investment decisions.

Several reasons can be presented to explain the failure of something that previously seemed to work, among them we highlight the increasing liquidity of equity markets, potentiated by the broader access to trading technology and decentralization, the more difficult access to bank financing, despite the low interest rates, specifically after the subprime-crisis, and especially, the misfit of accounting standards to the reality of twenty-first century firms.

The current accounting standards, particularly regarding intangible assets (that allegedly are not recognized as such) has been heavily criticized by some academics, of which we highlight Baruch Lev, who has already numerous and seminal publications about this matter, to which he has dedicated a great part of his research over the years, argues that market, and the valuations that it provides have not changed that much, we are just not able to see this clearly since the accounting standards provide us incomplete information (Lev, 2018). The current standard, by providing investors less accurate information, causes deficient capital allocation, and penalizes the most inventive and innovative firms, and consequently investors and the economy at large.

Along this dissertation we will propose an alternative framework to measure this philosophy's performance during the last decades. We will also discuss the pertinence of the usage of static metrics to define value, and we will devote a substantial part of our work in understanding how the (non) recognition of intangible investments as such, especially those that are internally generated may contribute to the apparent loss of edge in the eyes of the academia.

The framework that we will present next will focus on providing a more complex and real-world-adjusted assessment of the pertinence of value investing nowadays than did previous authors (Cornell & Damodaran, 2021; Fama & French, 2020; Lev & Srivastava, 2019). This model will be grounded on the following aspects: be able to use different decision variables along time (contrarily to PE / PBV ratios *ad eternum*, as it was the common practice until now) if the model recognizes pertinence of this approach, and evaluate on a yearly basis, what are the optimal values for each decision variable to open and close a long position. During all the work developed is underlying the idea that this approach could have been applied anywhere on time, and the results would have been the same. Consequently, this approach is purely retrospective, meaning, every time a new variable is identified, or a new threshold is estimated, the model has no grounds to fundament that decision unless the data that was already available to the market at that time, and so, this approach can still be applied in the future, since its implementation is just contingent on data regarding past events.

CHAPTER 2

Literature review

This chapter will serve as the basis for conducting our research. We will firstly address what is value investing, and what is the insight of Finance academics regarding this subject in recent years, followed by experts' intuition regarding the Efficient Market Hypothesis, and the ability of investors to obtain excess returns on a regular and consistent basis. We will finally investigate modern time accounting standards, especially those related to the capitalization of intangible assets, and observe how they may affect financial information and consequently, value.

2.1. Value investing

2.1.1. Definition

Lev and Srivastava (2019, p. 2) define value investing as "finding diamonds in the rough – going long on low-valued ("value") stocks and shorting highly-valued ("glamour") equities, thereby capturing companies whose stock prices are temporarily undervalued or overvalued by investors, relative to fundamentals.".

This is an investment theory developed by Columbia Business School's professors Benjamin Graham (1894-1976) and David Dodd (1885-1988). According to Columbia Business School itself, this investment theory was developed during the 1920's and was materialized on the classic finance book "Security Analysis" (1934). Later on, Graham rewrote his views on investments on "The Intelligent Investor" (1949) (The Heilbrunn Center for Graham & Dodd Investing, n.d.).

This is a long term, fundamentals-based philosophy that sits on the premise that investors, and consequently, the market is irrational, or at least experiences occasional inefficiencies, and in those occasions the price of a security will deviate from its intrinsic value, and taking advantages of these situations will allow investors to obtain abnormal returns, when the securities price matches again its intrinsic value. This theory is deeply related to information, and how news are perceived by the market. Graham and Dodd believed that investors systematically overreacted to new information, whether favorable or not, and that creates mismatches between pricing and value in the stock market.

As the years went by, it became patent that this approach to investment was not immutable, and since Graham and Dodd's original formulation of this theory, many other followers have implemented and adapted it, in order to keep up with the evolution of economic, financial, political and social dimensions. Cornell & Damodaran (2021) point out several branches of value investing, that present deviations from the original idea, a great starting point to demonstrate value investing is a mutable theory and have been evolving since it was idealized.

Firstly, Mechanical value investing, is probably the branch that presents less deviations from the original formulation, and it distinguishes value stocks based on low PE, or low PBV ratios. This position is mostly assumed by academics and information services, since it is quantifiable and convenient.

Cerebral value investing is a more sophisticated approach and considers not only the firm's financial and operational conditions, as a decision factor, but also qualitative criteria, such as management quality, solid competitive advantages (moats), and others. Warren Buffet, Charlie Munger and Peter Lynch are some examples of well-known investors who follow this approach. Warren Buffet once said that "It's far better to buy a wonderful company at a fair price than a fair company at a wonderful price" (Buffet, 1990, para.146), which we believe it is the clearest way of defining this approach in comparison to the original idea.

Big Data value investing is the third and the most recent deviation from the original thesis. It sits on the original premises of low valuation but is complemented by the analysis of enormous amounts of data, assisted with modern technology like statistical programs, risk analysis and even machine learning, trying to trace a more complete profile of the firm, analyzing other quantitative beyond the PE and PB ratios, and trying to anticipate financial information before it being disclosed.

Passive value investing consists of conducting the investment decisions according to the screens originally describe by Graham (1949). It is a series of 10 conditions, and the stocks which meet them are, according to Graham, worthwhile investments. Many investors have changed and adapted the original screens, but the premises remain: companies that fulfill cheapness, safety and profitability fixed criteria will (expectedly) deliver excess returns.

Contrarian value investing is a most information focused approach. If, according to the original thesis the market overreacts both to bad and good news, and price will eventually return to the fair value of the stock, contrarian value Investors will explore what they consider to be a market inefficiency and make profits from the overreaction of the market to the news.

Activist value investing is a more direct approach where investors assume a more practical positioning regarding their investments. The targets are cheap, badly run companies, with potential to be improved. These investments are usually led by individuals or organizations that have enough capital to assume decision taking positions, in order to influence management, and even give raise to a turnaround if needed, in order to try to make the business to correspond to its own potential. Investors such as Carl Icahn and Bill Ackman are well known adopters of this philosophy.

2.1.2. The insight from the academia regarding value investing

As every other theory, value investing has a legion of defenders, and its critics. In order to be aware of the insight on the performance of value investing through the last half decade, we revised the recent work from important authors in Finance (Cornell & Damodaran, 2021; Fama & French, 2020; Lev & Srivastava, 2019), and all of them point different experiences and slight changes on their approach but the conclusions seem to coincide: value investing does not provide the hedge it became famous for, especially since the financial downturn initiated with the Lehman Brothers collapse, and it needs a quick reinvention.

We can point out various reasons for this to happen such as advances in trading technology, the inadaptation of accounting rules to twenty-first century firms, the changes on the way central banks conducted monetary policy, especially since the subprime crisis, the easier access to equity markets, their increasing liquidity consequently, decreasing the potential mismatching between price and value.

The aspect that all these studies have in common is that the investigators define value as low PBV and/or low PE stocks. As we have seen before, mechanical value investing is the most suitable approach for studies like these, however, given all the evolution that has been occurring since the original formulation, we believe it is simplistic to define value based on this criteria, it is impossible to understand a company's situation just attending to these ratios, especially in a time of increasing corporate and business complexity, and on a study, where the firms analysis is performed by an algorithm, and the characteristics that can only be perceived by a human (the management quality, the strength when compared to the competition, the innovation) are ignored. This is one of the most important deviations from the existing literature we want to input: to add considerably more realism and complexity not only by girding ourselves with mechanical value investing, but by running the extra mile.

2.2. The efficient market hypothesis

2.2.1. Definition

The Efficient Market Hypothesis was introduced by Fama (1970), and is a theory that states, in its strong form, that stock prices reflect the whole information set available to the market, and then, value and price are two concepts that will coincide entirely with no deviations through time, meaning, the price of a stock will reflect its fair value at any moment, being then impossible to obtain risk-adjusted excess returns (alpha). This is clearly inconsistent with value investing's premise that is possible to obtain superior returns taking advantage of market overreaction to new information, and inefficiencies in pricing securities relatively to their fair value.

2.2.2. The efficient market hypothesis nowadays

In Malkiel (2003), the author, a famous champion of the Efficient Market Hypothesis, rewrote his views on the theory, after several other books and papers published regarding this subject. The author starts by quoting his own views of this theory, with some sarcasm: "a blindfolded chimpanzee throwing darts at the Wall Street Journal could select a portfolio that would do as well as the experts" (Malkiel, 1973, p.165) referring implicitly the benefits of passive strategies.

Malkiel (2003) clarifies that the market is efficient, despite having some occasional moments of inefficiency, and argues for this with some examples, like the 1987 crash, what is commonly known as the "Black Monday", the Dot.Com bubble of the 2000's, and other examples where stock pricing appeared not to be provided by an efficient capital allocation market, but it is also referred that in some of these periods it was also impossible to identify arbitrage opportunities, and the market eventually returned to what the researcher considers as being a position of efficiency, and so, punctual occasions of inefficiency are not enough to generate excess risk adjusted returns in the long term and on a regular basis.

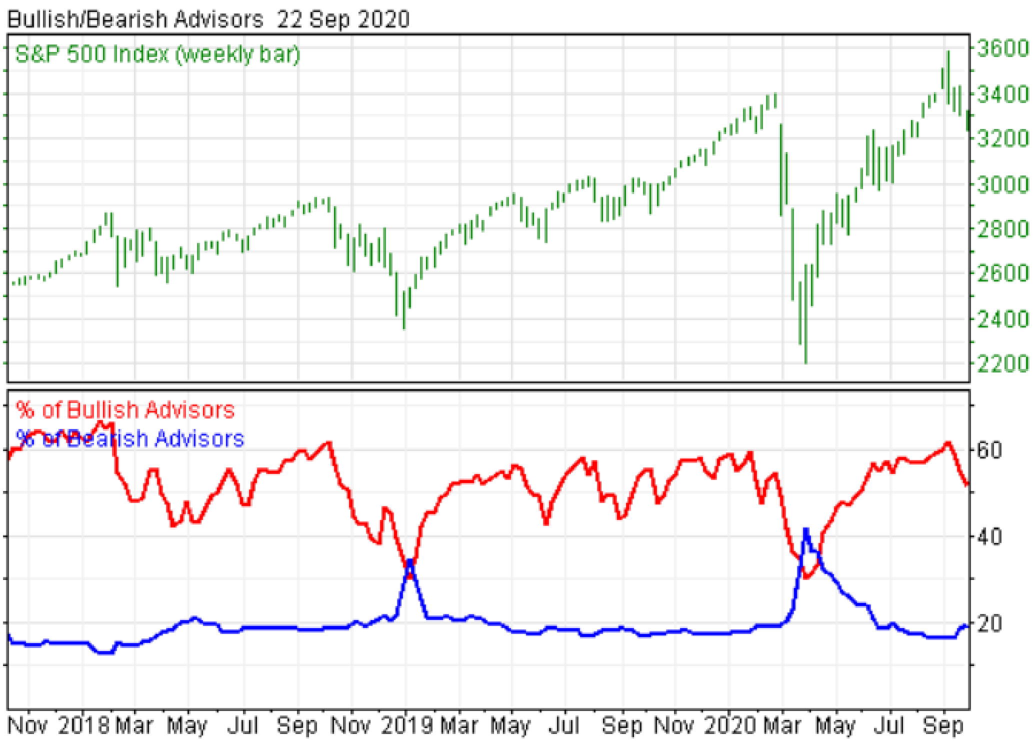
However, there are several profound arguments that make us doubt about this theory: even assuming that every investor has all the information as his disposal, it is unrealistic to believe that everyone will take the most advantage of the available information, or at least has the capability and the knowledge to do so.

Maines et al. (2003) documented the state of the art about the treatment of intangibles at the time and concluded that investors systematically underestimate the future benefits of intangible capital investment, and consequently, high R&D firms. As these benefits materialize themselves on subsequent earnings the market understands the undervaluation and this leads to abnormal returns, a clear sign of market inefficiency on its original definition. We will get deeper on this matter on the following section.

Investors Intelligence (n.d.) reports allow us to compare investors sentiment regarding the market with index quotation, and we can observe they are extremely correlated through chart analysis. Investors' sentiment usually reaches it maximum immediately prior to a crash or an economic recess, and hits is minimum immediately after. If the market is truly efficient, the market should understand stock's price does not match their intrinsic value, and for us, having some trading days when the indexes dropped dozens of decimal points is a clear sign of inefficiency. The available information must be virtually the same there was before the crash, there must have just been an event that made investors look at it in another way and understand the discrepancy between price and value, but firms in general are worth virtually the same.

Graph 2.1

Investors' Expectations VS S&P500 Quotation



Source: Investors Intelligence (n.d.)

2.2.3. The pertinence of risk measures

Risk is defined in finance (trough Beta) as the volatility of a security when compared to a benchmark (Investopedia, n.d.). However, Graham (1949) suggests that price is directly correlated with risk, implying increasing risk as a security price increases (as long as this price variation is not caused by the underlying firms' fundamentals substantial change). The rationale is that higher prices imply higher probability of overpricing. These two definitions are clearly inconsistent, since one stock's price decrease (*ceteribus paribus*) implies a beta increase, and a risk decrease according to Graham. This makes us wonder regarding the accuracy of an absolute measure to quantify risk, being it such a complex concept, and so dependent on so many variables besides price volatility, like management quality, leverage, industry, size, business cycle stage, interest rates, profitability record, and others that even the Fama-French multi factor model is not able to tackle all these dimensions. Can we guarantee that all stocks preform in a way that it is impossible to obtain risk adjusted excess returns assuming the possibility of usage of an incomplete risk measure?

2.3. Modern time accounting and the treatment given to intangible assets

The current accounting standards impose that almost all the investment made in intangible capital is immediately expensed, via research and development (R&D) or Sales, General and administrative (SG&A) accounts, and this investment will only be reflected on the balance sheet under very particular circumstances, and when fulfilling some extremely hard criteria.

However, the capitalization of an intangible investment acquired to a third party, or in consequence of a corporate acquisition, is a lot easier for acquiring companies. This matter has been assuming crescent importance, as the corporate world has been evolving far quicker than the accounting standards. Experts consider that this resistance to change on the part of regulators causes serious harm to both investors, firms, capital markets and the economy at large (Lev, 2018).

This raises one important question: even if we are able to clearly identify good investment opportunities, and to build a strong portfolio, how exposed are we to the possibility of basing our investment decisions on financial data that wrongly, or at least less accurately reflects important items, such as earnings, asset value, or the capital structure, on a regular basis, and that in the end may potentially affect investors' performance, especially value investors, who heavily base their investment decisions on fundamentals, which may be (potentially) biased.

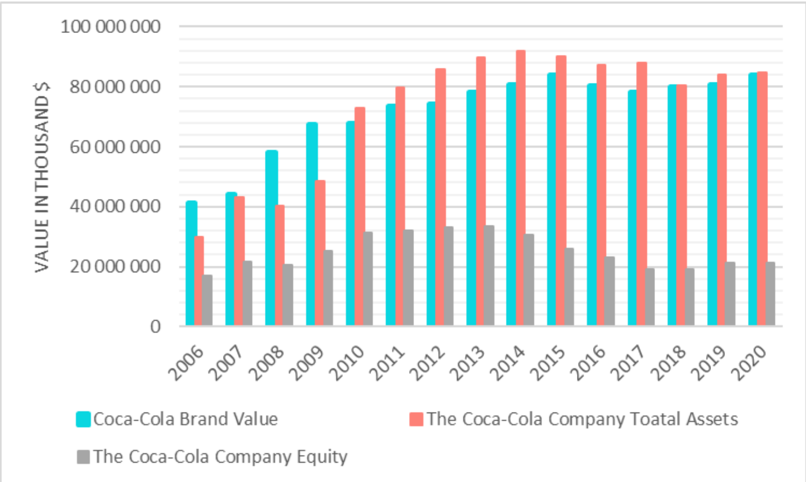
Intangible assets' treatment is in our opinion one of the most relevant components of our work, therefore, it will also be one of the themes we will address with greater depth.

This situation creates biased financial information and harms the most innovative and dynamic firms. And even on the situations an internally generated intangible is capitalized, it remains being unfair for the developer, once that asset will be registered on the accounting by its cost, and a similar intangible but acquired to a third party will be registered by its acquisition value.

Firms like The Coca-Cola company®, invest billions of dollars annually in promoting their brands and products, but this is not reflected in the books (Lynch & Rothchild, 2000). This is nothing but an investment, and these brands and products have value *per se* since they obviously create future benefits to the firm. However, these are not registered as assets on The Coca-Cola company® balance sheet (The Coca-Cola Company, 2021). Furthermore, The Coca-Cola company® should not only be registered as an asset, as it is probably the firm's biggest asset: In 2020 the company's total asset were registered by $80B, and in the same year, the Coca-Cola® brand was valued in about the same value.

Graph 2.2

The Coca-Cola Company® Total Assets VS Brand Value



Data source: Statista (2022); Eikon® Refinitiv Terminal DataStream (2021)

2.3.1. Historical context

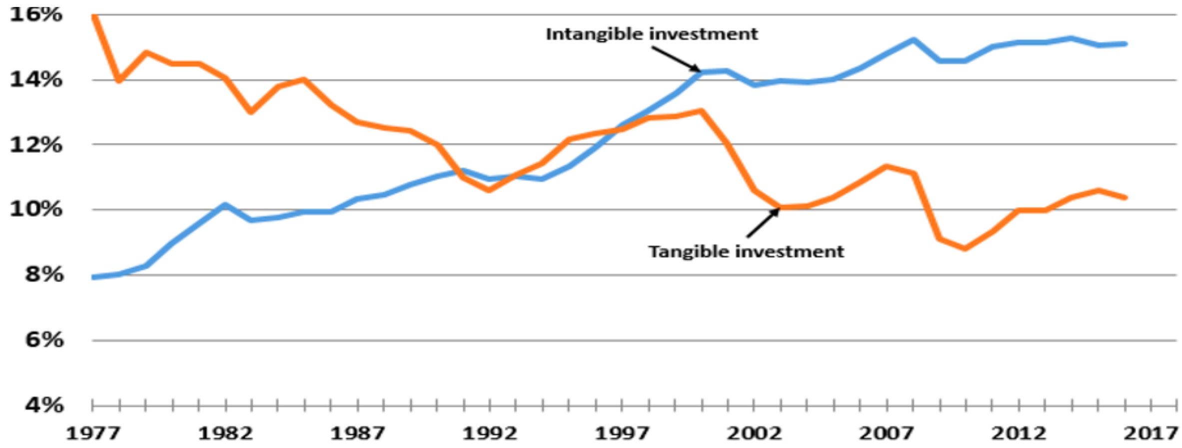
Paton & Littleton (1940 as cited in Lev, 2018) defined accounting objectives, and even being in a time when intangible assets had little or no importance on firms' balance sheets, the need of capitalizing intangible investments was implicit on these objectives.

Until the 1980's, corporate investment was mostly directed to tangible assets, and even though there may already be some erroneous treatment of intangible assets, this was an accounting line that had low impact on the global value assessment of the firm. Since then, intangible assets have been acquiring more and more importance on firms' balance sheets, and on the investment plans (Lev & Srivastava, 2019), and this have been producing increasing financial information bias, and decreasing the informational power.

According to Lev (2018), between 1977 and 2016, the aggregate investment in tangible assets relative to gross value added declined continuously from 16% to 10%, a 38% drop, while the investment in intangible assets almost doubled under the same period, going from 8% to 15%.

Graph 2.3

Investment rates in tangible and intangible assets (investment relative to gross value added), private industries 1977-2017



Source: Lev & Srivastava (2019)

As this problem started impacting the informational usefulness of financial information, the academia started proposing new models and adjustments to the current standard, to ease the capitalization of intangible assets (Enache & Srivastava, 2017; Ewens, Peters, & Wang, 2018; Hulten & Hao, 2008; Lev, 2018; Ohlson, 2006), namely those generated internally.

However, the accounting standard setters (firstly the Financial Accounting Standards Board (FASB), and then the International Accounting Standards Board (IASB)) seem to disagree, and moved gradually over the past few decades from the income statement model (also known as the revenue/expense view), emphasizing on the revenue-cost matching, to the balance sheet model (also known as the asset/liability view), focusing on the periodic valuation of assets and liabilities at fair values (Rosa, 2014), followed by the Statement of Financial Accounting Standards No. 2 (1974).

This created an even bigger informational mismatch regarding this matter, since relatively to a Property, Plant and Equipment (PPE) asset, naturally the revenue-expense match will occur: the asset will only start being depreciated when it is available for use, and consequently, able to generate return, and the depreciation expenses will (hopefully) be correlated with the revenue that assets generate. In the case of intangible assets developed in-house, the costs will mostly occur during the R&D stage, meaning, by the time that asset (potentially) starts generating income, most of the costs will have already occurred and recorder on accounting.

2.3.2. The impossibility of capitalizing some internally generated intangible assets

As discussed before, the accounting criteria that allow the capitalization of internally generated assets are rigid and hardly achievable when compared to intangible assets acquired to a third party, or in consequence of a corporate acquisition.

Generally accepted accounting principles (GAAP) - the accounting standards for domestic American publicly traded firms – define an asset as "(…) probable future economic benefits owned or controlled by the entity" (Financial Accounting Standards Board, 2008).

In this section we will present some common arguments in favor of the current standard, and some counterarguments:

- The future benefits that may be generated by these investments is highly uncertain.
    - That is true, and it is even uncertain if the investment will generate any benefit at all, apart from the experience and knowledge acquired by the firm during its development.
    - However, this does not prevent in-process acquired R&D and development projects from being capitalized as a consequence of a corporate acquisition for example. The question here is to attenuate the different treatment given to acquired and internally generated intangible capital.

  - Moreover, there are no risk-free investments, at least in the normal activity of a non-financial company, the certainty of the possible outcome regarding an investment is an abstract criterion, that is one of the reasons that created the need for impairments in accounting, and we could easily find examples of far more certain intangible investments that are not capitalized, than other tangibles that are (Ex: The uncertainty associated to a pharmaceutical or biotech company's inventories - the risk of default on the payment by the client, the risk of becoming obsolete - when compared to the uncertainty surrounding a patent value: it might even be obsolete before the patent expiration, a characteristic that is shared with inventories, but has no default risk associated).
- The fair value of these assets is highly uncertain, and there are barely any liquid markets of intangible assets due to their specificity.
  - GAAP allows firms which acquire an intangible asset to value it following the discounted cash-flow method. The discount rate will deal with uncertainty of future benefits and provide a fair proxy for valuation, and the same could be applied to internally generated assets.
  - Furthermore, we believe it is far better having an erroneous valuation of an asset, and preform rigorous impairment tests from time to time, than assuming by default that a resource is valueless and provide that type of information to the stakeholders.
- The capitalization of intangible assets opens an opportunity for income statement manipulation and fraud.
  - Again, that is a valid argument, however, goodwill for example is maybe much more subjective when determining its fair value than any another intangible investment. Besides, specialized firms of brand valuation, for example, exist in the market for several time, and at least public companies are subject to audit and impairment tests. The message consequent impairments pass the investors represents potentially a greater loss than the upside potential of manipulation of intangibles' value.

    - In addition, the current standard represents greater income manipulation potential than if these investments were capitalized. In the current standard, a decrease in the intangible investment in $1 represents an equal increase on the income before tax. If the intangibles that are currently expensed were capitalized, a $1 cut on investment's impact on earnings before tax will be as small as the number of years of that asset's useful life (assuming straight line depreciation) (Lev, 2018).
- The broader and easier access to financial data smooths the potential faults of the current accounting standards.
    - (Lev & Gu, 2016) have proven the opposite. In their book, the authors recognized the easier and generalized access to financial data, and improved financial analysis techniques and software, but in fact, they recorded increasing uncertainty (measured trough the standard deviation) regarding the specialists' consensus estimates for corporate earnings, when compared to the actual values since 1976 until 2013.

To sum up, accounting standards must be built with the ultimate purpose of serving the best interest of the stakeholders and reflect as accurately as possible the financial and operational reality of a firm. Lev (2018) demonstrated that the current standards harm investors, the capital allocation, the efficient market dynamics, the economy at large and the (best) companies, those who develop their own technology, try to be ahead of the competition and create valuable input for themselves and for the world at large. We believe accounting standards should be thought on the interested parties' best interests, and despite existing other areas where we believe accounting rules should be revised, we also believe the treatment of intangibles is the most glaring issue.

CHAPTER 3

Data

In this section we will present the dataset that supported our study, and thereafter, we will summarize all the changes the dataset has suffered until being ready to serve as input to our model and provide some intuition regarding the reasons that gave origin to this need of working the data out and the objectives we wanted to reach with it.

3.1. Raw data

In order to pursue the goal this thesis intends to achieve we extracted our raw data from an Eikon® Terminal: accounting information about all the listed and the already delisted firms from the National Association of Securities Dealers Automatic Quotation System (NASDAQ) from 01/01/1970 to 31/12/2020.

We extracted the variables from the terminal in the simplest way possible, meaning, no computed fields have been extracted unless those that were indispensable (Table 3.1), those that come directly from the firms' financials, so that we could grant the highest level of scrutiny, and customize the financial ratios and indicators formulas as we please, as it will become evident on the following section.

Table 3.1

Variables Obtained from an Eikon® Terminal

Variable	Eikon Variable Code
Total Assets	WC02999
Avg Fully-Diluted Shares Outs	WC05194
Common Shares Outstanding	WC05301
Common Dividends (Cash)	WC05376
Total Intangible Other Assets-Net	WC02649
Total Liabilities	WC03351
Net Inc Before Extra/Pfd Divs	WC01551
Preferred Dividends (Cash)	WC05401
Preferred Stock	WC03451
Price	P
Research & Development Expense (R&D)	WC01201
Selling, General & Administrative Expenses (SG&A)	WC01101
Treasury Stock	WC03499

Table 3.2

Intermediate Calculations Variables

Variable
Adjusted R&D (AR&D)
Adjusted SG&A (ASG&A)
Adjusted Liabilities (AL)
Adjusted Equity (AE)
Adjusted Nº of Shares (ANS)
Adjusted Net Income (ANI)
Book Value per Share (BVS)
Earnings per Share (EPS)
Divided per Share (DPS)
Adjusted DPS (ADPS)
5 Year Average EPS (AVGEPS)

Table 3.3

Decision Variables

Variable	Type of variable
Intangibles to Assets (IA)	Y
Liabilities to Assets (LA)	Y
5 Years EPS Average Growth (EPSAG)	Y
5 Years EPS Coumpound Growth (EPSG)	Y
Return on Assets (ROA)	Y
Return on Equity (ROE)	Y
Price/Earnings Ratio (PE)	W
Price-to-Book Ratio (PB)	W
Average PE (AVGPE)	W
Dividend Yield (DY)	W

Y → Annual Variable
W → Weekly Variable

3.2. Data adjustments

We computed and adapted the ratios and other indicators' computation to what we believe it should be done to best serve our purpose, and according to some guidelines provided by the experience of some famous value investors, such as Buffett & Clark (2010), and others. The formulae used to compute the financial ratios that will support the analysis can be found along the present chapter.

3.2.1 Firms included in the data set

Due to data unavailability regarding some of the financial variables that had to be obtained from the Eikon® Terminal, some companies had to be removed from our sample. Despite this, we are still working with total of 2553 from Nasdaq (Annex AD).

3.2.2. Considerations regarding the capital structure

According to Buffett & Clark (2010), preferred shares tend to indicate the absence of lasting competitive advantages, and their presence in one firm's balance sheet may indicate financing problems and carry a series of disadvantages compared to other forms of financing: preferred dividends are not deductible for tax effects, contrarily to what happens to interest expenses.

Besides this, creditors will have priority in receiving their credit, when compared to preferred shareholders receiving their invested capital in the case of default, so the implicit interest that preferred shares carry in the form of preferred dividends will also be aggravated because of the additional risk these titles carry.

Chatfield, Chatfield, Baloglu, & Poon (2020) found strong evidence that financially weak firms are more likely to issue preferred stock. One of the typical explanations for this is that firms mostly rely on more creative funding sources (like convertible bonds, or preferred stock) when their access to the traditional funding sources is more difficult (mainly because of fragile financial position, that may compromise a new common stock or bonds issue, and difficult the access to bank financing).

In our opinion preferred shares carry too much debt characteristics to be considered equity, we can see them as perpetual bonds (assuming no conversion rights) and so, all the firms' capital structure from our sample have been readjusted in order to reclassify preferred shares as debt instead of equity. Logically, preferred dividends started being accounted as nondeductible interest, and so this adjustment will also impact every year's net income, but not what is being accounted as tax obligations. In our notation Y states for a given year, and W represents a week within year Y.

$$AL_Y = Liabilities_Y + Preferred\ Stock_Y \tag{3.1}$$

$$AE_Y = Equity_Y - Preferred\ Stock_Y \tag{3.2}$$

3.2.3. Net income

As the base for the Net Income computation, we used the Net Income Before Extraordinary Items and Preferred Dividends (Net Income). Extraordinary items may severely impact the interpretation of financial information, especially in years where this item assumes bigger importance when compared to the operational activity of the firm. The impact of these items on the financial ratios may be far more severe than the way they can impact the fair value of a firm, and even if they are expressive enough to exert pressure on the share price, they have a non-operational and extraordinary character, they do not (hopefully) represent a pattern and so, extraordinary items have been discarded from the analysis.

Furthermore, and as referred above, preferred dividends will be accounted to the computation of net income but will have no impact for taxation purposes.

$$ANI_Y = Net\ Income_Y - Prefered\ Dividends_Y \tag{3.3}$$

3.2.4. Number of outstanding shares

Our original intention was to always consider the fully diluted number of shares, meaning, taking in to account the conversion of all convertible securities outstanding, and the exercise of all options and warrants in the computation of “per share” ratios. We believe this is not just a conservative way of evaluating an investment, and as referred above, companies with bigger difficulties in obtaining financing will need to resort to more creative financing sources, and this includes typically preferred shares and convertible bonds. So, this adjustment is also a form of penalizing weaker companies, and make it harder for companies like these, to enter our value portfolio.

However, the database only had the fully diluted number of shares information for more recent years, and not to all the firms, so what we did was to apply the fully diluted number of shares on the ratio computation as much as possible, and for the situations where this information was unavailable, consider the stated number of common shares outstanding.

$$ANS_N = \begin{cases} Fully\ Diluted\ Nº\ Shares_Y, & Fully\ Diluted\ Nº\ Shares_Y \neq NA \\ Common\ Shares_Y, & Fully\ Diluted\ Nº\ Shares_Y = NA \end{cases} \tag{3.4}$$

3.2.5. Dividends and treasury stock

As the total annual value of dividends, we consider not only all the distributed dividends for one year, independently of their nature (including extraordinary and special dividends), except from preferred dividends, that will be accounted as non-deductible interest costs, but we will also consider the annual variation on the treasury stock account, either positive or negative.

Due to data contingencies, we cannot have access to a more exact timeframe on the payment of dividends than a yearly timeframe, so we will assume that all dividends were paid on the 31st of December of each year, even the special and extraordinary dividends.

Repurchase programs allow firms to accomplish the same goals of a dividend distribution, but without having to make shareholders pay taxes immediately. Instead, of that, buyback programs will theoretically increase the share prices in the amount of the volume of shares bought, divided by the number of outstanding shares, allowing shareholders to delay the taxation of that implicit dividend, potentially *ad eternum*, until the investor decides to close the position on that stock, which ultimately will decrease the present value of taxation.

For this reason, share repurchase programs are getting popular in the corporate world, and we believe if we consider this as an implicit dividend, the amount a firm spends each year repurchasing shares, should be accounted as a dividend when computing dividend-related ratios, like the dividend yield.

This adjustment will only produce effects when evaluating the pertinence of dividend yield's importance as a decision variable (ADPS), but when it comes to the dividends earned for each opened position, we will only obviously take into account Common Dividends (DPS).

$$DPS_Y = \frac{Common\ Dividends\ (Cash)_Y}{Common\ Shares\ Outstanding_Y} \tag{3.5}$$

$$ADPS_Y = \frac{Common\ Dividends_Y + Treasury\ Stock_Y + Treasury\ Stock_{Y-1}}{Common\ Shares\ Outstanding_{Y-1}} \tag{3.6}$$

3.2.6. Remaining formulae

The following formulae are the consequence of the adjustments we intended to apply to the data set and have been being exposed until now.

$$BVS_Y = \frac{AE_Y}{ANS_Y} \tag{3.7}$$

$$EPS_Y = \frac{ANI_Y}{ANS_Y} \tag{3.8}$$

$$5YAEPS_Y = \frac{\sum_{i=0}^{4}(ANI_{Y-i})}{4} \tag{3.9}$$

$$IA_Y = \frac{Total\ Intangible\ Other\ Assets_Y - Net_Y}{Total\ Assets_Y} \tag{3.10}$$

$$LA_Y = \frac{AL_Y}{Total\ Assets_Y} \tag{3.11}$$

$$5YEPSAG_Y = \frac{\sum_{i=1}^{4}\left(\frac{EPS_{Y-i+1} - EPS_{Y-i}}{EPS_{Y-i}}\right)}{4} \tag{3.12}$$

$$5YEPSG_Y = \sqrt[4]{\frac{EPS_Y}{EPS_{Y-4}}} - 1 \tag{3.13}$$

$$ROA_Y = \frac{ANI_Y}{Total\ Assets_Y} \tag{3.14}$$

$$ROE_Y = \frac{AE_Y}{Total\ Assets_Y} \tag{3.15}$$

$$PE_W = \frac{Price_W}{EPS_{Y-1}} \tag{3.16}$$

$$PBV_W = \frac{Price_W}{BVS_{Y-1}} \tag{3.17}$$

$$AVGPE_W = \frac{Price_W}{AVGEPS_{Y-1}} \tag{3.18}$$

$$DY_W = \frac{DPS_{Y-1}}{Price_W} \tag{3.19}$$

3.2.7. The treatment of intangible investments

The adjustments regarding intangibles are the main transformation we intend to apply to the data set. We have delved deeper our motivations for this above, and we will capitalize and depreciate part of the investment made in intangibles, that currently, according to the actual accounting standards, are entirely expensed. To apply this methodology, we followed Ewens, Peters & Wang (2018) fully capitalized the R&D and the investment component of SG&A, and the subsequent depreciation of these assets. The need to distinguish the investment component of SG&A arises from the fact that this accounting line of the income statement contains what we consider to be expenses that should be reclassified as assets, such as marketing expenses, and others that are, in our opinion, well classified as expenses, like office supplies.

Ewens et al. (2018) propose three different approaches to capitalize and amortize R&D and the investment component of SG&A. After trying to distinguish them all and trying to understand which one suits best our dataset, we found very similar results in each approach's explanatory power of stocks returns, and so, we decided to assume the most conservative position and use the "no markup" assumption, meaning we capitalize intangible assets based on their cost, without having any consideration for what could (expectedly) be their market value. This assumption results on a 24% annual geometric depreciation rate for the total expenditures on R&D, a 53% capitalization of the SG&A expenses, now reclassified as assets: the investment component of SG&A, to which will be applied a 20% annual geometric depreciation rate. This last assumption, following Ewens, Peters, & Wang (2018), is based on the literature, contrarily to the previous ones which have been estimated.

This adjustment was applied to all the data set and resulted on two different sets of data: Raw data, all the decision variables without considering this adjustment, and intangible-adjusted data, now considering the capitalization and subsequent depreciation of the until now di considered intangible investments. These two data sets will oppose to each other, and allow us to establish comparisons regarding the pertinence of this matter, and how improved might potentially be an investor's performance by stepping aside from the current standard.

CHAPTER 4

Methodology

In this chapter we will present all the methods, models and techniques applied in this thesis, and justify their purpose and their need.

4.1. Panel data

Panel data, also known as longitudinal data, refers to a statistical method that is used to analyze two-dimensional data, usually different cross-sections across time.

These types of data allow us to create more realistic analysis, as we can both work with a variety of cross sections (in this case, different companies) and simultaneously, an extended time horizon, and are commonly used to model problems related to economics, finance, epidemiology, and health statistics.

In our case, panel data models will be applied to clarify what variables better explain stock returns' variation and allow us to create a set of variables of interest for each decade, which will serve as input for the model to understand on what should be based the stock picking process.

We will distinguish the methods that will be applied, summarize the underlying assumptions regarding each method and enunciate the techniques used to select the most appropriate method.

We can define the general expression for a panel data model as follows:

$$Y_{it} = a_i + b_1 * X_{1_{it}} + \cdots + b_k * X_{k_{it}} + \nu_{it} \tag{4.1}$$

$$\varepsilon_{it} = \nu_{it} + \mu_i \tag{4.2}$$

$$a_i = a + \mu_i \tag{4.3}$$

$$E[\varepsilon_{it} | X_{it}] = 0 \tag{4.4}$$

Where a is the intercept of each firm (i). b represents the estimated slope affected to k explanatory variables (X). t represents the time period.

The total errors (ε_{it}) can be disaggregated in two components: the idiosyncratic effect (ν_{it}) that represents an element that varies randomly for all individuals (companies) and time periods, and μ_i states for the unobserved heterogeneity, it is the term that explains the differences between individuals (companies).

Following Wooldridge (2012), the assumptions around an OLS regression are:

- There is a linear relationship between the explanatory variables and the dependent variable.
- The existence of a random sample, implying the absence of autocorrelation (or serial correlation).
- The absence of perfect multicollinearity[1].
- The explanatory variables are exogeneous [2](what implies zero conditional mean). The error term is not dependent on the explanatory variables, as it is a random variable, the explanatories do not carry any information regarding its value.
- Homoscedasticity[3], meaning there is equal residuals' variance, and they are uncorrelated among themselves.
- The residuals normally distributed.

The compliance with the first five assumptions, implies we are facing best linear unbiased estimators (BLUE). However, panel data models, especially when applied to real life data may easily violate these assumptions, once these data sets combine time series with cross section data, the model will face the typical problems relative to both types of data.

4.1.1. Pooled ordinary least squares (OLS) model

According to Mesquita, Fernandes, & Filho (2021), this model considers that even if every individual present differences between each other, it is assumed the explanatory variables already carry all the relevant information, meaning the main factors that distinguish these observations are already implicit in the model, and so it is not needed to control other unobserved factors (μ_i), ignoring the existence of fixed and random effects.

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[1] Multicollinearity implies increasing coefficients variance, and consequently increasing on the probability of finding not statistically significant results.

[2] The violation of this assumption results on omitted variable bias.

[3] Heteroscedasticity does not imply estimators' bias nor inconsistency, but affects the confidence intervals and significance tests.

In our case, the use of pooled OLS regression model will imply the assumption that all companies, under the same circumstances (implied by the financial ratios) will generate the same returns, it would be like assuming all stock prices behave the same way, disregarding aspects like size, industry, or phase on the business cycle.

This way, it will only be one a for the entire population, and the unobserved factors will be allocated to as noise the error parameter.

If the pooled OLS regression model ignores the differences between individuals, and if these differences are represented on the original model (4.1) by the unobserved heterogeneity, this parameter will be excluded, what yields the following formula for the pooled OLS model (4.5).

$$Y_{it} = a + b_1 * X_{1_{it}} + \cdots + b_k * X_{k_{it}} + \varepsilon_{it} \tag{4.5}$$

4.1.2. Fixed effects model

This model, in opposition to the previous one, considers the existence of individual effects, but eliminates the fixed effects from the model, whose values are invariable for each individual along time (economiaetv, 2020b): a and μ_i. This is achieved by applying the within transformation, keeping only in the model the data variations for each individual and consequently excluding the data variations between individuals.

The reason for the application of this procedure is that usually the unobserved heterogeneity is correlated to at least one explanatory variable. This transformation grants unbiased and consistent estimators.

Bellow we exemplify the within transformation, which consists of the expression of the variables in mean deviations, having 4.1 as starting point.

$$\overline{Y_\iota} = a_i + b_1 * \overline{X_{1_\iota}} + \cdots + b_k * \overline{X_{k_\iota}} + \overline{\nu_\iota} \tag{4.6}$$

Applying the within transformation principle, we get the following expression:

$$Y_{it} - \overline{Y_\iota} = (a_i - a_i) + b_1 * \left(X_{1_{it}} - \overline{X_{1_\iota}}\right) + \cdots + b_k * \left(X_{k_{it}} - \overline{X_{k_\iota}}\right) + (\nu_{it} - \overline{\nu_\iota}) \tag{4.7}$$

Knowing that by assumption (4.4) holds, we can rewrite (4.7) as follows:

$$Y_{it} - \overline{Y_\iota} = b_1 * \left(X_{1_{it}} - \overline{X_{1_\iota}}\right) + \cdots + b_k * \left(X_{k_{it}} - \overline{X_{k_\iota}}\right) + \nu_{it} \tag{4.8}$$

As explanatory variables are independent of all errors, the k intercepts can be unbiasedly estimated rearranging equation 4.6.

$$a_i = \overline{Y_\iota} - b_1 * \overline{X_{1_\iota}} - \cdots - b_k * \overline{X_{k_\iota}} \tag{4.9}$$

This model can also be expressed in the usual regression framework and added of $N - 1$ dummy variables, being N the number of firms under analysis, to allow our analysis to consider the individual effects, through the existence of one different intercept for each firm. To this approach we call the one way least-squares dummy variable (LSDV), whose corresponding equation is presented below:

$$Y_{it} = a_1 + \sum_{j=2}^{N} a_j * d_{ij} + b_1 * X_{1_{it}} + \cdots + b_k * X_{k_{it}} + \nu_{it} \tag{4.10}$$

$$d_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \tag{4.11}$$

The parameters a_j and X_{it} can be estimated through the application of the OLS model. The existence of $N - 1$ dummy variables allow us to avoid the perfect multicollinearity problem, and the analysis is made based on the a_1 estimate, in comparison with the others (economiaetv, 2020a). The relevance of the individual characteristics of each firm can be evaluated comparing the accuracy of this model against the pooled OLS model, with no dummies.

4.1.3. Random effects model

In the random effect model, the term that explains the differences between companies (unobserved heterogeneity) is considered to be a random variable (Curto, 2018), and consequently a_i will also be a random variable, being this the main distinguish from fixed effects model.

This model also implies the assumption that the unobserved heterogeneity is uncorrelated to the explanatory variables (Torres-Reyna, 2007).

Attending to 4.1 and 4.3 we can derive the random effects model's expression, where μ_i will capture the variation between firms (between variation), and ν_{it} will capture the variation effects among the data of a specific individual (within variation):

$$Y_{it} = a_i + b_1 * X_{1_{it}} + \cdots + b_k * X_{k_{it}} + \nu_{it} \tag{4.1}$$

$$\Leftrightarrow Y_{it} = (a + \mu_i) + b_1 * X_{1_{it}} + \cdots + b_k * X_{k_{it}} + \nu_{it} \tag{4.12}$$

The model's parameters can be estimated applying a linear transformation to 4.12, as follows:

$$Y_{it} - \theta_i * \overline{Y_\iota} = a * (1 - \theta_i) + b_1 * \left(X_{1_{it}} - \theta_i * \overline{X_{1_\iota}}\right) + \cdots + b_k * \left(X_{k_{it}} - \theta_i * \overline{X_{k_\iota}}\right) + a_i * (1 - \theta_i) + (\nu_{it} - \theta_i * \overline{\nu_\iota}) \tag{4.13}$$

Where θ_i is given by:

$$\theta_i = \sqrt{\frac{\sigma^2{}_\nu}{t_i * \sigma^2{}_\mu + \sigma^2{}_\nu}} \tag{4.14}$$

After this we can immediately conclude that both the fixed effects and the pooled OLS models are particular cases of the random effects model. In practice $\theta_i$will never be zero nor one, but if θ_i is close to zero, the random effect model's estimates will get closer to the pooled OLS estimates, as well as when θ_i is close to one, the random effects model's estimates will be similar to the fixed effects model' estimates(Wooldridge, 2012).

4.2 The application of each model

4.2.1. Pooled OLS model

As exposed above, the pooled OLS model works under the assumption that even considering that there are differences between firms, and the way the corresponding price changes due to alterations on the financial ratios' values, this information is already included and carried by the explanatory variables, and so, one single regression line will explain all the observations. However, if there are unobserved factors (expressed by μ_i) that are systematic instead of random, the pooled OLS model will no longer be the most appropriate one to describe the relationship we intend to (Mesquita et al., 2021).

If we have unobserved factors correlated with at least one explanatory variable, we will be towards a case of omitted variable bias and the estimation for the parameter b will be inconsistent (economiaetv, 2020a).

Hence, the main motivation for avoiding the use of pooled OLS model is the need of working with the heterogeneity implicit in the error term in a more sophisticated way than this model allows us.

4.2.2. Fixed effects model

The Fixed effects model, as exposed above, by eliminating the unexplained heterogeneity term from the model, grants consistent and unbiased estimators, since most of the times μ_i is correlated with at least one of the explanatory variables. Nevertheless, this model's estimator's variance will be greater than those obtained from the pooled OLS model, as the prior are estimated in mean deviation (economiaetv, 2020b).

The LSDV model, as the prior, allow us to obtain information regarding the unobserved factors, and the estimators are consistent and identical to those obtained from the fixed effects model. However, the existence of too much dummy variables, like what happens in our particular case, we will have a decreasing on the number of degrees of freedom, what affects statistical inference. It can also cause high levels of multicollinearity (Marques, 2000).

4.2.3. Random effects model

Regarding the random effects model, we assume the composed error term, ε_{it}, is uncorrelated with any of the explanatory variables, otherwise the estimators will be biased and inconsistent (Torres-Reyna, 2007).

We also assume the composed error mean is zero (4.15), and its variance is given by the sum of the variances of the unobserved heterogeneity term, and the idiosyncratic error (Jirata, 2014) (4.16). However, the composed error is homoscedastic, it is possible to demonstrate it is autocorrelated, and its autocorrelation is given by equation 4.17:

$$E(\varepsilon_{it}) = 0 \tag{4.15}$$

$$Var(\varepsilon_{it}) = \sigma^2{}_\mu + \sigma^2{}_\nu \tag{4.16}$$

$$\rho = E(\varepsilon_{it}, \varepsilon_{is}) = \frac{\sigma^2{}_\mu}{\sigma^2{}_\mu + \sigma^2{}_\nu} \tag{4.17}$$

Hence, one firms' residuals are correlated among themselves, to solve this problem, the generalized least squares (GLS) should be used instead of the traditional OLS.

4.3. Testing for the selection of the most appropriate model

4.3.1. Fischer Test (F Test)

$$\boldsymbol{H_0}\text{: } \boldsymbol{All\ individuals\ have\ the\ same\ coeficients}$$
$$\boldsymbol{H_1}\text{: } \boldsymbol{Different\ individuals\ have\ different\ coeficients}$$

The F test is used to assess which of the two models: pooled OLS or fixed effects suits better the dataset under analysis. This process is commonly referred in the literature as testing for *poolability* (Kunst, 2009). This test's null hypothesis states that all single firms have the same intercept, characteristic of the pooled OLS model. So, the rejection of the null implies specific characteristics registered among the firms, and in that case, the fixed effect model is more adequate to describe the data under analysis.

4.3.2. Breusch-Pagan Lagrange Multiplier (LM) test

$$\boldsymbol{H_0: \sigma^2{}_{\mu_i} = 0}$$
$$\boldsymbol{H_1: \sigma^2{}_{\mu_i} \neq 0}$$

In order to choose from the pooled OLS model and the random effects model, we will apply the Breusch-Pagan LM test. It seeks to determine whether the variance of the individual effects is zero or not (Machado, 2021). The randomness of the unexplained heterogeneity is a characteristic of the random effects model, and so its covariance will not expectedly be zero. So, the rejection of the null hypothesis implies the existence of individual characteristics that distinguish the firms among themselves and directs us towards the random effects model as being the most appropriate.

4.3.3. Hausman test

$$\boldsymbol{H_0: Cov(\mu_i, X_{it}) = 0}$$
$$\boldsymbol{H_1: Cov(\mu_i, X_{it}) \neq 0}$$

The Hausman test gauges to identify the best model to fit our data set from the fixed and the random effects model. The main difference between the two models is the validity of the hypothesis that the specific characteristics from the firms are not correlated with at least one of the explanatory variables. If we verify that hypothesis, then both models are consistent, but the random effects model saves $N - 1$ degrees of freedom when compared to the fixed effects, securing more efficient coefficient estimates (Mesquita et al., 2021). If we reject the null, the fixed effects is the model we should select, since this implies the random effects model will produce biased and inconsistent coefficient estimates.

CHAPTER 5

The value investing model

To pursue our analysis, we defined three major action lines: the definition of value indicators for each decade, the establishment of thresholds to guide our model in opening and closing positions in our value portfolio, and the idealization and building of the model itself. The outcome will be a self-managed model that will allow us to measure the performance of a hypothetical value portfolio and verify the pertinence of value investing as an investment philosophy nowadays. Due to data management contingencies, this model will only be able to open long positions, and these investment decisions will be taken on a weekly basis.

5.1 The definition of the value indicators

This section is devoted to the selection of the variables that best define value along time, from those computed as explained above, that constitute our potential decision variables.

To do so we started for regressing all variables against returns on an annual basis. To exclude the price variation influence from our analysis, which would add bias and underserved explanatory power to variables that are price-dependent, we used only prince-unrelated variables: for example, instead of using the price earnings ratio, we used the earnings purely.

For each decade, to each variant (adjusted and gross variables) of the stocks included on the Nasdaq Exchange, we assumed as valid value determinant variables, that with such an explanatory power that contributed with a p-value inferior to 10% for the whole regression capability of explaining returns.

To the period of 1980 to 1989 the information regarding intangible assets was not disclosed to most firms, or at least this information was not available on the Eikon® Terminal, so we ignored it for this analysis. To the case of IA, DPS and EPSG we assumed them as being zero for every year the information regarding one of the variables was not available.

To the remaining cases, when a given variable was not available, we excluded the full observation from the dataset.

We runed all the three regression models presented on the previous chapter and selected the one which best suits our dataset following the tests presented above, and the result is summarized on table 5.1.

Table 5.1

Variables of Interest

Decision Variables							
Exchange	Model	1980		1990		2000	
		Variables	p-value	Variables	p-value	Variables	p-value
Nasdaq	Gross						
	Best-Fit Model						
		Random		Pooled		-	
	Pooled	LA ROA	0.01523 9.625e-11	EPSG	0.005751	-	-
	Fixed	ROA	3.673e-11	-	-	-	-
	Random	ROA	5.285e-11	EPSG	0.0205773	-	-
	Adjusted						
	Best-Fit Model						
		Random		Pooled		Random	
	Pooled	EPS LA ROA	0.012308 0.003515 1.336e-05	IA LA EPSG	0.03181 0.03149 0.03590	BVS EPS EPSG DPS1 DPS2 AVGEPS ROA	0.02841 0.01036 6.954e-14 0.03722 0.02727 0.02448 7.159e-08
	Fixed	EPS LA EPSG ROA	0.0001237 0.0673861 0.0081226 4.42e-06	ROA	0.03111	BVS EPS IA EPSG ROA	0.00308 0.00063 9.898e-09 3.279e-07 4.384e-07
	Random	EPS LA EPSG ROA	0.002123 0.013340 0.074965 6.125e-06	-	-	BVS EPS IA EPSG ROA	0.0004807 0.0011259 0.0051646 9.436e-11 3.359e-07

5.2 The threshold definition

We defined thresholds for each variable on a year basis, meaning the variables were defined and estimated for each decade, but every year of the corresponding decade, the model will base its acting on different threshold values. Those thresholds were defined for one year, based on the three previous years, and the methodology behind this is Solver application for Excel.

Solver, runed under the evolutionary method (the one which runs through all the dataset, allowing to always find the relative maximum (in our case), and allows us working with non-linear relationships. For each year, we sought to find the threshold values that allowed us to maximize the returns generated by each currency unit invested during the three previous years, based on the one under analysis. We established boundaries to all the variables we used, in a way that we ensure we were not allowing a nonsensical value to be considered as valid, but broader enough for us to allow the model taking its decisions without the need of touching the boundaries (Table 5.2). Besides, we did not allow that at any time, the three-year period portfolio could be formed from more than 40 stocks, and we should have a minimum of 5 transactions during every three-year period.

We repeated this process for each year, to each variant: adjusted and gross variables.

Table 5.2

Boundaries imposed to Solver Application for Excel

	Opening Threshold					
	PBV	PE	IA	LA	EPSG	ROA
Upper Boundary	Maximum Value of the series	30	Maximum Value of the series	1	Maximum Value of the series	Maximum Value of the series
Lower Boundary	0	0	0	0	Minimum Value of the series	-1
Aditional conditions	$PBV_{Opening} > PBV_{Closing}$	$PE_{Opening} < PE_{Closing}$	$IA_{Opening} > IA_{Closing}$	$LA_{Opening} < LA_{Closing}$	$EPSG_{Opening} > EPSG_{Closing}$	$ROA_{Opening} > ROA_{Closing}$

	Closing Threshold					
	PBV	PE	IA	LA	EPSG	ROA
Upper Boundary	Maximum Value of the series	80	Maximum Value of the series	1	Maximum Value of the series	Maximum Value of the series
Lower Boundary	0	0	0	0	Minimum Value of the series	-1

5.3 The model idealization

The model itself was designed and built under the following baseline premises: recognize the fulfilment of the conditions imposed by the thresholds and measure the portfolio's performance by decade.

We allowed a stock to be included on the portfolio every time that stock satisfied at least 66% of the thresholds in the case we have three decision variables, 50% if we have two, and 100% if we just have one.

Every time that during a decade the best-fit panel data model could not find at least three decision variables, we used also the one(s) given by the remaining models, and every time there was any variable that suffered changes weekly, we imposed the PE Ratio as one of the decision variables, to allow the investment decisions to occur on a weekly basis, instead of annually.

Due to data management problems, we were only able to use a maximum of three decision variables per decade, even though there are multiple occasions we could use way more, especially when it comes to intangible-adjusted variables.

We excluded budget contingencies from the analysis, and so, we assumed an equal invested amount on every investment opportunity (despite the stocks' prices), not to inhibit our actions, in a way that no stock could be prevented from integrating the value portfolio except for not fulfilling the parameters defined on the thresholds and do not compromising the portfolio profitability at any time due to lack of liquidity.

So, every week the model accessed, based on each year's thresholds, what stocks should be included on the portfolio, what should be maintained, and finally, the ones that reached a such a degree of overvaluation that should be sold. This procedure is conducted for every week, and the result is the measurement of the return generated for every currency unit invested on the portfolio on the beginning of each decade.

As introduced above, to what concerns dividends distribution we assumed the whole dividends distributed on a given year, are paid to investors on the 31st of December of that same year, and we ignored the traditional two-day delay between the record date and the ex-dividend date. For practical terms we assumed an investor who owns a stock in the last week of the year will be entitled to all dividends distributed by the corresponding firm on that very year.

CHAPTER 6

Analysis of the results

In this section we will present and discuss the most relevant aspects revealed through the development of this project. We will start by analyzing the efficiency of the panel data models in selecting the variables that distinguish across decades, the good from the bad investment opportunities, according to value investing, and continue by exposing the pertinence of the results, their meaning, and what we can acknowledge form them.

Regarding the value metrics, it is clear the input provided to the literature by Lev (2018): Massive expensing of intangible investments deteriorated earnings' relevance (and consequently increasing the mismatch between the accounting value and the fair value of a firm, since we will be hypothetically working with biased information), and when comparing the raw model results, with those that suffered adaptations to consider the capitalization of intangible investments, it is more than clear the increase on the number of metrics the model could select as being appropriate to explain returns. Furthermore, it is also clear the decreasing number of relevant explanatory variables identified by the raw data model along time. This supports strong evidence of the relevance of the capitalization of these type of investments, and the loss of explanatory power of the financial data along time, and along the growing importance of the intangible investments.

However, when analyzing the results, we will see the intangible-adjusted portfolio clearly underperformed the raw data one. We attribute this to the fact that we could only work with up to three decision variables. This fact did not affect the raw data portfolio, since in the best-case scenario, the model could only identify three decision variables (Table 5.1), contrarily to what happened with the intangible-adjusted model, whose output regarding the number of relevant decision variables was far broader, as exposed above.

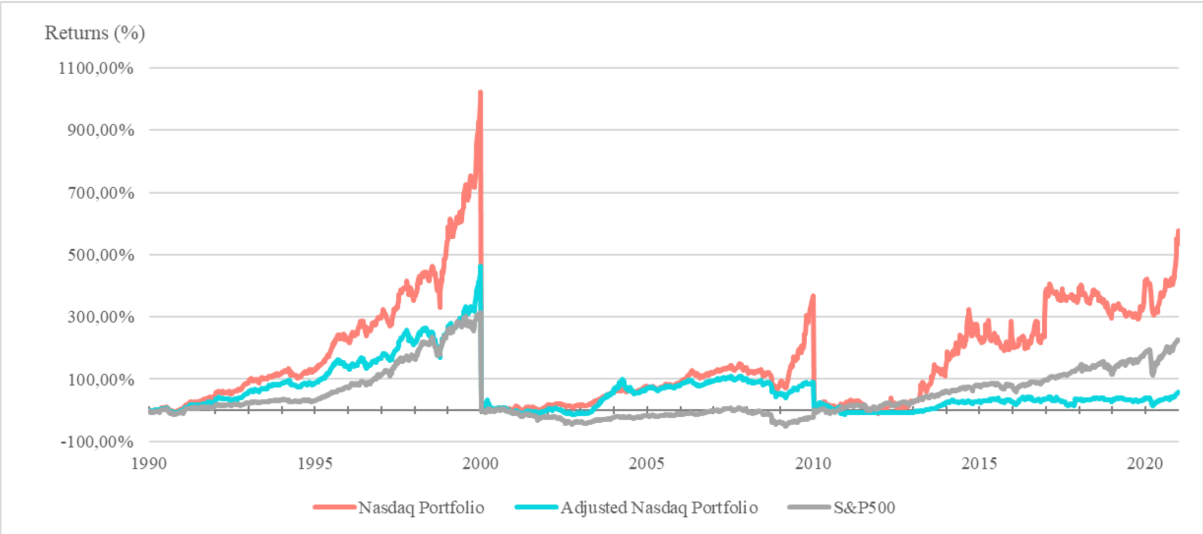
Nevertheless, we still believe this was our output because of data management contingencies, despite not being able to proof the intangible-adjusted model would overperform the remaining. The question is: Is this enough to grant value investing (with adjusted intangibles data) did not lose its edge? And the answer is quite dubious, and ambiguous. We would say it is plausible: as we have said, we could not prove it, but not because this approach was completely wrong. We have no evidence that makes us doubt of its success, we just have not the means to test it with the rigidity this question deserves.

In fact, up to the point we were able to conduct this experience with no restrictions, the signals were far more encouraging than the raw data model – namely, much valid decision variables when we run the intangible-adjusted data when compared to the raw dataset, evidencing higher explanatory power from the former when compared to the latter. The development of the idea that accounting standards require a quick reinvention is reinforced after conducting this experience, and this lack of update is harming the financial information users, and gradually decreasing the explanatory power of this information as the importance of intangible investments keep growing on firms' investment plans. Because of this, the intangible investment treatment, the way it affects information, investors, and especially how this can create biased new information is definitely one matter we believe to be a priority when it comes not only to future research, but also to accounting standards revision.

On the other hand, we can surely claim the predominance of the raw data model when compared to the S&P500 benchmark. We have implemented a strategy that was able to beat the benchmark on a regular basis, generating the so desired abnormal returns (Graph 6.1).

Graph 6.1

Grow in value of one dollar invested on each portfolio on the beginning of each decade



However, and again, due to data availability contingencies, we were not able to conduct the analysis on a broader time horizon. It would be interesting to understand the behavior of the model when compared to the benchmark on the decades of the 1970's and the 19080's, what would allow us to establish comparisons with the 1990's and understand if the loss of competitiveness exhibited by the model in the last decades is explained exclusively with the lower annualized returns general market, or if on the other hand, in those times the investment in intangible assets was not as a relevant matter as it is nowadays, this strategy would be able to obtain satisfying returns.

It would be particularly interesting to observe the portfolio's performance behavior trough some troubled times along the 1970's and the 1980's, like the 1970's bear market, along the OPEC's oil embargo in 1973 (first oil shock), the Volker's bear market in the early 1980's, and the black Monday, in 1987. It would be especially interesting to analyze how would be the stock picking process, not only because of these financial recessions and market crashes, but also because of the fact that in this period, the number of publicly traded firms was much lower, limiting the stock picking process, but easing the threshold estimation, and more clearly bounding stock picking to a narrower niche.

Although, we believe the benchmark performance does not only depend entirely on the stocks' price variation, but it also influences investors' expectations, sends powerful signal to the market, and so, individual stock's price will also be influenced by the past performance of the reference indexes. Because of this, we are confident that our analysis is complete enough to support our conclusions, even by disregarding the 1970's and the 1980's decades.

Again, the important question is: is this enough for us to claim value investing is still valid as an investment strategy? And in this case the answer is "Yes". We believe our results are more than satisfying and attending to the S&P500 as the comparison metric, our value portfolio did deliver superior annualized returns along all the three decades. Jones& Netter (2008), when analyzing the Eugene Fama's formulation of the efficient market hypothesis, stated, beyond other things, that the constant generation of excess risk adjusted returns was impossible, and give us the impression that an occasional positive alpha is a matter of luck. Malkiel (2003), when revising his views on the same theory, stated the market is efficient, despite having some occasional moments of inefficiency, but this was neither sustainable across time, nor enough to obtain abnormal returns. We instead, believe a thirty-year time horizon is a broad enough timeframe for us to push away the "luck" argument (Table 6.1).

Table 6.1

Annualized Returns

Annualized Returns			
Year	Nasdaq	Adjusted	S&P500
1990's	27,36%	18,86%	15,32%
2000's	16,69%	6,68%	-2,44%
2010's	18,99%	4,25%	11,37%

CAPÍTULO 7

Concluding remarks

We tried to put upfront the success of value investing as an investment strategy, and the validity of the criteria the academia uses to measure success and performance of this strategy. The outcome is clear: The criteria used to measure performance lack a quick reinvention, and not the strategy itself.

In this work we proposed an alternative framework, more complex, but also more complete, updated and adjusted to reality and to each case in specific. We understand the current standard is the easier way of evaluating this, however, we could not allow our statements to be biased because we just decided to follow the easy way instead of trying to understand progress along time and adapt our analysis to that.

Already 88 years have passed since “Security Analysis” was written. Is it fair to use the same performance criteria for almost a century? We do not believe so, especially when what idealized initially has been changing as the years passed by.

We also provided insight in how mutable this investment strategy is, and it is evident on how the decision variables’ relevance change over time.

Finally, we demonstrated value investing is still able to generate excess returns to those who adopt this philosophy, however, we believe the results exposed on the previous chapter can still be improved, since along the work we devolved we faced several limitations.

These setbacks were mostly due to the inability of the means we had on our disposal to deal with the enormous amounts of data we required, namely when it came to threshold estimation.

Firstly, we could not work with all the decision variables we identified and despite this not affecting the raw data model, this surely impacted the output from the intangible-adjusted model. This was probably the most disappointing setback of our experience, since it prevents us from establishing fair comparisons between the raw data and the intangible-adjusted models. However, Solver and Excel will automatically bug when trying to impose a marginal increase on the number of decision variables, and we had to adapt our strategy. We tried to test this with different computers, and the outcome was the same for all of them, and even working with just three variables, there were situations when the estimation of the thresholds for one single year took us one whole day.

These restrictions also prevented us from working with a broader dataset: initially we planned on working with both New York Stock Exchange (NYSE) and NASDAQ stocks, and we had to adapt our project to just include the latter. This adaptation resulted on a decreasing on the number of potential stocks from 4539 to 2553. Yet, we believe it is still wide enough to support our analysis and provide robust conclusions.

We were also prevented from estimating the absolute best threshold for each year. When Solver runs under the evolutionary method it grants us a good estimate for the solution of our problem, but not the optimal one. To grant we are closer to the optimum solution, we will need to tight the algorithm's criteria, what will also imply more time needed to solve each problem.

We believe with our work we provided some interesting input for future research. This is an innovative approach, and as far as we know, not a usual framework especially in the academic community. For those who are interested on this thematic, we believe there are two main areas that can still be explored/improved: First of all, we would try to run the same experience, with the same principals, but with improved computer power. The heaviest calculations were performed in our case with a computer whose specifications are summarized on Annex AE, and we still faced several difficulties, as exposed above. Another solution may be the usage of another optimization tool different that Solver. Assuming this limitation is overcome in the future, besides solving the problems presented above, new opportunities arise, for example, working with a Long/Short strategy, what has already been recognized as generating higher returns when applied to value investing (Lev & Srivastava, 2019) and take advantage of times when the market is in general overvalued.

Furthermore, we believe it would also be interesting to allow the model to analyze not only financial, but also economic data, trying to understand different stages of the economic cycle and adjust how conservative should be the stock picking process, but for this we will probably also need more powerful statistical tools.

Additionally, we noticed that the definition of thresholds was affected by our imposition of a maximum of 40 stocks for each three-year portfolio narrowing the possible values the thresholds may assume, as well as the amplitude, as the number of stocks quoted on Nasdaq increased along time. We recommend for future studies to apply a moving measure, optimally a percentage that could be applied to the total number of stocks quoted at each time.

Lastly, and since this is a hot theme and discloses new opportunities in several areas, and finance is no exception, we believe even better results could be achieved applying machine learning to the definition of decision variables, and the computation of thresholds. Trying to set a forecast, instead of decision variables only changing every ten years, or a three-year trailing, exclusively based on past events, to define thresholds.

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Annexes

Annex A Pooled OLS Regression for the 1980-1989 period – NASDAQ Raw Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq80, model = "pooling",
    index = c("id", "year"))

Unbalanced Panel: n = 142, T = 1-9, N = 737

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-0.943143 -0.257300 -0.057645  0.181334  2.779155

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept) -6.3765e-02  5.8224e-02 -1.0952   0.27380
BVS          1.1646e-04  7.8746e-05  1.4790   0.13958
EPS         -1.7779e-05  3.5208e-05 -0.5050   0.61373
LA           2.0416e-01  8.3925e-02  2.4327   0.01523 *
EPSAG       -7.5064e-04  2.6161e-03 -0.2869   0.77425
EPSG         2.9946e-02  5.9895e-02  0.5000   0.61724
DPS1        -8.7638e-02  4.8405e-01 -0.1811   0.85638
DPS2        -3.1280e-02  5.7967e-01 -0.0540   0.95698
DPS          1.1698e-01  4.5387e-01  0.2577   0.79669
AVGEPS      -1.9652e-04  1.3505e-04 -1.4551   0.14607
ROA          2.1711e+00  3.3048e-01  6.5697 9.625e-11 ***
ROE          1.4860e-01  1.0052e-01  1.4783   0.13976
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    149.48
Residual Sum of Squares: 132.04
R-Squared:      0.11666
Adj. R-Squared: 0.10326
F-statistic: 8.70434 on 11 and 725 DF, p-value: 1.3403e-14
```

Annex B Random Effects Regression for the 1980-1989 period – NASDAQ Raw Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq80, model = "within",
    index = c("id", "year"))

Unbalanced Panel: n = 142, T = 1-9, N = 737

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.141425 -0.218226 -0.020963  0.178186  2.557600

Coefficients:
          Estimate  Std. Error t-value  Pr(>|t|)
BVS     5.9495e-05  8.9535e-05  0.6645    0.5066
EPS    -4.9123e-05  6.4102e-05 -0.7663    0.4438
LA      1.8791e-01  2.4464e-01  0.7681    0.4427
EPSAG   1.0126e-03  4.5170e-03  0.2242    0.8227
EPSG   -9.6749e-02  6.7904e-02 -1.4248    0.1548
DPS1   -1.9949e-01  6.3415e-01 -0.3146    0.7532
DPS2    5.3963e-01  8.0848e-01  0.6675    0.5047
DPS    -3.4188e-01  8.0676e-01 -0.4238    0.6719
AVGEPS  5.1455e-05  2.6773e-04  0.1922    0.8477
ROA     3.6513e+00  5.4128e-01  6.7456 3.673e-11 ***
ROE     5.6249e-02  1.1955e-01  0.4705    0.6382
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    127.8
Residual Sum of Squares: 113.09
R-Squared:      0.11512
Adj. R-Squared: -0.1152
F-statistic: 6.90668 on 11 and 584 DF, p-value: 5.1584e-11
```

Annex C Random Effects Regression for the 1980-1989 period – NASDAQ Raw Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq80, model = "random",
    random.method = "nerlove", index = c("id", "year"))

Unbalanced Panel: n = 142, T = 1-9, N = 737

Effects:
                 var std.dev share
idiosyncratic 0.1534  0.3917  0.64
individual    0.0864  0.2939  0.36
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.2002  0.4881  0.5940  0.5359  0.5940  0.5940

Residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.03502 -0.24475 -0.04093 -0.00012  0.18077  2.62294

Coefficients:
               Estimate  Std. Error z-value  Pr(>|z|)
(Intercept) -8.0617e-02  9.0370e-02 -0.8921    0.3724
BVS          9.9572e-05  7.8589e-05  1.2670    0.2052
EPS         -1.3981e-05  3.4523e-05 -0.4050    0.6855
LA           2.0193e-01  1.3238e-01  1.5254    0.1272
EPSAG       -1.5518e-04  3.4433e-03 -0.0451    0.9641
EPSG        -4.2380e-02  6.0772e-02 -0.6974    0.4856
DPS1        -9.5261e-02  5.3790e-01 -0.1771    0.8594
DPS2         1.5492e-01  6.5644e-01  0.2360    0.8134
DPS         -6.1332e-02  5.8766e-01 -0.1044    0.9169
AVGEPS      -1.6683e-04  1.3687e-04 -1.2189    0.2229
ROA          2.6290e+00  4.0060e-01  6.5627 5.285e-11 ***
ROE          1.2994e-01  1.0489e-01  1.2388    0.2154
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    135.04
Residual Sum of Squares: 120.47
R-Squared:      0.10793
Adj. R-Squared: 0.094395
Chisq: 84.4112 on 11 DF, p-value: 2.0574e-13
```

Annex D F Test for the 1980-1989 period – NASDAQ Raw Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 + DPS2 + DPS +  ...
F = 0.69424, df1 = 141, df2 = 584, p-value = 0.9956
alternative hypothesis: significant effects
```

Annex E Breusch-Pagan Lagrange Multiplier for the 1980-1989 period – NASDAQ Raw Data

```
        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 + DPS2 + DPS +  ...
chisq = 7.219, df = 1, p-value = 0.007214
alternative hypothesis: significant effects
```

Annex F Pooled OLS Regression for the 1990-1999 period – NASDAQ Raw Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq90,
    model = "pooling")

Unbalanced Panel: n = 571, T = 1-10, N = 3074

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.45786 -0.39824 -0.13744  0.16215 98.85606

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  3.1351e-01  6.1239e-02  5.1194 3.254e-07 ***
BVS          1.1340e-06  4.8415e-06  0.2342  0.814818
EPS         -1.7050e-05  8.1061e-05 -0.2103  0.833418
IA          -2.2596e-02  3.0260e-01 -0.0747  0.940478
LA          -1.2887e-01  8.0073e-02 -1.6094  0.107624
EPSAG        1.2398e-05  6.4149e-03  0.0019  0.998458
EPSG         3.9460e-01  1.4278e-01  2.7636  0.005751 **
DPS1         6.4083e-02  1.6153e-01  0.3967  0.691605
DPS2        -6.4076e-02  1.6153e-01 -0.3967  0.691636
DPS         -1.4775e-04  2.9732e-04 -0.4970  0.619258
AVGEPS       6.0406e-05  1.4307e-04  0.4222  0.672896
ROA         -1.0148e-01  1.6233e-01 -0.6252  0.531909
ROE          4.2965e-02  3.2222e-02  1.3334  0.182493
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    11443
Residual Sum of Squares: 11394
R-Squared:      0.0043162
Adj. R-Squared: 0.00041282
F-statistic: 1.10576 on 12 and 3061 DF, p-value: 0.35029
```

Annex G Fixed Effects Regression for the 1990-1999 period – NASDAQ Raw Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq90,
    model = "within", index = c("id", "year"))

Unbalanced Panel: n = 571, T = 1-10, N = 3074

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-13.235648  -0.299337  -0.036831   0.195162  86.730529

Coefficients:
          Estimate  Std. Error t-value Pr(>|t|)
BVS     1.4338e-05  3.1614e-05  0.4535   0.6502
EPS    -5.3444e-06  1.0297e-04 -0.0519   0.9586
IA     -2.7329e-01  7.8305e-01 -0.3490   0.7271
LA     -2.2846e-01  3.0088e-01 -0.7593   0.4477
EPSAG  -4.0214e-04  1.0011e-02 -0.0402   0.9680
EPSG    2.5065e-01  1.6936e-01  1.4800   0.1390
DPS1    1.1162e-01  1.8820e-01  0.5931   0.5532
DPS2   -1.1152e-01  1.8820e-01 -0.5926   0.5535
DPS    -6.5660e-05  3.9952e-04 -0.1643   0.8695
AVGEPS -9.6913e-06  2.4395e-04 -0.0397   0.9683
ROA     2.6913e-01  3.4559e-01  0.7788   0.4362
ROE     5.9058e-02  5.1606e-02  1.1444   0.2526

Total Sum of Squares:    9812.9
Residual Sum of Squares: 9780.6
R-Squared:      0.0032966
Adj. R-Squared: -0.22957
F-statistic: 0.686593 on 12 and 2491 DF, p-value: 0.76594
```

Annex H Random Effects Regression for the 1990-1999 period – NASDAQ Raw Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq90,
    model = "random", random.method = "nerlove",
    index = c("id", "year"))

Unbalanced Panel: n = 571, T = 1-10, N = 3074

Effects:
                 var std.dev share
idiosyncratic 3.1817  1.7837 0.846
individual    0.5780  0.7603 0.154
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.08008 0.27611 0.38396 0.33310 0.40416 0.40416

Residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -5.546  -0.371  -0.116   0.002   0.173  94.506

Coefficients:
               Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)  2.7550e-01  7.6140e-02  3.6183 0.0002965 ***
BVS         -5.4650e-08  5.5154e-06 -0.0099 0.9920943
EPS         -1.6845e-05  8.0846e-05 -0.2084 0.8349460
IA           1.3903e-02  3.8348e-01  0.0363 0.9710793
LA          -6.9007e-02  9.1370e-02 -0.7552 0.4500993
EPSAG        5.6574e-06  7.2736e-03  0.0008 0.9993794
EPSG         3.4071e-01  1.4713e-01  2.3157 0.0205773 *
DPS1         8.8001e-02  1.6451e-01  0.5349 0.5927071
DPS2        -8.7962e-02  1.6451e-01 -0.5347 0.5928718
DPS         -1.2118e-04  3.0128e-04 -0.4022 0.6875295
AVGEPS       5.3060e-05  1.5249e-04  0.3480 0.7278696
ROA          4.4077e-02  1.8234e-01  0.2417 0.8089843
ROE          4.1881e-02  3.3126e-02  1.2643 0.2061312
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    10586
Residual Sum of Squares: 10555
R-Squared:      0.0029673
Adj. R-Squared: -0.00094134
Chisq: 9.87317 on 12 DF, p-value: 0.62709
```

Annex I F Test for the 1990-1999 period – NASDAQ Raw Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
F = 0.72076, df1 = 570, df2 = 2491, p-value = 1
alternative hypothesis: significant effects
```

Annex J Breusch-Pagan Lagrange Multiplier for the 1990-1999 period – NASDAQ Raw Data

```
        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
chisq = 0.61282, df = 1, p-value = 0.4337
alternative hypothesis: significant effects
```

Annex K Pooled OLS Regression for the 2000-2009 period – NASDAQ Raw Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq00,
    model = "pooling")

Unbalanced Panel: n = 1051, T = 1-10, N = 6275

Residuals:
     Min.    1st Qu.     Median    3rd Qu.       Max.
  -45.6392   -11.7354    -8.6363    -3.6047 42376.9875

Coefficients:
               Estimate  Std. Error t-value Pr(>|t|)
(Intercept)  1.2076e+01  8.2958e+00  1.4557   0.1455
BVS          2.0720e-05  4.8737e-04  0.0425   0.9661
EPS         -4.5144e-04  9.5337e-03 -0.0474   0.9622
IA          -2.3366e+01  4.0326e+01 -0.5794   0.5623
LA          -1.5144e-02  5.8203e-01 -0.0260   0.9792
EPSAG       -2.8296e-03  9.2343e-03 -0.3064   0.7593
EPSG        -2.0530e+01  1.6167e+01 -1.2699   0.2042
DPS1         4.1920e-03  4.1966e-01  0.0100   0.9920
DPS2        -3.2757e-03  4.2912e-01 -0.0076   0.9939
DPS         -1.3752e-01  1.4100e+00 -0.0975   0.9223
AVGEPS       9.2016e-04  1.0110e-02  0.0910   0.9275
ROA         -7.7420e-02  7.8372e-01 -0.0988   0.9213
ROE          2.4626e-01  6.3648e-01  0.3869   0.6988

Total Sum of Squares:    1797400000
Residual Sum of Squares: 1796800000
R-Squared:      0.00035305
Adj. R-Squared: -0.0015626
F-statistic: 0.184297 on 12 and 6262 DF, p-value: 0.999
```

Annex L Fixed Effects Model for the 2000-2009 period – NASDAQ Raw Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq00,
    model = "within", index = c("id", "year"))

Unbalanced Panel: n = 1051, T = 1-10, N = 6275

Residuals:
      Min.     1st Qu.      Median     3rd Qu.        Max.
-2.1198e+04 -1.3536e+00 -6.1464e-02  9.6755e-01  2.1198e+04

Coefficients:
          Estimate  Std. Error t-value Pr(>|t|)
BVS     2.1266e-05  1.9332e-03  0.0110   0.9912
EPS    -1.1676e-04  9.1662e-03 -0.0127   0.9898
IA     -1.9198e-01  7.4329e+01 -0.0026   0.9979
LA      6.4590e-03  5.1095e-01  0.0126   0.9899
EPSAG   3.0091e-02  8.0301e-01  0.0375   0.9701
EPSG   -8.8706e+00  1.4935e+01 -0.5939   0.5526
DPS1    3.2949e-03  3.4765e-01  0.0095   0.9924
DPS2   -3.1742e-03  3.5586e-01 -0.0089   0.9929
DPS    -2.9502e-03  1.2931e+00 -0.0023   0.9982
AVGEPS -9.2307e-05  2.0285e-02 -0.0046   0.9964
ROA     1.3234e-01  8.5567e-01  0.1547   0.8771
ROE     1.4586e-02  5.3227e-01  0.0274   0.9781

Total Sum of Squares:    898920000
Residual Sum of Squares: 898850000
R-Squared:      7.5434e-05
Adj. R-Squared: -0.20367
F-statistic: 0.0327659 on 12 and 5212 DF, p-value: 1
```

Annex M Random Effects Model for the 2000-2009 period – NASDAQ Raw Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = Nasdaq00,
    model = "random", random.method = "nerlove",
    index = c("id", "year"))

Unbalanced Panel: n = 1051, T = 1-10, N = 6275

Effects:
                   var  std.dev share
idiosyncratic 143243.3    378.5 0.499
individual    143838.3    379.3 0.501
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.2936  0.6227  0.6673  0.6404  0.6991  0.6991

Residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  -8990      -9      -6      -2      -4   33405

Coefficients:
               Estimate  Std. Error z-value Pr(>|z|)
(Intercept)  2.2329e+01  1.6741e+01  1.3338   0.1823
BVS          3.5281e-05  8.4958e-04  0.0415   0.9669
EPS         -1.6744e-04  8.8467e-03 -0.0189   0.9849
IA          -2.9941e+01  5.9829e+01 -0.5004   0.6168
LA          -1.4094e-02  5.2345e-01 -0.0269   0.9785
EPSAG       -1.8371e-03  1.0564e-02 -0.1739   0.8619
EPSG        -1.4280e+01  1.4954e+01 -0.9549   0.3396
DPS1         3.0183e-03  3.6189e-01  0.0083   0.9933
DPS2        -2.5715e-03  3.7063e-01 -0.0069   0.9945
DPS         -6.0457e-02  1.3017e+00 -0.0464   0.9630
AVGEPS       6.4501e-04  1.3849e-02  0.0466   0.9629
ROA          3.7804e-02  7.8075e-01  0.0484   0.9614
ROE          1.0073e-01  5.5448e-01  0.1817   0.8558

Total Sum of Squares:    1197600000
Residual Sum of Squares: 1197200000
R-Squared:      0.00036564
Adj. R-Squared: -0.00155
Chisq: 1.25525 on 12 DF, p-value: 0.99995
```

Annex N F Test for the 2000-2009 period – NASDAQ Raw Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
F = 4.9587, df1 = 1050, df2 = 5212, p-value < 2.2e-16
alternative hypothesis: significant effects
```

Annex O Hausman Test for the 2000-2009 period – NASDAQ Raw Data

```
        Hausman Test

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
chisq = 6.5178, df = 12, p-value = 0.8878
alternative hypothesis: one model is inconsistent
```

Annex P Pooled OLS Regression for the 1980-1989 period – NASDAQ Intangible-Adjusted Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq80, model = "pooling",
    index = c("id", "year"))

Unbalanced Panel: n = 145, T = 1-9, N = 740

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.028812 -0.258310 -0.061292  0.175107  2.829787

Coefficients:
              Estimate  Std. Error t-value  Pr(>|t|)
(Intercept) -0.07658430  0.05917018 -1.2943  0.195970
BVS          0.00019510  0.00066527  0.2933  0.769401
EPS         -0.00465921  0.00185667 -2.5094  0.012308 *
LA           0.26330132  0.08991770  2.9282  0.003515 **
EPSAG        0.01052915  0.01529967  0.6882  0.491549
EPSG        -0.05012843  0.09465830 -0.5296  0.596570
DPS1         0.39355357  0.48111751  0.8180  0.413625
DPS2        -0.09908280  0.63878269 -0.1551  0.876776
DPS         -0.38792190  0.55196242 -0.7028  0.482402
AVGEPS       0.00579682  0.00360670  1.6072  0.108436
ROA          1.90116588  0.43364572  4.3841 1.336e-05 ***
ROE          0.05919585  0.20103220  0.2945  0.768491
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    159.44
Residual Sum of Squares: 140.32
R-Squared:      0.11991
Adj. R-Squared: 0.10661
F-statistic: 9.01715 on 11 and 728 DF, p-value: 3.3396e-15
```

Annex Q Fixed Effects Regression for the 1980-1989 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq80, model = "within",
    index = c("id", "year"))

Unbalanced Panel: n = 145, T = 1-9, N = 740

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-1.191778 -0.219915 -0.022946  0.186064  2.417421

Coefficients:
         Estimate Std. Error t-value  Pr(>|t|)
BVS     0.0067829  0.0049756  1.3632 0.1733370
EPS    -0.0089435  0.0023142 -3.8646 0.0001237 ***
LA      0.5060647  0.2761610  1.8325 0.0673861 .
EPSAG   0.0287010  0.0268731  1.0680 0.2859531
EPSG   -0.3105619  0.1169271 -2.6560 0.0081226 **
DPS1    0.3970286  0.5741120  0.6916 0.4894932
DPS2    0.1077072  0.7714606  0.1396 0.8890127
DPS    -0.5357736  0.6265928 -0.8551 0.3928692
AVGEPS -0.0223888  0.0209225 -1.0701 0.2850233
ROA     2.9264200  0.6314644  4.6343  4.42e-06 ***
ROE     0.1254222  0.2632425  0.4765 0.6339313
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    136.16
Residual Sum of Squares: 122.1
R-Squared:      0.10329
Adj. R-Squared: -0.1347
F-statistic: 6.11557 on 11 and 584 DF, p-value: 1.5526e-09
```

Annex R Random Effects Regression for the 1980-1989 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 +
    DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq80, model = "random",
    random.method = "nerlove", index = c("id", "year"))

Unbalanced Panel: n = 145, T = 1-9, N = 740

Effects:
                  var std.dev share
idiosyncratic 0.16500 0.40620 0.689
individual    0.07436 0.27268 0.311
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1697  0.4804  0.5553  0.4958  0.5553  0.5553

Residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-1.02812 -0.24216 -0.05633  0.00198  0.19391  2.62668

Coefficients:
              Estimate Std. Error z-value  Pr(>|z|)
(Intercept) -0.1341001  0.0829950 -1.6158  0.106146
BVS          0.0005060  0.0010362  0.4883  0.625334
EPS         -0.0057118  0.0018590 -3.0724  0.002123 **
LA           0.3127120  0.1263711  2.4746  0.013340 *
EPSAG        0.0194412  0.0194002  1.0021  0.316290
EPSG        -0.1805196  0.1013770 -1.7807  0.074965 .
DPS1         0.3256277  0.4995333  0.6519  0.514489
DPS2         0.0529725  0.6631242  0.0799  0.936330
DPS         -0.4460199  0.5602767 -0.7961  0.425991
AVGEPS       0.0037999  0.0049431  0.7687  0.442054
ROA          2.2157460  0.4899876  4.5220 6.125e-06 ***
ROE          0.0598738  0.2189294  0.2735  0.784481
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    144.94
Residual Sum of Squares: 130.37
R-Squared:      0.10056
Adj. R-Squared: 0.086968
Chisq: 79.3992 on 11 DF, p-value: 1.9281e-12
```

Annex S F Test for the 1980-1989 period – NASDAQ Intangible-Adjusted Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 + DPS2 + DPS +  ...
F = 0.60524, df1 = 144, df2 = 584, p-value = 0.9998
alternative hypothesis: significant effects
```

Annex T Breusch-Pagan Lagrange Multiplier for the 1980-1989 period – NASDAQ Intangible-Adjusted Data

```
        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Returns ~ BVS + EPS + LA + EPSAG + EPSG + DPS1 + DPS2 + DPS +  ...
chisq = 13.455, df = 1, p-value = 0.0002444
alternative hypothesis: significant effects
```

Annex U Pooled OLS Regression for the 1990-1999 period – NASDAQ Intangible-Adjusted Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq90,
    model = "pooling")

Unbalanced Panel: n = 506, T = 1-10, N = 2860

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.31026 -0.40210 -0.13385  0.16635 98.72809

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  4.7617e-01  1.0412e-01  4.5734 5.004e-06 ***
BVS         -5.5009e-06  9.7060e-05 -0.0567   0.95481
EPS         -1.0667e-04  3.2769e-04 -0.3255   0.74482
IA          -3.8343e-01  1.9708e-01 -1.9455   0.05181 .
LA          -2.7674e-01  1.2860e-01 -2.1519   0.03149 *
EPSAG       -4.3331e-04  5.4261e-03 -0.0799   0.93636
EPSG         3.4252e-01  1.6318e-01  2.0990   0.03590 *
DPS1         5.2068e-02  1.3914e-01  0.3742   0.70827
DPS2        -4.8945e-02  1.3066e-01 -0.3746   0.70799
DPS         -4.9283e-02  5.3876e-02 -0.9148   0.36040
AVGEPS       2.8336e-04  6.7099e-04  0.4223   0.67283
ROA         -1.3833e-02  2.7860e-01 -0.0497   0.96040
ROE          1.0224e-02  4.0467e-02  0.2527   0.80056
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    11120
Residual Sum of Squares: 11068
R-Squared:      0.0046843
Adj. R-Squared: 0.00048907
F-Statistic: 1.11658 on 12 and 2847 DF, p-value: 0.34128
```

Annex V Fixed Effects Regression for the 1990-1999 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq90,
    model = "within", index = c("id", "year"))

Unbalanced Panel: n = 506, T = 1-10, N = 2860

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-13.194040  -0.301105  -0.035381   0.190093  86.736407

Coefficients:
          Estimate  Std. Error t-value Pr(>|t|)
BVS     0.00031221  0.00070599  0.4422  0.65837
EPS    -0.00015549  0.00076730 -0.2026  0.83943
IA     -0.75587208  0.63867765 -1.1835  0.23673
LA     -0.06901560  0.52802038 -0.1307  0.89602
EPSAG  -0.00633123  0.01030591 -0.6143  0.53906
EPSG    0.23101653  0.19160824  1.2057  0.22807
DPS1    0.08411158  0.18621661  0.4517  0.65154
DPS2   -0.07103173  0.16954274 -0.4190  0.67528
DPS    -0.02234388  0.20531397 -0.1088  0.91335
AVGEPS -0.00178998  0.00401491 -0.4458  0.65576
ROA     1.19471233  0.55387548  2.1570  0.03111 *
ROE     0.02039808  0.04853297  0.4203  0.67431
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    9621.8
Residual Sum of Squares: 9577
R-Squared:      0.0046626
Adj. R-Squared: -0.21506
F-statistic: 0.914238 on 12 and 2342 DF, p-value: 0.53161
```

Annex W Random Effects Regression for the 1990-1999 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq90,
    model = "random", random.method = "nerlove",
    index = c("id", "year"))

Unbalanced Panel: n = 506, T = 1-10, N = 2860

Effects:
                var std.dev share
idiosyncratic 3.349   1.830 0.744
individual    1.154   1.074 0.256
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1376  0.3940  0.5258  0.4573  0.5258  0.5258

Residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -6.985  -0.362  -0.100   0.001   0.172  93.025

Coefficients:
               Estimate  Std. Error z-value Pr(>|z|)
(Intercept)  3.4741e-01  1.4259e-01  2.4365  0.01483 *
BVS          3.8169e-06  1.2349e-04  0.0309  0.97534
EPS         -1.3156e-04  3.6739e-04 -0.3581  0.72028
IA          -3.1401e-01  2.8976e-01 -1.0837  0.27850
LA          -8.5169e-02  1.6861e-01 -0.5051  0.61347
EPSAG       -1.8287e-03  6.5690e-03 -0.2784  0.78072
EPSG         2.7659e-01  1.6963e-01  1.6306  0.10298
DPS1         5.4674e-02  1.3877e-01  0.3940  0.69359
DPS2        -5.2900e-02  1.3037e-01 -0.4058  0.68490
DPS         -4.1189e-02  6.7616e-02 -0.6092  0.54241
AVGEPS       3.0543e-04  7.4168e-04  0.4118  0.68048
ROA          4.7378e-01  3.4298e-01  1.3814  0.16716
ROE          1.3303e-02  4.1559e-02  0.3201  0.74889
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    10110
Residual Sum of Squares: 10079
R-Squared:      0.0030639
Adj. R-Squared: -0.0011381
Chisq: 8.99459 on 12 DF, p-value: 0.70339
```

Annex X F Test for the 1990-1999 period – NASDAQ Intangible-Adjusted Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
F = 0.72202, df1 = 505, df2 = 2342, p-value = 1
alternative hypothesis: significant effects
```

Annex X Breusch-Pagan Lagrange Multiplier for the 1990-1999 period – NASDAQ Intangible-Adjusted Data

```
        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
chisq = 1.2052, df = 1, p-value = 0.2723
alternative hypothesis: significant effects
```

Annex Y Pooled OLS Regression for the 2000-2009 period – NASDAQ Intangible-Adjusted Data

```
Pooling Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq00,
    model = "pooling")

Unbalanced Panel: n = 834, T = 1-10, N = 5403

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1.72772 -0.38192 -0.13944  0.14202 23.67421

Coefficients:
               Estimate  Std. Error t-value  Pr(>|t|)
(Intercept)  1.9168e-01  3.5030e-02  5.4719 4.653e-08 ***
BVS          3.3867e-05  1.5449e-05  2.1922   0.02841 *
EPS          9.3011e-05  3.6267e-05  2.5646   0.01036 *
IA          -6.4577e-02  5.9024e-02 -1.0941   0.27397
LA          -6.3399e-02  3.9759e-02 -1.5946   0.11086
EPSAG       -7.0108e-05  3.8340e-04 -0.1829   0.85492
EPSG         2.3181e-01  3.0872e-02  7.5086 6.954e-14 ***
DPS1         6.1174e-02  2.9356e-02  2.0839   0.03722 *
DPS2        -5.9177e-02  2.6799e-02 -2.2082   0.02727 *
DPS         -1.9187e-02  1.6967e-02 -1.1309   0.25817
AVGEPS      -7.1926e-05  3.1964e-05 -2.2502   0.02448 *
ROA          4.0226e-01  7.4566e-02  5.3946 7.159e-08 ***
ROE          1.1835e-02  1.2246e-02  0.9664   0.33387
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    5113.6
Residual Sum of Squares: 5002.7
R-Squared:      0.021687
Adj. R-Squared: 0.019509
F-statistic: 9.95693 on 12 and 5390 DF, p-value: < 2.22e-16
```

Annex Z Random Effects Regression for the 2000-2009 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Within Model

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq00,
    model = "within", index = c("id", "year"))

Unbalanced Panel: n = 834, T = 1-10, N = 5403

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-4.533570 -0.316877 -0.057228  0.198366 21.019108

Coefficients:
          Estimate  Std. Error t-value  Pr(>|t|)
BVS     9.6389e-05  3.2551e-05  2.9612   0.00308 **
EPS     1.4282e-04  4.1752e-05  3.4207   0.00063 ***
IA     -1.0785e+00  1.8779e-01 -5.7431 9.898e-09 ***
LA     -5.7131e-03  7.6237e-02 -0.0749   0.94027
EPSAG  -5.8505e-05  4.9804e-04 -0.1175   0.90649
EPSG    1.9052e-01  3.7253e-02  5.1142 3.279e-07 ***
DPS1    3.0695e-02  4.2523e-02  0.7219   0.47042
DPS2   -1.4340e-02  3.8312e-02 -0.3743   0.70821
DPS    -2.0359e-02  2.4012e-02 -0.8479   0.39656
AVGEPS -1.8732e-04  1.1781e-04 -1.5901   0.11188
ROA     5.8498e-01  1.1564e-01  5.0588 4.384e-07 ***
ROE     8.1355e-03  1.3383e-02  0.6079   0.54328
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    4411.5
Residual Sum of Squares: 4284.1
R-Squared:      0.028879
Adj. R-Squared: -0.15119
F-statistic: 11.2931 on 12 and 4557 DF, p-value: < 2.22e-16
```

Annex AA Random Effects Regression for the 2000-2009 period – NASDAQ Intangible-Adjusted Data

```
Oneway (individual) effect Random Effect Model
   (Nerlove's transformation)

Call:
plm(formula = Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG +
    DPS1 + DPS2 + DPS + AVGEPS + ROA + ROE, data = A_Nasdaq00,
    model = "random", random.method = "nerlove",
    index = c("id", "year"))

Unbalanced Panel: n = 834, T = 1-10, N = 5403

Effects:
                 var std.dev share
idiosyncratic 0.7929  0.8905 0.777
individual    0.2281  0.4776 0.223
theta:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.1188  0.3944  0.4497  0.4339  0.4921  0.4921

Residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-2.4012 -0.3560 -0.1206  0.0006  0.1527 22.4819

Coefficients:
              Estimate  Std. Error z-value  Pr(>|z|)
(Intercept)  2.3841e-01  4.7074e-02  5.0646 4.093e-07 ***
BVS          6.7142e-05  1.9231e-05  3.4913 0.0004807 ***
EPS          1.1825e-04  3.6305e-05  3.2570 0.0011259 **
IA          -2.3533e-01  8.4150e-02 -2.7966 0.0051646 **
LA          -6.4341e-02  5.0782e-02 -1.2670 0.2051536
EPSAG       -1.5131e-05  4.2036e-04 -0.0360 0.9712867
EPSG         2.0982e-01  3.2401e-02  6.4757 9.436e-11 ***
DPS1         5.0071e-02  3.4734e-02  1.4416 0.1494292
DPS2        -4.2170e-02  3.1554e-02 -1.3364 0.1814047
DPS         -2.0358e-02  1.9768e-02 -1.0298 0.3030886
AVGEPS      -6.3257e-05  3.9945e-05 -1.5836 0.1132810
ROA          4.4638e-01  8.7490e-02  5.1021 3.359e-07 ***
ROE          1.0756e-02  1.2119e-02  0.8875 0.3747851
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    4683.3
Residual Sum of Squares: 4591.6
R-Squared:      0.01958
Adj. R-Squared: 0.017397
Chisq: 109.129 on 12 DF, p-value: < 2.22e-16
```

Annex AB F Test for the 2000-2009 period – NASDAQ Intangible-Adjusted Data

```
        F test for individual effects

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
F = 0.91755, df1 = 833, df2 = 4557, p-value = 0.9437
alternative hypothesis: significant effects
```

Annex AC Breusch-Pagan Lagrange Multiplier for the 2000-2009 period – NASDAQ Intangible-Adjusted Data

```
        Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data:  Returns ~ BVS + EPS + IA + LA + EPSAG + EPSG + DPS1 + DPS2 +  ...
chisq = 15.006, df = 1, p-value = 0.0001072
alternative hypothesis: significant effects
```

Annex AD Stock Dataset

Stock	NASDAQ Ticker
APPLE INC	@AAPL
MICROSOFT CORP	@MSFT
AMAZON.COM INC	@AMZN
TESLA INC	@TSLA
ALPHABET INC	@GOOGL
NVIDIA CORPORATION	@NVDA
META PLATFORMS INC	@FB
ADOBE INC	@ADBE
BROADCOM INC	@AVGO
CISCO SYSTEMS, INC.	@CSCO
PEPSICO, INC.	@PEP
COSTCO WHOLESALE	@COST
COMCAST CORPORATION	@CMCSA
NETFLIX INC	@NFLX
INTEL CORPORATION	@INTC
QUALCOMM INC	@QCOM
PAYPAL HOLDINGS INC	@PYPL
TEXAS INSTRUMENTS	@TXN
ADVANCED MICRO	@AMD
INTUIT INC	@INTU
T-MOBILE US INC	@TMUS
HONEYWELL INTERNATNL	@HON
AMGEN INC	@AMGN
APPLIED MATERIALS	@AMAT
STARBUCKS CORP	@SBUX
CHARTER COMMU	@CHTR
INTUITIVE SURGICAL	@ISRG
BOOKING HOLDINGS	@BKNG
MICRON TECHNOLOGY	@MU
MONDELEZ	@MDLZ
ANALOG DEVICES, INC.	@ADI
AUTOMATIC DATA PROC	@ADP
CME GROUP INC	@CME
LAM RESEARCH CORP	@LRCX
CSX CORPORATION	@CSX
GILEAD SCIENCES, INC	@GILD
FISERV INC	@FISV
MODERNA INC	@MRNA
ACTIVISION BLIZZARD	@ATVI
EQUINIX, INC.	@EQIX
MARVELL TECHNOLOGY	@MRVL
REGENERON PHARMA	@REGN
VERTEX PHARMA INC	@VRTX

AUTODESK INC	@ADSK
FORTINET INC	@FTNT
ILLUMINA, INC.	@ILMN
KEURIG DR PEPPER INC	@KDP
KLA	@KLAC
MARRIOTT INT'L	@MAR
NXP SEMICONDUCTORS	@NXPI
COGNIZANT TECHNOLOGY	@CTSH
MERCADOLIBRE INC	@MELI
PALO ALTO	@PANW
AMERICAN ELECTRIC	@AEP
ATLASSIAN CORP	@TEAM
EXELON CORPORATION	@EXC
IDEXX LABORATORIES	@IDXX
LUCID GROUP INC	@LCID
MONSTER BEVERAGE	@MNST
O REILLY AUTOMOTIVE	@ORLY
PAYCHEX INC	@PAYX
SYNOPSYS INC	@SNPS
WORKDAY	@WDAY
ZOOM VIDEO COMM	@ZM
ALIGN TECHNOLOGY INC	@ALGN
CADENCE DESIGN SYST	@CDNS
CINTAS CORPORATION	@CTAS
DATADOG INC	@DDOG
DEXCOM, INC.	@DXCM
ELECTRONIC ARTS, INC	@EA
KRAFT HEINZ CO	@KHC
LULULEMON ATHLETIC	@LULU
MICROCHIP TECHNOLOGY	@MCHP
NASDAQ INC	@NDAQ
WALGREENS BOOTS	@WBA
WILLIS TOWERS WAT	@WTW
BIOGEN INC	@BIIB
CROWDSTRIKE HOLD	@CRWD
EBAY INC.	@EBAY
OLD DOMINION FREIGHT	@ODFL
SBA COMMUNICATIONS	@SBAC
SVB FINANCIAL GROUP	@SIVB
T ROWE PRICE	@TROW
XCEL ENERGY INC	@XEL
ZSCALER	@ZS
COPART INC	@CPRT
DOLLAR TREE, INC	@DLTR
FASTENAL COMPANY	@FAST
FIFTH THIRD BANCORP	@FITB

MATCH GROUP	@MTCH
PACCAR INC.	@PCAR
ROSS STORES, INC.	@ROST
TRADE DESK INC	@TTD
VERISK ANALYTICS	@VRSK
ANSYS, INC.	@ANSS
CDW CORP	@CDW
CERNER CORPORATION	@CERN
COCA-COLA	@CCEP
COSTAR GROUP, INC.	@CSGP
DOCUSIGN INC	@DOCU
EXPEDIA GROUP INC	@EXPE
MONGODB INC	@MDB
NORTHERN TRUST CORP	@NTRS
OKTA INC	@OKTA
ON SEMICONDUCTOR	@ON
PELOTON INTERACTIV	@PTON
SEAGEN INC	@SGEN
SIRIUS XM HOLDINGS	@SIRI
TRACTOR SUPPLY CO	@TSCO
VERISIGN, INC.	@VRSN
ZEBRA TECHNOLOGIES	@ZBRA
AMERICAN AIRLINES	@AAL
BAKER HUGHES CO	@BKR
CINCINNATI FINL CORP	@CINF
DIAMONDBACK	@FANG
ENPHASE ENERGY	@ENPH
HORIZON THERAPE	@HZNP
J B HUNT TRANSPORT	@JBHT
HUNTINGTON BANCSHR	@HBAN
ICON PLC	@ICLR
NETAPP INC.	@NTAP
PLUG POWER INC.	@PLUG
PRINCIPAL FINL GROUP	@PFG
SEAGATE TECHNOLOGY	@STX
SIGNATURE BANK	@SBNY
SKYWORKS SOLUTIONS	@SWKS
SS&C TECHNOLOGIES	@SSNC
TAKE	@TTWO
TRIMBLE INC	@TRMB
ULTA BEAUTY INC	@ULTA
VIACOMCBS INC	@VIAC
ZOOMINFO	@ZI
AKAMAI TECHNOLOGIES	@AKAM
ALLIANT ENERGY CORP	@LNT
ALNYLAM PHARMACEUTIC	@ALNY

ARCH CAPITAL GROUP	@ACGL
BIO-TECHNE CORP	@TECH
BIOMARIN PHARMA	@BMRN
CAESAR	@CZR
CARLYLE GR	@CG
CHECK POINT SOFTWARE	@CHKP
ENTEGRIS, INC.	@ENTG
ETSY INC	@ETSY
EXPEDITORS INTL WASH	@EXPD
HOLOGIC INC	@HOLX
HOST HOTELS	@HST
ICAHN ENTERPRISES	@IEP
INCYTE CORP.	@INCY
INSULET CORPORATION	@PODD
LKQ CORPORATION	@LKQ
MONOLITHIC POWER SYS	@MPWR
NORTONLIFEL	@NLOK
NUANCE COMMUNICATION	@NUAN
POOL CORPORATION	@POOL
ROKU INC	@ROKU
ROYALTY PHARMA	@RPRX
SOLAREDGE TECH	@SEDG
SPLUNK	@SPLK
TERADYNE INC	@TER
VIATRIS INC	@VTRS
WESTERN DIGITAL CORP	@WDC
YANDEX N V	@YNDX
ABIOMED INC	@ABMD
AMERCO	@UHAL
APA CORP (US)	@APA
AVIS BUDGET GROUP	@CAR
BALLARD POWER	@BLDP
BENTLEY SYSTEMS INC	@BSY
BRUKER CORPORATION	@BRKR
CH ROBINSO	@CHRW
CITRIX SYSTEMS INC	@CTXS
COGNEX CORP	@CGNX
CRISPR THERAP	@CRSP
CYRUSONE	@CONE
DENTSPLY SIRONA	@XRAY
EAST WEST BANCORP	@EWBC
EXACT SCIENCES CORPN	@EXAS
F5 INC	@FFIV
FIRST CITIZENS BANC	@FCNCA
FOX CORP	@FOXA
GAMING AND LEISURE	@GLPI

HASBRO INC	@HAS
SCHEIN (HENRY) INC	@HSIC
IAC/INTER	@IAC
HENRY, (JACK) & ASSC	@JKHY
LPL FINANCIAL	@LPLA
LYFT INC	@LYFT
MARKETAXESS HLDGS	@MKTX
MASIMO CORPORATION	@MASI
MIDDLEBY CORP	@MIDD
MORNINGSTAR, INC.	@MORN
NORDSON CORPORATION	@NDSN
OPEN TEXT CORP	@OTEX
PAYLOCITY HOLDI	@PCTY
PTC INC	@PTC
QORVO INC	@QRVO
REGENCY CENTERS CORP	@REG
REPLIGEN CORPORATION	@RGEN
STAR BULK CARRIERS	@SBLK
STEEL DYNAMICS, INC.	@STLD
SUNPOWER CORPORATION	@SPWR
UNITED AIR	@UAL
XP INC	@XP
ZIONS BANCORP	@ZION
ZYNGA INC	@ZNGA
10X GENOMICS INC	@TXG
1LIFE HEALTH	@ONEM
1ST SOURCE CORP	@SRCE
2U INC	@TWOU
A-MARK PRECIOUS	@AMRK
AAON, INC.	@AAON
ACADIA HEALTHCARE	@ACHC
ACADIA PHARMA	@ACAD
ACCOLADE	@ACCD
ACI WORLDWIDE INC	@ACIW
ACM RESEARCH INC	@ACMR
ADAPTHEALTH CORP	@AHCO
ADAPTIVE BIOTECH	@ADPT
ADDUS HOMECARE	@ADUS
ADTRAN INC	@ADTN
ADVANCED ENERGY INDS	@AEIS
ADVANTAGE SOLUTIONS	@ADV
AEROVIRONMENT INC	@AVAV
AGILYSYS INC	@AGYS
AGIOS PHARM	@AGIO
AGNC INVESTMENT CORP	@AGNC
AIR TRANSPORT	@ATSG

ALARMCOM HLDG INC	@ALRM
ALECTOR INC	@ALEC
ALKERMES	@ALKS
ALLEGIANCE BAN	@ABTX
ALLEGIANT TRAVEL	@ALGT
ALLIANCE RESOURCE	@ARLP
ALLOGENE THERAPE	@ALLO
ALPHA & OMEGA	@AOSL
ALPHATEC HLDGS	@ATEC
ALLSCRIPTS HEALTH	@MDRX
ALT	@ALTR
ALTRA INDUSTRIAL	@AIMC
AMBARELLA INC	@AMBA
AMC NETWORKS INC	@AMCX
AMDOCS LTD	@DOX
AMEDISYS, INC.	@AMED
AMERICAN WOODMARK	@AMWD
AMERANT BANCORP INC	@AMTB
AMERICAN NATIONAL	@ANAT
AMERIS BANCORP	@ABCB
AMERISAFE, INC.	@AMSF
AMICUS THERAPEUTICS	@FOLD
AMKOR TECHNOLOGY INC	@AMKR
AMPHASTAR PHARMA	@AMPH
AMYRIS INC	@AMRS
ANAPTYSBIO INC	@ANAB
ANAVEX LIFE	@AVXL
ANDERSONS INC	@ANDE
ANGIODYNAMICS, INC.	@ANGO
ANTERIX INC	@ATEX
APELLIS PHARMACEUT	@APLS
APOGEE ENTERPRISES	@APOG
APOLLO MEDICAL	@AMEH
APPFOLI	@APPF
APPIAN	@APPN
ARCBEST CORP	@ARCB
ARCUTIS BIOTHERA	@ARQT
ARENA PHARMA	@ARNA
ARKO CORP.	@ARKO
ARRIVAL	@ARVL
ARROWHEAD PHARMA	@ARWR
ARVINAS INC	@ARVN
ASPEN TECHNOLOGY INC	@AZPN
ASTEC INDUSTRIES INC	@ASTE
ATARA BIO	@ATRA
ATLANTIC UNION	@AUB

ATLANTICUS HOLDINGS	@ATLC
ATLAS AIR WORLDWIDE	@AAWW
ATLANTICA SUSTAIN	@AY
ATRICURE, INC.	@ATRC
ATRION CORPORATION	@ATRI
AURINIA PHARMA	@AUPH
AVEPOINT INC	@AVPT
AVID BIOSERVICES INC	@CDMO
AVID TECHNOLOGY INC	@AVID
AVIDITY BIOSCIENCES	@RNA
AVNET INC	@AVT
AXCELIS TECHNOLOGIES	@ACLS
AXON ENTERPRISE INC	@AXON
AXONICS INC	@AXNX
AXSOME THERAP	@AXSM
AZENTA INC	@AZTA
B RILEY FINAN	@RILY
BALCHEM CORPORATION	@BCPC
BANCFIRST CORP	@BANF
BANCORP INC (THE)	@TBBK
BANDWIDTH INC	@BAND
BANK OZK	@OZK
BANNER CORPORATION	@BANR
BEACON ROOFING SUP	@BECN
BEAM THERAP	@BEAM
BED BATH & BEYOND	@BBBY
BERRY CORP	@BRY
BETTERWARE	@BWMX
BEYOND MEAT INC	@BYND
BGC PARTNERS, INC.	@BGCP
BIGCOMMERCE	@BIGC
BIOCRYST PHARMA	@BCRX
BIOLIFE SOLUTIONS	@BLFS
BJ'S RESTAURANTS INC	@BJRI
BLACKBAUD, INC.	@BLKB
BLACKLINE INC	@BL
BLINK CHARGING CO	@BLNK
BLOOMIN' BRAND	@BLMN
BLUCORA INC	@BCOR
BLUEPRINT MED	@BPMC
BOK FINANCIAL CORP	@BOKF
BOTTOMLINE TECH	@EPAY
BRIDGEBIO PHARMA INC	@BBIO
BRIGHTHOUSE	@BHF
BROOGE ENERGY LTD	@BROG
BROOKLINE BANCORP	@BRKL

BRP GROUP INC	@BRP
BTRS HOLDINGS INC	@BTRS
CAL-MAINE FOODS INC	@CALM
CALAVO GROWERS INC	@CVGW
CALUMET SPECIALTY	@CLMT
CAMDEN NATIONAL CORP	@CAC
CANADIAN SOLAR INC	@CSIQ
CANOO INC	@GOEV
CAPITOL FEDERAL FIN	@CFFN
CARDIOVASCULAR	@CSII
CARDLYTICS INC	@CDLX
CAREDX INC	@CDNA
CARETRUST REIT INC	@CTRE
CARGURUS INC	@CARG
CASELLA WASTE SYSTEM	@CWST
CASEY'S GEN STORES	@CASY
CASSAVA SCIENCES INC	@SAVA
CASTLE BIO	@CSTL
CATHAY GEN BNCP	@CATY
CAVCO INDUSTRIES	@CVCO
CBTX INC	@CBTX
CDK GLOBAL INC	@CDK
CELLDEX THERAPEUTICS	@CLDX
CELSIUS HOLDINGS INC	@CELH
CENTENNIAL RESOURCE	@CDEV
CENTURY ALUMINUM CO	@CENX
CERENCE INC	@CRNC
CEREVEL	@CERE
CERUS CORPORATION	@CERS
CEVA INC	@CEVA
CHAMPIONX	@CHX
CHANGE H	@CHNG
CHEESECAKE FACTORY	@CAKE
CHEFS' WAREHOUSE INC	@CHEF
CHEMOCEN	@CCXI
CHILDREN'S PL	@PLCE
CHURCHILL DOWNS INC	@CHDN
CIMPRESS NV	@CMPR
CIRRUS LOGIC, INC.	@CRUS
CITY HOLDING COMPANY	@CHCO
CLARUS CORP	@CLAR
CLEAN ENERGY FUELS	@CLNE
CLEARFIELD, INC.	@CLFD
CLOVER HEALT	@CLOV
CMC MATERIALS INC	@CCMP
COCA-COLA CON	@COKE

CODEXIS, INC	@CDXS
COGENT COMM	@CCOI
COHERENT, INC.	@COHR
COHERUS BIO	@CHRS
COHU, INC.	@COHU
COLUMBIA BKG SYS INC	@COLB
COLUMBIA FINANCIAL	@CLBK
COLUMBIA SPORTSWEAR	@COLM
COLUMBUS MCKINNON	@CMCO
COMMERCE BANCSHARES	@CBSH
COMMSCOPE HOLD	@COMM
COMMUNITY TRUST BANC	@CTBI
COMMVAULT SYSTEMS	@CVLT
CONDUENT INC	@CNDT
CONNECTONE BANCORP	@CNOB
CONSTRUCTION PARTNER	@ROAD
CORCEPT THERAPEUTICS	@CORT
CORSAIR GAM	@CRSR
CORVEL CORPORATION	@CRVL
COUPA	@COUP
COVETRUS INC	@CVET
COWEN INC	@COWN
CRACKER BARREL	@CBRL
CREDIT ACCEPTANCE	@CACC
CRINETICS PHARMA	@CRNX
CROCS, INC.	@CROX
CROSS COUNTRY HEALTH	@CCRN
CROSSFIRST	@CFB
CRYOPORT, INC.	@CYRX
CSG SYSTEMS INT'L	@CSGS
CSW INDUSTRI	@CSWI
CUREVAC BV	@CVAC
CVB FINANCIAL CORP	@CVBF
CYBERARK	@CYBR
CYTOKINETICS, INC.	@CYTK
DAVE & BUSTER'S	@PLAY
DENALI THERA	@DNLI
DENNY'S CORP.	@DENN
DIGI INTERNATIONAL	@DGII
DIGITAL TURBINE	@APPS
DIME COMMUNITY	@DCOM
DIODES INCORPORATED	@DIOD
DISCOVERY INC	@DISCA
DISH NETWORK	@DISH
DIVERSIFIED HEA	@DHC
DOMO INC	@DOMO

DORCHESTER MINERALS	@DMLP
DORMAN PRODUCTS INC	@DORM
DRAFTKINGS INC	@DKNG
DROPBOX	@DBX
DUCK CREEK TECH	@DCT
DYNAVAX TECH CORP	@DVAX
EAGLE BANCORP, INC.	@EGBN
EBIX, INC.	@EBIX
ECHOSTAR CORPORATION	@SATS
EDITAS MEDICIN	@EDIT
ENANTA PHARM	@ENTA
ENCORE CAPITAL GRP	@ECPG
ENCORE WIRE CORP	@WIRE
ENDO INTERNAT	@ENDP
ENERGY RECO	@ERII
ENSIGN GROUP	@ENSG
ENSTAR GROUP LIMITED	@ESGR
ENTERPRISE FIN'L	@EFSC
EPLUS INC.	@PLUS
ERIE INDEMNITY	@ERIE
ESTABLISHMENT LABS	@ESTA
EURONET WORLDWIDE	@EEFT
EVERBRIDGE INC	@EVBG
EVO PAYMENTS INC	@EVOP
EXELIXIS, INC.	@EXEL
EXLSERVICE HLDGS	@EXLS
EXP WORLD HOLD	@EXPI
EXPONENT, INC.	@EXPO
EXTREME NETWORKS	@EXTR
FARADAY FUTURE	@FFIE
FARO TECHNOLOGIES	@FARO
FATE THERAPEUT	@FATE
FERROGLOBE PLC	@GSM
FIBROGEN	@FGEN
FIRST BANCORP	@FBNC
FIRST BANCSHARES	@FBMS
FIRST BUSEY CORP	@BUSE
FIRST FIN'L BANCORP	@FFBC
FIRST FINL BANKSHARE	@FFIN
FIRST	@FFWM
FIRST HAWAIIAN INC	@FHB
FIRST INTERSTATE	@FIBK
FIRST MERCHANTS CORP	@FRME
FIRST MID-ILLINOIS	@FMBH
FIRST MIDWEST BANC	@FMBI
FIRST SOLAR, INC.	@FSLR

FIRSTCASH	@FCFS
FIVE BELOW INC	@FIVE
FIVE9 INC	@FIVN
FLEX LTD	@FLEX
FLUSHING FIN'L CORP	@FFIC
FOCUS FINANCIAL	@FOCS
FORMFACTOR, INC.	@FORM
FORRESTER RESEARCH	@FORR
FORTERRA INC	@FRTA
FORWARD AIR CORP	@FWRD
FOX FACTORY	@FOXF
FRANCHISE GR	@FRG
FRANKLIN ELECTRIC CO	@FELE
FREEDOM HOLDING CORP	@FRHC
FRESHPET INC	@FRPT
FRONT	@FTDR
FUELCELL ENERGY INC	@FCEL
FULGENT GENETICS INC	@FLGT
FULTON FINL CORP	@FULT
G-III APPAREL GROUP	@GIII
GENTEX CORPORATION	@GNTX
GENTHERM INC	@THRM
GERMAN AMERICAN	@GABC
GIBRALTAR INDUSTRIES	@ROCK
GLADSTONE COMMERCIAL	@GOOD
GLADSTONE	@LAND
GLOBAL BLOOD TH	@GBT
GOGO	@GOGO
GOLAR LNG LTD	@GLNG
GOLDEN ENTERTAINM	@GDEN
GOLDEN OCEAN	@GOGL
GOODRX HOLDINGS INC	@GDRX
GOODYEAR TIRE	@GT
GOOSEHEAD INSURANCE	@GSHD
GOPRO INC	@GPRO
GRAND CANYON EDU	@LOPE
GREAT LAKES DREDGE	@GLDD
GREAT SOUTHERN BANC	@GSBC
GREEN PLAINS INC	@GPRE
GREENSKY INC	@GSKY
GRID DY	@GDYN
GROCERY OUTLET HO	@GO
GUARDANT HEALTH INC	@GH
H&E EQUIPMENT SVCS	@HEES
HAIN CELESTIAL GROUP	@HAIN
HALOZYME THERAPEUTIC	@HALO

HAMILTON LANE	@HLNE
HANCOCK WHITNEY	@HWC
HANMI FINANCIAL	@HAFC
HARBORONE	@HONE
HARMONIC INC.	@HLIT
HARMONY BIOSCIENCES	@HRMY
HAWAIIAN HOLDINGS	@HA
HAWKINS, INC.	@HWKN
HEALTH CATALYST INC	@HCAT
HEALTHCARE SVCS	@HCSG
HEALTHEQUITY INC	@HQY
HEALTHSTREAM, INC.	@HSTM
HEARTLAND EXPRESS	@HTLD
HEARTLAND FINANCIAL	@HTLF
HEIDRICK & STRUGGLES	@HSII
HELEN OF TROY LTD	@HELE
HERITAGE COMMERCE	@HTBK
HERITAGE FINANCIAL	@HFWA
HERON THERAPEUTICS	@HRTX
HESKA CORPORATION	@HSKA
HIBBETT	@HIBB
HIGHPEAK ENERGY INC	@HPK
HINGHAM INSTITUTION	@HIFS
HOLLYSYS AUTOMATION	@HOLI
HOMESTREET INC	@HMST
HOPE BANCORP INC	@HOPE
HORIZON BANCORP INC	@HBNC
HOSTESS BRANDS INC	@TWNK
HOUGHTON MIFFLIN	@HMHC
HUB GROUP, INC.	@HUBG
HURON CONSULTING GRP	@HURN
ICF INTNL INC	@ICFI
ICHOR HOLDINGS LTD	@ICHR
ICU MEDICAL INC	@ICUI
IES HOLDINGS	@IESC
IHEARTMEDIA INC	@IHRT
II-VI INCORPORATED	@IIVI
IMMUNITYBIO INC	@IBRX
IMMUNOGEN INC	@IMGN
IMPINJ INC	@PI
INARI MEDICAL INC	@NARI
INDEPENDENT BANK	@IBTX
INDEPENDENT BNK CORP	@INDB
INDUS REALTY	@INDT
INDUSTRIAL LOGISTI	@ILPT
INFINERA CORPORATION	@INFN

INGLES MARKETS, INC	@IMKTA
INHIBRX INC	@INBX
INMODE LTD	@INMD
INNOSPEC INC	@IOSP
INNOVIVA	@INVA
INOTIV INC	@NOTV
INOVIO PHARMA	@INO
INSIGHT ENTERPRISES	@NSIT
INSMED INCORPORATED	@INSM
INTEGRA LIFESCI	@IART
INTELLIA THE	@NTLA
INTER PARFUMS, INC.	@IPAR
INTERACTIVE BROKERS	@IBKR
INTERDIGITAL INC	@IDCC
INTERFACE, INC.	@TILE
INT'L BANCSHARES	@IBOC
INTERSECT ENT INC	@XENT
INTRA-CELLULAR	@ITCI
INVESTORS BANCORP	@ISBC
IONIS PHARMACEUT	@IONS
IOVANCE BIOTH	@IOVA
IPG PHOTONICS CORP	@IPGP
IRHYTHM TECHNOLOGIE	@IRTC
IRIDIUM COMMUNICATI	@IRDM
IROBOT CORPORATION	@IRBT
IRONWOOD	@IRWD
ITEOS THERAP	@ITOS
ITRON INC	@ITRI
IVERIC BIO INC	@ISEE
J & J SNACK FOODS	@JJSF
JACK IN THE BOX INC	@JACK
JAMES RIVER	@JRVR
JAMF HOLDING CORP	@JAMF
JAZZ PHA	@JAZZ
JETBLUE AIRWAYS CORP	@JBLU
JFROG LTD	@FROG
JOHN B. SANFILIPPO	@JBSS
JOHNSON OUTDOORS	@JOUT
JOINT CORP	@JYNT
KAISER ALUMINUM CORP	@KALU
KARUNA THERAP	@KRTX
KARYOPHARM	@KPTI
KEARNY FIN CORP	@KRNY
KEROS THE	@KROS
KFORCE INC.	@KFRC
KODIAK SCIENCES INC	@KOD

KORNIT DIGITAL LTD	@KRNT
KRATOS DEFENSE	@KTOS
KRYSTAL BIOTECH INC	@KRYS
KULICKE AND SOFFA	@KLIC
KURA ONCO	@KURA
KYMERA THERAPEUTICS	@KYMR
LAKELAND BANCORP INC	@LBAI
LAKELAND FINANCIAL	@LKFN
LAMAR ADVERTISING CO	@LAMR
LANCASTER COLONY	@LANC
LANDSTAR SYSTEM INC.	@LSTR
LANTHEUS HOLD	@LNTH
LATTICE SEMICONDUCTR	@LSCC
LAUREATE EDUCATION	@LAUR
LEMAITRE VASCULAR	@LMAT
LENDINGTREE INC	@TREE
LGI HOMES INC	@LGIH
LIBERTY BROAD	@LBRDA
LHC GROUP, INC.	@LHCG
LIBERTY GLOBAL	@LBTYA
LIBERTY MEDIA	@FWONA
LIGAND PHARMA	@LGND
LIGHTWAVE L	@LWLG
LINCOLN ELECTRIC	@LECO
LINDBLAD EXPEDITIONS	@LIND
LITTELFUSE INC	@LFUS
CYBERONICS, INC.	@LIVN
LIVE OAK BAN	@LOB
LIVEPERSON, INC.	@LPSN
LOVESAC CO	@LOVE
LUMENTUM HOLDIN	@LITE
LUMINAR TECHN	@LAZR
MACOM TECHNOLOGY	@MTSI
MACROGENICS INC	@MGNX
MADRIGAL PHARMACEU	@MDGL
MAGNITE INC	@MGNI
MAKEMYTRIP LTD	@MMYT
MALIBU BOATS	@MBUU
MANDIANT INC	@MNDT
MANHATTAN ASSOCIATES	@MANH
MANNKIND CORPORATION	@MNKD
MANTECH INTL	@MANT
MARATHON DIGIT	@MARA
MARTEN TRANSPORT	@MRTN
MATTEL INC	@MAT
MATTHEWS INT'L CORP	@MATW

MAXLINEAR, INC	@MXL
MCGRATH RENTCORP	@MGRC
MEDPACE HOLDINGS	@MEDP
MERCER INTERNATIONAL	@MERC
MERCHANTS BANCORP	@MBIN
MERCURY SYSTEMS INC	@MRCY
MERIDIAN BIOSCIENCE	@VIVO
MERIT MEDICAL SYSTEM	@MMSI
MERUS	@MRUS
MESA LABORATORIES	@MLAB
META FINANCIAL GROUP	@CASH
MGE ENERGY, INC.	@MGEE
MGP INGREDIENTS	@MGPI
MICROSTRATEGY INC	@MSTR
MICROVAST H	@MVST
MIDDLESEX WATER CO	@MSEX
MILLERKNOLL INC	@MLKN
MIMECAST LTD	@MIME
MIRATI THERAP	@MRTX
MKS INSTRUMENTS, INC	@MKSI
MODIVCARE INC	@MODV
MOMENTIVE GLO	@MNTV
MONARCH CASINO	@MCRI
MONEYGRAM INTN'L INC	@MGI
MONRO INC	@MNRO
MORPHIC HOLDING INC	@MORF
MR COOPER GRO	@COOP
MYR GROUP, INC	@MYRG
MYRIAD GENETICS, INC	@MYGN
NANOSTRING TECHN	@NSTG
NAPCO SECURITY SYS	@NSSC
NATERA	@NTRA
NATIONAL BEVERAGE	@FIZZ
NATIONAL ENERGY SERV	@NESR
NATIONAL INSTRUMENTS	@NATI
NATIONAL RESEARCH	@NRC
NAT	@EYE
NATIONAL WESTERN	@NWLI
NATUS MEDICAL	@NTUS
NAVIENT CORP	@NAVI
NBT BANCORP INC	@NBTB
NCINO INC	@NCNO
NEKTAR THERAPEUTICS	@NKTR
NEOGEN CORPORATION	@NEOG
NEOGENOMICS INC	@NEO
NETGEAR, INC.	@NTGR

NETSCOUT SYSTEMS INC	@NTCT
NEUROCRINE	@NBIX
NEW FORTRESS ENERGY	@NFE
NEW YORK MORTGAGE	@NYMT
NEWEGG COM	@NEGG
NEWELL BRANDS INC	@NWL
NEWMARK GROUP INC	@NMRK
NEWS CORP	@NWSA
NEXSTAR MEDIA GROUP	@NXST
NEXTGEN HEALTHCARE	@NXGN
NGM BIO	@NGM
NICOLET BANKSHARES	@NCBS
NIKOLA CORP	@NKLA
NLIGHT INC	@LASR
NMI HOLDINGS	@NMIH
NORTHFIELD BANCORP	@NFBK
NORTHWEST BAN	@NWBI
NORTHWESTERN CORP	@NWE
NOVANTA INC	@NOVT
NOVAVAX INC	@NVAX
NOVOCURE	@NVCR
NURIX THERAP	@NRIX
NUTANIX INC	@NTNX
NUVASIVE INC	@NUVA
NV5 GLOBAL	@NVEE
OCEANFIRST FINL CORP	@OCFC
OCUGEN INC	@OCGN
ODP CORP	@ODP
OFFICE PROPERTIES	@OPI
OLD NATIONAL BANCORP	@ONB
OLLIE'S BARGAIN	@OLLI
OMEGA FLEX, INC.	@OFLX
OMNICELL, INC.	@OMCL
ONESPAWORLD	@OSW
OPENDOOR	@OPEN
OPKO HEALTH INC	@OPK
OPTIMIZERX CORP	@OPRX
OPTION CARE	@OPCH
ORGANOGENESIS HOLD	@ORGO
ORIGIN BANCORP INC	@OBNK
ORTHOPEDIATRICS	@KIDS
OSI SYSTEMS, INC.	@OSIS
OTTER TAIL CORP	@OTTR
OUTSET MEDICAL	@OM
OVERSTOCK.COM INC	@OSTK
PACIFIC PREMIER BANC	@PPBI

PACIFIC	@PACB
PACIRA BIOSCI	@PCRX
PACTIV EVERGREEN	@PTVE
PACWEST BANCORP	@PACW
PAE INC	@PAE
PALOMAR HOLD	@PLMR
P.A.M. TRANSPORT	@PTSI
PAN AMERICAN SILVER	@PAAS
PAPA JOHN'S INT'L	@PZZA
PATRICK INDUSTRIES	@PATK
PATTERSON CO INC	@PDCO
PATTERSON-UTI ENGY	@PTEN
PAYA	@PAYA
PC CONNECTION INC	@CNXN
PDC ENERGY INC	@PDCE
PDF SOLUTIONS INC	@PDFS
PEGASYSTEMS INC	@PEGA
PENN NATIONAL	@PENN
PEOPLES BANCORP INC.	@PEBO
PEOPLE'S UNITED	@PBCT
PERDOCEO EDU	@PRDO
PERFICIENT INC	@PRFT
PERION NET	@PERI
PHOTRONICS INC	@PLAB
PINNACLE FINANCIAL	@PNFP
PILGRIM'S PRIDE CORP	@PPC
PLAINS ALL AMER PIPE	@PAA
PLAINS GP	@PAGP
PLAYA HOTELS	@PLYA
PLEXUS CORP	@PLXS
POPULAR, INC.	@BPOP
PORCH GROUP INC	@PRCH
POTLATCHDELTIC	@PCH
POWER INTEGRATIONS	@POWI
PRA GROUP INC	@PRAA
PREFERRED BANK	@PFBC
PREMIER	@PINC
PREMIER FIN	@PFC
PRICESMART, INC.	@PSMT
PRIMORIS SERVICES	@PRIM
PROCAPS GROUP SA	@PROC
PROGRESS SOFTWARE	@PRGS
PROGYNY INC	@PGNY
PROTAGONIST THERAP	@PTGX
PROTHENA CORPORATI	@PRTA
PTC THERAPEUTICS	@PTCT

PULMONX	@LUNG
QCR HOLDINGS, INC	@QCRH
QUALYS	@QLYS
QUANTERIX CORP	@QTRX
QUIDEL CORPORATION	@QDEL
QUINSTREET	@QNST
QURATE RETAIL INC	@QRTEA
R1 RCM INC	@RCM
RACKSPACE TEC	@RXT
RADIUS GLOBA	@RADI
RADNET INC	@RDNT
RADWARE LTD	@RDWR
RAMBUS INC.	@RMBS
RAPID7 INC	@RPD
RBC BEARINGS INC	@ROLL
REATA PHARMAC	@RETA
RED ROCK RESORTS INC	@RRR
REDFIN CORP	@RDFN
REGENXBIO	@RGNX
RELAY	@RLAY
RENASANT CORPORATION	@RNST
RENEWABLE ENERGY	@REGI
RENT-A-CENTER, INC.	@RCII
REPAY HOLDINGS CORP	@RPAY
REPLIMUNE	@REPL
REPUBLIC BANCORP INC	@RBCAA
RETAIL OPPORTUNITY	@ROIC
REVANCE THERAP	@RVNC
REVOLUTION MEDI	@RVMD
REYNOLDS CONSUMER	@REYN
RIOT BLOCKCHAIN INC	@RIOT
ROCKET	@RCKT
ROYAL GOLD, INC.	@RGLD
S&T BANCORP INC	@STBA
SABRA HEALTH	@SBRA
SABRE CORP	@SABR
SAGE THER	@SAGE
SAFETY INSURANCE GP	@SAFT
SAIA INC	@SAIA
SANDERSON FARMS INC	@SAFM
SANDY SPRING BANCORP	@SASR
SANGAMO THERAPE	@SGMO
SANMINA CORP	@SANM
SAPIENS INTL CORP	@SPNS
SAREPTA THERAP	@SRPT
SCANSOURCE, INC.	@SCSC

SCHNITZER STEEL INDS	@SCHN
SCHOLASTIC CORP	@SCHL
SCHRODIN	@SDGR
SCIENTIFIC GAMES	@SGMS
E W SCR	@SSP
SEACOAST BANKING	@SBCF
SEI INVESTMENTS	@SEIC
SELECTIVE INSURANCE	@SIGI
SEMTECH CORP	@SMTC
SERVICE PROPERT	@SVC
SHENANDOAH TELECOM	@SHEN
SHOCKWAVE	@SWAV
SHOE CARNIVAL, INC.	@SCVL
SHYFT GROUP	@SHYF
SIERRA ONCOLOGY INC	@SRRA
SILGAN HOLDINGS INC.	@SLGN
SILICON LABORATORIES	@SLAB
SILK ROAD MED	@SILK
SIMMONS FIRST NAT'L	@SFNC
SIMULATIONS PLUS INC	@SLP
SINCLAIR BROADCAST	@SBGI
SITIME	@SITM
SKYWEST, INC.	@SKYW
SLEEP NUMBER CORP	@SNBR
SLM CORPORATION	@SLM
SMART GLOBAL	@SGH
SMITH & WESSON	@SWBI
SONOS	@SONO
SORRENTO	@SRNE
SOUTHSIDE BANCSHARES	@SBSI
SOUTHSTATE CORP	@SSB
SPARTANNASH CO	@SPTN
SPRINGWORKS THE	@SWTX
SPROUT SOCIAL INC	@SPT
SPROUTS FARMER	@SFM
SPS COMMERCE, INC.	@SPSC
SSR MINING INC	@SSRM
STAAR SURGICAL CO	@STAA
STAGWEL	@STGW
STATE AUTO FINANCIAL	@STFC
STEPSTONE GROUP INC	@STEP
STERICYCLE, INC.	@SRCL
STERLING CONSTRU	@STRL
STEVEN MADDEN LTD	@SHOO
STITCH FIX INC	@SFIX
STOCK YARDS	@SYBT

STONECO	@STNE
STONEX GROUP INC	@SNEX
STRATASYS LTD	@SSYS
STRATEGIC EDUCATION	@STRA
SUMO LOGIC,	@SUMO
SUNDIAL GROWERS INC	@SNDL
SUNRUN INC	@RUN
SUPER MICRO COMPUTER	@SMCI
SUPERNUS PHARM	@SUPN
SURGERY PART	@SGRY
SYNAPTICS INC	@SYNA
SYNDAX PHARM	@SNDX
SYNEOS HEALTH	@SYNH
TANDEM	@TNDM
TANGO	@TNGX
TATTOOED CHEF INC	@TTCF
TECHTARGET, INC.	@TTGT
TENABLE HOLDINGS INC	@TENB
TERAWULF INC	@WULF
TETRA TECH INC	@TTEK
TX CAPITAL BANCSHRS	@TCBI
TEXAS ROADHOUSE, INC	@TXRH
TFS FINANCIAL CORP	@TFSL
TG THERAPEUTICS	@TGTX
REALREAL INC	@REAL
SIMPLY GOOD FOODS CO	@SMPL
THRYV HOLDINGS INC	@THRY
TILRAY BRANDS INC	@TLRY
TIVITY HEALTH INC	@TVTY
TOWNE BANK	@TOWN
TRADEWEB MARKETS INC	@TW
TRAVERE THERAP	@TVTX
TRICO BANCSHARES	@TCBK
TRIMAS CORPORATION	@TRS
TRIPADVISO	@TRIP
TRISTATE CAPITAL	@TSC
TRIUMPH BAN	@TBK
TRUPAN	@TRUP
TRUSTMARK CORP	@TRMK
TTEC HOLDINGS INC	@TTEC
TTM TECHNOLOGIES	@TTMI
TUCOWS, INC.	@TCX
TURNING P	@TPTX
TWIST BIOSCIENCE	@TWST
UFP INDUS	@UFPI
ULTRA CLEAN HOLDINGS	@UCTT

ULTRAGENYX	@RARE
UMB FINANCIAL CORP	@UMBF
UMPQUA HOLDINGS CORP	@UMPQ
UNIQURE NV	@QURE
UNITED BANKSHARES	@UBSI
UNITED COMMUNITY	@UCBI
UNITED THERAPEUTICS	@UTHR
UNITI GROUP INC	@UNIT
UNIVERSAL DISPLAY	@OLED
UNIVEST FINANCIAL	@UVSP
UPWORK INC	@UPWK
URBAN OUTFITTERS	@URBN
US ECOLOGY INC	@ECOL
VALLEY NATIONAL BANC	@VLY
VAREX IMAGING CORP	@VREX
VARONIS SYSTEM	@VRNS
VAXCYTE INC	@PCVX
VEECO INSTRUMENTS	@VECO
VELODYNE LIDAR INC	@VLDR
VERACYTE INC	@VCYT
VERICEL CORP	@VCEL
VERINT SYSTEMS INC.	@VRNT
VERITEX HOLD	@VBTX
VERRA MOBILITY CORP	@VRRM
VIASAT, INC.	@VSAT
VIAVI SOLUTIONS	@VIAV
VICOR CORPORATION	@VICR
VIEWRAY INC	@VRAY
VIPER ENERGY	@VNOM
VIR BIOTECH	@VIR
VIRTU FINANCIAL INC	@VIRT
VIRTUS INVESTMENT	@VRTS
VISTEON CORP	@VC
VONAGE HOLDINGS	@VG
VROOM INC	@VRM
WARNER MUSIC GRP CO	@WMG
WASHINGTON FEDERAL	@WAFD
WASHINGTON TRUST	@WASH
WD-40 COMPANY	@WDFC
WEATHERFORD INTERNTL	@WFRD
WENDYS	@WEN
WERNER ENTERPRISES	@WERN
WESBANCO, INC.	@WSBC
WESTAMERICA BANCORP	@WABC
WILLSCOT	@WSC
WINGSTOP INC	@WING

WINMARK CORPORATION	@WINA
WINTRUST FINANCIAL	@WTFC
WISDOMTREE INVT	@WETF
WIX.COM	@WIX
WOODWARD INC	@WWD
WORLD ACCEPTANCE	@WRLD
WSFS FINANCIAL CORP	@WSFS
WW INTERNATIONAL INC	@WW
WYNN RESORTS, LTD	@WYNN
XENCOR INC	@XNCR
XENON PHARMA	@XENE
XEROX HOLDINGS CORP	@XRX
XPEL	@XPEL
XPERI HOL	@XPER
ZENTALIS PHARMA	@ZNTL
ZIFF DAVIS INC	@ZD
ZILLOW GROUP INC	@ZG
ZOGENIX INC	@ZGNX
ZUMIEZ INC.	@ZUMZ
1-800-FLOWERS.COM	@FLWS
180 LI	@ATNF
1895 BANCORP	@BCOW
22ND CENTURY	@XXII
89BIO	@ETNB
9 METERS BIO	@NMTR
AADI BIOSCIENCE INC	@AADI
ABEONA THERAPEUTICS	@ABEO
ABVC BIOPH	@ABVC
AC IMMUNE SA	@ACIU
ACACIA RESEARCH	@ACTG
ACCELERATE DIAGNOS	@AXDX
ACCURAY INC	@ARAY
ACELRX PHARMA	@ACRX
ACER THERAPEUT	@ACER
ACHIEVE LIFE SCIEN	@ACHV
ACLARIS THERAP	@ACRS
ACNB CORP	@ACNB
ACORDA THERAP	@ACOR
ACUTUS MEDI	@AFIB
ADAMIS PHAR	@ADMP
ADDVANTAGE TECHLGS	@AEY
ADIAL PHARMACEUTICAL	@ADIL
ADICET BIO INC	@ACET
ADMA BIO	@ADMA
ADVANCED EMI	@ADES
ADVENT TECH	@ADN

ADVERUM BIOTECHN	@ADVM
AEGLEA BIO THE	@AGLE
AEHR TEST SYSTEMS	@AEHR
AEMETIS	@AMTX
AERIE PHARMA	@AERI
AERSALE CORP	@ASLE
AETHLON MEDICAL INC.	@AEMD
AFFIMED NV	@AFMD
AFFINITY BANCSHARES	@AFBI
AFYA LTD	@AFYA
AGENUS INC	@AGEN
AGILE THERAP	@AGRX
AGILETHOUGHT INC	@AGIL
AGM GROUP HOLD	@AGMH
AGROFRESH	@AGFS
AIKIDO PHARMA	@AIKI
AILERON T	@ALRN
AIR T, INC.	@AIRT
AIRGAIN INC	@AIRG
AKEBIA THERA	@AKBA
AKERNA CORP	@KERN
AKERO THERAPEUTICS	@AKRO
AKOUOS	@AKUS
AKOUSTIS TECHNOLOG	@AKTS
ALAUNOS THERA	@TCRT
ALBERTON ACQ	@ALAC
ALBIREO PHARMA	@ALBO
ALDEYRA THERAP	@ALDX
ALERISLIFE INC	@ALR
ALERUS FINANCIAL	@ALRS
ALICO, INC.	@ALCO
ALIMERA SCIENCES	@ALIM
ALITHYA GROUP	@ALYA
ALJ REGIONAL	@ALJJ
ALKALINE WATER	@WTER
ALLAKOS INC	@ALLK
ALLIED MOTION TECH	@AMOT
ALLEN	@ALNA
ALLIED ESPORTS	@AESE
ALLIED HEALTHCARE	@AHPI
ALLOT LTD	@ALLT
ALLOVIR INC	@ALVR
ALPINE 4 HOLD	@ALPP
ALPINE IMMUNE	@ALPN
ALTAMIRA THER	@CYTO
ALTIMMUNE INC	@ALT

ALTISOURCE PORTFOLIO	@ASPS
ALTO INGREDIENTS INC	@ALTO
ALTUS MIDSTREAM CO	@ALTM
ALX ONCOLOGY	@ALXO
AMERICA FIRST	@ATAX
AMALGAMATED BANK	@AMAL
AMERICAN SOFTWARE	@AMSWA
AMERICA'S CAR-MART	@CRMT
AMERICAN NATIONAL	@AMNB
AMERICAN OUTDOOR	@AOUT
AMERICAN PUBLIC	@APEI
AMERICAN REBEL	@AREB
AMERICAN RESOUR	@AREC
AMERICAN	@AMSC
AMERICAN VIRTUAL	@AVCT
AMERISERV FINANCIAL	@ASRV
AMES NATIONAL CORP	@ATLO
AMESITE INC	@AMST
AMMO INC	@POWW
AMPLITECH GROUP	@AMPG
AMTECH SYSTEMS, INC.	@ASYS
VISTAS	@ANGH
ANGI INC	@ANGI
ANI PHARMACEUTICALS	@ANIP
ANIKA THERAPEUTICS	@ANIK
ANIXA BIOS	@ANIX
ANNEXON	@ANNX
ANTARES PHARMA, INC.	@ATRS
ANTELOPE ENTER	@AEHL
APOLLO ENDOSURGERY	@APEN
APPHARVEST INC	@APPH
APPLIED DNA SCIENCES	@APDN
APPLIED GENETIC	@AGTC
APPLIED MOLECULAR	@AMTI
APPLIED OPT	@AAOI
APPLIED THERAP	@APLT
APPLIED UV INC	@AUVI
APPTECH PA	@APCX
APREA THERA	@APRE
APTEVO THERA	@APVO
APTINYX INC	@APTX
APTORUM GROUP LTD	@APM
APYX MEDI	@APYX
AQUA METALS INC	@AQMS
AQUABOUNTY TECH	@AQB
AQUESTIVE	@AQST

ARAVIVE INC	@ARAV
ARBUTUS BIOPHARMA	@ABUS
ARCA BIOPHARMA	@ABIO
ARCADIA BIOSC	@RKDA
ARCIMOTO INC	@FUV
ARCO PLATFORM LTD	@ARCE
ARCTURUS THERAPE	@ARCT
ARDELYX INC	@ARDX
ARIDIS PHARM	@ARDS
ARK RESTAURANTS CORP	@ARKR
ARROW FINANCIAL CORP	@AROW
ART'S-WAY MFG CO	@ARTW
ARTELO BIOSCIENCES	@ARTL
ARTESIAN RESOURCES	@ARTNA
ASIA PACIFIC	@APWC
ASPEN GR	@ASPU
ASPIRA WOMEN	@AWH
ASSEMBLY BIOSCIENCES	@ASMB
ASSERTIO HOLD	@ASRT
AST SPACEMOBILE INC	@ASTS
ASTRIA THER	@ATXS
ASTRONICS CORP	@ATRO
ASTRONOVA	@ALOT
ASTROTECH CORP	@ASTC
ASURE SOFTWARE INC	@ASUR
ATERIAN INC	@ATER
ATHENEX INC	@ATNX
ATHERSYS, INC.	@ATHX
ATHIRA PHARMA INC	@ATHA
ATIF HOLDING	@ATIF
ATLANTIC AMERICAN	@AAME
ATLANTIC CAPITAL BAN	@ACBI
ATLAS TECHNICAL	@ATCX
ATN INTERNATIONAL	@ATNI
ATOMERA INC	@ATOM
ATOSSA THERAP	@ATOS
ATRECA INC	@BCEL
ATYR PHARMA INC	@LIFE
AUBURN NAT'L. BANC.	@AUBN
AUDIOEYE	@AEYE
AUTOSCOPE TECHNO	@AATC
AUTOWEB INC	@AUTO
AVALO	@AVTX
AVALON GLOBOCARE	@AVCO
AVENUE THE	@ATXI
AVEO PHARMACEUTICALS	@AVEO

AVIAT NETWORKS INC	@AVNW
AVINGER INC	@AVGR
AVROBIO INC	@AVRO
AWARE, INC.	@AWRE
AXCELLA HEALTH	@AXLA
AXOGEN INC	@AXGN
AXT INC	@AXTI
AYALA PHARMA	@AYLA
AYRO INC	@AYRO
AYTU BIOPHARMA INC	@AYTU
BOS BETTER ONLINE	@BOSC
BANK FIRST CORP	@BFC
BANK OF MA	@BMRC
BANK OF PRINCETON	@BPRN
BANK OF SC CORP	@BKSC
JAMES FINANCIAL	@BOTJ
BANK7 CORP	@BSVN
BANKFINANCIAL CORP	@BFIN
BANKWELL FINANCIAL	@BWFG
BARFRESH FOOD	@BRFH
BARRETT BUSINESS	@BBSI
BASSETT FURNITURE	@BSET
BAUDAX BIO	@BXRX
BAYCOM CORP	@BCML
BBQ HOLDINGS	@BBQ
BCB BANCORP, INC.	@BCBP
BEAM GLOBAL	@BEEM
BEASLEY BROADCAST GR	@BBGI
BEL FUSE	@BELFA
BELLEROPHON	@BLPH
BELLICUM PHARMA	@BLCM
BENEFITFOCUS INC	@BNFT
BERKELEY LIGHTS INC	@BLI
BEYOND AIR INC	@XAIR
BEYONDSPRING INC	@BYSI
BIG 5 SPORTING GOODS	@BGFV
BIMI INTERNATIONAL	@BIMI
BIO-KEY INTERNTL	@BKYI
BIO-PATH HOLD	@BPTH
BIOCARDIA INC	@BCDA
BIOCEPT INC	@BIOC
BIOCERES	@BIOX
BIODELIVERY SCIENCES	@BDSI
BIOLASE INC	@BIOL
BIOMERICA, INC.	@BMRA
BIONANO GENOMICS	@BNGO

BIORESTORATIVE	@BRTX
BIOSIG TECH	@BSGM
BIOTRICITY INC	@BTCY
BIOVIE INC	@BIVI
BIOXCEL THERAP	@BTAI
BIT BROTHE	@BTB
BIT DIGITAL INC	@BTBT
BLACK DIAMOND	@BDTX
BLACKBOXSTOCKS INC	@BLBX
BLADE AIR	@BLDE
BLUE HAT INTE	@BHAT
BLUE BIRD CORP	@BLBD
BLUE STAR FOODS	@BSFC
BLUEBIRD BIO INC	@BLUE
BLUECITY HOLDING	@BLCT
BLUEKNIGHT ENERGY	@BKEP
BOGOTA FINANCIAL	@BSBK
BONE BIOLOG	@BBLG
BONSO ELECTRONIC	@BNSO
BORQS TECHNOLOGIES	@BRQS
BOXLIGHT CORP	@BOXL
BRAINSTORM CELL	@BCLI
BRICKELL BIOTECH INC	@BBI
BRIDGELINE DIGITAL	@BLIN
BRIDGEWATER BAN	@BWB
BRIDGFORD FOODS CORP	@BRID
BRIGHTCOVE INC	@BCOV
BROADWAY FINANCIAL	@BYFC
BROADWIND	@BWEN
BROOKLYN I	@BTX
BSQUARE CORPORATION	@BSQR
BTCS INC	@BTCS
BURGERFI	@BFI
BUSINESS FIRST	@BFST
BYRNA TECHN	@BYRN
C&F FINANCIAL CORP	@CFFI
CABALETTA BIO	@CABA
CADIZ INC.	@CDZI
CAESARSTONE LTD	@CSTE
CALADRIUS BIO	@CLBS
CALAMP CORP	@CAMP
CALIFORNIA BANCORP	@CALB
CALITHERA BIOS	@CALA
CALYXT INC	@CLXT
CAMBIUM NET	@CMBM
CAMBRIDGE BANCORP	@CATC

CANTALOUPE INC	@CTLP
CANTERBURY PARK	@CPHC
CAPITAL CITY BANK	@CCBG
CAPITAL BANCORP INC	@CBNK
CAPITAL PRODUCT	@CPLP
CAPRICOR THERA	@CAPR
CAPSTAR FINANCIAL	@CSTR
CAPSTONE TURBINE	@CGRN
CARA THERAPEUTICS	@CARA
CARDIFF ONCO	@CRDF
CARECLOUD INC	@MTBC
CAREMAX INC	@CMAX
CARLOTZ INC	@LOTZ
CARPARTS.COM INC	@PRTS
CARROLS RESTAURANT	@TAST
CARTER BANK	@CARE
CARVER BANCORP, INC.	@CARV
CASA SYSTEMS INC	@CASA
CASI PHARMACEUTICALS	@CASI
CASS INFORMATION SYS	@CASS
CATALYST BIOSCIENCES	@CBIO
CATALYST PHARMA	@CPRX
CB FINANCIAL	@CBFV
CBAK ENERGY TECH	@CBAT
CECO ENVIRONMENTAL	@CECE
CELCUITY INC	@CELC
CELLECTAR BIO	@CLRB
CELSION CORPORATION	@CLSN
CELULARIT	@CELU
CEMTREX INC	@CETX
CENNTRO ELECTRIC	@CENN
CENTOGENE NV	@CNTG
CENTRAL GARDEN & PET	@CENT
CENTRAL VALLEY COMM	@CVCY
CENTURY CASINOS, INC	@CNTY
CERAGON NETWORKS LTD	@CRNT
CERBERUS CYBER	@CISO
CF BANKSHARES INC	@CFBK
CHAMPIONS ONCOLOGY	@CSBR
CHARLES & COLVARD	@CTHR
CHECK CAP LTD	@CHEK
CHECKMATE PHARMA	@CMPI
CHECKPOINT THERAP	@CKPT
CHEMBIO DIAGNOSTICS	@CEMI
CHEMUNG FINANCIAL	@CHMG
CHICKEN SOUP FOR	@CSSE

CHIMERIX	@CMRX
CHINA AUTOMOTIVE	@CAAS
CHINA HGS REAL E	@HGSH
CHINA JO-JO	@CJJD
CHINA LIBERA	@CLEU
CHINA NATURAL RES	@CHNR
CHINA RECYCLING	@CREG
CHINA SXT PHA	@SXTC
CHINOOK THERAPE	@KDNY
CHOICEONE FINANCIAL	@COFS
CHROMADEX	@CDXC
CHUY'S HOLD	@CHUY
CIDARA THER	@CDTX
CIM COMMERCIAL	@CMCT
CINCINNATI BANCORP	@CNNB
CINEDIGM CORP	@CIDM
CITI TRENDS, INC.	@CTRN
CITIUS PHARMA	@CTXR
CITIZENS COMMUN	@CZWI
CITIZENS HOLDING CO	@CIZN
CIVISTA BANCSHARES	@CIVB
CLEANSPARK INC	@CLSK
CLEARONE INC	@CLRO
CLEARPOINT NEURO	@CLPT
CLEARSIDE BIOMEDICAL	@CLSD
CLEARSIGN TECHNO	@CLIR
CLENE INC.	@CLNN
CLOVIS ON	@CLVS
CLPS INC	@CLPS
COMPUTER PROGRAMS &	@CPSI
CNB FINANCIAL CORP	@CCNE
CNS PHARM	@CNSP
CO-DIAGNO	@CODX
COASTAL FINANCIAL	@CCB
CODA OCTOPUS GROUP	@CODA
CODE CHAIN	@CCNC
CODORUS VALLEY BANC	@CVLY
COFFEE HLDG CO	@JVA
COGENT BIOSCI	@COGT
COHBAR INC	@CWBR
COLLEGIUM PHARMA	@COLL
COLLPLANT BIOTECH	@CLGN
COLONY BANKCORP, INC	@CBAN
COLOR STAR TECH	@CSCW
COMMERCIAL VEHICLE	@CVGI
COMMUNICATIONS SYST	@JCS

COMMUNITY FIN	@TCFC
COMMUNITY WEST BANC	@CWBC
COMPUTER TASK GROUP	@CTG
COMSCORE, INC.	@SCOR
COMSOVE	@COMS
COMSTOCK HOLDING	@CHCI
COMTECH TELECOM	@CMTL
CONCERT PHARMA	@CNCE
CONCRETE PUMP	@BBCP
CONFORMIS INC	@CFMS
CONIFER HOLDINGS INC	@CNFR
CONN'S INC	@CONN
CONSOLIDATED COMMN	@CNSL
CONS WATER CO. LTD	@CWCO
CONSUMER PORTFOLIO	@CPSS
CONTRAFECT	@CFRX
CORBUS PHARMAC	@CRBP
CORMEDIX INC	@CRMD
CORTEXYME INC	@CRTX
CORVUS PHAR	@CRVS
COVENANT LOGISTICS	@CVLG
CPI CARD	@PMTS
CPS TECHN	@CPSH
CRA INTL INC	@CRAI
CREATD INC	@CRTD
CREATIVE MEDICAL	@CELZ
CREATIVE REAL	@CREX
CRESCEN	@CCAP
CREXENDO	@CXDO
CROWN CRAFTS INC	@CRWS
CROWN ELECTROKI	@CRKN
CRYO-CELL INT'L INC	@CCEL
CSI COMPRESSCO LP	@CCLP
CSP INC.	@CSPI
CTI BIOPHARMA CORP	@CTIC
CITIZENS & NORTHERN	@CZNC
CUE BIOPHARMA INC	@CUE
CUENTAS INC	@CUEN
CULLMAN BANCORP	@CULL
CUMBERLAND PHARMA	@CPIX
CURIOSITYSTREAM INC	@CURI
CURIS INC	@CRIS
CUTERA, INC.	@CUTR
CVD EQUIPMENT CORP	@CVV
CYANOTECH CORP	@CYAN
CYBEROPTICS CORP	@CYBE

CYCLACEL PHARMA	@CYCC
CYCLERION THERAP	@CYCN
CYCLO THERAP	@CYTH
CYMABAY THERAPEUTICS	@CBAY
CYREN LTD	@CYRN
CYTOMX THERAPE	@CTMX
CYTOSORBENTS	@CTSO
DAILY JOURNAL CORP	@DJCO
DAKTRONICS, INC.	@DAKT
DALLASNEWS CORP	@DALN
DARE BIOSCIENCE	@DARE
DARIOHEALTH CORP	@DRIO
DASEKE INC	@DSKE
DATA I/O CORPORATION	@DAIO
DATA STORAGE CORP	@DTST
DATASEA INC	@DTSS
DAVIDSTEA INC	@DTEA
DAWSON GEOPHYSICAL	@DWSN
DECIPHERA PHARMA	@DCPH
DEL TACO RESTAURANTS	@TACO
DELCATH SYSTEMS INC	@DCTH
DERMTECH INC	@DMTK
DESTINATION XL	@DXLG
DESWELL INDUSTRIES	@DSWL
DIAMOND HILL INVEST	@DHIL
DIFFUSION PHARMAC	@DFFN
DIGIMARC CORP	@DMRC
DIGITAL ALLY INC	@DGLY
DIXIE GROUP INC.	@DXYN
DLH HOLDINGS	@DLHC
DMC GLOBAL INC	@BOOM
DOGNESS INTERNATION	@DOGZ
DOLPHIN ENTERT	@DLPN
DONEGAL GROUP INC.	@DGICA
DRAGON VICTORY INTE	@LYL
DULUTH HOLDINGS INC	@DLTH
DUOS TECHNOLOGIES	@DUOT
DURECT CORP	@DRRX
DXP ENTERPRISES INC	@DXPE
DYADIC INTN'L INC	@DYAI
DYNATRONICS CORP	@DYNT
DYNE THERAPEUTICS	@DYN
DZS INC	@DZSI
EAGLE BANCORP	@EBMT
EAGLE BULK SHIP	@EGLE
EAGLE PHARMA	@EGRX

EASTERN CO	@EML
EASTSIDE DISTILLING	@EAST
EBANG INTERNATIONAL	@EBON
ECMOHO LTD	@MOHO
ECOARK HOLDINGS	@ZEST
EDESA BIOTECH INC	@EDSA
EDUCATIONAL DEV CORP	@EDUC
EGAIN CORP	@EGAN
EHEALTH, INC.	@EHTH
EIGER BIOPHARMA	@EIGR
EKSO BIONICS	@EKSO
EL POLLO LOCO	@LOCO
ELECTRAMECCANICA	@SOLO
ELECTRIC LAST	@ELMS
ELECTRO-SENSORS INC	@ELSE
ELECTROCORE, INC.	@ECOR
ELEDON PHA	@ELDN
ELMIRA SAVINGS BANK	@ESBK
ELOX	@ELOX
ELTEK LTD	@ELTK
ELYS GAME TE	@ELYS
EMCLAIRE FIN'L CORP.	@EMCF
EMCORE CORPORATION	@EMKR
ENDRA LIFE	@NDRA
ENERGOUS CORP	@WATT
ENERGY FOCUS INC.	@EFOI
ENGLOBAL CORPORATION	@ENG
ENLIVEX THERAPE	@ENLV
ENOCHIAN BIOSCIENCES	@ENOB
ENSYSCE BIOSCIENCES	@ENSC
ENTASIS THERAPEUTICS	@ETTX
ENTERA BIO LTD	@ENTX
ENTERPRISE BANCORP	@EBTC
ENVERIC BIOS	@ENVB
ENVVENO	@NVNO
B RILEY PRINCIPAL	@EOSE
EPIZYME INC	@EPZM
EPSILON ENERGY LTD.	@EPSN
EQONEX LTD	@EQOS
EQUILLIUM	@EQ
EQUITY BANCSHARES	@EQBK
ESCALADE, INC	@ESCA
ESPERION THERAPEUTIC	@ESPR
ESPORTS ENTERTAI	@GMBL
ESQUIRE FINANCIAL	@ESQ
ESSA BANCORP, INC.	@ESSA

ESSA PHARMA	@EPIX
ETON PHARMACEUT	@ETON
EURO TECH HOLDING	@CLWT
EURODRY LTD	@EDRY
EUROSEAS LTD.	@ESEA
EVELO BIOSCI	@EVLO
EVER GLORY INTER	@EVK
EVERQUOTE INC	@EVER
EVERSPIN TECHN	@MRAM
EV	@EVFM
EVOKE PHARMA	@EVOK
EVOLUS INC	@EOLS
EVOLV TECHNOLOGIES	@EVLV
EVOLVING SYSTEMS INC	@EVOL
EXAGEN INC	@XGN
EXELA TECHNOLOGIE	@XELA
EXICURE INC	@XCUR
EYENOVIA	@EYEN
EYE	@EYPT
EZCORP, INC.	@EZPW
F-STAR THE	@FSTX
FALCON MINERALS CORP	@FLMN
FARMER BROS CO	@FARM
FARMERS & MERCHANTS	@FMAO
FARMERS NATIONAL	@FMNB
FARMMI INC	@FAMI
FAT BRANDS INC	@FAT
FATHOM HOLDINGS INC	@FTHM
FEDNAT HOLDING CO	@FNHC
FENNEC PHARMA	@FENC
FFBW INC	@FFBW
FG FINA	@FGF
FIDELITY D & D BANC	@FDBC
FIESTA RESTAURANT	@FRGI
FINANCIAL INSTITUT	@FISI
FINGERMOTION INC	@FNGR
FINWARD BANCORP	@FNWD
FIRST BANCORP INC	@FNLC
FIRST BAN	@FRBA
FIRST BUS FINL SVCS	@FBIZ
FIRST CAPITAL, INC.	@FCAP
FIRST COMMUNITY CORP	@FCCO
FIRST COMMUNITY	@FCBC
FIRST FINANCIAL CORP	@THFF
FIRST FINANCIAL	@FFNW
FIRST GUARANTY BANC	@FGBI

FIRST INTERNET BANC	@INBK
FIRST NATIONAL CORP	@FXNC
FIRST NORTH	@FNWB
FIRST OF LONG ISLAND	@FLIC
FIRST SAVINGS FIN	@FSFG
FIRST SEACOAST	@FSEA
FIRST US BANCSHARES	@FUSB
FIRST UNITED CORP	@FUNC
FIRST WAVE	@FWBI
FIRST WESTERN	@MYFW
FLEXSHOPPER INC	@FPAY
FLEXSTEEL INDUSTRIES	@FLXS
FLUENT INC	@FLNT
FLUIDIGM	@FLDM
FLUX POWER HOLD	@FLUX
FNCB BANCORP INC	@FNCB
FOCUS UNIVERSAL	@FCUV
FONAR CORPORATION	@FONR
FORIAN INC	@FORA
FORMA THERAP	@FMTX
FORTE BIOSC	@FBRX
FORTRESS BIOTECH INC	@FBIO
FORWARD INDUSTRIES	@FORD
FOSSIL GROUP INC	@FOSL
L B FOSTER CO	@FSTR
FRANKLIN FINANCIAL	@FRAF
FRANKLIN	@FKWL
FREIGHTCAR AME	@RAIL
FREQUENCY ELECTRONIC	@FEIM
FREQUENCY THER	@FREQ
FRP HOLDINGS INC	@FRPH
FS BANC	@FSBW
FUEL TECH INC	@FTEK
FULL HOUSE RESORTS	@FLL
FUNKO INC	@FNKO
FUSION PHARMA	@FUSN
FUTURE FINTECH	@FTFT
FUWEI FILMS (HLDGS)	@FFHL
FVCBANK	@FVCB
G MEDICAL INNOVA	@GMVD
G WILLI FOOD INTN'L	@WILC
G1 THERAPEUTICS INC	@GTHX
GAIA INC	@GAIA
GALECTIN THERAP	@GALT
GALERA THERAPEUTICS	@GRTX
GALMED PHARMA	@GLMD

GAMIDA CELL LTD	@GMDA
GAN LTD	@GAN
GARRETT MOTION INC	@GTX
GAUCHO GROUP	@VINO
GCM GROSVENOR	@GCMG
GEMINI THERAP	@GMTX
GENASYS INC	@GNSS
GENCOR INDUSTRIES	@GENC
GENERATION BIO CO	@GBIO
GENERATION	@GBNY
GENIUS BRAN	@GNUS
GENOCEA BIO	@GNCA
GENPREX INC	@GNPX
GEOSPACE	@GEOS
GEOVAX LABS INC	@GOVX
GERON CORP	@GERN
GEVO	@GEVO
GIGAMEDIA LTD	@GIGM
GILAT SATELLITE	@GILT
GLEN BURNIE BANCORP	@GLBZ
GLOBAL SELF	@SELF
GLOBAL WATER	@GWRS
GLOBUS MARITIME LTD	@GLBS
GLORY STAR NEW	@GSMG
GLYCO	@GLYC
GOHEALTH INC	@GOCO
GOLDEN NUG	@GNOG
GOSSAMER BIO INC	@GOSS
GRAYBUG VI	@GRAY
GREAT ELM GROUP INC	@GEG
GREEN PLAIN	@GPP
GREENBOX	@GBOX
GREENE COUNTY BANC	@GCBC
GREENLAND TEC	@GTEC
GREENLANE HOLD	@GNLN
GREENLIGHT CAPITAL	@GLRE
GREENPRO	@GRNQ
GREENWICH LIFE	@GLSI
GRINDROD SHIPPING	@GRIN
GRITSTONE BIO INC	@GRTS
GROM SOCIAL ENTERPRI	@GROM
GROUPON INC	@GRPN
GROWGENERATION CORP	@GRWG
GSE SYSTEMS, INC.	@GVP
GSI TECHNOLOGY INC	@GSIT
GT BIOPHARMA INC	@GTBP

GTY TECHNOLOGY	@GTYH
GUARANTY BANCSHARES	@GNTY
GUARANTY FEDERAL	@GFED
GUARDION HEALTH SCI	@GHSI
GULF ISLAND	@GIFI
GULF RESOURCES	@GURE
GWG HOLD	@GWGH
GYRODYNE CO OF AMER.	@GYRO
HACKETT GROUP INC	@HCKT
HALL OF FAME	@HOFV
HALLADOR ENERGY CO	@HNRG
HALLMARK FINANCIAL	@HALL
HAPPINESS DEV	@HAPP
HARBOR CUSTOM DEV	@HCDI
HARPOON THERAPEUTICS	@HARP
HARROW HEALTH	@HROW
HARTE-HANKS, INC.	@HHS
HARVARD BIOSCIENCE	@HBIO
HAWTHORN BANCSHARES	@HWBK
HAYNES INTERNATIONAL	@HAYN
HBT FINANCIAL	@HBT
HEALTH SCIENCES	@HSAQ
HELBIZ INC	@HLBZ
HELIUS MEDICAL	@HSDT
HEMISPHERE MEDIA	@HMTV
HENNESSY ADVISORS	@HNNA
HEPION	@HEPA
HERITAGE CRYSTAL	@HCCI
HERITAGE GLOBAL INC	@HGBL
HF FOODS GROUP INC	@HFFG
HIGHWAY HLDGS LTD	@HIHO
HIREQUEST INC	@HQI
HISTOGEN	@HSTO
HMN FINANCIAL, INC.	@HMNF
HOME BANCORP, INC	@HBCP
HOME FEDERAL BANCORP	@HFBL
HOMETRUST BANC	@HTBI
HOMOLOGY MEDIC	@FIXX
HOOKER	@HOFT
HOOKIPA PHARMA INC	@HOOK
HOTH THERAPEUTICS	@HOTH
HTG MOLECULAR	@HTGM
HUDSON CAPITAL INC.	@HUSN
HUDSON GLOBAL INC	@HSON
HUDSON TECHNOLOGIES	@HDSN
HUMANIGEN INC	@HGEN

HURCO COMPANIES, INC	@HURC
HUTTIG BUILDING	@HBP
HV BANCOR	@HVBC
HYCROFT MININ	@HYMC
HYRECAR INC	@HYRE
I3 VERTICALS INC	@IIIV
IBEX LTD	@IBEX
ICAD, INC.	@ICAD
ICC HOLDINGS INC	@ICCH
IDEAL POWER INC	@IPWR
IDEANOMICS INC	@IDEX
IDEAYA BIO	@IDYA
IDENTIV INC	@INVE
IDERA PHARMA	@IDRA
IF BANC	@IROQ
IGM BIOSCIENCES INC	@IGMS
IMAC HOLDINGS INC	@IMAC
IMARA INC	@IMRA
IMEDIA BRAND	@IMBI
IMMATICS NV	@IMTX
IMMERISON CORP	@IMMR
IMMUCELL CORPORATION	@ICCC
IMMUNIC INC	@IMUX
IMMUNOVANT	@IMVT
INDEPENDENT BANK	@IBCP
INFINITY PHARMA	@INFI
INFLARX NV	@IFRX
INFORMATION SERVICES	@III
INFRASTRUCTURE AND	@IEA
INMED PHARMA	@INM
INMUNE BIO INC	@INMB
INNODATA INC	@INOD
INNOVATIVE SOLUTIONS	@ISSC
INNOVIZ TECHN	@INVZ
INOGEN INC	@INGN
INOZYME PHARMA INC	@INZY
INPIXON	@INPX
INSEEGO CORP	@INSG
INSIGNIA SYSTEMS INC	@ISIG
INSPIRED ENTERTAIN	@INSE
INSPIREMD INC	@NSPR
INTELLICHECK INC	@IDN
INTERCEPT PHARMA	@ICPT
INTERGROUP CORP	@INTG
INTERLINK ELECTRS	@LINK
INTERNATIONAL MONEY	@IMXI

INTEVAC, INC.	@IVAC
INTERNATIONAL	@IGIC
INTRICON CORPORATION	@IIN
INTRUSION, INC.	@INTZ
INVESTAR HOLD	@ISTR
INVESTCORP CREDIT M	@ICMB
INVESTORS TITLE CO	@ITIC
INVIVO THERA	@NVIV
INVO BIOSCIENCE	@INVO
IPSIDY INC	@AUID
IRADIMED	@IRMD
IRIDEX CORPORATION	@IRIX
ISUN INC	@ISUN
ITERIS INC	@ITI
ITERUM THERAPEUT	@ITRM
ITURAN LOCATION	@ITRN
INTEGRITY APPLICAT	@IGAP
IZEA WORLDWIDE INC	@IZEA
J W MAY	@MAYS
JAGUAR HEALTH INC	@JAGX
JAKKS PACIFIC, INC.	@JAKK
JANONE INC	@JAN
JASPER	@JSPR
JERASH HOLDINGS	@JRSH
JEWETT-CAMERON TRADI	@JCTCF
JOUNCE THERA	@JNCE
KAIVAL BRANDS INNOVA	@KAVL
KAIXIN AUTO HOLDINGS	@KXIN
KALA PHA	@KALA
KALEIDO BIOSCI	@KLDO
KALVISTA PHARMAC	@KALV
KANDI TECHNOLOG	@KNDI
KASPIEN HOLDINGS INC	@KSPN
KATAPULT HOLD	@KPLT
KELLY SERVICES, INC.	@KELYA
KEMPHARM INC	@KMPH
KENTUCKY FIRST FED	@KFFB
KEWAUNEE SCIENTIFIC	@KEQU
KEY TRONIC CORP	@KTCC
KEZAR LIFE SCI	@KZR
KIMBALL ELEC	@KE
KIMBALL INT'L INC	@KBAL
KINGSTONE CO	@KINS
KINIKSA PHARMA	@KNSA
KINTARA THERAPEUTICS	@KTRA
KIORA	@KPRX

KIRKLAND'S, INC.	@KIRK
KLX ENERGY SERVICES	@KLXE
KOPIN CORP	@KOPN
KOSS CORPORATION	@KOSS
KUBIENT	@KBNT
KURA SUSHI USA INC	@KRUS
KVH INDUSTRIES, INC.	@KVHI
LA JOLLA PHARMA CO	@LJPC
LAKE SHORE BANCORP	@LSBK
LAKELAND INDUSTRIES	@LAKE
LANDEC CORPORATION	@LNDC
LANDMARK BANCORP	@LARK
LANDS' END, INC.	@LE
LANDSEA HOMES CORP	@LSEA
LANTERN PHARM	@LTRN
LANTRONIX, INC.	@LTRX
LARIMAR THERAP	@LRMR
LAWSON PRODUCTS, INC	@LAWS
LAZYDA	@LAZY
LCNB CORP	@LCNB
LEAFLY HOLDINGS	@LFLY
LEAP THERAPEUTICS	@LPTX
LEE ENTERPRISES INC	@LEE
LEGACY HOUSING CORP	@LEGH
LEVEL ONE BAN	@LEVL
LEXARIA BIOSCIENCE	@LEXX
LEXICON	@LXRX
LIBERTY LATIN	@LILA
LIBERTY TRIP	@LTRPA
LIFEMD INC	@LFMD
LIFETIME BRANDS INC	@LCUT
LIFEVANTAGE CORP	@LFVN
LIFEWAY FOODS, INC.	@LWAY
LIGHTBRIDGE CORP	@LTBR
LIGHTPATH TECH	@LPTH
LIMELIGHT NETWORKS	@LLNW
LIMESTONE BANCORP	@LMST
LIMINAL BI	@LMNL
LIMONEIRA CO	@LMNR
LINCOLN EDU SVCS	@LINC
LIPOCINE	@LPCN
LIQTECH INTER	@LIQT
LIQUID MEDIA	@YVR
LIQUIDIA CORP	@LQDA
LIQUIDITY SVCS INC	@LQDT
LIVE VENTURES INC	@LIVE

LIVEONE INC	@LVO
LIXTE	@LIXT
LMP AUTOMOT	@LMPX
LOGAN RIDGE	@LRFC
LOGICBIO THERAP	@LOGC
LOOP INDUSTRIES	@LOOP
LORDSTOWN	@RIDE
LOTTERY.COM INC	@LTRY
LSI INDUSTRIES INC.	@LYTS
LUMOS PHARMA	@LUMO
LUNA INNOVATIONS	@LUNA
LUO	@LKCO
LUTHER BURBANK	@LBC
LYRA	@LYRA
MACATAWA BANK CORP	@MCBC
MAGENTA THERAPEUTICS	@MGTA
MAGYAR BANCORP, INC.	@MGYR
MAIDEN HOLD	@MHLD
MAINSTREET BANKSH	@MNSB
MALVERN BANCORP INC	@MLVF
MAMAMANCINI	@MMMB
MAMMOTH ENERGY	@TUSK
MANHATTAN BRIDGE	@LOAN
MANITEX INTER	@MNTX
MANNATECH INC	@MTEX
MARCHEX, INC.	@MCHX
MARIN SOFT	@MRIN
MARINE PETROLEUM	@MARPS
MARINUS PHARMA	@MRNS
MARKER T	@MRKR
ASCENDANT DIGITAL	@MKTW
MARRONE BIO	@MBII
MARTIN MID PART LP	@MMLP
MASTERCRAF	@MCFT
MATRIX SERVICE CO	@MTRX
MAWSON INFRAST	@MIGI
MAXEON SOLAR	@MAXN
MDJM LTD	@MDJH
MEDALIST DIVERSIFIED	@MDRR
MEDALLION FINAN'L	@MFIN
MEDA	@MDVL
MEDIACO HOLDING	@MDIA
MEDIWOUND LTD	@MDWD
MEI PHARMA INC	@MEIP
MEIRAGTX HOLDINGS	@MGTX
MERCANTILE BANK CORP	@MBWM

MERCURITY FIN	@MFH
MERIDIAN CORP	@MRBK
MERRIMACK PHARMA	@MACK
MERSANA THERA	@MRSN
MESA AIR GROUP INC	@MESA
META MATERIA	@MMAT
METACRINE INC	@MTCR
METEN HOLDING	@METX
METROCITY BANK	@MCBS
MICROBOT MEDICAL INC	@MBOT
MICROVISION INC	@MVIS
MICT INC	@MICT
MID PENN BANCORP	@MPB
MID-SOUTHERN B	@MSVB
MIDDLEFIELD BANC	@MBCN
MIDLAND STATES	@MSBI
MIDWEST HOLDING INC	@MDWT
MIDWESTONE FINANCIAL	@MOFG
MILESTONE PHARMACEU	@MIST
MIMEDX GROUP, INC	@MDXG
MIND C T I LTD	@MNDO
MIND TECHNOLOGY INC	@MIND
MINERVA NEURO	@NERV
MINIM I	@MINM
MIRUM PHARMA	@MIRM
MITEK SYSTEMS INC	@MITK
MMTEC	@MTC
MOBIQUITY TECH	@MOBQ
MODULAR MEDICAL	@MODD
MOLECULAR TEMPLATE	@MTEM
MOLECULIN BIOTECH	@MBRX
MOMENTUS INC	@MNTS
MONOPAR THE	@MNPR
MOTORCAR PARTS OF AM	@MPAA
MOTUS GI HOLDINGS	@MOTS
MOXIAN (BVI)	@MOXC
MULLEN AUTOMOTIVE	@MULN
MUSCLE MAKER INC	@GRIL
MUSTANG BIO INC	@MBIO
MVB FINANCIAL CORP	@MVBF
MY SIZE INC	@MYSZ
MYMD PHARMA	@MYMD
NANO-X IMAG	@NNOX
NANTHEALTH INC	@NH
NATHAN'S FAMOUS, INC	@NATH
NATIONAL BANKSHARES	@NKSH

NATIONAL CINEMEDIA	@NCMI
NATIONAL SECURITY	@NSEC
NATURAL ALTERNATIVES	@NAII
NATURAL HEALTH TREND	@NHTC
NATURES SUNSHINE	@NATR
NAUTILUS BIOT	@NAUT
NCS MULTISTAGE	@NCSM
NEMAURA MED	@NMRD
NEOLEUKIN THERAPE	@NLTX
NEONODE INC.	@NEON
NEPHROS, INC.	@NEPH
NET 1 UEPS TECH	@UEPS
NETSOL TECHNOLOGIES	@NTWK
NEUBASE THERAPE	@NBSE
NEUROBO PHARMA	@NRBO
NEUROMETRIX, INC.	@NURO
NEURONETICS INC	@STIM
NEUROONE MEDIC	@NMTC
NEWAGE INC	@NBEV
NEWTEK BUSINESS SERV	@NEWT
NEXTCURE	@NXTC
NEXTDECADE CORP	@NEXT
NEXTPLAT	@NXPL
NEXTPLAY TECHNO	@NXTP
NI HOLDINGS INC	@NODK
NICHOLAS FINANCIAL	@NICK
NISUN INTERNATIONAL	@NISN
NKARTA INC	@NKTX
NN INC	@NNBR
NOODLES & CO	@NDLS
NORTECH SYSTEMS INC	@NSYS
NORTHEAST BANK	@NBN
NORTHEAST COMMUNITY	@NECB
NORTHERN TECH	@NTIC
NORTHRIM BANCORP	@NRIM
NORTHWEST PIPE CO	@NWPX
NORWOOD FINANCIAL	@NWFL
NOVA LIFE	@NVFY
NOVAN INC	@NOVN
NOVO INTEGRA	@NVOS
NRX PHARMACE	@NRXP
NUCANA PLC	@NCNA
NUTRIBAND INC	@NTRB
NUVVE HOLDING CORP	@NVVE
NUWELLIS INC	@NUWE
NUZEE	@NUZE

NVE CORPORATION	@NVEC
NXT-ID INC	@NXTD
NYMOX PHARMA	@NYMX
OAK VALLEY	@OVLY
OBLONG INC	@OBLG
OBSEVA SA	@OBSV
OCEAN BIO-CHEM	@OBCI
OCONEE FEDERAL	@OFED
OCULAR THERA	@OCUL
OCUPHIRE PHARMA INC	@OCUP
ODYSSEY MARINE EXP	@OMEX
OHIO VY BANC CORP	@OVBC
THE OLB GROUP	@OLB
OLD POINT FINANCIAL	@OPOF
OLD SECOND BANCORP	@OSBC
OLYMPIC STEEL, INC.	@ZEUS
OMEROS CORP	@OMER
OMNIQ CORP	@OMQS
ONCOCYTE CORP	@OCX
ONCOLOGY	@TOI
ONCONOVA THER	@ONTX
ONCOSEC MEDICAL	@ONCS
ONCTERNAL	@ONCT
ONDAS HOLDINGS INC	@ONDS
ONE GROUP	@STKS
ONE STOP SYSTEMS INC	@OSS
ONESPAN INC	@OSPN
ONEWATER	@ONEW
ONTRAK INC	@OTRK
OP BANCORP	@OPBK
OPGEN INC	@OPGN
OPIANT PHARMACEU	@OPNT
OPORTUN FINANCIAL	@OPRT
OPTIBASE LTD	@OBAS
OPTICAL CABLE CORP	@OCC
OPTIMUMBANK HOLDINGS	@OPHC
OPTINOSE INC	@OPTN
ORAMED PHARMA	@ORMP
ORANGE COUNTY BANCOR	@OBT
ORASURE TECHNOLOGIES	@OSUR
ORBITAL ENERGY	@OEG
ORGANOVO HOLD	@ONVO
ORGENESIS INC	@ORGS
ORIC PHARMA	@ORIC
ORIGIN AGRITECH LTD	@SEED
ORIGIN MATERI	@ORGN

ORION ENERGY SYS	@OESX
ORRSTOWN FINANCIAL	@ORRF
ORTHOFIX MEDI	@OFIX
OTONOMY INC	@OTIC
OUTLOOK THERA	@OTLK
OVID THERAPEUTIC	@OVID
OXBRIDGE RE	@OXBR
OYSTER POINT	@OYST
P & F INDUSTRIES	@PFIN
PAINREFORM	@PRFX
PALISADE BIO INC	@PALI
PALTALK	@PALT
PANBELA THERAPE	@PBLA
PARATEK PHARMA	@PRTK
PARK CITY GROUP, INC	@PCYG
PARK OHIO HLDGS	@PKOH
PARKE BANCORP INC	@PKBK
PARTNERS BANCORP	@PTRS
PASSAGE BIO INC	@PASG
PATHFINDER BANCORP	@PBHC
PATRIOT NAT'L BANC	@PNBK
PATRIOT TRANSPORT	@PATI
PAVMED INC	@PAVM
PAYSIGN INC	@PAYS
PCB BANCORP	@PCB
PCSB FINANCIAL CORP	@PCSB
PCTEL, INC.	@PCTI
PDS BIO	@PDSB
PEAPACK-GLADSTONE	@PGC
PENNANT	@PNTG
PENNS WOODS BANCORP	@PWOD
PEOPLES FINL SERV	@PFIS
PEOPLES BANCORP	@PEBK
PERASO	@PRSO
PERFORMANCE SHIP	@PSHG
PERFORMANT FI	@PFMT
PERMA-FIX ENVIRONMEN	@PESI
PERMA-PIPE IN	@PPIH
PERSONALIS INC	@PSNL
PET	@PETQ
PETMED EXPRESS, INC.	@PETS
PFSWEB, INC.	@PFSW
PHARMACYTE BIO	@PMCB
PHASEBIO PHARM	@PHAS
PHATHOM PHARMA	@PHAT
PHIBRO ANIMAL HEALTH	@PAHC

PHIO PH	@PHIO
PHUNWARE INC	@PHUN
PIERIS PHARMA	@PIRS
PINGTAN MARINE ENT	@PME
PIONEER BANCORP INC	@PBFS
PIONEER POWER SOL	@PPSI
PIXELWORKS, INC.	@PXLW
PLBY GROUP INC	@PLBY
PLIANT THERAPEUTICS	@PLRX
PLUMAS BANCORP	@PLBC
PLURISTEM THERA	@PSTI
PLUS THERAPE	@PSTV
PLX PHARMA INC	@PLXP
PMV PHAR	@PMVP
POLAR POWER INC	@POLA
POLARITYTE INC	@PTE
POLYPID LTD	@PYPD
PONCE FINANCIAL	@PDLB
PORTAGE BIOTECH INC	@PRTG
POSEIDA	@PSTX
POTBELLY CORP	@PBPB
POWELL INDUSTRIES	@POWL
POWERBRIDGE TECH	@PBTS
POWERFLEET	@PWFL
PRECIGEN	@PGEN
PRECIPIO INC	@PRPO
PRECISION BIO	@DTIL
PREDICTIVE ONCOLOGY	@POAI
PREFORMED LINE PROD	@PLPC
PRELUDE THER	@PRLD
PRIMEENERGY RES	@PNRG
PRIMIS FINANCIAL	@FRST
PRO-DEX INC	@PDEX
PROCESSA PHARMA	@PCSA
PROFESSIONAL	@IPDN
PROFESSIONAL	@PFHD
PROFIRE ENERGY, INC	@PFIE
PROGENITY INC	@PROG
PROPHASE LABS	@PRPH
PROQR THERA	@PRQR
PROTAGENIC THERAP	@PTIX
PROTARA THERAP	@TARA
PROVENTION BIO INC	@PRVB
PROVIDENT BANCORP	@PVBC
PROVIDENT FIN'L HLDG	@PROV
PRUDENTIAL BANCORP	@PBIP

PSYCHEMEDICS CORP	@PMD
PUHUI WEALTH INV	@PHCF
PULMATRIX INC	@PULM
PULSE BIOSCIENCES	@PLSE
PUMA BIOTECH	@PBYI
PURE CYCLE CORP	@PCYO
PURPLE INNOVATION	@PRPL
PYXIS TANKERS INC	@PXS
Q&K INTERNATIONAL	@QK
QUALIGEN THERA	@QLGN
QUANTUM CORPORATION	@QMCO
QUANTUM COMPUTING	@QUBT
QUEST RESOURCE	@QRHC
QUICKLOGIC CORP	@QUIK
QUMU CORP	@QUMU
RADA ELECT	@RADA
RADCOM LTD	@RDCM
RADIUS HEALTH	@RDUS
RAMACO RESOURCES INC	@METC
RANDOLPH BANCORP INC	@RNDB
RANGER OIL CORP	@ROCC
RAPT THERAPEUT	@RAPT
RATTLER MIDSTREAM	@RTLR
RAVE RESTAURANT	@RAVE
RBB BANCORP	@RBB
RCI HOSPITALITY	@RICK
R C M TECHN	@RCMT
READING INTERNTL	@RDI
REALNETWORKS, INC.	@RNWK
RECON TECHNOLOGY	@RCON
RECRO PHAR	@REPH
RECRUITER.COM	@RCRT
RED CAT HOLDINGS INC	@RCAT
RED RIVER BANCSH	@RRBI
RED ROBIN GOURMET	@RRGB
RED VIOLET INC	@RDVT
REED'S INC	@REED
REGULUS THERA	@RGLS
REKOR SYSTE	@REKR
RELIANCE GLOB	@RELI
RELMADA THERAPEUTICS	@RLMD
REMARK HOLDINGS INC	@MARK
RENOVAREX	@RENO
REPUBLIC FIRST BANC	@FRBK
REPARE THERAP	@RPTX
REPRO-MED SYSTEMS	@KRMD

RESOURCES CONNECTION	@RGP
RESEARCH FRONTIERS	@REFR
RESEARCH SOLUTIONS	@RSSS
RESHAPE	@RSLS
RESONANT	@RESN
RETO ECO	@RETO
REVIVA PHARMA	@RVPH
REWALK ROBOTICS LTD	@RWLK
REZOLUTE INC	@RZLT
RF INDUSTRIES, LTD.	@RFIL
RGC RESOURCES, INC.	@RGCO
RHINEBECK BANCORP	@RBKB
RHYTHM PHARMA	@RYTM
RIBBON COM	@RBBN
RICEBRAN TECH	@RIBT
RICHARDSON ELECTRONI	@RELL
RICHMOND MUTUAL	@RMBI
RIGEL PHARMACEUTICAL	@RIGL
RIMINI STREET INC	@RMNI
RIVERVIEW BANCORP	@RVSB
RMR GROUP INC	@RMR
ROCKWELL MEDICAL	@RMTI
ROCKY BRANDS INC	@RCKY
ROCKY MOUNTAIN	@RMCF
RUBICON TECHNOLOGY	@RBCN
RUBIUS THERA	@RUBY
RUMBLEON INC	@RMBL
RUSH ENTERPRISES INC	@RUSHB
RVL PHARM	@RVLP
S&W SEED COMPANY	@SANW
SAGA COMMUNICATIONS	@SGA
SALARIUS PHA	@SLRX
SALEM MEDIA GROUP	@SALM
SALISBURY BANCORP	@SAL
SANARA MEDTECH INC	@SMTI
SATSUMA PHARMA	@STSA
SAVARA INC	@SVRA
SAVE FOODS INC	@SVFD
SB FINANCIAL GROUP	@SBFG
SCHMITT INDUSTRIES	@SMIT
SCHOLAR ROCK HOL	@SRRK
SCIENJOY HOLD	@SJ
SCIPLAY	@SCPL
SCPHARMAC	@SCPH
SECURITY NATL FINL	@SNFCA
SCWORX CORP	@WORX

SCYNEXIS	@SCYX
SEACHANGE INTL INC	@SEAC
SEANERGY MARITIME	@SHIP
SEASPINE	@SPNE
SECOND SIGHT	@EYES
SECUREWORKS	@SCWX
SEELOS THERA	@SEEL
SELECTA BIOSCIENCE	@SELB
SEL	@SLS
SEMILEDS	@LEDS
SENECA FOODS CORP.	@SENEB
SENESTECH INC	@SNES
SENMIAO TECHNOLOGY	@AIHS
MAGAL SECURITY SYS	@SNT
SENSUS HEALTHCARE	@SRTS
SERES THERA	@MCRB
SERVICESOURCE	@SREV
SESEN BIO INC	@SESN
SG BLOCKS INC	@SGBX
SHARPLINK GAMING LTD	@SBET
SHARPS COMPLIANCE	@SMED
SHIFT TECH	@SFT
SHIFTPIXY INC	@PIXY
SHINECO INC	@SISI
SHORE BANCSHARES	@SHBI
SHOTSPOTTER INC	@SSTI
SI-BONE INC	@SIBN
SIEBERT FINANCIAL	@SIEB
SIENTRA INC	@SIEN
SIERRA BANCORP	@BSRR
SIERRA WIRELESS INC	@SWIR
SIGA TECHNOLOGIES	@SIGA
SIGMA LABS INC	@SGLB
SIGMATRON INT'L	@SGMA
SILICOM LTD	@SILC
SILVERCREST ASSET	@SAMG
SILVERSUN TECH	@SSNT
SINGULARITY FUTURE	@SGLY
SINOVAC BIOTECH LTD	@SVA
SINTX TECH	@SINT
SIO GENE	@SIOX
SIYATA MOBILE	@SYTA
SKILLFUL CRAFTSMAN	@EDTK
SMART SAND INC	@SND
SMARTFINANCIAL INC	@SMBK
SMILEDIRECTC	@SDC

SMITH MICRO SOFTWARE	@SMSI
SMITH-MIDLAND CORP	@SMID
SOC TELEMED INC	@TLMD
SOCKET MOBILE, INC.	@SCKT
SOL GEL TECH	@SLGL
SOLID BIOSCIENCES	@SLDB
SOLIGENIX, INC.	@SNGX
SOLUNA HOLDINGS INC	@SLNH
SONIC FOUNDRY INC	@SOFO
SONIM TECHNOL	@SONM
SONNET BIOTHERA	@SONN
SONO-TEK CORPORATION	@SOTK
SONOMA PHARMAC	@SNOA
SOTHERLY HOTELS INC	@SOHO
SOUND FINANCIAL	@SFBC
SOUTH PLAINS	@SPFI
SOUTHERN FIRST	@SFST
SOUTHERN MISSOURI	@SMBC
SP PLUS CORP	@SP
SPAR GROUP INC	@SGRP
SPECTRUM PHARMACTL	@SPPI
SPERO THERAPE	@SPRO
SPHERE 3D CORP	@ANY
SPIRIT OF TEXAS BAN	@STXB
SPOK HOLDINGS INC	@SPOK
SPORTSMAN'S	@SPWH
SRAX INC	@SRAX
STABILIS	@SLNG
STAFFING 360 SOL	@STAF
STAR EQUI	@STRR
STATERA	@STAB
STEALTHGAS, INC.	@GASS
STEEL CONNECT INC	@STCN
STERLING BANCORP INC	@SBT
STOKE THE	@STOK
STRATA SKIN	@SSKN
STRATTEC SEC CORP	@STRT
STRATUS PROPERTIES	@STRS
STREAMLINE HEALTH	@STRM
SUMMER INFANT, INC.	@SUMR
SUMMIT FINANCIAL GRP	@SMMF
SUMMIT STATE BANK	@SSBI
SUMMIT THERA	@SMMT
SUMMIT	@WISA
SUNOPTA INC	@STKL
SUNWORKS INC	@SUNW

SUPER LEAGUE	@SLGG
SUPERCOM	@SPCB
SUPERIOR GROUP	@SGC
SURFACE ONCOLOGY INC	@SURF
SURGALIGN HOLD	@SRGA
SURGEPAYS	@SURG
SURMODICS, INC.	@SRDX
SUTRO BIOPHARMA INC	@STRO
SWK HOLDINGS CORP.	@SWKH
SYNALLOY CORPORATION	@SYNL
SYNCHRONOSS TECH	@SNCR
SYNLOGIC INC	@SYBX
SYPRIS SOLUTIONS INC	@SYPR
SYROS PHARMACEUTI	@SYRS
T2 BIOSYSTEMS INC	@TTOO
TABULA RASA HEALTHCA	@TRHC
TACTILE SYSTEMS TECH	@TCMD
TAITRON COMPONENTS	@TAIT
TALKSP	@TALK
TARGET HOSPIT	@TH
TAT TECHNOLOGIES LTD	@TATT
TAYLOR DEVICES INC	@TAYD
TAYSHA GENE	@TSHA
TCR2 THERAPEUTICS	@TCRR
TD HOLDINGS	@GLG
TDH HOLDINGS INC	@PETZ
TELA BIO INC	@TELA
TELESAT CORP	@TSAT
TEMPEST THE	@TPST
TENAX THERAPEUTICS	@TENX
TERRITORIAL BANCORP	@TBNK
TESSCO TECHNOLOGIES	@TESS
TFF PHARMA	@TFFP
THE9 LTD	@NCTY
THERAPEUTICSMD	@TXMD
THERAVANCE BIO	@TBPH
THERMOGENE	@THMO
TILE SHOP	@TTSH
TIMBERLAND BANCORP	@TSBK
TIPTREE INC	@TIPT
TITAN MACHINERY	@TITN
TITAN PHARMACEUTICAL	@TTNP
TMC THE MET	@TMC
TOMI ENVIRONMENTAL	@TOMZ
TONIX PHARMACE	@TNXP
TOP SHIPS INC.	@TOPS

TOUGHBUILT	@TBLT
TPI COMPOSITES INC	@TPIC
TRACON PHARM	@TCON
TRANSACT TECH INC	@TACT
TRANSCAT, INC.	@TRNS
TRANSMEDICS	@TMDX
TRAVELCENTERS	@TA
TRAVELZOO	@TZOO
TREAN INSURANCE	@TIG
TREVENA	@TRVN
TREVI THERAP	@TRVI
TRICIDA	@TCDA
TROOPS INC	@TROO
TRUECAR INC	@TRUE
TRUSTCO BANK CORP NY	@TRST
TRXADE HEALTH	@MEDS
TSR, INC.	@TSRI
TURTLE BEACH CORP	@HEAR
TWIN DISC INC	@TWIN
TYME TECHN	@TYME
UCOMMUNE	@UK
UFP TECHNOLOGIES	@UFPT
ULTRALIFE CORP	@ULBI
UNICO AMERICAN CORP	@UNAM
UNION BANKSHARES	@UNB
UNITED BANCORP, INC.	@UBCP
UNITED BANCSHARES	@UBOH
UNITED FIRE	@UFCS
UNITED-GUARDIAN, INC	@UG
UNITED INSURANCE	@UIHC
UNITED SECURITY	@UBFO
UNITY BANCORP, INC.	@UNTY
UNITY BIOTECHNOLOGY	@UBX
UNIVERSAL ELEC	@UEIC
UNIVERSAL LOGISTICS	@ULH
UNIVERSAL STAINLESS	@USAP
UPLAND SOFTWARE INC	@UPLD
URBAN-GRO INC	@UGRO
URBAN ONE INC	@UONEK
UROGEN PHARMA LTD	@URGN
U.S. ENERGY CORP.	@USEG
US GLOBAL INVE	@GROW
US GOLD CORP	@USAU
US WELL SERVICES INC	@USWS
U.S. LIME & MINERALS	@USLM
USA TRUCK, INC.	@USAK

USIO INC	@USIO
UTAH MEDICAL PRODS	@UTMD
UTSTARCOM	@UTSI
VACCINEX	@VCNX
VALUE LINE INC	@VALU
VANDA PHARMA	@VNDA
VASTA PLATFORM LTD	@VSTA
VAXART INC	@VXRT
VBI VACCINES	@VBIV
VENUS CONCEPT INC	@VERO
VERA BRADLEY INC	@VRA
VERAS	@VSTM
VE	@VERB
VERICITY INC	@VERY
VERIFYME INC	@VRME
VERITONE INC	@VERI
VERRICA PHARMA	@VRCA
VERTEX INC	@VERX
VERTEX ENERGY	@VTNR
VERU INC	@VERU
VIA RENEWABLES INC	@VIA
VICTORY CAPITAL	@VCTR
PICO HOLDINGS INC	@VWTR
VIKING THERAPEU	@VKTX
VILLAGE BANK & TRUST	@VBFC
VILLAGE FARMS	@VFF
VILLAGE SUPER MARKET	@VLGEA
VINCERX PHARMA INC	@VINC
VINCO VENTURES INC	@BBIG
VIRACTA	@VIRX
VIRCO MFG	@VIRC
VIRGINIA NATIONAL	@VABK
VIRIDIAN THERAP	@VRDN
VIRTRA INC	@VTSI
VISLINK TECHNO	@VISL
VISTAGEN	@VTGN
VITAL FARMS	@VITL
VITRU LTD	@VTRU
VIVEVE MEDICAL INC	@VIVE
VIVOPOWER	@VVPR
VOXX INTERN	@VOXX
VOYAGER THERAPEU	@VYGR
VSE CORPORATION	@VSEC
VTV THERAPEUTICS INC	@VTVT
VUZIX CORP	@VUZI
VYANT BIO INC	@VYNT

VYNE THERAPEUTIC	@VYNE
WAH FU EDU	@WAFU
WAITR HOLDINGS INC	@WTRH
WATERSTONE FIN	@WSBF
WAVE LIFE SCI	@WVE
WAVEDANCER INC	@WAVD
WAYSIDE TECHNOLOGY	@WSTG
WEST BANCORPORATION	@WTBA
WESTERN NEW ENG	@WNEB
WEYCO GROUP, INC.	@WEYS
WHEELER REAL ESTAT	@WHLR
WHERE FOOD COMES	@WFCF
WHOLE EARTH BRA	@FREE
WILHELMINA INTER	@WHLM
WILLAMETTE VALLEY	@WVVI
WILLDAN GROUP, INC.	@WLDN
WILLIAM PENN	@WMPN
WILLIS LEASE FINANCE	@WLFC
WINDTREE THERAP	@WINT
WM TECH	@MAPS
WORKHORSE GROUP INC	@WKHS
WORKSPORT	@WKSP
WVS FINANCIAL CORP.	@WVFC
X4 PHARMA	@XFOR
XBIOTECH INC	@XBIT
XCEL BRANDS	@XELB
XENETIC BIOSCIENCES	@XBIO
XER	@XERS
XOMA	@XOMA
XPRESSPA GROUP INC	@XSPA
Y-MABS THERAPEUT	@YMAB
YATRA ONLINE INC	@YTRA
YELLOW CORP	@YELL
YIELD10 BIOSCIENCE	@YTEN
YORK WATER CO	@YORW
YUMANITY THER	@YMTX
YUNHONG CTI	@CTIB
ZHONGCHAO INC	@ZCMD
ZIVO BIOSCIENCE INC	@ZIVO
ZK INTERNATIONAL	@ZKIN
ZOSANO PHARMA	@ZSAN
ZOVIO INC	@ZVO
ZW DATA ACTION	@CNET
ZYNERBA PHARMA	@ZYNE
ZYNEX INC.	@ZYXI
A2Z	@AZ

ABSOLUTE SOFTWARE	@ABST
ACASTI PHARMA INC	@ACST
ACUITYADS HOLDINGS	@ATY
AETERNA ZENTARIS INC	@AEZS
AKUMIN INC	@AKU
APTOSE BIOSCIENCES	@APTO
ASSURE HOLDINGS	@IONM
AUDIOCODES LTD	@AUDC
AURORA CANNABIS INC	@ACB
BELLUS HEALTH	@BLU
BENITEC BIO	@BNTC
BITFARMS LTD	@BITF
BREAKING DATA CORP	@BRAG
BRIACELL THERAPEUTIC	@BCTX
BRP INC	@DOOO
BURCON NUTRASCIENCE	@BRCN
CAMTEK LTD	@CAMT
CANOPY GROWTH CORP	@CGC
CARDIOL THERAPEUTIC	@CRDL
COLLIERS INTL	@CIGI
COMPUGEN	@CGEN
VIACOMCBS INC	@VIACA
URBAN ONE INC	@UONE
TUSCAN HOLDIN	@THCA
SENECA FOODS CORP.	@SENEA
RUSH ENTERPRISES INC	@RUSHA
READING INTERNTL	@RDIB
QURATE RETAIL INC	@QRTEB
PURECYCLE TEC	@PCT
OPTHEA LTD	@OPT
NEWS CORP	@NWS
MALACCA STRAITS ACQ	@MLAC
LIVEVOX HOL	@LVOX
LIBERTY TRIP	@LTRPB
LIBERTY MEDIA	@FWONK
LIBERTY SIRIUS XM	@LSXMK
LIBERTY SIRIUS XM	@LSXMB
LIBERTY LATIN	@LILAK
LIBERTY GLOBAL	@LBTYK
LIBERTY GLOBAL	@LBTYB
LIBERTY BROAD	@LBRDK
KELLY SERVICES, INC.	@KELYB
FOX CORP	@FOX
EAST RESOURCES	@ERES
EMERGE	@ETAC
DONEGAL GROUP INC.	@DGICB

DISCOVERY INC	@DISCK
DISCOVERY INC	@DISCB
CHP MERGER CORP	@CHPM
CENTRAL GARDEN & PET	@CENTA
BEL FUSE	@BELFB
AVITA MEDICAL INC	@RCEL
ACE CONVERGENCE	@ACEV
ALPHABET INC	@GOOG
XORTX THERAP	@XRTX
WESTPORT FUEL	@WPRT
VIQ SOLUTIONS	@VQS
VINTAGE WINE	@VWE
VIEMED HEALTHCARE	@VMD
VICINITY MOTOR CORP	@VEV
VERY GOOD	@VGFC
VERSUS SYSTEMS INC	@VS
VERSABANK	@VBNK
VALENS COMPANY	@VLNS
URANIUM ROYALTY	@UROY
TRANSGLOBE ENERGY	@TGA
TOWER SEMICONDUCTOR	@TSEM
TORM PLC	@TRMD
TITAN MEDICAL INC.	@TMDI
THERATECHNOLOGIES	@THTX
SKYLIGHT HEALTH	@SLHG
SIGMA LITHIUM CORP	@SGML
SANGOMA TECHNOLOGIES	@SANG
REAL BROKER	@REAX
QUIPT HOME	@QIPT
PYROGENESIS CAN	@PYR
PROFOUND MEDICAL	@PROF
POINTS INTN'L LTD	@PCOM
PERPETUA RES	@PPTA
ORGANIGRAM	@OGI
ONCOLYTICS BIOTECH	@ONCY
NOVA LTD	@NVMI
NEPTUNE TECHNOLOGIES	@NEPT
NEOVASC INC	@NVCN
MOGO INC (BRITIS	@MOGO
MISSION PROD	@AVO
MIND MEDICINE	@MNMD
METHANEX CORP	@MEOH
MEDICINOVA INC	@MNOV
MEDICENNA THERAPE	@MDNA
MCLOUD T	@MCLD
MAXCYTE	@MXCT

MAGIC SOFTWARE	@MGIC
LOGITECH INTERNAT	@LOGI
LARGO INC	@LGO
KAMADA LTD.	@KMDA
INTERCURE LTD	@INCR
IMV INC	@IMV
IMMUNOPRECIS	@IPA
HUT 8 MINING CORP	@HUT
HIVE BLOCKCHAIN TECH	@HIVE
HIGH TIDE INC	@HITI
HEXO CORP	@HEXO
GREENPOWER	@GP
GREENBROOK TMS INC	@GBNH
FSD PHARMA INC	@HUGE
FIRSTSERVICE CORP	@FSV
EVOGENE LTD	@EVGN
ENTHUSIAST GAMING	@EGLX
ENGINE GAMING	@GAME
ELBIT SYSTEMS LTD	@ESLT
DRAGANFLY	@DPRO
DOCEBO INC	@DCBO
DIRTT ENVIRONMENTAL	@DRTT
DIGIHOST TECH	@DGHI
DIAMEDICA THERAPE	@DMAC
DESCARTES SYSTEMS GR	@DSGX
CRONOS GROUP INC	@CRON

Annex AE	Computer Specifications

Computer Specifications	
Brand	MSI
Model	PE62 7RD
System Type	x64 Based PC
Processor	Intel® Core^{TM} i7-7700HQ CPU
Motherboard	MS-16J9
RAM	16,0 GB
Disk	512 GB