Where Has All the Data Gone?*

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Abstract

The finance industry is transforming into a data industry. As data used to inform investments becomes more central, we need to measure the quantity of data investors have about various assets. Informed by a structural model, we develop such a cross-sectional measure. We show how our measure differs from price informativeness and use it to document a new fact: Data about large growth firms is becoming increasingly abundant, relative to data about other firms. Our structural model offers an explanation for this data divergence: Large growth firms' data became more valuable, as big firms got bigger and growth magnified the effect of these changes in size.

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Data is becoming more central to the practice of finance. In order to address the myriad of questions that are arising about data value and data choice, we need a quantitative measure of data being used by market participants. Firms want to know: How much do others know about various types of assets? This paper develops a data measure to answer this question.

The challenges with measuring data processing are many-fold. For one, it is not directly observable. While some of it is bought and sold, much of it is not. There are proxies available – like counts of news stories, information technology expenditures, or analyst coverage. These are suggestive, but are quite crude, especially if one wants a precise answer to the question: how much information about stocks did investors extract through data processing? Measures of the information contained in market prices do reflect the amount of data, but are also influenced by market volatility or the price sensitivity to data, factors which differ across assets.

We address these challenges by building a simple structural model to guide our measurement. The model shows how data is related to and yet distinct from concepts like price informativeness. It also provides a formula to correct a price information measure for the effect of asset characteristics, and obtain a pure measure of data.

Next, we use this toolkit to study cross-sectional patterns in data in the US equity market over the past few decades. We group assets by size and growth prospects: we chose these dimensions because they drive the value of data processing in the model. Our analysis reveals a new fact: diverging trends in data processing across different assets. Investors in large growth firms are basing their decisions on more and more data. For other assets, data appears stagnant, in comparison. In other words, ever-growing reams of financial data may be helping price assets more accurately. But this additional data might not deliver financial efficiency benefits for the vast majority of firms. This divergence is consistent with reduced-form measures, like price informativeness measures and analyst coverage patterns, with different magnitudes. However, quantifying the magnitude of the divergence in units of data precision is valuable, beyond the reduced-form evidence.

The third contribution of the paper is to explore data valuation. We find that the value of data depends on firm size and growth. This finding is what motivated us to sort firms by size and growth in the empirical analysis. These are dimensions along which data choices should vary. When we use size and growth estimates to quantify data value, we uncover a potential

explanation for data divergence: The value of large, growth firm data has diverged, as large firms have grown relatively larger.

Section 1 begins with a simple model designed to relate data precision to observables. Our theoretical framework is a standard noisy rational expectations framework with multiple assets. The theory points to a particular moment as a natural starting point for our analysis of data processing: Estimate the coefficient on prices in a regression of future cashflows on a constant, prices and controls. This coefficient, referred to as price informativeness by papers like Bai, Philippon, and Savov (2016), measures how closely prices reflect future firm outcomes. This is obviously affected by the amount of data processed but also depends on other firm characteristics, making trends in this variable hard to interpret or attribute solely to changes in data processing. Our model overcomes this difficulty: it offers a simple expression that relates the price informativeness measure to data, in a way that holds with minimal theoretical assumptions. Specifically, it can be decomposed into components that depend on data processing, cashflow growth and volatility. The cashflow and volatility can be directly estimated from financial market observables, which allows us to back out a precise measure of data processed by investors.

Section 2 provides detail of how we estimate our model structurally. This includes the description of our sample, our variable construction, as well as the moments used for the structural estimation.

In Section 3, we report how informativeness of prices changes across different classes of assets and decompose that change into changes in volatility, growth and data. We find that, over the last 50 years, data about most firms has stagnated. However, one category of data has become much more abundant: information about large growth firms. Strikingly, while firm growth and volatility have also changed over time, their changes work against this trend for the most part. For example, by themselves, they would imply falling price informativeness for large-growth firms as well. Thus, our measurement exercise reveals that data divergence is the key to understanding the changes over the last few decades. We also contrast our measure, both theoretically and quantitatively, with other measures such as price informativeness, comovement and absolute price informativeness.

Finally, Section 4 uses the model to explore the underlying drivers of this rising abundance

of data processing on large-growth firms. Specifically, we compute a model implied value of data, which is increasing in the size of the firm, volatility of its cashflows and growth prospects. While this is not surprising *per se*, the model yields a simple formula that shows exactly how these characteristics interact, offset and amplify each other. This measure allows us to precisely rank assets based on the value of learning about them, which then predicts the types of assets are learned about.

We find that value of data about large growth stocks has diverged in recent years, which offers a potential explanation for the trends we see in data processing. A key factor behind this divergence is a similar pattern in firm size: large firms got much larger, compared to small firms. Since an increase in size allows investors to take larger positions based on their data processing, the divergence in size makes larger firms even more attractive to learn about. Finally, growth amplifies changes in the value of data. To be precise, growth multiplies size in data value. Although data for all large firms became more valuable as large firms got bigger, in most decades, this effect was strongest for the large growth firms. The fact that our prediction about value of data is consistent with the data patterns we see, both offers an explanation for our facts, and gives us greater confidence in our measurement approach.

Thus, as overall data processing capacity increased in the economy, most of it seems to have gone to learning about the prospects of large growth firms. Other types of firms benefited little from this data revolution.

Related Literature Our methodology is most related to Bai, Philippon, and Savov (2016) and Davila and Parlatore (2016a), who propose measures of price informativeness. Their measure captures the ability of prices to forecast or aggregate information. Such a measure is valuable because it may relate to real efficiency.[1] Similarly, measures of comovement, synchronicity or R^2 (Durnev, Morck, and Yeung, 2004) measure aggregate price variation, relative to stock-specific price variation. Our question differs. We want to know how the allocation of

[1]There is an extensive literature on how asset price informativeness affects real investment. (Ozdenoren and Yuan, 2008; Bond and Eraslan, 2010; Goldstein, Ozdenoren, and Yuan, 2013; David, Hopenhayn, and Venkateswaran, 2016; Dow, Goldstein, and Guembel, 2017; Dessaint, Foucault, Fresard, and Matray, 2018) complement our work by showing how the financial information trends we document could have real economic effects. Bond, Edmans, and Goldstein (2012) review this literature, concluding that the relationship between market efficiency and real efficiency is not necessarily monotone and depends on the environment.

financial data precision, across asset types, has changed over time. Our measure is valuable because we need it to value or choose data. Section 2.3 compares these measures and reveals important differences: Noise, size and growth all drive a wedge between the previously-used price informativeness or comovement measures and our data measure. We measure these wedges and find they are quantitatively large. Finally, previous exercises did not explain why trends emerged. Our approach does.

Empirical work in this area primarily uses proxies for data or information, such as news consumption (Ben-Rephael, Carlin, Da, and Israelsen, 2019), social media text (Ranco, Aleksovski, Caldarelli, Grcar, and Mozetic, 2015), analyst coverage (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012), or earnings announcements (Martineau, 2017). These papers measure the effect of a particular information channel and for the most part, are interested in cross-sectional determinants rather changes over time. Our goal is to measure all the information investors use, from all channels, and to document how that has changed over time.

Work by Stambaugh (2014) and Glode, Green, and Lowery (2012) does explain the reason for overall information trends. But their focus is on aggregate trends that affect all assets. These authors highlight forces such as rising institutional ownership and indexation. Such forces could be incorporated into our measurement framework by changing the marginal benefit of all firms' data. But our focus is on why these trends differ across asset classes and what part of that change is information versus divergent asset characteristics.

Finally, the way in which we model data has its origins in information theory/computer science, and is similar to work on rational inattention (Sims, 2003; Maćkowiak and Wiederholt, 2009; Kacperczyk, Nosal, and Stevens, 2015). Similar equilibrium models with information choice have been used to explain income inequality (Kacperczyk, Nosal, and Stevens, 2015), information aversion (Andries and Haddad, 2017), home bias (Mondria, Wu, and Zhang, 2010; Van Nieuwerburgh and Veldkamp, 2009), and mutual fund returns (Pástor and Stambaugh, 2012), among other phenomena. Related microstructure work explores the frequency of information acquisition and trading (Kyle and Lee, 2017; Dugast and Foucault, 2016; Chordia, Green, and Kottimukkalur, 2016; Crouzet, Dew-Becker, and Nathanson, 2016). Empirical work in this vein (Katz, Lustig, and Nielsen, 2017) finds evidence of rational inattention like information frictions in the cross section of asset prices. What we add to this literature is using the

theory for structural estimation. Our structure allows us to distinguish changes in information from changes in asset characteristics.

1 A Structural Framework for Data Measurement

The main objective of the paper is to develop a measure of investors' data precision from asset prices. This is related to measures of price informativeness. But we know that informativeness also reflects differences in price-earnings ratios, related to firm growth, and differences in firm price volatility. One approach would be to simply control for such asset characteristics in a linear regression. However, one problem with this approach is that growth and volatility themselves affect the value of collecting and processing data and therefore, are likely to be correlated with investors' data. As such, adding them as controls can remove some of what we hope to measure. Another problem is non-linearity: the effect of growth, for example, is probably not additive. In fact, this is exactly what happens in our model, where it interacts with the measure of data multiplicatively. Furthermore, our goal is to develop a measure of data processing that guides the choice of valuation of data by investors. In order to do so, it needs to be consistent with – or interpretable in terms of – a valuation or data portfolio choice model. For all these reasons, we turn to a structural approach to inform us about how to properly measure data.

We work with the simplest theoretical framework that achieves this objective. The setup is a standard noisy rational expectations model with multiple assets, in the spirit of Admati (1985) and Van Nieuwerburgh and Veldkamp (2009). The model yields simple, intuitive expressions for the objects of interest, including a measure of price informativeness, as a function of both asset characteristics and investor data. These expressions form the basis for an empirical strategy that disentangles asset characteristics from investor data, using observable moments of stock prices and cash flows.

Model A unit measure of investors trade multiple stocks (indexed by f). We assume that these assets belonging to different groups (indexed by j), where assets within a group share a number of parameters. The empirical analogues and the rationale for choosing will be described in detail in Section 2.2. A share is a claim to a stream of dividends. Dividends grow at different

rates across groups. We denote the group-specific growth rate by g_j. The flow dividend of stock f in group j in period 1 has two random innovations – one that is correlated across firms and the other idiosyncratic (i.e. stock-specific). These are denoted by $\bar{\epsilon}_{fj1}$ and ϵ_{fj1} respectively. For our baseline analysis, we will assume that the correlated innovation has a one-factor structure, i.e. it is the product of a firm-specific loading and the realization of an aggregate factor: $\bar{\epsilon}_{fj1} = \tilde{\beta}_{f,j}\bar{\epsilon}_1$, where $\tilde{\beta}_{f,j}$ is the firm-specific loading.[2] The idiosyncratic component is normally distributed with a zero mean. Formally,

$$d^*_{fj1} = g_j d^*_{fj0} + \bar{\epsilon}_{fj1} + \epsilon_{fj1},, \qquad \epsilon_{fj1} \sim N(0, \Sigma_{jd}). \tag{1}$$

The dividends for periods $s = 2, 3....$ are given by $d^*_{fjs} = g_j^{s-1} d^*_{fj1}$.

The assumption of no residual uncertainty after period 1 is only for simplicity. It implies that the value of the stock at the end of period 1 is given by [3]

$$V^*_{fj1} \equiv \sum_{s=1}^{\infty} \frac{d^*_{fjs}}{r^s} = \frac{r}{r - g_j} d^*_{fj1} \ . \tag{2}$$

where r is the riskless rate. Note how g_j enters the factor that determines the earnings-to-valuation ratio. This will be helpful for the interpretation of g_j as growth later on.

Supply The supply of each asset has a (commonly known) asset-specific mean $\overline{x}_{fj}$ as well as an unobserved random component $\tilde{x}_{fj} \sim N(0, \Sigma_{jx})$. Assets within a group have the same mean supply, i.e. $\overline{x}_{fj} = \overline{x}_j$. Formally, the total supply of asset f in group j is $\overline{x}_j + \tilde{x}_{fj}$ shares. Thus, as with the cashflow process, parameters driving asset supply are group-specific.

Preferences and Portfolio Choice Investors, indexed by i, are endowed with an initial wealth $\overline{W}^i$ and mean-variance preferences over their end-of-period wealth.

At the start of period 1, investors make portfolio choices, conditional on an information set

[2] In the Appendix B.3, we show that our results hold under a more complicated, group-level multi-factor structure.

[3] An obvious alternative assumption is that all uncertainty is not resolved at the end of period 1 and investors sell their assets at a market price, which depends, among other things, on the information of future participants, as in Farboodi and Veldkamp (2017). This delivers a similar solution, except that the dependence on future information introduces another fixed point problem, which complicates the analysis considerably, without providing additional insight.

$\mathcal{I}^i$. Formally, investor i with absolute risk aversion ρ_i chooses $\{q_j^i\}$, the number of shares of asset j, to solve:

$$\max_{\{q_{fj}^i\}} \mathbb{E}[U^i|\mathcal{I}^i] = \max_{\{q_{fj}^i\}} \rho_i \mathbb{E}\left[W^i|\mathcal{I}^i\right] - \frac{\rho_i^2}{2} Var(W^i|\mathcal{I}^i) \; . \tag{3}$$

$$\text{where} \qquad W^i = r\overline{W}^i + \sum_j \sum_f q_{dj}^i (V_{fj1}^* - rP_{fj1}^*).$$

r is the riskless rate, P_{fj1}^* is the equilibrium market clearing price of asset f in group j and V_{fj1}^* is the present discounted asset value from (2). At the end of the period, d_{fj1} is observed, investors sell their holdings and consume.

This mean-variance representation is a simple way to a broad array of preference specifications. For example, the coefficient of absolute risk aversion ρ_i is allowed to be any non-random function of initial wealth, $\overline{W}^i$. Thus, these preferences could be derived from decreasing absolute risk aversion preferences, or even constant relative risk aversion, in initial wealth.

Information Our focus is on data used to pick stocks, rather than for timing the overall market. This focus is motivated by our interest in cross-asset differences, which empirically seem to be driven mostly by stock-specific factors. In our sample, more than 90% of the variation in prices is stock-specific. Moreover, time-variation in cross-sectional moments is easier to precisely estimate. [4]

With this goal in mind, we make the simplifying assumption that all investors know the common component of the asset payoffs (i.e. the aggregate factor $\bar{\epsilon}_1$). This assumption, along with the structure of payoffs and preferences, allows us to analyze asset-specific learning without making further assumptions on the distribution of the common component.

For each risky asset f in group j, investor i privately observes k_j^i data points. We call k_j^i investor i's *net private data* about asset j. Each data point is a noisy private signal (with errors

[4]Having said that, one could easily adapt the framework and the empirical strategy to measure data about aggregate factors instead.

that are iid across assets and investors) of the end-of-period asset-specific cashflow ϵ_{fj1}:[5]

$$\eta_{fj}^{i,m} = \epsilon_{fj1} + e_{fj}^{i,m}, \qquad\qquad e_{fj}^{i,m} \sim_{iid} N(0,1) ,$$

for $m \in \{1, \ldots, k_j^i\}$. The average amount of private data about asset j in the market is

$$K_j = \int k_j^i \, di \, . \tag{4}$$

In addition, investors also observe the realized market-clearing price P_{fj1}^* (characterized later) and also optimally incorporate the information contained in that price. Thus, investor i's information set, for asset f in group j, consists of the dividend realization in period 0, a set of private signals, and the market-clearing price: $\mathcal{I}^i = \{\{d_{fj0}^*\}, \{\eta_{fj}^{i,m}\}_{m=1}^{k_j^i}, \{P_{fj1}^*\}\}$. We conjecture (and later verify) that the information in the market price can be expressed as a signal of the cash-flow innovation, ϵ_{fj1} with additive Gaussian noise. Then, Bayes' law for normally distributed random variables yields the following expression for investor i's precision about the cashflow d_{fj1}^* of any assets in group j, denoted $(\Sigma_j^i)^{-1}$:

$$(\Sigma_j^i)^{-1} \equiv Var[\epsilon_{fj1}|\mathcal{I}^i]^{-1} = \Sigma_{jd}^{-1} + (\Sigma_{jp}^i)^{-1} + k_j^i \, , \tag{5}$$

where $(\Sigma_{jp}^i)^{-1}$ is the precision of the market price signal (to be characterized later). This notation allows for the possibility that different investors learn differently from market prices. This could occur, e.g., if it was costly to extract information from prices. The symmetric case, with $(\Sigma_{jp}^i)^{-1} = \Sigma_{jp}^{-1}$ is a natural starting point and is maintained in our characterization of equilibrium below.

The average market-wide precision, denoted $\left(\overline{\Sigma}_j\right)^{-1}$, is

$$\begin{aligned}(\overline{\Sigma}_j)^{-1} &= \int (\Sigma_j^i)^{-1} di = \Sigma_{jd}^{-1} + \int (\Sigma_{jp}^i)^{-1} di + \int k_j^i di \\ &= \Sigma_{jd}^{-1} + \Sigma_{jp}^{-1} + K_j \, . \end{aligned} \tag{6}$$

[5]This language suggests discrete numbers of signals. Since working with discrete variables complicates the analysis considerably and adds little insight, we treat k_j^i as a continuous variable. Formally, we can take a quasi-continuous limit. If each data point has variance α, this limit takes the number of data points to be αk_j^i and then sends $\alpha \to \infty$. In the limit, the precision of the set of signals becomes continuous.

where Σ_{jp}^{-1} and K_j are (market-wide) averages of the precision gained from the price signal and net private data respectively.

Equilibrium A rational expectations equilibrium is a set of functions for prices P_{fj1}^*, and portfolio choices q_{fj}^i such that, (i) given the induced information sets $\mathcal{I}^i$, the portfolio choices solve (3), and (ii) markets clear, i.e. $\forall f, j$, $\int q_{fj}^i di = \overline{x}_j + \tilde{x}_{fj}$.

To solve for the equilibrium, we conjecture a linear form for the price function and solve for the corresponding coefficients. We relegate the details to the Appendix and present the solution in the following result:

Proposition 1. *In equilibrium, the price of asset j is given by:*

$$rP_{fj1}^* = A_{fj} + B_j \epsilon_{fj1} + C_j \tilde{x}_{fj} \ , \tag{7}$$

where

$$A_{fj} = \bar{P}_{fj1} + \left(\frac{r}{r-g_j}\right) g_j d_{fj0}^* - \bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j \ , \tag{8}$$

$$B_j = \frac{r}{r-g_j}\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right) \ , \tag{9}$$

$$C_j = -\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \left(\frac{K_j \Sigma_{jx}}{\bar{\rho}} + 1\right) \ . \tag{10}$$

$$\Sigma_{jp}^{-1} = \left(\frac{B_j}{C_j}\right)^2 \Sigma_{jx}^{-1} \tag{11}$$

$\bar{\rho}^{-1} := \overline{\Sigma}_j \int \rho_i^{-1} (\Sigma_j^i)^{-1} di$ is a precision-weighted average of investors' risk tolerance.[6] The term $\bar{P}_{fj1}$ captures the valuation of the common component of dividends ($\bar{\epsilon}_{fj}$).

Equation (9) shows that the coefficient on current innovations to cash-flows, B_j, is the usual Gordon growth factor, $\frac{r}{r-g_j}$, adjusted by a factor $\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)$. This factor captures the effects of data processing by investors, thus we call it *data*. If investors have no data at all about asset j (apart from their prior), then the average posterior variance $\overline{\Sigma}_j$ is equal to the prior variance Σ_{jd}, and the coefficient $B_j = 0$. In other words, the price cannot possibly reflect information that no investor has learned. At the other extreme, if the average investor is perfectly informed about current cashflows, then $\overline{\Sigma}_j = 0$ and $B_j = \frac{r}{r-g_j}$, the Gordon growth factor. Thus, the

[6] Assuming $\bar{\rho}$ is constant across assets amounts to assuming that risk tolerance and precision are either uncorrelated, or do not covary differently for different assets.

extent to which the stock price covaries with cashflow innovations is informative about how much data related to asset j is processed by the average investor.

Equation (11) characterizes the precision of the price as a signal of future dividends. The linear form of the equilibrium price implies that it is informationally equivalent to $\frac{rP^*_{fj1}-A_{fj}}{B_j} = \epsilon_{fj1} + \frac{C_j}{B_j}\tilde{x}_{fj}$, i.e. a noisy signal of the innovation to cashflows with a precision $\left(\frac{B_j}{C_j}\right)^2 \Sigma^{-1}_{jx}$. The signal is more precise when the sensitivity of the equilibrium price to fundamentals relative to supply noise (B_j/C_j) is high, or the variance of supply Σ_{jx} is low.

Next, we construct a moment, which we term stock-specific price informativeness, or $PINF$, that will guide our empirical strategy in the following section. Formally, we define s-period-ahead stock-specific price informativeness of group-j as:

$$PINF_{js} \equiv \frac{Cov(d^*_{fjs}, P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)}{StdDev(P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)} \tag{12}$$

This moment captures the extent to which the stock-specific components of current prices and cashflows s periods ahead covary with each other. As we will see in the next section, this can be easily estimated with a simple linear regression using data on market capitalization, cashflows and assets.

Our framework implies that $PINF_{js}$ can be expressed as follows:

$$PINF_{js} = \underbrace{\frac{\Sigma_{jd}}{StdDev(P_{fj1})}}_{\text{volatility}} \quad \underbrace{\frac{g^s_j}{r-g_j}}_{\text{growth}} \quad \underbrace{\left[1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right]}_{data}. \tag{13}$$

where $P_{fj1} = rP^*_{fj1} - A_{fj}$ is the component of prices that pertains to the stock-specific innovation, ϵ_{fj1}. Equation (13) forms the core of our analysis. It reveals that $PINF_{js}$ can be decomposed into three parts. We term the first component *volatility*: it is the ratio of the variability of cashflow innovations to that of prices. All else equal, an asset whose prices are more volatile (relative to cashflows) will exhibit a lower degree of informativeness.[7]

The second component is related to *growth*. Intuitively, a faster growing cashflow process implies that prices load on current cashflows to a greater extent. This increases their covariance and contributes to a higher $PINF$. In our structure, growth prospects (or equivalently, the

[7] This insight also appears in Davila and Parlatore (2016b).

cashflow 'multiple') are summarized by the parameter g_j. More generally, the growth component is related to any characteristic that scales up prices, relative to cashflows.

Finally, the last term reflects *data*: the more information the average investor has about cash-flows, the lower is $\overline{\Sigma}_j$ and therefore, the higher is $PINF_{js}$. This link is what makes $PINF$ an informative moment for our purposes. Our empirical strategy involves estimating the growth and volatility components from observables and using them to recover the data component from the observed $PINF$. [8]

2 Estimation of the Structural Model

This section describes how we estimate our structural model to construct our data measure. We describe our sample in detail, as well as construction of variables and moments used for the structural estimation. We also discuss how these estimates relate the the corresponding objects in the model.

2.1 Data Sample and Data Adjustments

All data are for the U.S. market, over the period 1962–2016. Stock prices come from CRSP (Center for Research in Security Prices). All accounting variables are from Compustat. We measure prices at the end of March and accounting variables at the end of the previous fiscal year, typically December. This timing convention ensures that market participants have access to the accounting variables that we use as controls. In line with common practice, we exclude firms in the finance industry (SIC code 6).

The equity valuation measure, i.e. the empirical counterpart for the price P^*_{fj1} in the model, is market capitalization over total assets, denoted $M^*_{f,j,t}/A^*_{f,j,t}$. For our cash-flow variable, d^*_{fjs}, is proxied using earnings over assets. More precisely, we take earnings before interest and taxes (the $EBIT$ variable in Compustat), denoted $E^*_{f,j,t}$ and divide by current total assets $A^*_{f,j,t}$. Both ratios are winsorized at 1%.

[8] Note that this *data* component reflects the effect of both information extracted from the price signal and net private data processing. We will show how we can disentangle these different types of data from observable time series.

We make a couple of adjustments to the raw data. The first is to deal with inflation, which can create predictability in nominal earnings and prices. This is particularly relevant for periods of high inflation, such as the 1960s and 1970s. Therefore, we adjust all cash-flow variables with a GDP deflator. The second pertains to exiting firms. Our preferred solution is to only consider periods during which a firm has non-missing information.[9]

Finally, motivated by our focus on measuring stock-specific data, we remove the common (or aggregate) components from both cashflows and prices. To do this, we first construct the analogous 'market' variables using total assets, market capitalization and $EBIT$ for the universe of S&P 500 firms. Then, separately for each stock in our sample, we project our cashflow and price series for the period 1960-2012 on the corresponding market variables (and a constant) and extract a residual. In what follows, we denote this firm-specific component of prices and cashflows by $\frac{M_{f,j,t}}{A_{f,j,t}}$ and $\frac{E_{f,j,t}}{A_{f,j,t}}$ respectively.

2.2 Variable Construction

Size, Growth and Volatility Sorting, measuring, and mapping these variables to the model is critical for our approach. We start by describing our strategy to sort individual stocks into groups. We choose two particular characteristics to construct our groups: size and growth. This choice is motivated by two considerations. First, as we will show in Section 3, the value of data to an investor is closely tied to the overall size of the asset and the growth prospects. Second, these are canonical asset pricing groups, so using them allows us to make contact with the empirical asset pricing literature that examines how large and growth stocks differ from their small and value counterparts.[10] At the same time, the reader should not be led into thinking that we are pricing risk factors, as would traditionally be done in that literature. Recall that our price and cashflow variables have been stripped of common factors, leaving only firm-specific components. As such, we are looking at whether firms with these size and growth characteristics have different prevalence of data about their *firm-specific* cash flows.

[9] Our results are also robust if we make cash-flows zero when the firm exits or to use a weighted industry cash-flow as a proxy, as in Bai, Philippon, and Savov (2016) (along with the delisting price as the equity valuation variable).

[10] Of course, we could have used other asset-pricing factors (e.g. momentum, beta) to group firms as well, but their link to the value of data about firm-specific factors is less clear.

We group firms into Large and Small, based on whether or not they belong to the 500 largest firms in terms of market capitalization. Next, we classify firms into Growth and Value based on their book-to-market ratio (defined as the difference between total assets and long term debt, divided by the firm's market capitalization). Firms in the top three deciles of book-to-market we call value firms, while those in the bottom three deciles are our growth firms. Combining these two dimensions yields 4 groups: Small Growth, Large Growth, Small Value and Large Value. The number of firms in each of these groups for each decade starting with the 1960s is reported in Table 4 in the appendix.

Connecting Measures to the Model To understand why we give the empirical measures of size and growth the same names as the objects $\bar{x}$ and g in the model, we need to consider why these parameters matter and then ask if these empirical measures capture the relevant concerns.

Size matters because there is more asset value to profit from, with good information. In reality, assets that investors can actively trade large positions on are the equity of high market-capitalization firms. These are more valuable to learn about because if an investors gets very good or bad news, they can make a big trade on that information and earn a big profit. In the model, greater size means more shares. Our empirical notion of a share is \$1 worth of the asset. This is just a normalization. 500 shares worth \$2 each, with variance 4, or one with 1000 shares, worth \$1 each, with variance 1, are isomorphic representations. We then measure everything else – number of shares, prices, dividends, second moments – consistent with this normalization. Thus, the number of shares is simply given by the value (in dollars) of the firm's assets. For consistency, prices and cashflows "per share" are a firm's market cap and EBIT, divided by the value of its assets.

Growth (g) matters for data because it scales the earnings-to-valuation ratio. Firms with high g have prices that are a high multiple of earnings and therefore have prices that are very sensitive to earnings news. Growth is a scaling factor. In the data, market-to-book performs a similar function. It scales up the asset's value for a given level of earnings. In both cases, growth increases the loading of prices on cashflows, through the Gordon growth term $\frac{r}{r-g_j}$. In other words, the same amount of cash-flow data affects growth firms' prices by more.

Estimating $PINF$ The starting point for our approach to measuring data is estimating stock-specific price informativeness as defined in (12) and characterized in (13). Recall that this moment captures the extent to which stock prices in year t reflect cash-flows in year $t+s$ and can be estimated from a regression of the latter on the former, along with controls for other observable asset characteristics. Given our interest in long-term trends, we perform this exercise separately for each of the 4 groups in each decade (starting with the 1960s). Specifically, we run the following cross-sectional regression separately for each asset group j and decade:

$$\frac{E_{f,j,t+s}}{A_{f,j,t}} = \alpha_j + \beta_{j,s} \cdot \frac{M_{f,j,t}}{A_{f,j,t}} + \gamma_j \cdot X_{f,j,t} + \epsilon_{f,j,t+s} \tag{14}$$

where $E_{f,j,t+s}/A_{f,j,t}$ is the cash-flow ($EBIT$) of firm f in group j in year $t+s$, scaled by its total assets in year t; $\log(M_{f,j,t}/A_{f,j,t})$ is market capitalization scaled by total assets; and $X_{f,j,t}$ are a set of firm-level controls, namely past earnings and industry fixed effects, meant to capture publicly available information. We use $s = 3$ in our estimation.

To obtain the measure in (12), we scale the coefficient $\beta_{j,s}$ by the variability of the regressor:[11]

$$PINF_{js} = \beta_{js} \cdot \sigma_j^{M/A} , \tag{15}$$

where $\sigma_j^{M/A}$ denotes the cross-sectional standard deviation of $\frac{M_{f,j,t}}{A_{f,j,t}}$ (conditional on controls). This strategy and the measure $PINF_{js}$ is very closely related to the one in Bai, Philippon, and Savov (2016).[12] From our perspective, it is a convenient starting point for recovering the object we are ultimately interested in, namely the extent of data processed about firm-specific factors.

3 Results

Next, we employ this framework to measure cross-sectional and time series patterns of data in the market. We further separate this information into cross-asset differences in the efficiency with which market aggregates net private data, i.e. investor data above and beyond what could

[11] We use the absolute value of the estimated price informativeness, since the theory cannot reconcile negative estimates (this only matters for a couple of observations and does not affect conclusions about longer term trends).

[12] There are some important differences, both conceptual and measurement-related. See Section 3.2 and Appendix F for more details.

	1960s	1970s	1980s	1990s	2000s	2010s
Persistence g_j:						
Small Growth	0.830	0.877	0.702	0.725	0.740	0.741
Large Growth	0.988	0.981	0.954	0.949	0.917	0.912
Small Value	0.829	0.697	0.538	0.572	0.669	0.636
Large Value	0.901	0.865	0.853	0.813	0.828	0.851
Variance of Innovations Σ_{jd}:						
Small Growth	0.005	0.007	0.019	0.022	0.017	0.013
Large Growth	0.002	0.002	0.002	0.003	0.003	0.003
Small Value	0.002	0.004	0.009	0.008	0.009	0.006
Large Value	0.002	0.001	0.001	0.001	0.002	0.001

Table 1: **Estimated Cash Flow Parameters: Persistence/Growth g_j, Variance of Innovation Σ_{jd}.** Persistence g_j is estimated by running regressions of cashflows on their lagged values, as specified in equation (1). Σ_{jd} is estimated as the variance of residuals from a projection of cashflows on controls.

possibly be extracted from prices.

Extracting Data from $PINF$ Equation (13) shows that we need to remove the effects of volatility and growth from the estimate of informativeness in order to isolate the data component. For this, we need quantitative estimates of these two components for each group and decade. The volatility component is related to the variability of the unpredictable innovation in cash-flows and the (conditional) standard deviation of prices. These are estimated by projecting our cash-flow and price measures on a set of controls and calculating the standard deviation of the residuals (again, separately for each group and decade). The resulting estimates for the variance of the innovation to cashflows (Σ_{jd}) is reported in the bottom panel of Table 1. Dividing this by the (conditional) standard deviation of prices yields the volatility component in (13).

Next, we turn to the estimation of the growth component. Recall that this term arises because growth rates influence the factor by which earnings are scaled in the equilibrium pricing equation (7): in other words, the growth factor $\frac{r}{r-g_j}$converts per-period cashflows to the same units as price. It is closely related to the price-earnings ratio, though the latter will also pick up effects of informational frictions and risk premia.

We estimate growth rates (by group and decade) by running regressions of cashflows on their lagged values. The resulting autoregressive coefficients map directly into g_j and are reported in the top panel of Table 1. As we would expect, growth firms generally have higher growth rates (relative to their counterparts in the corresponding value category). Assuming a riskless interest rate of 2.5% ($r = 1.025$), these estimates directly yield $\frac{g_j^s}{r-g_j}$, the growth component.[13]

3.1 Data Divergence

The estimates of PINF, along with the corresponding growth and volatility components in (13), allow us to back out the information component $1 - \frac{\bar{\Sigma}_j}{\Sigma_{jd}}$, our measure of data. Specifically, for each decade-group, we divide the estimated PINF for that decade-group by the corresponding growth and volatility components, as defined in (13), to back out the implied data term:

$$1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}} = \frac{PINF_{j,s}}{\frac{g_j^s}{r-g_j} \quad \frac{\Sigma_{jd}}{Std(P_{fj1})}} \tag{16}$$

Our decade-by-group estimates for $PINF$ and its components[14] are reported in Table 2. We plot these estimates along with fitted linear trend lines for each series in Figure 1. Critically, the top left panel shows that $PINF$ has trended up for the Large-Growth group, much faster than for all other groups. The top right panel reveals that changes in data played a central role in the divergence.

The remaining panels in Figure 1 show the trends in other components. In particular, the growth component (bottom right panel) highlights why it is important to distinguish between data and a measure like price informativeness.[15] Growth declines most dramatically for large-growth assets. By itself, this trend should have reduced the informativeness of (the stock-specific components of) those assets. Had this change been larger, we might have found $PINF$ and

[13] In our baseline analysis, we use $r = 1.025$ for the entire sample. In Appendix B, specifically in Figure 5, we relax this assumption and show that our results are robust to using decade-specific values for interest rates.

[14] For one decade-group pair, the right hand side of (16) produced an estimate larger than 1, which would be inconsistent with the structural model. We therefore top-coded those estimates using a bound of 0.95. This adjustment made only a negligible difference to the overall trends.

[15] The decline in g_j for large-growth firms is consistent with Gschwandtner (2012), who also finds a long run decline in the persistence of firm profits. This could reflect, for example, an increase in competition because of globalization.

	1960s	1970s	1980s	1990s	2000s	2010s
PINF						
Small Growth	0.012	0.003	0.003	0.008	0.013	0.007
Large Growth	0.015	0.014	0.018	0.011	0.037	0.023
Small Value	0.003	0.007	0.003	0.002	0.011	0.004
Large Value	0.003	0.006	0.002	0.003	0.014	0.001
Volatility						
Small Growth	0.005	0.008	0.012	0.013	0.011	0.010
Large Growth	0.002	0.002	0.003	0.002	0.002	0.003
Small Value	0.016	0.054	0.064	0.044	0.037	0.034
Large Value	0.012	0.017	0.012	0.011	0.013	0.008
Growth						
Small Growth	2.94	4.56	1.07	1.27	1.42	1.44
Large Growth	25.87	21.34	12.33	11.31	7.17	6.69
Small Value	2.91	1.03	0.32	0.41	0.84	0.66
Large Value	5.91	4.06	3.60	2.54	2.88	3.53
Data						
Small Growth	0.84	0.08	0.22	0.50	0.80	0.50
Large Growth	0.36	0.40	0.57	0.44	0.95	0.95
Small Value	0.06	0.12	0.12	0.10	0.36	0.17
Large Value	0.04	0.09	0.04	0.10	0.38	0.03

Table 2: **Stock-Specific Price Informativeness and its Components.** The table reports structurally estimated values of the various terms in equation (13) using cashflow parameters in Table 1. The left hand side is estimated using equations (14) and (15).

data moving in opposite directions. Instead, the rise in data about large-growth firms was sufficiently large that it overwhelmed the effect of declining growth on informativeness.

Market Information vs Net Private Data Next, we explore where data came from. Was the firm specific data information mined from public prices, or was it extracted from other sources? To answer this question, we decompose overall information, $\bar{\Sigma}_j^{-1}$, into its components as in (6). Specifically, the prior or unconditional precision (Σ_{jd}^{-1}), the information content of the price signal (Σ_{jp}^{-1}) and the net private data (K_j). To estimate the second component, namely the information conveyed by the price signal, we run (14) with $s = 0$ and calculate the variance

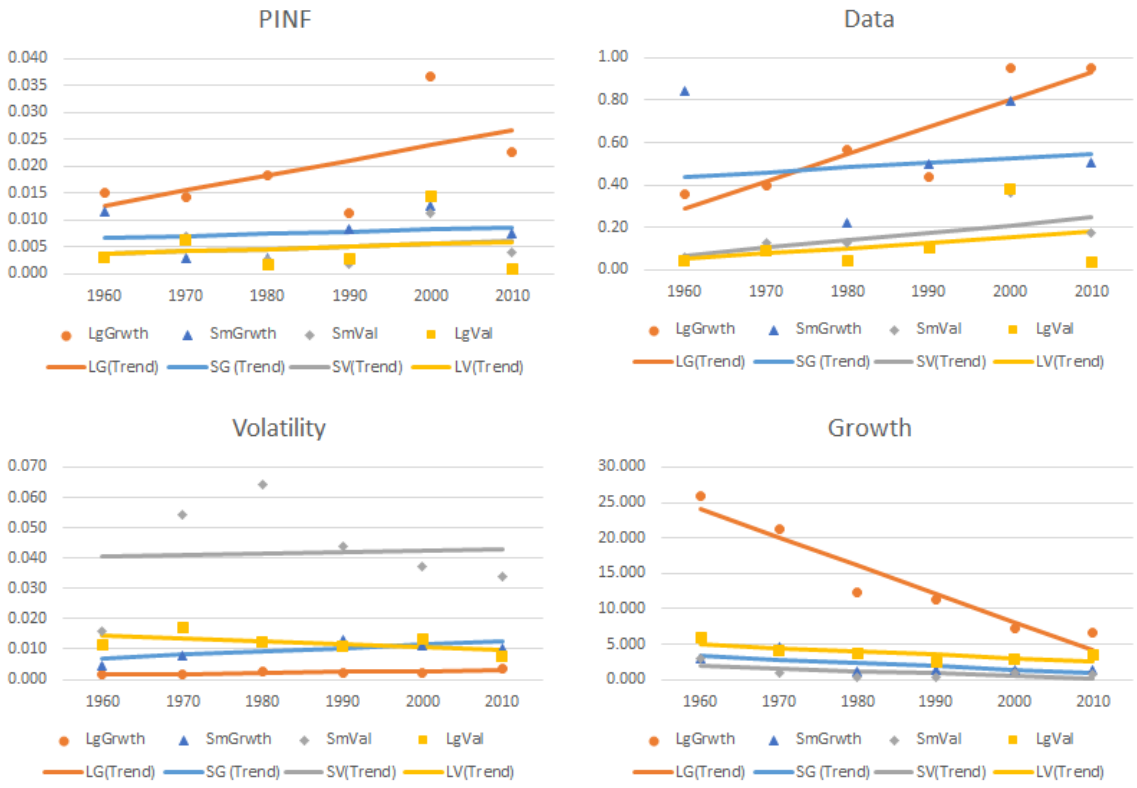


Figure 1: **Data Divergence: Trends in Data and Other Components of Stock-Specific Price Informativeness.** Graphical representation of Table 2. For each component, the dots show the estimates reported in Table 2 while the corresponding lines show the (linear) trend.

of the residuals, denoted by $Var(e_{fj})$. Appendix A.3 derives the following mapping between Σ_{jp} and $Var(e_{fj})$:

$$\Sigma_{jp} = \frac{Var(e_{fj}) \cdot \Sigma_{jd}}{\Sigma_{jd} - Var(e_j)} \,. \tag{17}$$

Substituting the resulting estimates of Σ_{jp}, along with the overall market information $\overline{\Sigma}_j^{-1}$ and the prior precision, Σ_{jd}^{-1}, into (6) yields the net private data for each group-decade, K_j:

$$K_j = \overline{\Sigma}_j^{-1} - \Sigma_{jd}^{-1} - \Sigma_{jp}^{-1} \tag{18}$$

Table 3 presents the estimates for price information Σ_{jp}^{-1} and net private data K_j, by group and decade. Figure 2 plots the associated fitted trend-lines. They show a generally declining trend in firm-specific market information across all groups. The trends in total data, most notably the rise for Large-Growth stocks, can be attributed mostly to changes in net private rather than price information.

Note from Table 3 that the estimates for net private data K_j are negative in some cases, particularly in the early part of the sample for value stocks. This happens when the PINF (or more precisely, the price-earnings covariance) is less than what it would be if all investors were learning the maximum possible from market prices. In other words, this pattern suggests that the average investor may not fully process all the information contained in prices (e.g. because learning from prices is also costly). In such a scenario, our approach to decomposing total data would over-estimate price information Σ_{jp}^{-1}, or equivalently, under-estimate K_j. However, since price information accounts for only a small fraction of total information, this source of mis-measurement is small, relative to the trends in data processing.

Dating the Data Revolution Table 3 also tells us when financial markets started to embrace big data: net private data rose sharply during the 2000's for all groups. Investors in all four types of assets more than quadruple their private precision between the 1990's and 2000's. This is the same time as the widespread adoption of information technology in the financial sector (Abis, 2018) and is consistent with a rapid advance in data technology in the last two decades. But, more interestingly, this rise was the most stark for the large growth firms: in other words,

	1960s	1970s	1980s	1990s	2000s	2010s
Price Information, Σ_{jp}^{-1}:						
Small Growth	10	1	0	1	1	0
Large Growth	80	18	82	41	55	16
Small Value	77	20	3	0	3	0
Large Value	130	105	72	41	8	1
Net Private Information, K_j:						
Small Growth	1013	12	15	45	236	75
Large Growth	269	362	451	193	7151	5868
Small Value	-49	13	14	13	59	33
Large Value	-106	-33	-40	45	258	30

Table 3: **The Sources of Information.** Price information and net private data are estimated using (17) and (18) respectively.

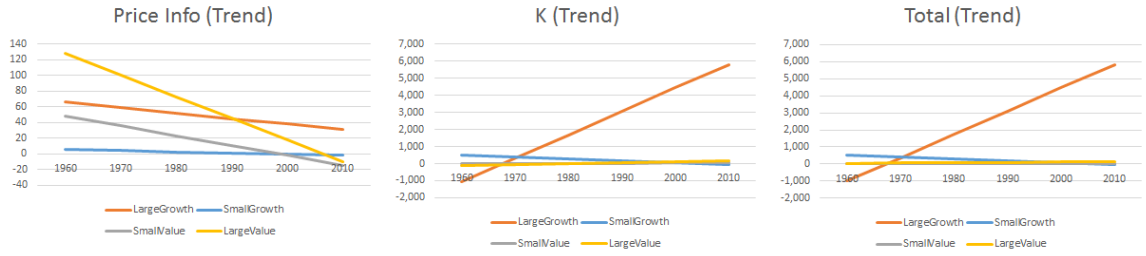


Figure 2: **Rising Large-Growth Firm Data Comes from Net Private Information** Graphical representation of the trends in the estimates reported in Table 3. For each component, the plot shows the linear trend fitted to the estimates from the table. Total is the sum of Price Information (Σ_{jp}^{-1}) and Net Private Information (K). This total is the same as Data, plotted in Figure 1.

the data revolution disproportionately favored learning about large-growth firms, contributing significantly to the trend of data divergence.

Adjusting Data for Market Power We know that market power can effect price informativeness, but how does it affect our measure of data? From Kyle (1989), we know that incorporating market power involves replacing the conditional variance $V[f_t|\mathcal{I}_i]$ with $V[f_t|\mathcal{I}_i] + \lambda/\rho$, where λ is Kyle's lambda, the price impact of a unit of demand and ρ is absolute risk aversion.

What this means for measurement is that, if we are ignoring investor market power, we then are overestimating the conditional variance. Conversely, we are underestimating data precision.

So, our estimates might be considered a lower bound on the size of the data stock. However, the measure of $V[f_t|\mathcal{I}_i] + \lambda/\rho$ is useful, by itself. This sum is the object that appears in the marginal value of data when investors have market power.

3.2 Relating Data to Other Information Measures

There are a number of measures for the information embedded in prices in the literature. In this subsection, we clarify how our *data* measure is different from them.

Price Informativeness $PINF$, which measures stock-specific price informativeness is an input in our measurement strategy and is closely related to the one in Bai, Philippon, and Savov (2016). As we discussed earlier, it is conceptually different from our data measure. PINF measures the extent to which (the stock-specific components of) prices and future cashflows co-vary, which is also affected by growth and volatility effects in addition to data processing. We develop a tool designed to isolate the latter and show that is has diverged over the last few decades.

Our analysis also differs in its focus on firm-specific factors. We remove aggregate/common components from both cashflows and prices while Bai, Philippon, and Savov (2016) work with unadjusted cashflows and so pick up informativeness of prices with respect to both common and stock-specific factors. There are a couple of other measurement differences as well. First, we work with $\frac{MktVal}{Assets}$ in levels, rather than logs, to be consistent with our structural model. Furthermore, the price informativeness measure in Bai, Philippon, and Savov (2016) is obtained by scaling the regression coefficient of the current price by the *unconditional* standard deviation of prices, while our structural framework suggests scaling by the standard deviation of prices *conditional* on the controls. These adjustments tighten the connection to the structural model and affect magnitudes but, as we will show below, do not significantly change the overall trends.

Figure 3 plots the trend in the price informativeness measure of Bai, Philippon, and Savov (2016), estimated decade-by-decade for 4 sub-samples of firms: Large-Growth, Large-Value, Small-Growth and Small-Value. It shows that informativeness has increased for the Large-Growth group, but declined for the others. While Bai, Philippon, and Savov (2016) also noted the divergence between firms in and out of the S&P 500, we show that this is a size effect, not

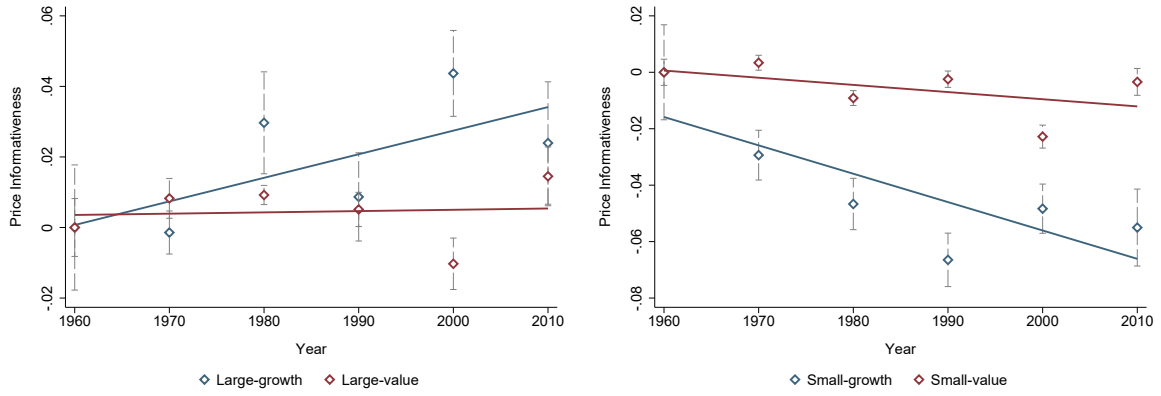


Figure 3: **Price Informativeness by Firm Size and Growth.** The diamonds show the estimated price informativeness defined as in Bai, Philippon, and Savov (2016), along with 95% confidence intervals. For the detailed specification, see equation (36) in Appendix F. Large firms are the 500 largest by market capitalization and small denotes the rest. Firms in the bottom (top) 30% are labeled growth (value) firms. The lines are fitted trend lines.

an index inclusion effect. [16]

Comovement, R^2, and Synchronicity Many papers have applied comovement, synchronicity or R^2 approaches to measuring stock market informativeness across countries (Durnev, Morck, and Yeung, 2004; Edmans, Jayaraman, and Schneemeier, 2016). These measures are valuable tools for cross-country analysis of price movements, but are not appropriate for measuring the precision of data, about one type of firm versus another. For example, asset comovement (R^2) could be high because of aggregate information is precise, causing many assets to move with that aggregate information, or because stock-specific information is imprecise. Any mapping to data precision requires decomposing aggregate and stock-specific data, which in turn, requires an independent measure of one or the other. Our approach explicitly constructs that measure and uses the structure of the model to back out data processing.

Furthermore, an R^2 measure shares many of the same interpretation problems of the price informativeness measure. To see why, note from the pricing equation (7), if the aggregate cash flow shock $\bar{\epsilon}$ is observed, the R^2 is the explained sum of squares $B^2var(\bar{\epsilon})$, divided by the total sum of squares, $B^2var(\bar{\epsilon})+C^2var(\epsilon)+D^2var(\tilde{x})$. Just like PINF, these quantities depend on the

[16] Appendix F.1 shows that the informativeness of stocks currently in the S&P 500 is similar to non-S&P 500 stocks with similar characteristics. Furthermore, price informativeness trends consistently over size deciles. These results suggests that differences in asset characteristics, rather than inclusion in S&P 500 *per se*, is the source of the divergence.

coefficients, like B and C, which are affected by the amount of data, but also are contaminated by volatility and scaling terms like growth. For example, Brogaard, Nguyen, Putnins, and Wu (2018) argue that stock return comovement, as measured by R^2, has increased significantly over time, because idiosyncratic price noise declined.

Absolute Price Informativeness Davila and Parlatore (2016a) propose an alternative measure of "absolute price informativeness," which captures the ability of asset prices to aggregate dispersed information. Their measure is the precision of an unbiased signal of the current cashflow innovation, constructed from prices. In our setting, this corresponds to Σ_{jp}^{-1}, what we call "price information" in Table 3 and Figure 2.

As Figure 2 shows, absolute price informativeness declines across all four asset groups. Thus, despite *more* net private data processed by investors about stock-specific characteristics (higher K_j) prices actually became *less* accurate as signals (the Davila-Parlatore notion of price informativeness). This difference arises because the noise component of prices (from the $C_j\tilde{x}_j$) grew over time and overwhelmed the rising covariance with fundamentals.

This finding differs from Davila and Parlatore (2016a) primarily because we strip out the aggregate component of prices and cash flows, while they do not. If we re-do their exercise with raw prices and earnings, price information does show a rising trend. These results suggest that prices may be getting better at aggregating market information, but are becoming less clear signals about firm-specific cashflow risk.

Other Proxies for Data Many papers explore proxies for information, including news counts, analyst coverage, advertising or social media text (see examples cited below). Of course, these proxies are useful for qualitative validation and do not obviate the need for a quantitative measure like ours. Moreover, while these document interesting cross-sectional patterns, to the best of our knowledge, none of them focus on how these patterns have changed over time, especially over the horizons we are interested in.

Coverage by equity analysts on Wall Street is a natural proxy for information processing. Hong, Lim, and Stein (2000) and Guo and Mota (2020) analyze determinants of coverage, but do not discuss time trends. In Appendix E, we estimate time trends in analyst coverage (using

the I/B/E/S database of analyst forecasts) and show that there was a sharp increase in the relative coverage of growth firms during the 2000s and 2010s. This is particularly striking for large firms and the timing of this increase lines up quite well with the results of our structural approach.

Of course, it is worth noting that analyst coverage is likely a rather crude measure of data precision. For one, it doesn't capture variation in quality of data processing, both in the cross-section and over time. An analyst might be reporting mostly redundant or low-quality information that does little to reduce investor uncertainty (in fact, to the extent it disagrees with other analysts' forecasts, it might even seed uncertainty). Moreover, analyst coverage also does not capture data processing done in-house by investors (e.g. hedge funds), which has arguably displaced work traditionally done by sell-side analysts over time. So while this evidence is reassuring and suggestive, it hardly displaces the need for a data precision measure, nor does it reveal the source of the divergent data trends.

Firms also use advertising to convey information to outsiders. Chemmanur and Yan (2019) examine the effect of such advertising on stock prices and find that the effects are smallest for large-growth firms. Our model suggests that new information, such as that contained in an ad, is likely to have small effects when the existing information is already of high quality. In other words, one explanation for findings in Chemmanur and Yan (2019) is that data on large growth firms is relatively abundant, consistent with our results. Note that similar to the literature on analyst coverage, this paper also focuses on the cross-section and not changes over time. Nevertheless, the fact that the cross-sectional evidence is broadly consistent with our story is a re-assuring finding.

4 Why Did Large Growth Firm Data Become More Abundant?

Our results show that, while asset characteristics did change over this period, divergence in the price informativeness for Large-Growth firms came predominantly from data divergence. This raises an obvious question: why did so many investors process increasing amounts of data

about large growth stocks and not about other assets?

One possibility is that data choices changed over time because the cost of data changed. For this to explain our findings, the cost of large growth firm data must be falling, relative to the cost of data about other firms. Given that we have no direct evidence to support or quantify this channel, we focus on the relative benefit of data on large growth firms. Here, our structural framework can help us talk about how observed changes in asset characteristics should change the value of data and through that, data choices. This is the approach we take: we abstract from differences in costs, use the estimates from the structural model to see whether the model-implied benefit of data has changed in a manner consistent with observed patterns in data choices across groups. This does not rule out – and in fact, is complementary to – the possibility of changes in relative costs.

One might be tempted to look at equilibrium *marginal* values for this purpose. However, they are not very useful in predicting the *amount* of data allocated to different assets. This is because equilibrium forces push to equate marginal values across assets. In other words, in equilibrium, agents will process different amounts of data for different assets up to a point where the marginal value of additional data processing is the same. We are interested in explaining how much data is processed about a particular asset – the equilibrium marginal value cannot tell us that. The same logic that Berk and Green (2004) applied to mutual fund flows also applies to data flows: Equilibrium forces should equalize marginal returns.

If equilibrium marginal value does not reliably explain the amount of data processing, what does? One candidate is *the initial value of data*, defined as the value of the first increment of precision, i.e. the marginal utility gain from a unit of data in a hypothetical world where no one else processed any data on that asset. The basic idea is that assets with the highest initial value will see the most amount of data processed (even if all assets have the same marginal value in equilibrium)[17] If the assets for which data processing is high also have high initial values of information, this could explain the data divergence we see in the previous section.

[17]This concept is related to what is sometimes referred to as a water-filling equilibrium in the information choice literature. In equilibrium, agents sequentially choose risk factors to learn about: learning about a risk is like filling its 'bucket' with water. Once sufficiently full, investors move on to filling the next deepest bucket. Our value of information can be thought of the depth of each bucket, before being filled with water. At the optimum, all buckets will be filled to the same level (equal marginal value), but the deepest buckets will have consumed the most amount of water.

We use the model to estimate the initial value of one unit of processed data (one precision unit) about each asset type, in each decade. We find that the value of learning about large firms rose substantially over this period, both in absolute terms as well as relative to small firms. The divergence in data value was driven by the increase in large firms' relative size. This surge in the relative size of large firms is the same divergence in firm size documented by Davis and Haltiwanger (2015). The source of this divergence is the subject of an active debate in the macroeconomics and IO literatures.

4.1 Derivation of Initial Value of Information

To arrive at the value of information, we compute the *ax-ante* expected utility and determine its sensitivity to information choice. *Ex-ante* expected utility of investor i from assets in group j is given by

$$\mathbb{E}[U_j^i] = \frac{1}{2}\mathbb{E}\left[(\Pi_j^i)^2\right]\left(\frac{r}{r-g_j}\right)^{-2} \quad (\Sigma_j^i)^{-1} \qquad \text{where} \qquad \Pi_j^i \equiv \mathbb{E}[V_j - P_j r|\mathcal{I}^i]. \tag{19}$$

(Π_j^i) is the interim (i.e. conditional on a data set $\mathcal{I}^i$) expected profit per share of asset j, and $(\Sigma_j^i)^{-1}$ is investor i's posterior precision about cashflows. This form of expected utility arises in a large class of noisy rational expectations models. Intuitively, investor i's interim profits are $q_j^i\Pi_j^i$. The optimal asset demand q_j^i is proportional to $Var[V|\mathcal{I}_i]^{-1}\Pi_j^i$ where $Var[V|\mathcal{I}_i]^{-1} = \left(\frac{r}{r-g_j}\right)^{-2}(\Sigma_j^i)^{-1}$.

Equation (19) directly shows that the marginal utility of a unit increase in the investor's posterior precision is $\frac{1}{2}\mathbb{E}\left[(\Pi_j^i)^2\right]\left(\frac{r}{r-g_j}\right)^{-2}$. This is the marginal value of data. Data is more valuable when profits are expected to be high (in absolute value)[18] and/or more volatile because that makes the expected value of the squared profit high.

Next, we compute the unconditional expected profit per share. [19]

$$\mathbb{E}\left[\Pi_j^i\right] = \bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j \ . \tag{20}$$

[18] High negative expected profits are also valuable, because they present profitable shorting opportunities. The 1/2 in eq. (19) comes from subtracting a variance term in the formula for the mean of a log-normal variable.

[19] Note $\mathbb{E}\left[(\Pi_j^i)^2\right] = (\mathbb{E}\left[\Pi_j^i\right])^2 + Var(\Pi_j)$. See Appendix C for the derivation of $Var[\Pi_j^i]$ and other details.

Thus, the expected profit per share is the product of the total amount of asset j risk borne by the average investor, scaled by aggregate risk aversion $\bar{\rho}$. Faster growth, or equivalently, a higher valuation-to-cash-flow ratio (higher $\frac{r}{r-g_j}$) means greater uncertainty about the discounted values of the entire cash-flow stream, for a given level of uncertainty about current cash-flows ($\overline{\Sigma}_j$). Similarly, larger supply (higher $\bar{x}_j$) implies more risk exposure for the average investor's portfolio and therefore, a larger compensation in the form of expected profits. In other words, it is more valuable to learn about large, fast-growing firms with greater uncertainty.

To compute the *initial* value of data, we simply replace the equilibrium information level $\overline{\Sigma}_j$ with its value before any data is processed, the prior variance Σ_{jd} in (19). Then, compute the partial derivative with respect to $(\Sigma_j^i)^{-1}$. This is what we call the *initial value of information* (VI_j):

$$VI_j = \frac{1}{2}\left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^2 \Sigma_{jd}^2 \bar{x}_j^2\right] + \frac{1}{2}\Sigma_{jd} \tag{21}$$

The first term in (21) is related to the mean of the expected profit per share of asset j from (20). As we saw earlier, higher growth (g_j), larger size ($\bar{x}_j$) and more uncertainty (Σ_{jd}) all raise VI_j, making information about the asset's cash-flows more valuable. Moreover, these factors enter multiplicatively and therefore, amplify each other. This interaction makes Large-Growth firms valuable for many investors to learn about.

The second term in (21) stems from the variance of expected profits per share. Quantitatively, however, this term is dominated by the first term, because $\frac{r}{r-g_j}$ and $\bar{x}_j$ are both large, relative to other terms. In other words, most of the variation in the value of the information, both in the cross-section and over time, comes from changes in the size and scale of profitable trading opportunities.

4.2 Estimation of Initial Value of Information

We construct a time series for the value of information (VI_j), for each of the four asset groups by decade. Computing VI_j requires parameters already estimated in Section 2, as well as risk aversion $\bar{\rho}$ and the asset supply ($\bar{x}_j$). To estimate total supply, we first calculate the average (book) value of assets of firms in group j by decade. We then project firm-level assets on

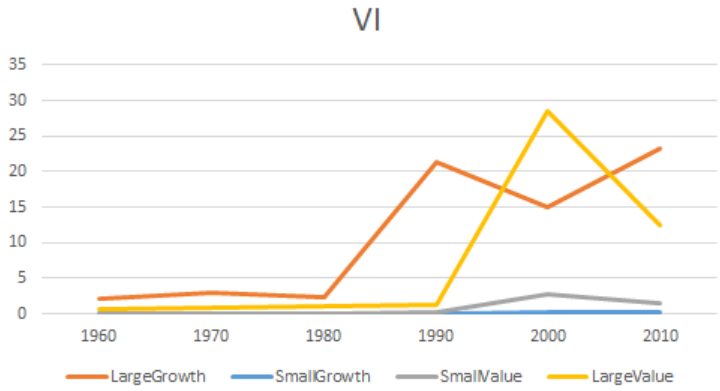


Figure 4: **The Initial Value of Information, by Asset Class, over Time.** The initial value of information VI_j is defined in (21). g_j and Σ_{jd} estimates are reported in Table 1, while $\bar{x}_j$ estimates are reported in Table 4. $r = 1.025$ and $\bar{\rho} = 0.02$.

total assets of the S&P 500 and estimate the fraction of the variance that is unexplained by the regressor (i.e. 1-R^2). The value of assets associated with stock-specific component is then obtained by multiplying this factor (the average value for each group) and the average book value of assets (also by group, reported in Table 4 in the appendix). Finally, we assume the risk aversion coefficient is $\bar{\rho} = 0.02$.

The resulting estimates in Figure 4 offer a simple explanation for why so much data has been processed for large firms, especially large growth firms. Information about such firms is more valuable. Both size and growth increase the value of information, which is also amplified by their interaction. The combination of being large and growing quickly makes a firm a desirable target for data analysis. In the figure, the value of information for small growth and small value stocks is very close to zero, orders of magnitude lower than the value of the large firms' data.

The time series for VI_j in Figure 4 shows a dramatic rise in the value of large firms' information during the 1990s and 2000s. These patterns are driven almost entirely by movements in the first term in (21). Why did this component rise so sharply and then fall? The increase can be traced to the rise in their size ($\bar{x}_j$): in other words, large firms grew larger (both in absolute and relative terms) during the 1990s and 2000s, raising expected profits per share and making data about them more valuable.

The value of large value firms' information surpasses that of large growth firms for one decade in our sample. This was likely the combined result of a decrease in the growth prospects

of large growth firms and a rise in the relative size of large value firms. One possibility is that these changes in firms' characteristics was unexpected. If data processing can be frictionlessly reallocated, one would expect a quick reaction to the surprise change in growth and size. But, in reality, research expertise takes time to build: time to hire personnel, and time for them to develop the necessary knowledge. As a result, it is quite likely that, much like physical capital, information processing is slow to adjust. A full exploration of this possibility is a question for another paper.

5 Conclusions

Financial services are increasingly centered around data processing. Making optimal data choices and valuing data requires knowing the precision of other market participants' forecasting data. We develop a tool to measure this data precision. Our tool can be applied in many possible ways to various groupings of assets.

Since our framework tells us that size and growth make data valuable, we use our tool to measure data for firms sorted by size and growth. We find data divergence: Investors seem to be processing more and more data about large growth assets, but not about others.

To explore why data processing might diverge, we use the estimated structural model to impute a value of data. We find that the value of large growth firm data has increased, primarily because these firms grew larger. Larger firms are more valuable to learn about, particularly if they are also expected to grow faster. While our tool has uncovered a new fact and suggested a logical explanation for it, there will surely be many reasons to want to measure data along other dimensions, as we continue to learn more about the financial data economy.

References

Abis, S. (2018): "Man vs. Machine," Columbia University working paper.

Admati, A. (1985): "A noisy rational expectations equilibrium for multi-asset securities markets," *Econometrica*, 53(3), 629–57.

Andries, M., and V. Haddad (2017): "Information Aversion," NBER Working Paper.

Bai, J., T. Philippon, and A. Savov (2016): "Have Financial Markets Become More Informative?," *Journal of Financial Economics*, 122 (35), 625–654.

Ben-Rephael, A., B. Carlin, Z. Da, and R. Israelsen (2019): "Information consumption and asset pricing," Discussion paper.

Berk, J., and R. C. Green (2004): "Mutual fund flows and performance in rational markets," *Journal of Political Economy*, 112, 1269–1295.

Bond, P., A. Edmans, and I. Goldstein (2012): "The Real Effects of Financial Markets," *Annual Review of Financial Economics*, 4, 339–360.

Bond, P., and H. Eraslan (2010): "Information-based trade," *Journal of Economic Theory*, 145(5), 1675–1703.

Brogaard, J., H. Nguyen, T. Putnins, and E. Wu (2018): "What Moves Stock Prices? The Role of News, Noise and Information," Working Paper, University of Washington.

Chemmanur, T. J., and A. Yan (2019): "Advertising, attention, and stock returns," *Quarterly Journal of Finance*, 9(03), 1950009.

Chordia, T., C. Green, and B. Kottimukkalur (2016): "Rent Seeking by Low Latency Traders: Evidence from Trading on Macroeconomic Announcements," Working Paper, Emory University.

Crouzet, N., I. Dew-Becker, and C. Nathanson (2016): "A Model of Multi-Frequency Trade," Northwestern University Working Paper.

David, J., H. Hopenhayn, and V. Venkateswaran (2016): "Information frictions, Misallocation and Aggregate Productivity," *Quarterly Journal of Economics*, 131 (2), 943–1005.

Davila, E., and C. Parlatore (2016a): "Identifying Price Informativeness," NYU Working Paper.

——— (2016b): "Volatility and Informativeness," NYU Working Paper.

Davis, S. J., and J. Haltiwanger (2015): "Dynamism Diminished: The Role of Credit Conditions," *in progress.*

Dessaint, O., T. Foucault, L. Fresard, and A. Matray (2018): "Ripple Effects of Noise on Corporate Investment," Working Paper, Princeton University.

Dow, J., I. Goldstein, and A. Guembel (2017): "Incentives for Information Production in Markets where Prices Affect Real Investment," *Journal of the European Economic Association*, 15(4), 877–909.

Dugast, J., and T. Foucault (2016): "Data Abundance and Asset Price Informativeness," Working Paper, HEC.

Durnev, A., R. Morck, and B. Yeung (2004): "Value-enhancing capital budgeting and firm-specific stock return variation," *The Journal of Finance*, 59(1), 65–105.

Edmans, A., S. Jayaraman, and J. Schneemeier (2016): "The source of information in prices and investment-price sensitivity," *Journal of Financial Economics*, Forthcoming.

Fama, E. F., and K. French (1995): "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Finance*, 50(1), 131–155.

Farboodi, M., and L. Veldkamp (2017): "Long Run Growth of Financial Technology," Discussion paper, National Bureau of Economic Research.

Glode, V., R. Green, and R. Lowery (2012): "Financial Expertise as an Arms Race," *Journal of Finance*, 67(5), 1723–1759.

Goldstein, I., E. Ozdenoren, and K. Yuan (2013): "Trading frenzies and their impact on real investment," *Journal of Financial Economics*, 109(2), 566–82.

Gschwandtner, A. (2012): "Evolution of Profit Persistence in the USA: Evidence from Three Periods," *The Manchester School*, 80 (2), 172–209.

Guo, Y., and L. Mota (2020): "Should Information be Sold Separately? Evidence from MiFID II," *Journal of Financial Economics*, forthcoming.

Hong, H., and M. Kacperczyk (2010): "Competition and bias," *The Quarterly Journal of Economics*, 125(4), 1683–1725.

Hong, H., T. Lim, and J. C. Stein (2000): "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies," *The Journal of Finance*, 55(1), 265–295.

Kacperczyk, M., J. Nosal, and L. Stevens (2015): "Investor Sophistication and Capital Income Inequality," Imperial College Working Paper.

Kacperczyk, M., J. Nosal, and S. Sundaresan (2018): "Market Power and Informational Efficiency," Working Paper, Imperial College London.

Katz, M., H. Lustig, and L. Nielsen (2017): "Are Stocks Real Assets? Sticky Discount Rates in Stock Markets," *The Review of Financial Studies*, 30(2), 539–587.

Kelly, B., and A. Ljungqvist (2012): "Testing asymmetric-information asset pricing models," *The Review of Financial Studies*, 25(5), 1366–1413.

Kyle, A., and J. Lee (2017): "Toward a Fully Continuous Exchange," SSRN Working Paper.

Kyle, A. S. (1989): "Informed Speculation with Imperfect Competition," *Review of Economic Studies*, 56(3), 317–355.

Maćkowiak, B., and M. Wiederholt (2009): "Optimal sticky prices under rational inattention," *American Economic Review*, 99 (3), 769–803.

Martineau, C. (2017): "The Evolution of Market Price Efficiency around Earnings News," Working Paper University of Toronto.

Mondria, J., T. Wu, and Y. Zhang (2010): "The determinants of international investment and attention allocation: Using internet search query data," *Journal of International Economics*, 82 (1), 85–95.

Ozdenoren, E., and K. Yuan (2008): "Feedback Effects and Asset Prices," *The Journal of Finance*, 63(4), 1939–1975.

Pástor, L., and R. F. Stambaugh (2012): "On the size of the active management industry," *Journal of Political Economy*, 120, 740–781.

Ranco, G., D. Aleksovski, G. Caldarelli, M. Grcar, and I. Mozetic (2015): "The Effects of Twitter Sentiment on Stock Price Returns," PLOS working paper.

Sims, C. (2003): "Implications of rational inattention," *Journal of Monetary Economics*, 50(3), 665–90.

Stambaugh, R. (2014): "Presidential Address: Investment Noise and Trends," *Journal of Finance*, 69 (4), 1415–1453.

Van Nieuwerburgh, S., and L. Veldkamp (2009): "Information immobility and the home bias puzzle," *Journal of Finance*, 64 (3), 1187–1215.

Appendices

A Structural Framework: Derivations

A.1 Proof of Proposition 1

Solving for the equilibrium follows a standard guess-and-verify procedure, widely used in the noisy rational expectations equilibrium (REE) literature. First, we express total demand for each asset j, as a function of price (P_{j1}), and equate it with total supply ($\bar{x} + \tilde{x}_j$). Then, we match coefficients on both sides of this market clearing condition to obtain a system of equations in A_j, B_j, C_j. Specifically, all constant terms are equated to A_j; terms that multiply ϵ_{j1} get equated to B_j and finally, those multiplying $\tilde{x}_j$ must equal C_j. Simplifying that system of equations yields the stated result.

A.2 Decomposing Price Informativeness: Derivation of Equation (13)

$$PINF_{j,s} = \frac{Cov(d^*_{fjs}\ ,\ P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)}{StdDev(P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)} = g^s_j \frac{Cov(d^*_{fj1}\ ,\ P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)}{StdDev(P^*_{fj1}|d^*_{fj0}, \bar{\epsilon}_1)} \tag{22}$$

$$= g^s_j \frac{Cov(\epsilon_{fj1}\ , P_{fj1})}{StdDev(P_{fj1})} = \frac{g^s_j}{r} \frac{B_j \Sigma_{jd}}{StdDev(P_{fj1})} \tag{23}$$

$$= \frac{\Sigma_{jd}}{StdDev(P_{fj1})} \quad \frac{g^s_j}{r - g_j} \quad \left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right) \tag{24}$$

where the last line uses the expression for B_j from (9).

A.3 Estimating Σ_{jp}: Derivation of Equation (17)

The stock-specific components of cash-flows and prices, i.e. the residuals after conditioning on $(d^*_{fj0}, \bar{\epsilon}_1)$, are given by:

$$d_{fj1} = \epsilon_{fj1} \tag{25}$$

$$P_{fj1} = \tilde{A}_j + \frac{B_j}{r}\epsilon_{fj1} + \frac{C_j}{r}\tilde{x}_{fj}\ , \tag{26}$$

where $\tilde{A}_j = -\bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j$. The coefficients from regressing d_{fj1} on P_{fj1} and a constant are:

$$\hat{\beta}_j = \frac{Cov(\epsilon_{fj1}, P_{fj1})}{Var(P_{fj1})} = \frac{rB_j\Sigma_{jd}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}} ,$$
$$\alpha_j = \mathbb{E}(\epsilon_{fj1}) - \hat{\beta}_j \mathbb{E}\left(\tilde{A}_j + (B_j/r)\epsilon_{fj1} + (C_j/r)\tilde{x}_j\right) = -\hat{\beta}_j \tilde{A}_j ,$$

where we use $\mathbb{E}[\epsilon_{fj}] = \mathbb{E}[\tilde{x}_{fj}] = 0$. The estimated residuals and their variance are:

$$\begin{aligned} e_{fj} &= \epsilon_{fj1} - \alpha_j - \hat{\beta}_j\left(\tilde{A}_{fj} + \frac{B_j}{r}\epsilon_{fj1} + \frac{C_j}{r}\tilde{x}_{fj}\right) \\ &= \left(1 - \hat{\beta}_j\frac{B_j}{r}\right)\epsilon_{fj1} - \hat{\beta}_j\frac{C_j}{r}\tilde{x}_{fj} , \\ &= \left(1 - \frac{B_j\Sigma_{jd}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}}B_j\right)\epsilon_{fj1} - \left(\frac{B_j\Sigma_{jd}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}}\right)C_j\tilde{x}_{fj} , \\ &= \left(\frac{C_j^2\Sigma_{jx}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}}\right)\epsilon_{fj1} - \left(\frac{B_j^2\Sigma_{jd}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}}\right)\frac{C_j}{B_j}\tilde{x}_{fj} , \\ &= \left(\frac{\frac{C_j^2}{B_j^2}\Sigma_{jx}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)\epsilon_{fj1} - \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)\frac{C_j}{B_j}\tilde{x}_{fj} , \\ \Rightarrow \quad Var(e_{fj}) &= \left(\frac{\frac{C_j^2}{B_j^2}\Sigma_{jx}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)^2\Sigma_{jd} + \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)^2\frac{C_j^2}{B_j^2}\Sigma_{jx} . \end{aligned} \tag{27}$$

Noting that $\Sigma_{jp} = \frac{C_j^2}{B_j^2}\Sigma_{jx}$, we can write (27) more succinctly as

$$Var(e_{fj}) = \left(\frac{\Sigma_{jp}}{\Sigma_{jd} + \Sigma_{jp}}\right)^2\Sigma_{jd} + \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \Sigma_{jp}}\right)^2\Sigma_{jp} = \frac{\Sigma_{jp}\Sigma_{jd}}{\Sigma_{jd} + \Sigma_{jp}} . \tag{28}$$

Solving (28) for Σ_{jp} yields the expression in (17).

B Structural Estimation: Details and Additional Results

B.1 Sample Size

Table 4 lists the number of firms and average value of assets for the firms in our sample, separately for each decade and each asset group.

	1960s	1970s	1980s	1990s	2000s	2010s
Number of firms						
Small Growth	1,699	4,739	7,224	9,253	6,444	3,505
Large Growth	1,696	4,229	6,270	7,963	5,662	3,327
Small Value	1,734	4,664	7,229	9,153	6,382	3,472
Large Value	1,653	4,040	6,146	7,742	5,534	3,272
Average assets ($ millions)						
Small Growth	125	173	109	175	410	599
Large Growth	2,697	3,510	3,521	8,661	12,928	13,802
Small Value	517	565	852	2,140	4,478	5,398
Large Value	6,129	11,592	15,726	22,003	52,550	61,588

Table 4: **Number of Firms and Total Assets by Decade and Type**

B.2 Time-varying Interest and Growth Rates

In our baseline estimation, we assumed a constant $r = 1.025$ over time. In this subsection, we show that this is not a critical assumption. In particular, we compute the actual average real interest rate for each decade (defined as the difference between 1-year nominal Treasury yield from the Federal Reserve Board's H15 release and realized inflation over the subsequent year, computed using the PCE Price Index) and use that series to re-estimate the growth and information components of price informativeness (note that the volatility component remains unaffected). Figure 5 plots the estimated trends for all three components and looks very similar to the baseline results in Figure 1.

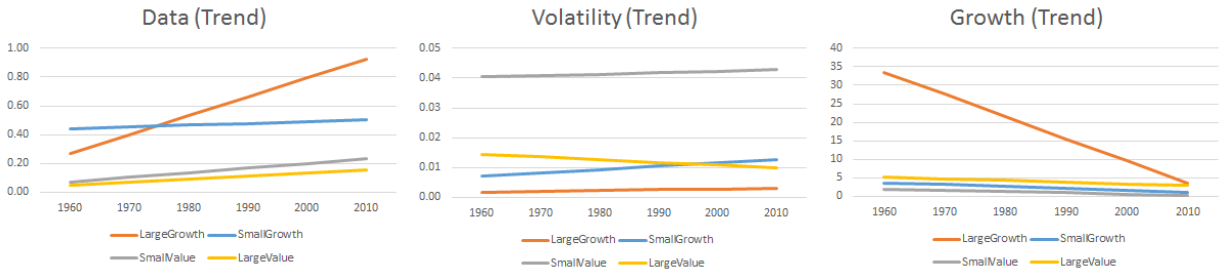


Figure 5: **Time-Variation in Riskless Rate.** The plots show a linear trend fitted to the structural estimates of the components of PINF as described in (13) and decade-specific interest rates. For details of how the interest rates r are estimated, see text.

B.3 Alternative Specification for Common Component

In this section, we show that our results about the trends in data processing hold under an alternative assumption about the common component in firm cashflows. Recall that in the baseline analysis, we imposed a single factor structure on the common component. Now, we allow for multiple aggregate factors with group-specific weights. Specifically, the correlated component is now given by

$$\bar{\epsilon}_{fj1} = \sum_{h=1}^{H} \tilde{\beta}_{jh} \bar{\epsilon}_{h1} \ ,$$

where H is the number of aggregate factors and $\tilde{\beta}_{jh}$ are the group-specific loadings.

Under these conditions, we can strip out the correlated components by taking out a group-year fixed effect from the observed cashflow and price variables. The rest of the estimation procedure to estimate PINF and its components remains unchanged. The results from this version are shown in Figure 6. Comparing it to our baseline results, reveals that the overall pattern of divergence emerges even under this alternative approach, indicating that our conclusions are not sensitive to how we adjust for common components.

C Marginal Value of Information

C.1 Derivations

Interim expected utility, i.e. after chosen information and prices are observed, is

$$\mathbb{E}[U_j^i|\mathcal{I}^i] = \frac{1}{2} \ \frac{(\mathbb{E}[V_{j1} - rP_{j1}|\mathcal{I}^i])^2}{Var[V_{j1} - rP_{j1}|\mathcal{I}^i]} = \frac{1}{2} \ \frac{(\Pi_j^i)^2}{\left(\frac{r}{r-g_j}\right)^2} (\Sigma_j^i)^{-1} \tag{29}$$

Note that, from an ex-ante perspective, Π_j^i is a random variable, since it is a function of the data observed by i. In our Gaussian setting, the posterior variance, Σ_j^i, depends only on second moments

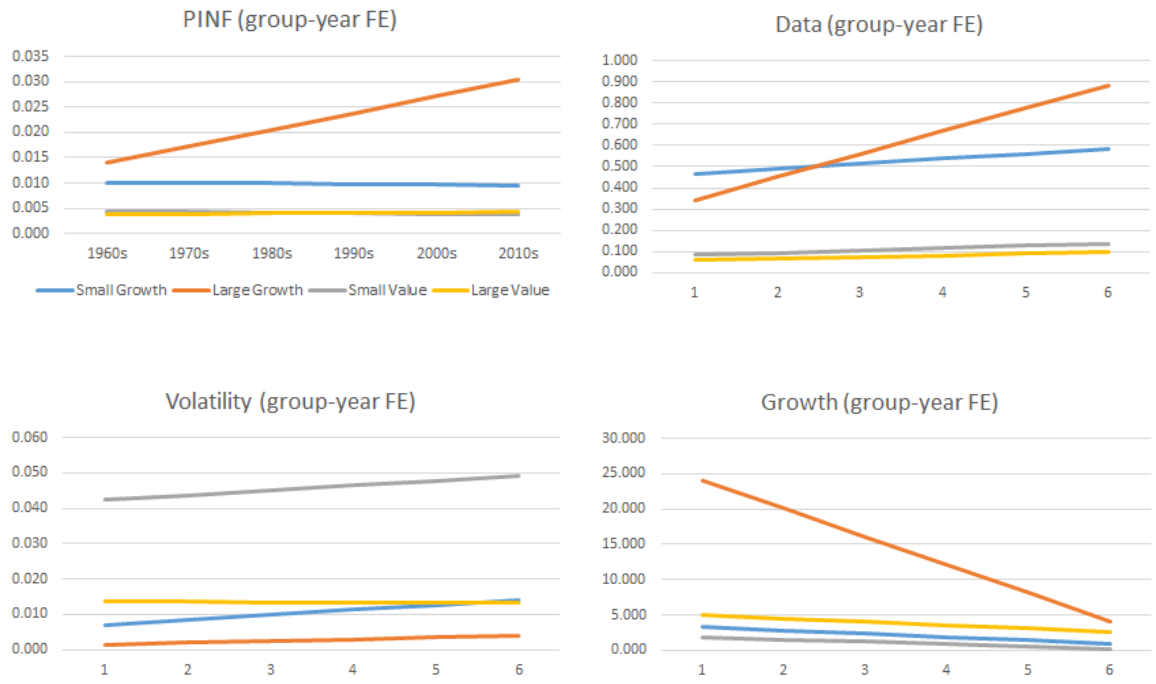


Figure 6: **Data Divergence: Using group-year fixed effects.** Structural estimation of equation(13) after residualizing cashflows and prices using a group-year fixed effect. For each component, the lines plot a linear trend fitted to our structural estimates.

(which are known *ex-ante*, i.e. before data is observed). *Ex-ante* expected utility therefore becomes:

$$\mathbb{E}[U_j^i] = \mathbb{E}[\mathbb{E}[U_j^i|\mathcal{I}^i]] = \frac{1}{2}\frac{\mathbb{E}\left[(\Pi_j^i)^2\right]}{\left(\frac{r}{r-g_j}\right)^2} \quad (\Sigma_j^i)^{-1} \tag{30}$$

$$= \frac{1}{2}\left[\frac{(\mathbb{E}\left[\Pi_j^i\right])^2 + Var(\Pi_j^i)}{\left(\frac{r}{r-g_j}\right)^2}\right] \quad (\Sigma_j^i)^{-1}\ , \tag{31}$$

The unconditional mean and variance of expected profit per share can be computed directly from the equilibrium price function:

$$\mathbb{E}\left[\Pi_j^i\right] = \bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j\ . \tag{32}$$

$$Var(\Pi_j^i) = B_j^2\Sigma_{jp} + \left(\frac{r}{r-g_j} - B_j\right)^2(\Sigma_{jd} - \Sigma_j^i) - 2\left(\frac{r}{r-g_j} - B_j\right)B_j\Sigma_j^i \tag{33}$$

The variance of expected profit depends, among other things, on the equilibrium pricing coefficient B_j and the noise in the price signal Σ_{jp}. Higher sensitivity to dividends or more noise leads to more *ex-ante* variability in expected profits. Substituting the mean and variance of the expected profit per share into (31), we get:

$$\begin{aligned}
\mathbb{E}[U_j^i] &= \left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^4\overline{\Sigma}_j^2\bar{x}_j^2\right]\frac{(\Sigma_j^i)^{-1}}{2\left(\frac{r}{r-g_j}\right)^2} \\
&+ \left[B_j^2\Sigma_{jp} + \left(\frac{r}{r-g_j} - B_j\right)^2(\Sigma_{jd} - \Sigma_j^i) - 2\left(\frac{r}{r-g_j} - B_j\right)B_j\hat{\Sigma}_j^i\right]\frac{(\Sigma_j^i)^{-1}}{2\left(\frac{r}{r-g_j}\right)^2} \\
&= \left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^2\overline{\Sigma}_j^2\bar{x}_j^2 + \left(\frac{B_j}{\frac{r}{r-g_j}}\right)^2\Sigma_{jp} + \left(1 - \frac{B_j}{\frac{r}{r-g_j}}\right)^2\Sigma_{jd}\right]\frac{(\Sigma_j^i)^{-1}}{2} + H_j \\
&= \left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^2\overline{\Sigma}_j^2\bar{x}_j^2 + \left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2\Sigma_{jp} + \left(\frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2\Sigma_{jd}\right]\frac{(\Sigma_j^i)^{-1}}{2} + H_j \\
&= M_j \cdot (\Sigma_j^i)^{-1} + H_j
\end{aligned}$$

where

$$M_j = \frac{1}{2}\left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^2\overline{\Sigma}_j^2\bar{x}_j^2\right] + \frac{1}{2}\left[\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2\Sigma_{jp} + \left(\frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2\Sigma_{jd}\right] \tag{34}$$

is the marginal value of information for asset j and the precision of the price signal and H_j is an

equilibrium constant that does not depend on i's information.

Note that M_j is a function, among other things, of the amount of data processed by the average investor (through $\overline{\Sigma}_j^2$ and Σ_{jp} terms). The value of information in (21) in the main text removes these effects by setting $\overline{\Sigma}_j^2 = \Sigma_{jd}$. The implications for Σ_{jp} comes from the pricing coefficients – see (11). If no data is processed by others, then no information can be revealed in prices, so $B_j = 0$ and $\Sigma_{jp} = \infty$. At the same time, the term $\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2$ becomes zero. Using L'Hospital's rule, we can show that the latter dominates and therefore, the product becomes zero in the no-information limit. Combining, the value of information M_j reduces to the expression for VI_j in (21).

D Evolution of Firm Size

Figure 7 show that S&P 500 firms got larger, relative to non-S&P 500 firms. Here, we use market capitalization as our measure, but the pattern looks similar with assets as well. As we showed in Section 4 in the main text, size is a key determinant of the value of information, so this diverging trend in size helps explain the diverging trends in data.

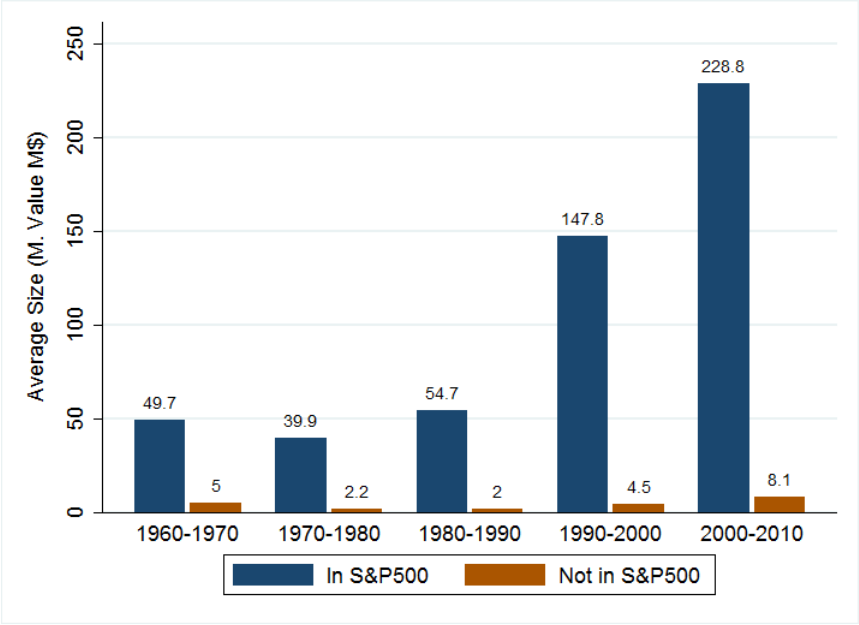


Figure 7: **S&P 500 Firms Became Larger relative to Non-S&P 500 Firms.** The graph shows the average size of S&P 500 and non-S&P 500 firms over time. Size is defined as firm's total market value in 2009 dollars. The sample contains publicly listed non-financial firms from 1960 to 2010.

E Evidence from Analyst Coverage

In this section, we present some evidence suggestive of increased data processing with respect to growth firms. We use the I/B/E/S database to estimate time trends in analyst coverage for different sub-samples of firms. Formally, we regress the number of analysts at the firm-year level on a growth dummy, interacted with dummies for five-year windows. We estimate this regression (allowing for year fixed effects) separately for large firms and for small firms. The coefficient on the growth dummy thus represents the relative coverage of growth firms. The results, presented in Figure 8 below, show a sharp increase in the relative coverage of growth firms. This is particularly striking for large firms and the timing of this increase lines up quite well with the results of our structural approach.

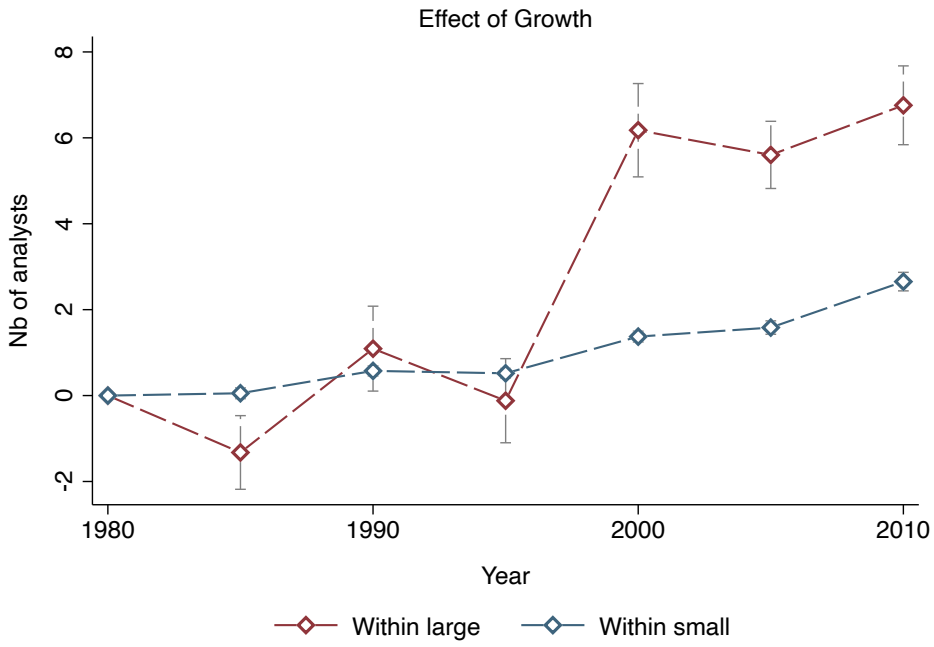


Figure 8: **Analyst Coverage Has Increased for Growth Firms.** The graph reports coefficients β_t from the following regression: $\textit{Number of Analysts}_{it} = \beta_t \textit{Growth}_i \times \textit{Half-decade}_t + \delta_t + e_{it}$, where $\textit{Growth}_i$ is a dummy equal to one if the firm is a growth firm and $\textit{Half-decade}_t$ is a dummy for each five year interval starting from 1985. We estimate the regression separately for large firms (the red line) and small firms (the blue line).

Of course, it is worth noting that analyst coverage is likely a rather crude measure of data precision. For one, the number of analysts doesn't capture variation in quality of data processing, both in the cross-section and over time. An analyst might be reporting mostly redundant or low-quality information that does little to reduce investor uncertainty (in fact, to the extent it disagrees with other analysts' forecasts, it might even seed uncertainty). Finally, analyst coverage also does not capture data processing done

in-house by investors (e.g. hedge funds), which has arguably become more important over time. So while this evidence is reassuring and suggestive, it is not a substitute for a structural data precision measure.

F Price Informativeness: Additional Empirical Results

This appendix performs a number of exercises to show the evolution of price informativeness, defined as in Bai, Philippon, and Savov (2016). It is worth keeping in mind that these reduced-form patterns are hard to interpret because they confound changes in information with variation in other characteristics, precisely why a structural approach is necessary. Having said that, these are still instructive and helps us connect our findings to various papers studying price informativeness.

Formally, we follow Bai, Philippon, and Savov (2016) and estimate the following specification: [20]

$$\frac{E^*_{f,j,t+s}}{A^*_{f,j,t}} = \alpha_j + \beta_{j,s} \cdot \ln\left(\frac{M^*_{f,j,t}}{A^*_{f,j,t}}\right) + \gamma_j \cdot X_{f,j,t} + \epsilon_{f,j,t+s} \tag{35}$$

and define price informativeness as

$$PINF^*_{j,s} = \beta_{j,s}\sigma_j^{M^*/A^*} \ , \tag{36}$$

where $\sigma_j^{M^*/A^*}$ denotes the (unconditional) standard deviation of $\ln\left(\frac{M^*_{f,j,t}}{A^*_{f,j,t}}\right)$. Finally, since we are interested in longer term trends, we fit the following trendline (separately for each j):

$$PINF^*_{j,s,t} = \overline{PINF^*}_{j,s}\left(1 + Trend_{j,s} \cdot \frac{t - 1962}{2010 - 1962}\right) + e_{j,s,t} \tag{37}$$

The coefficient of interest is $\overline{PINF^*}_{j,s} \cdot Trend_{j,s}$, which describes how price informativeness changes over the period 1962-2010.

Price Informativeness for Largest (Smallest) Firms Has Been Rising (Falling). In order to explore the connection between firm size and informativeness, we estimate $PINF^*_{j,s}$ and its trend for two sub-samples: 'largest' and 'small' firms, where 'largest' comprises the 500 largest firms, by market cap, and small the rest.

[20] Throughout this appendix, we work with *unadjusted* prices and cashflows, i.e. without taking out common components, in order to maintain comparability to Bai, Philippon, and Savov (2016) and the rest of the literature.

Dep. Var	Price Informativeness					
Sample (j)	S&P 500		Large Firms		Small Firms	
Horizon	s=3	s=5	s=3	s=5	s=3	s=5
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{PINF^*}_{j,s} \cdot Trend_{j,s}$	.016***	.027***	.0035	.019***	-.052***	-.057***
	(.006)	(.006)	(.004)	(.0065)	(.0038)	(.0061)
$\overline{PINF^*}_{j,s}$	.033***	.038***	.041***	.048***	.043***	.054***
	(.0023)	(.0036)	(.0023)	(.0038)	(.0018)	(.0029)
Observations	17,650	16,114	19,193	17,680	61,034	49,238
Sector FE	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 5: **Price Informativeness: The Role of Firm Size.** Results from estimating (37) for different sub-samples of firms. Large firms are the 500 largest firms based on market capitalization. Small firms are the rest. Newey-West standard errors with four lags are in parentheses. *** denotes significance at the 1% level.

Table 5 reports the results for S&P 500 firms (columns 1-2), largest firms (columns 3-4) and small firms (column 5-6). The increase in price informativeness is very similar for S&P 500 firms and the set of largest firms, both for 3-year (columns 1 and 3) and 5-year horizons (columns 2 and 4). By contrast, the price informativeness of small firms, which started from roughly the same levels as that of largest firms in 1962, fell sharply over this time period. These patterns are robust to alternative criterion for size: we also split the sample into deciles of size, and find that moving from the lowest decile to the highest decile of size implies a 17-fold increase in price informativeness (c.f. Appendix F.3).

Next, we explore the relationship between growth and price informativeness. We classify firms based on their current book-to-market ratio, following Fama and French (1995). Specifically, firms in the bottom 30% by book-to-market are labeled 'growth' firms and the top 30% 'value' firms. We then run our price informativeness regressions (35) separately for these two groups.

Columns (1) and (2) of Table 6 reveal that price informativeness declines for both growth and value firms. However, when we split each category between large and small, we find that large growth firms show a significant increase (positive coefficient in column 4) while the small growth group displays the sharpest decline (column 3). In other words, growth firms drive both the rise in price informativeness for large firms and the declining trend for smaller firms. The informativeness for value firms, both large and small, shows more modest declines. The rate of change in small value firms' (column 5) price

informativeness is half that of small growth firms (column 3). The divergence is summarized in Figure 9, which plots the linear trends in price informativeness for large vs. small firms (left panel) and for large-growth vs. large-value firms (right panel). Both panels exhibit divergence. Recall from Figure 3 that small firms, both growth and value, show a declining trend.

Dep. Var	Price Informativeness ($s = 5$)					
Sample (j)	Growth	Value	Growth–Small	Growth–Large	Value–Small	Value–Large
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{PINF^*}_{j,s} \cdot Trend_{j,s}$	-.035***	-.02***	-.058***	.04***	-.024***	-.01*
	(.0083)	(.0039)	(.011)	(.01)	(.0044)	(.0052)
$\overline{PINF^*}_{j,s}$	.052***	.014***	.054***	.053***	.017***	.005*
	(.0052)	(.0024)	(.007)	(.0067)	(.0027)	(.0029)
Observations	31,988	28,066	23,110	8,814	24,823	3,167
Sector FE	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Table 6: **Price Informativeness Trends: The Role of Firm Growth.** This table presents results from estimating (37) for different sub-samples of firms. Large refers to the 500 largest firms in our data – the rest are labeled Small. Growth firms are those in the bottom 30% of the distribution of book-to-market; value firms are in the top 30%. Newey–West standard errors, with four lags are in parentheses. *** denotes significance at the 1% level.

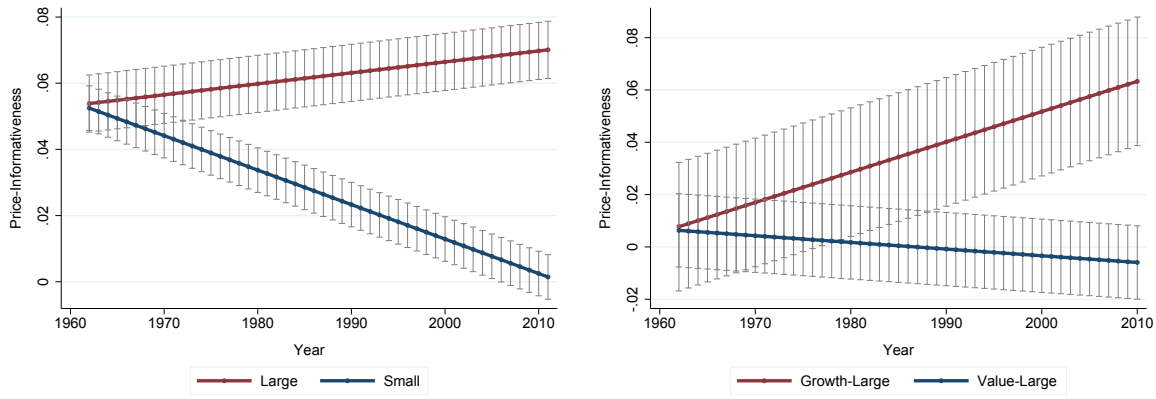
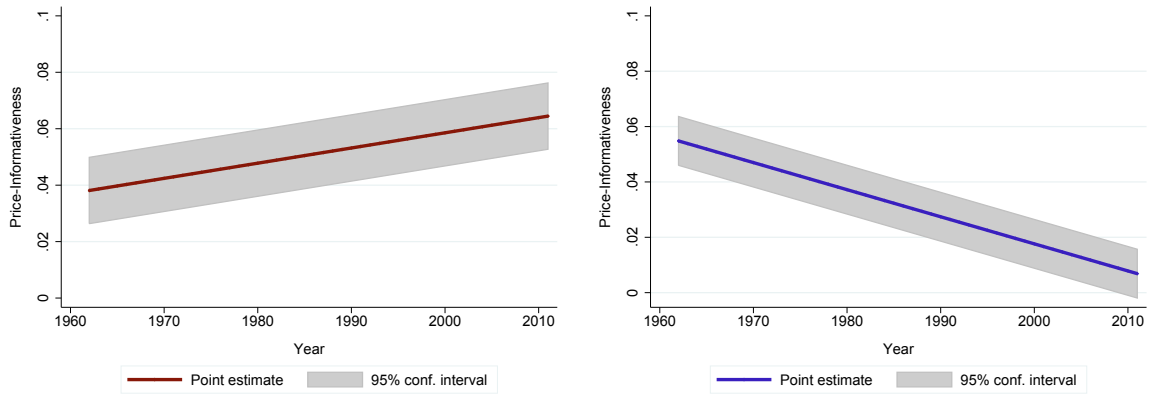


Figure 9: **Large and Small Firms' Price Informativeness Diverges.** The plots show the trends in price informativeness for horizon $s = 5$, estimated using (37), along with 95% confidence interval based on Newey-West standard errors with four year lags. Large refers to the 500 largest firms in our data – the rest are labeled Small. Growth firms are those in the bottom 30% of the distribution of book-to-market; value firms are in the top 30%.



S&P 500 Whole Sample

Figure 10: **Price Informativeness is Falling (Rising) for all Public Firms (S&P 500 Firms).** The plots show the trends in price informativeness, estimated using (37), along with 95% confidence interval based on Newey-West standard errors with 5–lags. The left panel depicts S&P 500 nonfinancial firms, while the right shows results for the whole sample.

F.1 Price Informativeness in the S&P 500

Price Informativeness for all Public Firms (S&P 500 Firms) Has Been Falling (Rising). The two panels of Figure 10 plot the fitted values from (37) for the subsample of firms in the S&P 500 (left) and the universe of listed firms (right). The figures show that although informativeness rose for the S&P 500 firms, it fell for the market as a whole.

Table 7 quantifies the magnitude of the divergent trends for S&P 500 and non-S&P 500 firms and shows that they are both statistically significant and economically large. $\overline{PINF^*}_{j,s}$ reports the magnitude of the predictive power of stock prices for future cashflows at the beginning of our sample period. Because we normalize the time trend between zero and one, the coefficient on $\overline{PINF^*}_{j,s} \cdot Trend_{j,s}$ can be directly interpreted as the total evolution of price informativeness over the period. For the S&P 500 sample, price informativeness at the 5–year horizon rose by 70% (0.026/0.038). For the non–S&P 500 firms, it fell by around 80%. In all cases, the evolution is significant at the 1% level.

To explore whether there is something specific to firms in the S&P 500, we perform two different tests. First, we looked at firms that have never been included in the S&P 500 but are relatively close in terms of market capitalization and size. It turns out these firms exhibit a rise in price informativeness nearly identical to that of the S&P 500 firms (though the levels of price informativeness are somewhat different). This suggests that the rising trend in price informativeness has more to do with firm characteristics (like size) rather than inclusion in the S&P 500 *per se* (though being part of the index does increase the *level* of informativeness somewhat).

Dep. Var	Price Informativeness			
Sample (j)	S&P 500		Non S&P 500	
Horizon	s=3	s=5	s=3	s=5
	(1)	(2)	(3)	(4)
$\overline{PINF^*}_{j,s} \cdot Trend_{j,s}$	.016***	.026***	-.047***	-.048***
	(.0037)	(.006)	(.0027)	(.0045)
$\overline{PINF^*}_{j,s}$	.033***	.038***	.046***	.056***
	(.0023)	(.0036)	(.0018)	(.0028)
Observations	17,662	16,120	105,580	86,550
Sector FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓

Table 7: **Price Informativeness Grew (Fell) for S&P 500 (other) Firms.** This table shows the estimates of (37) for different subsamples of firms. Newey–West standard errors, with four lags are in parentheses. *** denotes significance at the 1% level.

We also looked at firms that were in the S&P 500 only for a part of our sample period. We estimate two separate specifications of Equation (35) – one for the period of the firm life when it is in the S&P 500 and for when it is not. We find that, among the sample of firms that are in the S&P 500 at some point in their life, the trend in price informativeness is similar for firms currently in and out of the S&P 500. In levels, price informativeness is actually higher when a firm is not in the S&P 500, than when they are in.

F.2 Other Possible Data Groupings

One potential concern with our analysis is that growth and size are not the characteristics that are driving these trends, but are correlated with other, more relevant firm characteristics. In this subsection, we discuss a couple of other groupings of firms that might help dig into this further.

Technology Firms. A potential explanation for the decrease in informativeness for the market as a whole is that the share of firms, whose shares are harder to price – specifically high tech firms – has increased over time. Could the increased prevalence of technology firms also explain divergence? However, we find that quantitatively, the rise of such firms explains little of the divergence in price informativeness, because the technology-related time trends in the large firm and small firm samples were not sufficiently different.

We use R&D intensity (R&D spending scaled by assets) as a proxy for high tech intensity. First, we sort the full sample of firm-year observations into deciles of R&D intensity. We then estimate price informativeness for each decile, using the same method as before. We find that price informativeness declines strongly with R&D intensity, as we conjectured.

Next, we analyze changes in R&D composition in the cross-section. We use inclusion in the S&P 500 as our indicator of being a large firm. In both the S&P 500 and the non-S&P 500 sample, the fraction of firms investing more in R&D has increased steadily. The share of high-tech firms has grown slightly more rapidly in the full sample than in the S&P 500 sample. Until the early 80's, the high-tech shares for S&P 500 and non-S&P 500 firms track each other closely. There is some signs of divergence in the mid-80's, when the share of high-tech firms increases more in the whole sample, essentially driven by a rapid entry rate of tech firms. But then, in the early 2000's, the share of tech firms in the S&P 500 increases and converges to that of the non-S&P 500 sample. Thus, there isn't a clear trend in the tech composition of the different sub-samples. We therefore conclude that prevalence of tech firms, while it may explain the average decline in informativeness, cannot explain the cross-sectional divergence.

Note also that our structural approach explicitly adjusts the effect of differences in fundamentals, e.g. a more volatile or faster growing cash-flow. So to the extent that technology firms are different for these reasons, our analysis in that section adjusts for technology intensity, and finds divergence.

Market Power. Recent work suggests that market power is rising in the US economy over the last few decades. In Kacperczyk, Nosal, and Sundaresan (2018), market power considerations reduces price informativeness: large investors with price impact trade less aggressively on their information, leading to lower price informativeness. This could be a potential explanation for the overall decline in price informativeness. This would imply that price informativeness we estimate is a lower bound (as is our structural measure of data). But, for this to explain why only large, growth firms have much more informative prices than they used to, w would have to argue that the market for those stocks has become much more competitive over time. To the best of our knowledge, there is no evidence which suggests enormous increases in competition in some equity markets and the evaporation of competition in others.

F.3 Price Informativeness by Size

In this subsection, we show that price informativeness varies systematically by size. Specifically, we pool all firm-year observations and construct deciles of firm size (defined as market value in 2009 dollars). We then run the cross-sectional regression (35) within each bin, i.e. the subscript j now refers to a size bin and estimate $PINF^*_{j,s}$. The results, presented in Figure 11, show

a clear pattern: the informativeness of large firms is significantly higher than those of smaller firms, especially for those at the very top.

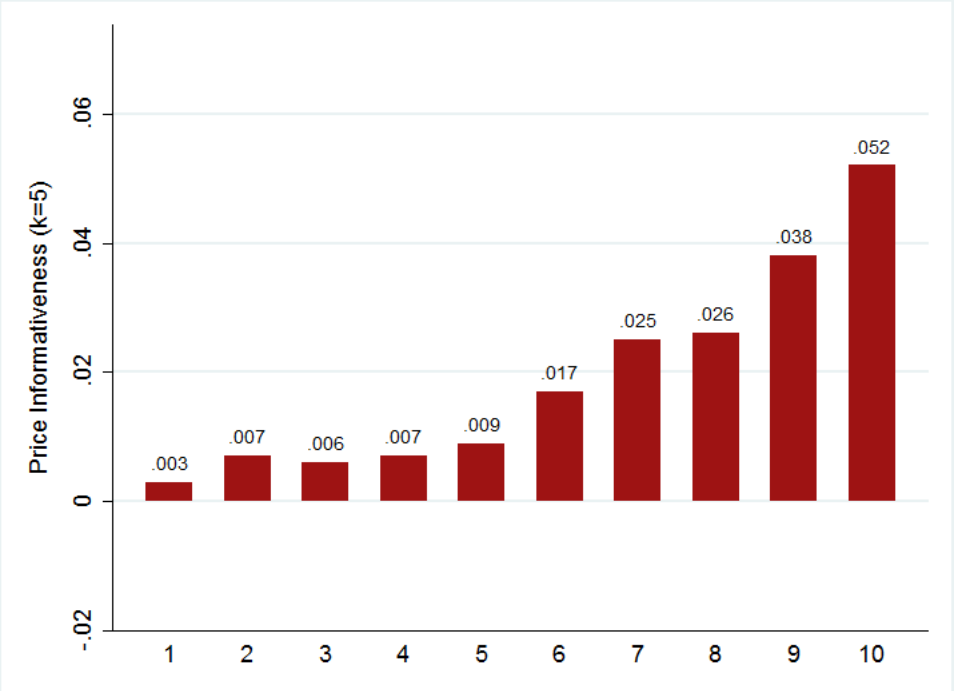


Figure 11: **Price Informativeness by Decile**. The figure shows the average $PINF^{*}_{j,s,t}$, defined as in (36), over the entire sample for each size decile. We run the regression in (35) for each year $t = 1962, ..., 2010$ with horizon $s = 5$ for each size decile. The sample contains publicly listed non-financial firms from 1962 to 2010.