Where Has All the Data Gone?

Maryam Farboodi*　　Adrien Matray†

Laura Veldkamp‡　　Venky Venkateswaran§

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Abstract

As financial technology improves and data becomes more abundant, do market prices reflect this growing information and allocate capital more efficiently? While a number of recent studies have documented rises in aggregate price efficiency, we show that there are large cross-sectional differences. The previously-documented increases are driven by a rise in the informativeness of large, growth stocks. The informational efficiency of smaller assets' prices or prices of assets with less growth potential are either flat or declining. We document these new facts and use a structural model to decompose changes in price informativeness into the effects of changes in information and in growth or volatility characteristics of the assets. Finally, by computing the initial value of data implied by our structural model, we show that these findings could be explained partly by the fact that large firms have grown relatively larger. Since growth magnifies the effect of changes in size, processing data about large-growth firms has becoming more and more valuable, relative to other firms.

*MIT Sloan and NBER; farboodi@princeton.edu

†Princeton University; amatray@princeton.edu

‡Columbia Business School, NBER, and CEPR; lv2405@columbia.edu

§NYU Stern School of Business, NBER; vvenkate@stern.nyu.edu

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As financial technology improves and data becomes more abundant, do market prices reflect this growing information and allocate capital more efficiently? While a number of recent studies have documented rises in aggregate price efficiency, it turns out that there are large cross-sectional differences. The previously-documented increases in aggregate efficiency (Bai, Philippon, and Savov, 2016) are driven by a rise in the informativeness of large, growth stocks. The informational price efficiency of smaller assets or assets with less growth potential is flat or declining. We document these new facts and use structural estimation to decompose informational efficiency into parts due to information changes and effects due to changing growth or volatility characteristics of the assets. Finally, by computing the expected marginal value of data implied by our structural model, we learn that these findings could be explained by the fact that large growth firms' data is becoming relatively more valuable: As large firms grow larger, and growth magnifies the effect of their change in size, the marginal value of processing large growth firm data is becoming more and more valuable, compared to the value of other firms' data. In short, 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.

We begin by measuring price informativeness in a traditional way: Estimate the coefficient on prices in a regression of future asset payoffs on a constant, prices and asset characteristics. This coefficient reveals how useful prices are in forecasting future firm outcomes. Our main empirical finding is price informativeness divergence. The rise in price informativeness found in Bai, Philippon, and Savov (2016) is there. Their sample is S&P 500 firms. Those are large firms. For small firms, and for the entire sample, price informativeness declines. The large-firm increase in price informativeness does not come from all large firms. It is concentrated in a subset, the large growth firms.

These facts have multiple interpretations. One interpretation is that data analysis is being concentrated on large growth firms. Another interpretation is that perhaps the characteristics of large growth firms have changed over time, in a way that affects the price informativeness measure. Both turn out to be true and the forces may well be related. Since changes in asset characteristics can also change the incentives to produce information, it is important to impose some structure on the problem.

To decompose information and asset characteristics, we use a structural approach. We derive an expression for price informativeness that holds with minimal theoretical assumptions. Price information is comprised of terms that depend on information, cashflow growth and volatility. By measuring price informativeness, cash flow growth and volatility in the data, we can back out a measure of market information about the firm. We find that information about most firms has stagnated for the last 50 years. There is only one category of information that has become more abundant: information about large, growth firms. While firm growth and volatility have changed over time, these changes work against the trend – alone, they would reduce price informativeness. Thus, the measurement exercise teaches us that the rise in price informativeness observed for large growth firms is likely to be a result of more information or in other words, more data processing.

Size shows up in our analysis in two ways. First, when we split the data in to small and large firms, we find they have different growth and volatility, which affect the informativeness measure directly. Second, size affects the value of information about the firm. This offers a potential explanation for the empirical informativeness trend: Data went to the largest firms because investors can use that data to take large positions in those assets. Large growth firms grew most. Therefore, when data processing capacity increased, most of the new data processed was about the large growth firms. Other firms' equity prices did not benefit from the information processing revolution.

Related literature Our contribution, relative to the literature is two-fold: 1) We explore cross-sectional differences in a traditional measure of price informativeness (Bai, Philippon, and Savov, 2016); and 2) we propose a new structural method for uncovering the amount of data being processed about each class of assets in a given period.

Our methodology is most related to Davila and Parlatore (2016a), who propose an alternative measure of price informativeness, but one designed to answer a different question. Their measure captures the ability of prices to aggregate information. They compute the ability of asset payoffs to back-cast prices, asset-by-asset, but without examining time trends. Our question is about how the allocation of financial data processing has changed over time. Identifying how data processing changed is more difficult, because it requires separating forces that change the information content of prices from information itself. Our simple structural model of equilibrium asset prices suggests that noise, size and the growth potential of a firm all interact to drive a wedge between data and all the previously-used price informativeness measures. We document these wedges and find they are substantial. Large firms have more informative prices than small ones. Growth firms' prices are more informative than value firms' and the interaction effects are large and significant. Importantly, these cross-asset differences are growing. Finally, our structural approach also has the advantage that it uncovers changes in the marginal value of data. This help us to understand the reasons for why large, growth firms' data evolves so differently.

Trends in the aggregate information environment are also explored in work by Stambaugh (2014) and Glode, Green, and Lowery (2012). 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 data. But our focus is on why these trends differ across asset classes and what part of that change is information versus asset characteristics.

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). Davila and Parlatore (2016a) share our focus on price information, but do not examine its time trend or cross-sectional differences. 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. Our model extends Farboodi and Veldkamp (2017) by adding multiple, heterogeneous assets. What we add to this literature is using the theory for structural estimation. The structure allows us to distinguish changes in information from changes in asset characteristics.

Examinations of the effects of improved data processing are scarce. Empirical work primarily examines whether particular data sources, such as social media text, predict asset price movements (Ranco, Aleksovski, Caldarelli, Grcar, and Mozetic, 2015). In contrast, many papers have developed approaches to measuring stock market informativeness across countries (Edmans, Jayaraman, and Schneemeier, 2016), or (Durnev, Morck, and Yeung, 2004). These measures are valuable tools for cross-country analysis, but are not consistent with our theoretical framework and are not appropriate for comparing the informativeness of large and small firms. For example, Brogaard, Nguyen, Putnins, and Wu (2018) argue that stock return comovement, as measured by R^2, has increased significantly over time, suggesting less information. But, they conclude that much of this is from the decline of idiosyncratic noise in prices, not less information. Martineau (2017) shows that information (earnings news) is incorporated more quickly into prices, in recent times. That could reflect more information, or some of the many regulatory changes dictating what gets announced, to whom and when. For our purposes, these measures are problematic because there are mechanical reasons why the R^2 of large firm returns may be higher, and growing, and their earnings announcements incorporated more quickly.

Explorations of how information production 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. Our work also contributes to the debate on the sources of capital misallocation in the macroeconomy,[1] as we add an explanation for why financial markets may be providing better guidance over time for some firms, but not for others.

1 Empirical Patterns in Price Informativeness

In this section, we study patterns in a well-known measure of price informativeness – specifically, the one used by Bai, Philippon, and Savov (2016).[2] Our focus is on cross-sectional heterogeneity: we will show that some assets, notably large growth stocks, tend to have higher price informativeness compared to other assets and this gap has risen over the past few decades.

[1] See e.g., Hsieh and Klenow (2009) or Restuccia and Rogerson (2013) for a survey.

[2] In Section 3.2, we show that the same cross-sectional patterns we document also hold for the measure of price informativeness proposed by Davila and Parlatore (2016a).

This measure is known to have many problems. We do not disagree. Our preferred measure of information in financial markets will emerge from the structural estimation we do in the next section. This section simply motivates that analysis by showing new and puzzling cross sectional patterns in a pre-existing measure. These facts motivate our choice of what features to put in the structural model we estimate.

1.1 Measuring Price Informativeness

Data 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 main equity valuation measure is market capitalization over total assets, M/A and the main cash flow variable is earnings over assets, or more precisely, earnings before interest and taxes, (denoted $EBIT$ in Compustat), scaled by current total assets. Both ratios are winsorized at 1%.

Since we are interested in the extent to which current prices reflect future earnings, we need to make two other adjustments. 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 1960s and 1970s. Therefore, we adjust all cash-flow variables with GDP deflator. Second, we need to deal with firms exiting the sample. We use the delisting price as the last price the firm was in the sample and we consider different assumptions for cash-flows. Our preferred version solution is to only consider periods during which a firm has non-missing information but our results are also robust to assigning zero cash-flows when the firm exits or to use a weighted industry cash-flow as a proxy, as in Bai, Philippon, and Savov (2016).

Price informativeness Our baseline measure of price informativeness is the one used by Bai, Philippon, and Savov (2016). It captures the extent to which asset prices in year t reflect cash-flows in year $t+s$ and is constructed by regressing the latter on the former, along with controls for other observable asset characteristics. This cross-sectional regression is run at each date t, separately for each asset group j:

$$\frac{E_{f,j,t+s}}{A_{f,j,t}} = \alpha_{j,t} + \beta_{j,s,t} \cdot \log\left(\frac{M_{f,j,t}}{A_{f,j,t}}\right) + \gamma_{j,t} \cdot X_{f,j,t} + \epsilon_{f,j,t}, \tag{1}$$

where $E_{f,j,t+s}/A_{f,j,t}$ is the cash-flow 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 adjust for potential autocorrelation by using Newey-West standard errors with four lags.

The coefficient of interest is $\beta_{j,s,t}$, which captures the informativeness of the market prices. To obtain our measure of (the trend in) price informativeness, we follow Bai, Philippon, and Savov (2016) and scale $\beta_{j,t}$ by the variability of the regressor: :

$$PINF_{j,s,t} = \beta_{j,s,t} \cdot \sigma_{j,t}^{M/A} \tag{2}$$

where $\sigma_{j,t}^{M/A}$ denotes the cross-sectional standard deviation of $\log\left(\frac{M_{f,j,t}}{A_{f,j,t}}\right)$ in year t. Finally, since we are interested in longer term trends, we estimate the following specification (separately for each asset group j):

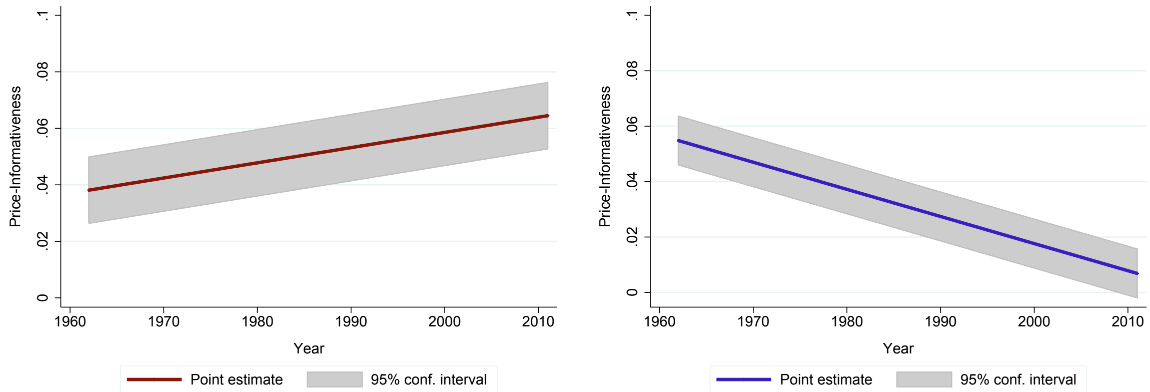
$$PINF_{j,s,t} = \overline{PINF}_{j,s}\left(1 + Trend_{j,s} \cdot \frac{t-1962}{2010-1962}\right) + e_{j,s,t} \tag{3}$$

where we normalize the calendar time variable t so that it takes values between 0 and 1.

1.2 Divergence of Price Informativeness

We begin by looking at aggregate trends in price informativeness. The left panel of Figure 1 plots the trend in price informativeness – the fitted value from (3) – for the universe of listed firms. It shows that price informativeness has fallen over time for the market as a whole. In fact, over the past 50 years, this declining trend has eviscerated almost all of the information content in prices. The right panel contrasts this with firms included in the S&P 500, the sample of firms studied by Bai, Philippon, and Savov (2016). Consistent with their findings, we find

Figure 1: **Price Informativeness is Falling (Rising) for all Public Firms (S&P 500 Firms).** The plots show the trends in price informativeness, estimated using (3), along with 95% confidence interval based on Newey-West standard errors with 5–lags. The left figure contains S&P 500 nonfinancial firms, while the right figure contains all publicly listed nonfinancial firms excluding S&P 500 firms.



S&P 500 | Whole Sample

that price informativeness has risen over time for these firms. Over this time period, price informativeness has increased by about 50% of its original level.

In other words, the past few decades have been marked by diverging trends in informativeness. We will show that this divergence is tied to a broader phenomenon – price informativeness for large-growth firms has been growing, both in absolute terms and relative to other firms. Since such firms are disproportionately represented in the S&P 500 , price informativeness for this has diverged from that of the market as a whole.[3]

Price informativeness for large (small) firms has been rising (falling). In order to explore the connection between firm size and informativeness, we compute our estimates for two sub-samples: one is the 500 largest firms – irrespective of whether they are in the S&P 500 or not – and the other, the rest of the firms. We refer to these sub-samples as 'large' and 'small' respectively.

Table 1 reports the results for S&P 500 firms (columns 1-2), large firms (columns 3-4) and small firms (column 5-6). The increase in price informativeness is very similar for S&P 500 firms and large firms, both for 3-year (columns 1 and 3) and 5-year horizons (columns 2 and

[3] Appendix A.2 shows that the informativeness of stocks currently in the S&P 500 is similar to non-S&P 500 stocks with similar characteristics. This suggests that differences in asset characteristics, rather than inclusion in S&P 500 *per se*, is the source of the divergence.

4). By contrast, the price informativeness of small firms, which started from roughly the same levels as that of large 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 A.1).

Table 1: **Price Informativeness: The Role of Firm Size**

This table presents results from estimating (3) for different sub-samples of firms. Newey–West standard errors, with four lags are in parentheses. *** denotes significance at the 1% level.

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***	.026***	-.0014	.016***	-.047***	-.051***
	(.0037)	(.006)	(.0036)	(.0059)	(.0028)	(.0046)
$\overline{PINF}_{j,s}$	.033***	.038***	.041***	.048***	.043***	.054***
	(.0023)	(.0036)	(.0023)	(.0038)	(.0018)	(.0029)
Observations	17,662	16,120	22,121	20,307	22,121	82,343
Sector FE	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓

Growth firms are central to information divergence. Next, we explore the relationship between growth and price informativeness. Following Fama and French (1995), we rank firms based on their current book-to-market ratio (defined as the difference between total assets and long term debt, divided by the firm's market capitalization). The bottom 30% are labeled 'growth' firms and the top 30% 'value' firms. We then run our price informativeness regressions (1) separately for these two groups.

Columns (1) and (2) of Table 2 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, show more modest declines. Small, value firms (column 5) experience a smaller decline in price informativeness. The rate of change in small value firms price informativeness is half that of small growth firms (column 3). The information divergence is summarized in Figure 2, 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 show a clear divergence.[4]

Table 2: **Price Informativeness Trends: The Role of Firm Growth**
This table presents results from estimating (3) 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.

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	✓	✓	✓	✓	✓	✓

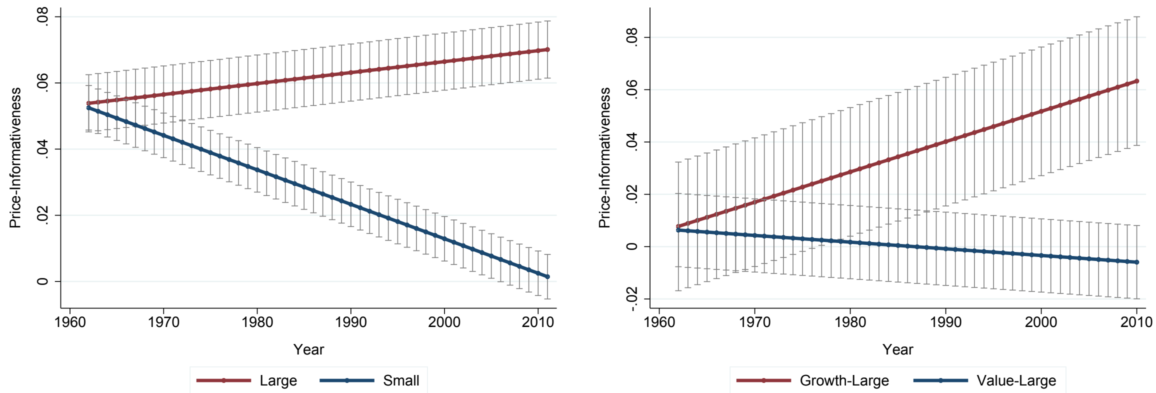
1.3 Other Possible Data Groupings

It is possible that growth, value and size are not, themselves, the relevant characteristics. They may well be a proxy for some other correlated firm or asset characteristics. While we cannot rule this out, nor do we need to, there are a couple of other groupings of assets that might be natural or informative to consider before we proceed.

Market power. Recent work suggests that market power may be growing throughout the economy. In Kacperczyk, Nosal, and Sundaresan (2018), market power reduces price informa-

[4]Small firms, both growth and value, show a declining trend – see Figure 8 in the Appendix.

Figure 2: **Large and Small Firms' Price Informativeness Diverges.** The plots show the trends in price informativeness for horizon $s = 5$, estimated using (3), 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%.



tiveness. Investors with price impact trade less aggressively on their information. This produces less informative prices. So market power can interact with the measure of informativeness, and thus with the measurement of data. Sorting assets according to the price impact of the investors in those assets is not straightforward. It is also not likely to explain our information divergence. If market power increased and this reduced price informativeness, it could be one reason for the overall decline in price informativeness. In that case, our data estimates would then be a lower bound on true data processing. But then to explain why large, growth firms have much more informative prices than they used to, that market would have to be far more competitive than it was 50 years ago. We know of no evidence that suggests enormous increases in competition in some equity markets and the evaporation of competition in others.

Technology firms. Could the increased prevalence of technology firms explain information divergence? Appendix A.3 documents that tech firms do have a lower level of price informativeness, on average. However, a simple cut of the data suggests that the rise of technology firms is unlikely to account for the divergent trends. The share of tech firms in the large and small firm samples is similar over time. Therefore, the composition change cannot explain our new fact: the divergence in informativeness of large and small firms' prices, over time.

Note also that our structural approach in the next section will strip out 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 still finds divergence.

However we group the data, the conclusion is the same: If the changes in price informativeness were driven by changes in information, then, despite the data revolution, there is no more data available about most firms now than there was 50 years ago. There is a small set of firm that have benefitted from all the information technology change; those are large, growth firms. For those firms, the ability of prices to forecast future fundamentals has risen substantially, roughly six-fold. But that interpretation is complicated by the fact that measuring informativeness and measuring information is not the same thing. To address this gap, we turn next to a different approach.

2 A Structural Framework for Measurement

2.1 Why do we need a structural framework?

What do these divergent trends reflect? In particular, to what extent do they point to changes in data processing? The key difficulty in interpreting these facts is that price informativeness is an endogenous object that reflects not just information but also depends on other characteristics such as growth prospects and volatility. For example, a rising trend in informativeness could arise from a trend in cash-flow growth, which affects the sensitivity of prices to expected cash-flows or because of increases data processing, which causes expected cash-flows to more closely track the true values. It could also reflect time variation in the extent of noise-induced variability in prices.

One possibility is to use a rich set of fixed effects in the reduced-form specification, but that will still leave us with the challenge of disentangling trends in data processing from other types of time variation. Therefore, we pursue a different approach and use a simple structural model as a measurement framework. This allows us to tease out the extent to which trends in price informativeness from the previous section are due to changes in firm characteristics, versus data processing.

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 price informativeness as a function of both asset characteristics and investor information. These form the basis for an empirical strategy that disentangles asset characteristics from information using observable moments of stock prices and cash flows, providing a deeper understanding of the trends in the previous section.

2.2 Model

A unit measure of investors trade multiple assets. Each asset is to be interpreted as shares in a representative firm in group $j \in \{SmallGrowth, LargeGrowth, LargeValue, SmallValue\}$. To lighten notation, we suppress the firm subscript and use j to refer to firm-level variables.

A share is a claim to a dividend stream. The flow dividend of asset j in period s, denoted $\{d_{js}\}, s = 1, 2, ...,$ follows a AR(1) process with normally distributed innovations and is independent across assets. [5] Formally, for $s = 1, 2....,$

$$d_{js} = g_j \; d_{js-1} + \epsilon_{js}, \qquad \epsilon_{js} \sim^{iid} N(0, \Sigma_{jd}) \tag{4}$$

We consider the simplest formulation, with a single round of trading. We then interpret time series data as repeated instances of this one-shot formulation. At the start of period 1, investors make portfolio choices (conditional on an information set, described later). At the end of the period, d_{j1} is observed, investors sell their holdings and consume. Our key simplifying assumption is that this sale occurs at a price equal to the expected value of dividends, discounted at the (gross) riskless rate $r > 1$.[6] Given our assumption on the cashflow process, this expected

[5] The assumption of independence is motivated by our focus on idiosyncratic rather than aggregate variation, i.e. a stock-picking rather than a market timing perspective. Having said that, it is not difficult to relax this assumption and allow for correlation across assets. Signals and data processing would then be about independent risk factors, as in Van Nieuwerburgh and Veldkamp (2009).

[6] A natural alternative assumption here is that investors sell their assets at a market price, which is a function, among other things, of 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.

discounted value, denoted by V_{j1}, is given by:

$$V_{j1} \equiv \mathbb{E}\left[\sum_{s=1}^{\infty} \frac{d_{js}}{r^s} \middle| d_{j1}\right] = \frac{r}{r - g_j} d_{j1} \ . \tag{5}$$

Thus, an asset with more persistent cash-flows (e.g. growth stock) will have a greater sensitivity of valuations to current cashflows. This allows us to capture time series properties of cash-flow processes within our one-shot trading model.

Supply: The supply of each asset j has a (commonly known) asset-specific mean $\overline{x}_j$ as well as an unobserved random component. Formally, the total supply is $\overline{x}_j + \tilde{x}_j$ shares, where $\tilde{x}_j \sim N(0, \Sigma_{jx})$.

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. They choose their portfolios, conditional on an information set $\mathcal{I}^i$. Formally, investor i chooses $\{q_j^i\}$, the number of shares of asset j, to solve:

$$\max_{\{q_j^i\}} \quad \mathbb{E}[U^i|\mathcal{I}^i] \quad = \quad \max_{\{q_j^i\}} \qquad \rho_i \mathbb{E}\left[W^i|\mathcal{I}^i\right] - \frac{\rho_i^2}{2} Var(W^i|\mathcal{I}^i) \ . \tag{6}$$

$$\text{where} \qquad W^i = r\overline{W}^i + \sum_j q_j^i (V_{j1} - rP_{j1}). \tag{7}$$

This mean-variance representation can include a broad array of preference specifications. The coefficient of absolute risk aversion ρ_i can 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: For each risky asset j, each investor observes k_j^i data points. Each data point is a noisy private signal of the end-of-period cashflow d_{j1}:[7]

$$\eta_j^{i,m} = d_{j1} + e_j^{i,m}, \qquad e_j^{i,m} \sim N(0,1) \ .$$

The average amount of data about asset j in the market is

$$K_j = \int k_j^i \, di \ . \tag{8}$$

In addition, investors can condition their orders on the realized market-clearing price (P_{j1}) and also optimally incorporate the information contained in that price. Finally, at the end of each period, dividends are paid and thus observed. Thus, investor i's information set comprises, for each asset j, the dividend realization from the previous period d_{j0}, a set of private signals $\{\eta_j^{i,m}\}$ and the market-clearing price, denoted P_{j1}. We conjecture (and later verify) that the information in the market price can be expressed as a signal of the cash-flow innovation with additive Gaussian noise. Given this information set, Bayes' law for normally distributed random variables yields the following expression for investor i's precision, denoted $(\Sigma_j^i)^{-1}$:

$$(\Sigma_j^i)^{-1} \equiv Var[d_{j1}|\mathcal{I}_i]^{-1} = \Sigma_{jd}^{-1} + \Sigma_{jp}^{-1} + k_j^i \ , \tag{9}$$

where Σ_{jp}^{-1} is the precision of the market price signal (to be characterized later). The average market-wide precision, denoted $\left(\overline{\Sigma}_j\right)^{-1}$, is

$$(\overline{\Sigma}_j)^{-1} = \int (\Sigma_j^i)^{-1} di = \Sigma_{jd}^{-1} + \Sigma_{jp}^{-1} + K_j \ . \tag{10}$$

Equilibrium: A rational expectations equilibrium is a set of functions for the price, P_{j1}, and portfolio choices q_j^i such that, (i) given the induced information sets $\mathcal{I}^i$, the portfolio choices solve (6) and (ii) markets clear, i.e. $\forall j$, $\int q_j^i di = \overline{x}_j + \tilde{x}_j$.

To solve for equilibrium, we conjecture a linear form for the price function and solve for the

[7] 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.

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:*

$$rP_{j1} = A_j + B_j \epsilon_{j1} + C_j \tilde{x}_j \ , \tag{11}$$

where

$$A_j = \left(\frac{r}{r-g_j}\right) g_j d_{j0} - \bar{\rho} \left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j \ , \tag{12}$$

$$B_j = \frac{r}{r-g_j}\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right) \ , \tag{13}$$

$$C_j = -\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \left(\frac{K_j \Sigma_{jx}}{\bar{\rho}} + 1\right) \ . \tag{14}$$

$$\Sigma_{jp}^{-1} = \left(\frac{B_j}{C_j}\right)^2 \Sigma_{jx}^{-1} \tag{15}$$

where $\bar{\rho}^{-1} := \overline{\Sigma}_j \int \rho_i^{-1} (\Sigma_j^i)^{-1} di$ is a precision-weighted average of investors' risk tolerance. Assuming $\bar{\rho}$ is constant across assets amounts to assuming that risk tolerance and precision are either uncorrelated, or not covary differently across assets.

Equation (13) shows B_j, that the coefficient on current innovation to cash-flows, is the usual Gordon growth factor, $\frac{r}{r-g_j}$, adjusted for average information about cashflows, captured by the factor $1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}$. Recall that the average posterior precision $(\overline{\Sigma}_j)^{-1}$ is the sum of the prior, the precision of the price signal (Σ_{jp}^{-1}) and the average amount of data processed, K_j. If investors do not have any information 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 $B_j = 0$. 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 extent to which the stock price covaries with cashflow innovations provides us with direct evidence about how informed the average investor is.

Equation (15) characterizes the precision of market information, i.e. from the price signal. To derive it, note that the linear form of the equilibrium price implies that it is informationally equivalent to $\frac{rP_{j1} - A_j}{B_j} = \epsilon_{j1} + \frac{C_j}{B_j}\tilde{x}_j$, i.e. a noisy signal of the innovation to cashflows with a precision $\left(\frac{B_j}{C_j}\right)^2 \Sigma_{jx}^{-1}$. The signal is less precise when the the equilibrium sensitivity of the price to supply (relative to cash-flows) times the variance of supply is high.

Price informativeness: Recall that the price informativeness measure in Section 1 is estimated by regressing cashflows s periods ahead on current prices, controlling for, among other things, the most recent cashflow. Using the equilibrium pricing equation (11), we can express s-period-ahead price informativeness as: [8]

$$PINF_{j,s} \equiv \frac{Cov(d_{js}, P_{j1}|d_{j0})}{StdDev(P_{j1}|d_{j0})} = \underbrace{\frac{Var(d_{j1}|d_{j0})}{StdDev(P_{j1}|d_{j0})}}_{\text{volatility}} \underbrace{\frac{g_j^s}{r-g_j}}_{\text{growth}} \underbrace{\left[1-\frac{\overline{\Sigma}_j}{Var(d_{j1}|d_{j0})}\right]}_{information} . \quad (16)$$

Equation (16) forms the core of our analysis of price informativeness. It reveals that $PINF_{j,s}$ has three components. The first is *volatility*: specifically, the variability of cashflows relative to prices. All else equal, an asset whose prices are more volatile (relative to cashflows) will exhibit lower price informativeness.[9] The second component is related to *growth*: a more persistent, or faster growing, process will lead to a greater sensitivity of future cashflows to current ones. Under our AR(1) structure, this is summarized by the autoregressive coefficient, g_j. Since prices aggregate information about current cash-flows, a higher g_j, all else equal, makes them covary more strongly with future cashflows, resulting in higher price informativeness. Finally, the last term reflects *information*: the less uncertain the average investor is about cash-flows (for example, due to increased data processing K_j), the lower is $\overline{\Sigma}_j$, and therefore, the higher is price informativeness at all horizons.

3 Estimation of the Structural Framework

Next, we employ the framework developed in the previous section to interpret the findings from Section 1. In particular, we take the measures of price informativeness from Section 1 and purge them of growth and volatility effects. What is left reveals the cross-sectional and time series patterns of information in the market. We further separate this information into cross-asset differences in the efficiency with which markets aggregate a given amount of data

[8] See Appendix B.3 for the derivation.
[9] This insight also appears in Davila and Parlatore (2016b).

	1960s	1970s	1980s	1990s	2000s	2010s
Growth g_j:						
Small Growth	0.859	0.917	0.752	0.775	0.799	0.818
Large Growth	0.996	0.992	0.972	0.967	0.938	0.931
Small Value	0.847	0.741	0.622	0.661	0.798	0.756
Large Value	0.885	0.892	0.842	0.875	0.876	0.791
Volatility Σ_{jd}:						
Small Growth	0.019	0.023	0.040	0.053	0.036	0.027
Large Growth	0.009	0.008	0.011	0.015	0.013	0.008
Small Value	0.006	0.007	0.008	0.012	0.011	0.008
Large Value	0.002	0.003	0.003	0.002	0.006	0.002

Table 3: Estimated cash flow parameters: persistence/growth g_j and innovation variance Σ_{jd}.

and differences in the data quantity or prevalence.

3.1 Data Processing vs Asset Characteristics

Our empirical strategy is to directly measure the growth and volatility components in (16) and then remove these estimates from PINF, to obtain the information term $\bar{\Sigma}_j$. To study cross-sectional variation, we classify stocks into one of four groups: Small-Growth, Large-Growth, Small-Value and Large-Value, based on the same criteria used in Section 1. Given our focus on long-term trends, we analyze the time-series by estimating each decade separately. Specifically, for each decade and asset group, we estimate PINF, growth and volatility. Then, we divide PINF for that decade-group by the growth and volatility of that decade-group's assets, as in (16).

To measure the growth component, we estimate equation (4) by running a pooled regression on cashflow data. The resulting estimates of the AR(1) coefficient, g_j, and the volatility of innovations, Σ_{jd}, for each decade-group are reported in Table 3. Assuming a riskless interest rate of 2.5% ($r = 1.025$), they directly yield $\frac{g_j^s}{r-g_j}$, the growth component. [10]

Next, note that the numerator of volatility component, $Var(d_{j1}|d_{j0})$, is simply the variance of innovations, Σ_{jd}, also reported in Table 3. The denominator, $Std(P_{j1}|d_{j0})$, is obtained (again,

[10] In our baseline analysis, we use $r = 1.025$ for the entire sample. In Appendix ??, specifically in Figure 9, we relax this assumption and show that our results are robust to using the actual time path of riskless rates.

for each group-decade pair) by projecting prices (or more precisely, market capitalization scaled by assets) on controls (including past earnings).

Finally, we estimate price informativeness for each decade-group as described in Section 1.[11] We can then recover the information component using:

$$1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}} = \frac{PINF_{j,s}}{\frac{g_j^s}{r-g_j} \frac{\Sigma_{jd}}{Std(P_{j1}|d_{j0})}} \tag{17}$$

Our decade-by-group estimates for price informativeness and its components are reported in Table 6 in Appendix C.1. In line with our focus on longer term trends (and to facilitate comparison with the facts in Section 1), we plot the fitted trendlines for each series in Figure 3. The first panel reproduces the patterns documented in Section 1. Price informativeness has trended up for the Large-Growth group, but has remained constant/declined for all other groups. The top right panel reveals that changes in the information component played a central role in the divergence. The trends in this component parallel those in price informativeness overall: rising for the large-growth assets and stagnating/falling for the others. [12]

The remaining panels in Figure 3 show other systematic changes in asset characteristics over time. In particular, the growth component, reflecting the persistence of cash-flows, is declining. This 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. Note that this decline is most dramatic for the large-growth assets, which by itself should have reduced their price informativeness relative to other assets. In other words, the rise in the information component for large-growth firms is sufficiently large that it overwhelms the effect of declining cash-flow persistence on informativeness.[13] Finally, the volatility component

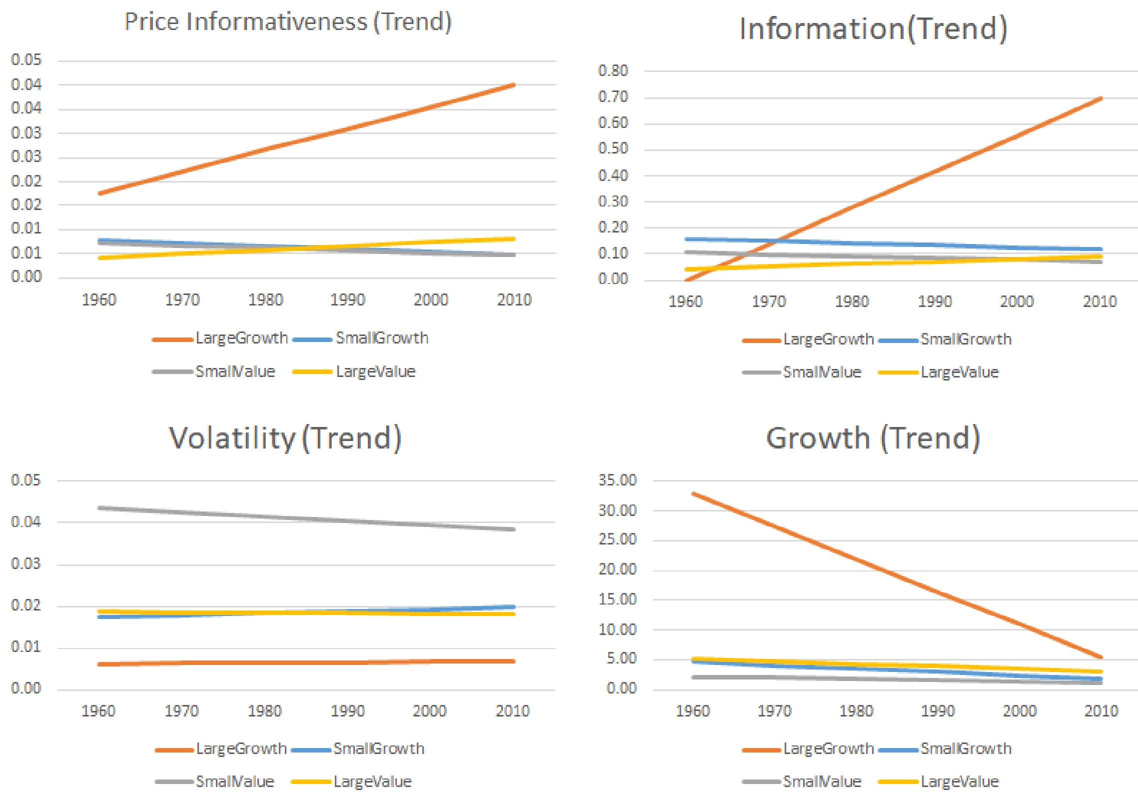
[11] We make two modifications to tie the estimation closer to the theory: first, we use $\frac{M}{A}$ in levels (instead of logs). Second, we use the absolute value of the estimated price informativeness, since the theory cannot reconcile negative estimates (this only matters for a couple of observations and does not affect conclusions about longer term trends).

[12] Table 4 sheds further light on the timing of the increase for large growth firms: it shows that the information component divergence spiked around the 2000's, the same time as the widespread adoption of information technology in the financial sector (Abis, 2018).

[13] In Figure 10, we conduct a counterfactual decomposition holding the growth component for each group fixed at its 1960s level. This moderates the magnitude of the divergence somewhat, but the basic pattern – an increase in information processing for the Large-Growth group and modest declines for the other three groups – survives. This exercise shows that controlling for changes in asset fundamentals is important for an accurate *quantitative* estimate of information.

Figure 3: **Trends in Price Informativeness**.

For each component, the plots show a linear trendline fitted to the estimates reported in Table 6.



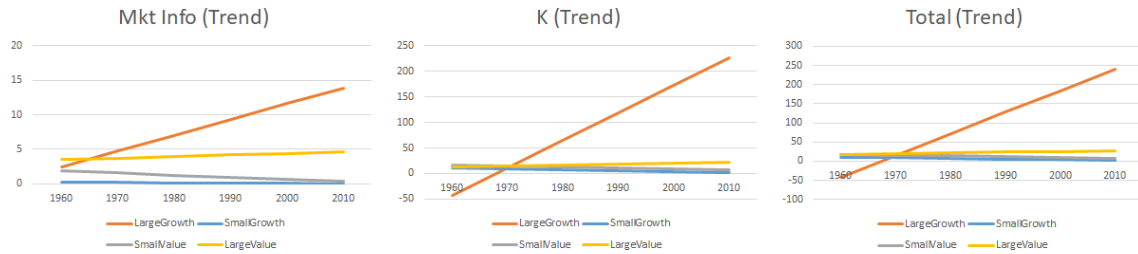
shows significant cross-sectional heterogeneity but is relatively stable over time.

Market information vs private data. Next, we explore where information came from: Did it stem from better information aggregation through prices or from increased data processing? To answer this question, we decompose overall information, $\bar{\Sigma}_j^{-1}$, into its components as in (10): specifically, the prior or unconditional variance of dividends ($\Sigma_{jd} := Var(d_{j1}|d_{j0})$), the information content of the price signal (Σ_{jp}^{-1}) and a price noise term $Var(e_j)$. The term $Var(e_j)$ is the noise with which prices predict contemporaneous earnings. To estimate $Var(e_j)$, we first estimate (1) with $s = 0$ and equate $Var(e_j)$ to the variance of the residuals. Appendix C derives the following mapping, which yields an estimate for Σ_{jp} for each group by decade:

$$\Sigma_{jp} = \frac{Var(e_j) \cdot \Sigma_{jd}}{\Sigma_{jd} - Var(e_j)} \,. \tag{18}$$

Figure 4: **Large, Growth Trend Comes from Both Market Information and Private Information**.

For each component, the plots show a linear trendline fitted to the estimates reported in Table 4. Volatility, growth and information are the three terms in eq. 16. Specifically, information is the estimate of $\left[1 - \frac{\overline{\Sigma}_j}{Var(d_{j1}|d_{j0})}\right]$, which includes both price information and data processing.



Equation (18) thus . Substituting Σ_{jp}, along with overall information $\overline{\Sigma}_j^{-1}$ and the prior precision, Σ_{jd}^{-1} into (10) yields the market-wide data processed, K_j:

$$K_j = \overline{\Sigma}_j^{-1} - \Sigma_{jd}^{-1} - \Sigma_{jp}^{-1} \tag{19}$$

Table 4 presents the estimates for price information Σ_{jp}^{-1} and data processing K_j, by decade. Figure 4 plots the associated fitted trend-lines. The precision of the price signal for large-growth firms rose modestly in recent years, but much of the increase in overall information over the past few decades can be attributed to increases in data processing.

	1960s	1970s	1980s	1990s	2000s	2010s
Market information. Σ_{jp}^{-1}						
Small Growth	0.36	0.01	0.00	0.03	0.10	0.00
Large Growth	2.97	7.86	4.75	1.61	18.85	13.02
Small Value	0.34	4.46	0.11	0.03	1.48	0.00
Large Value	0.28	6.99	2.27	6.22	8.39	0.12
Private information, K_j:						
Small Growth	19.28	0.64	0.41	5.07	11.46	0.42
Large Growth	9.13	11.69	18.31	13.54	250.27	245.09
Small Value	5.81	27.57	13.26	4.47	15.53	1.47
Large Value	8.85	12.79	20.01	34.23	17.77	16.05

Table 4: The sources of information

3.2 Other Measures of Price Informativeness

Davila and Parlatore (2016a) propose an alternative measure of "absolute' price informativeness." It captures the "ability of asset prices to aggregate dispersed information". Their measure is the precision of an unbiased signal constructed from prices of the current cash-flow innovation.In our setting, this corresponds to Σ_{jp}^{-1}. It is the same as what we call "market information" in Table 4 and Figure 4.

The divergence between small and large firm information remains intact under this alternative measure: Large growth firms have market prices that convey more information and that informativeness increases dramatically over time. [14] For all other groups, informativeness stagnates or declines. In fact, the divergence is even more stark under this alternative measure of price informativeness. The results in Figure 4 suggest a reason why both measures show the same patterns. They show that more data processed by investors (higher K_j) was the key driver of the time trends, which leads to prices being both more accurate as signals (the Davila-Parlatore notion of price informativeness) and being more sensitive to cashflows (the Bai-Philippon-Savov measure).

Note that, like our baseline informativeness measure, the Davila-Parlatore one is also influenced by the fundamental characteristics of the asset: from equation (15), we see that Σ_{jp} is a function of the equilibrium coefficients B_j and C_j and therefore, asset characteristics that affect these (e.g. cash-flow growth) will also have an effect on Σ_{jp}. To be clear, this does not negate the value of this measure: it merely underscores the value of separating asset characteristics from information, even in the context of this measure.

4 Why the Surge in Large Growth Firm Data?

Our results show that, while asset characteristics did change over this period, divergence in the price informativeness for large-growth firms came predominantly from changes in information, and in particular, data processing by investors. This raises an obvious question: why did so

[14] Davila and Parlatore (2016a) use the entire time series to estimate market information for individual stocks. We group assets into categories based on observable characteristics like size and growth and estimate price informativeness by group-decade, which highlights how price informativeness has diverged for certain types of assets (e.g. large-growth stocks).

many investors process increasing amounts of data about large, growth stocks and not about other assets?

To understand why investors have processed more data about one asset or another, one might naturally ask what the marginal value of processed data is for each asset. But in this setting, marginal values can be misleading. The reason is that, when many investors process high-value data, they make the data less valuable for others to process. High marginal values predict more data processing. But more data processing lowers the marginal value. In equilibrium, data processing choices should push down all marginal values until the equal marginal cost. This is 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 marginal value does not reliably explain the amount of data processing, what does? The initial value of data is what the value of the first increment of precision would be, if no one else processed any data on that asset. Using our framework and estimates, we can estimate that initial value. This would explain the data processing patters we see in the previous section, if the asset types for which data processing is high also turn out to have high initial values of information.[15]

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. This 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.

[15]This concept is related to what is sometimes referred to as a water-filling equilibrium in the information choice literature. Equilibrium is often computed letting agents sequentially choose risk factors to learn about. Using 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 is the depth of each bucket, before being filled with water. See our follow-up paper (Farboodi et. al., 2019)for estimates of the equilibrium marginal value of information as well.

4.1 Deriving the initial value of information

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

$$\mathbb{E}[U_j^i] = \frac{1}{2}\mathbb{E}\left[(\Pi_j^i)^2\right]\left(\frac{r}{r-g_j}\right)^{-2} (\Sigma_j^i)^{-1} \quad \text{where} \;\; \Pi_j^i \equiv \mathbb{E}[V_j - P_j r|\mathcal{I}^i]. \tag{20}$$

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 asset j's 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 $Var[V|\mathcal{I}_i]^{-1} = \left(\frac{r}{r-g_j}\right)^{-2}(\Sigma_j^i)^{-1}$. The 1/2 comes from subtracting a variance term.

Equation (20) 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)[16] and/or more volatile because that makes the expected value of the squared profit high.

Next, we compute the unconditional expected profit per share: [17]

$$\mathbb{E}\left[\Pi_j^i\right] = \bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j \; . \tag{21}$$

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 more persistent cash-flows (higher $\frac{r}{r-g_j}$) means greater uncertainty about payoffs (or 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 overall risk 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 pre-data value, the prior variance Σ_{jd} in (20). Then, compute the partial derivative

[16] High negative expected profits are also valuable, because they present profitable shorting opportunities.

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

with respect to $(\Sigma_j^i)^{-1}$. This is what we call the *initial value of information* (VI_j):

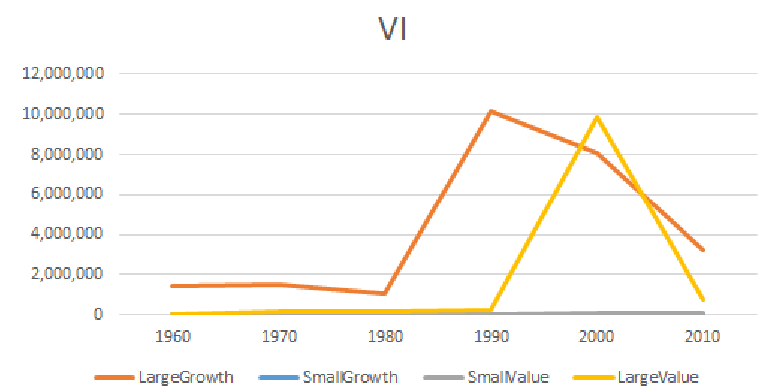
$$VI_j = \frac{1}{2}\left[\bar{\rho}^2\left(\frac{r}{r-g_j}\right)^2 \Sigma_{jd}^2 \bar{x}_j^2\right] + \frac{1}{2}\Sigma_{jd} \tag{22}$$

The first component in (22) is related to the mean of the expected profit per share of asset j from (21). As we saw earlier, higher growth (g_j), larger size $(\bar{x}_j)$ and more uncertainty $(\overline{\Sigma}_j)$ all raise this object, 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 particularly valuable to learn about.

The second term in (22) 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 expected profits.

4.2 Estimated initial value of information.

Figure 5: **The Initial Value of Information, by Asset Class, over Time**.



The initial value of information is defined in (22).

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 3, as well as risk aversion $\bar{\rho}$ and the asset supply $(\bar{x}_j)$. To estimate total supply by decade, we take the average (book) value of assets of firms in group j. We assume the risk aversion coefficient is

$\bar{\rho} = 2$.

The resulting estimates in Figure 5 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 almost indistinguishable from the x-axis, orders of magnitude lower than the value of the large firms' data.

The time series for VI_j in Figure 5 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 (22). 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 decline in the 2010s stems from a fall in the estimated variability of cashflows Σ_{jd}. This is consistent with the low price of volatility options (the VIX) during this period.

The value of large-value firms' information surpasses that of large growth firms' information for one decade in our sample. This was 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 groups take time to build, time to hire, and time to develop expertise. It could be that, much like physical capital, information processing expertise is slow to adjust. A full exploration of this possibility is a question for another paper.

5 Conclusions

The ability of financial prices to transmit information about firm profitability is often regarded a measure of the efficiency or success of financial markets. As data processing technologies have improved, one might expect this to increase in the information content of all prices.

Instead, what we find is that price informativeness has diverged across assets. While prices of large, growth stocks are getting more informative, the extent of information in prices of all other assets is stagnant or declining. This could reflect changes in information or changing asset characteristics. To disentangle trends in various factors influencing informativeness, we estimate a structural model and decompose the traditional measure of informativeness into changes in growth, volatility and information. This decomposition only strengthens the puzzle: 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 marginal 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. This offers a partial explanation for the diverging trends in the information content of prices – investors chose to analyze the most valuable data, that pertaining to large, growth firms.

If data continues to become more and more abundant, eventually, the value of additional information about large-growth firms should fall, due to diminishing returns. Over time, would expect to see equalization of marginal value. The improvements in data technology should eventually be applied to study other firms. However, given the substantial – and growing – inequality in firm sizes, data convergence could take a long time.

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Appendices

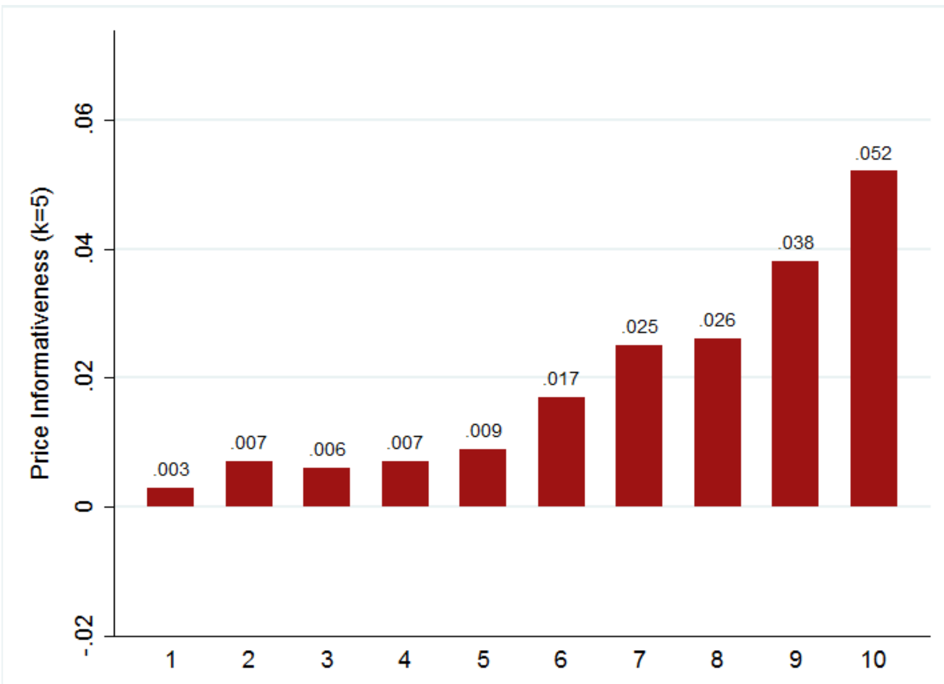
A Additional Empirical Results

This appendix contains additional results about the evolution of price informativeness.

A.1 Price Informativeness by Size

To estimate price informativeness by size, we pool all firm-year observations and construct deciles of firm size (defined as market value in 2009 dollars).[18] We then run the cross-sectional regression (1) within each bin, i.e. the subscript j now refers to a size bin. Price informativeness is then obtained by scaling the coefficient, as in (2). The results, presented in Figure 6, show a clear pattern: the informativeness of large firms is significantly higher than those of smaller firms. This is particularly true for the largest firms, i.e. those in the top decile.

Figure 6: **Price Informativeness by Decile**. Price informativeness is defined as in (Eq 2). We run the regression in (1) for each year $t = 1962, ..., 2010$, horizon $s = 5$ and size decile. The sample contains publicly listed non-financial firms from 1962 to 2010. The graph shows the average $PINF_{j,s,t}$ over the entire sample for each decile.



[18]This size variable has been shown to matter in the context of CEO compensation, for instance in (Gabaix and Landier (2008).

A.2 Price Informativeness in the S&P 500

Table 5 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. *Price Info (t=0)* reports the magnitude of the predictive power of stock prices for future cash–flows at the beginning of our sample period. Because we normalize the time trend between zero and one, the coefficient on *Price Info*$\times$*Trend* 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.

Table 5: **Price Informativeness Grew (Fell) for S&P 500 (other) Firms.**
This table shows the estimates of (3). Newey–West standard errors, with four lags are in parentheses. *** denotes significance at the 1% level.

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	✓	✓	✓	✓

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).

In other results, 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 1 – 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.

A.3 Is this All About Tech Firms?

A potential explanation for the decrease in price 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. However, we find that quantitatively, the rise of such firms explains little of the divergence in price informativeness, because the tech 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.

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. Then, in the mid-80's trends diverge. The share of high-tech firms increases more in the whole sample, essentially driven by a rapid entry rate of tech firms. Then, in the early 2000's, the share of tech firms in the S&P 500 increases and tech-shares for S&P 500 and non-S&P 500 converge again. Since the tech composition of the samples did not trend, the prevalence of tech firms, while it may explain the average decline in informativeness, cannot explain the cross-sectional divergence.

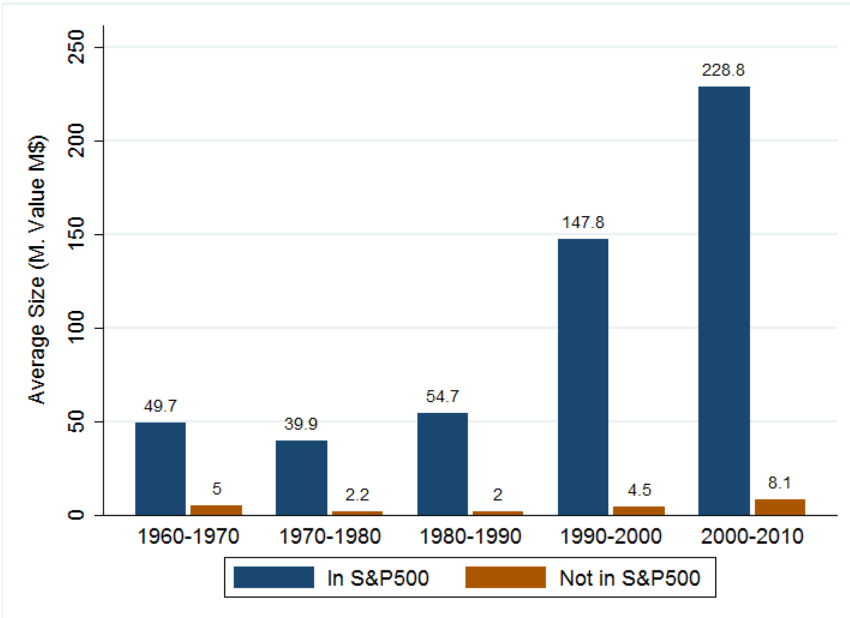
A.4 Evolution of Firm Size

Figure 7 show that S&P 500 firms got larger, relative to non-S&P 500 firms. 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 could help explain the diverging trends in informativeness.

A.5 Price Informativeness by Firm Size and Growth

Figure 8 plots the trend in price informativeness – estimated using (3) – for 4 sub-samples of firms: Growth-Large, Value-Large, Growth-Small and Value-Small. It shows that informa-

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.



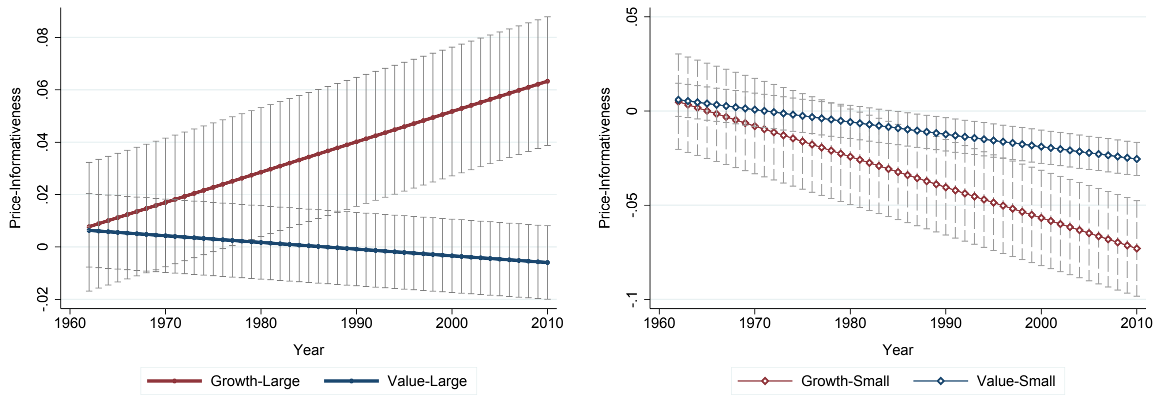
tiveness has increased for the Growth-Large group, but declined or remained constant for the others.

B Structural Framework: Derivations

B.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.

Figure 8: **Price Informativeness by Firm Size and Growth**.



B.2 Decomposing Price Informativeness: Derivation of (16)

$$PINF_{j,s} = \frac{Cov(d_{js}\ , P_{j1}|d_{j0})}{StdDev(P_{j1}|d_{j0})} = g_j^s \frac{Cov(d_{j1}\ , P_{j1}|d_{j0})}{StdDev(P_{j1}|d_{j0})} \tag{23}$$

$$= g_j^s \frac{Cov(\epsilon_{j1}\ , P_{j1})}{StdDev(P_{j1}|d_{j0})} = \frac{g_j^s}{r} \frac{B_j \Sigma_{jd}}{StdDev(P_{j1}|d_{j0})} \tag{24}$$

$$= \frac{\Sigma_{jd}}{StdDev(P_{j1}|d_{j0})} \quad \frac{g_j^s}{r - g_j} \quad \left[1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right] \tag{25}$$

where the last line uses the expression for B_j from (13).

B.3 Estimating Σ_{jp}: Derivation of (18)

Prices and cash-flows conditional on d_{j0} can be expressed as[19]

$$d_{j1}|d_{j0} = \epsilon_{j1} \tag{26}$$

$$P_{j1}|d_{j0} = \tilde{A}_j + \frac{B_j}{r}\epsilon_{j1} + \frac{C_j}{r}\tilde{x}_j\ , \tag{27}$$

where $\tilde{A}_j = A_j/r - \frac{r}{r-g_j} g_j d_{j0}$. The regression coefficients are then given by

$$\beta_j = \frac{Cov(\epsilon_{j1}, P_{j1}|d_{j0})}{Var(P_{j1}|d_{j0})} = \frac{rB_j\Sigma_{jd}}{B_j^2\Sigma_{jd} + C_j^2\Sigma_{jx}}\ ,$$

$$\alpha_j = \mathbb{E}(\epsilon_{j1}) - \beta_j \mathbb{E}\left(\tilde{A}_j + (B_j/r)\epsilon_{j1} + (C_j/r)\tilde{x}_j\right) = -\beta_j \tilde{A}_j\ ,$$

[19] As in the main text, we suppress the firm subscript for all the variables.

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

$$
\begin{aligned}
e_j = d_{j1}|d_{j0} - \alpha_j - \beta_j P_{j1}|d_{j0} &= \left(1 - \beta_j \frac{B_j}{r}\right)\epsilon_{j1} - \beta_j \frac{C_j}{r}\tilde{x}_j \ , \\
&= \left(1 - \frac{B_j \Sigma_{jd}}{B_j^2 \Sigma_{jd} + C_j^2 \Sigma_{jx}} B_j\right)\epsilon_{j1} - \left(\frac{B_j \Sigma_{jd}}{B_j^2 \Sigma_{jd} + C_j^2 \Sigma_{jx}}\right) C_j \tilde{x}_j \ , \\
&= \left(\frac{C_j^2 \Sigma_{jx}}{B_j^2 \Sigma_{jd} + C_j^2 \Sigma_{jx}}\right)\epsilon_{j1} - \left(\frac{B_j^2 \Sigma_{jd}}{B_j^2 \Sigma_{jd} + C_j^2 \Sigma_{jx}}\right)\frac{C_j}{B_j}\tilde{x}_j \ , \\
&= \left(\frac{\frac{C_j^2}{B_j^2}\Sigma_{jx}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)\epsilon_{j1} - \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)\frac{C_j}{B_j}\tilde{x}_j \ , \\
\Rightarrow \quad Var(e_j) &= \left(\frac{\frac{C_j^2}{B_j^2}\Sigma_{jx}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)^2 \Sigma_{jd} + \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \frac{C_j^2}{B_j^2}\Sigma_{jx}}\right)^2 \frac{C_j^2}{B_j^2}\Sigma_{jx} \ . \qquad (28)
\end{aligned}
$$

Noting that $\Sigma_{jp} = \frac{C_j^2}{B_j^2}\Sigma_{jx}$, we can write (28) more succinctly as

$$
Var(e_j) = \left(\frac{\Sigma_{jp}}{\Sigma_{jd} + \Sigma_{jp}}\right)^2 \Sigma_{jd} + \left(\frac{\Sigma_{jd}}{\Sigma_{jd} + \Sigma_{jp}}\right)^2 \Sigma_{jp} = \frac{\Sigma_{jp}\Sigma_{jd}}{\Sigma_{jd} + \Sigma_{jp}} \ . \qquad (29)
$$

Solving (29) for Σ_{jp} yields the expression in (18).

C Structural Estimation: Additional Results

C.1 Baseline Estimates

Table 6 presents our estimates for price informativeness and its components by decade and group.

C.2 Time-varying interest and growth rates

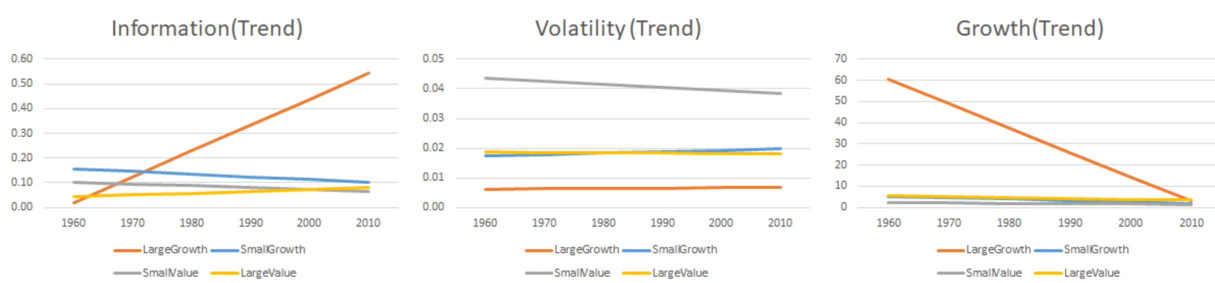
In our baseline estimation, we assumed a constant $r = 1.025$ over time. In this subsection, we show that this is not a critical assumption. In particular, we compute the actual average real interest rate for each decade (defined as the difference between 1-year nominal Treasury yield from the Federal 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 9 plots the estimated trends for all three components and looks very similar to the baseline results in Figure 3.

	1960s	1970s	1980s	1990s	2000s	2010s
Price Informativeness						
Small Growth	0.013	0.002	0.001	0.010	0.013	0.000
Large Growth	0.018	0.022	0.027	0.020	0.054	0.031
Small Value	0.004	0.014	0.003	0.002	0.013	0.001
Large Value	0.001	0.008	0.004	0.006	0.017	0.001
Volatility, $\frac{Var(d_{j1}\|d_{j0})}{Std(P_{j1}\|d_{j0})}$						
Small Growth	0.012	0.02	0.020	0.025	0.019	0.015
Large Growth	0.005	0.006	0.008	0.007	0.007	0.005
Small Value	0.029	0.053	0.045	0.052	0.037	0.030
Large Value	0.012	0.025	0.021	0.015	0.028	0.010
Growth, $\frac{g_j^s}{r-g_j}$						
Small Growth	3.82	7.10	1.56	1.86	2.25	2.64
Large Growth	34.45	29.75	17.23	15.48	9.44	8.55
Small Value	3.42	1.44	0.60	0.79	2.24	1.61
Large Value	4.97	5.32	3.26	4.49	4.50	2.12
Information, $1-\frac{\overline{\Sigma}_j}{Var(d_{j1}\|d_{j0})}$						
Small Growth	0.28	0.01	0.02	0.21	0.30	0.01
Large Growth	0.10	0.13	0.20	0.18	0.78	0.69
Small Value	0.04	0.18	0.10	0.05	0.15	0.01
Large Value	0.02	0.06	0.06	0.08	0.14	0.04

Table 6: Price informativeness and components.

Figure 9: **Time-variation in riskless rates.**

The plots show a linear trendline fitted to components of price informativeness estimated using (16) and decade-specific interest rates. For details of how r is estimated, see text.

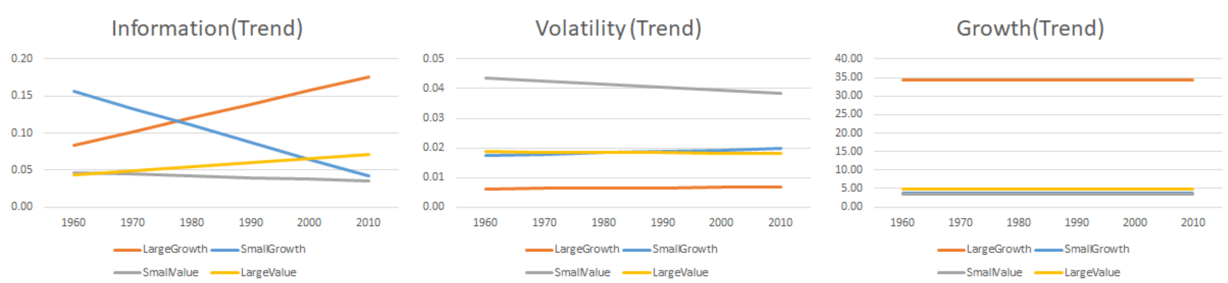


Next, we explore the role by changes in the estimated growth rate of cashflows. To answer that question, we re-estimate the model assuming that the cash-flow growth rate (g_j) each group was fixed at the level estimated for the 1960s. The results, presented in Figure 10, still show a clear pattern of divergence across groups: information processed increases for large growth firms, albeit less dramatically than in the baseline version (note that the scale in the

Information panel in Figure 10 is much smaller than the corresponding one in 3) and the pattern of stagnation/decline for the others remain intact.

Figure 10: **Time variation in growth rates**.

The plots show a linear trendline fitted to components of price informativeness estimated using (16) with the persistence parameter held fixed at its estimated value for the 1960s.



D Marginal value of information

D.1 Derivations

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

$$\mathbb{E}[U_j^i|\mathcal{I}^i] = \frac{1}{2}\frac{(\mathbb{E}[V_{j1} - rP_{j1}|\mathcal{I}^i])^2}{Var[V_{j1} - rP_{j1}|\mathcal{I}^i]} = \frac{1}{2}\frac{(\Pi_j^i)^2}{\left(\frac{r}{r-g_j}\right)^2}(\Sigma_j^i)^{-1} \tag{30}$$

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

$$\mathbb{E}[U_j^i] = \mathbb{E}[\mathbb{E}[U_j^i|\mathcal{I}^i]] = \frac{1}{2}\frac{\mathbb{E}\left[(\Pi_j^i)^2\right]}{\left(\frac{r}{r-g_j}\right)^2}\ (\Sigma_j^i)^{-1} \tag{31}$$

$$= \frac{1}{2}\left[\frac{(\mathbb{E}\left[\Pi_j^i\right])^2 + Var(\Pi_j^i)}{\left(\frac{r}{r-g_j}\right)^2}\right]\ (\Sigma_j^i)^{-1}\ , \tag{32}$$

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

$$\mathbb{E}\left[\Pi_j^i\right] = \bar{\rho}\left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j \bar{x}_j \ . \tag{33}$$

$$Var(\Pi_j^i) = B_j^2 \Sigma_{jp} + \left(\frac{r}{r-g_j} - B_j\right)^2 (\Sigma_{jd} - \Sigma_j^i) - 2\left(\frac{r}{r-g_j} - B_j\right) B_j \Sigma_j^i \tag{34}$$

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 (32), 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

$$M_j = \frac{1}{2}\left[\bar{\rho}^2 \left(\frac{r}{r-g_j}\right)^2 \overline{\Sigma}_j^2 \bar{x}_j^2\right] + \frac{1}{2}\left[\left(1 - \frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2 \Sigma_{jp} + \left(\frac{\overline{\Sigma}_j}{\Sigma_{jd}}\right)^2 \Sigma_{jd}\right] \tag{35}$$

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 (22) 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 (15). 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 (22).