Have Financial Markets Become More Informative?

Jennie Bai, Thomas Philippon, and Alexi Savov [*]

April 2014

Abstract

The finance industry has grown, financial markets have become more liquid, and information technology allows arbitrageurs to trade faster than ever. But have market prices then become more informative? We construct a model with information acquisition and investment to link financial development, price informativeness, and allocational efficiency. We then use market prices to construct the model-implied informativeness measure, essentially the predictable component of future earnings based on market prices, going back to 1960. We find that informativeness has increased at long horizons (three to five years) and is unchanged at shorter horizons. The long-horizon increase is strongest among retail and services firms, among growth firms, and among firms with option listings.

---

1 Introduction

Fama (1970) writes, "The primary role of the capital market is allocation of ownership of the economy's capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions... under the assumption that security prices at any time 'fully reflect' all available information." In an ideal market, therefore, prices convey strong signals about productivity, and this information drives investment. To assess progress towards this ideal, we measure the information content of prices by using them to predict earnings and investment. We trace the evolution of price informativeness in the U.S. over the last five decades.

During this period, a revolution in computing has transformed finance: lower trading costs have led to a flood of liquidity.[1] Modern information technology delivers a vast array of data instantly and at negligible cost. Concurrent with these trends, the finance industry has grown, its share of GDP more than doubling. Within this context, we ask: Have market prices become more informative?

The first task is to come up with the right measure of informativeness. We build a model that combines Tobin's (1969) q-theory of investment with the noisy rational expectations framework of Grossman and Stiglitz (1980). When more information is produced, prices become stronger predictors of earnings. We define price informativeness to be the standard deviation of the predictable component of earnings based on prices and we show that it is directly related to welfare, as in Hayek (1945): information enables the efficient allocation of investment, which promotes economic growth.

We then construct our price informativeness measure by running yearly regressions of future earnings on current equity valuation ratios, conditional on current earnings and sector fixed effects. We look at one-, three-, and five-year forecast horizons as our analysis shows that this is the range in which the predictive power of market prices is manifested. These regressions compare firms in the same sector in a given year and ask whether those with

---

[1]In 1960, the typical share turned over once every five years; in 2012 it did so every three to four months.

higher market valuations tend to deliver subsequently higher earnings than those with lower valuations.

The answer is yes, market prices are informative about future earnings. We focus on trends. We find that price informativeness is unchanged at short horizon such as one year, but it has increased at long horizons of three to five years. In magnitudes, our long-horizon informativeness measure is about 50% higher in 2010 than in 1960.

In the cross section, we find that the increase in long-horizon informativeness is strongest among firms in the retail and services sector. It is also concentrated among growth firms, defined as those with above-median valuation ratios. These results suggest that markets have improved specifically in evaluating firms with less tangible sources of value.

Consistent with the hypothesis that the increase in long-horizon price informativeness is specifically related to trading in financial markets, we find that it is stronger among firms with traded options. The idea is that options provide informed traders with more efficient ways to trade on their information, thus facilitating price discovery.

For most of the paper, we restrict the analysis to S&P 500 firms. In contrast, running the same tests on the universe of stocks appears to show a decline in informativeness. We argue, however, that this decline is likely due to changing firm composition. Indeed, the observable characteristics of non-S&P 500 firms have changed dramatically, whereas those of S&P 500 firms have not. This motivates our focus on S&P 500 firms.

Two technical aspects of our methodology are worth noting. First, we work in real terms, deflating all nominal quantities by the GDP deflator. Absent this adjustment, informativeness would appear higher in the high-inflation period of the 1970s due to the multiplicative nature of inflation, masking any underlying trend.

Second, in order to look at long horizons, it is necessary to deal with firm delistings. More subtly, it is trends in delistings that are of key concern since it is trends in informativeness that are of key interest. Indeed, the merger waves of the 1980s and 1990s validate this concern, with one in five S&P 500 firms delisting within five years at the peaks of these waves. We

3

account for delistings in the following way: when a firm delisted, we use its delisting market value from CRSP to purchase a stake in a portfolio of stocks in the same two-digit industry. We then use the fraction of the earnings of the portfolio that corresponds to the value of this stake to fill in the delisted firm's earnings.

As further robustness, to more fully control for discount rate effects, we also run regressions of returns on market prices. Although noisy, return forecastability shows no trend, which suggests that the increase in price informativeness for earnings is not explained by a reduction in expected return variation across stocks.

As Hirshleifer (1971) pointed out, price informativeness comes in two varieties with different implications for capital allocation. Bond, Edmans, and Goldstein (2012) call these *real price efficiency* (RPE) and *forecasting price efficiency* (FPE). RPE refers to information that is genuinely new, or revelatory, for decision makers such as firm managers. FPE, on the other hand, is information that is available even in the absence of market prices and is merely reflected in them. It is only RPE that contributes to the efficient allocation of investment, though we note that different pieces of information are revelatory to different decision makers (managers, competitors, suppliers, customers, regulators, or others), so overall price informativeness remains of interest.

Nevertheless, the distinction between RPE and FPE is fundamental, and we seek to disentangle them. Our model offers a way of doing so. Since RPE increases the total amount of information available to managers, it increases the strength of the relationship between investment and future earnings. We call this investment informativeness and show that it is linked to welfare. We check whether investment informativeness has increased by running regressions of earnings on investment (the informativeness measure is again the standard deviation of the predictable component). We find it has not, and this is true for both R&D and CAPX. This result suggests that RPE has remained stable, though we note that investment is less well measured than prices.

Looking at the relationship between market prices and investment, we find that prices have

become stronger predictors of R&D. This is not true of CAPX, likely due to the decreasing importance of CAPX for firms in our sample. The result on prices and R&D provides independent support for our main finding that long-horizon price informativeness has increased in a test that does not use earnings.

As a final exercise, we construct a model-implied measure of the unit cost of information production in markets. Using our long-horizon estimates, we find that information costs have declined steadily for S&P 500 firms over the last fifty years.

In the Appendix, we show that our results are robust to adjusting for debt in calculating the valuation ratio. We also report a parallel set of results for corporate bond markets, using a firm's bond spread as the valuation measure. We find weaker informativeness than with equities, but the trends over time are broadly consistent.

The rest of this paper proceeds with an overview of the literature, followed by exposition of the model, empirical results, and concluding remarks.

2 Related literature

Over the last 30 years, the U.S. financial sector has grown six times faster than GDP. At its peak in 2006, the financial sector contributed 8.3% to U.S. GDP compared to 4.9% in 1980 and 2.8% in 1950 (see Philippon (2008) and Greenwood and Scharfstein (2012) for detailed discussions). A classic literature studies the impact of the financial sector on economic growth (Levine 2005 provides a survey).[2] Greenwood and Jovanovic (1990), among others, argue that finance accelerates innovation and growth by producing information that improves the allocation of resources.

More recently, the financial crisis of 2007–2009 led to a challenge of the idea that finance promotes growth. Rajan (2005) suggests that financial complexity raises the probability of a

---

[2]In his survey of the literature on financial development and growth, Levine (2005) splits the role of the financial industry into five broad functions: 1) information production about investment opportunities and allocation of capital; 2) mobilization and pooling of household savings; 3) monitoring of investments and performance; 4) financing of trade and consumption; 5) provision of liquidity, facilitation of secondary market trading, diversification, and risk management. Our focus is on (1).

catastrophic meltdown. Gennaioli, Shleifer, and Vishny (2012) show that in the presence of neglected tail risks, financial innovation can increase fragility. Bolton, Santos, and Scheinkman (2011) provide a model in which rents in the financial sector attract an excessive share of human capital. By relating financial sector output to its cost, Philippon (2012) finds that the unit cost of financial intermediation has increased in recent decades.

It is difficult to discern a clear relationship between financial sector growth and aggregate growth in the U.S. data. Aggregate growth is driven by many factors other than finance. A more powerful test exploits cross-sectional variation. In this line, Rajan and Zingales (1998) and Morck, Yeung, and Yu (2000) use the cross-country variation in financial development. Our approach is to consider firm-level variation, which allows us to study the evolution of markets in the U.S. over time.

We contribute to the finance-and-growth literature by examining the information channel empirically. We measure the extent to which market valuations differentiate firms that will deliver high profits from those that will not. We define price informativeness to be the resulting predictable component of profitability and we track it over five decades. To closely examine resource allocation, we also relate prices to investment.

A large literature with seminal papers by Grossman and Stiglitz (1980), Glosten and Milgrom (1985), Kyle (1985), and Holmström and Tirole (1993) studies the incentives of traders to produce new information. A general result is that prices must be somewhat confounding, or "noisy", to compensate traders for the cost of mining new information. As financial technology develops and this cost shrinks, the information content of prices increases. Under this proposition, we can back out the cost efficiency of the information production sector from the observed level of informativeness.

Bond, Edmans, and Goldstein (2012) survey the literature on information production, emphasizing the challenge of separating the genuinely new information produced in markets, *real price efficiency* (RPE), from what is already known and merely reflected in prices, or *forecasting price efficiency* (FPE). We follow their lead and seek to disentangle the two, while

also looking at overall price informativeness. Our model allows us to do so by looking at the relationship between investment and earnings.

A number of papers provide empirical evidence for the link between prices and investment. Chen, Goldstein, and Jiang (2007) show that the price sensitivity of corporate investment is stronger when prices contain information (using microstructure measures) that is not otherwise available to firm managers. Sunder (2004) and Baker, Stein, and Wurgler (2003) show that a stock price increase eases the financing constraints of firms and enables them to increase investments. Turley (2012) exploits a regulatory shock to show that lower transaction costs increase short-term price informativeness. Bond, Edmans, and Goldstein (2012) provide additional references.

On the theoretical side, papers on the link between financial markets and investment include Fishman and Hagerty (1992), Leland (1992), Khanna, Slezak, and Bradley (1994), Boot and Thakor (1997), Subrahmanyam and Titman (1999), Fulghieri and Lukin (2001), Bond, Goldstein, and Prescott (2010), Kurlat and Veldkamp (2012), Ozdenoren and Yuan (2008), Goldstein, Ozdenoren, and Yuan (2013). As Dow and Gorton (1997) shows, it is possible for prices to accurately forecast firm values without helping managers make better investment decisions.

Our contribution to this literature is twofold. First, we construct theory-based and welfare-grounded measures of price informativeness and we distinguish RPE from FPE. Second, we trace the evolution of these measures over a long period characterized by unprecedented growth in information technology and market liquidity. We therefore provide a broader perspective on the information channel in the U.S.

Price informativeness is also affected by disclosure, and changes in disclosure have received strong attention in the accounting literature (see the surveys by Healy and Palepu (2001) and Beyer, Cohen, Lys, and Walther (2010)). Although major regulatory actions such as Reg. FD in 2000 and Sarbanes-Oxley in 2002 have been implemented, the question of their effects

on disclosure is unsettled.[3] There is also conflicting evidence on whether Reg. FD led to a decrease in information asymmetry among investors.[4] It is even less clear how such disclosure regulation has affected price informativeness. Our main tests do not provide a way to explicitly control for changes in disclosure. However, we do not see any abrupt changes around particular regulatory initiatives such as Reg FD in 2000 or Sarbanes-Oxley in 2002. We also provide cross-sectional results, for example using option listings, that hold disclosure rules fixed.

A second related strand of the accounting literature studies value relevance, the impact of accounting metrics on market values (Holthausen and Watts 2001). Our approach is to measure the extent to which market values predict—as opposed to react to—accounting metrics, specifically earnings and investment.

While our focus is on long-term trends in price informativeness, other studies consider business-cycle variation in information production. For example, in Van Nieuwerburgh and Veldkamp (2006), information production rises in booms. This dynamic is absent from our model, but our time series informativeness measure do fluctuate somewhat at business cycle frequencies (for example, informativeness drops sharply at the end of the NASDAQ boom in 2000).

In sum, our paper lies at the intersection of the finance-and-growth and information-production literatures. We believe that measuring the information content of prices helps to assess the social value of a growing financial sector.

---

[3]Heflin, Subramanyam, and Zhang (2003) find no evidence of increased volatility around earnings announcements after Reg. FD, or significant deterioration in analyst forecast accuracy, which suggests that the information available to market participants was not reduced. In contrast, Wang (2007) reports that after the passage of Reg. FD, some firms cut back on issuing earnings guidance. However, Bushee, Matsumoto, and Miller (2004) provide evidence that disclosure remained constant or even increased after the passage of Reg. FD. Kothari, Ramanna, and Skinner (2009) find that firms reduced their withholding of bad news relative to good news after Reg. FD was implemented.

[4]Bushee, Matsumoto, and Miller (2004), Gintschel and Markov (2004), and Eleswarapu, Thompson, and Venkataraman (2004), find a decrease in bid-ask spreads after Reg. FD. Others find the opposite: Sidhu, Smith, Whaley, and Willis (2008) suggest that the adverse selection component of the bid-ask spread increased after Reg. FD.

3 Model

We link financial development, information production, investment, and welfare by combining the noisy rational expectations framework of Grossman and Stiglitz (1980) with Tobin's (1969) q-theory of investment. Traders produce information that is aggregated in markets and used by managers in setting investment. In turn, managers produce internal information that is revealed to market participants through investment. We highlight the role of prices in promoting efficient investment, or *real price efficiency* (RPE), and show how to distinguish it from *forecasting price efficiency* (FPE). Our model generates comparative statics on the relationships between financial development, fundamental uncertainty, and price informativeness that we take to the data in the following sections.

Consider an economy that evolves over three dates, $t = 0, 1, 2$. At date 0, traders decide on the quality of their information. Trading and corporate investment take place simultaneously at date 1. Final payoffs are realized at date 2. We develop and solve the model from date 2 backwards.

A. Investment

On date 2, the value of the firm's output is $(1 + z)\left(\overline{k} + k\right)$ where $\overline{k}$ denotes assets in place, k is the amount invested at time 1 and $z \sim N\left(0, h_z^{-1}\right)$ is a random productivity shock. The cost of investment is $k + \frac{\gamma}{2}k^2$, where the quadratic component captures adjustment costs. We normalize the interest rate to zero, so the value of the firm conditional on the realization of z is simply[5]

$$v\left(z, k\right) \;=\; \overline{k} + z\left(\overline{k} + k\right) - \frac{\gamma}{2}k^2. \tag{1}$$

---

[5]For simplicity we have normalized the average productivity to one. Note that k can be negative, which simply means that the firm sells some of its existing capital.

When the manager chooses k at date 1, she has access to two sources of information. She observes the private signal $\eta = z + \epsilon^\eta$, and the (endogenous) market value of her company, which, as we show later, can be summarized by a sufficient statistic $\theta = z + \epsilon^\theta$. The disturbances ϵ^θ and ϵ^η are orthogonal to each other and to z, and we denote by h_η and h_θ the precisions of the signals.[6] The table below summarizes the information structure of the model.

Agent	Action	Direct information	Inferred information
Manager	Invests k	$\eta = z + \epsilon^\eta$	θ from p
Trader	Buys x shares	$s = z + \epsilon^s$	η from k

Given the available information, the manager forms a conditional estimate of productivity

$$\mathbb{E}\left[z|\theta,\eta\right] = \frac{h_\theta\theta + h_\eta\eta}{h_z + h_\theta + h_\eta}. \tag{2}$$

The manager chooses investment to maximize the value of the firm. The optimal investment policy satisfies the first order condition

$$k^\star(\theta,\eta) = \frac{1}{\gamma}\mathbb{E}\left[z|\theta,\eta\right]. \tag{3}$$

As in classical q-theory, investment is increasing in expected productivity, and from (2) we know that the response is stronger when signals are more precise. Information facilitates efficient investment. Maximized firm value is

$$\mathbb{E}\left[v^\star|\theta,\eta\right] = (1 + \mathbb{E}\left[z|\theta,\eta\right])\overline{k} + \frac{1}{2\gamma}\mathbb{E}\left[z|\theta,\eta\right]^2. \tag{4}$$

Taking unconditional expectations (or aggregating over many ex-ante identical firms), and

---

[6] In other words, we define $h_\eta = 1/\sigma_\eta^2$ where σ_η is the standard deviation of ϵ^η, and similarly for θ.

using the fact that the unconditional mean of z is zero, we see that aggregate wealth is

$$\mathbb{E}\left[v^{\star}\right] \;=\; \overline{k} + \frac{1}{2\gamma}\mathbb{V}\left(\mathbb{E}\left[z|\,\theta,\eta\right]\right), \tag{5}$$

where $\mathbb{V}\left(\mathbb{E}\left[z|\,\theta,\eta\right]\right)$ measures total informativeness in the economy. We can state the following result:

Proposition 1. *Aggregate wealth is increasing in total informativeness $\mathbb{V}\left(\mathbb{E}\left[z\mid\theta,\eta\right]\right)$, which is given by*

$$\mathbb{V}\left(\mathbb{E}\left[z\mid\theta,\eta\right]\right) = \frac{h_{\theta} + h_{\eta}}{h_{z} + h_{\theta} + h_{\eta}}\sigma_{z}^{2}. \tag{6}$$

Proof of Proposition 1. The claim follows from Equation (5) and the formula is an application of Equation (34) in Appendix A. $\qquad\square$

Equation (5) says that aggregate firm value is the sum of existing capital $\overline{k}$ plus the value of growth options. Information increases the value of the firm's growth options via the manager's ability to respond by optimizing investment. Aggregate wealth increases with the quantity of information available to managers when they make investment decisions. Since managers learn from their own experience and from prices, the key measure is the dispersion of conditional expected productivity conditional on private signals η and public signals θ. This dispersion is also reflected in the distribution of investment across firms.

A useful result for our empirical work is that total informativeness can be calculated as the predicted variation (the coefficient times the standard deviation of the regressor) from a regression of future productivity z on current investment k. Since our focus is on markets, we are interested in the contribution coming from θ. A key challenge lies in extracting θ from prices since prices also depend on η. In other words, we seek to separate RPE (managers learning from prices) from FPE (investors learning from managers). In the next section, we show that this can be achieved by running separate regressions of earnings on investment and prices.

B. Trading

Informed demand and market clearing. The market signal θ is produced by investors and transmitted via prices. On date 1, a measure-m continuum of informed traders receive a common signal $s = z + \epsilon^s$ with precision h_s. Traders observe the price and the investment decision k^*, which reveals η given the price.[7] We assume a common signal because it is not crucial for our analysis that traders learn from each other via prices. What is crucial is that managers learn from prices (to capture RPE) and that traders learn from investment (to capture FPE).

Informed traders choose their demand x for the firm's shares to maximize a standard mean-variance objective:

$$\max_x \; \mathbb{E}\left[U\,|\,s, \eta\right] \;\; = \;\; x\left[\mathbb{E}\left[v\,|\,s, \eta\right] - p\left(k + \overline{k}\right)\right] - \frac{\alpha}{2}x^2\mathbb{V}\left[v\,|\,s, \eta\right], \tag{7}$$

where p is the price per unit of book value i.e, Tobin's q. We normalize the supply of shares to 1, so x is both the number of shares and the fraction of the firm owned by informed traders. The assumption that s is common among traders allows us to drop θ from the conditioning set. The optimal portfolio demand of informed traders is

$$x \;\; = \;\; \frac{\mathbb{E}\left[v\,|\,s, \eta\right] - p\left(k + \overline{k}\right)}{\alpha\mathbb{V}\left[v\,|\,s, \eta\right]}. \tag{8}$$

Following Grossman and Stiglitz (1980) we assume the presence of uninformed noise traders who demand $1 + u/\left(\overline{k} + k\right)$ shares with $u \sim N\left(0, \sigma_u^2\right)$ and $\sigma_u > 0$.[8] The market clearing

---

[7]Assuming that investment is public preserves the linearity of the traders' filtering problem, which makes the model tractable. If it is not, the model may overstate the level of the informativeness of prices. Since our focus is instead on trends, factors such as changes in disclosure can potentially affect our results. To get at this issue, we can look at the periods surrounding significant regulatory actions such as Reg FD in 2000. We also provide cross-sectional results using option listings that hold disclosure rules fixed.

[8]The assumption that average demand is one is only here to simplify notation. The assumption that the noise is scaled by $\overline{k} + k$ makes it comparable to the demand of informed traders. One can think of noise traders as behaving like informed traders but based on the wrong signal u.

condition is then $mx + u / \left(\overline{k} + k \right) = 0$, and this leads to equilibrium prices

$$p = \frac{\mathbb{E}\left[v \mid s, \eta\right]}{k + \overline{k}} + \frac{\mathbb{V}\left[v \mid s, \eta\right]}{\left(k + \overline{k}\right)^2} \frac{\alpha}{m} u = \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}} + \mathbb{E}\left[z \mid s, \eta\right] + \mathbb{V}\left[z \mid s, \eta\right] \frac{\alpha}{m} u. \tag{9}$$

The second step uses Equation (1). The conditional expected productivity is $\mathbb{E}\left[z \mid s, \eta\right] = \frac{h_s s + h_\eta \eta}{h_z + h_s + h_\eta}$ and the residual variance is $\mathbb{V}\left[z \mid s, \eta\right] = \frac{1}{h_z + h_s + h_\eta}$. Therefore we can write the market clearing price as

$$p = \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}} + \frac{h_s s + h_\eta \eta + \frac{\alpha}{m} u}{h_z + h_s + h_\eta}. \tag{10}$$

The first term is the value of assets in place net of investment costs. Since k is observable, this first term is known by all agents. Equation (10) shows that prices contain valuable information about the fundamental z. As we have argued, however, it is crucial to distinguish how managers learn from prices and how an uninformed econometrician learns from prices.

Price informativeness: From Equation (10), we see that the price is proportional to $h_s s + h_\eta \eta + \frac{\alpha}{m} u$. Therefore, the price alone reveals a signal $z + \frac{h_s \epsilon^s + h_\eta \epsilon^\eta + \frac{\alpha}{m} u}{h_s + h_\eta}$ about z. The precision of this signal is

$$h_p = \frac{(h_s + h_\eta)^2}{h_s + h_\eta + (\alpha/m)^2 \sigma_u^2}. \tag{11}$$

We can therefore construct the conditional expectation $\mathbb{E}\left[z \mid p\right]$ and our measure of overall price informativeness

$$\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right) = \frac{h_p}{h_p + h_z} \sigma_z^2. \tag{12}$$

13

We see that, in the limit, this measure converges to perfect information. Since $\lim_{h_s \to \infty} h_p = \lim_{h_\eta \to \infty} h_p = \infty$, we have

$$\lim_{h_s \to \infty} \mathbb{V}\left(\mathbb{E}\left[z|p\right]\right) \;=\; \lim_{h_\eta \to \infty} \mathbb{V}\left(\mathbb{E}\left[z|p\right]\right) \;=\; \sigma_z^2. \tag{13}$$

Price informativeness (12) forms the basis of our empirical tests. It is identified as the predicted variation (coefficient times standard deviation of the regressor) of a regression of earnings z on prices p (both scaled by assets). We see from (11) that informativeness comes from two sources. The first is that prices reveal information about the traders' signal s. This information is useful to managers and affects economic decisions and real allocations. It is therefore associated with *real price efficiency*, or RPE. The second source of information is that managers' actions (here investment) reveal their information η, which is then reflected in the price, thanks to informed traders. This information is not useful to managers and does not affect real allocations. It is simply a reflection of *forecasting price efficiency*, or FPE. The third piece is noise trading, which simply decreases price informativeness.

Quantifying RPE: Managers orthogonalize prices with respect to their internal information to extract the revelatory component θ, the source of RPE. More precisely, since they already know η, managers can extract $h_s s + \frac{\alpha}{m} u$ from the price in Equation (10), so we can define the sufficient statistic θ as

$$\theta \;\equiv\; s + \frac{1}{h_s}\left(\frac{\alpha}{m}\right) u. \tag{14}$$

The precision of θ is given by

$$\frac{1}{h_\theta} \;=\; \frac{1}{h_s} + \frac{1}{h_s^2}\left(\frac{\alpha}{m}\right)^2 \sigma_u^2. \tag{15}$$

14

From Equation (15), we see that RPE falls to zero when traders collect no information: $\lim_{h_s \to 0} h_\theta = 0$. RPE approaches full information when traders have infinite precision, $\lim_{h_s \to \infty} h_\theta = \infty$, for two reasons: ($i$) s becomes very informative; and (ii) the residual risk becomes small so informed traders trade very aggressively.

Separating RPE and FPE: Since prices are noisy while investment is not, traders have more information than managers, and managers have more information than prices. This observation allows us to disentangle RPE and FPE.

Proposition 2. *We can rank the information sets of an econometrician observing only prices, $\{p\}$, a manager or an econometrician observing prices and investment, $\{\theta, \eta\}$, and an informed trader, $\{s, \eta\}$, relative to the upper bound on total information σ_z^2 as follows:*

$$\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right) \quad < \quad \mathbb{V}\left(\mathbb{E}\left[z \mid \theta, \eta\right]\right) \quad < \quad \mathbb{V}\left(\mathbb{E}\left[z \mid s, \eta\right]\right) \quad < \quad \sigma_z^2. \tag{16}$$

Furthermore, $\frac{\partial}{\partial h_s}\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right) = \frac{\partial}{\partial h_\eta}\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right)$ and $\frac{\partial}{\partial h_s}\mathbb{V}\left(\mathbb{E}\left[z \mid s, \eta\right]\right) = \frac{\partial}{\partial h_\eta}\mathbb{V}\left(\mathbb{E}\left[z \mid s, \eta\right]\right)$, whereas $\frac{\partial}{\partial h_s}\mathbb{V}\left(\mathbb{E}\left[z \mid \theta, \eta\right]\right) < \frac{\partial}{\partial h_\eta}\mathbb{V}\left(\mathbb{E}\left[z \mid \theta, \eta\right]\right)$.

Proof of Proposition 2. See Appendix A. $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ $\square$

The first part of Proposition 2 can also be stated as a ranking of precisions, $h_p < h_\theta + h_\eta < h_s + h_\eta < \infty$. The first inequality is due to the fact that by supplementing prices with investment, more of the noise in prices can be filtered out. The second is due to residual noise, and the third to residual uncertainty.

The second part of Proposition 2 shows that the information content of prices is driven equally by information produced in financial markets and inside the firm. The information available to the manager, however, depends less strongly on market-sourced than internally-sourced information. The reason for this is that prices are noisy and so part of the information produced in markets is lost to the manager.

Proposition 2 gives us a way to disentangle RPE and FPE by showing that price informativeness and investment informativeness respond differently to these two components of the overall flow of information.

Noise trading and expected returns: We are also interested in measuring expected returns as they allow us to control for changes in noise trading. Let $r = \frac{v}{\overline{k}+k} - p$ be the dollar return per share. In Appendix A, we show that

$$\mathbb{E}\left[r\,|\,p\right] \;=\; -\frac{\left(\alpha/m\right)^2 \sigma_u^2}{\left(\alpha/m\right)^2 \sigma_u^2 + \left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)}\left(p - \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}}\right). \qquad (17)$$

From here, it is straight-forward to compute the predicted variation of returns $\mathbb{V}\left(\mathbb{E}\left[r\,|\,p\right]\right)$. These calculations show that return forecastability regressions allow us to detect changes in the level of noise trading.

So far, we have derived welfare-based measures of informativeness and developed techniques for separating the revelatory from the forecasting component of prices. Our final task is to link informativeness to financial development.

C. Information acquisition

The trader's demand in (8) gives her date-1 conditional expected utility

$$\mathbb{E}\left[U\,|\,s,\eta\right] \;=\; \frac{1}{2\alpha\mathbb{V}\left[v\,|\,s,\eta\right]}\left(\mathbb{E}\left[v\,|\,s,\eta\right] - p\left(k + \overline{k}\right)\right)^2 \;=\; \frac{\alpha}{2}\mathbb{V}\left[z\,|\,s,\eta\right]\left(\frac{u}{m}\right)^2, \qquad (18)$$

where in the second equality we substitute for v and p from Equations (1) and (9). The trader's utility increases in the amount of noise trading scaled by the quantity of informed agents. Using $\mathbb{V}\left[z\mid s,\eta\right] = \frac{1}{h_z + h_s + h_\eta}$ and taking unconditional expectations at time 0, we get

$$\mathbb{E}\left[U\right] \;=\; \frac{\alpha}{2}\frac{\sigma_u^2/m^2}{h_z + h_s + h_\eta}. \qquad (19)$$

16

Let $\psi/2$ be the cost of becoming an informed trader. For simplicity, we model advances in information technology at the extensive margin, i.e. the cost of becoming informed.[9] Free entry then requires

$$\sigma_u^2/m^2 \;=\; (h_z + h_s + h_\eta)\,\frac{\psi}{\alpha}. \tag{20}$$

With endogenous information, we get total price informativeness and RPE

$$h_p \;=\; \frac{h_s + h_\eta}{1 + \left(1 + \frac{h_z}{h_s + h_\eta}\right)\alpha\psi}, \qquad\qquad h_\theta \;=\; \frac{h_s}{1 + \left(1 + \frac{h_z + h_\eta}{h_s}\right)\alpha\psi}. \tag{21}$$

We can therefore state the following proposition:

Proposition 3. *A fall in information costs ψ and a rise in uncertainty h_z^{-1} each lead to an increase in both RPE h_θ and total price informativeness h_p.*

In the next section, we measure total informativeness empirically and examine its evolution over time.

4 Data and methodology

We obtain stock prices from CRSP. The test on option listings uses listing dates from the CBOE. All accounting measures are from COMPUSTAT. The GDP deflator, which we use to adjust for inflation, is from the Bureau of Economic Analysis. Our main sample period is from 1960 to 2013 at an annual frequency. We focus on the main aspects of our methodology, with the remaining detail in Appendix B.

In most tests, we limit attention to S&P 500 non-financial companies, which represent the bulk of the U.S. non-financial corporate sector. As we show, the characteristics of these firms

---

[9]We have also worked out the case where ψ captures the cost of obtaining more precise information. The results are similar, but the derivation is longer since we have to specify what happens when a trader obtains a more precise signal that her competitors. To avoid these unnecessary complications, we use the extensive margin approach.

have remained relatively stable over time, allowing for a cleaner comparison of the information content of their market prices over time. We also report results for the universe of non-financial firms, whose composition has changed substantially.

Our main equity valuation measure is the log-ratio of market capitalization to total assets. Taking logs mitigates skewness and is generally betterbehaved. We also show robustness results in Appendix B using the book value of long-term debt to control for leverage effects. We use stock prices from the end of March and accounting variables from the end of the previous fiscal year, typically December. This ensures that market participants have access to the accounting variables which we use as controls.

We measure future earnings as future EBIT scaled by today's total assets. Scaling by today's assets and not future assets allows firms to increase their profits by growing, consistent with our model. We use today's EBIT over assets as a control. We similarly measure future investment as future R&D or CAPX over today's assets, and current investment as today's R&D or CAPX over today's assets.

Since we are interested in real informativeness, we deflate all nominal quantities by the GDP deflator. Inflation impacts our left-side variables as they are ratios of future quantities over today's assets. Without adjusting, the high inflation of the 1970s potentially biases our informativeness measure upward as inflation is multiplicative.

We focus on the one-, three-, and five-year horizons motivated by results in Section 5.A below, which show that this is the range in which the information content of prices for earnings is maximized.

In order to consider long horizons, however, we must account for firm delistings. Delistings can potentially bias the level of our informativeness measure if market valuations and delistings are correlated. Since we are looking for trends, it is the change in delisting rates that is of the main concern.

The top two panels of Figure 1 show the number of S&P 500 firms delisted within one, three, and five years at a given point in our sample. Whereas the one-year delisting rate is low

and stable, the three-year and especially the five-year rate are high and, more importantly, appear to increase with pronounced waves in the 1980s and 1990s. Since most S&P 500 delistings (645 out of 749 in our sample) occur when a firm is acquired, this pattern naturally coincides with passing merger waves.

Figure 1 about here.

We deal with delistings as follows. When a firm is delisted during our forecasting window, we record its delisting capitalization (delisting price plus dividend times shares outstanding) from CRSP. We construct a portfolio of all the remaining firms in the same industry defined at the two-digit SIC code, and record its total earnings over time. We calculate the fraction of the total value of this industry portfolio that can be purchased with the delisting capitalization of the delisted firm. We then fill in the delisted firm's missing earnings with the same fraction of the industry portfolio's total earnings. We do the same for investment. The interpretation of this procedure is that when a firm is delisted, we invest the delisting proceeds in a portfolio of firms in the same industry and use the earnings accruing in this portfolio as a stand-in for the earnings of the delisted firm, which avoids looking ahead.

Table I about here.

Table I presents summary statistics for our sample. S&P 500 firms are as expected bigger and typically more profitable than the universe of firms. They invest more in absolute terms, but not relative to assets.

The middle left panel of Figure 1 shows the distribution of our equity valuation measure, the log-ratio of market capitalization to total assets ($\log M/A$), over time for S&P 500 non-financial firms. We see that while the level of valuations has gone up and down with the market, the cross-sectional distribution of valuations has remained stable.

The middle right panel of Figure 1 shows that the cross-sectional distribution of profitability (E/A) has also remained stable for S&P 500 firms. By contrast, R&D expenditure (bottom

left) has become more skewed, whereas CAPX (bottom right) has become more compressed. We return to the implications of the changing nature of investment in Section 5.G.

5 Empirical results

For our main results, we construct time series of predicted variations of equity prices for earnings, investment, and returns, and of investment for earnings. We control for current earnings and investment to avoid attributing obvious public information to prices. We include sector fixed effect as a simple control for discount rates, while we also look directly at returns later in the paper. We look for trends in these series as evidence of changing informativeness.

A. Informativeness and horizon

Our first task is to pick the right forecasting horizon. To do so, we assess equity price informativeness unconditionally at horizons up to ten years by running the regressions

$$
\frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1} \right) \times \left(\mathbf{1}_t \right) + \epsilon_{i,t} \qquad (22)
$$

for $k = 1, \ldots 10$ years, where $\mathbf{1}_t$ is the year fixed effect and $\mathbf{1}_{SIC1}$ is the sector (one-digit SIC code) fixed effect. When earnings are missing for any year $t+k$, we use the procedure outlined in Section 4 to fill them in. Price informativeness is measured as the predicted variation from this regression, namely $a_t \times \sigma_t (\log M/A)$. In this section, we average this predicted variation over time and look across horizons.

Figure 2 about here.

Figure 2 plots the resulting average informativeness by horizon, presented as a fraction of the overall standard deviation of ex post earnings. We see that equity prices can account for up to one third of the dispersion of ex post earnings, and that is conditional on current

earnings. The forecasting contribution of prices is 25% at one year, and 35% by three to five years at which point it levels off and eventually starts to decline.

These results suggest that investors are contributing signals that are realized three to five years in the future with persistent effects beyond that. Whereas next year's earnings can be predicted with this year's earnings, market prices are most useful at medium to long horizons. Based on these findings, we conduct the remaining analysis at the one-, three-, and five-year forecast horizons.

B.   Market prices and earnings

We now turn to analyzing equity price informativeness over time by running our benchmark regression (22), this time restricting attention to $k = 1$, 3, and 5. The results are presented in Figure 3 and the first three columns of Table II.

Figure 3 and Table II about here.

Looking at Figure 3, the two left panels plot the coefficients a_t over time. The middle panels display the equity market predicted variation, given by the product of the forecasting coefficient a_t and the cross-sectional standard deviation of the valuation ratio, $\sigma_t (\log M/A)$. The predicted variation measures the size of the predictable component of earnings that is due to prices, or price informativeness in the model. The two right-side plots show the contribution to the regression R^2 from including market prices.[10]

As shown in the figure, market prices are positive predictors of future earnings at both short and long horizons. The forecasting coefficient, predicted variation, and marginal R^2 are all a bit higher at the longer horizon. The 3-year and 5-year estimates are also somewhat noisier than the 1-year estimate, but all comfortably above zero. We note a drop in the predictive power of prices at the end of the NASDAQ boom in 2000, but this drop is short-

---

[10]Specifically, the marginal R^2 is defined as the difference between the R^2 from the full forecasting regression and the R^2 from a regression that omits $\log M/A$ as a predictor.

lived. The forecasting coefficients remain flat throughout our sample at one year ($k =1$), but they increase somewhat at three and five years ($k = 3$ and 5).

Our key result comes from the middle panels, which plot price informativeness. While we see no evidence of increasing informativeness at one year, there is a clear positive trend at three and five years.[11] That is, the extent to which equity markets distinguish firms that will deliver high or low earnings three to five years in the future has increased over time.

The first three columns of Table II present a formal test. The results confirm the pattern in Figure 3. The table shows coefficient estimates from time-series regressions of the predicted variation of equity prices for earnings on a constant and decade-based dummy variable. The baseline decade is the 1960s. At each horizon, the constant is positive and significant and larger than the slope coefficients, confirming that valuations and earnings are on average positively related.

At one year, the coefficients on the decade dummies are small and insignificant, confirming that one-year informativeness has remained constant throughout our sample. At three and five years, however, we see coefficients that are almost invariably increasing, as well as significant (with Newey-West standard errors) in the latter decades of the sample. The point estimates suggest that while flat at one year, equity price informativeness at three and five years has increased by about 50% since 1960.

C. Price informativeness in the cross section

In this section we examine price informativeness across industry sectors and across valuation levels, all within the S&P 500. The results are presented in Figure 4.

Figure 4 about here.

The top four panels of Figure 4 look at price informativeness at three and five years for manufacturing firms and for retail and services firms. In the case of manufacturing firms, we

---

[11]Figure B.1 in the appendix shows that these results are robust to adjusting for debt by adding the book value of debt to the market value of equity when calculating the valuation ratio.

see only a modest though well-measured increase in price informativeness at three and five years. Retail and services firms, on the other hand, show a stronger if noisier trend. Thus the rise in price informativeness at long horizons is concentrated in the retail and services sector.

The bottom panels of Figure 4 split firms into two groups: those with above-median and below-median valuation ratios. The idea is that the importance of growth options to firm value may have increased over time and that growth options may be more difficult to value than assets in place. The valuation ratio serves as a proxy.

Surprisingly, it is actually the high-valuation firms that have higher price informativeness. Moreover, informativeness has remained flat for the low-valuation group but it has grown for the high-valuation group.

The results in this section show that the improvement in price informativeness is concentrated among groups of firms that are a priori more difficult to value, non-manufacturing firms and growth firms.

D. Comparison between S&P 500 firms and all firms

In this section, we compare the price informativeness of S&P 500 firms to that of the broader CRSP universe. The results are presented in Figure 5. The top left panel shows a dramatic difference in fundamental uncertainty between the two groups. Starting in the 1970s, the dispersion in earnings across all firms increases dramatically until it levels off in the mid 1980s at about four times the level observed among S&P 500 firms. This period coincides with the rise of NASDAQ. The tech boom of the late 1990s sees a second, smaller increase in earnings dispersion.

Figure 5 and Table III about here.

The top right panel of Figure 5 shows that as the earnings dispersion of all firms has increased, so has their price dispersion. In contrast, S&P 500 firms show only modest evidence of increased price dispersion, principally around 2000.

In our model, holding noise constant, increased price dispersion is associated with more informative prices and higher welfare. However, we see from the bottom two panels of Figure 5 that for all firms, price informativeness drops steadily at three years and a bit more modestly at five years. Table III confirms these results. Thus, for all firms, we actually observe a decline in price informativeness.

The apparent decline in price informativeness for all firms is not explained by the increased uncertainty seen in the rise of earnings dispersion. In our model, higher earnings dispersion actually increases the equilibrium level of price informativeness as it increases the supply of information. Instead, it must be some other characteristic related to the cost of information that is responsible. We view these results as motivating our focus on S&P 500 firms, whose observable characteristics have remained stable.

E. Option listing and informativeness

Our results so far show that price informativeness among S&P 500 firms has grown at long horizons. It has decreased among all firms, likely due to changing firm characteristics. We are left with the possibility that even S&P 500 firms, though their observable characteristics appear stable, may have changed along some unobservable dimension that might cause price informativeness to rise for reasons unrelated to financial markets.

To check this possibility, we examine cross-sectional instead of time-series variation in a firm's exposure to financial markets. Specifically, we compare S&P 500 firms that have options listed on the CBOE to those that do not. Option trading on the CBOE began in 1973. Option market contributes to price discovery by increasing liquidity and providing embedded leverage as well as a low-cost way to conduct short selling.

Table IV about here.

To run the comparison, we calculate the predicted variation of prices for earnings based on regression (22) separately for listed and unlisted stocks and take their difference. We then

regress this difference on decade-based dummies. The negative constant suggests that listed firms actually had lower price informativeness in the 1970s. As the positive and significant coefficients in subsequent decades show, however, price informativeness has since risen for listed firms relative to unlisted firms so that by the end of the sample the gap is actually reversed.

We therefore see that the increase in price informativeness is relatively higher among firms with traded options. This result is consistent with the interpretation that greater liquidity and trading are at least in part responsible for the observed increase in price informativeness.

F. Investment and earnings

Our main finding so far is that price informativeness, while flat at short horizons, has increased at long horizons. This could be due to either greater forecasting power (FPE), or greater production of new information (RPE). As our model shows, we can separate the two by looking at investment informativeness, the predicted variation of investment for earnings. All else equal, higher FPE should leave investment informativeness unchanged, whereas higher RPE should cause it to rise.

One challenge is that investment unlike prices is measured with error. It is enough for us to assume that the error with which we observe investment is constant. At the same time, the rise in importance of R&D during our sample may have increased the measurement error of investment since R&D is arguably less well-measured than CAPX. [12]

To measure investment informativeness, we regress future earnings on current R&D as well as CAPX. We include current earnings as a control together with our usual sector-year fixed effects. Specifically, the R&D regression has the form:

$$\frac{E_{i,t+k}}{A_{i,t}} \;=\; a_t \left(\frac{R\&D_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1} \right) \times \left(\mathbf{1}_t \right) + \epsilon_{i,t},$$

[12]In the next section we run regressions of investment on prices so that by placing investment on the left side of the regression, the impact of measurement error is mitigated.

for $k = 1, 3$, and 5. The CAPX regression is analogous. We focus on the predicted variation $a_t \times \sigma_t\, (R\&D/A)$ (or $a_t \times \sigma_t\, (CAPX/A)$), and we report the coefficients a_t and the contribution of investment to the R^2 of the regression for completeness.

Figures 6 and 7 about here.

Figure 6 documents a generally positive relationship between R&D investment and future earnings in the next 3-5 years, evidenced by the significance of α coefficients. Firms that undertake more R&D tend to be more profitable in the future, even after controlling for current profitability. By contrast, Figure 7 shows little evidence of a correlation between capital expenditure and future earnings except for a few spikes. Under both tangible and intangible investment measures, however, the trend of their predictable variations on earnings remains flat, either at short or long horizons. These inferences are confirmed in the regressions presented in Table V.

Table V about here.

The key result in Figures 6 and 7 and Table V is that unlike price informativeness, investment informativeness has not increased, even at long horizons.[13] This suggests that RPE viewed from inside the firm has remained stable.

G.   Market prices and investment

To further explore the relationship between prices and investment, we leave out earnings and run forecasting regressions of investment on prices. We call the resulting predicted variation price informativeness for investment. In our model, price informativeness for investment is equal to the price informativeness for future earnings divided by the investment adjustment cost. Thus, price informativeness for investment can provide additional validation for our

---

[13]We have checked that this result is robust to the following variations: using logs, including R&D and CAPX together, including lags, looking across sectors and across valuation levels.

results on price informativeness for earnings. We can also go beyond our model and use prices to predict future investment at different horizons.

We begin with R&D expenditure. We run the regression

$$
\begin{aligned}
\frac{R\&D_{i,t+k}}{A_{i,t}} &= a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{R\&D_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t \\
&\quad + d_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times (\mathbf{1}_t) + \epsilon_{i,t}.
\end{aligned}
\tag{23}
$$

We include current R&D as a control since R&D spending tends to persist. The results in Figure 8 show that higher market valuations are associated with more R&D spending, as expected.

The predicted variation shows a clear upward trend: prices have become stronger predictors of R&D. The effect is present even at one year, and about equally strong at three and five years. These results are confirmed in the regressions in the middle columns of Table II. The predicted variation of equity prices for R&D is positive and it increases significantly starting in the 2000s. The increase is consistent across the one-, three- and five-year horizons. The effect is large, price informativeness for R&D investment has doubled over our sample.

Figures 8 about here.

The increasing pattern in Figure 8 extends our main result of increasing price informativeness for earnings. We also see that prices predict R&D at somewhat shorter horizons than earnings (one to three versus three to five years). A picture emerges in which a high valuation today is associated with higher R&D in the near term and higher earnings in the long term.

Turning to physical investment, we check whether market valuations are associated with higher CAPX. Analogously to the R&D regression, we run

$$
\begin{aligned}
\frac{CAPX_{i,t+k}}{A_{i,t}} &= a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{CAPX_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t \\
&\quad + d_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times (\mathbf{1}_t) + \epsilon_{i,t}.
\end{aligned}
\tag{24}
$$

Figure 9 shows that a higher equity valuation is associated with more capital expenditure, particularly at the longer horizons. However, there is no trend in the forecasting coefficient, the predicted variation, or the marginal R^2 up to the 2000s, and a downward dip afterwards. The last three columns of Table II confirm this result.

Figures 9 about here.

These results for CAPX contrast with our findings for R&D. A possible explanation is that technological change has reduced the importance of CAPX. Indeed, Figure 1 shows that the median level of CAPX for S&P 500 firms has declined from a peak of 8% of total assets in 1980 to only about 4% today. R&D, on the other hand, has remained steady around 3%.

H. Market prices and returns

Our model shows that price informativeness is affected by the level of noise in prices. It is possible that the observed increase in price informativeness is due to lower levels of noise rather than increased information production. To check this possibility, we run regressions of ex post returns on prices. In our model, prices orthogonalize returns and fundamentals, so expected returns depend solely on the noise term.

To implement this idea, we run our standard predictability regression with log-returns on the left:

$$\log R_{i,t \to i,t+k} \;=\; a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times (\mathbf{1}_t) + \epsilon_{i,t}. \quad (25)$$

The results are presented in Figure 10. Overall, due to the high variability of returns, the predicted variation of prices for returns is less precisely measured than that for earnings. Nevertheless, the series is level off, especially compared to earnings informativeness. A sharp dip in 2000 coincides with the end of the NASDAQ boom, but it is short-lived. Table VI presents a formal test. We see only a few significant decade-based coefficients over the full

sample, but these alternate between positive and negative signs.[14]

We conclude that there is no evidence that a change in the relationship between prices and returns that can account for the observed increasing pattern of price informativeness for earnings at long horizons.

I. The unit cost of information

We conclude by applying our model to extract an implied unit cost of information from our empirical informativeness measures. After some simple substitutions, the first order condition for information acquisition in Equation (20) of our model can be rewritten as

$$\frac{\alpha \psi}{h_s + h_\eta} = \sigma_z^2 \sqrt{\frac{\mathbb{V}\left(\mathbb{E}\left[r \mid p\right]\right)}{\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right)}}. \tag{26}$$

The left side represents the information cost ψ per unit of precision $h_s + h_\eta$, which cannot be identified separately from the traders' risk aversion coefficient α. The right side reflects the relative strength of return predictability due to noise trading and earnings predictability due to informed trading. Since all three components on the right are in principle measurable, we can back out an implied unit cost of information.

Figure 11 plots our estimates of the unit cost of information for the S&P 500 and for all firms separately, based on estimates at the five-year horizon. For S&P 500 firms, the unit cost of information is low and steadily declining, whereas for all firms it is high and increases dramatically. As reported in Figure 5, earnings dispersion for all firms rises sharply during the 1980s, whereas price informativeness actually falls. These two effects combine to produce the pattern in Figure 11.

---

[14]Using the abnormal return (i.e. subtracting the market) rather than the simple return has little impact on these results.

We attribute the rise in the implicit information cost for all firms to the changing composition of the broader universe of firms. However, the results for the sample of S&P 500 firms, whose characteristics have remained relatively stable, suggest that the cost of producing information in financial markets has steadily fallen over the last five decades.

6 Conclusion

We examine the extent to which financial market prices predict earnings over time. Our main finding is that over the past fifty years, the information content of prices has increased at forecast horizons of three to five years. Market prices have also become stronger predictors of R&D investment. The information content of investment, however, which we show is related to the total amount of information available to managers, is unchanged.

We focus on S&P 500 firms, whose observable characteristics have remained stable. Among all firms, price informativeness appears to decline, but this is likely due to changing firm characteristics. The rise in price informativeness for S&P 500 firms is concentrated among retail and services firms, and among growth firms. It is also concentrated among firms with traded options, underscoring the link between financial markets and price informativeness.

Against the backdrop of enormous improvements in information technology and a dramatic increase in trading, the measured increase in the information content of prices is substantially smaller. A possible explanation is that the relevant constraint for investors lies in the ability to interpret information rather than to store and transmit it. In the words of Herbert Simon (1971), "An information processing subsystem (a computer) will reduce the net demand on attention of the rest of the organization only if it absorbs more information, previously received by others, than it produces—if it listens and thinks more than it speaks."

References

Baker, Malcolm, Jeremy Stein, and Jeffrey Wurgler, 2003, When does the market matter? stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969–1006.

Beyer, Anne, Daniel A. Cohen, Thomas Z. Lys, and Beverly R. Walther, 2010, The financial reporting environment: Evidence from the last decade, *Journal of Accounting and Economics* 50, 296–343.

Bolton, Patrick, Tano Santos, and José Scheinkman, 2011, Cream skimming in financial markets, Working Paper, Columbia University.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *The Annual Review of Financial Economics* 4, 339–360.

Bond, Philip, Itay Goldstein, and Edward Simpson Prescott, 2010, Market-based corrective actions, *Review of Financial Studies* 23, 781–820.

Boot, Arnoud, and Anjan Thakor, 1997, Financial system architecture, *Review of Financial Studies* 10, 693–733.

Bushee, B., D. Matsumoto, and G. Miller, 2004, Managerial and investor responses to disclosure regulation: The case of reg fd and conference calls, *The Accounting Review* 79, 617–643.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619–650.

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: is there a connection?, *The Journal of Finance* 52, 1087–1129.

Eleswarapu, V., R. Thompson, and K. Venkataraman, 2004, The impact of regulation fair disclosure: Trading costs and information asymmetry, *Journal of Financial and Quantitative Analysis* 39, 209–225.

Fama, Engene, 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25(2), 383–417.

Fishman, Mike J., and Kathleen M. Hagerty, 1992, Insider trading and the efficiency of stock prices, *RAND Journal of Economics* 23, 106–122.

Fulghieri, Paolo, and Dmitry Lukin, 2001, Information production, dilution costs, and optimal security design, *Journal of Financial Economics* 61, 3–42.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2012, Neglected risks, financial innovation, and financial fragility, *Journal of Financial Economics* 104, 452 – 468.

Gilchrist, Simon, and Egon Zakrajsek, 2007, Investment and the cost of capital: New evidence from the corporate bond market, NBER Working Paper No. 13174.

Gintschel, A., and S. Markov, 2004, The effectiveness of regulation fd., *ournal of Accounting and Economics* pp. 293–314.

Glosten, Lawrence R, and Paul R Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Goldstein, Itay, Emre Ozdenoren, and Kathy Yuan, 2013, Trading frenzies and their impact on real investment, *Journal of Financial Economics* forthcoming.

Greenwood, Jeremy, and Boyan Jovanovic, 1990, Financial development, growth, and the distribution of income, *Journal of Political Economy* 98, 1076–1107.

Greenwood, Robin, and David Scharfstein, 2012, The growth of modern finance, *Working Paper, Harvard Business School*.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Gurkaynak, Refet S., Brian Sack, and Jonathan H. Wright, 2007, The u.s. treasury yield curve: 1961 to the present, *Journal of Monetary Economics* 54, 2291 – 2304.

Hayek, Friedrich August, 1945, The use of knowledge in society, *The American economic review* 35, 519–530.

Healy, P. M., and K. G. Palepu, 2001, A review of the empirical disclosure literature, *Journal of Accounting and Economics* 31, 405–440.

Heflin, F., K. Subramanyam, and Y. Zhang, 2003, Regulation fd and the financial information environment: Early evidence, *The Accounting Review* 78, 1–37.

Hirshleifer, Jack, 1971, The private and social value of information and the reward to inventive activity, *The American Economic Review* 61, 561–574.

Holmström, Bengt, and Jean Tirole, 1993, Market liquidity and performance monitoring, *Journal of Political Economy* pp. 678–709.

Holthausen, Robert W., and Ross L. Watts, 2001, The relevance of the value-relevance literature for financial accounting standard setting, *Journal of Accounting and Economics* 31, 3 – 75.

Khanna, Naveen, Steve Slezak, and Michael Bradley, 1994, Insider trading, outside search and resource allocation: Why firms and society may disagree on insider trading restrictions, *Review of Financial Studies* 7(3), 575–608.

Kothari, S. P., K. Ramanna, and D. Skinner, 2009, What should gaap in the future look like? a survey of past research as guidance for future standards, MIT Sloan School of Management working paper.

Kurlat, Pablo, and Laura Veldkamp, 2012, Shall we regulate financial information?, Stanford University and NYU working paper.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.

Leland, Hayne, 1992, Insider trading: Should it be prohibited?, *Journal of Political Economy* 100, 859–887.

Levine, Ross, 2005, Finance and growth: Theory and evidence, in Philippe Aghion, and Steven N. Durlauf, ed.: *Handbook of Economic Growth* vol. 1A . pp. 865–934. (Elsevier: Amsterdam).

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215–260.

Ozdenoren, Emre, and Kathy Yuan, 2008, Feedback effects and asset prices, *Journal of Finance* 63, 1939–1975.

Philippon, Thomas, 2008, The evolution of the us financial industry from 1860 to 2007: Theory and evidence, NBER Working Paper No. 13405.

———, 2012, Has the u.s. finance industry become less efficient? on the theory and measurement of financial intermediation, Working Paper, New York University.

Rajan, R.G., and L. Zingales, 1998, Financial dependence and growth, *American Economic Review* pp. 559–586.

Rajan, Raghuram G., 2005, Has finance made the world riskier?, *Proceedings of the 2005 Jackson Hole Conference organized by the Kansas City Federal Reserve Bank*.

Sidhu, B., T. Smith, R. Whaley, and R. Willis, 2008, Regulation fair disclosure and the cost of adverse selection, *Journal of Accounting Research* 46, 697–728.

Simon, Herbert A., 1971, *Designing Organizations for an Information-Rich World* pp. 37–72.

Subrahmanyam, Avanidhar, and Sheridan Titman, 1999, The going-public decision and the development of financial markets, *Journal of Finance* 54, 1045–1082.

Sunder, Jayanthi, 2004, Information production in stock markets and cost of bank debt, working paper.

Tobin, James, 1969, A general equilibrium approach to monetary theory, *Journal of Money, Credit and Banking* 1, 15–29.

Turley, Robert, 2012, Informative prices and the cost of capital markets, working paper.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2006, Learning asymmetries in real business cycles, *Journal of Monetary Economics* 53, 753–772.

Wang, I., 2007, Private earnings guidance and its implications for disclosure regulation, *The Accounting Review* pp. 1299–1332.

Warga, A.D., 1991, Corporate bond price discrepancies in the dealer and exchange markets, *The Journal of Fixed Income* 1, 7–16.

7 Appendix

This section contains model derivations as well as additional empirical analysis.

A Model appendix

General notation: In the paper, we often use some simple calculations summarized here. A typical agent in the model observes a signal x

$$x = y + \epsilon, \tag{27}$$

where y is the variable of interest. We assume that y and ϵ are independent normal variables with $\mathbb{E}[y] = \overline{y}$, $\mathbb{E}[\epsilon|\,y] = 0$, and precisions $h_y = \sigma_y^{-2}$ and $h_x = \sigma_\epsilon^{-2}$. After observing x the agent forms the conditional expectation

$$\mathbb{E}[y|\,x] = \frac{h_y \overline{y} + h_x x}{h_y + h_x} \tag{28}$$

and faces residual uncertainty

$$\mathbb{V}[y|\,x] = \frac{1}{h_y + h_x}. \tag{29}$$

We are often interested in the quantity of information

$$\mathbb{V}\left(\mathbb{E}[y|\,x]\right) = \mathbb{V}\left(\frac{h_x x}{h_y + h_x}\right) \tag{30}$$

$$= \left(\frac{h_x}{h_y + h_x}\right)^2 \sigma_x^2 \tag{31}$$

$$= \left(\frac{\sigma_y^2}{\sigma_\epsilon^2 + \sigma_y^2}\right)^2 \left(\sigma_y^2 + \sigma_\epsilon^2\right) \tag{32}$$

$$= \frac{h_x}{h_y + h_x} \sigma_y^2. \tag{33}$$

In the case of multiple signals, we simply have

$$\mathbb{V}\left(\mathbb{E}[y|\,x_1, x_2]\right) = \frac{h_{x_1} + h_{x_2}}{h_y + h_{x_1} + h_{x_2}} \sigma_y^2. \tag{34}$$

Ranking information sets:

Proof of Proposition 2. We want to show that

$$\mathbb{V}\left(\mathbb{E}[z|\,p]\right) < \mathbb{V}\left(\mathbb{E}[z|\,\theta, \eta]\right) < \mathbb{V}\left(\mathbb{E}[z|\,s, \eta]\right) < \sigma_z^2. \tag{35}$$

The right-most inequality follows from Equation (6). From Equation (15) we know that $h_\theta < h_s$. This directly implies $\mathbb{V}\left(\mathbb{E}[z|\,\theta, \eta]\right) < \mathbb{V}\left(\mathbb{E}[z|\,s, \eta]\right)$. The first inequality comes from

the fact that $h_p < h_\theta + h_\eta$ which can be shown from Equations (21) and (15):

$$\frac{(h_s + h_\eta)^2}{h_s + h_\eta + \frac{\alpha^2}{m^2}\sigma_u^2} < \frac{h_s^2}{h_s + \frac{\alpha^2}{m^2}\sigma_u^2} + h_\eta \tag{36}$$

$$\left(h_s + \frac{\alpha^2}{m^2}\sigma_u^2\right)(h_s + h_\eta)^2 < \left(h_s + \frac{\alpha^2}{m^2}\sigma_u^2\right)(h_s + h_\eta)^2 + \frac{\alpha^4}{m^4}h_\eta. \tag{37}$$

For the second part of the proposition, from Equations (11) and (12) it is clear that $\frac{\partial}{\partial h_s}\mathbb{V}\left(\mathbb{E}\left[z\mid p\right]\right) = \frac{\partial}{\partial h_\eta}\mathbb{V}\left(\mathbb{E}\left[z\mid p\right]\right)$. The same is true for $\mathbb{V}\left(\mathbb{E}\left[z\mid s, \eta\right]\right)$ by an application of Equation (34). To show that $\frac{\partial}{\partial h_s}\mathbb{V}\left(\mathbb{E}\left[z\mid \theta, \eta\right]\right) < \frac{\partial}{\partial h_\eta}\mathbb{V}\left(\mathbb{E}\left[z\mid \theta, \eta\right]\right)$, from Equation (6) it is enough to show that $\frac{\partial}{\partial h_s}h_\theta < 1$. From Equation (15),

$$h_\theta = \frac{h_s}{1 + \frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2}. \tag{38}$$

Without free entry (holding m fixed),

$$\frac{\partial}{\partial h_s}h_\theta = \frac{1}{1 + \frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2} + \frac{h_s}{\left[1 + \frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2\right]^2}\left[\frac{1}{h_s^2}\left(\frac{\alpha}{m}\right)^2\sigma_u^2\right] \tag{39}$$

$$= \frac{1 + \frac{2}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2}{1 + \frac{2}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2 + \left[\frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2\right]^2} < 1. \tag{40}$$

With free entry, using Equation (21),

$$\frac{\partial}{\partial h_s}h_\theta = \frac{1}{1 + \left(1 + \frac{h_z + h_\eta}{h_s}\right)\alpha\psi} + \frac{\frac{h_z + h_\eta}{h_s}\alpha\psi}{\left[1 + \left(1 + \frac{h_z + h_\eta}{h_s}\right)\alpha\psi\right]^2} \tag{41}$$

$$= \frac{1 + \left(1 + \frac{h_z + h_\eta}{h_s}\right)\alpha\psi + \frac{h_z + h_\eta}{h_s}\alpha\psi}{1 + 2\left(1 + \frac{h_z + h_\eta}{h_s}\right)\alpha\psi + \left(1 + \frac{h_z + h_\eta}{h_s}\right)^2\alpha^2\psi^2} < 1. \tag{42}$$

This completes the proof. $\qquad\square$

Expected returns: Recall that prices are given by

$$p = \frac{\mathbb{E}\left[v\mid s, \eta\right]}{k + \overline{k}} + \frac{\alpha}{m}u\frac{\mathbb{V}\left[v\mid s, \eta\right]}{\left(k + \overline{k}\right)^2}. \tag{43}$$

Therefore we can compute the firm's dollar return per share as

$$r = \frac{v}{\overline{k} + k} - p = \frac{v - \mathbb{E}\left[v\mid s, \eta\right]}{k + \overline{k}} - \frac{\frac{\alpha}{m}}{h_z + h_s + h_\eta}u \tag{44}$$

Conditional on prices, expected returns are

$$\mathbb{E}\left[r\mid p\right] \;=\; \mathbb{E}\left[\left.\frac{v - \mathbb{E}\left[v\mid s,\eta\right]}{k + \overline{k}}\right| p\right] - \frac{\frac{\alpha}{m}\mathbb{E}\left[u\mid p\right]}{h_z + h_s + h_\eta}. \tag{45}$$

Since $\mathcal{I}\left(p\right) \subset \mathcal{I}\left(s,\eta\right)$, we have $\mathbb{E}\left[\mathbb{E}\left[v\mid s,\eta\right]\mid p\right] = \mathbb{E}\left[v\mid p\right]$ so the first term is zero. Therefore,

$$\mathbb{E}\left[r\mid p\right] \;=\; -\frac{\frac{\alpha}{m}\mathbb{E}\left[u\mid p\right]}{h_z + h_s + h_\eta}. \tag{46}$$

Since

$$p - \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}} = \frac{h_s s + h_\eta \eta + \frac{\alpha}{m}u}{h_z + h_s + h_\eta} = \frac{\left(h_s + h_\eta\right)z + h_s\epsilon^s + h_\eta\epsilon^\eta + \frac{\alpha}{m}u}{h_z + h_s + h_\eta}, \tag{47}$$

we have the signal for $\frac{\alpha}{m}u$

$$\widehat{p} \;=\; \frac{\alpha}{m}u + \left(h_s + h_\eta\right)z + h_s\epsilon^s + h_\eta\epsilon^\eta, \tag{48}$$

where $\widehat{p}$ is a linear function of p. The variance of the "error" is $\left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)$. Therefore, $\mathbb{E}\left[\frac{\alpha}{m}u\mid p\right] = \frac{\alpha^2\sigma_u^2/m^2}{\alpha^2\sigma_u^2/m^2 + \left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)}\widehat{p}$ and expected returns are

$$\mathbb{E}\left[r\mid p\right] \;=\; -\frac{\left(\alpha/m\right)^2\sigma_u^2}{\left(\alpha/m\right)^2\sigma_u^2 + \left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)}\left(p - \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}}\right). \tag{49}$$

The predicted return is the firm's dollar return per share, though we use percentage returns in our tests. The predicted variation of returns using prices is

$$\mathbb{V}\left(\mathbb{E}\left[r\mid p\right]\right) \;=\; \left(\frac{\alpha^2\sigma_u^2}{\alpha^2\sigma_u^2 + m^2\left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)}\right)^2\mathbb{V}\left(p\right) \tag{50}$$

$$\;=\; \frac{1}{\left(h_z + h_s + h_\eta\right)^2}\frac{\left[\left(\alpha/m\right)^2\sigma_u^2\right]^2}{\left(\alpha/m\right)^2\sigma_u^2 + \left(h_s + h_\eta\right)\left(1 + \left(h_s + h_\eta\right)\sigma_z^2\right)}. \tag{51}$$

B   Measures of valuation, profitability and investment

Equity market valuation: We use the ratio of market capitalization to total assets to capture the information contained in equity prices. Total assets are reported in a firm's 10-K filing at the end of its fiscal year, usually in December. Market capitalization is based on the stock price at the end of March of the next year. In this way, our accounting control variables are in the information set of market participants on the day we measure prices. Stock prices and volume are from the Center for Research in Security Prices (CRSP) from 1960 to 2013.

Profitability and investment: Testing the predictions of our models requires empirical proxies for profitability and investment. A natural choice as the proxy for profitability is net income. This item represents the income of a company after all expenses such as income

taxes and minority interest, but before provisions for common and/or preferred dividends. An alternative proxy is earnings before interest and taxes (EBIT), or operating income after depreciation (OIADP). These represent operating income (sales) minus cost of goods sold, selling, general, and administrative expenses, and depreciation/amortization. In the empirical tests, we use EBIT. The results are similar using net income.

Investment by non-financial firms can be both tangible and intangible. For tangible investment, we use capital expenditures ("CAPX" in COMPUSTAT), which represents cash outflow used for a company's property, plant and equipment, excluding amounts arising from acquisitions. For intangible investment, we use research and development (R&D) expense (denoted as "XRD" in COMPUSTAT), which represents all costs incurred during the year that relate to the development of new products or services. Besides profitability and investment, we collect other firm characteristics from COMPUSTAT such as total assets ("AT"). We also obtain earnings announcement dates from COMPUSTAT. This data starts in 1970 and refers to the first date on which earnings are reported by the press or news wires.

Adjusting for debt: Figure B.1 follows Figure 3 in the paper while adjusting for debt when computing market valuations. Specifically, instead of $\log(M/A)$, the valuation measure is $\log[(M + D)/A]$, where D is the book value of long-term debt from COMPUSTAT. We see that as in our benchmark results, price informativeness increases at three and five years.

C   Bond price informativeness

This appendix examines the informativeness of corporate bond prices analogous to our equity price informativeness results.

Bond market valuation: We use the spread between corporate bond yields and Treasury yields to capture the information contained in bond prices. We collect month-end market prices of corporate bonds from the Lehman/Warga database and Mergent Fixed Income Datascope. These bonds are senior unsecured bonds with a fixed coupon schedule. The Lehman/Warga database covers the period from 1973 to 1997 (Warga (1991) has the details). Mergent Datascope provides daily bond yields from 1998 to 2013. To be consistent with our equity valuation measure, we also use yields form the end of March.

To calculate the corporate credit spread, we match the yield on each individual bond to the yield on the Treasury with the closest maturity. The continuously-compounded zero-coupon Treasury yields are from the daily estimates of the U.S. Treasury yield curve reported in Gurkaynak, Sack, and Wright (2007). To mitigate the effect of outliers in our analysis, we follow Gilchrist and Zakrajsek (2007) and eliminate all observations with negative credit spreads and with spreads greater than 1,000 basis points. This selection criterion yields a sample of 4,433 individual bonds issued by 615 firms from 1973 to 2013. Our final sample contains about 25,000 firm-year observations with non-missing bond spreads.

Bond prices and earnings   We measure bond market informativeness by relating credit spreads and future earnings. Analogously to our equity price informativeness regression (22),

we run

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \left(y_{i,t} - y_{0,t}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}, \qquad (52)$$

where $y_t - y_0$ is the yield of firm i's bonds in excess of the duration-matched Treasury yield.

Figure C.1 and Table C.1 about here.

Figure C.1 shows that the predictive power of yield spreads is modest, perhaps because most S&P 500 firms have good credit. The forecasting coefficients are rarely two standard errors from zero. Nevertheless, the point estimates are negative, so higher spreads are associated with slightly lower future earnings, as one would expect. Although low and noisy, the predicted variation spikes higher in the latter decades of our sample. The point estimates of the corresponding regression in Table C.1 are indeed increasingly negative, particularly at longer horizons. However, they are not statistically significant, so we cannot reject the hypothesis that bond price informativeness remains unchanged.

Bond prices and R&D expenditure Figure C.2 shows the extent to which corporate bond spreads forecast R&D. The predicted variations are close to zero before the 2000s but exhibit a growing trend afterwards. The regressions in Table C.1 tell a similar story. These results are perhaps surprising since technology firms tend to have low levels of debt. Nevertheless, they parallel our results on equity price informativeness.

Figure C.2 and Figure C.3 about here.

Bond prices and capital expenditure Figure C.3 shows that lower bond spreads are not significantly associated with higher capital expenditure. The forecasting coefficients are small and noisy, and there is no evidence of a trend in the bond market-predicted variation or the marginal R^2. The last three columns in Table C.1 confirm these findings.

Table I. **Summary statistics**

Means, medians, and standard deviations of key variables for S&P 500 non-financial firms and for all firms in CRSP. Market capitalization is from CRSP in millions of dollars measured at the end of March of year t. Total assets, earnings EBIT, capital expenditure CAPX, and research and development R&D are from COMPUSTAT in millions of dollars, measured in December of year $t-1$. Nominal quantities are adjusted using the GDP deflator ($= 100$ in 2009). Next, $\log(M/A)$ is the log-ratio of market cap to assets. E/A is EBIT over assets, $R\&D/A$ is R&D over assets, and $CAPX/A$ is $CAPX$ over assets. All ratios are winsorized at the 1% level. The main sample period is from 1960 to 2013.

	S&P 500			All firms		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Market cap	9,936	3,083	27,009	1,535	120	9,890
Total assets	10,735	3,780	29,680	1,822	160	11,170
EBIT	1,061	385	2,665	163	10	1,005
R&D	376	87	964	57	3	359
CAPX	725	217	1,928	121	8	726
$\log(M/A)$	-0.17	-0.20	0.88	-0.20	-0.22	1.07
E/A	0.12	0.11	0.08	0.03	0.08	0.22
$R\&D/A$	0.04	0.02	0.04	0.08	0.03	0.13
$CAPX/A$	0.07	0.06	0.05	0.07	0.05	0.07
Firm-year obs.		24,302			208,760	

Table II. Equity price informativeness

Time series regressions of the predicted variation of equity prices for earnings, R&D, and CAPX. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t (\log M/A)$ from the forecasting regressions $E_{i,t+k}/A_{i,t} = a_t \log(M_{i,t}/A_{i,t}) \times \mathbf{1}_t + b_t(E_{i,t}/A_{i,t}) \times \mathbf{1}_t + c_{s(i,t),t}(\mathbf{1}_{SIC_1}) \times (\mathbf{1}_t) + \epsilon_{i,t}$, and similarly for $R\&D_{i,t+k}/A_{i,t}$ and $CAPX_{i,t+k}/A_{i,t}$ (see Figures 3, 8, and 9). Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$PredVar_t(Y|\log M/A) = a + \sum_d b_d \times \mathbf{1}_{t\in d} + \epsilon_t$$

for $Y = E/A$, $R\&D/A$, and $CAPX/A$, and decades $d = 1970$–$79\ldots,\ 2010$–13. The omitted group is 1960–1969. Newey–West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all S&P 500 non-financial firms from 1960 to 2013.

$100\times$	$PredVar(E/A\|\log M/A)$			$PredVar(R\&D/A\|\log M/A)$			$PredVar(CAPX/A\|\log M/A)$		
	$k=1$	$k=3$	$k=5$	$k=1$	$k=3$	$k=5$	$k=1$	$k=3$	$k=5$
Constant	2.07***	3.18***	4.18***	0.25***	0.63**	1.21**	0.91***	1.82***	2.19***
	(0.12)	(0.25)	(0.13)	(0.09)	(0.25)	(0.48)	(0.27)	(0.42)	(0.34)
1970–79	−0.04	0.64	−0.17	−0.11	−0.12	−0.64	−0.29	−0.20	−0.23
	(0.17)	(0.52)	(0.39)	(0.10)	(0.26)	(0.52)	(0.32)	(0.45)	(0.37)
1980–89	−0.18	1.01**	1.83***	0.03	0.42	0.32	0.44	1.24**	1.91***
	(0.22)	(0.42)	(0.15)	(0.10)	(0.26)	(0.50)	(0.30)	(0.58)	(0.62)
1990–99	−0.18	1.34***	1.44***	0.03	0.53	0.34	−0.13	0.66	0.81**
	(0.24)	(0.40)	(0.42)	(0.12)	(0.37)	(0.52)	(0.28)	(0.52)	(0.35)
2000–09	−0.18	1.51**	2.20***	0.90***	1.01***	1.20**	−0.24	−0.87*	−0.88**
	(0.30)	(0.60)	(0.36)	(0.20)	(0.28)	(0.56)	(0.35)	(0.43)	(0.37)
2010–13	−0.18	1.34***		0.24**	0.97***		−0.34	−0.17	
	(0.46)	(0.25)		(0.10)	(0.25)		(0.28)	(0.42)	
R^2	11%	18%	53%	61%	44%	42%	23%	46%	63%
N	53	51	49	53	51	49	53	51	49

Table III. **Equity price informativeness among all firms**

Time series regressions of the predicted variation of equity prices for earnings among all firms. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t \left(\log M/A\right)$ from the forecasting regressions $E_{i,t+k}/A_t = a_t \log\left(M_{i,t}/A_{i,t}\right) \times \mathbf{1}_t + b_t\left(E_{i,t}/A_{i,t}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}$ (see Figure 5). Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$PredVar_t\left(E/A|\log M/A\right) = a + \sum_d b_d \times \mathbf{1}_{t \in d} + \epsilon_t$$

for decades $d = 1970\text{--}79\dots$, 2010--13. The omitted group is 1960--1969. Newey-West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all non-financial firms from 1960 to 2013.

100×	$PredVar\left(E/A|\log M/A\right)$		
	$k = 1$	$k = 3$	$k = 5$
Constant	2.48***	3.71***	4.89***
	(0.15)	(0.30)	(0.39)
1970–79	0.35	0.81*	0.95*
	(0.22)	(0.42)	(0.55)
1980–89	−1.23***	−1.08**	−0.23
	(0.22)	(0.42)	(0.55)
1990–99	−1.85***	−1.76***	−0.35
	(0.22)	(0.42)	(0.55)
2000–09	−1.89***	−1.78***	−0.65
	(0.22)	(0.42)	(0.56)
2010–13	−1.56***	−1.69*	
	(0.32)	(0.99)	
R^2	80%	57%	18%
N	53	51	49

Table IV. **Equity price informativeness and option listing**

Time series regressions of the difference in predicted variation of equity prices for earnings between CBOE-listed and unlisted firms. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t (\log M/A)$ from the forecasting regressions $E_{i,t+k}/A_{i,t} = a_t \log (M_{i,t}/A_{i,t}) \times \mathbf{1}_t + b_t (E_{i,t}/A_{i,t}) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}$. Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$\Delta PredVar_t (E/A| \log M/A) = a + \sum_d b_d \times \mathbf{1}_{t \in d} + \epsilon_t$$

for decades $d = 1980\text{–}89\ldots, 2010\text{–}13$, where $\Delta PredVar_t (E/A| \log M/A) \equiv PredVar_t (E/A| \log M/A, listed) - PredVar_t (E/A| \log M/A, unlisted)$ is the difference in the predicted variation of equity prices for earnings between those firms are listed on the CBOE and those that are not (as of year t). The omitted group is 1973–1979. Newey-West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all S&P 500 non-financial firms from 1973 to 2013.

100×	$\Delta PredVar (E/A| \log M/A)$		
	$k = 1$	$k = 3$	$k = 5$
Constant	−0.88***	−1.49**	−1.62***
	(0.19)	(0.57)	(0.39)
1980–89	0.67**	1.11*	0.60
	(0.32)	(0.64)	(0.80)
1990–99	1.34***	2.16**	2.26
	(0.34)	(1.00)	(1.63)
2000–09	1.05**	2.19**	2.65**
	(0.48)	(0.96)	(1.14)
2010–13	1.26***	2.04***	
	(0.37)	(0.57)	
R^2	22%	20%	14%
N	40	38	36

Table V. Investment informativeness

Time series regressions of the predicted variation of R&D and CAPX for earnings. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t (R\&D/A)$ from the forecasting regressions $E_{i,t+k}/A_{i,t} = a_t (R\&D_{i,t}/A_{i,t}) \times \mathbf{1}_t + b_t (E_{i,t}/A_{i,t}) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}$, and similarly for $CAPX_{i,t}/A_{i,t}$ (see Figures 6 and 7). Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$PredVar_t (E/A|Y) = a + \sum_d b_d \times \mathbf{1}_{t \in d} + \epsilon_t$$

for $Y = R\&D/A$ and $CAPX/A$, and decades $d = 1970$–$79\ldots$, 2010–13. The omitted group is 1960–1969. Newey-West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all S&P 500 non-financial firms from 1960 to 2013.

$100\times$	$PredVar (E/A\|R\&D/A)$			$PredVar (E/A\|CAPX/A)$		
	$k=1$	$k=3$	$k=5$	$k=1$	$k=3$	$k=5$
Constant	0.64***	1.64***	2.62***	0.16***	0.45***	0.78***
	(0.19)	(0.21)	(0.33)	(0.05)	(0.09)	(0.17)
1970–79	−0.27	−0.50*	−1.08***	−0.11**	−0.25**	−0.66***
	(0.21)	(0.25)	(0.34)	(0.05)	(0.10)	(0.20)
1980–89	−0.13	−0.57	−.77	−0.04	−0.30**	−0.50**
	(0.23)	(0.47)	(0.54)	(0.07)	(0.14)	(0.23)
1990–99	0.07	−0.02	−0.83**	−0.05	0.02	−0.08
	(0.21)	(0.32)	(0.37)	(0.08)	(0.20)	(0.43)
2000–09	0.02	0.01	−0.12	0.30**	0.27	0.27
	(0.30)	(0.36)	(0.45)	(0.14)	(0.35)	(0.43)
2010–13	−0.12	−0.72***		0.23	−0.09	
	(0.37)	(0.21)		(0.31)	(0.09)	
R^2	5%	8%	13%	23%	14%	13%
N	53	51	49	53	51	49

Table VI. Equity prices and returns

Time series regressions of the predicted variation of equity prices for returns. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t (\log M/A)$ from the forecasting regressions $\log R_{i,t \to t+k} = a_t \log (M_{i,t}/A_{i,t}) \times \mathbf{1}_t + b_t (E_{i,t}/A_{i,t}) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}$ (see Figure 10). Market cap M is measured as of the end of March following the firm's fiscal year end. The log return is from April of year t through March of year $t+k$. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$PredVar_t (\log R| \log M/A) \;=\; a + \sum_d b_d \times \mathbf{1}_{t \in d} + \epsilon_t$$

for decades $d = 1970–79\dots$, 2010–13. The omitted group is 1960–1969. Newey-West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all S&P 500 non-financial firms from 1960 to 2013.

100×	$PredVar (\log R\| \log M/A)$		
	$k=1$	$k=3$	$k=5$
Constant	−3.00***	−8.36***	−10.67***
	(0.62)	(1.09)	(1.86)
1970–79	−1.41	−1.24	−4.71
	(1.74)	(3.58)	(3.94)
1980–89	0.21	4.39**	5.60*
	(1.19)	(1.91)	(3.24)
1990–99	0.98	3.03*	4.12
	(0.86)	(1.58)	(2.67)
2000–09	−6.60*	−4.21	−5.29
	(3.60)	(6.28)	(9.05)
2010–13	2.08**	4.29***	
	(0.87)	(1.21)	
R^2	23%	13%	14%
N	54	52	50

Table C.1. Bond yield spread informativeness

Time series regressions of the predicted variation of bond yield spreads for earnings, R&D, and CAPX. The predicted variations are obtained as $PredVar_t = a_t \times \sigma_t (y - y_0)$ from the forecasting regressions $E_{i,t+k}/A_{i,t} = a_t (y_{i,t} - y_{0,t}) \times \mathbf{1}_t + b_t (E_{i,t}/A_{i,t}) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}$, and similarly for $R\&D_{i,t+k}/A_{i,t}$ and $CAPX_{i,t+k}/A_{i,t}$ (see Figures C.1, C.2, and C.3). The yield spread $y - y_0$ is the dollar-weighted yield on a firm's corporate bonds in excess of the duration-matched Treasury yield. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The table displays coefficients from the time series regression

$$PredVar_t (Y|y - y_0) = a + \sum_d b_d \times \mathbf{1}_{t \in d} + \epsilon_t$$

for $Y = E/A$, $R\&D/A$, and $CAPX/A$, and decades $d = 1980\text{–}89\ldots, 2000\text{–}10$. The omitted group is 1973–1979. Newey-West standard errors with k lags. ***, **, and * signify results significant at the 1%, 5%, and 10% levels, respectively. The sample consists of all S&P 500 non-financial firms from 1973 to 2013.

$100\times$	$PredVar$ $(E/A|y - y_0)$			$PredVar$ $(R\&D/A|y - y_0)$			$PredVar$ $(CAPX/A|y - y_0)$		
	$k = 1$	$k = 3$	$k = 5$	$k = 1$	$k = 3$	$k = 5$	$k = 1$	$k = 3$	$k = 5$
Constant	−0.52*	−0.70***	−0.53***	−0.01	−0.05	−0.07**	−0.17*	−0.33**	−0.37***
	(0.13)	(0.17)	(0.19)	(0.01)	(0.04)	(0.03)	(0.09)	(0.12)	(0.06)
1980–89	0.31	0.52***	0.31	−0.07	−0.12	−0.14*	0.00	0.14	0.11
	(0.17)	(0.17)	(0.20)	(0.04)	(0.07)	(0.08)	(0.12)	(0.13)	(0.07)
1990–99	0.19	0.12	−0.18	−0.04	−0.17	−0.20**	0.01	−0.09	−0.24
	(0.17)	(0.20)	(0.25)	(0.04)	(0.11)	(0.09)	(0.10)	(0.15)	(0.16)
2000–13	0.01	−0.16	−0.35	−0.44*	−0.54***	−0.91**	−0.01	0.09	−0.04
	(0.20)	(0.29)	(0.27)	(0.24)	(0.16)	(0.38)	(0.10)	(0.15)	(0.16)
R^2	11%	27%	12%	17%	25%	24%	2%	12%	9%
N	39	37	35	39	37	35	39	37	35

47

Figure 1. **The distributions of delistings, valuations, profitability, and investment**
The sample consists of non-financial firms in the S&P 500 index from 1960 to 2013. The top
two panels show the number of firms delisted within 3 and 5 years ($k = 3, 5$, solid red lines)
or 1 year ($k = 1$, dashed black line). The next four panels show medians (red line), 10th and
90th percentiles (gray shade). $\log M/A$ is the log of market capitalization over assets. E/A
is EBIT over assets. $R\&D/A$ and $CAPX/A$ are analogous for research and development,
and capital expenditure, respectively. Nominal quantities are adjusted by the GDP deflator.

48
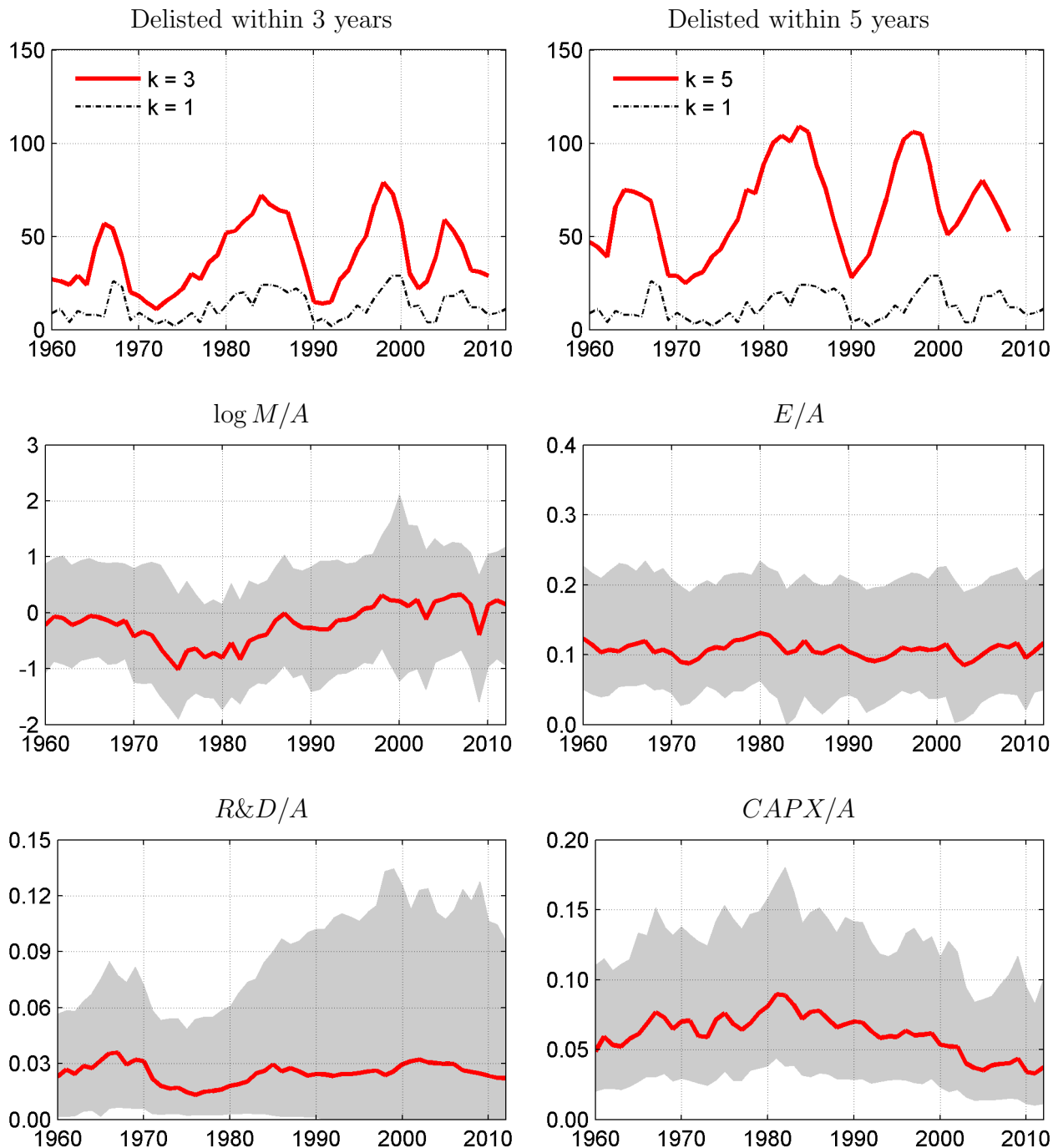
Figure 2. **Price informativeness by forecast horizon**

This figure plots the ratio of the predicted variation $a_t \times \sigma_t \left(\log M_t / A_t \right)$ divided by the total variation, $\sigma_t \left(E_{t+k} / A_t \right)$ from the regression:
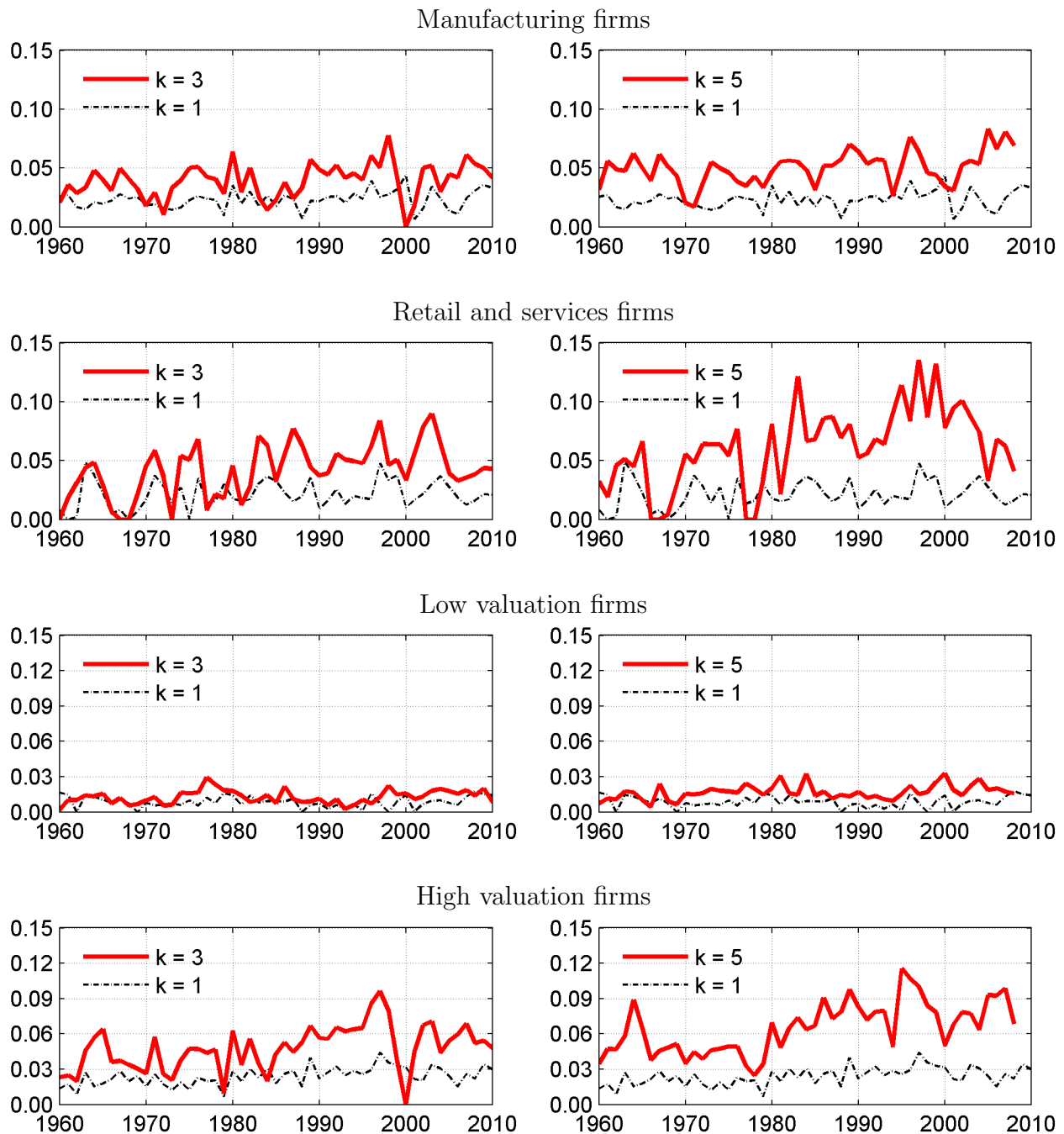
$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1} \right) \times \left(\mathbf{1}_t \right) + \epsilon_{i,t}.$$

We consider horizons up to 10 years, $k = 1, \ldots, 10$. Gray shade covers a 95% confidence interval using Newey-West standard errors. Market cap M is measured as of the end of March following the end of the firm's fiscal year. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. When earning observations are missing for any k, we use the procedure introduced in Section 4 to adjust for the delisting bias. The sample consists of all S&P 500 non-financial firms from 1960 to 2013.

$$\frac{\text{Predicted variation}}{\text{Total variation}} = \frac{a_t \sigma_t \left(\log M_t / A_t \right)}{\sigma_t \left(E_{t+k} / A_t \right)}$$

49
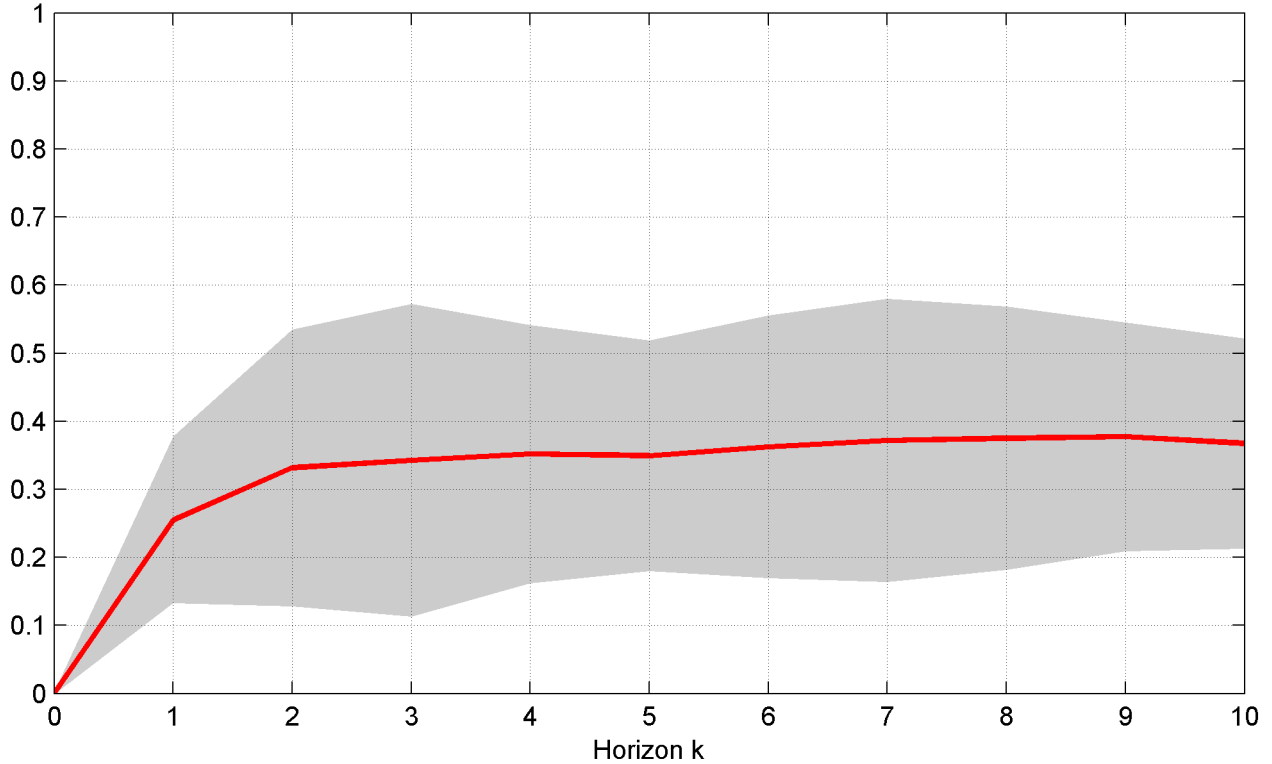
Figure 3. Forecasting earnings with equity prices

Results from the predictive regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t\left(\log M/A\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $\log M/A$.

Coefficients a_t Predicted variation $a_t \times \sigma_t\left(\log M/A\right)$ Marginal R^2

Figure 4. **Forecasting earnings with equity prices by sector and valuation**

Predicted variation from $E_{i,t+k}/A_{i,t} = a_t \log (M_{i,t}/A_{i,t}) \times \mathbf{1}_t + b_t (E_{i,t}/A_{i,t}) \times \mathbf{1}_t + \epsilon_{i,t}$. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The predicted variation is $a_t \times \sigma_t (\log M/A)$. Top row includes manufacturing firms only. Second row includes retail and services firms only. Third and fourth rows include firms with below- and above-median valuation ratios $\log M/A$ in a given year. Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. Nominal quantities are adjusted by GDP deflator. The underlying sample consists of S&P 500 non-financial firms from 1960 to 2013.

Manufacturing firms

Retail and services firms

Low valuation firms

High valuation firms

Figure 5. All firms versus S&P 500 firms

Earnings dispersion $\sigma_t\,(E/A)$, market valuation dispersion $\sigma_t\,(\log M/A)$, and coefficients a_t and predicted variation $a_t \times \sigma_t\,(\log M/A)$ from the forecasting regression

$$\frac{E_{i,t+k}}{A_{i,t}} \;=\; a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times (\mathbf{1}_t) + \epsilon_{i,t}.$$

run separately for S&P 500 non-financial firms and all non-financial firms, 1960 to 2013. Dispersion is measured as the cross-sectional standard deviation in E/A and $\log M/A$ in a given year. Predicted variation is the cross-sectional standard deviation of the valuation ratio times its forecasting coefficient. Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years. Nominal quantities are adjusted by GDP deflator.
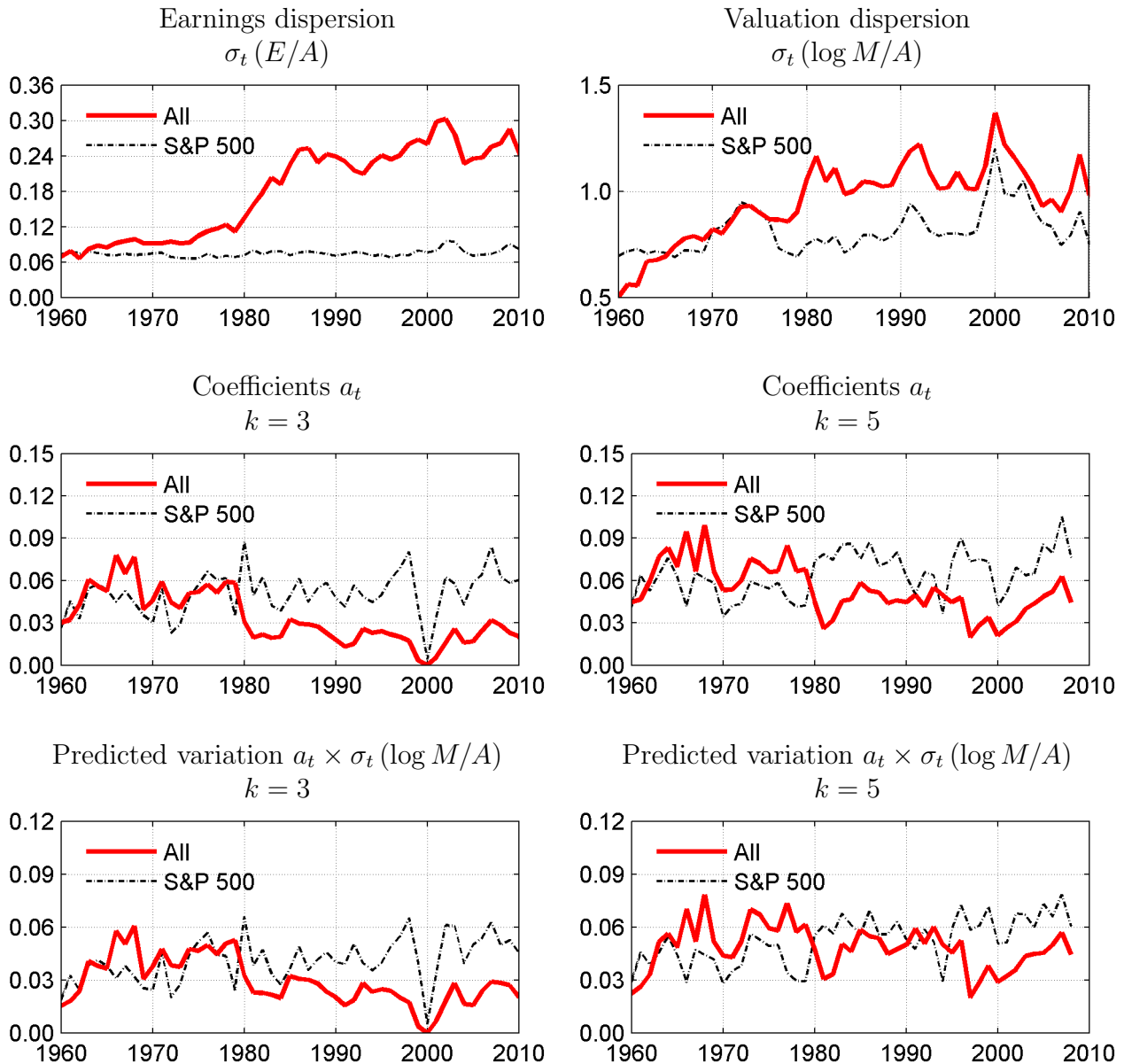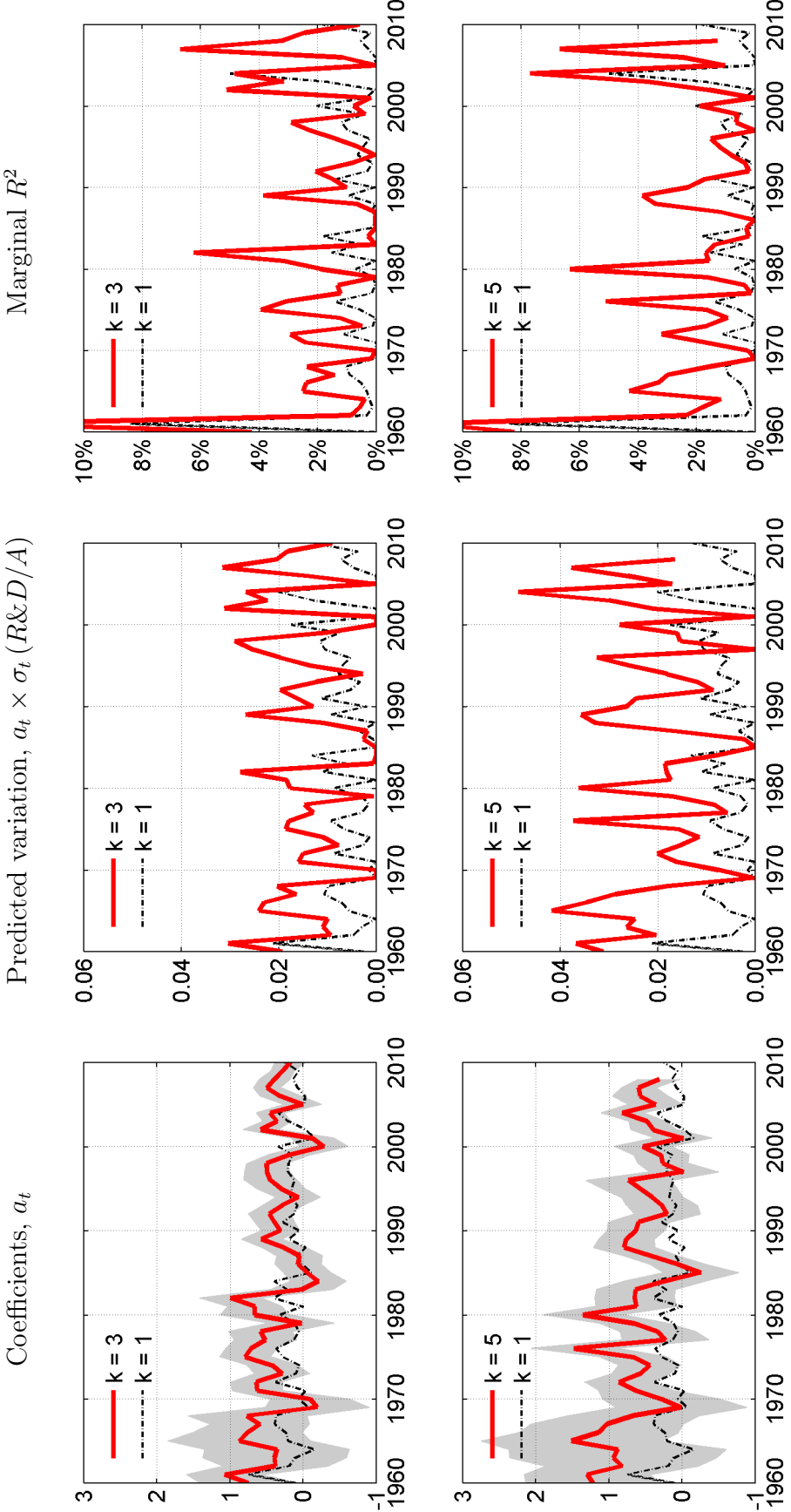
Figure 6. Forecasting earnings with R&D expenditure

Results from the predictive regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \left(\frac{R\&D_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The R&D-predicted variation is $a_t \times \sigma_t (R\&D/A)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $R\&D/A$.


53

Figure 7. Forecasting earnings with capital expenditure

Results from the predictive regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \left(\frac{CAPX_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s,t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The R&D-predicted variation is $a_t \times \sigma_t(CAPX/A)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $CAPX/A$.
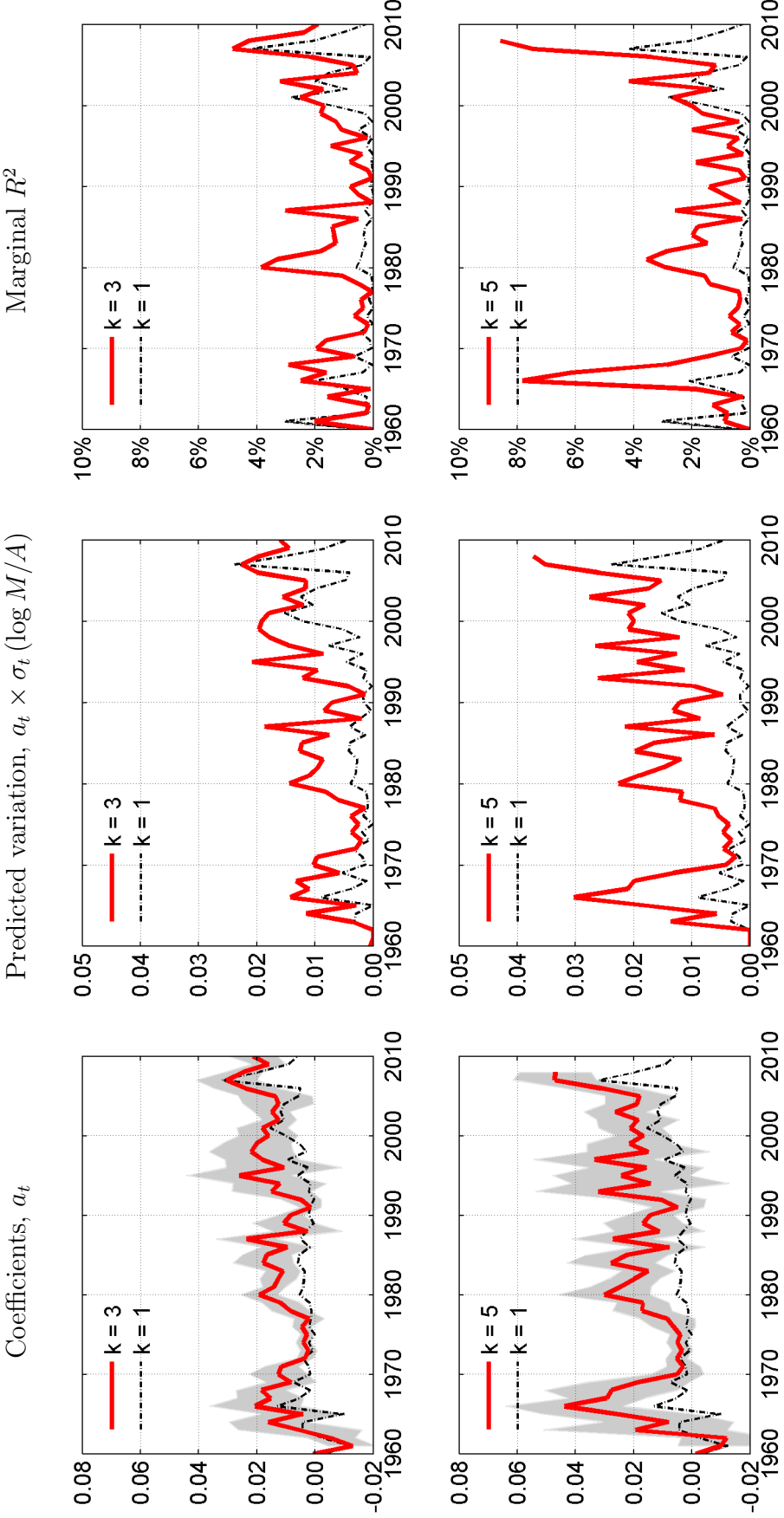

Coefficients, a_t Predicted variation, $a_t \times \sigma_t(CAPX/A)$ Marginal R^2

54
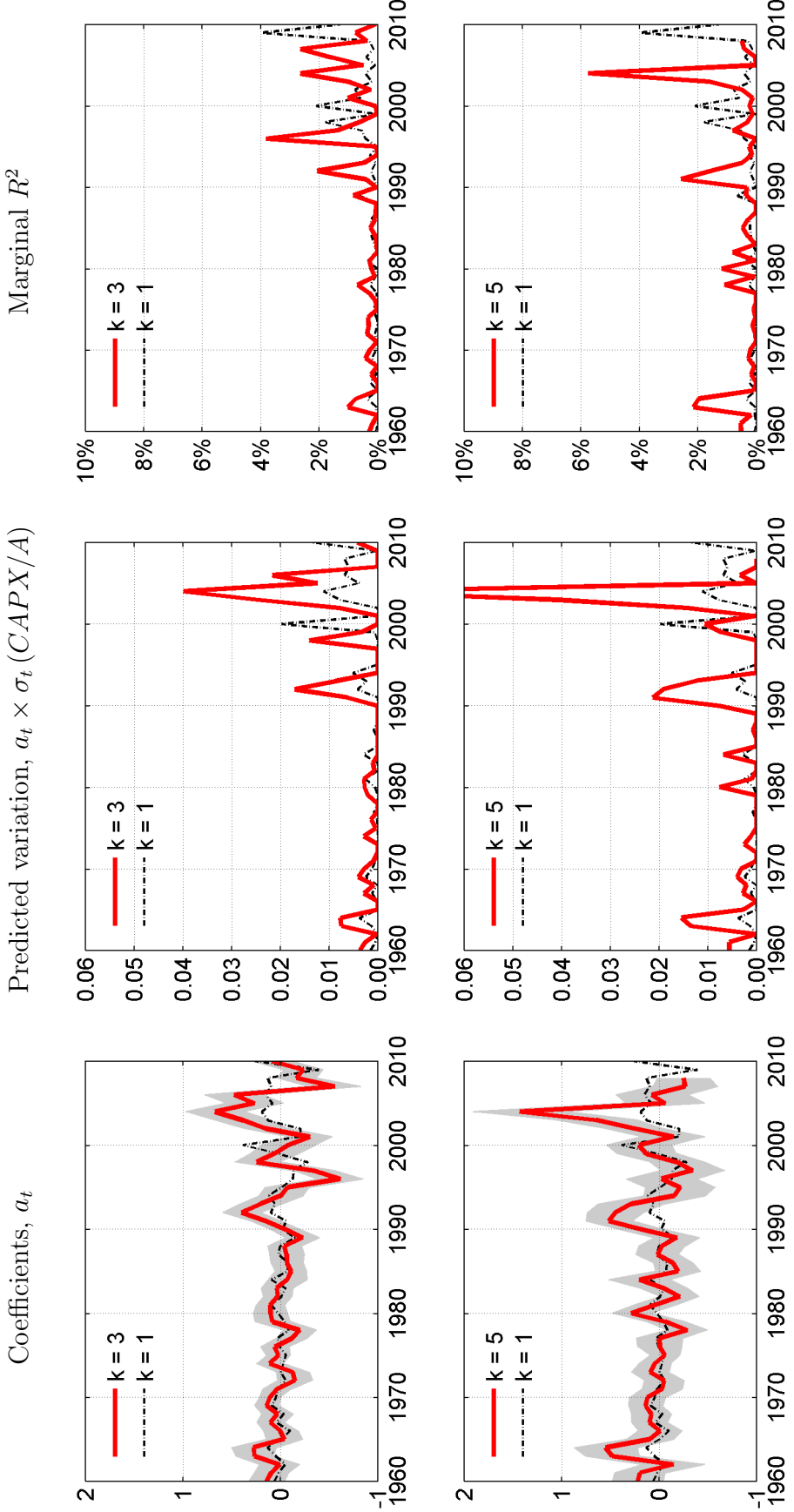
Figure 8. Forecasting R&D expenditure with equity prices

Results from the predictive regression

$$\frac{R\&D_{i,t+k}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{R\&D_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + d_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t \left(\log M/A\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $\log M/A$.

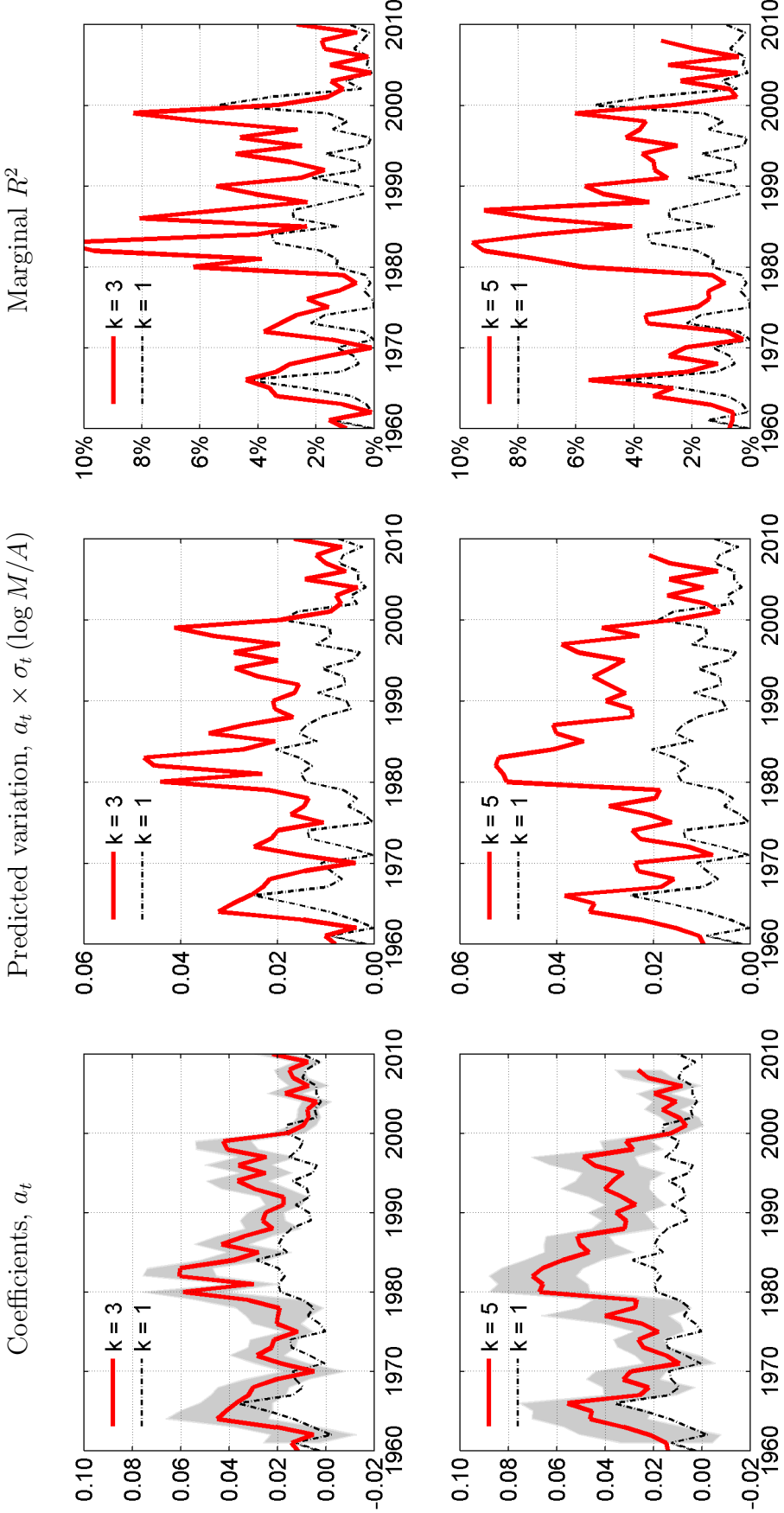Coefficients, a_t Predicted variation, $a_t \times \sigma_t$ ($\log M/A$)   Marginal R^2

55

Figure 9. Forecasting capital expenditure with equity prices

Results from the predictive regression

$$\frac{CAPX_{i,t+k}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{CAPX_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + d_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t$ ($\log M/A$). The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $\log M/A$.

Coefficients, a_t Predicted variation, $a_t \times \sigma_t$ ($\log M/A$)   Marginal R^2

56

Figure 10. Forecasting returns with equity prices

The predicted variation of prices for returns and earnings. The predicted variation is $a_t \times \sigma_t \left(\log M/A \right)$ from the forecasting regression

$$\log R_{i,t \to t+k} \text{ or } \frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1} \right) \times \left(\mathbf{1}_t \right) + \epsilon_{i,t}.$$

Market cap M is measured as of the end of March following the firm's fiscal year end. The log return is from April of year t through March of year $t+1$. Earnings E are measured as EBIT. The predicted variation for earnings is $\times 10$ for ease of comparison. $SIC1$ is the one-digit SIC code. The values for k are 1, 3 and 5 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator.
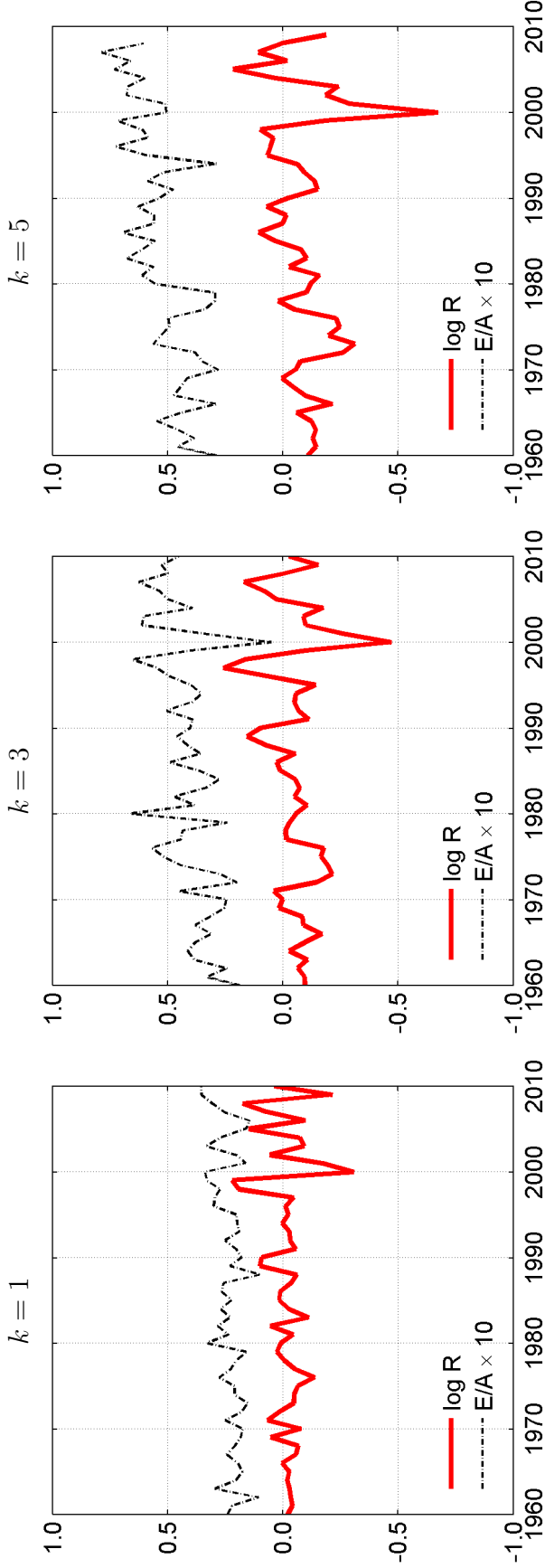
Figure 11. **The unit cost of information**

Model-based estimates of the unit cost of information at the five-year horizon. From Equation (26), the unit cost of information is $\frac{\alpha\psi}{h_s+h_\eta} = \sigma_z^2 \sqrt{\frac{\mathbb{V}(\mathbb{E}[r|p])}{\mathbb{V}(\mathbb{E}[z|p])}}$. Here ψ is the cost of becoming informed, α is the risk aversion of traders, h_s and h_η are the precisions of the traders' and internal signals. $\mathbb{V}(\mathbb{E}[z|p])$ and $\mathbb{V}(\mathbb{E}[r|p])$ are price and return informativeness, measured as the predicted variation, $a_t \times \sigma_t(\log M/A)$, with a_t from the forecasting regression

$$\log R_{i,t\to t+5} \text{ or } \frac{E_{i,t+5}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

For return informativeness, we use the sample mean (not the annual values) as this series is very noisy as shown in Figure 10. Total uncertainty σ_z is measured as the dispersion of earnings-over-assets. The sample consists of S&P 500 non-financial firms (left panel) and all non-financial firms (right panel) from 1960 to 2013.
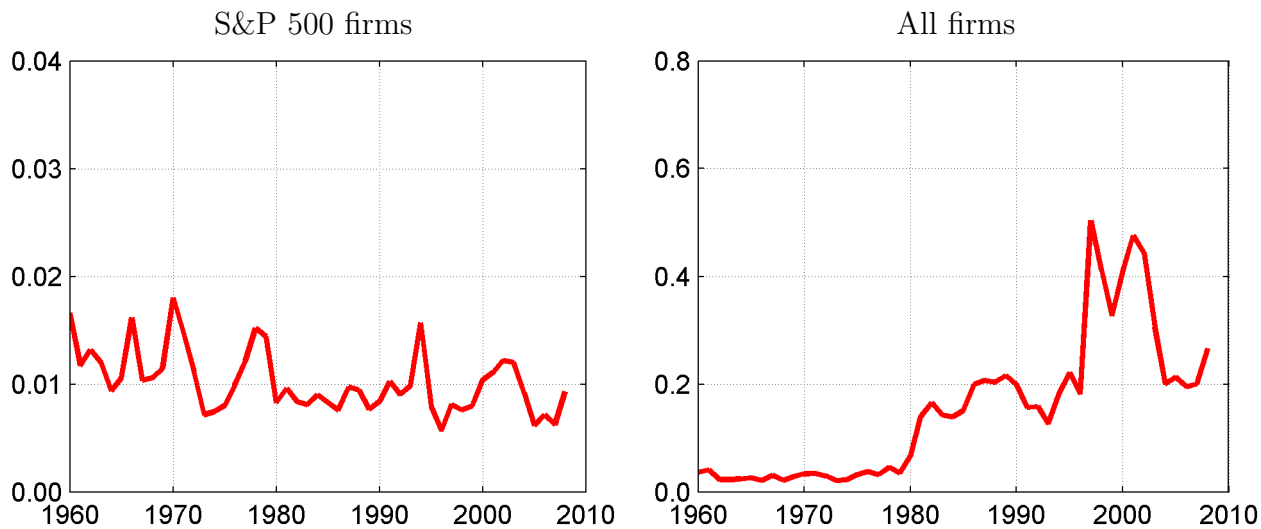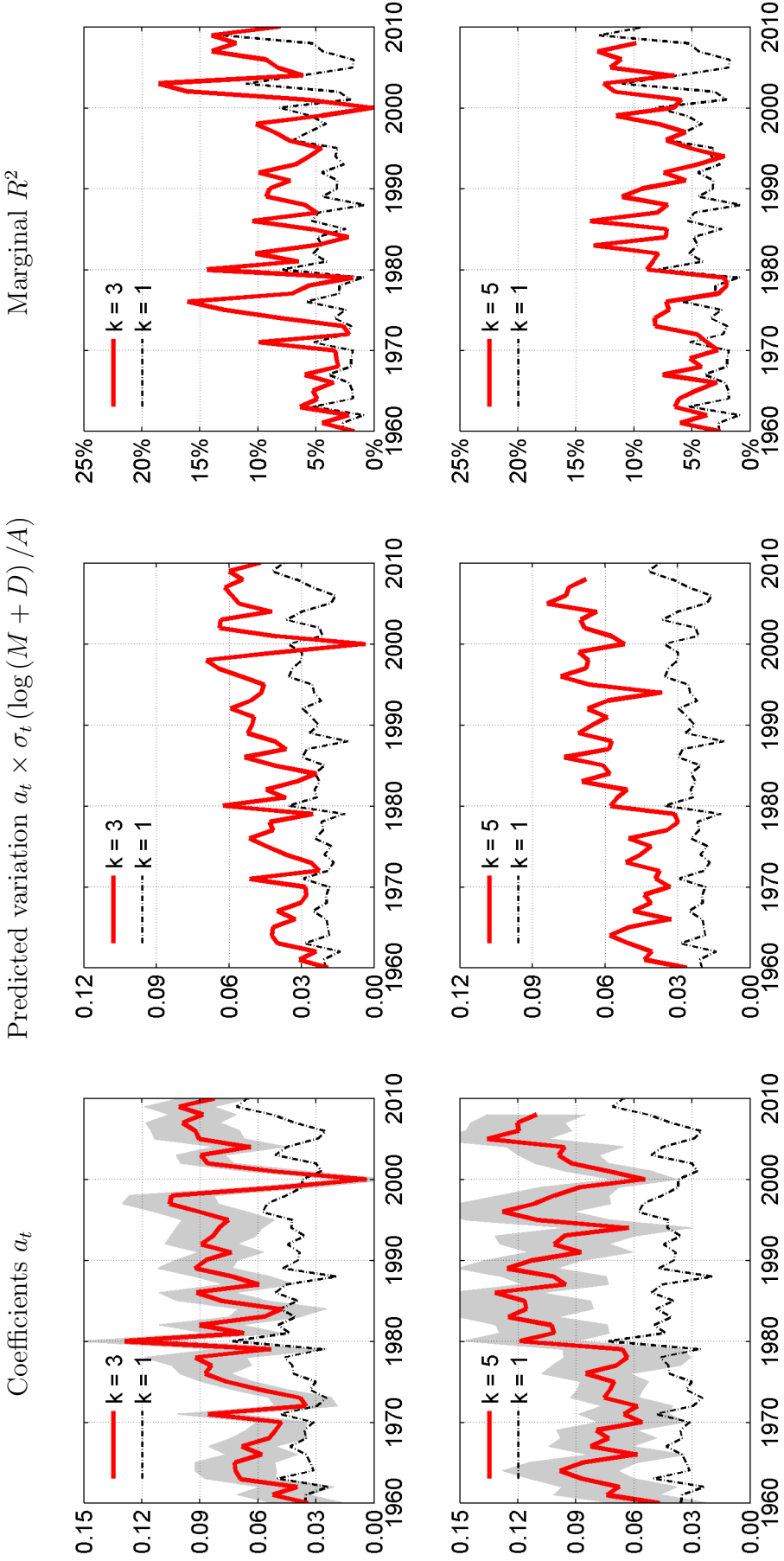
Figure B.1. Forecasting earnings with equity prices, adjusting for debt

Results from the predictive regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}+D_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Market cap M is measured as of the end of March following the firm's fiscal year end. Debt D is long-term debt. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1960 to 2013. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t \left(\log M/A\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $\log M/A$.

Coefficients a_t Predicted variation $a_t \times \sigma_t \left(\log\left(M+D\right)/A\right)$ Marginal R^2
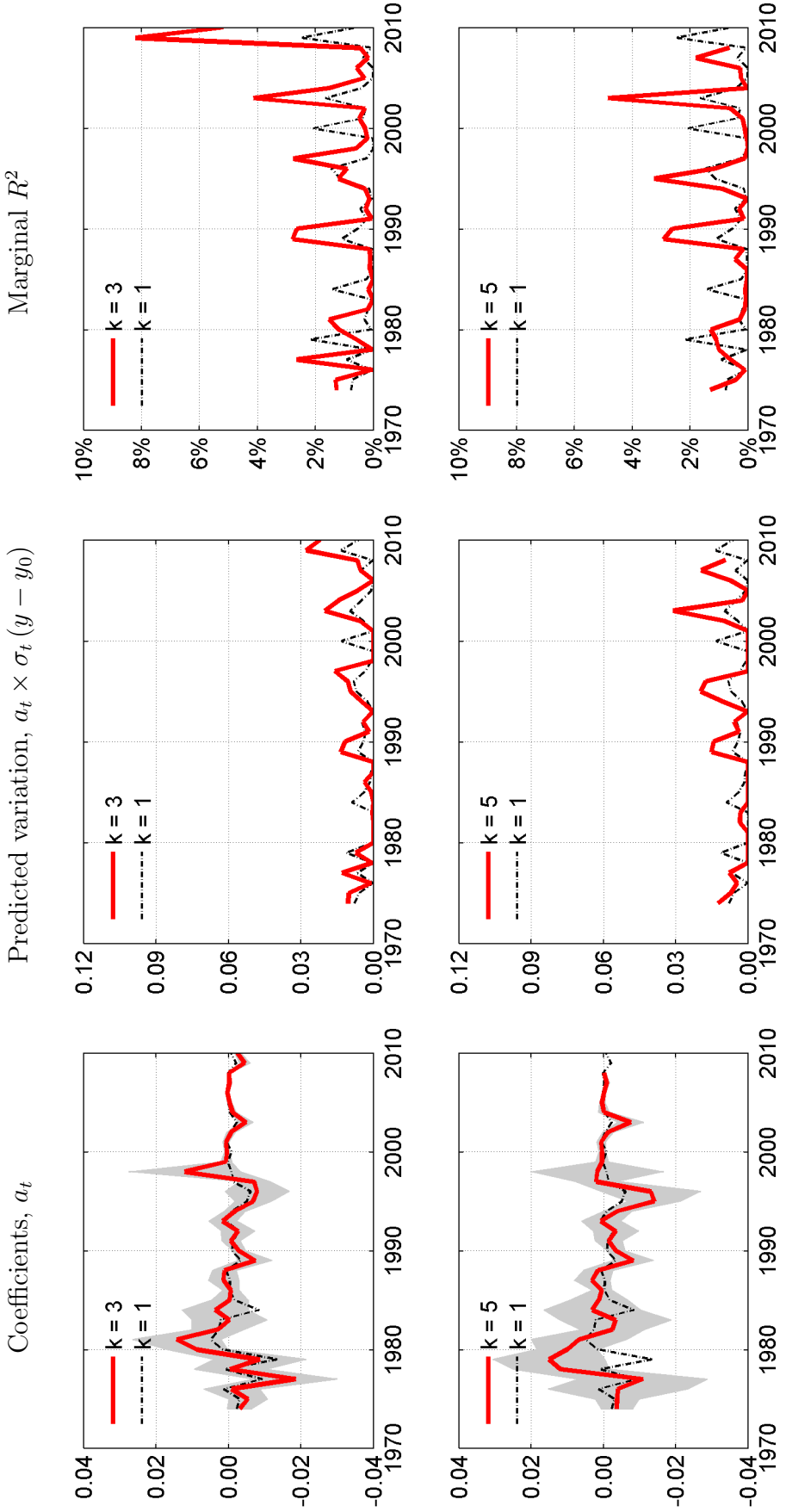
Figure C.1. Forecasting earnings with bond spreads

Results from the predictive regression

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \left(y_{i,t} - y_{0,t}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

Corporate bond spread $y_{i,t} - y_{0,t}$ is the difference between the average yield of corporate bonds issued by firm i in year t and the duration-matched Treasury yield in year t. Yields are measured at the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1973 to 2013, when bond data is available. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t \times \sigma_t (y - y_0)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting corporate bond spread $(y - y_0)$.
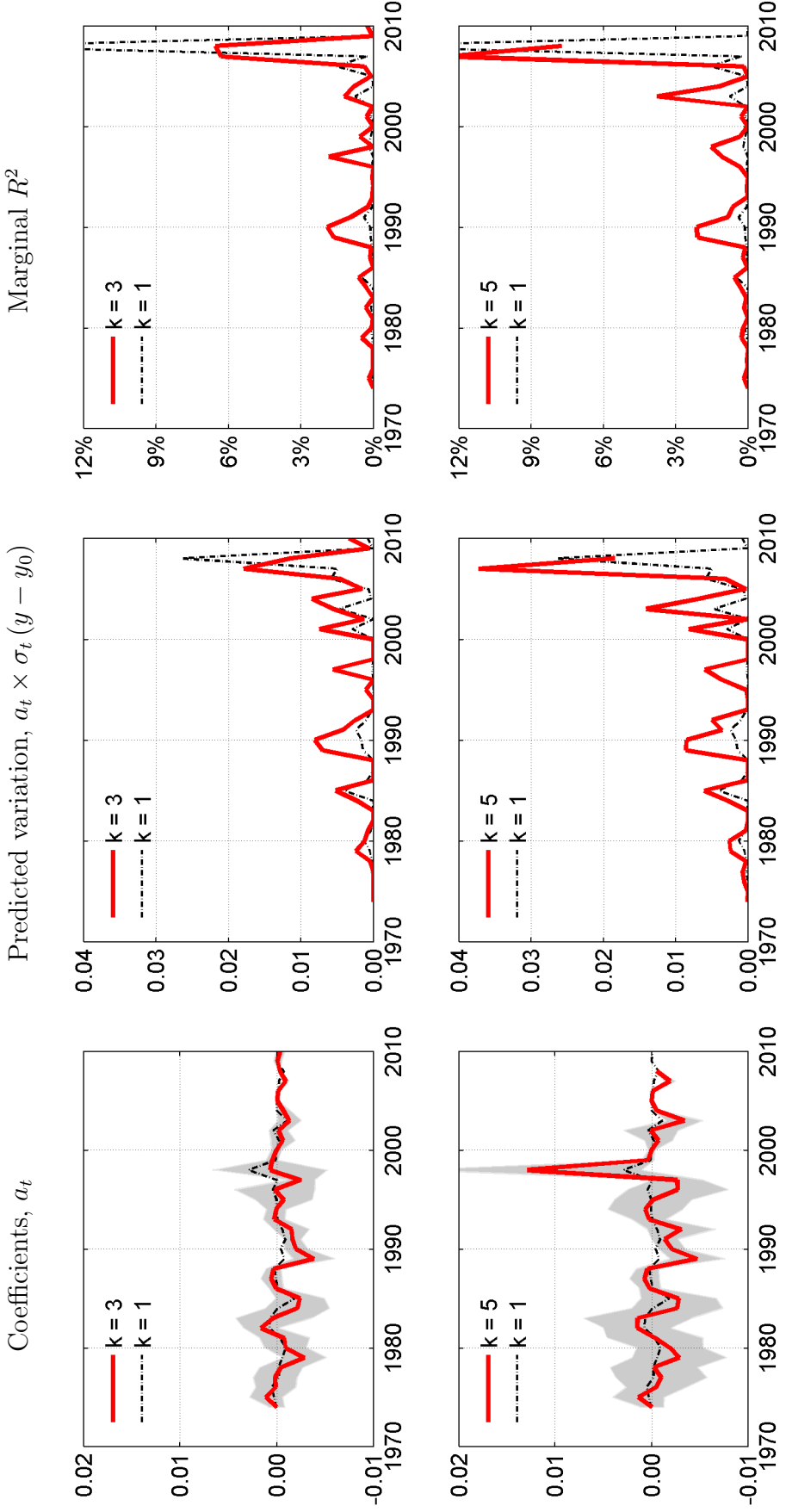

Coefficients, a_t

Predicted variation, $a_t \times \sigma_t (y - y_0)$

Marginal R^2

Figure C.2. Forecasting R&D expenditure with bond spreads

Results from the predictive regression

$$\frac{R\&D_{i,t+k}}{A_{i,t}} = a_t\left(y_{i,t} - y_{0,t}\right) \times \mathbf{1}_t + b_t\left(\frac{R\&D_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + d_{s,t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

The yield spread $y_{i,t} - y_{0,t}$ is the difference between the average yield of corporate bonds issued by firm i in year t and the duration-matched Treasury yield in year t. Yields are measured at the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1973 to 2013, when bond data is available. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t \times \sigma_t (y - y_0)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $y - y_0$.

Coefficients, a_t Predicted variation, $a_t \times \sigma_t (y - y_0)$ Marginal R^2

Figure C.3. Forecasting capital expenditure with bond spreads

Results from the predictive regression

$$\frac{CAPX_{i,t+k}}{A_{i,t}} = a_t \left(y_{i,t} - y_{0,t} \right) \times \mathbf{1}_t + b_t \left(\frac{CAPX_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + d_{s,t} \left(\mathbf{1}_{SIC1} \right) \times \left(\mathbf{1}_t \right) + \epsilon_{i,t}.$$

Corporate bond spread $y_{i,t} - y_{0,t}$ is the difference between the average yield of corporate bonds issued by firm i in year t and the duration-matched Treasury yield in year t. Yields are measured at the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 3 and 5 years (solid red lines) and 1 year (dashed black line). The sample consists of all S&P 500 non-financial firms from 1973 to 2013, when bond data is available. Nominal quantities are adjusted by GDP deflator. The coefficients a_t are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t \times \sigma_t (y - y_0)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $y - y_0$.

Coefficients, a_t

Predicted variation, $a_t \times \sigma_t (y - y_0)$

Marginal R^2