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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 use stock and bond prices to forecast earnings and find that the information content of market prices has not improved since 1960. We use a model with information acquisition and investment to link financial development, price informativeness, and allocational efficiency. As information costs fall, the predictable component of future earnings should rise and hence improve capital allocation and welfare. We find that this component has remained stable over the past 50 years. When we decompose price informativeness into real price efficiency and forecasting price efficiency, we find that both have remained stable.

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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 information 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 and we show that it is directly related to welfare, as in Hayek (1945): information promotes the efficient allocation of investment, which leads to economic growth.

Our main results are based on regressions of future earnings on current valuation ratios, controlling for current earnings. We look at both equity and corporate bond markets. We include one-digit industry-year fixed effects to absorb time-varying cross-sectional differences in the cost of capital. This regression compares firms in the same sector and asks whether

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

firms with higher market valuations tend to produce higher earnings in the future than firms with lower valuations. The answer is yes, but, surprisingly, the amount of informativeness has not changed since 1960.

By itself, constant price informativeness does not imply constant information production in markets. It is possible that information production has simply migrated from inside firms to markets. Hirshleifer (1971) first noted the dual role of prices in revealing new information and reflecting existing information. Bond, Edmans, and Goldstein (2012) call the revelatory component of price informativeness *real price efficiency* (RPE), and the forecasting component *forecasting price efficiency* (FPE). The financial sector adds value only to the extent that it reveals information that would otherwise be unavailable to decision makers. Of course, almost any bit of information is revelatory to someone, so total price informativeness remains a variable of interest. Nevertheless, the distinction between RPE and FPE is fundamental, and we seek to disentangle them. Our model provides a way of doing so. When managers rely on prices, they import the price noise into their investment policies. When markets reveal no new information, managers ignore them and prices remain noisy but investment does not. In the opposite case, when all information is produced in markets, managers use prices and both investment and prices are equally noisy. Information increases the predictive power of both prices and investment, but a rise in the revelatory component of prices increases price informativeness disproportionately.

To see if the constant price informativeness could mask a substitution from forecasting (FPE) to revealing (RPE) information, we check to see if the predictable component of earnings based on investment has changed. We find it has not. Based on our model, this implies that neither FPE nor RPE has risen over the last five decades. To rule out the possibility that an increase in noise, or discount rate variation, also masks greater information production, we run regressions of ex post returns on prices. Our results show that discount rate variation has also remained stable.

Our strongest positive finding is that a higher equity valuation is more closely associated with R&D investment now than in the past. The same is not true of capital expenditure. However, the increased predictability of R&D is not related to increased predictability of earnings, so we cannot conclude that informativeness has increased.

For most of the paper, we examine S&P 500 stocks whose characteristics have remained stable. 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 consistent with changing firm characteristics: the typical firm today is more difficult to value. This motivates our focus on S&P 500 firms.

We note that a rise in uncertainty cannot explain our results but instead strengthens them. In our model, greater uncertainty increases informativeness as it raises the return to becoming informed. In the data, we see an increase in the dispersion of ex post earnings among all firms, which is consistent with greater uncertainty. This is not the case among S&P 500 firms, on which most of our analysis is based.

It remains possible that S&P 500 firms have also changed even if their observable characteristics appear stable. For example, disclosure rules have changed over time. To control for this possibility, we run a cross-sectional test. Specifically, we compare the price informativeness of firms that have CBOE-listed options, to that of firms that do not. Option markets provide greater opportunity for traders to express negative views, take leverage, and tailor their positions. These factors should spur information production. Instead, we find that price informativeness is the same for CBOE-listed and unlisted stocks.

As a final exercise, we construct a model-implied measure of the unit cost of information production in markets. We find that this measure has remained flat for S&P 500 firms over the last fifty years.

In the Appendix, we present an alternative, model-free measure of informativeness based on earnings announcement returns (Appendix D). We find that earnings surprises (in terms of returns) have increased. We also show that the information content of agricultural commodity futures prices has remained constant as well (Appendix E).

The rest of this paper proceeds with an overview of the literature, followed by our 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 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 the 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.

[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).

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 have 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. Our model allows us to do so. We also note that few pieces of information, if any, are known to all affected decision makers. While firm managers arguably possess a highly refined information set, others may not. For example, potential industry entrants, competitors, customers, creditors, or regulators may benefit from the role of prices in summarizing a firm's financial statements. For this reason, we are also interested in total informativeness.

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 more 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. 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. Firstly, we construct theory-based and welfare-relevant measures of price informativeness and we distinguish RPE from FPE. Secondly, we trace the evolution of these measures over a 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. and we uncover a challenge for future research, namely the fact that, contrary to common wisdom, the quality of prices does not seem to have improved over time.

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

[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.

to control for changes in disclosure, though we examine the periods surrounding well-known regulatory initiatives such as Reg FD in 2000 and Sarbanes-Oxley in 2002. We also provide cross-sectional results 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 at business cycle frequencies (for example, informativeness drops sharply after 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. Our contention is that measuring the information content of prices helps to assess the social value of a growing financial sector.

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 next section.

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]

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

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

[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.

[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.

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

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

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

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

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

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

Taking unconditional expectations (or aggregating over many ex-ante identical firms), and using the fact that the unconditional mean of z is zero, we see that aggregate wealth is

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

where $\mathbb{V}\left(\mathbb{E}\left[z\right|\theta,\eta]\right)$ 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 (33) in Appendix A. □

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.

An important 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 productivity 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

[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 examine the periods surrounding well-known regulatory actions such as Reg FD in 2000. We also provide cross-sectional results using option listings that hold disclosure rules fixed.

mean-variance objective:

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

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

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

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 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 line 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.

[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.

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 $\mathbb{E}[z \mid p]$ and our measure of overall price informativeness

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

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

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

Price informativeness (11) 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

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

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 will allow 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:*

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

Moreover, consider an increase in h_s holding $h_s + h_\eta$ constant. Then $\mathbb{V}\left(\mathbb{E}\left[z \mid p\right]\right)$ and $\mathbb{V}\left(\mathbb{E}\left[z \mid s, \eta\right]\right)$ remain constant, and $\mathbb{V}\left(\mathbb{E}\left[z \mid \theta, \eta\right]\right)$ falls.

Proof of Proposition 2. See Appendix A. □

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 contemplates a scenario where information production migrates to financial markets from inside the firm so that external precision h_s rises while internal precision h_η rises. It shows that in this case the information content of prices remains unchanged as higher RPE compensates for lower FPE, but that the information available to managers falls, and hence welfare falls also. The reason is that managers cannot fully filter out the noise in prices, so when information production leaves the firm the quality of their overall signal deteriorates.

We have formulated this result with an eye towards our empirical results which suggest unchanged price informativeness. This result by itself is consistent with higher RPE and lower FPE. Proposition 2 gives us a way to test this possibility, i.e. to separate RPE and FPE, by also looking at the information content of investment.

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

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

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

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

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

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

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

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

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 evolu-

[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.

tion over time.

4 Data

We obtain stock prices from CRSP, and bond prices from the Lehman/Warga database and Mergent Fixed Income Datascope. The test on option listings use listing dates from the CBOE. All accounting measures are from COMPUSTAT. Our main sample period is from 1960 to 2011 at an annual frequency. Bond data is available since 1973. We also use daily stock price data in our announcement-day volatility tests, which starts in 1970.

Our key equity valuation measure is the log-ratio of market capitalization to total assets and our key bond valuation measure is a firm's credit spread. In Appendix C, we also show results using the sum of market cap and the book value of debt in order to control for leverage effects. We use equity and bond 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 our conditioning variables.

We measure future profitability as future EBIT over today's assets. This allows firms to increase their profits by growing, as they do in our model. We measure current investment alternatively as the log-ratio of R&D or CAPX to assets, and future investment as the log-ratio of future R&D or CAPX to today's assets. We consider horizons of between one and three years. Appendix B at the end of the paper explains our measures in greater detail.

In Appendix D, we show tests using earnings surprises, calculated as the three-day CAR around earnings announcements. In Appendix E, we also calculate the informativeness of corn, wheat and soybeans futures prices.

In most tests, we limit attention to S&P 500 non-financial companies, which represent the bulk of the U.S. nonfinancial corporate sector. The set of firms in this sample has remained relatively stable over time, allowing us to compare the informativeness of their market prices over several decades. For comparison, we also report results for the full set of non-financial firms, whose composition has seen substantial change.

Table I about here.

Table I presents summary statistics. S&P 500 stocks are typically more profitable than the universe of stocks. They invest more in absolute terms, but not relative to assets. Their credit spreads are only a bit lower. S&P 500 stocks are also less volatile unconditionally and they experience smaller earnings surprises.

Our model suggests that the dispersion in prices is a partial indicator of price informativeness (it also depends on discount rate variation). Figure 1 shows the distribution of the ratio of market capitalization to total assets (M/A) over time for the non-financial firms in the S&P 500. For the bulk of the distribution, cross-sectional dispersion has remained stable, falling from 1960 to 1980 and then recovering. More prominently, in the second half of the 1990s valuations become dramatically more right-skewed. Skewness peaks in 2000 before subsiding. The dot-com boom aside, price differentiation has grown modestly, though a few firms with very high valuations stand out. In the results section, we check whether these changes are associated with a better forecast of future profitability.

Figure 1 about here.

Figure 1 also shows that the cross-sectional distribution of profitability has remained stable and symmetric for firms in the S&P 500. By contrast, investment, specifically R&D expenditure, has both grown and become more skewed. We show that investment and valuation are related in the empirical section.

5 Empirical results

For our main results, we construct time series of predicted variations of prices for earnings, investment, and returns, and of investment for earnings. Guided by our model, we look for trends in these series as evidence of changing informativeness.

A. Market prices and earnings

We begin by measuring price informativeness, the predicted variation (the forecasting coefficient times the standard deviation of the regressor) of prices for future earnings. Our model shows that price informativeness is a key ingredient in aggregate welfare. It also shows that prices both reveal new information (RPE) and reflect existing information (FPE), and offers a way of separating the two empirically. Although we are particularly interested in RPE since it represents the added value of the financial sector, it is also useful to track overall price informativeness over time since all information contributes to welfare.

We always control for current earnings and investment to avoid attributing obvious public information to prices. This raises the bar slightly, but by omitting many other readily available signals, we are giving prices a better shot at forecasting, which turns out to be a conservative stance given our results.

To ensure that our controls are available to investors at the time of forecasting, we always match accounting data for a given year with market prices from March of the following year. As most companies end their fiscal years in December, this means that our market prices are typically recorded three months after our accounting variables. This approach also errs on the side of giving market prices a better shot at forecasting.

To control for discount rate effects, we include year-sector dummies. We also look at returns separately later in the paper.

In sum, in our main tests we exploit within-sector cross-sectional differences in valuations to forecast earnings and investment. While our focus is on the S&P 500, we also present results for the full set of stocks.

A.1. Equity prices and earnings

Our first regression forecasts future earnings with equity prices. We run

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

where $\mathbf{1}_t$ is an indicator variable for year t and $\mathbf{1}_{SIC1}$ is an indicator variable at the one-digit SIC industry level. We take logs of the market-to-assets ratio to mitigate its skewness. By interacting all our predictors with year fixed effects, we avoid making a strong functional form assumption. We forecast at the one-, two-, and three-year horizons ($k = 1, 2, 3$). We always scale by current assets as companies can legitimately boost profits by growing.

Figure 2 about here.

Figure 2 depicts the results of regression (22). The two plots on the left show the evolution of the coefficients a_t at the one- and three-year horizons. The middle plots display the equity market-predicted variation, given by the product of the forecasting variable coefficient a_t and its cross-sectional dispersion $\sigma_t (\log M/A)$. The predicted variation measures the size of the predictable component of earnings that is due to prices, or total price informativeness in the model. The two right-side plots show the contribution to the regression R^2 from including market prices.[10]

Figure 2 shows that market prices are positive predictors of future earnings at both the short and long horizons. The forecasting coefficient and marginal R^2 are a bit higher and the predicted variation is a bit larger at the 3-year horizon. The 3-year estimates are also somewhat noisier, but 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-lived. Overall, the coefficients a_t remain flat throughout our sample.

Our key result is that we find no evidence of an increasing trend in equity price informativeness. The predicted variation of prices has remained remarkably stable over the past fifty years, the sharp drop around 2000 notwithstanding. Although prices do help separate firms that will be more profitable from those that will be less profitable, the extent to which they do so now is about the same as in the past.

[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.

Table II presents a formal test. The first two columns run panel regressions of future earnings on the log market-to-assets ratio interacted with five-year dummies. Combining the data into five-year periods avoids printing fifty yearly coefficients. We scale the valuation ratio by its yearly standard deviation so we can interpret the forecasting coefficient as the predicted variation of prices. We also include current earnings and one-digit industry controls and their interactions, as well as year fixed effects. To be conservative, we use simple OLS standard errors that increase the chance of rejecting the null of constant informativeness.

Table II about here.

The results in Table II confirm the pattern in Figure 2. The predicted variation of prices for future earnings is positive but unchanged over the past five decades. Three of the nine five-year periods come in significant but they are spread about evenly throughout the sample and the coefficients are not monotonic.

A.2. Bond prices and earnings

Turning to the bond market, we check how credit spreads predict earnings. Analogously to our equity regression, we run

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t\left(y_{i,t} - y_{0,t}\right) \times \mathbf{1}_t + b_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}, \tag{23}$$

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

Figure 3 about here.

Figure 3 shows that the predictive power of yield spreads is modest, perhaps because most S&P 500 firms have sterling credit. The forecasting coefficients are rarely two standard errors from zero. Nevertheless, on average higher spreads are associated with slightly lower future earnings, as expected. Predictability is strongest in the late 1970s when credit risk was of particularly high concern. The marginal R^2 is reliably low and noisy. These results are confirmed formally in the panel regressions in Table III.

Table III about here.

Our next task is to check whether the stability of price informativeness reflects (*i*) unchanged information production on the part of investors (RPE), (*ii*) a substitution from internal to market-based information, or (*iii*) a rise in discount rate variation accompanied by higher information production. We examine (*ii*) by looking at investment and (*iii*) by looking at returns.

B. Investment and earnings

Our model shows that overall price informativeness could remain constant even if market-based information production (RPE) is rising as long as internal information production (FPE) is falling. In other words, firms could be substituting from internal to market-based sources of information in a way that leaves total price informativeness constant. We also showed, however, that this substitution should make the predicted variations of prices and investment for earnings more similar. Since we found that total price informativeness is constant, under this mechanism investment informativeness should come down. This happens because in order to keep total price informativeness constant, internal and market-based information must be substituted one-for-one. But in that case investment informativeness has to fall since the presence of noise makes it difficult for managers to extract information from prices.

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. Note, however, that in this case our results can be viewed as providing an upper bound on RPE: If the error in measured investment has indeed risen, then investment informativeness should have fallen relative to price informativeness, even without RPE rising relative to FPE.

We regress future earnings on current investment-over-assets. We present results for both R&D investment and CAPX. We include current earnings as a control together with our usual industry-times-year fixed effects. Specifically, the R&D regression has the form:

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

The CAPX regression is analogous. We focus on the predicted variation $a_t \times \sigma_t \left(R\&D/A \right)$ (or $a_t \times \sigma_t \left(CAPX/A \right)$ for CAPX) and we report the coefficients a_t and the contribution of the $R\&D$ variable to investment for completeness.

Figures 4 and 5 about here.

Figure 4 documents a generally positive relationship between R&D investment and future earnings, at least at the three-year horizon. Firms that undertake more R&D tend to be more profitable in the future, even after controlling for current profitability. By contrast, Figure 5 shows little evidence of a correlation between capital expenditure and future earnings.

These interpretations are confirmed in the panel regressions presented in Table IV. R&D is a positive predictor of earnings but its forecasting power has not changed over the sample. CAPX is an unreliable predictor.

Table IV about here.

Overall, investment appears to be a positive but weak predictor of earnings. In the model, since prices are noisy, investment is generally more informative than prices. However, this result is likely due to measurement error. It is the lack of trend rather than the level that suggests constant RPE versus FPE. Our results so far are thus consistent with a stable amount of overall information, as well as a stable mix between market-based and internally-sourced information.

C. Market prices and investment

To further explore the relationship between prices and investment, we leave out earnings and run forecasting regressions of future investment on prices. We call the resulting predicted variation price informativeness for investment. In our model, it is equal to the price informativeness for earnings scaled by the adjustment cost. Intuitively, investment is proportional to expected earnings and prices are proportional to expected earnings plus noise. Thus, price informativeness for investment is driven by the size of the noise component and the adjustment cost.

C.1. Equity prices and R&D expenditure

We begin with R&D expenditure, which may be of particular interest as its funding requires well-developed equity markets due to low asset pledgeability. During our sample, the importance of R&D has increased, as has its dispersion across firms (see Figure 1).

We add current R&D as an additional control since R&D spending tends to persist. We run the regression

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

The results in Figure 6 show that higher market valuations are associated with more R&D spending: firms with high valuations invest more, as expected. This result holds even after controlling for current R&D (removing this control makes the effect larger).

The predicted variation shows a clear upward trend; prices have become stronger predictors of R&D. The effect is stronger at the three-year horizon, suggesting a substantially forward-looking relationship. These results are confirmed in panel regressions in the middle columns of Table II. The predicted variation of equity prices for R&D is positive and it increases starting in the 1990s. The increase is statistically significant both at the one- and three-year horizons.

Figures 6 and 7 about here.

Although it is tempting to interpret this result as increased information production, our results on earnings predictability are not consistent with this view. Within the context of our model, rising price informativeness for investment can be attributed to less noise in prices or lower adjustment costs. The evidence on noise later in the paper suggests it has not changed much. Outside our model, structural factors like the increased importance of technology may play a role, a possibility in line with our contrasting evidence on CAPX below.

C.2. Bond spreads and R&D expenditure

Turning to bond markets, Figure 7 shows no evidence that corporate bond spreads forecast R&D. The forecasting coefficients are close to zero and exhibit no trends. The panel regressions in Table III tell a similar story. These results are not surprising as R&D is by nature not well-suited to bond financing. R&D-intensive technology firms tend to issue few bonds if any.

C.3. Equity prices and capital expenditure

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

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

Figure 8 shows that a higher equity valuation is associated with more capital expenditure, particularly at the longer horizons. However, we see no evidence of a trend in the forecasting coefficient, the predicted variation, or the marginal R^2. The last two columns of Table II are consistent with Figure 8. This result contrasts with our findings for R&D and supports the interpretation that the nature of investment has changed.

Figures 8 and 9 about here.

C.4. Bond spreads and capital expenditure

As with R&D expenditure (Figure 7), Figure 9 shows that lower bond spreads are not 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 two specifications in Table III support these findings.

D. Market prices and returns

Our model shows that price informativeness is affected by the level of noise, or discount rate variation, in prices. It is possible that an increase in noise could mask an increase in information production, leaving measured informativeness constant. 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 returns on the left, focusing on the three-year horizon (results are the same at shorter horizons):

$$\log R_{i,t+3} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}. \quad (24)$$

The results are presented in Figure 10. Overall, due to the high volatility of returns, the discount rate component of prices is less precisely measured than the earnings component. Although bumpy, the series is level. A sharp drop in 2000 coincides with the end of the NASDAQ boom, but return predictability quickly recovers to its usual levels.

Table V about here.

Table V presents a formal test. In a panel regression of future returns on the valuation ratio interacted with five-year dummies (and controls), we see only a few significant differences over the full sample, but these alternate between positive and negative again due to the end of the NASDAQ boom.[11]

We conclude that there is no evidence of an increase in the discount rate component of prices that could account for the result that price informativeness remains unchanged.

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

In this section, we compare the predictability results for S&P 500 firms to those of the universe of stocks. The results are presented in Figure 11. 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 three times the level observed among S&P 500 firms. This period coincides with the rise of NASDAQ. The tech boom of the late 1990s is associated with a second but smaller increase in earnings dispersion. In our model, higher earnings dispersion actually increases the equilibrium level of price informativeness.

Figure 11 and Table VI about here.

The top right panel of Figure 11 shows that as the earnings dispersion of all firms has increased, so has their price dispersion. In contrast, S&P 500 firms show little evidence of increased price dispersion, except around 2000. In the context of our model, holding discount rate variation constant, increased price dispersion is associated with more informative prices and higher welfare. However, we see from the bottom two panels of Figure 11 that for all firms, the forecasting coefficient and its associated predicted variation drop precipitously around the same time as the dispersion across firms increases. Table VI shows the same

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

result in a panel regression setting. Overall, the increased price dispersion does not appear to be related to earnings even at a three-year horizon.

If anything, price informativeness appears to be decreasing for all firms, but this is likely due to changing firm characteristics.[12] Note that based on our model, it must be the case that the average non-S&P 500 firm is more costly to value, not simply more uncertain.

We view these results as motivating our focus on S&P 500 firms, whose observable characteristics have remained stable. In the next section, we use a cross-sectional test to further control the composition of firms in our sample.

F. Option listing and informativeness

Our results show that price informativeness among S&P 500 firms is unchanged, whereas it has decreased among all firms, likely due to changing firm characteristics. This leaves the possibility that S&P 500 firms have also changed somehow even though their ex post earnings distribution appears stable.

To check this possibility, we use cross-sectional variation in exposure to trading that is plausibly orthogonal to the unobserved factors that affect informativeness. 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 markets contribute to price discovery by increasing liquidity and providing embedded leverage and a low-cost way to short-sell. Mayhew and Mihov (2004) show that the CBOE is more likely to list stocks with higher equity turnover, creating a potential bias towards higher informativeness among listed stocks.

Figure 12 and Table VII 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. The results are in Figure 12. Table VII presents an accompanying formal test in the form of a panel regression that includes

[12]Indeed, the drop in informativeness is higher among NASDAQ stocks but it is not confined to that group.

triple interactions between market-to-assets ratio, a dummy variable for whether a firm is listed on the CBOE, and five-year dummies.

We find that price informativeness is positive and has remained flat for both listed and unlisted firms, as it has for the overall market. There is no evidence that listed firms have higher price informativeness. This suggests that changing firm characteristics cannot account for the stability of price informativeness among S&P 500 firms.[13]

G. The unit cost of information

In this section, we apply 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

$$\frac{\alpha\psi}{h_s + h_\eta} = \sigma_z^2 \sqrt{\frac{\mathbb{V}\left(\mathbb{E}\left[r|\, p\right]\right)}{\mathbb{V}\left(\mathbb{E}\left[z|\, p\right]\right)}}. \tag{25}$$

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.[14] 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 measurable, we can back out an implied unit cost of information.

A final obstacle to implementing this idea comes from the fact that as Figure 11 shows, the estimated price informativeness turns negative in some years. As a simple fix, we add one to each of the predicted variations in (25), i.e. we use $\sigma_z^2 \sqrt{\frac{1+\mathbb{V}(\mathbb{E}[r|p])}{1+\mathbb{V}(\mathbb{E}[z|p])}}$.

Figure 13 plots our estimates of the unit cost of information for the S&P 500 and for all firms separately. For S&P 500 firms, the unit cost of information is remarkably stable,

[13] Appendix D provides further evidence from a test based on earnings surprises that also includes firm fixed effects.

[14] One might argue that α has been falling as higher liquidity and a richer span of security payoffs have reduced the cost of diversification and hedging. In this case, according to the model price informativeness should have increased.

whereas for all firms it increases dramatically. As reported in Figure 11, earnings dispersion for all firms rises sharply during the 1980s, whereas the market-predicted variation actually falls. These two effects combine to produce the pattern in Figure 13.

Figure 13 about here.

We attribute the rise in the implicit information cost for all firms to the changing composition of firms in the economy. However, the results for the sample of S&P 500 firms, whose characteristics have remained stable, suggest that the cost of producing information in markets has not fallen over the last five decades.

6 Conclusion

We examine the extent to which stock and bond prices predict earnings. Our main finding is that the informativeness of financial market prices has not increased in the past fifty years. We decompose informativeness into a revelatory and a forecasting component by also looking at investment, and we find no evidence of increased information production in markets. We do find a stronger association between prices and R&D investment, but this does not translate into earnings predictability. We focus on S&P 500 firms, whose characteristics have remained stable. Among all firms, informativeness appears to decline, but this is likely due to changing firm characteristics. A cross-sectional test based on option listings supports our time series results.

These results appear to contradict the view that improvements in information technology and liquidity have increased information production. A possible explanation is that the relevant constraint for investors lies in the ability to interpret information rather than the ability 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."

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

$$x = y + \epsilon, \tag{26}$$

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

$$\mathbb{E}[y|\, x] = \frac{h_y \overline{y} + h_x x}{h_y + h_x} \tag{27}$$

and faces residual uncertainty

$$\mathbb{V}[y|\, x] = \frac{1}{h_y + h_x}. \tag{28}$$

We are often interested in the quantity of information

$$\begin{aligned}
\mathbb{V}(\mathbb{E}[y|\, x]) &= \mathbb{V}\left(\frac{h_x x}{h_y + h_x}\right) && (29)\\
&= \left(\frac{h_x}{h_y + h_x}\right)^2 \sigma_x^2 && (30)\\
&= \left(\frac{\sigma_y^2}{\sigma_\epsilon^2 + \sigma_y^2}\right)^2 \left(\sigma_y^2 + \sigma_\epsilon^2\right) && (31)\\
&= \frac{h_x}{h_y + h_x}\sigma_y^2. && (32)
\end{aligned}$$

In the case of multiple signals, we simply have

$$\mathbb{V}(\mathbb{E}[y|\, x_1, x_2]) = \frac{h_{x_1} + h_{x_2}}{h_y + h_{x_1} + h_{x_2}}\sigma_y^2. \tag{33}$$

Ranking information sets:

Proof of Proposition 2. We want to show that

$$\mathbb{V}(\mathbb{E}[z|\, p]) < \mathbb{V}(\mathbb{E}[z|\, \theta, \eta]) < \mathbb{V}(\mathbb{E}[z|\, s, \eta]) < \sigma_z^2. \tag{34}$$

The right-most inequality follows from Equation (6). From Equation (15) we know that $h_\theta < h_s$. This directly implies $\mathbb{V}(\mathbb{E}[z|\, \theta, \eta]) < \mathbb{V}(\mathbb{E}[z|\, s, \eta])$. The first inequality comes from the fact that $h_p < h_\theta + h_\eta$ which can be shown from Equations (21) and (15):

$$\frac{(h_s+h_\eta)^2}{h_s+h_\eta+\alpha^2\sigma_u^2} < \frac{h_s^2}{h_s+\alpha^2\sigma_u^2}+h_\eta \quad (35)$$

$$\left(h_s+\alpha^2\sigma_u^2\right)(h_s+h_\eta)^2 < \left(h_s+\alpha^2\sigma_u^2\right)(h_s+h_\eta)^2+\alpha^4\sigma_u^4 h_\eta. \quad (36)$$

For the second part of the proposition, let $h_s = h_{s,0}+\Delta$ and $h_\eta = h_{\eta,0}-\Delta$ for some initial values $h_{s,0}$ and $h_{\eta,0}$. Clearly, $h_{s,0}+h_{\eta,0} = h_s+h_\eta$ so $\mathbb{V}\left(\mathbb{E}\left[z|\, s,\eta\right]\right)$ is independent of Δ. From Equation (21), so is $\mathbb{V}\left(\mathbb{E}\left[z|\, p\right]\right)$ (this is also true in the short run without free entry). To show that $\mathbb{V}\left(\mathbb{E}\left[z|\, \eta,\theta\right]\right)$ falls, since $h_{s,0}$ and $h_{\eta,0}$ are chosen arbitrarily, it is enough to show that $\frac{\partial}{\partial\Delta}\left(h_\eta+h_\theta\right)|_{\Delta=0} < 0$ (see Equation (6)), i.e. that $\frac{\partial}{\partial\Delta}\, h_\theta|_{\Delta=0} < 1$. From Equation (15),

$$h_\theta = \frac{h_s}{1+\frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2}. \quad (37)$$

Note that by Equation (20), m is independent of Δ. Thus,

$$\frac{\partial}{\partial\Delta}\, h_\theta|_{\Delta=0} = \frac{1}{1+\frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2}+\frac{h_s}{\left[1+\frac{1}{h_s}\left(\frac{\alpha}{m}\right)^2\sigma_u^2\right]^2}\left[\frac{1}{h_s^2}\left(\frac{\alpha}{m}\right)^2\sigma_u^2\right] \quad (38)$$

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

$$< 1. \quad (40)$$

This completes the proof. □

Expected returns: Recall that prices are given by

$$p = \frac{\mathbb{E}\left[v|\, s,\eta\right]}{k+\overline{k}}+\frac{\alpha}{m}u\frac{\mathbb{V}\left[v|\, s,\eta\right]}{\left(k+\overline{k}\right)^2}. \quad (41)$$

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

$$r = \frac{v}{\overline{k}+k}-p = \frac{v-\mathbb{E}\left[v|\, s,\eta\right]}{k+\overline{k}}-\frac{\frac{\alpha}{m}}{h_z+h_s+h_\eta}u \quad (42)$$

Conditional on prices, expected returns are

$$\mathbb{E}\left[r|\, p\right] = \mathbb{E}\left[\left.\frac{v-\mathbb{E}\left[v|\, s,\eta\right]}{k+\overline{k}}\right|p\right]-\frac{\frac{\alpha}{m}\mathbb{E}\left[u|\, p\right]}{h_z+h_s+h_\eta}. \quad (43)$$

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

$$\mathbb{E}\left[r|\, p\right] = -\frac{\frac{\alpha}{m}\mathbb{E}\left[u|\, p\right]}{h_z+h_s+h_\eta}. \quad (44)$$

Since

$$p - \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}} = \frac{h_s s + h_\eta \eta + \frac{\alpha}{m}u}{h_z + h_s + h_\eta} = \frac{(h_s + h_\eta)\, z + h_s \epsilon^s + h_\eta \epsilon^\eta + \frac{\alpha}{m}u}{h_z + h_s + h_\eta}, \tag{45}$$

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

$$\widehat{p} \;=\; \frac{\alpha}{m}u + (h_s + h_\eta)\, z + h_s \epsilon^s + h_\eta \epsilon^\eta, \tag{46}$$

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

$$\mathbb{E}\left[r|\, p\right] \;=\; -\frac{(\alpha/m)^2\,\sigma_u^2}{(\alpha/m)^2\,\sigma_u^2 + (h_s + h_\eta)\left(1 + (h_s + h_\eta)\,\sigma_z^2\right)}\left(p - \frac{\overline{k} - \frac{\gamma}{2}k^2}{k + \overline{k}}\right). \tag{47}$$

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

$$\begin{aligned}\mathbb{V}\left(\mathbb{E}\left[r|\, p\right]\right) \;&=\; \left(\frac{\alpha^2\sigma_u^2}{\alpha^2\sigma_u^2 + m^2\,(h_s + h_\eta)\left(1 + (h_s + h_\eta)\,\sigma_z^2\right)}\right)^2 \mathbb{V}\,(p) &(48)\\ &=\; \frac{1}{(h_z + h_s + h_\eta)^2}\,\frac{\left[(\alpha/m)^2\,\sigma_u^2\right]^2}{(\alpha/m)^2\,\sigma_u^2 + (h_s + h_\eta)\left(1 + (h_s + h_\eta)\,\sigma_z^2\right)}. &(49)\end{aligned}$$

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. Given our results, this approach is conservative in that it gives market participants a better shot at forecasting. Stock prices and volume are from the Center for Research in Security Prices (CRSP) from 1960 to 2011.

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 2010. 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 2010. Our final sample contains about 18,000 firm-year observations with non-missing bond spreads.

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.

C Adjusting for debt

We present a variation of our benchmark results in Figure 2 by adding the book value of long-term debt to the market value of equity in the calculation of the valuation measure, which controls for leverage. In other words, we use $\log\left(\left(M+D\right)/A\right)$ instead of $\log M/A$.

Figure B.1 about here.

Based on the results in Figure B.1, we conclude that changes in firm leverage do not account for our result that price informativeness has remained stable.

D Volatility around earnings announcements

We look at volatility around earnings announcements as a model-free measure of informativeness. Better information should lead to smaller ex-post surprises. Here, we measure surprises with the magnitude of returns around earnings announcements. Specifically, for each firm in every year, we calculate three-day cumulative abnormal returns (CARs) around earnings announcements and take their absolute value. We also calculate share turnover during the same period. As a benchmark, we also report the same measures on non-announcement days. For a given level of overall volatility, the relative magnitude of announcement versus no-announcement returns reflects the ex-ante informativeness of market prices.

Figure C.1 about here.

Figure C.1 displays the results. Looking at S&P 500 firms, volatility on non-announcement days has remained flat, whereas announcement-day volatility has increased. At the start of the sample, volatility is similar across announcement and non-announcement days. By the end of the sample, volatility on announcement days is almost twice as high. In 2010, a typical three-day abnormal return is 5% on announcement days versus 2% on other days. This suggests that return surprises have grown rather than decreased over this period even as total volatility has remained stable.

For all firms, total volatility has increased somewhat as can be seen from the rising amount of volatility on non-announcement as well as announcement days. This observation further motivates our focus on S&P 500 firms. As with the S&P 500, the share of volatility on announcement days has risen dramatically so that in 2010 a typical three-day return is 8% around announcements versus 4% otherwise. Based on these results, we find no evidence of increased market price informativeness.

The bottom plots in Figure C.1 give additional context. They show that as the relative magnitude of announcement-day returns has increased, so has the share of announcement-day turnover. Like returns, turnover is similar across different days at the beginning of the sample but twice as high on announcement days towards the end. In 2010, the typical stock experiences 5% turnover in the three days following an earnings announcement, versus 2.5% during other three-day periods. These findings suggest a link between increased trading and increased volatility around earnings announcements.

Changes in regulation are a plausible explanation for increasing return surprises. For example Reg FD in 2000 limited firms' ability to disclose selective information. However, we see return surprises grow in the years prior to Reg FD. Nevertheless, it is still possible that tighter regulation has increased the cost of information production while other factors have increased it. Our framework does not allow us to decompose information costs further.

Table C.1 about here.

Table C.1 shows the results from a panel regression. We regress the difference in the magnitude of CARs between announcement and no-announcement days on five-year dummies, and in some cases turnover. Consistent with Figure C.1, the relative magnitude of announcement-day abnormal returns starts off low and in fact drops a bit in the first five years, and then increases sharply around 1990. At the end of the sample, the difference in CARs is over 2% higher than at the beginning, and this number is highly statistically significant. The numbers are a bit bigger for all firms than for the S&P 500.

The regression allows us to examine this trend within the firm, largely avoiding composition effects. We do this by including firm fixed effects in columns (2) and (4) of Table C.1. The results show that the increase in announcement surprises is almost as strong within firms as it is overall. For a given firm in the S&P 500, the magnitude of announcement-day returns is 1.5% bigger at the end of the sample than at the beginning. For all firms, the increase is over 2%.

As Figure C.1 suggests, some of this increase is associated with an increase in relative turnover around announcement days. Columns (3) and (4) of Table C.1 show that when we include the difference in turnover between announcement and no-announcement days, the magnitude of the trend in announcement-day returns is halved or nearly eliminated. For S&P 500 firms, the 2% increase drops to 0.1% and for all firms it drops from 2.8% to 1.3% when we include firm fixed effects.

These results suggest that markets today are just as surprised—if not more so—when firms release financial statements as in the past. These surprises are accompanied by a surge in trading activity. Based on this model-free measure, we find no evidence that financial markets have become more informative.

E Informativeness in commodity markets

Having considered stocks, bonds, and options, we turn to commodity futures. We obtain daily data on corn, soybeans and wheat futures since 1960 (other commodities are not available until later). These markets have seen a dramatic increase in trading by investors classified as speculators (as opposed to hedgers) in the past few decades. It is therefore natural to ask whether increased information-based trading has increased price informativeness.

Another advantage of foodstuffs is that unlike firms, they have remained essentially unchanged over our sample. Foodstuffs are also arguably simpler to value than other commodities like oil or gold.

The relevant measure of fundamentals in futures markets is the ex post delivery price, further simplifying our problem. To obtain a valuation measure, we scale the futures price by the current spot price. As futures markets are much more liquid and transparent than spot markets, futures prices carry important incremental information above and beyond the spot price (Hu and Xiong 2013).

In sum, we run the forecasting regressions

$$\log\left(\frac{C_{t+k}}{C_t}\right) = a + b_{y(t)} \log\left(\frac{F_{t,t+k}}{C_t}\right) \times \mathbf{1}_{y(t)} + \epsilon_t,$$

where C_t is the cash price at t, $F_{t,t+k}$ is the date-t price of futures for delivery on date $t+k$, and $\mathbf{1}_{y(t)}$ are year fixed effects. We look at futures that expire in the current month ($k = 0$) out to one year ($k = 11$). As before, we are interested in the predicted variation $b_y \sigma_y (\log F/C)$, where we calculate $\sigma_y (\log F/C)$ from the standard deviation of prices throughout the year.

Our regression asks whether higher futures prices given today's cash price correspond to a higher cash price in the future.

The results are in Figures C.2, C.3, and C.4. Informativeness is positive, so futures have significant predictive power over and above the spot price. Informativeness is low at short horizons where there is little to forecast. Remarkably, informativeness shows no trend in the past fifty years across all three markets.

Figures C.2, C.3, and C.4 about here.

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Table I. Summary statistics

Means and standard deviations of key variables for non-financial firms in S&P 500 index and in the universe. Market capitalization is from CRSP in millions of dollars. Total assets, EBIT, capital expenditure, and R&D are from COMPUSTAT in millions of dollars. Credit spreads are from the Lehman/Warga Database and Mergent Fixed Income Datascope, calculated in excess of the duration-matched Treasury bond, and reported in percent. Idiosyncratic volatility is the standard deviation of daily abnormal returns, in percent. Analyst dispersion over assets is the standard deviation in EPS forecasts from I/B/E/S, multiplied by the number of shares outstanding, and divided by total assets, reported in percent. Announcement $|CAR|$ is the absolute value of a firm's cumulative abnormal return over the three days following an earnings announcement, reported in percent. No-announcement $|CAR|$ is for all other three-day periods. Announcement turnover and no-announcement turnover are calculated analogously. Next, $\log(M/A)$ is the log-ratio of market cap to assets, E/A is EBIT over assets, $\log(R\&D/A)$ is the log-ratio of R&D over assets, and $\log(CAPX/A)$ is the log-ratio of $CAPX$ over assets. All ratios are winsorized at the 1% level. The main sample period is from 1960 to 2011. Bond data starts in 1973, analyst data in 1976, and earnings announcement data in 1970.

	S&P 500			All Firms		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Market capitalization	6,942	1,283	22,284	1,067	62	8,025
Total assets	7,439	1,885	24,875	1,244	87	9,139
EBIT	715	180	2,116	108	5	780
R&D	276	48	799	42	2	293
Capital expenditure	473	117	1,392	79	4	518
Credit spread	1.59	1.13	1.40	1.61	1.13	1.42
Idiosyncratic volatility	1.88	1.66	0.95	3.83	3.08	2.97
Analyst dispersion / Assets	0.07	0.00	0.70	0.54	0.02	2.56
Announcement $\lvert CAR\rvert$	3.68	2.93	2.82	6.17	4.79	5.29
No-announcement $\lvert CAR\rvert$	2.32	2.08	1.08	4.19	3.54	2.64
Announcement turnover	2.61	1.29	3.73	2.82	1.30	5.07
No-announcement turnover	1.61	0.96	2.02	1.62	0.94	2.28
$\log(M/A)$	-0.18	-0.22	0.89	-0.21	-0.23	1.09
E/A	0.12	0.11	0.08	0.03	0.08	0.22
$R\&D/A$	0.04	0.02	0.06	0.07	0.03	0.11
$CAPX/A$	0.12	0.07	0.15	0.13	0.06	0.21
Firm-year observations		23,463			202,703	

Table II. Equity price informativeness

Panel regressions of future earnings, research and development expenditure, and capital expenditure on the equity valuation ratio. The dependent variables are EBIT, R&D, and CAPX at $t{+}1$ and $t{+}3$ divided by total assets A in year t. The independent variables are the log market-to-assets ratio $\log(M/A)$ interacted with five-year dummies, as well as a set of controls. The market-to-assets ratio is standardized (divided by its cross-sectional standard deviation at t) so the coefficient can be interpreted as the standard deviation of the predictable component of the predicted variable. The controls are omitted for compactness. They include the standardized earnings over assets and one-digit SIC codes, both interacted with the five-year dummies, as well as year fixed effects. The $R\&D$ ($CAPX$) regressions also include current $R\%D$ ($CAPX$) over assets with associated five-year dummy interactions. S&P 500 firms over 1960 to 2010.

	E/A		$R\&D/A$		$CAPX/A$	
100×	$t+1$	$t+3$	$t+1$	$t+3$	$t+1$	$t+3$
$log\,(M/A)_t$	2.20***	3.63***	−0.20	−0.01	0.62***	1.71***
	(0.21)	(0.43)	(0.32)	(0.66)	(0.19)	(0.36)
× 1965–69	−0.18	−0.14	0.47	1.19	0.71***	0.72
	(0.27)	(0.56)	(0.43)	(0.85)	(0.24)	(0.45)
× 1970–74	−0.12	0.25	0.40	0.53	0.36	0.34
	(0.26)	(0.54)	(0.36)	(0.71)	(0.23)	(0.44)
× 1975–79	0.09	2.22***	0.26	0.38	−0.43*	0.32
	(0.26)	(0.53)	(0.35)	(0.70)	(0.23)	(0.43)
× 1980–84	0.58**	0.63	0.54	1.16*	1.07***	2.44***
	(0.25)	(0.53)	(0.35)	(0.69)	(0.23)	(0.43)
× 1985–89	−0.35	0.06	0.39	1.16*	0.28	0.36
	(0.25)	(0.53)	(0.35)	(0.70)	(0.23)	(0.43)
× 1990–94	−0.13	0.72	0.32	0.83	0.19	0.48
	(0.26)	(0.54)	(0.35)	(0.70)	(0.23)	(0.44)
× 1995–99	0.64**	1.36**	0.62*	1.35**	0.05	1.38***
	(0.26)	(0.55)	(0.35)	(0.69)	(0.23)	(0.44)
× 2000–04	0.58**	0.51	1.41***	1.57**	0.35	−0.80*
	(0.24)	(0.51)	(0.34)	(0.68)	(0.22)	(0.41)
× 2005–09	0.32	2.03***	1.20***	2.20***	0.24	−0.84*
	(0.25)	(0.56)	(0.35)	(0.70)	(0.23)	(0.45)
R^2	76%	50%	78%	66%	64%	42%
N	19,951	18,392	10,146	9,107	19,323	17,802

Table III. Yield spread informativeness

Panel regressions of future earnings, research and development expenditure, and capital expenditure on a firm's bond spread. The dependent variables are EBIT, R&D, and CAPX at $t+1$ and $t+3$ divided by total assets A in year t. The independent variables are the dollar-weighted yield on a firm's corporate bonds in excess of the duration-matched Treasury yield $y_i - y_0$, as well as a set of controls. The bond spread is standardized (divided by its cross-sectional standard deviation at t) so the coefficient can be interpreted as the standard deviation of the predictable component of the predicted variable. The controls are omitted for compactness. They include the standardized earnings over assets and one-digit SIC codes, both interacted with the five-year dummies, as well as year fixed effects. The $R\&D$ ($CAPX$) regressions also include current $R\%D$ ($CAPX$) over assets with associated five-year dummy interactions. S&P 500 firms over 1960 to 2010.

	E/A		$R\&D/A$		$CAPX/A$	
100×	$t+1$	$t+3$	$t+1$	$t+3$	$t+1$	$t+3$
$(y_i - y_0)_t$	−0.84	−0.73	0.01	0.02	−0.68	−1.06
	(0.55)	(1.27)	(0.38)	(0.64)	(0.42)	(0.94)
× 1975–79	0.32	−0.07	0.01	−0.07	0.69	1.32
	(0.58)	(1.32)	(0.40)	(0.68)	(0.44)	(0.97)
× 1980–84	0.94*	1.61	0.01	−0.03	0.87*	1.10
	(0.57)	(1.31)	(0.39)	(0.67)	(0.44)	(0.97)
× 1985–89	0.61	0.32	−0.03	−0.04	0.49	0.95
	(0.57)	(1.30)	(0.39)	(0.67)	(0.43)	(0.96)
× 1990–94	0.56	0.51	−0.04	−0.11	0.51	0.73
	(0.57)	(1.30)	(0.39)	(0.66)	(0.43)	(0.96)
× 1995–99	0.45	0.43	0.04	−0.06	0.56	0.70
	(0.57)	(1.30)	(0.39)	(0.66)	(0.43)	(0.95)
× 2000–04	0.28	0.26	−0.22	−0.76	0.44	0.76
	(0.57)	(1.30)	(0.39)	(0.66)	(0.43)	(0.96)
× 2005–09	0.60	0.44	−0.87**	−0.80	0.62	1.04
	(0.57)	(1.30)	(0.39)	(0.66)	(0.43)	(0.96)
R^2	70%	40%	70%	64%	73%	49%
N	7,764	7,013	4,871	4,414	7,674	6,951

Table IV. Investment informativeness

Panel regressions of future earnings on research and development and capital expenditures. The dependent variables are EBIT at $t+1$ and $t+3$ divided by total assets A in year t. The independent variables are R&D and CAPX over assets interacted with five-year dummies, as well as a set of controls. The R&D and CAPX over assets ratios are standardized (divided by their cross-sectional standard deviations at t) so the coefficients can be interpreted as the standard deviation of the predictable component of earnings. The controls are omitted for compactness. They include the standardized earnings over assets and one-digit SIC codes, both interacted with the five-year dummies, as well as year fixed effects. S&P 500 firms over 1960 to 2010.

		E/A				E/A	
100×		$t+1$	$t+3$			$t+1$	$t+3$
$R\&D/A$		0.94***	2.13***	$CAPX/A$		0.15	0.75***
		(0.36)	(0.75)			(0.14)	(0.29)
	× 1965–69	−0.28	−0.24		× 1965–69	−0.18	−0.49
		(0.48)	(0.99)			(0.18)	(0.37)
	× 1970–74	−0.54	−0.64		× 1970–74	−0.16	−0.61*
		(0.40)	(0.83)			(0.18)	(0.37)
	× 1975–79	−0.48	−0.46		× 1975–79	−0.37**	−1.31***
		(0.39)	(0.81)			(0.18)	(0.37)
	× 1980–84	−0.19	−0.92		× 1980–84	−0.06	−0.90**
		(0.39)	(0.81)			(0.18)	(0.38)
	× 1985–89	−0.99**	−1.67**		× 1985–89	−0.48***	−1.26***
		(0.39)	(0.81)			(0.18)	(0.37)
	× 1990–94	−0.34	−0.67		× 1990–94	−0.03	−0.28
		(0.39)	(0.82)			(0.18)	(0.37)
	× 1995–99	−0.25	−0.05		× 1995–99	−0.72***	−1.44***
		(0.40)	(0.82)			(0.18)	(0.38)
	× 2000–04	−0.07	−0.97		× 2000–04	0.01	−0.29
		(0.39)	(0.83)			(0.18)	(0.38)
	× 2005–09	−0.73*	−0.47		× 2005–09	−0.16	−0.56
		(0.39)	(0.83)			(0.18)	(0.40)
R^2		72%	43%			73%	45%
N		10,320	9,452			19,350	17,811

Table V. Equity prices and returns

Panel regressions of future returns on the equity valuation ratio. The dependent variable is the future one- and three-year return R. The independent variables are the log market-to-assets ratio $\log(M/A)$ interacted with five-year dummies, as well as a set of controls. The market-to-assets ratio is standardized (divided by its cross-sectional standard deviation at t) so the coefficient can be interpreted as the standard deviation of the predictable component of the predicted variable. The controls are omitted for compactness. They include the standardized earnings over assets and one-digit SIC codes, both interacted with the five-year dummies, as well as year fixed effects. S&P 500 over 1960 to 2010.

	R	
100×	$t+1$	$t+3$
$log\,(M/A)_t$	−4.20**	−14.83***
	(1.67)	(3.81)
× 1965–69	1.46	2.15
	(2.13)	(4.86)
× 1970–74	0.96	0.98
	(2.07)	(4.72)
× 1975–79	−2.43	−0.76
	(2.04)	(4.69)
× 1980–84	1.61	0.70
	(1.99)	(4.60)
× 1985–89	3.79*	14.26***
	(1.99)	(4.62)
× 1990–94	3.34	5.83
	(2.04)	(4.68)
× 1995–99	15.08***	26.52***
	(2.05)	(4.76)
× 2000–04	−9.76***	−14.46***
	(1.95)	(4.80)
× 2005–09	−7.11***	5.21
	(2.00)	(4.61)
R^2	26%	18%
N	20,513	19,452

Table VI. All firms

Panel regressions of future earnings on the equity valuation ratio for the universe of nonfinancial firms. The dependent variables are EBIT at $t+1$ and $t+3$ divided by total assets A in year t. The independent variables are the log market-to-assets ratio $\log(M/A)$ interacted with five-year dummies, as well as a set of controls. The market-to-assets ratio is standardized (divided by its cross-sectional standard deviation at t) so the coefficient can be interpreted as the standard deviation of the predictable component of the predicted variable. The controls are omitted for compactness. They include the standardized earnings over assets and one-digit SIC codes, both interacted with the five-year dummies, as well as year fixed effects. Nonfinancial firms over 1960 to 2010.

		E/A	
100×		$t+1$	$t+3$
$log\,(M/A)_t$		2.53***	3.62***
		(0.30)	(0.53)
	× 1965–69	0.33	1.37**
		(0.34)	(0.61)
	× 1970–74	0.37	1.04*
		(0.33)	(0.58)
	× 1975–79	(0.37	1.46***
		(0.32)	(0.56)
	× 1980–84	−1.74***	−3.17***
		(0.32)	(0.56)
	× 1985–89	−1.63***	−2.28***
		(0.31)	(0.56)
	× 1990–94	−2.10***	−3.27***
		(0.31)	(0.55)
	× 1995–99	−1.81***	−3.71***
		(0.31)	(0.55)
	× 2000–04	−2.63***	−3.67***
		(0.31)	(0.55)
	× 2005–09	−1.61***	−2.51***
		(0.32)	(0.57)
R^2		68%	37%
N		172,164	143,758

Table VII. Equity price informativeness and option listing

Panel regressions of future earnings on the equity valuation ratio for CBOE-listed and unlisted firms. The dependent variables are EBIT at $t+1$ and $t+3$ divided by total assets A in year t. The independent variables are triple interactions of a dummy for whether a firm is listed on the CBOE or not, the log market-to-assets ratio $\log(M/A)$, and five-year dummies, as well as a set of controls. The market-to-assets ratio is standardized (divided by its cross-sectional standard deviation at t) so the coefficient can be interpreted as the standard deviation of the predictable component of the predicted variable. Only the coefficients for $\log(M/A)$ are shown for compactness. Additional controls include the standardized earnings over assets and one-digit SIC codes, both triple-interacted with the listing and five-year dummies, as well as year fixed effects interacted with the listing dummy. S%P 500 firms over 1973 to 2010.

			E/A	
100×			$t+1$	$t+3$
$log\,(M/A)_t$			1.91***	4.35***
			(0.25)	(0.54)
	× listed		0.18	−0.03
			(1.27)	(2.68)
	× listed	× 1975–79	−1.25	−2.79
			(1.32)	(2.77)
		× 1980–84	−0.86	−2.16
			(1.31)	(2.75)
		× 1985–89	−0.18	0.57
			(1.31)	(2.76)
		× 1990–94	0.57	1.88
			(1.31)	(2.76)
		× 1995–99	0.25	−0.21
			(1.32)	(2.79)
		× 2000–04	−0.32	0.24
			(1.31)	(2.75)
		× 2005–09	0.22	2.47
			(1.33)	(2.82)
R^2			75%	49%
N			15,284	13,805

Table C.1. The magnitude of earnings surprises

Results from the panel regression

$$|CAR_{i,t}|_{Ann.} - |CAR_{i,t}|_{No\,ann.} = a + b_t \mathbf{1}_t + c\,(Turn_{Ann.} - Turn_{No\,ann.})_{i,t} + f_i + e_{i,t}.$$

The dependent variable is the difference in the magnitude of cumulative abnormal returns (CARs) on announcement and no-announcement days for a given firm in a given year. On the right side, we include dummies for successive five-year periods (the omitted category is 1970 to 1975). Both CARs and turnover are in percent. In columns (3) and (4), we include the difference in share turnover between announcement and no-announcement days, $Turn_{Ann.} - Turn_{No\,ann.}$. Columns (2) and (4) include firm fixed effects. Standard errors are clustered by year. We report separate results for S&P 500 firms and for all firms.

	S&P 500				All Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	0.619***	0.833***	0.583***	0.522***	0.850***	1.291***	0.821***	1.101***
	(0.080)	(0.079)	(0.084)	(0.087)	(0.031)	(0.047)	(0.029)	(0.057)
1976–80	−0.340***	−0.314***	−0.360***	−0.329***	−0.396***	−0.362***	−0.405***	−0.384***
	(0.094)	(0.093)	(0.099)	(0.101)	(0.056)	(0.063)	(0.053)	(0.062)
1981–85	-.205**	−0.250***	−0.288***	−0.302***	−0.146**	−0.308***	−0.209***	−0.332***
	(0.089)	(0.089)	(0.089)	(0.090)	(0.057)	(0.068)	(0.060)	(0.069)
1986–90	0.069	−0.009	−0.100	−0.118	0.100	−0.241**	−0.023	−0.282***
	(0.133)	(0.139)	(0.125)	(0.130)	(0.099)	(0.105)	(0.089)	(0.097)
1991–95	0.478***	0.387***	0.161	0.137	0.634***	0.272***	0.333***	0.121
	(0.116)	(0.107)	(0.125)	(0.114)	(0.063)	(0.084)	(0.089)	(0.089)
1996–00	0.906***	0.715***	0.416**	0.373*	1.100***	0.569***	0.632***	0.324*
	(0.229)	(0.221)	(0.186)	(0.198)	(0.171)	(0.165)	(0.167)	(0.159)
2001–05	1.694***	1.221***	0.603***	0.469**	2.166***	1.515***	1.384***	1.017***
	(0.178)	(0.200)	(0.173)	(0.185)	(0.187)	(0.193)	(0.161)	(0.147)
2006–11	2.081***	1.505***	0.308	0.116	2.767***	2.169***	1.623***	1.338***
	(0.187)	(0.181)	(0.188)	(0.178)	(0.146)	(0.183)	(0.241)	(0.240)
$Turn_{Ann.}$			0.653***	0.779***			0.462***	0.440***
$-Turn_{No\,ann.}$			(0.042)	(0.053)			(0.070)	(0.074)
Firm F.E.	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.128	0.298	0.350	0.451	0.053	0.239	0.183	0.330

Figure 1. **The distribution of valuation, profitability, and investment**
The sample consists of non-financial firms in the S&P 500 index. The four plots show medians (red line), 10th and 90th percentiles (shaded bands). M/A is 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.

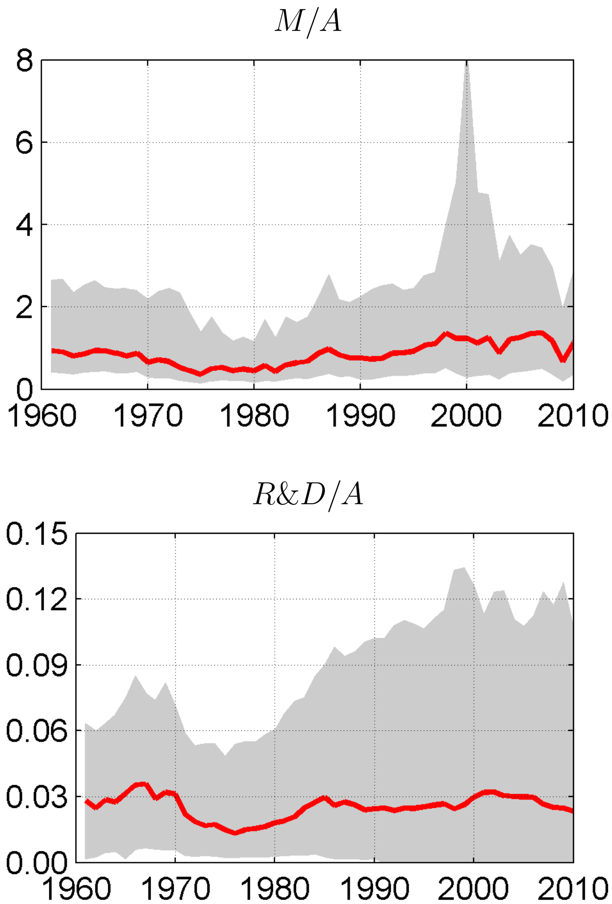


Figure 2. Forecasting earnings with equity prices

Results from the regression

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

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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. 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 $\log M/A$.

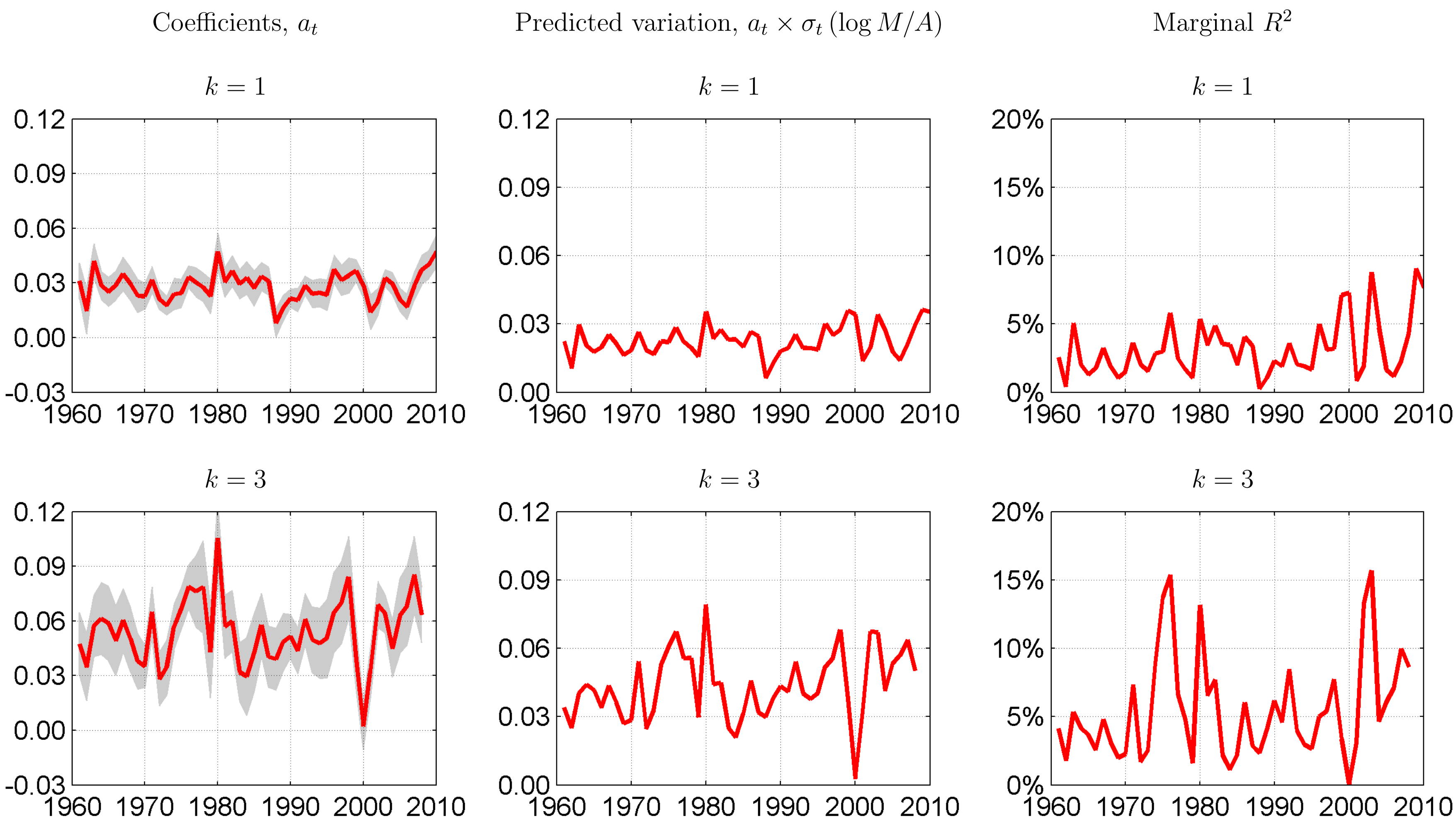


Figure 3. Forecasting earnings with bond spreads

Results from the regression

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

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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. 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 $(y - y_0)$.

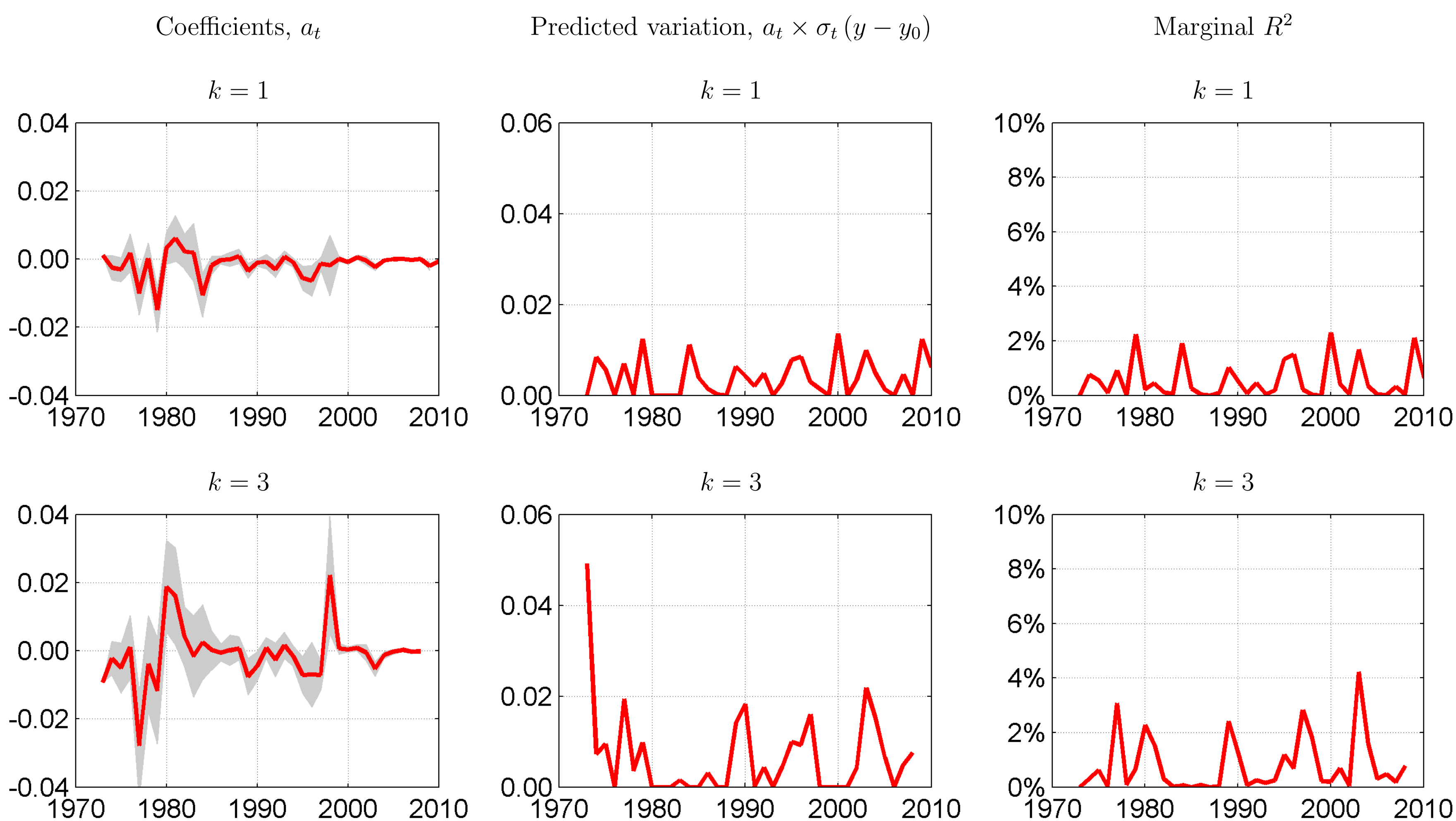


Figure 4. **Forecasting earnings with R&D expenditure**

Results from the 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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients a_t are plotted inside a 95% confidence band. The R&D-predicted variation is $a_t \times \sigma_t\left(R\&D/A\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $R\&D/A$.

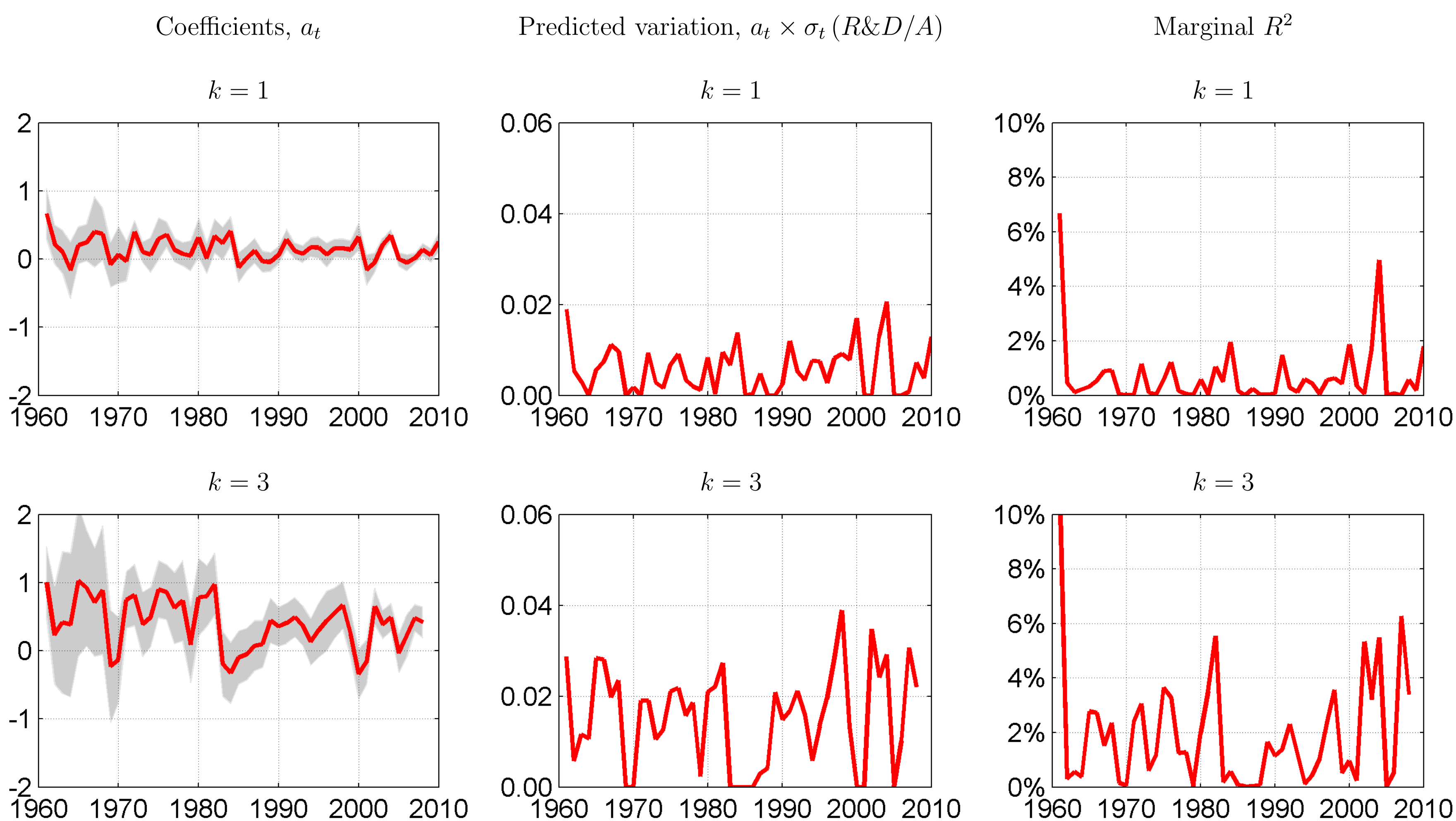


Figure 5. Forecasting earnings with capital expenditure

Results from the 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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. 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 $CAPX/A$.

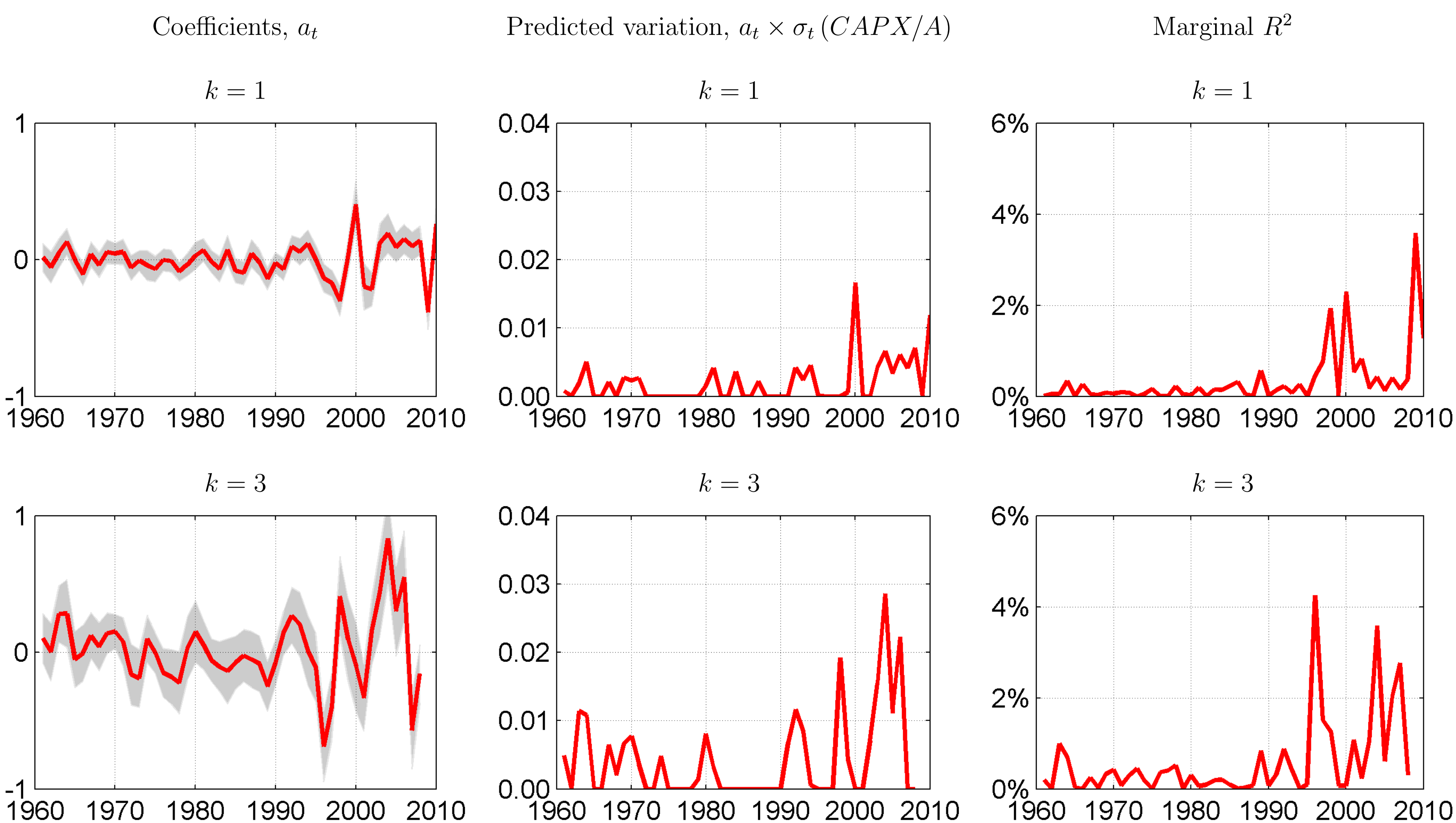


Figure 6. Forecasting R&D expenditure with equity prices

Results from the 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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. 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 $\log M/A$.

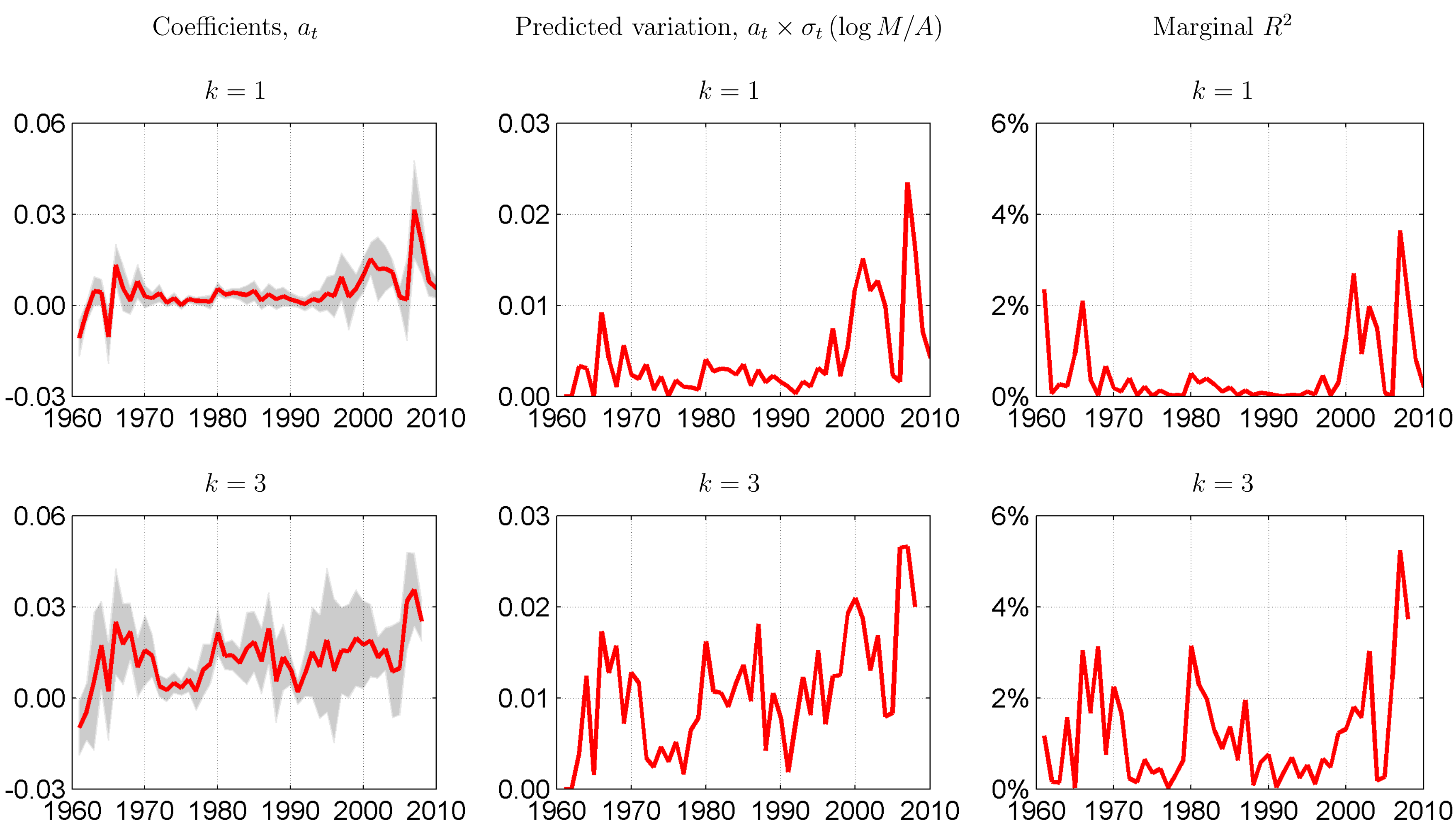


Figure 7. Forecasting R&D expenditure with bond spreads

Results from the 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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. 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 $y - y_0$.

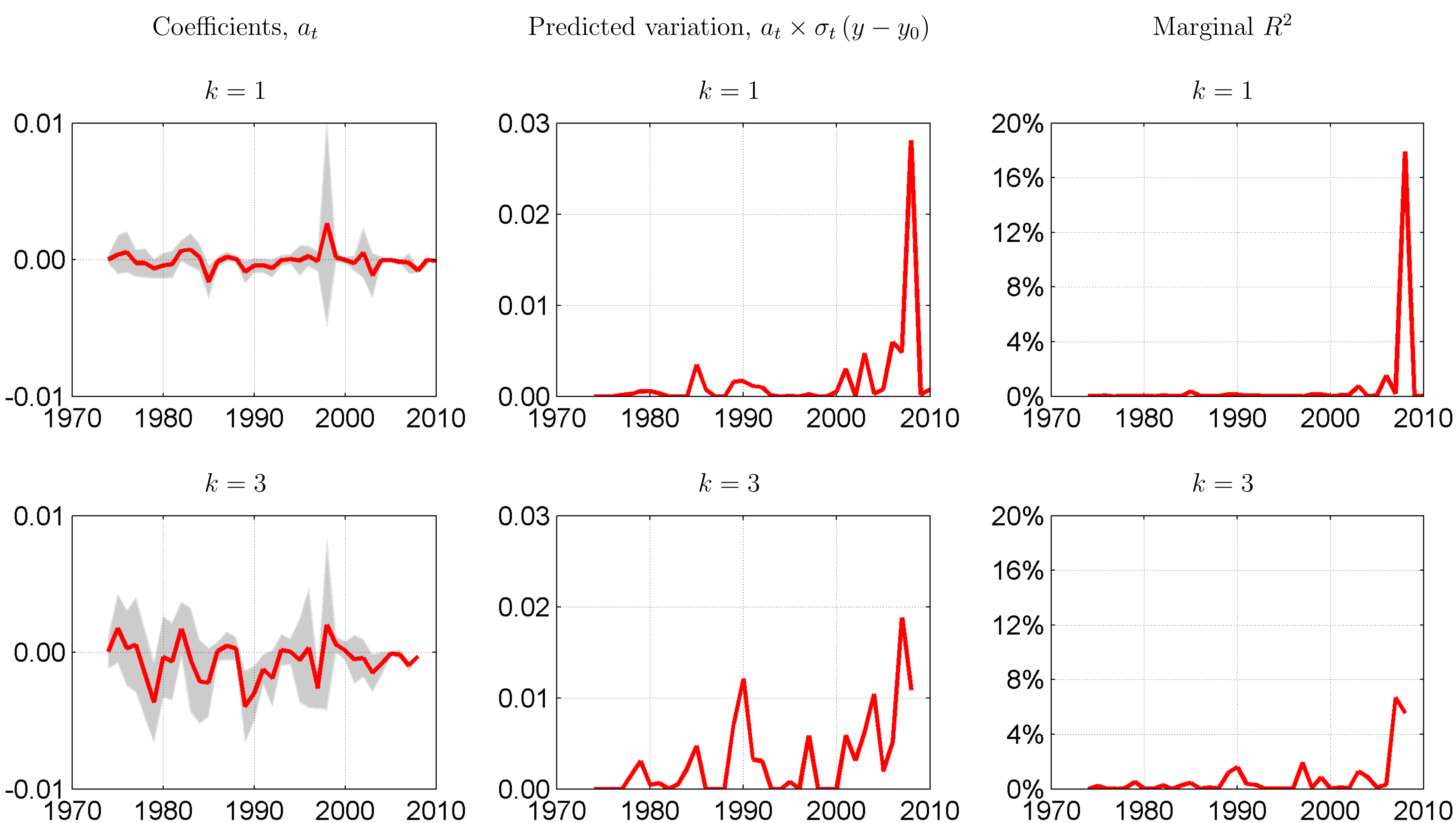


Figure 8. Forecasting capital expenditure with equity prices

Results from the regression

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

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ is the one-digit SIC code. The values for k are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. 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 $\log M/A$.

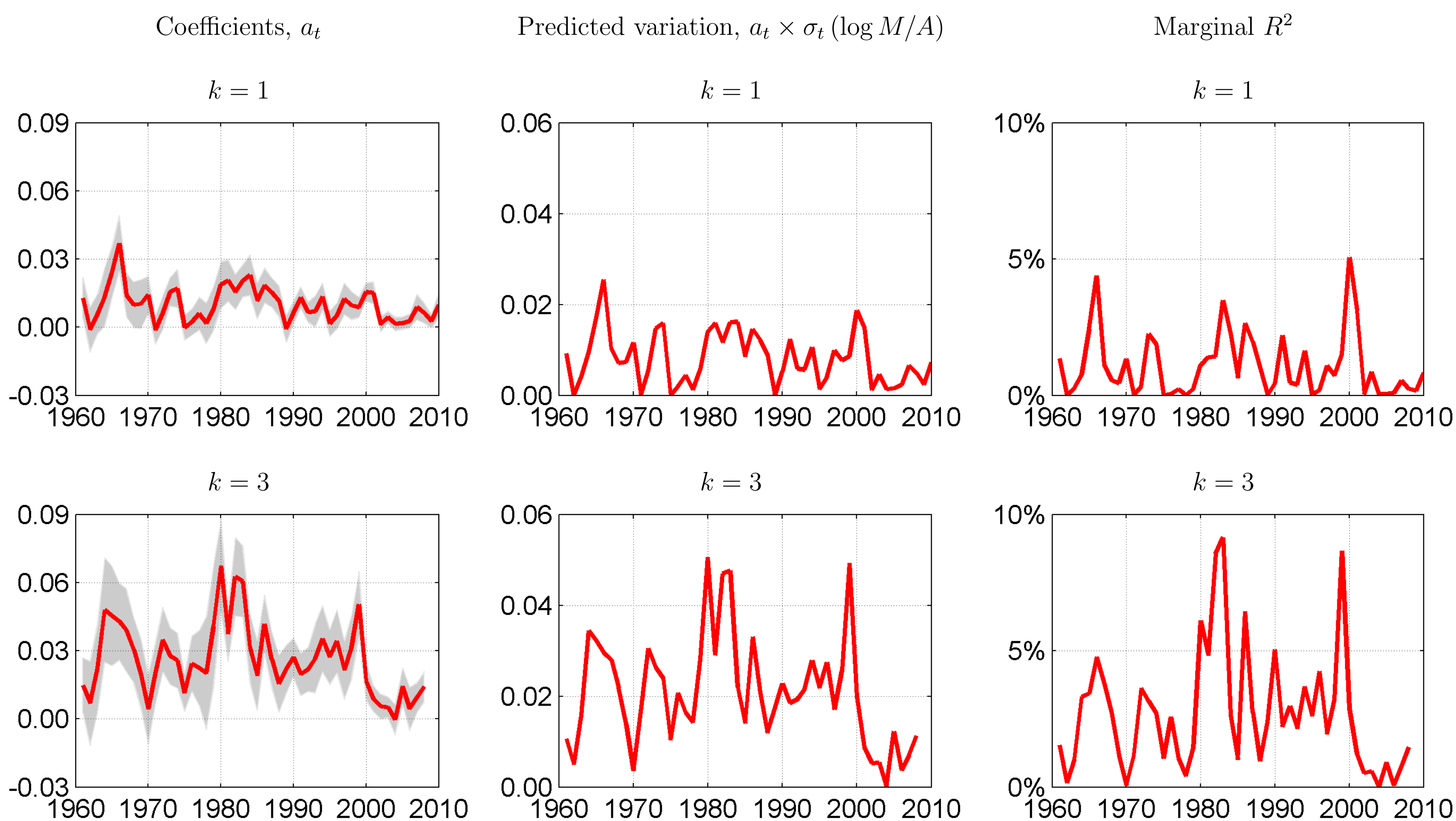


Figure 9. Forecasting capital expenditure with bond spreads

Results from the 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 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1972 to 2010, when bond data is available. The coefficients a_t are plotted inside a 95% confidence band. The bond market-predicted variation is $a_t\times\sigma_t\left(y-y_0\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $y-y_0$.

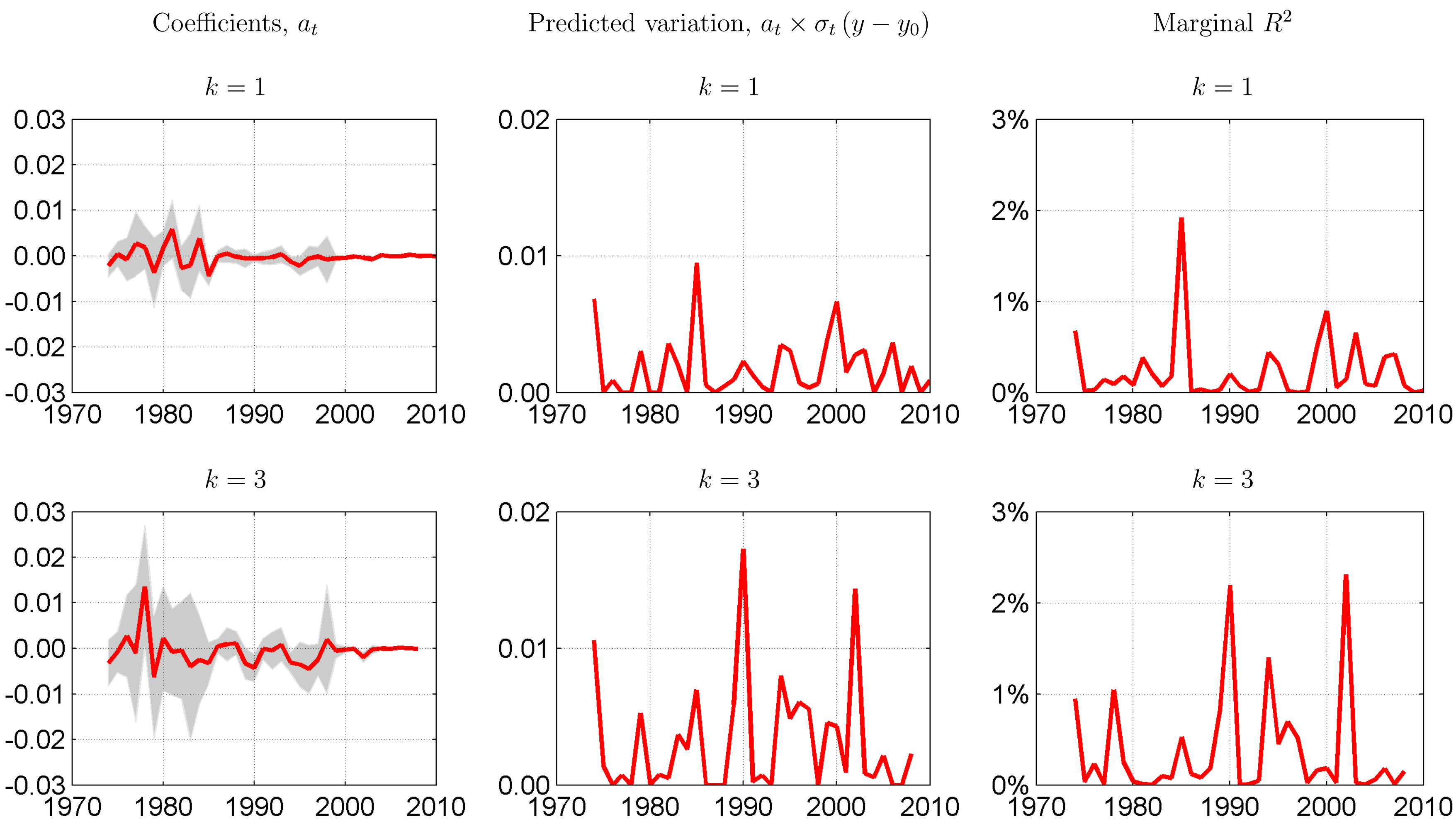


Figure 10. Forecasting returns with equity prices

This figure plots the predicted variation of prices for returns and earnings. The predicted variation is defined as $a_t \times \sigma_t (\log M/A)$ from the forecasting regression

$$\log R_{i,t\to t+3} / \frac{E_{i,t+3}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

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 sample consists of all S&P 500 non-financial firms from 1960 to 2010.

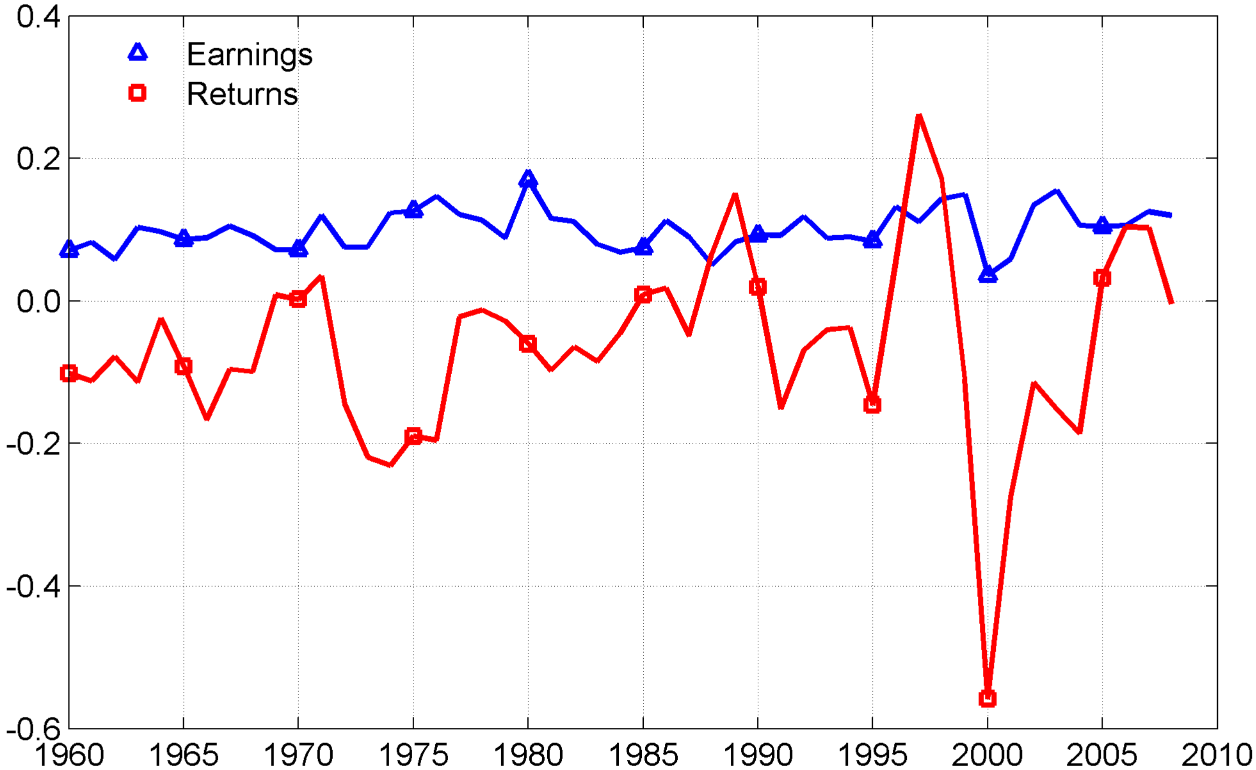


Figure 11. S&P 500 versus all firms

Earnings dispersion, market price dispersion, and results from the regression

$$\frac{E_{i,t+3}}{A_{i,t}} \quad = \quad a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

for the S&P 500 non-financial versus all non-financial firms. Dispersion is measured as the cross-sectional standard deviation in E/A and $\log M/A$ for 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. $SIC1$ is the one-digit SIC code. The equity market-predicted variation is $a_t \times \sigma_t\left(\log M/A\right)$.

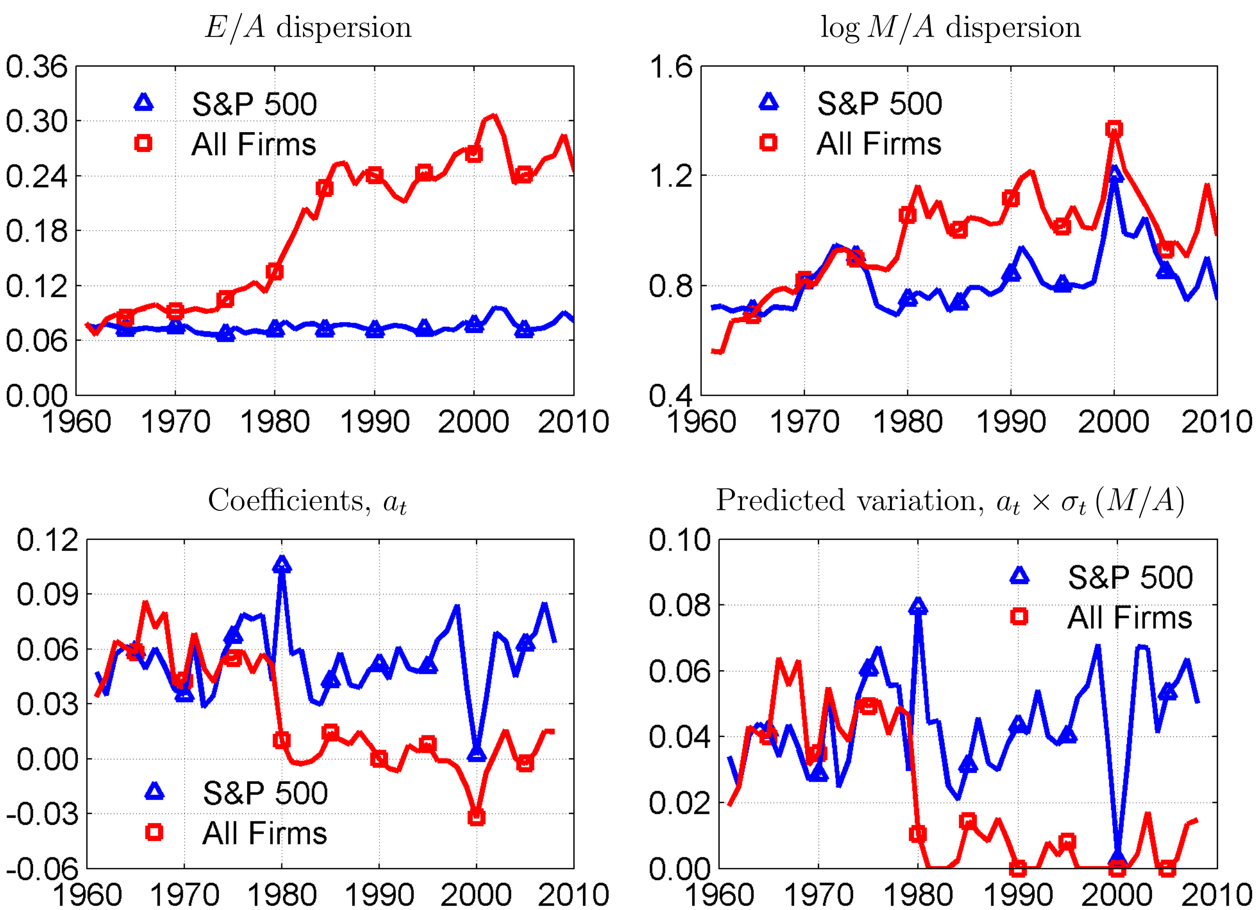


Figure 12. Option listing and price informativeness

This figure plots the predicted variation of prices for earnings for stocks with and without listed options. The predicted variation is defined as $a_t \times \sigma_t (\log M/A)$ from the forecasting regression

$$\frac{E_{i,t+3}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t} \left(\mathbf{1}_{SIC1}\right) \times \left(\mathbf{1}_t\right) + \epsilon_{i,t}.$$

The sample starts in 1973 when the first equity options were introduced by the CBOE.

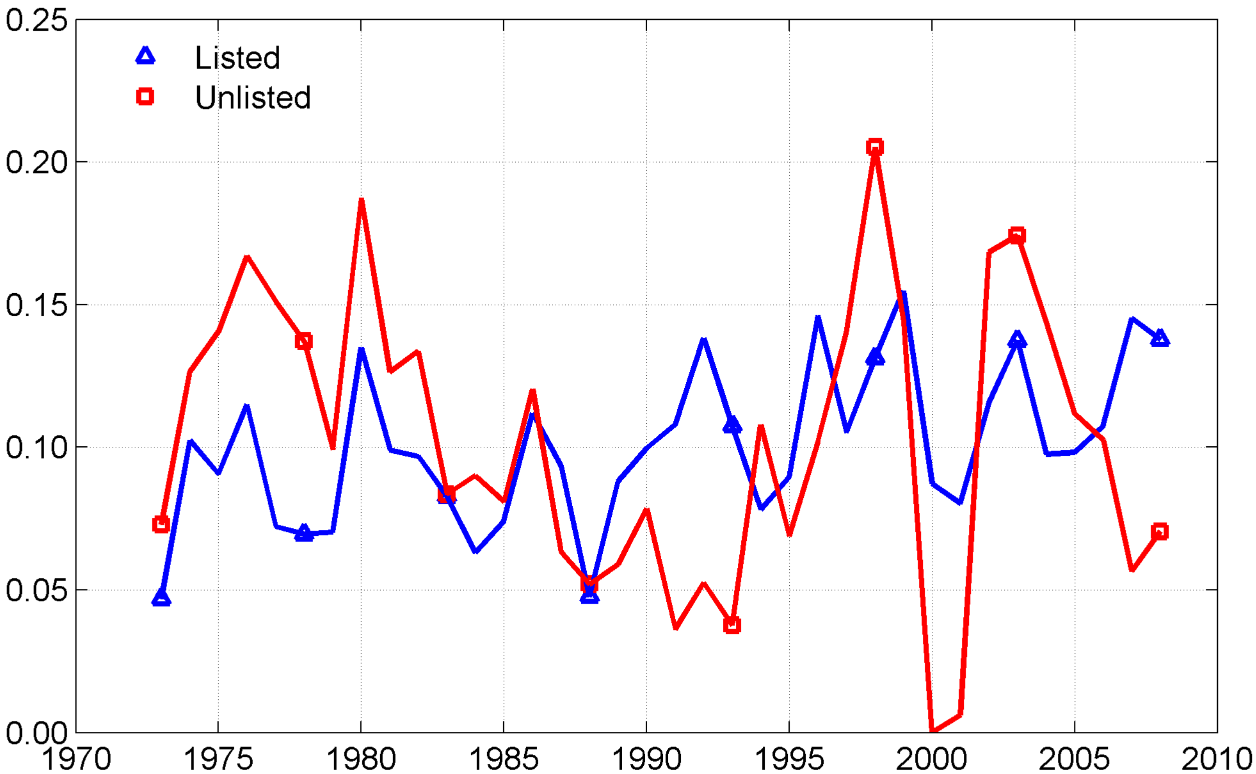


Figure 13. The unit cost of information

We plot estimates of $\sigma_z^2\sqrt{\frac{1+\mathbb{V}(\mathbb{E}[r|p])}{1+\mathbb{V}(\mathbb{E}[z|p])}}$, a measure of the unit cost of information. From Equation (25), the unit cost of information is $\frac{\alpha\psi}{h_s+h_\eta} = \sigma_z^2\sqrt{\frac{\mathbb{V}(\mathbb{E}[r|p])}{\mathbb{V}(\mathbb{E}[z|p])}}$. Adding one to each of the predicted variations improves the conditioning of the estimates (the predicted variation of earnings for the universe of all firms turns negative in some years). 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, $\mathbb{V}(\mathbb{E}[z|\,p])$ is price informativeness, measured as the predicted variation, $a_t \times \sigma_t(\log M/A))$, with a_t from the forecasting regression

$$\frac{E_{i,t+3}}{A_{i,t}} = a_t \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + b_t\left(\frac{E_{i,t}}{A_{i,t}}\right) \times \mathbf{1}_t + c_{s(i,t),t}\left(\mathbf{1}_{SIC1}\right) \times (\mathbf{1}_t) + \epsilon_{i,t}.$$

Similarly, $\mathbb{V}(\mathbb{E}[r|\,p])$ is obtained from a return forecasting regression. Total uncertainty σ_z is measured as the dispersion of ex-post earnings-over-assets. We consider S&P 500 firms and all firms separately from 1960 to 2011.

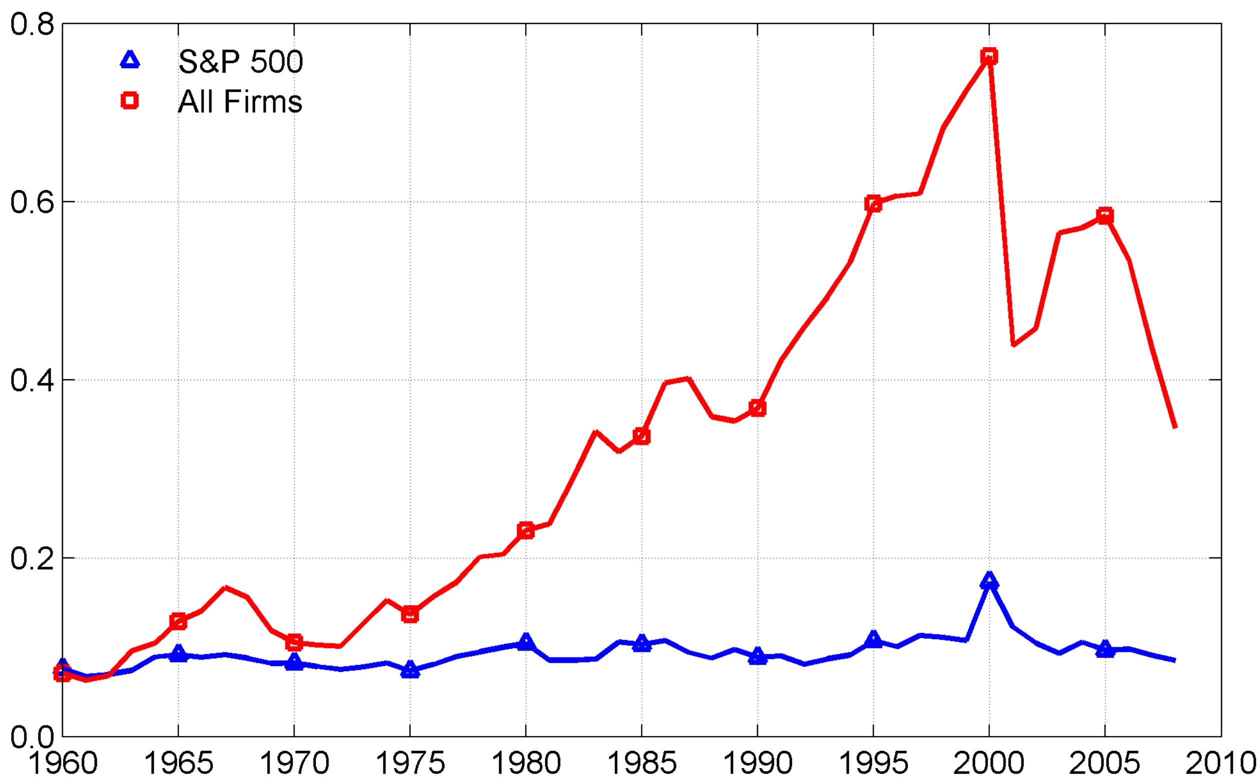


Figure B.1. **Adjusting for debt**

Results from the 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 is EBIT. $SIC1$ is the one-digit SIC code. The values for k are 1 and 3 years. The sample consists of all S&P 500 non-financial firms from 1960 to 2010. The coefficients a_t are plotted inside a 95% confidence band. The equity market-predicted variation is $a_t \times \sigma_t \left(\log\left(\left(M+D\right)/A\right)\right)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $\log\left(\left(M+D\right)/A\right)$.

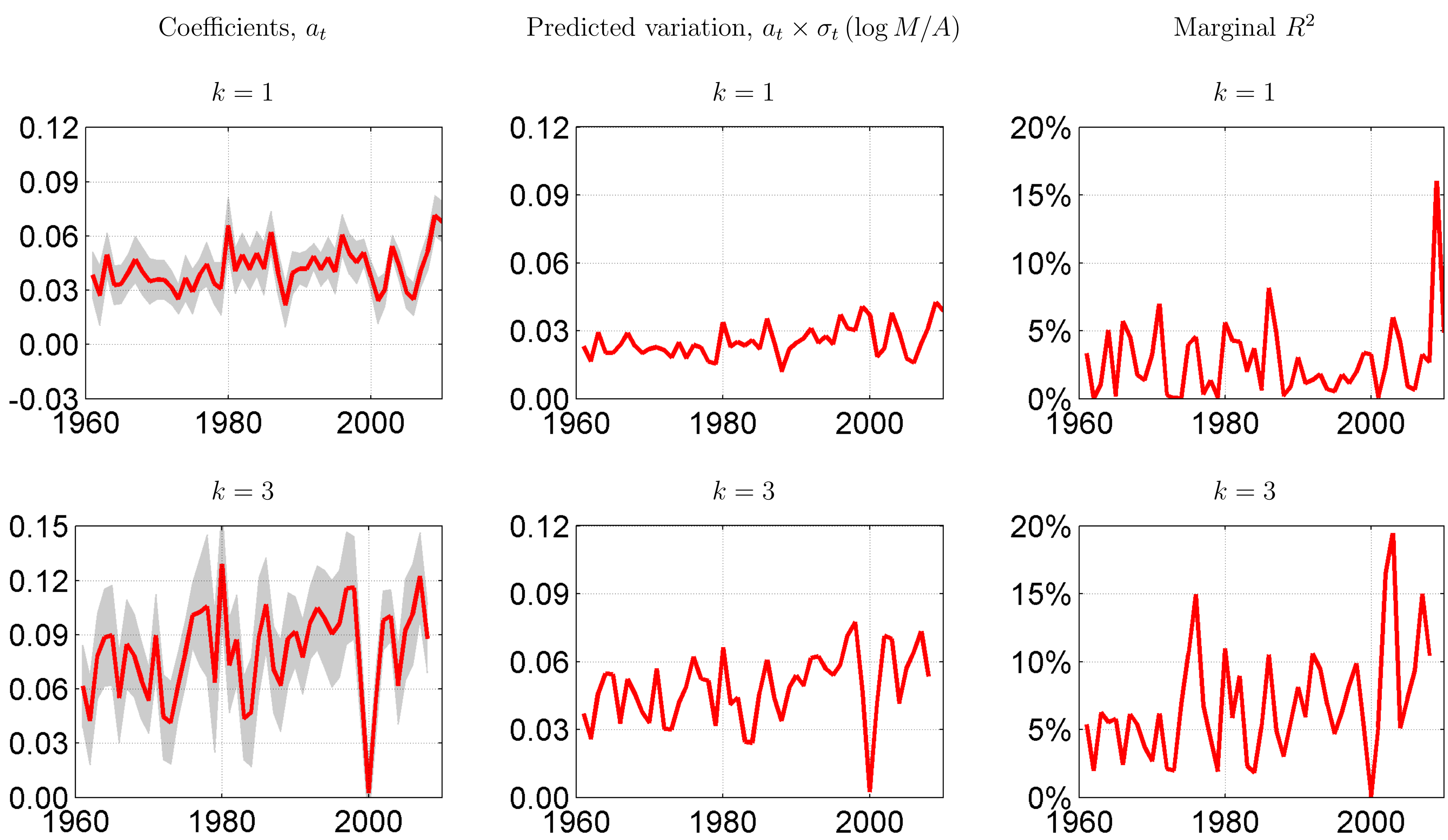


Figure C.1. Volatility and turnover around earnings announcements

For each firm in every year, we calculate the absolute value of three-day abnormal returns, $|CAR_{t\to t+2}|$, around earnings announcements ("Announcement") and on all other days ("No announcement"). We also calculate three-day turnover, $Turnover_{t\to t+2}$, (volume divided by shares outstanding) analogously. We plot averages across firms by year for the S&P 500 non-financial firms, and for all firms. Announcement dates are from COMPUSTAT and returns and volume are from CRSP. The sample period is from 1970 to 2011.

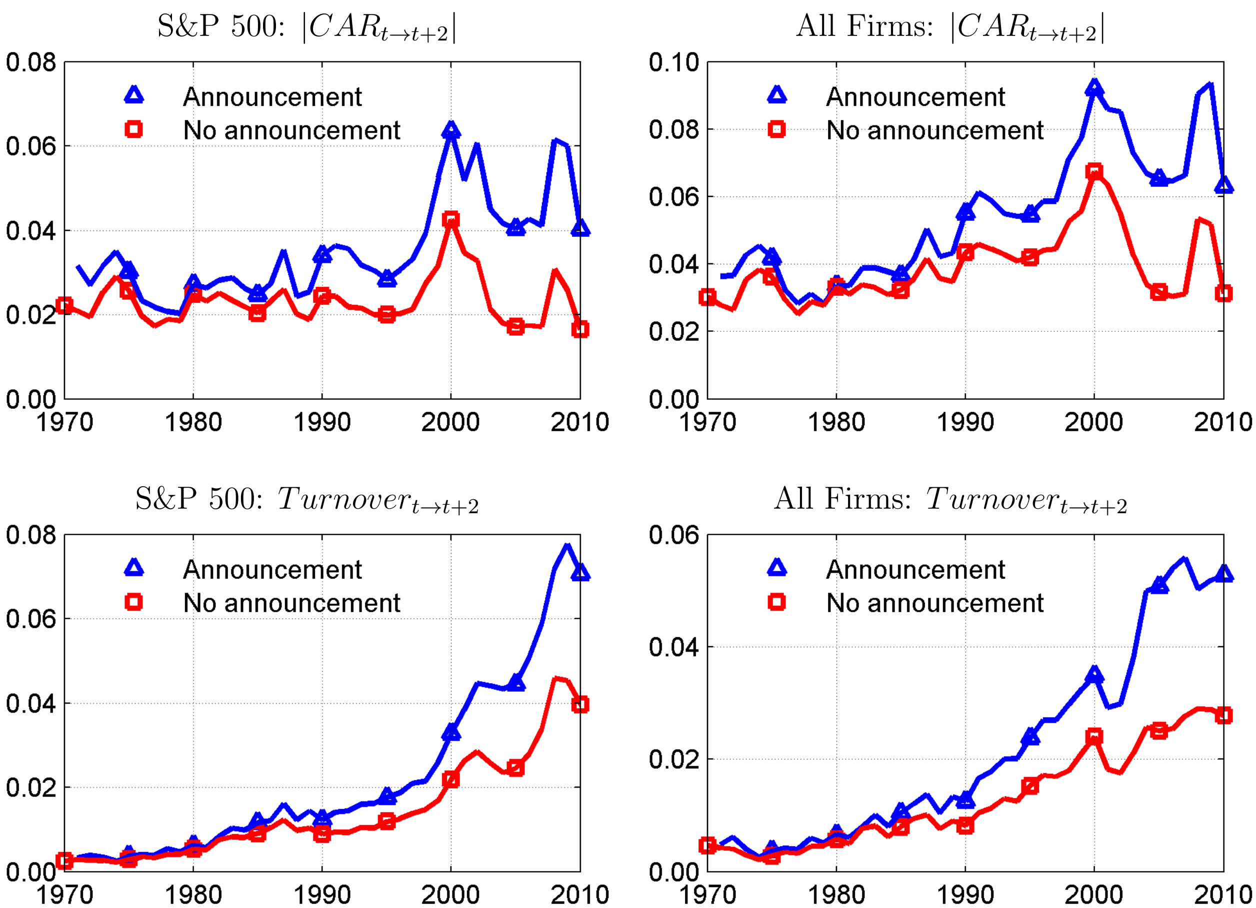


Figure C.2. **Corn futures**

Results from the regression

$$\log\left(\frac{C_{t+k}}{C_t}\right) \quad = \quad a + b_{y(t)} \log\left(\frac{F_{t,t+k}}{C_t}\right) \times \mathbf{1}_{y(t)} + \epsilon_t.$$

C_t is the cash price of corn on date t, $F_{t,t+k}$ is the date-t price of corn futures that expire on date $t+k$, and $\mathbf{1}_{y(t)}$ are year fixed effects. We present results for k ranging from zero (futures that expire in the current month) to eleven months (futures that expire in one year). We plot the predicted variation $b_y \times \sigma_y (\log F/C)$. The data covers the period from 1960 to 2010.

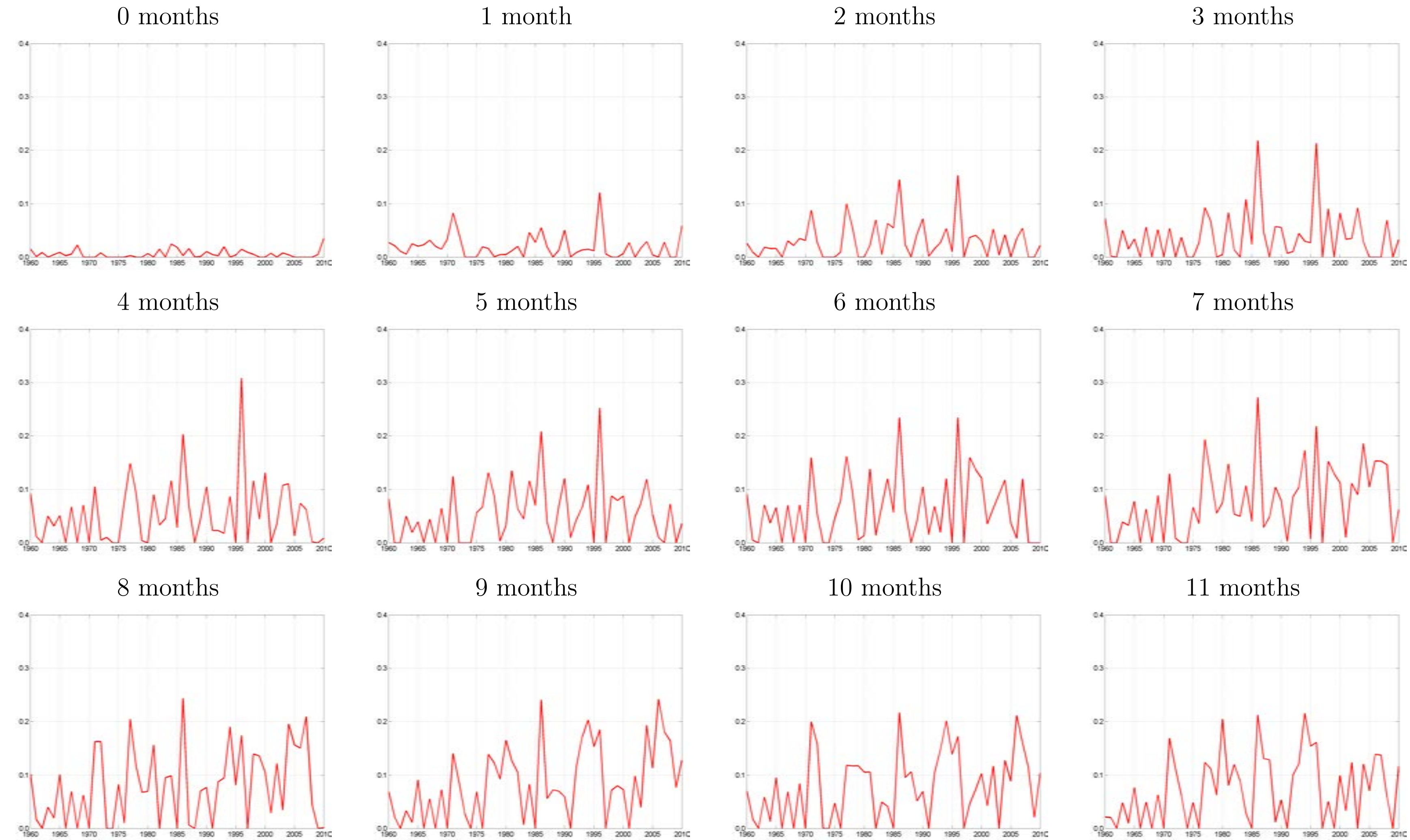


Figure C.3. **Soybean futures**

Results from the regression

$$\log\left(\frac{C_{t+k}}{C_t}\right) \;=\; a + b_{y(t)} \log\left(\frac{F_{t,t+k}}{C_t}\right) \times \mathbf{1}_{y(t)} + \epsilon_t.$$

C_t is the cash price of soybeans on date t, $F_{t,t+k}$ is the date-t price of soybean futures that expire on date $t+k$, and $\mathbf{1}_{y(t)}$ are year fixed effects. We present results for k ranging from zero (futures that expire in the current month) to eleven months (futures that expire in one year). We plot the predicted variation $b_y \times \sigma_y(\log F/C)$. The data covers the period from 1960 to 2010.

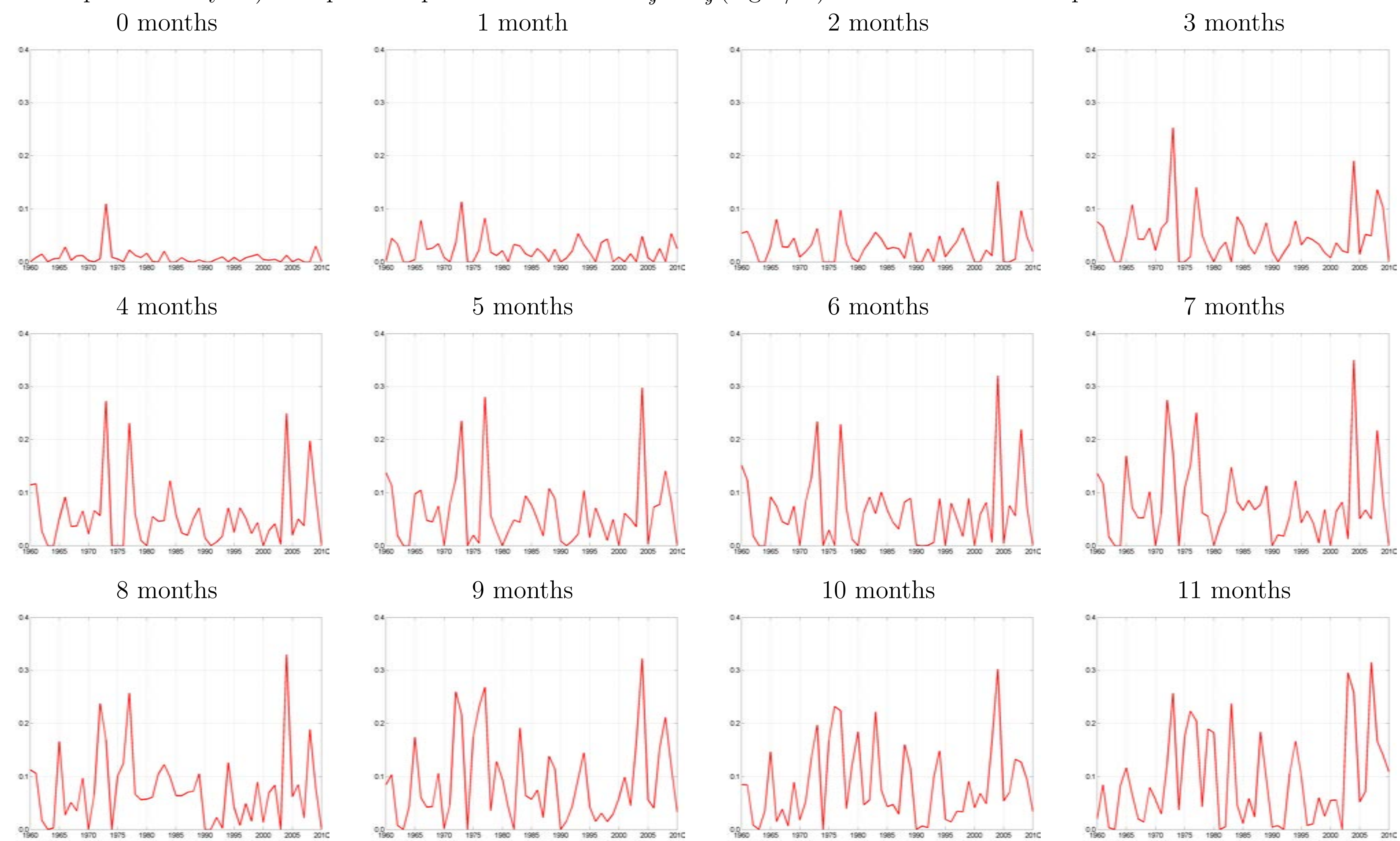


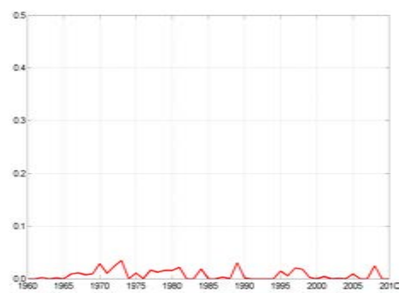
Figure C.4. **Wheat futures**

Results from the regression

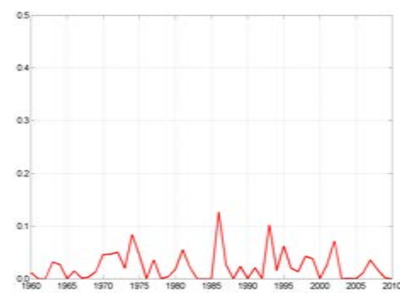
$$\log\left(\frac{C_{t+k}}{C_t}\right) \quad = \quad a + b_{y(t)} \log\left(\frac{F_{t,t+k}}{C_t}\right) \times \mathbf{1}_{y(t)} + \epsilon_t.$$

C_t is the cash price of wheat on date t, $F_{t,t+k}$ is the date-t price of wheat futures that expire on date $t+k$, and $\mathbf{1}_{y(t)}$ are year fixed effects. We present results for k ranging from zero (futures that expire in the current month) to eleven months (futures that expire in one year). We plot the predicted variation $b_y \times \sigma_y (\log F/C)$. The data covers the period from 1960 to 2010.

0 months

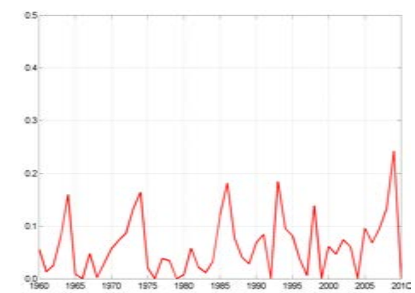


1 month

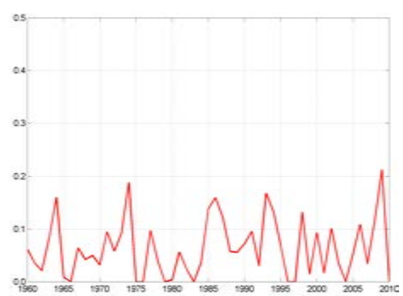


2 months

3 months



4 months

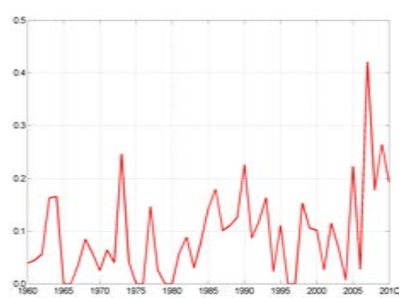


5 months

6 months

7 months

8 months



9 months

10 months

11 months