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Working Paper

Have financial markets become more informative?

Staff Report, No. 578

Provided in Cooperation with:

Federal Reserve Bank of New York

Suggested Citation: Bai, Jennie; Philippon, Thomas; Savov, Alexi (2012) : Have financial markets become more informative?, Staff Report, No. 578, Federal Reserve Bank of New York, New York, NY

This Version is available at:

<http://hdl.handle.net/10419/93638>

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Federal Reserve Bank of New York
Staff Reports

Have Financial Markets Become More Informative?

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Thomas Philippon
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Staff Report No. 578
October 2012



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JEL classification: G10, G14

Abstract

The finance industry has grown. Financial markets have become more liquid. Information technology has improved. But have prices become more informative? Using stock and bond prices to forecast earnings, we find that the information content of market prices has not increased since 1960. The magnitude of earnings surprises, however, has increased. A baseline model predicts that as the efficiency of information production increases, prices become more disperse and covary more strongly with future earnings. The forecastable component of earnings improves capital allocation and serves as a direct measure of welfare. We find that this measure has remained stable. A model with endogenous information acquisition predicts that an increase in fundamental uncertainty also increases informativeness as the incentive to produce information grows. We find that uncertainty has indeed increased outside of the S&P 500, but price informativeness has not.

Key words: financial markets, price informativeness, earnings, investment

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I. Introduction

Financial markets serve to allocate capital to its most productive uses. The difficulty lies in identifying these, and so the key to efficient capital allocation is the production of information (Schumpeter 1912). In well-functioning markets, investors motivated by private gain differentiate good ventures from bad. Through competition, their assessments are incorporated into market prices and valuations grow disperse. A high valuation results in low-cost funding, spurring investment. Ex post, the mark of financial sector efficiency is the strength of the relationship between today's prices, investment, and future profitability. We trace the evolution of this relationship in the United States over the past fifty years.

During this period, a revolution in computing has transformed financial markets. Lower trading costs have increased liquidity by an order of magnitude: in 1960, the typical stock turned over once every five years; today it does so every four months. At the same time, improved information technology delivers a vast array of financial data instantly and at negligible cost. Concurrent with these trends, the financial industry has grown, its share of GDP more than doubling from 2.5% to 5.5%. Within this context, we ask: have financial market prices become more informative?

We frame the analysis with a simple q -theory model that gives us the right measure of price informativeness. Both investment and future earnings increase in market prices. An increase in the supply of information leads to greater price dispersion as markets differentiate among firms. As a result, market prices become stronger predictors of earnings. The size of the predictable component is given by the dispersion in market prices times their forecasting coefficient. This measure of informativeness forms the basis of our empirical tests. Furthermore, since the ability to differentiate among firms leads to more efficient investment, informativeness is also a direct measure of aggregate welfare.

To understand the link between financial development and the supply of information, we also introduce a model with endogenous information acquisition in the spirit of Kyle (1985). A lower cost of information leads to higher informativeness as expected. In addition, a rise

in fundamental uncertainty also increases informativeness: in a competitive environment, the opportunity to learn increases the incentive to learn. This comparative static is relevant given the increased presence of highly uncertain firms in financial markets.

Our first empirical results show that earnings surprises have increased relative to overall volatility since 1990. The typical quarterly earnings surprise is about 2% larger in 2010 than in the period before 1990. Volatility on non-announcement days has increased very little. Earnings announcements are accompanied by a surge in trading volume, a recent phenomenon. Results are similar for S&P 500 firms, and for all firms generally, and they persist in a panel regression with firm fixed effects. Bigger surprises are inconsistent with increased price informativeness: informativeness increases ex-ante price variation and reduces it ex-post.

Our main results are based on regressions of future earnings on current valuation ratios, controlling for current earnings. We look at both equity and bond markets. We include one-digit industry-year fixed effects to absorb time-varying cross-sectional differences in the cost of capital. This regression asks whether two firms in the same sector with different market valuations tend to have different earnings. The answer is yes, but the amount of informativeness is unchanged since 1960. In the Appendix, we show similar results for commodity futures.

For most of the paper, we examine S&P 500 firms whose characteristics have remained stable. In contrast, running the same regression on the universe of firms appears to show a decline in informativeness. We argue, however, that this decline is consistent with a changing composition of firms: the representative firm today is harder to value. Consistent with this interpretation, we show that the proportion of firms with a high dispersion of analyst earnings forecasts has increased following the introduction of NASDAQ. These observations motivate our focus on S&P 500 firms.

To closely examine the mechanism by which markets allocate capital, we also run regressions of investment on valuation. Our strongest finding is that higher equity valuation is

more strongly associated with R&D spending now than in the past. This result is consistent with equity markets either spurring or rewarding future intangible investment. However, R&D spending does not forecast earnings strongly enough to translate into an increase in the predictability of earnings.

As a final exercise, we construct an implied measure of financial sector efficiency. This measure is based on our models and it reflects the unit cost of information production. We find that efficiency has remained surprisingly stable throughout the past fifty years, though it drops briefly around the end of the dot-com boom around 2000.

II. Related literature

Our paper is broadly related to three strands of the finance literature: (i) the relationship between finance and growth; (ii) the links between firm valuation and investment; and (iii) the empirical literature on firm-level predictability.

Over the last 30 years, the U.S. financial sector has grown six times faster than GDP (*Financial Times*).¹ A classic literature studies the impact of financial development on economic growth (Levine (2005) provides a survey). Schumpeter (1912) emphasizes the role of the banking sector in identifying the most promising entrepreneurs and supplying them with resources. By producing information and using it to improve the allocation of resources, finance accelerates innovation and growth. This idea was formalized by Greenwood and Jovanovic (1990), among others.

It is difficult to discern a relationship between financial sector growth and aggregate output in U.S. data. However, it is likely that aggregate productivity growth is driven by many factors. A more powerful test exploits cross-sectional differences at the firm level. This is the type of test conducted here.

Grossman and Stiglitz (1980), Kyle (1985), and Holmström and Tirole (1993) show that

¹“Why dealing with the huge debt overhang is so hard” by Martin Wolf, *Financial Times*, January 27, 2009.

the incentive to produce information is closely linked to the liquidity of financial markets. Deeper markets raise the reward for producing information, increase the informativeness of prices, and lead to improved capital allocation (Merton 1987). Rajan and Zingales (1998) show that finance-dependent industries grow faster in countries with more developed financial markets. Morck, Yeung, and Yu (2000) find that in these countries stock prices are more informative about firm-specific shocks. Rather than looking across countries, we study price informativeness in the US over time.

The financial crisis of 2008 raised concerns that the financial system may be “too large”. Philippon (2008), Bolton, Santos, and Scheinkman (2011) examine the equilibrium size of the financial sector. Philippon and Reshef (2007) study wages in the financial industry and conclude that a large part of the observed finance wage premium cannot be explained by skill differences, but may reflect rents.

The crisis has also challenged the belief that finance promotes growth. Rajan (2005) suggested that financial complexity may have increased the probability of a catastrophic meltdown. Gennaioli, Shleifer, and Vishny (2011) show that in the presence of neglected tail risks, financial innovation can increase fragility. By relating financial sector output to its cost, Philippon (2012) finds that the unit cost of financial intermediation has increased in recent decades. We construct our own measure of financial sector efficiency based on the informativeness of market prices.

The literature on the link between valuation and investment centers on the q -theory of Tobin (1969). Most studies find only a weak relationship between equity values and investment (Caballero 1999). Among the many possible explanations, Fazzari, Hubbard, and Petersen (1988) and Bernanke and Gertler (1989) focus on financing frictions. Philippon (2009) shows that bond-market q does a better job of fitting firm investment. Chen, Goldstein, and Jiang (2007) show that firms whose stocks experience more informed trading have a higher stock price sensitivity to investment. We examine the evolution of the relationship between market prices and investment over time.

Campbell, Lettau, Malkiel, and Xu (2001) show that idiosyncratic volatility has increased in the U.S. Our results suggest that this increase is not related to future profitability. We also find that much of the increase in idiosyncratic volatility can be attributed to increased earnings surprises.

III. Models

In this section we present two simple models to help us think about the link between financial market prices and efficiency. The first model is a version of the q -theory of investment. We use it to construct the welfare-based measure of price informativeness and efficiency. The second model is a version of Kyle (1985). We use it to understand the link between fundamental volatility, price informativeness and the cost of information. The second model allows us to distinguish the demand and supply of information, i.e., changes in desired information (linked to fundamental uncertainty) versus changes in the efficiency of the information acquisition technology.

A. Cross-sectional information, capital allocation, and welfare

Consider a two-period model. At time 1 firm i spends $k_i + \frac{\gamma}{2}k_i^2$. At time 2 firm i delivers the profit of $z_i k_i$, where z_i is firm productivity. Firm i maximizes its market value given the discount factor m :

$$v_i = \max_{k_i} \mathbb{E}[m z_i k_i] - k_i - \frac{\gamma}{2} k_i^2.$$

The FOC for investment is

$$k_i = \frac{\mathbb{E}[m z_i] - 1}{\gamma}.$$

Note that this equation is a particular case of the q -theory of investment. To see why, notice that the value of the firm at the end of time 1 is $\mathbb{E}[m z_i k_i]$. Tobin's q , defined as firm value

over book asset is simply $q_i \equiv \mathbb{E}[mz_i]$ and the FOC can be written

$$k_i = \frac{q_i - 1}{\gamma}. \quad (1)$$

Ex-ante (maximized) firm value is

$$v_i = \frac{1}{2\gamma} (\mathbb{E}[mz_i] - 1)^2.$$

We write firm productivity as

$$z_i \equiv \bar{z} + f_i + \epsilon_i.$$

Firm productivity has three components: \bar{z} is an aggregate shock, f and ϵ are both idiosyncratic (mean zero across firms), but f is forecastable (known at time 1) and ϵ is not (revealed at time 2). At the time investment is made, we have $\mathbb{E}[z_i] = \bar{z} + f_i$. Let G denotes the cdf of f across firms.

We can write

$$k_i - k_j = \frac{q_i - q_j}{\gamma} = \frac{1}{\gamma(1+r)} (f_i - f_j), \quad (2)$$

where $\mathbb{E}[m] = \frac{1}{1+r}$ and we have used the fact that ϵ is idiosyncratic. Equation (2) contains the key intuition of the basic model. In a cross section of firms, the model makes the following predictions:

1. Market price q forecasts futures earnings f ;
2. Investment k is explained by Tobin's q ;
3. Investment k forecasts future earnings f .

We want to test these predictions using firm-level cross-sectional data. Before doing so, however, we must understand exactly which measure we should use.

For simplicity (and without loss of generality) we consider an economy without aggregate risk, so m and \bar{z} are known at time 1.² Assuming that the parameters are such that $k \geq 0$ for all firms, we then have

$$k_i = \frac{m(\bar{z} + f_i) - 1}{\gamma} \quad (3)$$

and we can write $v_i = \frac{1}{2\gamma} ((m\bar{z} - 1)^2 + (mf_i)^2 + 2(m\bar{z} - 1)mf_i)$. We can then aggregate the value of all firms as:

$$\bar{V} \equiv \int_i v_i = \frac{1}{2\gamma} ((m\bar{z} - 1)^2 + m^2\sigma_f^2), \quad (4)$$

where we use the fact that f has mean-zero across firms, i.e., $\int_f f dG(f) = 0$, and we define the variance of the predictable component:

$$\sigma_f^2 \equiv \int_f f^2 dG(f).$$

Aggregate firm value \bar{V} is the sum of two components. The first term depends on average aggregate productivity. It is the term that corresponds to the “representative firm”. The second term is proportional to the variance of the idiosyncratic predictable component. It comes from the opportunity to reallocate capital across firms. Total spending at time 1 is

$$\int (k_i + \frac{\gamma}{2}k_i^2) = \frac{1}{2\gamma} (m^2(\sigma_f^2 + \bar{z}^2) - 1) \quad (5)$$

and total output at time 2 is

$$\bar{Y}_2 = \int z_i k_i = \frac{1}{\gamma} (m(\bar{z}^2 + \sigma_f^2) - \bar{z}) \quad (6)$$

It is easy to check that $\bar{V} = m\bar{Y}_2 - \int (k_i + \frac{\gamma}{2}k_i^2)$.

Finally, we can endogenize m by modeling the behavior of households/savers. They

²Aggregate risk does not change our analysis since we focus on the idiosyncratic component f . Therefore $E[mf] = fE[m]$. For the aggregate component, we would simply replace \bar{z} by the risk-adjusted mean $E[zm]/E[m]$.

maximize the inter-temporal utility:

$$u(c_1) + u(c_2).$$

They receive an endowment \bar{Y}_1 in the first period. They own an intermediary that finances all the firms. Idiosyncratic risk is diversified and there is no aggregate risk. The intermediary offers a safe interest rate $1/m$ to the consumers. The budget constraints of the consumers is $c_1 + mc_2 = \bar{Y}_1 + mD$, where D are the dividends paid by the intermediary (since technology has decreasing returns). We have the Euler condition

$$m = \frac{u'(c_2)}{u'(c_1)}.$$

In the aggregate we have the market clearing conditions $\bar{C}_1 = \bar{Y}_1 - \int (k_i + \frac{\gamma}{2}k_i^2)$ and $\bar{C}_2 = \bar{Y}_2 = \int z_i k_i$. Using the Euler condition we can then solve for m . Note that consumer wealth defined as $W \equiv \bar{Y}_1 + V$ is³

$$W = \bar{Y}_1 + \frac{1}{2\gamma} ((m\bar{z} - 1)^2 + m^2\sigma_f^2). \quad (7)$$

We can now consider a few special cases.⁴

³Note that by definition the value of the intermediary is the value of the underlying portfolio, i.e.,

$$mD = V.$$

This can easily be checked. Total borrowing from consumers is $\int (x_i + \frac{\gamma}{2}x_i^2)$. Given the interest rate, total dividends at time 2 are $D = \int z_i x_i - \frac{1}{m} \int (x_i + \frac{\gamma}{2}x_i^2) = \frac{V}{m}$.

⁴For instance, with CRRA preferences, $\frac{u'(c_2)}{u'(c_1)} = \left(\frac{c_2}{c_1}\right)^{-\rho}$ and m is implicitly given by

$$m = \left(\frac{\gamma\bar{Y}_1 - \frac{1}{2}((m\bar{z} + 1)(m\bar{z} - 1) + m^2\sigma_p^2)}{\bar{z}(m\bar{z} - 1) + m\sigma_p^2} \right)^\rho$$

Risk neutral consumers (or small open economy)

If consumers are linear then $m = 1$. This is also true if the consumers have access to saving opportunity at a fixed interest rate (normalized to zero for convenience). Then aggregate investment is $\bar{K} = \frac{\bar{z}-1}{\gamma}$ and final output is $\bar{Y}_2 = \frac{1}{\gamma} (\bar{z}(\bar{z} - 1) + \sigma_f^2)$. Welfare is simply

$$\mathcal{W} = \bar{C}_1 + \bar{C}_2 = \bar{Y}_1 + \frac{1}{2\gamma} ((\bar{z} - 1)^2 + \sigma_f^2) \quad (8)$$

Welfare is the sum of the current endowment plus the optimal production taking advantage of aggregate productivity and the predictable component of firm productivity. With linear preferences welfare equals wealth: $\mathcal{W} = W$.

No substitution

Suppose there is a fixed pool of savings available at time 1. In other words,

$$\int (k_i + \frac{\gamma}{2} k_i^2) = K, \quad (9)$$

is given. Note that welfare only depends on \bar{Y}_2 since \bar{Y}_1 and K are fixed:

$$\mathcal{W} = u(\bar{Y}_1 - K) + u(\bar{Y}_2).$$

We therefore only need to analyze \bar{Y}_2 . From (5) and (9), we get

$$m^2 = \frac{1 + 2\gamma K}{\sigma_f^2 + \bar{z}^2}$$

Therefore

$$\bar{Y}_2 = \frac{1}{\gamma} \left(\sqrt{(1 + 2\gamma K) (\bar{z}^2 + \sigma_f^2)} - \bar{z} \right) \quad (10)$$

Note that without idiosyncratic predictability we have simply $k = \frac{\sqrt{1+2\gamma K}-1}{\gamma}$ and $\bar{Y}_2 = \bar{z}k$.

Idiosyncratic news creates scope for reallocation of capital and lead to an improvement in

welfare. Of course, without aggregate substitution, the effect in (10) is muted relative to (8).

Proposition 1. *In both cases welfare depends on the standard deviation of the predictable component of firm productivity.*

B. Financial development and endogenous informativeness

We have seen that what matters for productive efficiency (and welfare) is the variance of the predictable component of firm productivity. The next question is: What is the link between financial development and the variance of the predictable component?

To answer this question we must endogenize prices and information acquisition. Then we will be able to address the following issues: Suppose the variance of total risk goes up. What does that imply? Will markets provide more or less information? How then should we scale the predictive regressions? Suppose that we want to measure financial market efficiency by running predictive regressions of future profits on current prices, should we then look at the R^2 of the regression, at the predicted variance, or at something else?

Kyle Model

The classic models are Grossman and Stiglitz (1980), Glosten and Milgrom (1985), and Kyle (1985). See Vives (2008) for a recent overview. For simplicity, we follow Kyle (1985). There is a single informed trader who behaves strategically. She takes into account her price impact. The terminal value is $v = \bar{v} + s + \epsilon$ where $s \sim N(0, \sigma_s)$ and $\epsilon \sim N(0, \sigma_\epsilon)$ with some underlying distributions (normal for simplicity but this is not required). The informed trader knows s and demands $x(s)$. Noise traders demand $u \sim N(0, \sigma_u)$. One market maker observes $y = x + u$ and sets the price p . Trades are cleared at the price p . All agents are risk neutral. The variables s , ϵ and u are independent.

The equilibrium is a fixed point. The informed trader refrains from trading too much to the extent there is price impact. But price impact depends on what the market maker (MM)

believes the informed trader is doing. Let us guess that the MM uses the pricing rule

$$p = \kappa + \lambda y$$

Given this rule, the informed trader maximizes expected profits

$$\mathbb{E}[(v - p)x | s] = \mathbb{E}[(\bar{v} + s + \epsilon - \kappa - \lambda x - \lambda u)x | s] = (\bar{v} + s - \kappa - \lambda x)x$$

We thus get the informed order flow

$$x(s) = \frac{\bar{v} - \kappa + s}{2\lambda}.$$

Note that when λ goes up, informed traders demand becomes less sensitive to private information.

Now MM must forecast $\mathbb{E}[v | y] = \mathbb{E}[\bar{v} + s | y]$. Since $y = x + u$ we can write $y = \frac{\bar{v} - \kappa + s}{2\lambda} + u$ and

$$2\lambda y + \kappa = \bar{v} + s + 2\lambda u$$

Therefore the optimal competitive price setting by MM is:

$$p = \mathbb{E}[v | y] = \frac{(2\lambda\sigma_u)^2 \bar{v} + (\sigma_s)^2 (2\lambda y + \kappa)}{(2\lambda\sigma_u)^2 + (\sigma_s)^2}$$

In equilibrium beliefs must be consistent, and we must have $p = \kappa + \lambda y$. Identifying term by term, we get

$$\kappa = \bar{v}.$$

The intuition is that informed traders' flow is positive if and only if $v > \bar{v}$. It also means that the average order flow is zero. For the slope coefficient, we get

$$\lambda = \frac{1}{2} \frac{\sigma_s}{\sigma_u}$$

The price impact is higher when there are fewer noise traders relative to the informational advantage of the informed trader, measured by σ_s .

Price Informativeness

How informative are prices in equilibrium? Suppose an econometrician runs the regression of future values on current prices:

$$v = \alpha + \beta p + \eta$$

We can use the model to predict what these regression would yield. The terminal value is $v - \bar{v} = s + \epsilon$. The price satisfies

$$p - \bar{v} = \lambda(x + u) = \frac{s}{2} + \frac{1}{2}\sigma_s \frac{u}{\sigma_u}.$$

Note that the term $\frac{u}{\sigma_u}$ has a volatility of one irrespective of the amount of noise trading. This comes from the endogenous response of MM and informed traders. If σ_u goes down, MM rationally increases λ , which then leads informed traders to trade less aggressively. The standard deviation of prices is

$$\sigma_p = \frac{1}{\sqrt{2}}\sigma_s,$$

and the covariance of prices with future fundamentals is

$$\mathbf{cov}(v - \bar{v}, p - \bar{v}) = \frac{1}{2}(\sigma_s)^2.$$

This suggests that in the linear regression of future value on current prices, we have $\beta = 1$.

Finally the correlation is

$$\mathbf{corr}(v - \bar{v}, p - \bar{v}) = \frac{1}{\sqrt{2}} \frac{\sigma_s}{\sigma_v}$$

In a linear regression of future value on current prices, the fit of the regression R^2 is the square correlation. Hence we have

$$R^2 = \frac{1}{2} \left(\frac{\sigma_s}{\sigma_v} \right)^2$$

The maximum value for the R^2 is $1/2$ even when the signal is perfect. The price cannot be fully informative because of the endogenous response of informed traders.

Endogenous Information Acquisition

Now consider the endogenous cost of information acquisition by the informed traders, denoted as π . The value for the informed trader conditional on signal s is

$$\mathbb{E}[\pi | s] = \lambda x^2 = \frac{1}{4\lambda} s^2$$

so the ex-ante value is

$$\mathbb{E}[\pi] = \frac{1}{4\lambda} \sigma_s^2$$

We assume that the σ_s is not directly observed by the MM (but of course is correctly forecastable in equilibrium). This implies that traders take λ as given when choosing the precision of their signals. The most a trader can learn is v which has a volatility σ_v . Then a good specification for the cost of obtaining a signal with volatility σ_s is

$$c(\sigma_s) = \psi \frac{\sigma_s}{\sigma_v - \sigma_s}$$

This captures the increasing cost of precise information as well as the upper bound on the amount that one could learn about, σ_v . The net value of information is therefore $\mathbb{E}[\pi] - c(\sigma_s)$. The first order condition for optimal information (σ_s) is $\frac{\sigma_s}{2\lambda} = \psi \frac{\sigma_v}{(\sigma_v - \sigma_s)^2}$. In equilibrium, since

Table I. Predictions of Model with Trading and Information Acquisition

Linear Regression	Exogenous Information	Endogenous Information
Predicted Variations	$\frac{1}{\sqrt{2}}\sigma_s$	$\frac{\sigma_v}{\sqrt{2}} - \sqrt{\frac{\psi\sigma_v}{2\sigma_u}}$
Price Volatility	$\frac{1}{\sqrt{2}}\sigma_s$	$\frac{\sigma_v}{\sqrt{2}} - \sqrt{\frac{\psi\sigma_v}{2\sigma_u}}$
R^2 of Linear Regression	$R^2 = \frac{1}{2} \left(\frac{\sigma_s}{\sigma_v} \right)^2$	$R^2 = \frac{1}{2} \left(1 - \sqrt{\frac{\psi}{\sigma_v\sigma_u}} \right)^2$
Amount Spent on Information		$\sqrt{\psi\sigma_v\sigma_u} - \psi$

$\lambda = \frac{1}{2} \frac{\sigma_s}{\sigma_u}$ we have

$$\sigma_s = \sigma_v - \sqrt{\frac{\psi\sigma_v}{\sigma_u}}$$

This FOC is valid as long as $\psi < \sigma_u\sigma_v$, otherwise we simply have $\sigma_s = 0$. The variance of the signal increases with the fundamental variance σ_v and with market liquidity (low λ). The amount spent on information gathering is

$$c(\sigma_s) = \sqrt{\psi\sigma_u\sigma_v} - \psi$$

This amount is inverse U-shaped in the cost parameter ψ . When $\psi = 0$, information is free. The maximum spent is for intermediate values of ψ . If we think of the finance industry as providing information, then the model implies that the amount spent of financial intermediation is highest for intermediate values of ψ . With endogenous information, the R^2 of the regression becomes

$$R^2 = \frac{1}{2} \left(1 - \sqrt{\frac{\psi}{\sigma_v\sigma_u}} \right)^2$$

We summarize our results in Table I.

The results in Table I generate testable predictions for our empirical analysis:

- Given fundamental volatility, the model predicts that improvement in financial market efficiency (lower ψ) should lead to a higher predicted variations. The impact on the

amount spent is ambiguous.

- If fundamental volatility increases (higher σ_v), the amount spent on information increases and predicted variations should also increase.⁵

The implication is as follows. If in the data we observe an increase in fundamental volatility, then predicted variations should increase over time even if efficiency (ψ) remains the same. With the particular functional forms that we have chosen, we would also see an increase in R^2 in that case because agents have more incentives to learn.

C. Discussion

The models presented above make several testable predictions. There are some practical issues, however. First, there are decision and implementation lags in investment, so we allow for lagged effects of equity and bond prices on investment.

Another issue is that the model assumes that markets and managers share the same information sets. The most relevant alternative hypothesis is that managers and markets disagree. There are two reasons for this. Managers and markets might not share the same information set. Suppose managers know more, then we would expect two things. First managers do not follow current market prices. Second, news about investment decisions would move market prices. Increases in investment expenditures would signal good prospects and lead to higher market prices. Alternatively, managers could put some weight on their own information and some weight on market prices. If markets become more informative, managers would put more weights and we would see an increase in the fit of the q -equation.

Governance might also be imperfect. In this case the markets are right but managers pursue their own goals. The investment equation might fail because managers do not maximize firm value. An improvement in governance would then lead to improvements in the fit of the q -equation for investment (1) without implying an improvement in the forecasting power of prices.

⁵Note that the parameters are restricted to $\psi < \frac{1}{2}\sigma_u\sigma_v$, so the comparative statics are unambiguous.

Finally the two models can be integrated. The technical cost of doing so is simply that with endogenous investment, cash flows becomes endogenous to signals, and the characterization of the fixed point is longer. Notice, however, that the FOC that we intend to test do not depend on this.

IV. Data

We obtain stock price data from CRSP, bond price data from the Lehman/Warga Database and Mergent Fixed Income Datascope. The tests on commodity futures in the appendix use data from the CME. All accounting measures are from COMPUSTAT. Analyst forecast dispersion comes from the I/B/E/S database. Our main sample period is from 1960 to 2011. Bond data is available since 1973 and analyst data since 1976. We 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. 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 current assets. This allows firms to increase their profits by growing, as they do in our q -theory 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 current assets.

We control for firm uncertainty with analyst EPS-forecast dispersion. We convert this dispersion into a percentage of total assets.

We also measure the volatility of returns around earnings announcements as an indicator of price informativeness. Specifically, we calculate the three-day cumulative abnormal return (CAR) around each earnings announcement and take its absolute value. For comparison, we

calculate the same measure on days with no earnings announcement, as well as three-day turnover.

In most tests, we limit attention to S&P 500 non-financial companies, which represent the bulk of the U.S. corporate sector. The firms in this sample have 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 II about here.

The Data Appendix at the end of the paper explains our measures in greater detail. Table II presents summary statistics. S&P 500 firms are typically more profitable than the universe of firms. They invest more, but not as a percentage of current assets. Their credit spreads are only a bit lower. S&P 500 firms are also less uncertain: They have lower idiosyncratic volatility and the dispersion in analysts forecasts about their earnings is smaller. Finally, S&P 500 firms have relatively smaller announcement-day returns than all firms. Both groups see the magnitude of their returns as well as their turnover increase by more than 50% around earnings announcements.

Our models suggest that the dispersion in prices is a key indicator of price informativeness. 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 empirical 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.

V. Empirical results

We begin our empirical analysis with preliminary evidence on financial market informativeness by looking at return volatility around earnings announcements. The full set of predictability regressions implied by our models follow.

A. Volatility around earnings announcements

Increased price informativeness 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 2 about here.

Figure 2 displays the results. Looking at S&P 500 firms, volatility on non-announcement days has remained stable, whereas announcement-day volatility has increased substantially. 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 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 2 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.

Table III about here.

Table III 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 2, 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, but not by much.

The regression framework 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 III. The results show that the relative increase in announcement surprises is almost as strong within firms as it is overall. For a given firm in the S&P 500, the relative 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 2 suggests, some of this increase is associated with an increase in relative turnover around announcement days. Columns (3) and (4) of Table III 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 test, we find no evidence that financial markets have become more informative.

B. Market prices and future earnings

Turning to the main predictions of our model, we check whether equity and bond market valuations have become stronger predictors of profitability and investment over time. Specifically, we look for trends in the coefficients, predicted variation, and R^2 of multivariate forecasting regressions. As our models show, the forecasting coefficient is driven by the price of risk. By contrast, the predicted variation of the regression captures the informativeness of prices and also serves as a key welfare measure. The predicted variation is given by the coefficient of our financial forecasting variable multiplied by its cross-sectional dispersion. The higher the predicted variation, the more informative are prices about future profitability. In turn, when profitability is more predictable, investment is more efficient and so growth is higher, linking financial markets to welfare. Finally, our model with endogenous information acquisition makes the stronger prediction that the entry of more uncertain firms (for example

high-tech firms) gives traders a sufficiently strong incentive to acquire information, so that the R^2 of the price-based forecast of future earnings increases.

To isolate the predictive power of financial markets, we always control for current profitability and investment. To ensure that our controls are available to investors at the time of forecasting, we always match financial 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 financial variables. This approach errs on the side of giving market prices a better shot at predicting future performance. To control for discount rate effects, we include year-industry dummies. We limit our controls to easily observable characteristics because we are interested in how much can be learned directly from prices. In sum, our tests exploit within-industry cross-sectional differences in valuations to forecast earnings and investment. Our main focus is on S&P 500 firms whose fundamental uncertainty has remained stable. Later, we show results for the full set of firms where we are careful to control for the underlying uncertainty.

Earnings and equity prices

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

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}, \quad (11)$$

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 their balance sheet.

Figure 3 about here.

Figure 3 depicts the results of regression (11). 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. The two right-most plots show the contribution to the regression R^2 from including market prices. 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.

Overall, Figure 3 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 market prices at the end of the tech boom in 2000, but this drop is short-lived. Overall, the coefficients a_t remain flat throughout our sample.

We find no evidence of a trend in the forecasting power of equity prices. The equity market-predicted variation has remained remarkably stable over the past fifty years, the sharp drop in 2000 notwithstanding. In other words, price dispersion within the S&P 500 has not increased enough to improve the predictability of future earnings. Within our models, this suggests that equity markets have not increased the efficiency of capital allocation, and by extension, general welfare. Finally, our stronger prediction that the R^2 increase with the arrival of more uncertain firms is also not borne out. This result suggests that the aggressiveness with which market participants produce information is not high enough to overcome increases in fundamental uncertainty.

Earnings and bond spreads

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

$$\frac{E_{i,t+k}}{A_{i,t}} = a_t (y_{i,t} - y_{0,t}) \times \mathbf{1}_t + b_t \left(\frac{E_{i,t}}{A_{i,t}} \right) \times \mathbf{1}_t + c_{s(i,t),t} (\mathbf{1}_{SIC1}) \times (\mathbf{1}_t) + \epsilon_{i,t}, \quad (12)$$

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

Figure 4 about here.

Figure 4 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. There is a slight downward trend in the coefficients and a slight upward trend in the predicted variation, both are more evident at the three-year horizon. However, predictability is strongest in the late 1970s when credit risk was of higher concern. The marginal R^2 is reliably low and noisy.

C. Market prices and investment

Financial markets facilitate the allocation of capital by spurring investment. Our models predict that higher valuations should be associated with higher investment. We check this prediction by running forecasting regressions.

Equity prices and R&D expenditure

We begin with R&D expenditure. R&D investment is of particular interest as its funding requires financial sophistication due to low asset pledgeability. Equity markets in particular are potentially important sources of R&D funding. During our sample, the importance of R&D has increased, as has its dispersion across firms (see Figure 1).

We run the regression

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

The results in Figure 5 show that higher market valuations are associated with more R&D late in our sample, even after we control for current earnings and current R&D.⁶ The effects are most pronounced at the three-year horizon.

Figures 5 and 6 about here.

Figure 5 also shows that the equity-predicted variation in R&D expenditure has risen. The result is most evident at the 3-year horizon. This lag suggests that market prices predict future investment rather than respond to past investment. The marginal R^2 also rises a bit in the 2000s but the pattern is very noisy. Overall, our findings indicate that equity markets have become stronger predictors of future R&D as R&D itself has gained a more prominent role in capital formation.

Bond spreads and R&D expenditure

Turning to bond markets, Figure 6 shows no evidence that corporate bond spreads forecast R&D. The forecasting coefficients are close to zero and exhibit no trends. 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.

⁶In unreported tests, omitting either control increases the magnitude of this effect.

Equity prices and capital expenditure

Turning to tangible investment, we check whether market valuations are associated with higher capital expenditure. Specifically, we run

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

Figure 7 shows that a higher equity valuation is associated with more capital expenditure, particularly at the longer horizons. However, we find no evidence of a trend in the forecasting coefficient, the predicted variation, or the marginal R^2 .

Figures 7 and 8 about here.

Bond spreads and capital expenditure

As with R&D expenditure (Figures 6) and 8 shows that 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 .

Figures 9 and 10 about here.

D. Earnings and investment

Leaving financial markets aside, we explore the relationship between investment and earnings. This is the key link between the allocation of capital and output. We begin by looking at R&D expenditure and earnings:

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

Figure 9 documents a generally positive relationship between R&D investment and future earnings, at least at the three-year horizon. By contrast, Figure 10 shows no evidence of a

correlation between capital expenditure and future investment. In both cases, investment is a weak predictor. Although market prices have become stronger predictors of R&D expenditure, R&D itself is only weakly associated with future earnings. As a result, the forecasting power of market prices for future earnings has remained unchanged.

VI. 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 of the comparison 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. Perhaps surprisingly, the tech boom of the late 1990s is associated with a much smaller increase in earnings dispersion.

Figure 11 about here.

The top right panel of Figure 11 shows that as the earnings dispersion of all firms increased, so did 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, 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. Overall, the increased price dispersion does not appear to be related to earnings even at a three-year horizon.

We view these results as motivating our focus on S&P 500 firms, whose fundamentals have remained stable. In the next section, we explore predictability for all firms by controlling for fundamental uncertainty.

A. Controlling for uncertainty

So far, our results suggest that the informativeness of prices has remained stable for S&P 500 firms. Figure 11 suggests, however, that predictability has declined outside of the S&P 500. A potential explanation for this result is the relative shift towards firms that are harder to value. In this section, we show further evidence consistent with this idea. We find that controlling for analyst forecast dispersion, a measure of firm uncertainty, price informativeness has remained stable. However, our models show that an increase in uncertainty alone does not predict lower informativeness. For informativeness to fall, there must be an increase of firms with high marginal information costs ψ , not simply high total uncertainty.

In the absence of a direct measure of information costs, we use the dispersion of analyst forecasts as a proxy for uncertainty. Specifically, we obtain the standard deviation of one-year-ahead earnings per share (EPS) estimates from I/B/E/S for firms with at least two analysts. We then calculate an uncertainty measure as

$$Uncertainty = \frac{(St.Dev.) \times (\#Shares)}{TotalAssets}.$$

Figure 12 plots the 50th, 90th, and 95th percentiles of *Uncertainty* over time. The rise in the 90th and 95th percentile cutoffs suggests that the composition of the stock market has shifted towards significantly harder-to-value firms.

Figure 12 about here.

Our goal is to see if firms comparable to the uncertain firms of 1976 maintain a stable level of predictability. We divide firms into two groups based on cutoffs from 1976, (the first year of the I/B/E/S dataset). The 90th percentile of *Uncertainty* in 1976 is about 0.5% and the 99th percentile is about 2%. We call firms with *Uncertainty* less than 0.5% low 1976 uncertainty firms and firms with *Uncertainty* between 0.5% and 2% high 1976 uncertainty firms.

Figure 13 shows the distribution of earnings and valuation ratios for firms grouped by uncertainty. The top left panel shows the dispersion of earnings over assets for our high and low 1976-uncertainty firms, as well as for all firms. The results support our approach by showing that firms with high uncertainty by 1976 standards indeed have more dispersed earnings that have remained stable. As the line for all firms shows, however, there has been an influx of even more uncertain firms over time. The bottom left panel of Figure 13 shows that whereas price dispersion for all firms is generally higher than either of our two groups, the price dispersion for high and low uncertainty firms is very similar.

Figure 13 about here.

The other four panels of Figure 13 contain our key results. They show that the predictability of firms with high uncertainty based on 1976 cutoffs has not declined, and in fact tracks the predictability of our low 1976-uncertainty firms well. By contrast, the predictability of all firms declines after 1980 as in Figure 11, revealing a firm composition effect.

Overall, Figure 13 suggests that holding firm uncertainty constant, predictability has remained stable even outside the S&P 500. However, financial markets now support much more uncertain firms than in the past, creating the appearance of a decline in aggregate predictability. These results are consistent with stable price informativeness in the face of increasing prevalence of firms that are more costly to value. One puzzling result is that price dispersion is just as high if not higher for the most uncertain firms; that is prices behave as if there is a lot of information about these firms.

B. Financial Market Efficiency

In this section, we calculate an implicit measure of the efficiency of the financial sector based on our model with endogenous information acquisition. Recall from our model that the

predicted variation $PredVar$ is given by

$$PredVar = \frac{\sigma_v}{\sqrt{2}} - \sqrt{\frac{\psi\sigma_v}{2\sigma_u}}.$$

As discussed earlier, the parameter restrictions are such that $PredVar$ is increasing in fundamental uncertainty σ_v . As firm uncertainty rises, holding information costs ψ fixed, prices become more informative as the payoff to possessing information increases.

The parameter ψ measures the cost of acquiring private information and therefore reflects the efficiency of the financial sector in evaluating firms. Since we can proxy for firm uncertainty with the cross-sectional dispersion in future earnings, we can obtain an implicit measure of efficiency under the assumption that noise trader demand is fixed:

$$\psi/\sigma_u = \frac{2}{\sigma_v} \left(\frac{\sigma_v}{\sqrt{2}} - PredVar \right)^2.$$

While we cannot control for noise trader demand, given our results one would have to argue that noise trader demand has been falling throughout our sample in a way that offsets a decline in the cost of information ψ .

Figure 14 about here.

Figure 14 plots our estimates of ψ/σ_u for the S&P 500 and for all firms. The estimate for S&P 500 firms is remarkably stable, whereas for all firms it increases dramatically. As noted earlier, 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 14.

We attribute the rise in the implicit information cost for all firms to the changing composition of firms in the economy. However, our sample of S&P 500 firms whose profile has remained stable, suggests that the cost of providing information through markets has not decreased. This result suggests that the financial sector has not become more efficient in

allocating capital via equity markets.

VII. Conclusion

We examine the extent to which stock and bond prices forecast future earnings. Our main finding is that financial market informativeness has not increased in the past fifty years. In fact, earnings surprises have grown relative to overall uncertainty. The efficiency of information production in the financial sector has remained stable.

These results appear to contradict the view that improvements in information technology have increased the availability of low-cost information. A possible explanation is that the relevant constraint for investors lies in the ability to interpret information rather than the ability to record it. If this is the case, a rise in the quantity of data need not improve informativeness or the allocation of resources.

Model appendix

Let us decompose firm i into an aggregate and an idiosyncratic components

$$z_{i\tau} = \bar{z}_\tau + \hat{z}_{i\tau}$$

and similarly for investment

$$x_{i\tau} = \bar{x}_\tau + \hat{x}_{i\tau}$$

Note this is assuming firms have the same beta of one. The bar-variables are aggregate and the hat-variables are idiosyncratic and mean-zero.

$$q_{it} = \mathbb{E}_t \sum_{\tau=t+1}^{\infty} m_{t,\tau} \left(\bar{z}_\tau + \hat{z}_{i\tau} + \frac{\gamma}{2} (\bar{x}_\tau + \hat{x}_{i\tau})^2 \right)$$

Consider the difference between two firms

$$q_{it} - q_{jt} = \mathbb{E}_t \sum_{\tau=t+1}^{\infty} m_{t,\tau} \left(\hat{z}_{i\tau} - \hat{z}_{j\tau} + \gamma \left(\bar{x}_\tau + \frac{\hat{x}_{i\tau} + \hat{x}_{j\tau}}{2} \right) (\hat{x}_{i\tau} - \hat{x}_{j\tau}) \right)$$

Since the hat-variables are idiosyncratic we get

$$q_{it} - q_{jt} = \mathbb{E}_t \sum_{\tau=t+1}^{\infty} (1 + r_{t,\tau})^{t-\tau} (\hat{z}_{i\tau} - \hat{z}_{j\tau}) + \Delta_{ijt}$$

where Δ measures the differences in growth options.

Data appendix

Equity market valuation

We use the ratio of market capitalization to total asset to capture the information contained in the equity market. The value of total asset is released in a firm's 10-K form 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, the market price is guaranteed to capture public information on profitability and investment. 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) during the period of 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 the equity market valuation, we also use end-of-March yields.

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 4433 individual bonds issued by 615 firms during the period 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 equivalently operating income after depreciation (OIADP). These two items both represent the operating income (sales) of a company after deducting expenses for cost of goods sold, selling, general, and administrative expenses, and depreciation/amortization. In the empirical tests, we use EBIT (scaled by total asset). 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) as the proxy, 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 also collect other firm characteristics from COMPUSTAT such as total asset (“AT”). We also obtain earnings announcement days from COMPUSTAT. This data starts in 1970 and refers to the first date on which earnings are published in the financial press and news wires.

Our measure of firm uncertainty uses data on analyst forecasts from I/B/E/S. We download the standard deviation of analyst forecasts for one-year-ahead earnings for each firm in every year. We take the average of this standard deviation within a year for each firm. To construct our uncertainty measure, we multiply by the number of shares, which converts the standard deviation into a total dollar amount, then divide by assets to get a measure of uncertainty as a percentage of firm assets.

Commodity futures

Having considered stocks and bonds, we turn to a derivatives market, namely 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 couple of decades. It is therefore natural to ask whether increased information-based trading has increased price informativeness in these markets.

A second advantage of foodstuff commodities is that there is less of a risk premium component in their prices. As a result, foodstuff futures prices are largely driven by expectations of future fundamentals.

The relevant measure of fundamentals in a futures market is the delivery price, further simplifying the problem. As a scaling factor, we use the current cash price, running the forecasting regressions

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

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 $a_y \times \sigma_y(\log F/C)$, where we calculate $\sigma_y(\log F/C)$ from the standard deviation of prices throughout the year.

The results are in Figures A1, A2, and A3. Informativeness is positive, 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 A1, A2, and A3 about here.

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Table II. 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 $ CAR $	3.68	2.93	2.82	6.17	4.79	5.29
No-announcement $ CAR $	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 III. The magnitude of earnings surprises

Results from the panel regression

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

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*** (0.080)	0.833*** (0.079)	0.583*** (0.084)	0.522*** (0.087)	0.850*** (0.031)	1.291*** (0.047)	0.821*** (0.029)	1.101*** (0.057)
1976 to 1980	-0.340*** (0.094)	-0.314*** (0.093)	-0.360*** (0.099)	-0.329*** (0.101)	-0.396*** (0.056)	-0.362*** (0.063)	-0.405*** (0.053)	-0.384*** (0.062)
1981 to 1985	-0.205** (0.089)	-0.250*** (0.089)	-0.288*** (0.089)	-0.302*** (0.090)	-0.146** (0.057)	-0.308*** (0.068)	-0.209*** (0.060)	-0.332*** (0.069)
1986 to 1990	0.069 (0.133)	-0.009 (0.139)	-0.100 (0.125)	-0.118 (0.130)	0.100 (0.099)	-0.241** (0.105)	-0.023 (0.089)	-0.282*** (0.097)
1991 to 1995	0.478*** (0.116)	0.387*** (0.107)	0.161 (0.125)	0.137 (0.114)	0.634*** (0.063)	0.272*** (0.084)	0.333*** (0.089)	0.121 (0.089)
1996 to 2000	0.906*** (0.229)	0.715*** (0.221)	0.416** (0.186)	0.373* (0.198)	1.100*** (0.171)	0.569*** (0.165)	0.632*** (0.167)	0.324* (0.159)
2001 to 2005	1.694*** (0.178)	1.221*** (0.200)	0.603*** (0.173)	0.469** (0.185)	2.166*** (0.187)	1.515*** (0.193)	1.384*** (0.161)	1.017*** (0.147)
2006 to 2011	2.081*** (0.187)	1.505*** (0.181)	0.308 (0.188)	0.116 (0.178)	2.767*** (0.146)	2.169*** (0.183)	1.623*** (0.241)	1.338*** (0.240)
$Turn_{Ann.}$			0.653*** (0.042)	0.779*** (0.053)			0.462*** (0.070)	0.440*** (0.074)
$-Turn_{No\ ann.}$								
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.

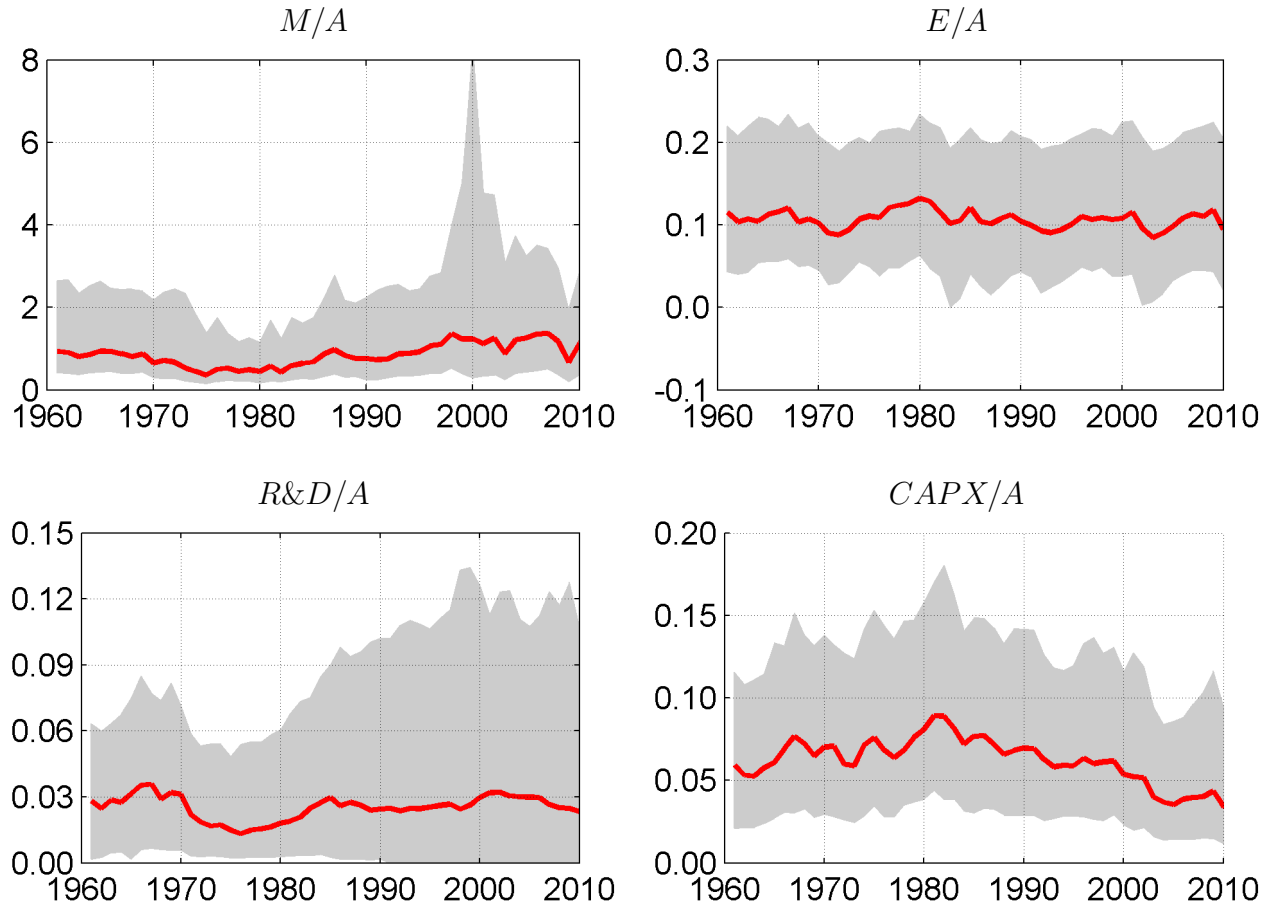


Figure 2. Volatility and turnover around earnings announcements

For each firm in every year, we calculate the absolute value of three-day abnormal returns, $|CAR_{t \rightarrow t+2}|$, around earnings announcements (“Announcement”) and on all other days (“No announcement”). We also calculate three-day turnover, $Turnover_{t \rightarrow t+2}$, (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.

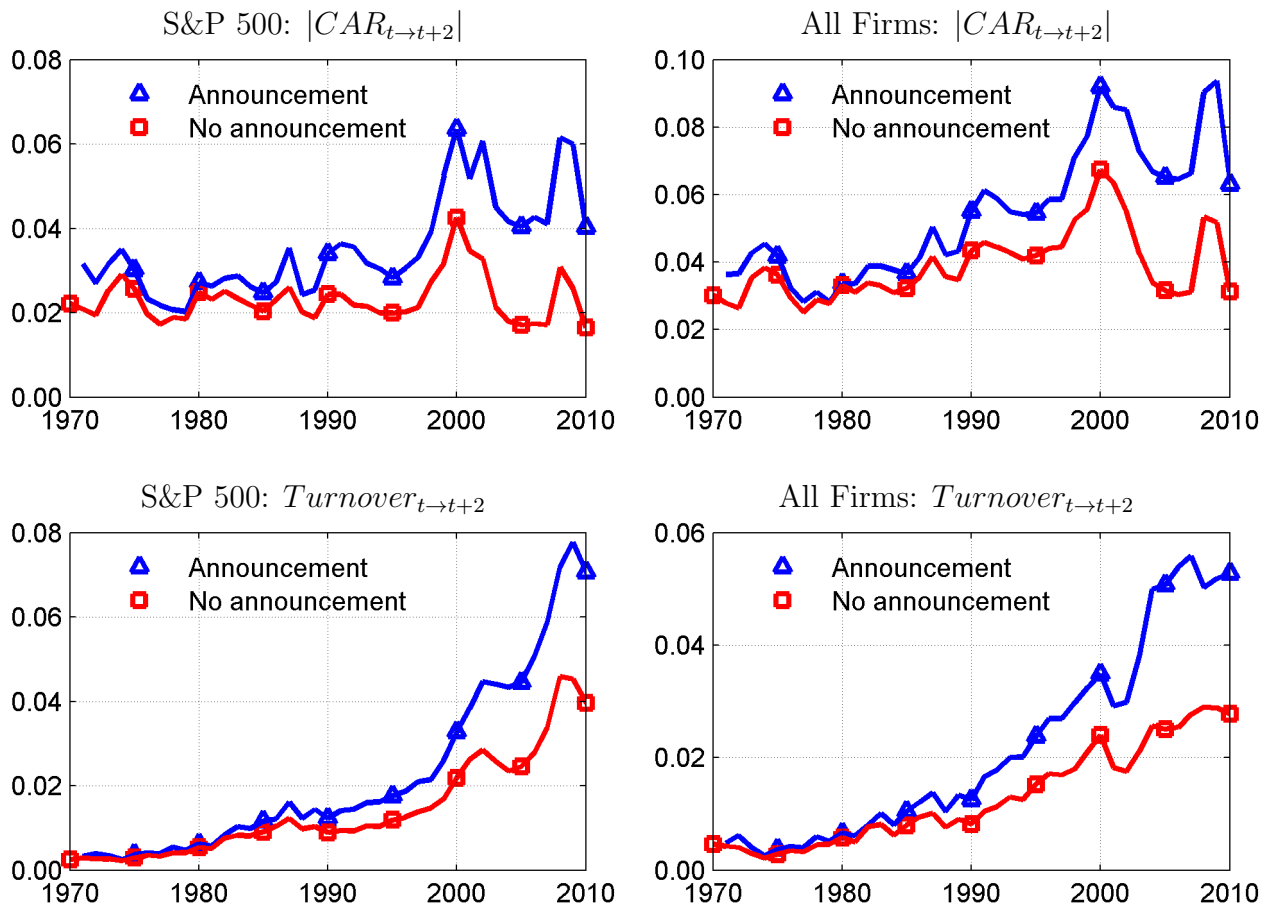


Figure 3. Forecasting earnings with equity prices

Results from the regression

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

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ 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 $\log M/A$.

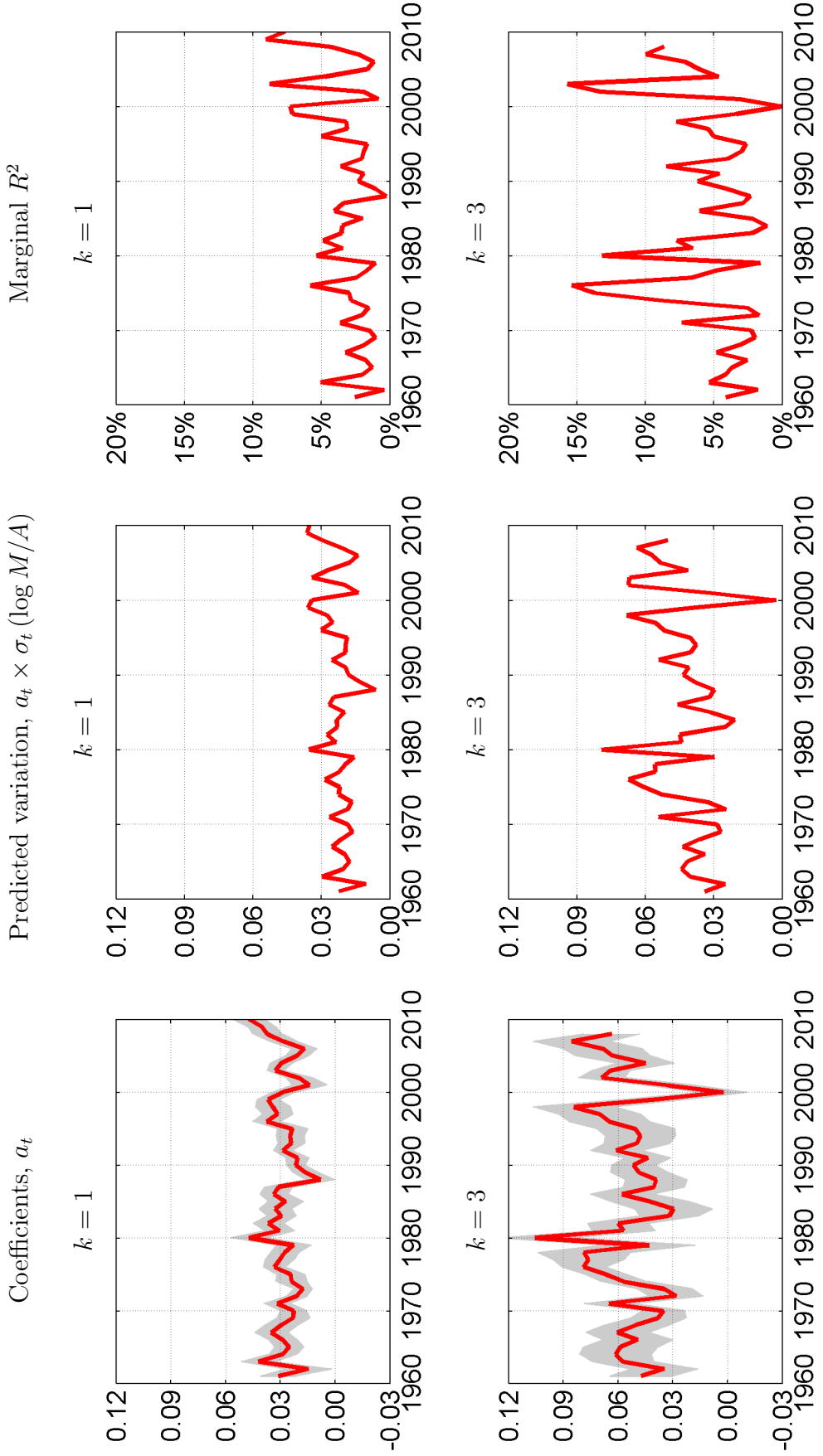


Figure 4. Forecasting earnings with bond spreads

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 ($y - y_0$).

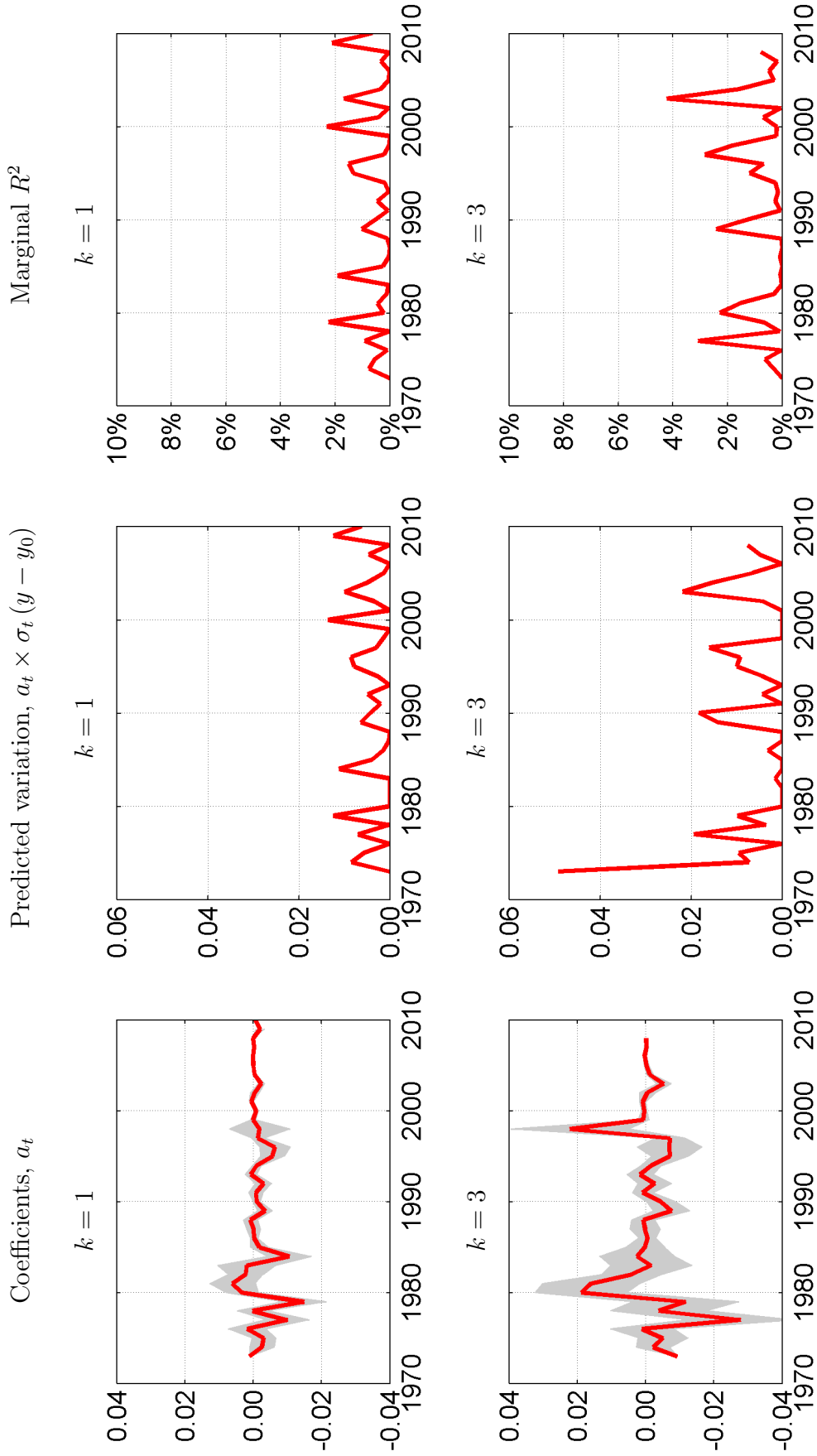


Figure 5. Forecasting R&D expenditure with equity prices

Results from the regression

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

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ 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 $\log M/A$.

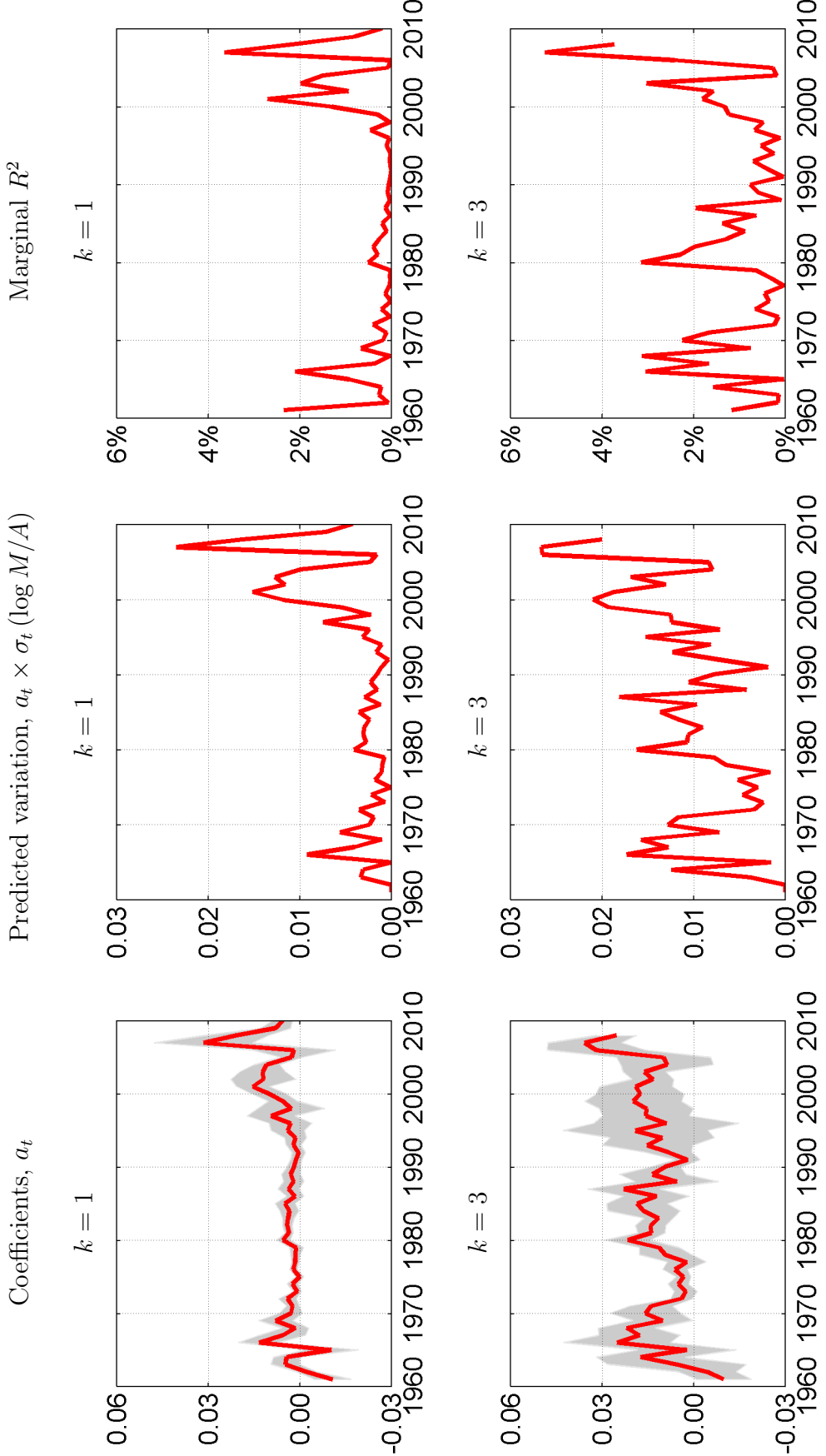


Figure 6. Forecasting R&D expenditure with bond spreads

Results from the regression

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

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 $y - y_0$.

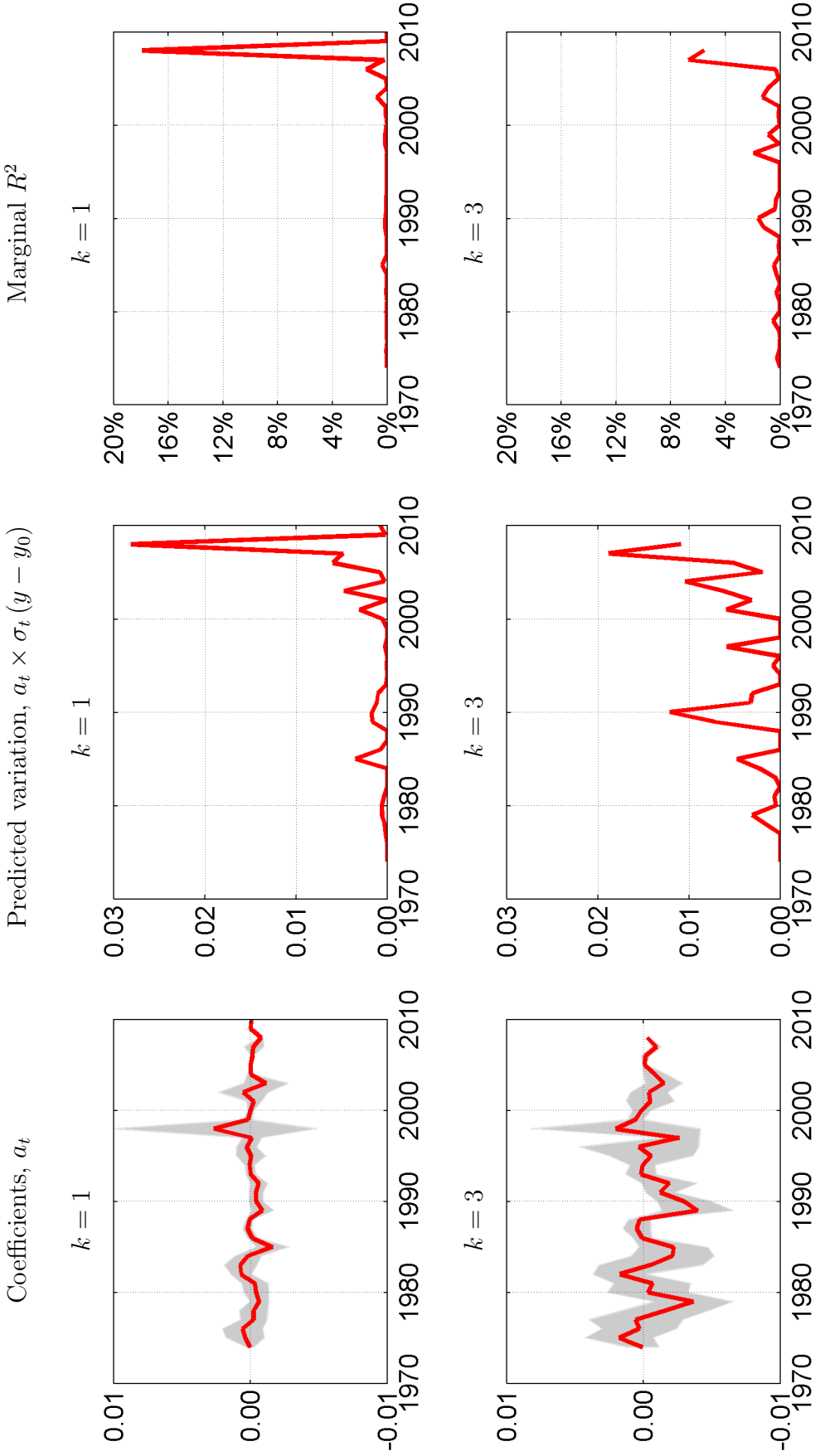


Figure 7. Forecasting capital expenditure with equity prices

Results from the regression

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

Market cap M is measured as of the end of March following the firm's fiscal year end. Earnings E are measured as EBIT. $SIC1$ 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 $\log M/A$.

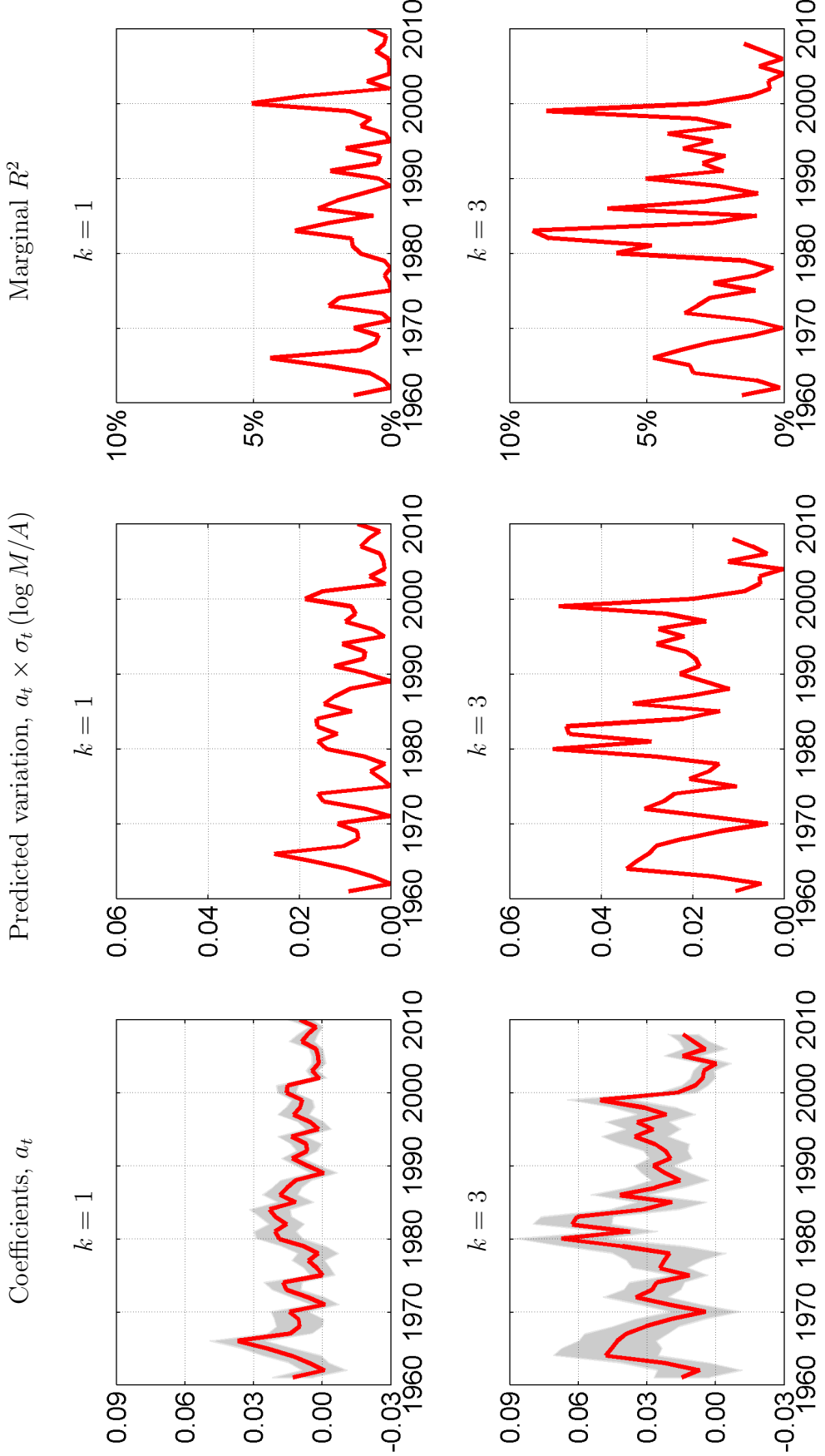


Figure 8. Forecasting capital expenditure with bond spreads

Results from the regression

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

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 $y - y_0$.

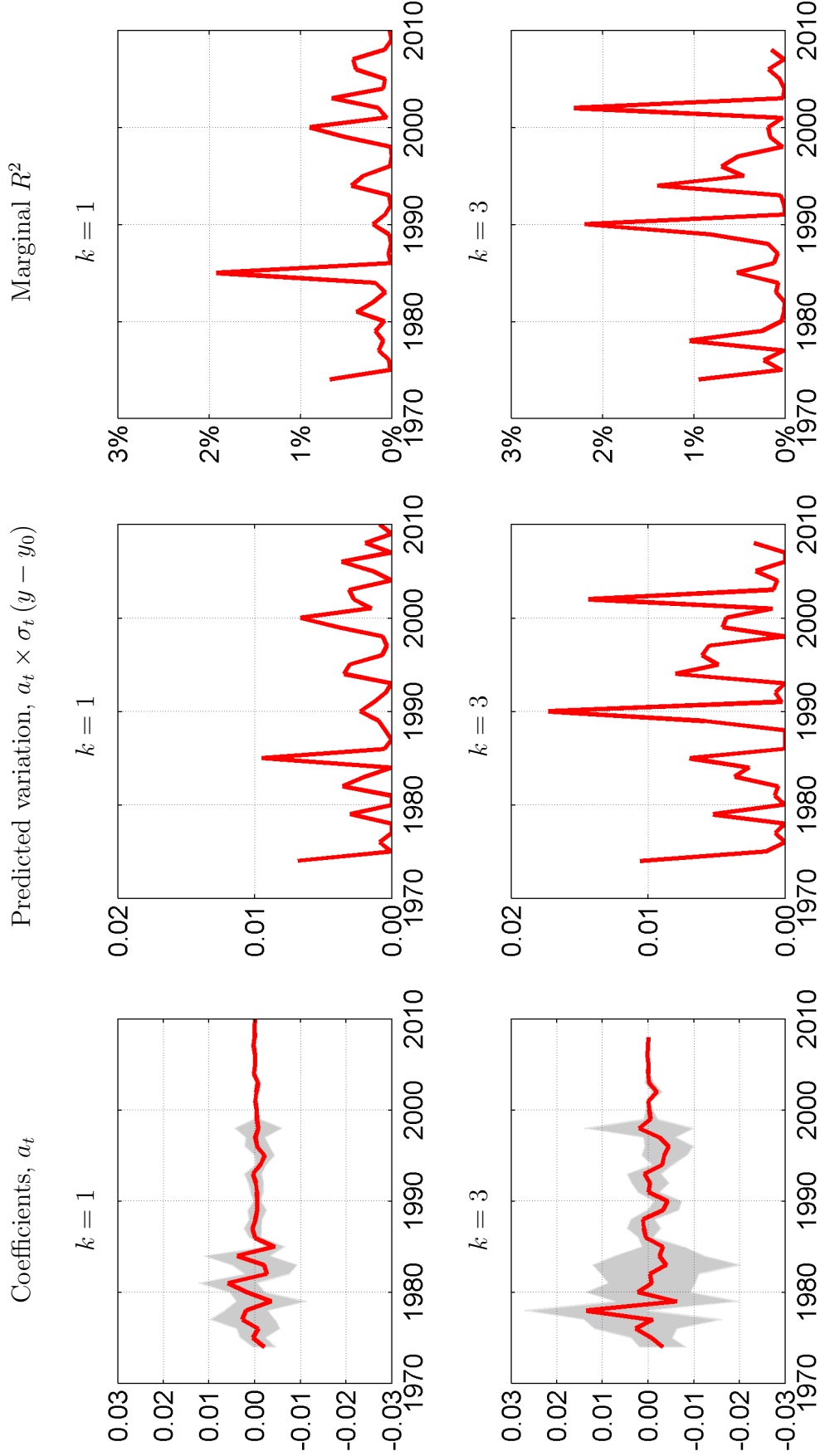


Figure 9. Forecasting earnings with R&D expenditure

Results from the regression

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

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 $a_t \times \sigma_t (R\&D/A)$. The marginal R^2 is the difference between the full-regression R^2 and the R^2 from a regression omitting $R\&D/A$.

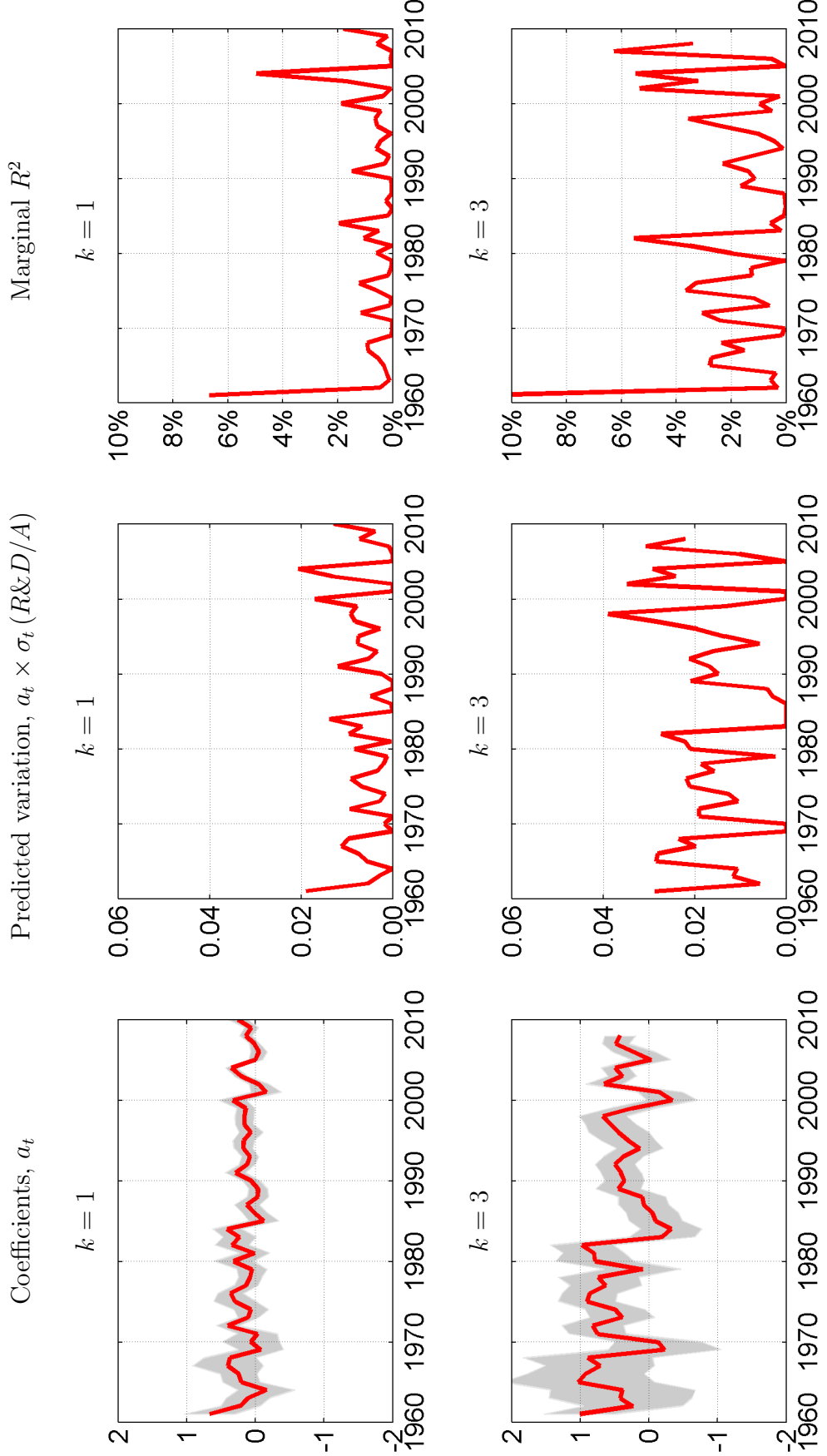


Figure 10. Forecasting earnings with capital expenditure

Results from the regression

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

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 $CAPX/A$.

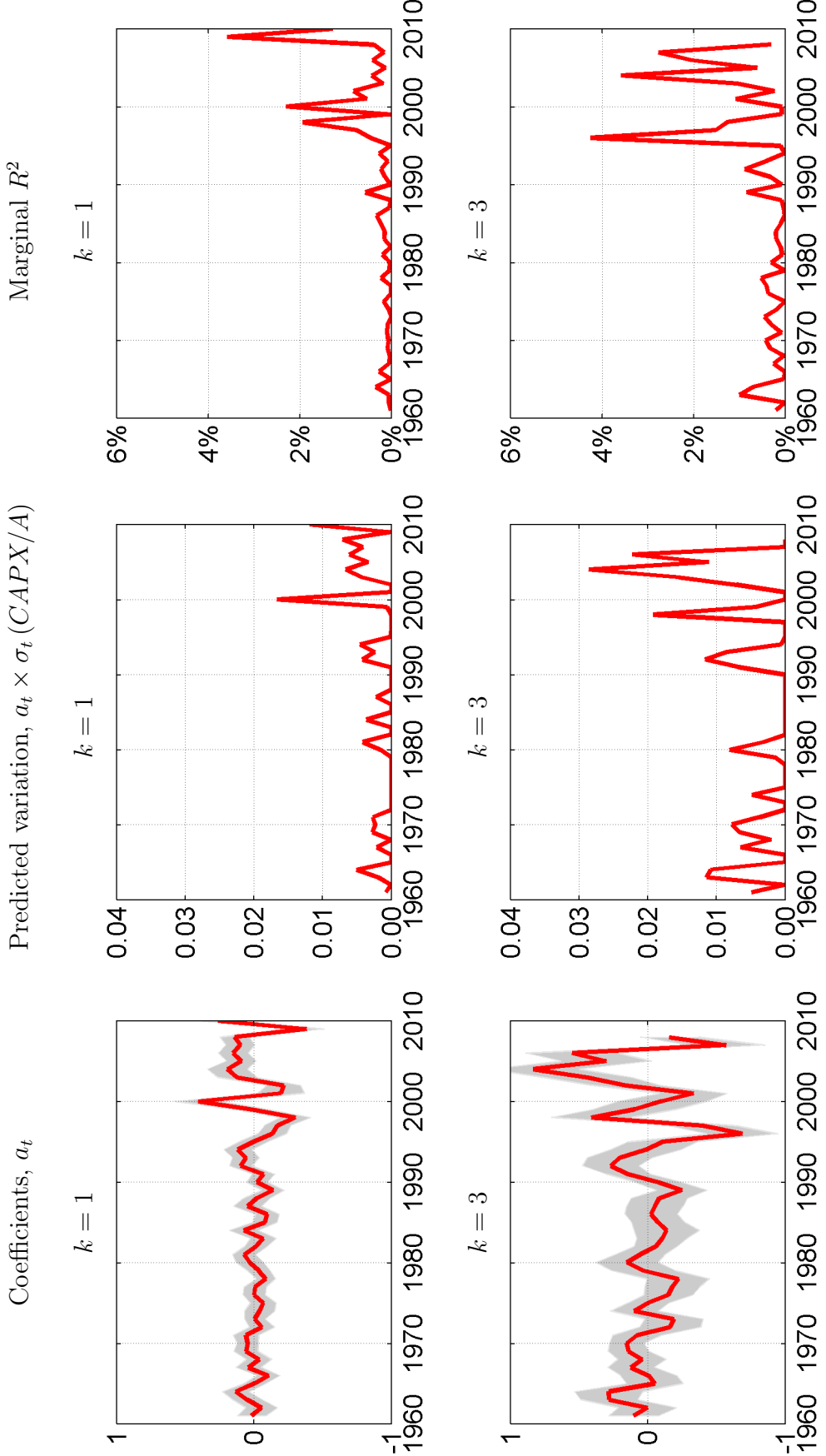


Figure 11. S&P 500 versus all firms

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

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

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 $a_t \times \sigma_t (\log M/A)$.

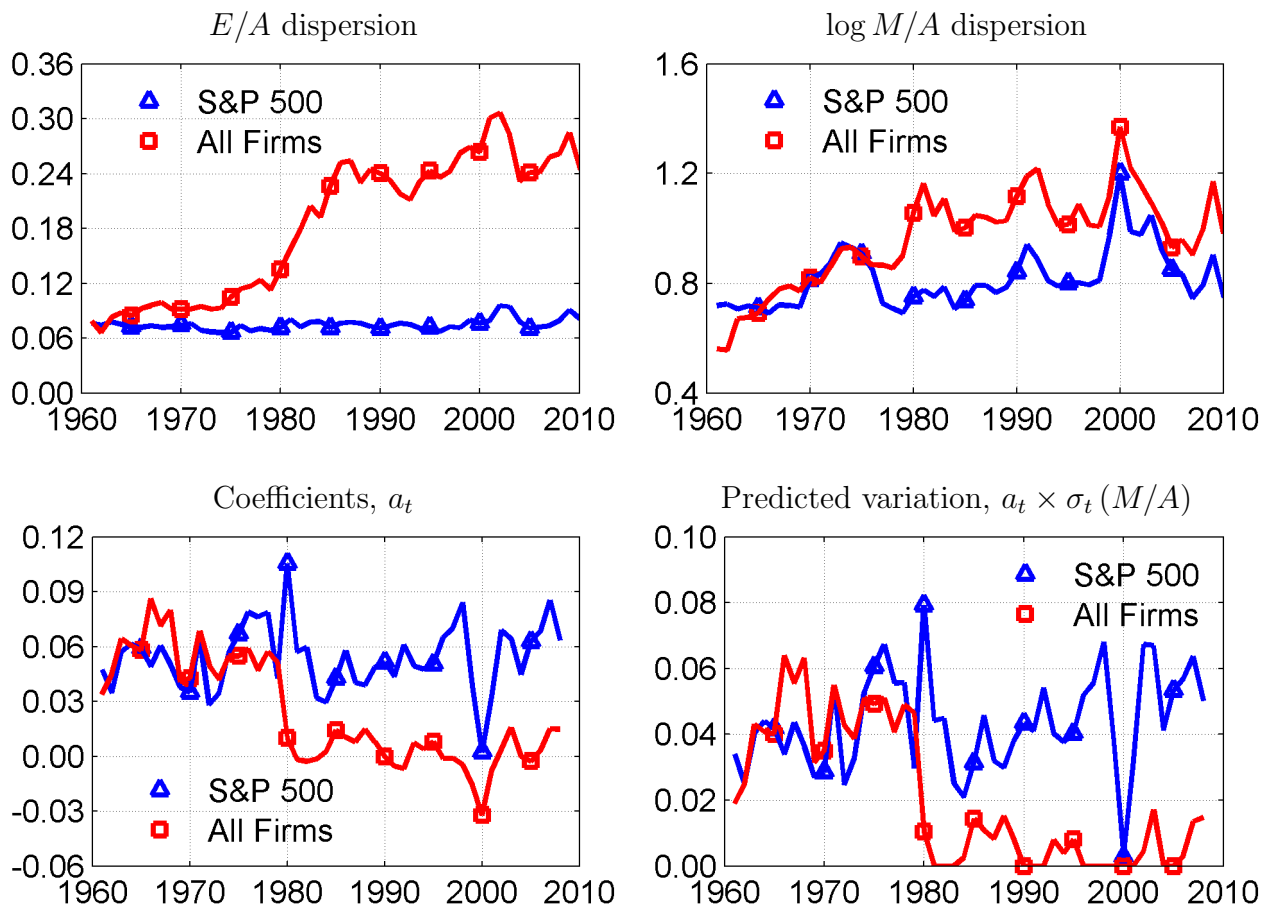


Figure 12. Firm uncertainty percentiles

We collect the standard deviation of one-year-ahead earnings per share estimates (EPS) for all firms with at least two analysts in the I/B/E/S database. We construct a proxy for firm uncertainty as

$$Uncertainty = \frac{(St.Dev.) \times (\#Shares)}{TotalAssets}.$$

We plot the 50th (median), 95th, and 95th percentiles of *Uncertainty* every year.

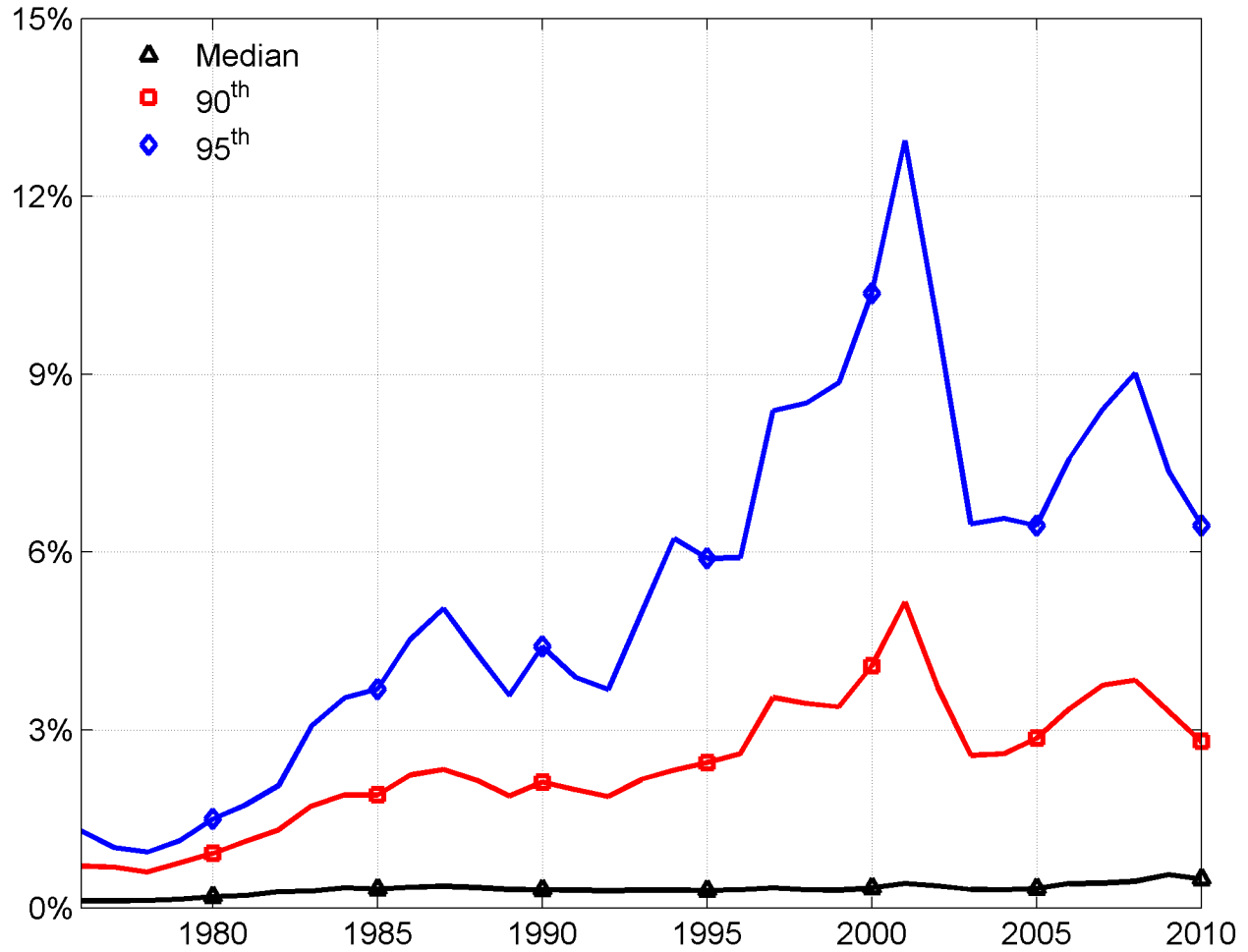


Figure 13. Firm uncertainty and informativeness

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

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

for high and low uncertainty firms as well as all 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 $a_t \times \sigma_t (\log M/A)$. Uncertainty is measured as the standard deviation of I/B/E/S one-year EPS forecasts times shares outstanding, divided by total assets. Firms with uncertainty between 0.5% and 2% (these cutoffs are based on the 90th and 99th percentiles of firm uncertainty in 1976) are classified as high 1976 uncertainty firms (Hi_{1976}) and those below 0.5% as low 1976 uncertainty firms (Lo_{1976}).

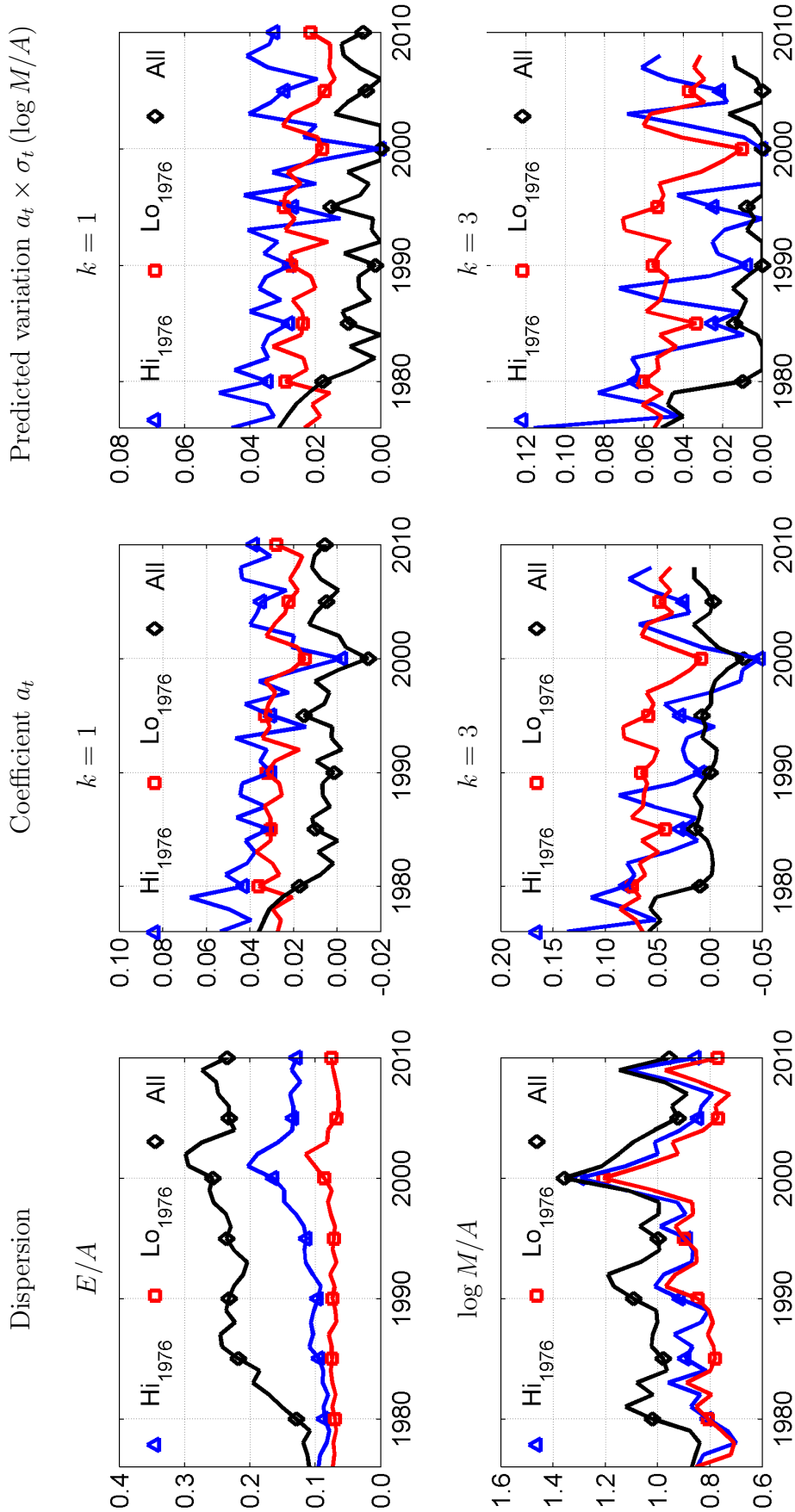


Figure 14. Financial sector efficiency

We plot the left side of

$$\psi/\sigma_u = \frac{2}{\sigma_v} \left(\frac{\sigma_v}{\sqrt{2}} - PredVar \right)^2,$$

where ψ is the cost of information acquisition and σ_u is the volatility of noise trader demand (see our model for details). $PredVar$ is the equity-market predicted variation, given by $a_t \times \sigma_t (\log M/A)$ with a_t from the forecasting regression

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

Our proxy for σ_v is the dispersion in future earnings $\sigma_t (E_{t+3}/A_t)$. We consider S&P 500 non-financial firms and all non-financial firms separately from 1960 to 2010.

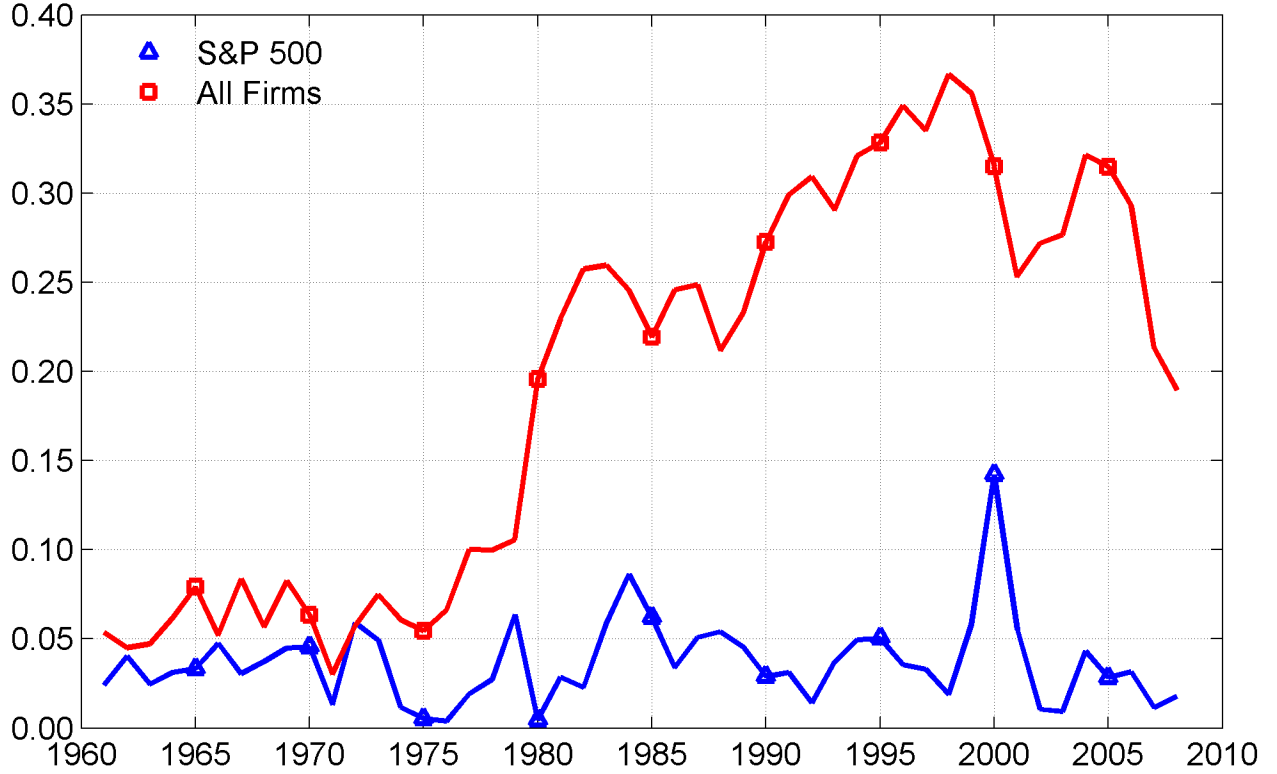


Figure A1. Corn futures

Results from the regression

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

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 $a_y \times \sigma_y (\log F/C)$. The data covers the period from 1960 to 2010.

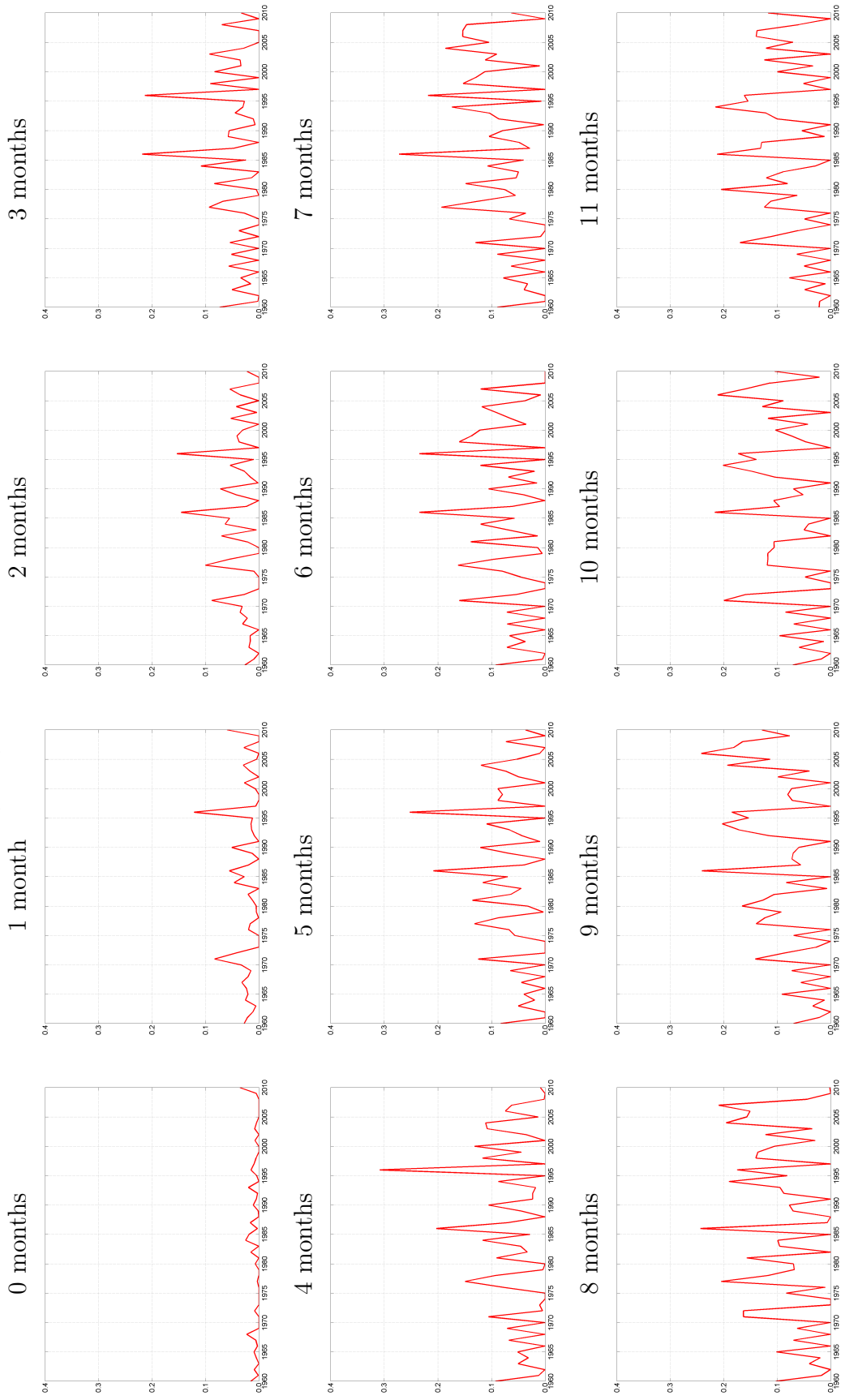


Figure A2. Soybean futures

Results from the regression

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

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 $a_y \times \sigma_y (\log F/C)$. The data covers the period from 1960 to 2010.

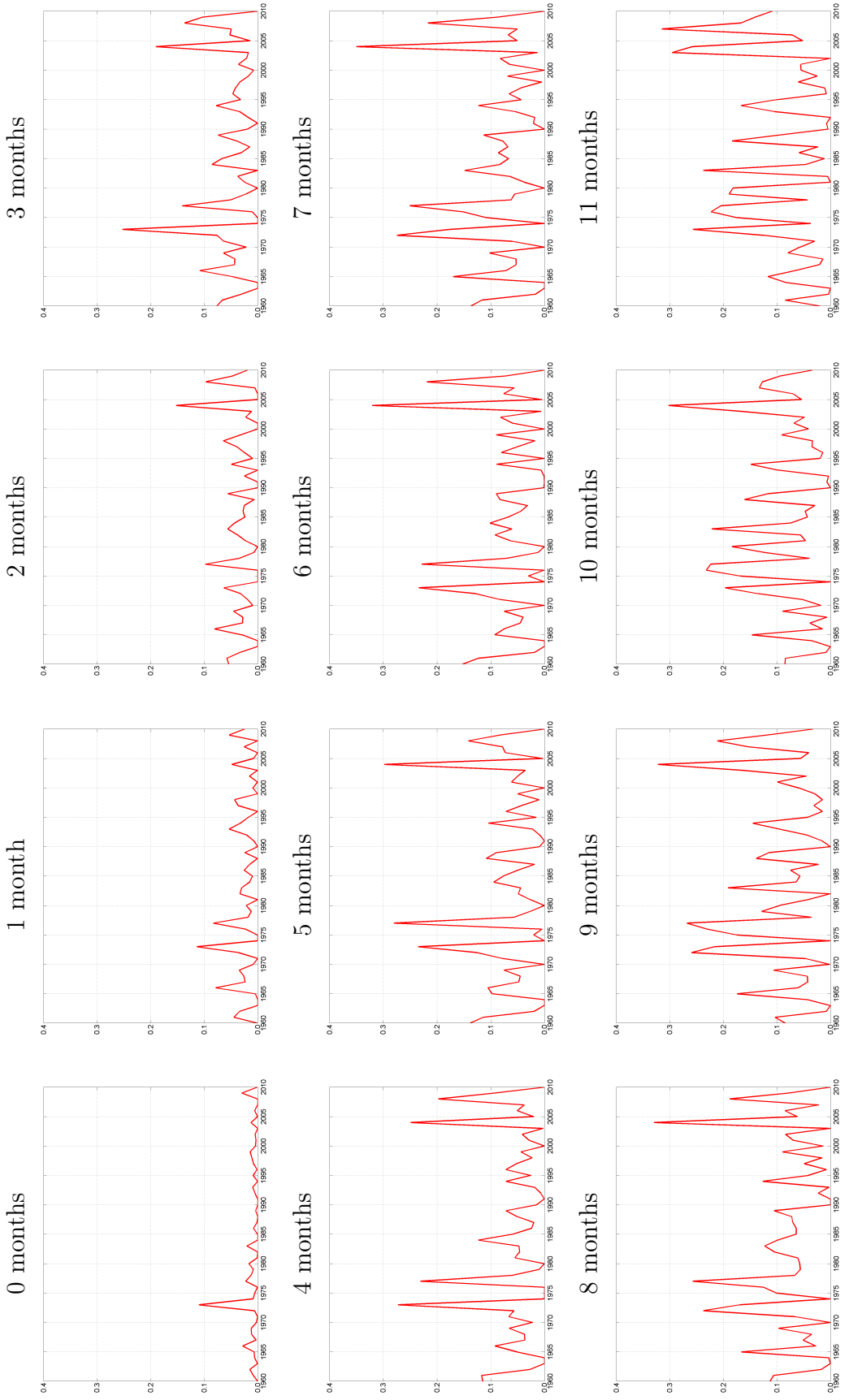


Figure A3. Wheat futures

Results from the regression

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

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 $a_y \times \sigma_y (\log F/C)$. The data covers the period from 1960 to 2010.

