An Online Appendix of "Technical Trading: A Trend Factor"

In this online appendix, we provide a comparative static analysis of the theoretical model as well as further robustness checks on the trend factor.

Appendix .1. Comparative Statics

In this subsection, we examine further on how the model parameters impact on the equilibrium price. Table .1 examines the comparative statics of the price with respect to the persistence parameter for π, α_π. In this table, we set $\alpha = 0.1$. Panel A shows the case for $\alpha_\pi = 0.1$ while Panel B the base case with $\alpha_\pi = 0.2$. This parameter has big impact on price. For example, when $w = 0.5$, $p = -5.6116$ for $\alpha_\pi = 0.1$, and $p = 16.2126$ for $\alpha_\pi = 0.2$. When π_t is more persistent with smaller α_π, the price is more sensitive to π_t and θ_t, while less sensitive to MV_t.

Table .2 examines the impact of parameter σ_π on the price. Panel A is based on $\sigma_\pi = 0.8$ and Panel B the base case parameter of $\sigma_\pi = 0.6$. There are two points to notice. First, the price is much reduced for increased σ_π due to higher risk premium. Second, the market can sustain more technical traders with trend following trading strategy. p_{mv} is positive up to $w = 0.7$ in Panel A. This is due to the fact that the technical traders are more conservative in using MA signal when π_t is more volatile and the regression R^2 is smaller.

Table .3 examines the impact of MA coefficient α on price. We set $w = 0.1$ with all base case parameters except for $\sigma_\pi = 0.8$. The main impact of α is on the sensitivity to MV_t signal. p_{mv} decreases dramatically from 0.0234 to 0.0007 when α increases from 0.1 to 12.

Table .4 examines the implication of w and α on the stock price volatility and the risk premium. From (**??**), the price process

$$dP_t = p_1 dD_t + p_2 d\pi_t + p_3 d\theta_t + p_4 dA_t = \mu_p dt + \sigma_p dZ_t, \tag{.1}$$

with the instantaneous volatility defined as

$$\sigma_p = \sqrt{(p_1\sigma_D)^2 + (p_2\sigma_\pi)^2 + (p_3\sigma_\theta)^2}. \tag{.2}$$

Recall the investment opportunity is

$$dQ = (D - rP)dt + dP = e_Q\Psi dt + \sigma_Q dB_t. \tag{.3}$$

Following Wang (1993), we can define the risk premium as $e_Q\Psi/P$. Since both the numerator and denominator are time-varying, we take the average

$$\begin{aligned} \bar{P} &= p + p_D\bar{\pi} + p_\pi\bar{\pi}, && (.4)\\ \bar{\Psi} &= (1, \bar{\pi}, \bar{\pi}, 0, \bar{P}/\alpha)^T. && (.5) \end{aligned}$$

Then the risk premium is

$$RP = \frac{e_Q \bar{\Psi}}{\bar{P}}, \tag{.6}$$

where e_Q is defined in Equation (**??**). Table .4 presents the σ_p and RP in terms of varying w and α. The price volatility increases as w increases, while the RP is not monotone as it varies in the same way as p.

Appendix .2. Control variables

To understand better about the trend factor, we also sort the stocks while controlling for a variety of firm characteristics that are known to predict cross-section returns. The sorting procedure has been widely used in the literature to check the robustness of the cross-section pricing power of predictors, examples of which are [1, 2], [3], [8], and [7], to name a few.

Consider, for example, how to control for the market size. We first sort stocks by the market size into five quintile groups, and then within each quintile of the market size, we sort the stocks further by their trend forecasts to construct five trend quintile portfolios. As a result, a total of 5×5 trend quintile portfolios are obtained. Each market size quintile has five trend quintile portfolios ranked from low to high by the trend forecasts, and each trend forecasts quintile has five trend quintile portfolios as well ranked from small to large by the market size. Finally, we average the resulting 5×5 trend quintile portfolios across the five quintiles of the market size to form five new trend quintile portfolios, all of which should have similar market size to achieve the effect of controlling for the market size. We then measure the performance of the trend quintile portfolios by the Fama-French alpha.

Table .5 provides the results of controlling for various firm characteristics. Panel A reports the performance of the 5×5 double-sorted trend quintile portfolios using the market size and forecasted expected returns as well as the results of controlling for the market size. It shows that the performance is much stronger for the small stocks. For the smallest stocks,[*] the High-Low spread portfolio yields a Fama-French alpha of 2.26% per month. Performance decreases as the market size increases. However even for the largest stocks, the abnormal performance of the High-Low spread portfolio is still significant both statistically and economically (0.88% per month). Controlling for the market size by averaging across the different market size quintiles, still yields a Fama-French alpha of 1.55% per month for the High-Low spread portfolio, identical to the performance reported in Table **??**, and is consistent with the insignificant size beta reported in Table **??** as well. The robustness to controlling for the market size suggests that the performance of the trend factor is not due to small stocks, which may not be too surprising because both the size and price filters are imposed in constructing the trend factor.

Panel B reports the performance of the trend quintile portfolios after controlling for other firm characteristics: the book-to-market ratio (B/M), last month return, the past six-month return skipping the first month, and percentage of zero returns. The superior performance remains largely unchanged. For example, controlling for B/M delivers a Fama-French alpha

[*]It is worth noting that the smallest decile stocks by NYSE size breakpoints are already excluded.

of 1.40% per month for the High-Low spread portfolio. Controlling for the last month return does reduce the performance to some extent - the High-Low spread portfolio now yields a Fama-French alpha of 1.27% per month. Controlling for liquidity is measured here by the percentage of zero returns, and the performance remains unchanged with the Fama-French alpha of 1.57% per month.

Appendix .3. Fama-MacBeth regressions

Portfolio sorting, although powerful and capable of capturing nonlinear predictive relation, is often difficult to control for other variables, and it also focuses on extreme portfolios. Fama-MacBeth regression, on the other hand, can control for many variables and focuses on the average (linear) effect. Therefore we run the Fama-MacBeth regression to further examine the robustness of the results. [6] argue that weighted least square (WLS) often generates better results than the OLS used in the first step of the Fama-MacBeth regression. For each stock, we estimate the stock variance using the whole sample period and use the inverse of the variance as the weight.

Table .6 reports the results of regressing the monthly returns on the trend forecasts (ER^{12}_{trd}) and various control variables using the weighted Fama-MacBeth cross-sectional regression framework. In the first regression, we examine the predictability of ER^{12}_{trd} while controlling for the market size and book-to-market ratio. As expected, ER^{12}_{trd} has a significant and positive coefficient indicating that the trend signals can predict future cross-section returns independent of the market size and book-to-market ratio. These results are consistent with the double sort results in Table .5. In the second regression, we add last-month return (R_{-1}, short-term reversal), six-month cumulative return ($R_{-6,-2}$, momentum), and last 60-month cumulative return ($R_{-60,-2}$, long-term reversal) as additional controls. ER^{12}_{trd} remains highly significant and the coefficient stays the same. In the third regression, idiosyncratic volatility, percentage of zeros, and share turnover are included as additional controls, but the results are similar. Similar results are also obtained when three accounting price ratio variables are added to the regression.

In the last four regressions in Table .6, we examine the predictability of two alternative trend forecasts, ER^{6}_{trd}, the expected return forecasted using the last six-month moving average of coefficients to proxy for the expected coefficients in Eq. **??**, and ER^{60}_{trd}, the expected return forecasted using the last 60-month moving average of coefficients to proxy for the expected coefficients in Eq. **??**. The results are surprisingly similar - both alternative trend forecasts are significant and positive.

Appendix .4. Trends and information uncertainty

In this section, we examine the performance of the trend forecasts for different groups of stocks that are characterized by different degrees of information uncertainty.

When information about stocks is very uncertain, or when the noise-to-signal ratio is very high, fundamental signals, such as earnings and economic outlook, are likely to be imprecise, and hence investors tend to rely more heavily on technical signals. Therefore, trend signals are likely more profitable for the high information-uncertain stocks than for the low information-uncertain stocks.

We use a number of variables to proxy for information uncertainty, including the market size, idiosyncratic volatility, trading turnover rate, analyst coverage (number of analysts following), and firm age. All the proxies are used in the previous literature. For example, [9] uses the market size, firm age, analyst coverage, analyst forecast dispersion, stock volatility, and cash flow volatility as proxies for information uncertainty. [4] use income volatility, stock volatility, analyst forecast dispersion and firm age to proxy for information uncertainty.[†]

We use double sort procedure described previously to examine the impact of information uncertainty on the performance of the trend forecasts. Briefly, we sort stocks first by the proxy of information uncertainty into three terciles, and then sort further stocks in each tercile into five trend quintile portfolios, thus producing 3×5 trend quintile portfolios. We also examine the performance of the trend forecasts after controlling for the information-uncertainty proxy by averaging across all levels of the information-uncertainty proxy as described previously.

The results for using the market size as the proxy for information uncertainty is reported earlier in Panel A of Table .5. The Fama-French alpha of the High-Low spread portfolio monotonically increases from 0.88% to 2.26% as the market size (information uncertainty) decreases (increases) from the largest to the smallest.

Table .7 reports the performance of the trend forecasts under different levels of information uncertainty as measured by other proxies. In Panel A the Fama-French alpha of the High-Low spread portfolio monotonically increases as the idiosyncratic volatility (information uncertainty) increases. The abnormal returns of both the weakest and the strongest trend forecasts quintiles change drastically as idiosyncratic volatility (information uncertainty) increases, but in the opposite directions. The abnormal return of the weakest trend forecasts quintile (Low) decreases as the information uncertainty increases, while the performance of the strongest trend forecasts quintile (High) increases at the same time. In other words, stocks with poor outlook perform even worse and stocks with strong outlook perform even better when idiosyncratic volatility is high or when information is more uncertain. As a result, the Fama-French alpha of the High-Low spread portfolio increases from 0.89% when the information uncertainty is the lowest to as high as 2.31% per month when the information uncertainty is the highest. In addition, controlling for the information uncertainty (idiosyncratic volatility) by averaging over the three terciles of idiosyncratic volatility yields similar performance to the single sort in Table **??**.

In Panel B a similar pattern is observed when trading turnover rate is used to proxy for information uncertainty - low turnover stocks have high degree of information uncertainty. The performance of the High-Low spread portfolio increases monotonically as the turnover rate (information uncertainty) decreases (increases); the Fama-French alpha increases from

[†]We also examine dispersions in analyst earnings forecasts and quarterly operating income volatility and obtain similar results, which are available upon request.

1.20% per month to 1.92% per month. Similarly, controlling for the trading turnover rate does not reduce the performance.

In Panel C, we use analyst coverage as a proxy for information uncertainty. Stocks that are followed by more analyst should have less information uncertainty. The performance of the High-Low spread portfolio monotonically increases as the number of analysts following (information uncertainty) decreases (increases) across the quintiles – the Fama-French alpha increases from 1.02% per month to 1.63% per month. Controlling for the number of analysts following by averaging across the terciles still yields similar abnormal returns.

Finally, We use the age of the firm to proxy for information uncertainty or noise-signal ratio in Panel D. Younger firms[‡] are subject to higher information uncertainty. We observe a similar pattern – from the oldest age quintile (Old) to the youngest age quintile (Young), the abnormal returns (Fama-French alphas) increase monotonically from 1.12% per month to 1.70% per month. Again, controlling for firm age still yields significant abnormal returns and the magnitude is similar to what is achieved in the single sort shown in Table **??**.

[‡]We exclude firms younger than two years old.

[1] Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

[2] Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: international and further u.s. evidence, *Journal of Financial Economics* 91, 1–23.

[3] Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2009, Dispersion in analysts earnings forecasts and credit rating, *Journal of Financial Economics* 91, 83–101.

[4] Berkman, Henk, Valentin Dimitrov, Prem C. Jain, Paul D. Koch, and Sheri Tice, 2009, Sell on the news: differences of opinion, short-sales constraints, and returns around earnings announcements, *Journal of Financial Economics* 92, 376–399.

[5] Newey, Whitney K. and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

[6] Shanken, Jay A. and Guofu Zhou, 2007, Estimating and testing beta pricing models: alternative methods and their performance in simulations, *Journal of Financial Economics* 84, 40–86.

[7] Wahal, Sunil and M. Deniz Yavuz, 2013, Style investing, comovement and return predictability, *Journal of Financial Economics* 107, 136–154.

[8] Yu, Jialin, 2011, Disagreement and return predictability of stock portfolios, *Journal of Financial Economics* 99, 162–183.

[9] Zhang, X. Frank, 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105–137.

Table .1: Stock Price vs α_π

The table shows the impact of the persistence of long run dividend level state variable α_π on the equilibrium stock price,

$$P_t = p + p_D D_t + p_\pi \pi_t + p_\theta \theta_t + p_{mv}(P_t - \alpha A_t).$$

The parameters are $r = 0.05, \rho = 0.2, \bar{\pi} = 0.85, \sigma_D = 1.0, \sigma_\pi = 0.6, \sigma_\theta = 3.0, \alpha_\theta = 0.4, \alpha_D = 1.0, \alpha = 0.1$. The two panels present the results for two different α_π for various w, the fraction of technical traders.

A. The case of $\alpha_\pi = 0.1$					
w	p	p_D	p_π	p_θ	p_{mv}
0	-4.6257	0.9524	6.3491	-7.6464	0.0000
0.1	-4.8919	1.1443	5.9320	-8.1713	-0.0050
0.2	-5.1220	1.3519	5.4653	-8.6938	-0.0091
0.3	-5.3205	1.5766	4.9541	-9.2211	-0.0132
0.4	-5.4817	1.8171	4.3926	-9.7421	-0.0163
0.5	-5.6116	2.0754	3.7850	-10.2645	-0.0194
0.6	-5.7112	2.3522	3.1298	-10.7872	-0.0225
0.7	-5.7757	2.6456	2.4227	-11.2981	-0.0246
0.8	-5.8118	2.9579	1.6664	-11.8057	-0.0267
0.9	-5.8207	3.2900	0.8594	-12.3092	-0.0288
1	-5.7971	3.6386	0.0000	-12.7928	-0.0299
B. The case of $\alpha_\pi = 0.2$					
0	6.8209	0.9524	3.8095	-1.0803	0.0000
0.1	8.6479	1.0225	3.6589	-1.1644	-0.0070
0.2	10.9427	1.1069	3.4747	-1.2565	-0.0152
0.3	13.4936	1.2093	3.2539	-1.3589	-0.0256
0.4	15.6019	1.3338	2.9918	-1.4736	-0.0395
0.5	16.2126	1.4825	2.6763	-1.5996	-0.0560
0.6	14.9448	1.6605	2.3011	-1.7382	-0.0764
0.7	12.5443	1.8719	1.8561	-1.8883	-0.1013
0.8	10.0112	2.1212	1.3313	-2.0469	-0.1312
0.9	7.8738	2.4191	0.7181	-2.2140	-0.1696
1	6.2033	2.7752	0.0000	-2.3826	-0.2180

Table .2: Stock Price vs σ_π

The table shows the impact of moving average parameter α on the equilibrium stock price,

$$P_t = p + p_D D_t + p_\pi \pi_t + p_\theta \theta_t + p_{mv}(P_t - \alpha A_t).$$

The parameters are $r = 0.05, \rho = 0.2, \bar{\pi} = 0.85, \sigma_D = 1.0, \alpha_\pi = 0.2, \sigma_\theta = 3.0, \alpha_\theta = 0.4, \alpha_D = 1.0$, and $\alpha = 0.1$. The moving average window is measured by $1/\alpha$. The two panels present the results for two different σ_π's for various w, the fraction of technical traders.

A. The case of $\sigma_\pi = 0.8$					
w	p	p_D	p_π	p_θ	p_{mv}
0	2.7574	0.9524	3.8095	-3.0589	0.0000
0.1	2.7623	1.0569	3.5380	-3.2505	0.0157
0.2	2.6579	1.1810	3.2649	-3.4967	0.0253
0.3	2.4217	1.3270	2.9796	-3.8034	0.0301
0.4	2.0582	1.4982	2.6754	-4.1803	0.0301
0.5	1.5911	1.6969	2.3432	-4.6341	0.0263
0.6	1.0538	1.9250	1.9751	-5.1708	0.0196
0.7	0.4749	2.1863	1.5652	-5.8013	0.0099
0.8	-0.1307	2.4806	1.1041	-6.5258	-0.0010
0.9	-0.7580	2.8118	0.5852	-7.3560	-0.0132
1	-1.4083	3.1785	0.0000	-8.2901	-0.0246
B. The case of $\sigma_\pi = 0.6$					
w	p	p_D	p_π	p_θ	p_{mv}
0	6.8209	0.9524	3.8095	-1.0803	0.0000
0.1	8.6479	1.0225	3.6589	-1.1644	-0.0070
0.2	10.9427	1.1069	3.4747	-1.2565	-0.0152
0.3	13.4936	1.2093	3.2539	-1.3589	-0.0256
0.4	15.6019	1.3338	2.9918	-1.4736	-0.0395
0.5	16.2126	1.4825	2.6763	-1.5996	-0.0560
0.6	14.9448	1.6605	2.3011	-1.7382	-0.0764
0.7	12.5443	1.8719	1.8561	-1.8883	-0.1013
0.8	10.0112	2.1212	1.3313	-2.0469	-0.1312
0.9	7.8738	2.4191	0.7181	-2.2140	-0.1696
1	6.2033	2.7752	0.0000	-2.3826	-0.2180

Table .3: Stock Price vs Moving Average Window: $w = 0.1$

The table shows the impact of moving average parameter α on equilibrium stock price, which is $P_t = p + p_D D_t + p_\pi \pi_t + p_\theta \theta_t + p_{mv}(P_t - \alpha A_t)$. The parameters are $r = 0.05, \rho = 0.2, \bar{\pi} = 0.85, \sigma_D = 1.0, \sigma_\pi = 0.8, \sigma_\theta = 3.0, \alpha_\pi = 0.5, \alpha_\theta = 0.4, \alpha_D = 1.0$. The moving average window is measured by $1/\alpha$. The fraction of technical traders is $w = 0.1$.

α	p	p_D	p_π	p_θ	p_{mv}
0.1	20.2743	0.9479	1.6396	-0.3808	0.0234
0.5	21.1403	0.9631	1.6655	-0.3869	0.0083
1	21.6564	0.9668	1.6726	-0.3894	0.0052
5	22.9756	0.9708	1.6822	-0.3936	0.0015
12	23.4179	0.9716	1.6843	-0.3947	0.0007

Table .4: Volatility and risk premium

The table shows the impact of the moving average parameter α on the equilibrium stock price volatility and long run risk premium. The parameters are $r = 0.05, \rho = 0.2, \bar{\pi} = 0.85, \sigma_D = 1.0, \sigma_\pi = 0.8, \sigma_\theta = 3.0, \alpha_\pi = 0.5, \alpha_\theta = 0.4, \alpha_D = 1.0$. The moving average window is measured by $1/\alpha$. The fraction of technical traders is $w = 0.1$.

	$\alpha = 1$		$\alpha = 0.1$	
w	σ_p	RP	σ_p	RP
0	4.0786	0.0282	4.0786	0.0282
0.1	4.1918	0.0158	4.2207	0.0173
0.2	4.3155	0.0036	4.3810	0.0073
0.3	4.4507	-0.0070	4.5620	-0.0008
0.4	4.5987	-0.0140	4.7660	-0.0059
0.5	4.7604	-0.0159	4.9935	-0.0070
0.6	4.9359	-0.0115	5.2434	-0.0036
0.7	5.1244	-0.0003	5.5109	0.0041
0.8	5.3222	0.0176	5.7865	0.0157
0.9	5.5240	0.0423	6.0551	0.0306
1	5.7198	0.0750	6.2951	0.0493

Table .5: Performance after Controlling for Firm Characteristics

This table reports the sort results of controlling for various firm characteristics. Stocks are first sorted by one of the control variables into five quintile groups, and then in each quintile stocks are further sorted to construct five trend quintile portfolios. We then average the resulting 5×5 trend quintile portfolios across the five quintiles of the control variable to form five new trend quintile portfolios, all of which should have similar levels of the control variable. In Panel A, we report the performance of the 5×5 quintile portfolios and the five new trend quintile portfolios after controlling for the market size. In Panel B, We report the performance of only the new trend quintile portfolios after controlling for the firm characteristics. The performance is measured by the Fama-French alpha in percentage. [5] robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from June 1930 to December 2013.

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Market Size	**Panel A: Market Size**					
Small	0.41**	0.78***	1.18***	1.50***	2.67***	2.26***
	(2.49)	(7.72)	(14.0)	(15.9)	(17.8)	(9.86)
2	-0.98***	-0.21***	0.12*	0.35***	0.87***	1.85***
	(-9.75)	(-3.07)	(1.90)	(5.44)	(9.99)	(11.7)
3	-0.86***	-0.16***	0.13*	0.36***	0.68***	1.53***
	(-10.3)	(-2.73)	(1.92)	(5.69)	(8.76)	(11.5)
4	-0.62***	-0.19***	0.01	0.31***	0.61***	1.23***
	(-8.26)	(-3.16)	(0.20)	(4.91)	(8.27)	(10.2)
Large	-0.50***	-0.13***	0.09**	0.18***	0.38***	0.88***
	(-8.08)	(-3.08)	(2.20)	(4.21)	(6.91)	(9.57)
Average over Market Size	-0.51***	0.02	0.31***	0.54***	1.04***	1.55***
	(-7.07)	(0.45)	(7.09)	(12.5)	(15.5)	(13.0)
	Panel B: Controlling for Firm Characteristics					
Average over B/M	-0.31***	0.02	0.21***	0.49***	1.09***	1.40***
	(-4.03)	(0.43)	(3.78)	(9.04)	(13.3)	(11.3)
Average over R_{-1}	-0.31***	0.06	0.22***	0.48***	0.96***	1.27***
	(-4.45)	(1.41)	(6.15)	(11.7)	(15.3)	(11.9)
Average over $R_{-6,-2}$	-0.47***	0.00	0.28***	0.50***	1.09***	1.56***
	(-6.54)	(0.12)	(7.10)	(11.7)	(16.0)	(13.3)
Average over %Zeros	-0.38***	0.07	0.30***	0.53***	1.18***	1.57***
	(-5.03)	(1.37)	(7.00)	(11.0)	(16.4)	(13.1)

Table .6: Fama-MacBeth Regression

This table reports the results of regressing monthly returns on the expected returns forecasted by the trend signals and other firm-specific variables. The regression is a modified Fama-MacBeth cross-sectional regression with weighted least square (WLS) in the first step. The weights are the inverse of the stock variance estimated from the whole sample period. For robustness, the table reports three specifications of the forecasted expected returns, ER^{12}_{trd}, ER^{6}_{trd}, and ER^{60}_{trd} using rolling 12-month, 6-month, and 60-month averages, respectively, to estimate the true coefficients. [5] robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from June 1930 to December 2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.17***	-0.19***	-0.11***	-0.18***	-0.15***	-0.15***	-0.18***	-0.22***
	(-6.40)	(-3.36)	(-6.31)	(-13.09)	(-6.91)	(-11.56)	(-5.83)	(-15.29)
ER^{12}_{trd}	0.67***	0.65***	0.44***	0.57***				
	(7.82)	(4.04)	(7.83)	(17.36)				
ER^{6}_{trd}					0.54***	0.50***		
					(8.84)	(15.39)		
ER^{60}_{trd}							0.71***	0.69***
							(6.44)	(19.18)
Log(Size)	-0.99**	-1.02**	-1.14***	-1.48***	-1.09**	-1.50***	-1.02**	-1.53***
	(-1.97)	(-2.24)	(-2.63)	(-3.44)	(-2.16)	(-3.47)	(-2.00)	(-3.45)
log(B/M)	1.53**	1.42**	1.44**	0.69	1.51**	0.64	1.50**	0.58
	(2.07)	(2.18)	(2.31)	(0.83)	(2.06)	(0.79)	(2.04)	(0.70)
R_{-1}		-0.22	-0.55***	-0.33***		-0.38***		-0.26***
		(-1.23)	(-6.93)	(-6.24)		(-6.55)		(-4.51)
$R_{-6,-2}$		0.15	0.73*	0.34		0.29		0.27
		(0.21)	(1.84)	(1.22)		(1.05)		(0.94)
$R_{-60,-2}$		1.57	0.94	-1.04		-1.11		-0.87
		(1.21)	(0.74)	(-1.40)		(-1.51)		(-1.19)
Idio Vol			-0.13	-0.10**		-0.11**		-0.12**
			(-1.14)	(-2.04)		(-2.07)		(-2.29)
%Zero			-0.37	-0.57*		-0.59*		-0.56*
			(-1.11)	(-1.83)		(-1.91)		(-1.71)
Turnover			0.54*	0.52***		0.54***		0.52***
			(1.83)	(2.82)		(2.98)		(2.78)
C/P				0.41***		0.41***		0.41***
				(3.75)		(3.90)		(3.68)
E/P				0.10		0.08		0.11
				(1.34)		(1.17)		(1.37)
S/P				-0.35*		-0.32		-0.41*
				(-1.71)		(-1.64)		(-1.71)

Table .7: Performance under Information Uncertainty

This table reports the performance of the trend quintile portfolios under information uncertainty proxied by idiosyncratic volatility (Panel A), share turnover rate (Panel B), number of analyst following (Panel C), and firm age (Panel D). Stocks are first sorted by one of the information uncertainty proxies into three tercile groups, and then in each tercile stocks are further sorted to construct five trend quintile portfolios. We report the Fama-French alphas for the resulting 3×5 trend quintile portfolios and the average across the three terciles of the information uncertainty proxy. The alphas are reported in percentage. [5] robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from June 1930 to December 2013.

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Idio Vol	**Panel A: Idiosyncratic Volatility**					
Low	-0.17***	0.14**	0.22***	0.39***	0.71***	0.89***
	(-2.67)	(2.41)	(4.13)	(6.84)	(10.9)	(9.84)
2	-0.40***	-0.02	0.32***	0.55***	1.10***	1.50***
	(-5.65)	(-0.34)	(5.80)	(9.55)	(15.5)	(14.1)
High	-0.78***	-0.22***	0.18***	0.65***	1.54***	2.31***
	(-6.17)	(-3.17)	(2.83)	(9.90)	(12.0)	(10.6)
Average over Idio Vol	-0.45***	-0.03	0.24***	0.53***	1.12***	1.57***
	(-6.41)	(-0.77)	(5.97)	(12.5)	(16.4)	(13.2)
Turnover	**Panel B: Turnover Rate**					
High	-0.40***	-0.06	0.21***	0.39***	0.80***	1.20***
	(-4.57)	(-0.98)	(3.23)	(5.87)	(8.60)	(10.4)
2	-0.43***	0.05	0.21***	0.53***	1.05***	1.49***
	(-6.57)	(1.03)	(3.93)	(10.8)	(16.1)	(15.8)
Low	-0.56***	0.11	0.24***	0.56***	1.35***	1.92***
	(-4.85)	(1.54)	(3.95)	(8.64)	(14.0)	(11.1)
Average over Turnover	-0.46***	0.03	0.22***	0.49***	1.07***	1.53***
	(-6.78)	(0.78)	(5.68)	(11.7)	(17.1)	(14.6)

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Analyst Coverage	**Panel C: Analyst Coverage**					
High	-0.54***	-0.14*	0.04	0.23***	0.48***	1.02***
	(-5.01)	(-1.72)	(0.58)	(2.61)	(4.65)	(6.77)
2	-0.53***	-0.03	0.27***	0.52***	0.97***	1.50***
	(-5.69)	(-0.40)	(3.47)	(6.72)	(10.4)	(11.1)
Low	-0.20**	0.23***	0.43***	0.70***	1.42***	1.63***
	(-2.23)	(3.90)	(7.67)	(11.4)	(16.4)	(12.7)
Average over Analyst Coverage	-0.50***	0.01	0.25***	0.49***	1.08***	1.57***
	(-6.97)	(0.26)	(5.80)	(10.6)	(16.0)	(13.3)
Firm Age	**Panel D: Firm Age**					
Old	-0.48***	-0.11*	0.09*	0.33***	0.63***	1.12***
	(-7.15)	(-1.95)	(1.66)	(5.46)	(8.76)	(11.2)
2	-0.43***	0.02	0.21***	0.48***	1.09***	1.52***
	(-6.11)	(0.43)	(4.08)	(9.60)	(14.4)	(13.1)
Young	-0.40***	0.14**	0.42***	0.66***	1.31***	1.70***
	(-4.64)	(2.38)	(7.72)	(11.6)	(16.1)	(13.4)
Average over Age	-0.50***	0.02	0.25***	0.51***	1.09***	1.58***
	(-6.92)	(0.47)	(5.88)	(11.2)	(16.2)	(13.5)