The High Volume Return Premium and Economic Fundamentals

(Internet Appendix)

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ABSTRACT

This appendix has eight sections. Section A reports replication results of Yang (1966, *Econometrica*) using daily data from 1963 to 2016. In Section B, we investigate time-series relation between daily trading volume and daily equity market index and economic activities. Section C reports additional summary statistics and discussion of the volume premium and other control variables used in the predictive regressions. In Section D, we construct and evaluate the predictive power of an aggregate measure of abnormal trading volume. Section E includes details on the construction of variables analyzed in Table 5 of the paper. Section F studies alternative measures of liquidity and (shocks to) idiosyncratic volatility that are used in the bivariate portfolio analysis. We discuss in Section G how to form the two types of mimicking portfolios used in Section 5.3. Finally, we collect 13 tables in Section H that are either referenced in this appendix or referenced but not reported in the paper.

A. Replication of Ying (1966)

In this section, we replicate the main results of Ying (1966) using the CRSP stock data for the period of July 1, 1963 through December 31, 2016. Overall, like Ying (1966), we also find evidence of past (change in) trading volume predicting future price changes, although the patterns are not always the same as those reported in Ying (1966) who uses S&P 500 stocks for the period of 1957-1962.

In estimating the aggregate daily price index and trading volume, we apply the same data filtering rules as the rest of the paper. Note that, as pointed out by Griffin, Nardari, and Stulz (2007), turnover may be influenced by trends in bid-ask spreads, commissions, and availability of information. These factors may have contributed to the general increase in trading activity through time. To remove the slowing moving average component, in later analysis, we de-trend turnover by first taking its natural log and then subtracting its six-month moving average (see, for example, Chen, Hong and Stein (2001) for a similar treatment). Empirically, the turnover series features a clear upward trend during the span of 53.5 sample years. In contrast, Ying (1966) only considers a five-year sample.

Closely follow Ying (1966), we first consider the effect of one-period lagged return ($\Delta\log(P_t)$), one-period lagged change in volume ($\Delta\log(V_t)$), and one-period lagged volume ($\log(V_t)$). Specifically, we conduct analysis of variance with a 3-way classification of these variables. To this end, we re-group the values of each of the variables into three classes, low (1), neutral (2), and high (3), as follows

Class 1 = $\{x|\ x \le (\mu_x - 0.25\sigma_x)\}$,

Class 2 = $\{x|\ (\mu_x - 0.25\sigma_x) < x \le (\mu_x + 0.25\sigma_x)\}$,

Class 3 = $\{x|\ (\mu_x + 0.25\sigma_x) < x\}$.

Table A1 summarizes the results (which replicates Table II of Ying (1966)). (1) The F-tests show that both $\Delta\log(P_t)$ and $\Delta\log(V_t)$ have significant effects on $\Delta\log(P_{t+1})$. In contrast, the level of volume ($\log(V_t)$) shows no such effect. (2) There is no interaction effect of $\Delta\log(P_t)$ and $\Delta\log(V_t)$ on

$\Delta\log(P_{t+1})$. Nor is there any interaction effect of $\Delta\log(P_t)$ and $\log(V_t)$ on $\Delta\log(P_{t+1})$. The interaction effect of $\Delta\log(V_t)$ and $\log(V_t)$ is significant at the 10% level. (3) The triple interaction effect of $\Delta\log(P_t)$, $\Delta\log(V_t)$, and $\log(V_t)$ is not significant at the 10% level. (4) The *t*-tests on individual coefficients from the regression underlying Table A1 reveal more interesting dynamics of the effects. For example, a large change in price today is followed by a large change in price tomorrow. Similarly, a large volume today predicts a large price increase tomorrow. The coefficients associated with the interaction effect of $\Delta\log(V_t)$ and $\log(V_t)$ suggest that a large volume today which continues from the previous trading day on average is followed by a large decrease in price. The price change is significant at the 5% level.

Table A2 reports the transition matrix between $\log(V_t)$ and $\Delta\log(P_{t+1})$ in Panel A, and between $\Delta\log(V_t)$ and $\Delta\log(P_{t+1})$ in Panel B. Confirming the results in Point (1) above, the last column of the Table A2 suggests that $\Delta\log(P_{t+1})$ increases with current volume $\log(V_t)$, whereas the relationship between $\Delta\log(V_t)$ and $\Delta\log(P_{t+1})$ is V-shaped.

To explore whether there is any longer-term relationship between prices and volume, we apply the cross-spectral analysis on the data. Table A3 reports the results which are estimated using software SAS. To save space, only selected frequencies are tabulated. The largest value (0.62) of coherency between $\log(\mathrm{P}_t)$ and $\log(\mathrm{V}_t)$ occurs at frequency 0.0051, which corresponds to approximately 11 time units (here trading days). At this frequency, the phase lead of $\log(\mathrm{V}_t)$ over $\log(\mathrm{P}_t)$ is 107 degrees in trigonometry, which is 11*(107/360) = 3.3 trading days (the estimated lead is 4 days in Ying (1966)). Based on this estimate, we then study the predictive power of the three factors, $\Delta^4\log(P_t)$, $\Delta^4\log(V_t)$, and $\log(V_t)$ for future price change $\Delta^4\log(P_{t+3})$, where $\Delta^4\log(P_t) = \log(P_t) - \log(P_{t-4})$, $\Delta^4\log(V_t) = \log(V_t) - \log(V_{t-4})$, and $\Delta^4\log(P_{t+3}) = \log(P_{t+3}) - \log(P_{t-1})$. As before, we conduct analysis of variance on $\Delta^4\log(P_{t+3})$ by using three classifications of each of the three factors. Table A4 summarizes the results. (1) The effect of three-period lagged price change and the levels of trading volume are both significant at the 1% level. In contrast, the three-period lagged change in volume has no effect on price, which is opposite to the estimated effect of one-period lagged change in volume as discussed earlier. (2) Three two-factor interaction effects are significant at the 5% or higher level. (3) However, the three-factor interaction effect is insignificant. We also repeat above regressions assuming that the phase lead of $\log(V_t)$ over $\log(P_t)$ is 4 trading days. All the results in Table A4 hold for the alternative model specification.

B. The time-series relation between daily trading volume and daily equity market index and economic activity

In this section, we investigate whether daily trading volume predicts daily return on the market portfolio and economic activities. There is a large literature on the lead-lag relationship between aggregate trading volume and market returns at the daily or higher frequencies. In comparison, there is much less research on the relationship between trading volume and real economic activity at the daily frequency mainly because of the lack of data.

The regression analysis is implemented within the standard framework for testing Granger non-causality. Trading volume is defined as before. The daily economic activity is proxied by the business conditions index (BCI_ADS) of Aruoba, Diebold, and Scotti (2009). The index is designed to track real business conditions at daily frequency by extracting from such economic indicators with mixed frequencies as weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real *GDP*. The average value of the BCI_ADS index is zero. Therefore, progressively bigger positive values indicate progressively better-than-average conditions. The Aruoba-Diebold-Scotti index is maintained by the Federal Reserve Bank of Philadelphia. We use the 2018 vintages of data.

Table A5 summarizes the results. To save space, parameter estimates for the constants and lagged dependent variables are not reported. The table shows that there is some marginal evidence of trading volume of a value-weighted portfolio predicting its returns. The positive predictive relation is much stronger in the equally-weighted portfolio. The last four panels suggest that the trading volume contains valuable information about future real economy even at the one-day horizon. The negative sign of the parameter associated with the business conditions index BCI_ADS means that investors tend to trade more when they receive news about future economy that is worse than average.

C. Additional results on data construction and their summary statistics

In constructing the volume-sorted portfolios, we closely follow Gervais, Kaniel, and Mingelgrin (2001) and Kaniel, Ozoguz, Starks (2012). For the purpose of asset pricing tests that typically use monthly returns, we set the last trading day of each month as the portfolio formation date and compute monthly, rather than 20-day, post-formation returns. We define a stock as a low- (high-) volume stock if its trading volume on the one-day formation period is among the lowest (highest) 10% of its 50 daily volumes prior to the formation period (inclusive). The remaining eight deciles are similarly defined. Stocks are eliminated for which the price or volume data are missing on the portfolio formation day. Stocks that are not traded for nine or more days or whose prices fall below $5 out of 50 trading days are also removed from the sample to alleviate the microstructure concerns associated with these securities. Stocks are excluded with less than one year of trading history to mitigate backfilling biases, and those delisted from the exchanges one year prior to the formation date. We also delete observations with an earnings or dividend announcement during a three-day window around the formation date as the volume-return relation during announcement periods may be different than in non-announcement periods (Kandel and Pearson, 1995).[1] Then, ten volume portfolios are formed by sorting all surviving stocks into ten low and high volume portfolios based on their volume classification at the end of each month (t). The value- and equal-weighted returns are computed for each of the ten portfolios for both the daily and monthly returns of month ($t + 1$).

DP is constructed as the sum of dividends accruing to the CRSP value-weighted portfolio over the previous year divided by the level of the market index. DEF is the yield spread between Moody's BAA and AAA corporate bonds. TERM is the difference between the ten-year government bond yield and the three-month Treasury bill rates. Bond yields are from the database of the Federal Reserve Bank of St. Louis.

In Table A6 we report additional descriptive statistics on the value- and equal-weighted high volume premium series as well as summary statistics for other portfolio factor returns and economic variables. Table A7 reports descriptive statistics for returns to the ten equal-weighted portfolio formed by one-way sort on abnormal trading volume.

Note from Panel A of Table A6 that the liquidity premium has an average of 0.26% per month, which is lower than some estimates reported in the literature (e.g., Lou and Shu, 2017). The reason is that, as pointed out in the paper, we exclude the sample observations around earning announcement periods the same way we do to estimate the volume premium. As previous research has shown, firms' earnings announcements have important effects on liquidity-related price changes. The liquidity factor based on shocks to illiquidity measure of Amihud (2002) has a higher average return of −0.70%,

[1] While Gervais, Kaniel, and Mingelgrin (2001) choose arbitrary days and weeks over which to estimate abnormal volume, Garfinkel and Sokobin (2006) study the high volume return premium by defining abnormal share trading volume in the three-day period *around earnings announcements* and find strong abnormal returns over the subsequent 60 trading days. As a robustness check, we also increase the portfolio formation period to the last three trading days of each month. The volume premiums are very close to the reported benchmark estimates. The noticeable change is that the number of stocks classified as medium/large and high volume falls to two digits in a few months.

meaning that stocks experiencing negative liquidity shocks have lower subsequent returns than stocks experiencing positive shocks. Similar results have been documented by Han and Huang (2018).

Panel A of Table A6 also shows that MKT, HML, RMW, and CMA all feature small but statistically significant first-order autocorrelations. The two macroeconomic variables, IP and ERN, are moderately autocorrelated whereas the four market condition variables, DP, DEF, TERM, and TB, are highly persistent.

Panel B of Table A6 shows that the value-weighted volume premium HVPVW is weakly correlated to some other portfolio returns with the correlation ranging from 0.06 (with RMW) to −0.19 (with UIML). Panel C reports that the illiquidity measure ILQ and the liquidity measure LIQ are contemporaneously correlated with the volume premium with coefficients 0.13 and −0.14, respectively. The volume premium is also weakly correlated with the four business cycle variables.

D. The predictive power of aggregate measures of abnormal trading volume

An advantage of the portfolio-based approach is that portfolio returns can provide a better measurement of the effect researchers try to capture than the underlying variables or characteristics on which the portfolios are formed. Throughout the paper, we examine the predictive power of the abnormally high volume effect by the volume premium. As an additional robustness check of the main results, in this section, we propose and compute an aggregate measure of abnormally high trading volume (HVM) and evaluate its predictive power for the growth rate of industrial production. Specifically, at the end of each month, for each stock, the percentile of the last trading day’s volume in the distribution of the immediately past 50 trading days (inclusive) is calculated (these percentiles are also the basis by which we derive the high volume return premium). The aggregate measure of abnormal trading volume is formed by averaging the percentiles over all stocks equally or weighted by their market capitalizations.

First, using our aggregate measures of abnormal trading volume, we find that a one-standard-deviation increase of value- and equal-weighted trading volume predicts one-month-ahead higher excess market returns by 0.25% and 0.39%, respectively. This result is consistent with Akbas, Genc, Jiang, and Koch (2017) who find that unusually high aggregate stock trading volume predicts higher future excess market returns.

Next, we evaluate the predictive performance of the value- and equal-weighted aggregate measures of abnormal volume (HVMVW and HVMEW). Table A10 summarizes the results. Similar to the high volume return premium, abnormally high trading volume also leads industrial production. In the univariate Regression I, a one-standard-deviation increase of the value-weighted abnormal volume (0.14) predicts a decrease in industrial production growth by 9.4 basis points. This estimate is very close to the performance of the volume premium which is 9.2 basis points in Table 2. The predictive coefficient of the aggregate volume measures becomes slightly larger in the multivariate regressions when the common return factors and two (il)liquidity measures are controlled for. The results under Model Specification 4 demonstrate that both the systemic risk factor CATFIN and the set of four business cycle variables are strong predictors for industrial production, which is consistent with the finding in Table 3 for the volume premium. However, controlling for these variables does not seem to have any significant impact on the predictive power of the aggregate measure of abnormal volume (recall that these variables combine to account for one-third of the predictive power of the volume premium in Table 3). The right half of Table A10 further indicates that all of these results hold true for the equal-weighted measure of abnormal trading volume.

E. Construction of variables used in Table 5 of the paper

We follow Fama and French (1992) and estimate the market beta (β^{MKT}) of individual stocks using prior 60 monthly returns when available. The size (SIZE) of the stock is computed as the log of the product of the share price and the number of shares outstanding. The book-to-market ratio (BM) is the log of the book value measured at the end of fiscal year ($t-1$) divided by the market value at the December of year ($t-1$). Momentum (MOM) is a measure of the stock's performance over the past 11 months (the month prior to the portfolio formation month is skipped to follow Jagadeesh and Titman (1993)). The short-term reversal (REV) measures the stock return over the prior month. A monthly coskewness measure of Harvey and Siddique (2000) (COSK) is computed as

$$COSK_{i,t} = \frac{(1/N_\kappa)\sum_{\kappa=1}^{N_\kappa}\left(\varepsilon_{i,t-\kappa}R_{m,t-\kappa}^2\right)}{\sqrt{(1/N_\kappa)\sum_{\kappa=1}^{N_\kappa}\left(\varepsilon_{i,t-\kappa}^2\right)}\left((1/N_\kappa)\sum_{\kappa=1}^{N_\kappa}\left(R_{m,t-\kappa}^2\right)\right)}, \tag{A1}$$

where $R_{m,t-\kappa}$ is monthly excess market returns in month ($t-\kappa$), $\varepsilon_{i,t-\kappa}$ is the residual from regression of excess returns to stock i ($R_{i,t-\kappa}$) on the market factor $R_{m,t-\kappa}$, and $N\kappa$ equals 60.

When estimating β^{VXO}, we also control for the market factor (Ang, Hodrick, and Zhang, 2006) (also see Model (4) in the paper). The regression is estimated using within-month daily data for the period of January 1986 through December 2016 when VXO is available. Finally, the estimation of annual growth rate of total assets (IAg) and the quarterly operating profitability (REQ) are similar to those we use earlier in the paper to construct the investment factor (I/A) and the return-on-equity factor (ROE) of Hou, Xue, and Zhang (2015).

F. Alternative measures of liquidity and (shocks to) idiosyncratic volatility use in bivariate portfolio analysis

As mentioned in the data section of the paper, following the literature, we construct the high volume return premium using stock returns in past 50 trading days. To conduct robustness checks on the results in Table 6, we employ these same 50 trading-day data to estimate (shocks to) idiosyncratic volatility and shocks to Amihud's (2002) measure of illiquidity. Specifically, idiosyncratic volatility of month t is defined as the properly scaled sum of most recent 17 squared daily returns (representing about one-third of 50 trading days) filtered by the Fama-French (1993) three factors. Shocks to idiosyncratic volatility is defined as the difference between this volatility estimate and that based on returns in the remaining two-thirds of the 50 trading days. Shocks to illiquidity (UILQ) is estimated using the same sampling strategies. We also examine the relationship between trading volume and a measure of liquidity studied by Fong, Holden, and Trzcinka (2017). This measure of liquidity is based on the incidence of zero returns and empirically estimated using within-month daily returns. Shocks to liquidity (ULIQ) is defined as the difference between current month liquidity and the average of the previous 12-month's estimates. As can be seen from the last columns of the four panels in Table A12, the basic results in Table 6 still hold that the measure of abnormal trading volume captures information that is significantly different from that captured by measures of idiosyncratic volatility and liquidity.

Note from Panel A of Table A12 that the volume premium in stocks experiencing the lowest illiquidity shocks (equivalently, the highest liquidity shocks) tend to have greater future returns than stocks experiencing the highest illiquidity shocks. Panels C and D also report that the volume effect is more evident in stocks exposed to the highest (shocks to) idiosyncratic volatility than in stocks exposed to the lowest (shocks to) idiosyncratic volatility. Because smaller stocks tend to be illiquid and have higher idiosyncratic volatility, these results are somewhat surprising given that the volume premium is larger in the small stocks in Panel A of Table 6. However, these types of results are not new. For example, Kaniel, Ozoguz, and Starks (2012) find that the high volume return premium effect is actually increasing, rather than decreasing, in analyst coverage. The results in Bali et al. (2014, Panel A of Table 5) also imply that the volume premium generally increases with liquidity shocks. Finally, Panel B of Table 12A indicates that the volume premium is larger in stocks exposed to the lowest liquidity shocks than in stocks exposed to the highest liquidity shocks when the Fong, Holden, and Trzcinka's (2017) measure of liquidity is used.

G. Constructions of two sets of mimicking portfolios

In this section, we discuss how to construct the two types of mimicking portfolios that are used in Section 5.3 of the paper. For more details on the mimicking portfolio strategy, see Breeden, Gibbons, and Litzenberger (1989), Lamont (2001), and Cochrane (2001).

To form the mimicking portfolio for news related to future industrial production growth, we closely follow Vassalou (2003) who employs the approach when exploring the economic content of the value and size premiums. Specifically, we consider the following predictive regression:

$$\mathrm{IP}_t = a + b^{*}\mathrm{BASE}_{t-1} + c_1{}^{*}\mathrm{DP}_{t-1} + c_2{}^{*}\ \mathrm{DEF}_{t-2} + c_3{}^{*}\ \mathrm{TERM}_{t-2} + c_4{}^{*}\mathrm{TB}_{t-1} + \varepsilon_t, \quad \text{(A2)}$$

where the set of 12 base assets (BASE_t) used to construct mimicking portfolio returns (MPR) consists of ten equity portfolios and two fixed income assets (because all returns are in excess of the risk-free rate, no restrictions are imposed on the parameter vector b). The equity portfolios are the above ten industry portfolios. The fixed income portfolios are two zero-investment trading strategies, DEFR and TERMR, where DEFR is the difference between returns on long-term corporate bonds and returns on long-term government bonds, and TERMR is defined as the difference between returns on long-term government bonds and short-term Treasury bill rates. Because only innovations earn a risk premium in asset returns (Campbell, 1996; Petkova, 2006), we follow Lamont (2001) and Vassalou (2003) and include in Model (A2) four control variables (DP, DEF, TERM, and TB) which also predict stock returns. The purpose of adding these controls is to "filter" the information in the mimicking portfolio, so that the mimicking portfolio returns only capture *news* pertaining to future industrial production growth.

The results for regression (A2) are summarized in Table A13, which can be understood as a qualification test of the mimicking portfolio as a proxy for news related to future industrial production growth.

To form mimicking portfolios for the five Chen, Roll, and Ross' (1986) factors, we use the following 40 equity portfolios as our base assets, ten equal-weighted size portfolios, ten equal-weighted book/market portfolios, ten equal-weighted profitability portfolios, and ten value-weighted momentum portfolios. These 40 portfolios feature a wide variety of return patterns as documented in the literature. We obtain returns to these portfolios again from professor Kenneth French's website. In the first step of the analysis, we regress each of the 40 asset return series on the five CRR factors and collect all slope coefficients in a matrix B of dimension (40 × 5). A covariance matrix V of dimension (40 × 40) is formed using the regression residuals. The weights assigned to each base assets are then calculated as a (5 × 40) matrix $w = (B'V^{-1}B)^{-1}B'V^{-1}$. Finally, we form the five factor-mimicking portfolios as Rw', where R is the matrix of monthly excess returns to the 40 base assets.

H. Tables

This section includes tables cited in the previous sections of this appendix as well as those that are cited but not reported in the paper.

Table A1 Analysis of variance of price changes at time (t + 1)

The analysis of variance in this table is based on three-way classifications of prices (P) and trading volume (V) for stocks traded in NYSE, Amex, and Nasdaq. The sample spans from July 1, 1963 to December 31, 2016. Trading volume is scaled by total shares outstanding and logged volume is further stochastically detrended using a window of six months (120 trading days). The values of change in log price ($\Delta\log(P_t)$) and volume ($\Delta\log(V_t)$), as well as log volume ($\log(V_t)$) are re-grouped into 1, 2, and 3 classes as defined in Section A.
All coefficient estimates from the underlying regressions have been multiplied by 100 for ease of presentation. Both prices and turnover are in logarithmic terms.

Factors & their states	Coef.	*t*-stat.	*F* tests: # of restrictions	*F* tests: *F*-ratio
ΔlnP(t)			2	39.11***
1	0 (excluded)			
2	0.12	2.75***		
3	0.22	4.64***		
ΔlnV(t)			2	3.82**
1	0 (excluded)			
2	0.07	1.17		
3	−0.04	−0.62		
lnV(t)			2	1.37
1	0 (excluded)			
2	0.05	0.78		
3	0.13	2.08**		
			4	0.34
ΔlnP(t) # ΔlnV(t)				
2 2	−0.05	−0.66		
2 3	0.14	1.65*		
3 2	−0.15	−1.78*		
3 3	0.09	1.04		
ΔlnP(t) # lnV(t)			4	0.33
2 2	−0.02	−0.21		
2 3	−0.00	−0.01		
3 2	−0.06	−0.70		
3 3	−0.04	−0.44		

ΔlnV(t) # lnV(t)			4	2.34*
2 2	−0.18	−1.89*		
2 3	−0.20	−2.20**		
3 2	0.08	0.84		
3 3	0.00	0.05		
ΔlnP(t) # ΔlnV(t) # lnV(t)			8	1.36
2 2 2	0.15	1.09		
2 2 3	0.10	0.81		
2 3 2	−0.17	−1.26		
2 3 3	−0.22	−1.79*		
3 2 2	0.25	1.83*		
3 2 3	0.15	1.15		
3 3 2	−0.04	−0.30		
3 3 3	−0.15	−1.28		
Const.	−0.11	−3.38***		

Table A2 The effect of trading volume on the distribution of price changes at time (t + 1)

The analysis in this table is based on prices (P) and trading volume (V) of stocks traded in NYSE, Amex, and Nasdaq. The sample spans from July 1, 1963 to December 31, 2016. Trading volume is scaled by total shares outstanding and logged volume is further stochastically detrended using a window of six months (120 trading days). The values of change in log price ($\Delta\log(P_t)$) and volume ($\Delta\log(V_t)$), as well as log volume ($\log(V_t)$) are re-grouped into 1, 2, and 3 classes as defined in Section A. The numbers in the transition matrix is the number of times $\Delta\log(P_{t+1})$ falls in class j when $\Delta\log(V_t)$ in Panel A (or $\Delta\log(V_t)$ in Panel B) falls in class i (i, j = , 1, 2, and 3).

Panel A. The effect of $\log(V_t)$

	Class	$\Delta\log(P_{t+1})$			Row mean of
		1	2	3	$\Delta\log(P_{t+1})$ (%)
	1	1852	1489	1870	0.010
$\log(V_t)$	2	1063	923	1123	0.030
	3	1692	1558	1898	0.055

Panel B. The effect of $\Delta\log(V_t)$

	Class	$\Delta\log(P_{t+1})$			Row mean of
		1	2	3	$\Delta\log(P_{t+1})$ (%)
	1	1737	1435	1809	0.032
$\Delta\log(V_t)$	2	1202	1024	1224	−0.001
	3	1668	1511	1858	0.054

Table A3 Cross spectral analysis of stock price and trading volume

The analysis in this table is based on prices (P) and trading volume (V) of stocks traded in NYSE, Amex, and Nasdaq. The sample spans from July 1, 1963 to December 31, 2016. Trading volume is scaled by total shares outstanding and logged volume is further stochastically detrended using a window of six months (120 trading days).

Frequency ($0 \sim \pi$)	Spectrum of log(P)	Spectrum of log(V)	Coherency btw. log(P) & log(V)	Phase lead of log(V) over log(P)
0.0000	669.1	0.053	0.427	0
0.0014	238.2	0.071	0.341	86
0.0033	22.60	0.053	0.237	−28
0.0051	7.485	0.047	0.617	107
0.0070	3.496	0.057	0.350	−132
0.0089	2.524	0.048	0.241	−140
0.0107	1.367	0.086	0.219	−59
0.0126	1.079	0.069	0.572	148
0.0145	0.770	0.067	0.526	−154
0.0163	0.717	0.091	0.433	−79
0.0182	0.712	0.100	0.202	−155
0.0201	0.340	0.234	0.252	96
0.0219	0.392	0.245	0.541	−58
0.0238	0.299	0.236	0.336	−109
0.0257	0.258	0.272	0.437	−58
0.0275	0.243	0.116	0.608	−53

Table A4 Analysis of variance of price changes at time (t + 3)

The analysis in this table is based on prices (P) and trading volume (V) of stocks traded in NYSE, Amex, and Nasdaq. The sample spans from July 1, 1963 to December 31, 2016. Trading volume is scaled by total shares outstanding and logged volume is further stochastically detrended using a window of six months (120 trading days). The values of change in log price $\Delta^4\log(P_t) = \log(P_t) - \log(P_{t-4})$, and the values of change in log volume $\Delta^4\log(V_t) = \log(V_t) - \log(V_{t-4})$, and the dependent variable is price change at time (t + 3), $\Delta^4\log(P_{t+3}) = \log(P_{t+3}) - \log(P_{t-1})$.

Factors & their states	Coef.	t-stat.	F tests: # of restrictions	F tests: F-ratio
Δ^4lnP(t)			2	196.5***
1	0 (excluded)			
2	0.18	2.09**		
3	0.38	4.45***		
Δ^4lnV(t)			2	0.26
1	0 (excluded)			
2	−0.16	−1.51		
3	−0.26	−2.09**		
lnV(t)			2	5.73***
1	0 (excluded)			
2	−0.08	−0.67		
3	−0.03	−0.24		
Δ^4lnP(t) # Δ^4lnV(t)				
2 2	0.33	2.06**	4	8.26***
2 3	0.40	2.05**		
3 2	0.30	1.98**		
3 3	0.38	3.27***		
Δ^4lnP(t) # lnV(t)			4	3.67***
2 2	0.14	0.80		
2 3	0.18	0.97		
3 2	0.16	0.95		
3 3	0.54	3.12***		
Δ^4lnV(t) # lnV(t)			4	2.59**
2 2	−0.21	−1.14		
2 3	0.14	0.74		
3 2	0.12	0.64		
3 3	−0.23	−1.28		
Δ^4lnP(t) # Δ^4lnV(t) # lnV(t)			8	1.11

2 2 2	0.01	0.02
2 2 3	−0.20	−0.73
2 3 2	−0.31	−1.05
2 3 3	0.12	0.43
3 2 2	0.09	0.35
3 2 3	−0.43	−1.70*
3 3 2	−0.02	−0.08
3 3 3	−0.02	−0.10
Const.	−0.17	−2.95***

Table A5 Predictive power of daily trading volume for stock returns and economic activities

VWRETD and EWRETD are CRSP value- and equal-weighted market portfolio returns with dividends, and VWRETX and EWRETX are the portfolio returns without dividends. VWVOL and EWVOL are the value- and equal-weighted measures of trading volume scaled by total shares outstanding. They are further logged and stochastically detrended using a 120-day window. These variables are estimated using U.S. daily sample covering the period from July 1, 1963 to December 31, 2016. BCI_ADS is the business conditions index of Aruoba, Diebold, and Scotti (2009). In the models, L_y is the maximum order of autocorrelation selected by Schwarz's Bayesian information criterion (BIC) (the results using the other information criterion AIC are very similar). "HC *t*-stat." is the heteroskedasticity-consistent *t*-statistic. Coefficient γ is multiplied by 100 in Panels A-D and by 10^4 in Panels E-H for ease of presentation.

L_y	β	*t*-stat.	*HC t*-stat.	*Adj*-R^2 (%)
Panel A. $VWRETD_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * VWRETD_{t-p+1} + \gamma * VWVOL_t + \varepsilon_{t+1}$				
2	0.060	1.566	1.204	0.42
Panel B. $VWRETX_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * VWRETX_{t-p+1} + \gamma * VWVOL_t + \varepsilon_{t+1}$				
2	0.059	1.534	1.180	0.79
Panel C. $EWRETD_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * EWRETD_{t-p+1} + \gamma * EWVOL_t + \varepsilon_{t+1}$				
4	0.246	8.096	5.871	5.39
Panel D. $EWRETX_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * EWRETX_{t-p+1} + \gamma * EWVOL_t + \varepsilon_{t+1}$				
4	0.246	8.095	5.869	5.39
Panel E. $BCI\_ADS_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * BCI\_ADS_{t-p+1} + \gamma * VWVOL_t + \varepsilon_{t+1}$				
18	–0.297	–1.864	–1.899	99.9
Panel F. $\Delta BCI\_ADS_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * \Delta BCI\_ADS_{t-p+1} + \gamma * VWVOL_t + \varepsilon_{t+1}$				
17	–0.317	–1.989	–2.023	99.9
Panel G. $BCI\_ADS_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * BCI\_ADS_{t-p+1} + \gamma * EWVOL_t + \varepsilon_{t+1}$				
18	–0.281	–1.909	–1.915	99.9
Panel H. $\Delta BCI\_ADS_{t+1} = \alpha + \sum_{p=1}^{L_y} \beta_p * \Delta BCI\_ADS_{t-p+1} + \gamma * EWVOL_t + \varepsilon_{t+1}$				
17	–0.293	–1.982	–1.987	99.9

Table A6 Summary statistics of factor returns and economic variables

The table reports the summary statistics of the monthly value-weighted high volume return premium (HVPVW), equal-weighted high volume return premium (HVPEW), Fama and French's (2015) five factors [excess stock market returns (MKT), the size premium (SMB), the value premium (HML), the profitability factor (RMW), and the investment factor (CMA)], the momentum factor (UMD) of Carhart (1997), the market-wide liquidity (LIQ) of Pástor and Stambaugh (2003), the illiquidity measure of Amihud (2002) (ILQ) and the corresponding return premium IML, the liquidity premium based on shocks to liquidity (UIML), the growth rates of industrial production (IP) and aggregate corporate earnings (ERN), the dividend-price ratio (DP), the default spread (DEF), the term spread (TERM), and the three-month Treasury bill rate (TB). The two volume premiums are constructed based on two independent sorts on size and the abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq. The means and standard deviations are both in percentage form. The sample spans from July 1963 to December 2016.

Q(p) is the Ljung-Box Q-statistic for the null hypothesis that there is no autocorrelation up to order p. We report p = 1 and 12. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics

Variable	Mean	Std. dev.	Skew.	Kurt.	AR(1)	Ljung-Box stat.	
						Q(1)	Q(12)
HVPVW	0.535	1.753	1.731	15.21	0.018	0.211	29. 95***
HVPEW	0.683	1.548	2.445	19.72	−0.030	0.586	28.11***
MKT	0.510	4.424	−0.524	4.927	0.072	3.363**	10.31
SMB	0.264	3.048	0.374	6.444	0.060	2.344	26.58***
HML	0.370	2.827	0.044	5.163	0.169	18.45***	24.52**
RMW	0.243	2.233	−0.342	16.06	0.143	13.19***	36.85***
CMA	0.308	2.011	0.286	4.621	0.125	10.14***	25.76**
UMD	0.665	4.223	−1.336	13.48	0.059	2.230	19.02*
IML	0.255	3.500	0.506	4.645	0.067	2.885*	38.70***
UIML	−0.698	2.640	−0.842	12.91	−0.012	0.095	24.67**
IP	0.206	0.738	−0.943	7.840	0.330	70.05***	258.8***
ERN	0.318	5.840	8.377	157.32	0.678	296.6***	786.3***
DP	2.802	1.008	0.413	2.397	0.991	633.0***	6833***
DEF	1.038	0.456	1.649	6.906	0.967	603.7***	4124***
TERM	1.048	1.171	−0.171	2.591	0.973	610.8***	4895***
TB	4.817	3.220	0.574	3.706	0.990	632.7***	6621***

Panel B. Correlations between the volume premiums and other factor returns

	MKT	SMB	HML	RMW	CMA	UMD	IML	UIML
HVPVW	−0.072	0.080	0.154	0.060	0.143	−0.092	0.132	−0.187
HVPEW	−0.058	0.121	0.154	0.006	0.126	−0.069	0.167	−0.220

Panel C. Correlations between the volume premiums and other variables

	ILQ	LIQ	DP	DEF	TERM	TB
HVPVW	0.131	−0.137	0.057	0.075	−0.066	0.080
HVPEW	0.132	−0.142	0.053	0.060	−0.062	0.109

Table A7 Summary statistics of ten equal-weighted volume-sorted portfolio returns

The table reports the summary statistics of the monthly excess returns to ten equally weighted portfolios sorted on abnormal trading volume. They are based on stocks traded in NYSE, Amex, and Nasdaq. The means and standard deviations are measured in percentages. The sample spans from July 1963 to December 2016.

Q(p) is the Ljung-Box Q-statistic for the null hypothesis that there is no autocorrelation up to order p. We report p = 1 and 12. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Portfolio decile	Mean	Std. dev.	Skew.	Kurt.	AR(1)	Ljung-Box stat.	
						Q(1)	Q(12)
Lo 10	0.011	5.723	−0.700	5.085	0.180	20.91***	26.78***
2-Dec	0.269	5.762	−0.658	5.075	0.159	16.29***	19.36*
3-Dec	0.403*	5.734	−0.612	4.946	0.155	15.54***	20.31*
4-Dec	0.506**	5.840	−0.671	5.202	0.149	14.32***	19.47**
5-Dec	0.677***	5.827	−0.528	4.936	0.137	12.08***	18.12
6-Dec	0.789***	5.763	−0.523	5.078	0.140	12.65***	19.68*
7-Dec	0.836***	5.702	−0.558	5.206	0.175	19.72***	27.01***
8-Dec	0.958***	5.763	−0.416	5.058	0.141	12.88***	20.64*
9-Dec	1.100***	5.765	−0.367	5.349	0.124	9.850***	18.15
Hi 10	1.271***	5.789	−0.217	5.855	0.108	7.556***	19.16*
High − Low	1.260***	2.567	2.397	19.61	−0.004	0.010	35.11***

Table A8 Additional Results on predictability of industrial production growth

The table summarizes the results of the following predictive regression

$$y_{t+1} = \alpha + \beta * \text{HVPVW}_t + \gamma' \text{X}_t + \varepsilon_{t+1}, \quad (1)$$

where the dependent variable y_t is the monthly growth rate of U.S. industrial production, and the predictive variables include the value-weighted high volume return premium (HVPVW) and one of the following five variables, the liquidity measure of Pastor and Stambaugh (2003) (LIQ), innovations in the liquidity measure (ULIQ), the orthogonalized investment sentiment of Baker and Wurgler (2006, 2007) (INV_SNT), the realized monthly variance of excess returns of the aggregate stock market portfolio (*MKT_VAR)* which is defined as the sum of squared daily returns in a month, and the associated realized monthly volatility (*MKT_VOL*). HVPVW is based on two independent sorts on size and the abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq. The sample spans from July 1963 to December 2016. Each entry in the table is the point estimate of coefficient β or γ. Numbers in parentheses are the associated HAC *t*-statistics. Constant terms are omitted to save space. The adjusted R^2s are in percentage.

Predictive variables	Univariate regressions	Bivariate regressions				
		I	II	III	IV	V
HVPVW	−0.052	−0.044	−0.049	−0.052	−0.039	−0.034
	(−2.760)	(−2.461)	(−2.634)	(−2.692)	(−2.282)	(−2.218)
LIQ	0.020	0.018				
	(3.365)	(3.240)				
ULIQ	0.015		0.014			
	(2.561)		(2.403)			
INV_SNT	−0.064			−0.064		
	(−1.573)			(−1.599)		
MKT_VAR	−0.507				−0.487	
	(−3.126)				(−3.076)	
MKT_VOL	−0.103					−0.010
	(−5.021)					(−5.023)
Adj-R^2		3.52	2.28	1.95	8.37	10.72

Table A9 Multivariate regressions of the equal-weighted high volume return premium as predictors of industrial production growth

The table summarizes the results of the following predictive regression

$$y_{t+1} = \alpha + \beta * \text{HVPEW}_t + \gamma' \text{X}_t + \varepsilon_{t+1}, \quad (1)$$

where the dependent variable y_t is the monthly growth rate of U.S. industrial production, the predictive variable HVPEW is the equal-weighted high volume return premium based on two independent sorts on size and the abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq, and the control variable set X_t includes Fama and French's (2015) five factors [excess stock market returns (MKT), the size premium (SMB), the value premium (HML), the profitability factor (RMW), and the investment factor (CMA)], the momentum factor (UMD) of Carhart (1997), the liquidity premium (UIML) based on shocks to illiquidity of Amihud (2002), a macro-index (CATFIN) that measures the aggregate level of risk taking in the financial sector (Allen, Bali, and Tang, 2012), and four market condition variables [dividend-price ratio (DP), term premium (TERM), default premium (DEF), and the three-month Treasury bill rate (TB)]. The sample covers the period from July 1963 to December 2016. The start date of CATFIN is January 1973. The start date of all other variables is July 1963. The end date of all the variables is December 2016. Each entry in the table is the point estimate of coefficient β for the volume premium. Numbers in parentheses are the associated HAC t-statistics. Constant terms (αs) are omitted to save space. The adjusted R^2s are in percentage.

Predictive variables	Model specifications						
	I	II	III	IV	V	VI	VII
HVPEW	−0.057	−0.062	−0.066	−0.062	−0.050	−0.041	−0.043
	(−2.795)	(−2.643)	(−2.693)	(−2.581)	(−2.570)	(−2.058)	(−2.523)
MKT		0.016	0.016	0.013			−0.001
		(2.303)	(1.603)	(1.744)			(−0.072)
SMB		0.019	0.018	0.020			0.018
		(1.948)	(1.376)	(1.899)			(1.331)
HML		0.013	0.011	0.021			−0.004
		(1.191)	(0.812)	(1.498)			(−0.225)
UMD		0.006					
		(0.832)					
UIML			−0.010				
			(−0.563)				
RMW				0.001			0.007
				(0.070)			(0.539)
CMA				−0.023			−0.008
				(−1.097)			(−0.308)
DP					−0.017	−0.079	−0.080
					(−0.413)	(−1.244)	(−1.237)
DEF					−0.500	−0.311	−0.327
					(−6.831)	(−3.214)	(−3.260)
TERM					0.179	0.232	0.229
					[5.124]	(5.483)	(5.635)
TB					0.047	0.074	0.075
					(2.953)	(3.481)	(3.530)
CATFIN						−0.014	−0.013
						(−4.377)	(−3.514)
Adj-R^2	1.29	2.59	2.60	2.53	9.63	15.30	15.04

Table A10 Predictive power of aggregate measures of abnormal trading volume

The table summarizes the results of the following predictive regression

$$y_{t+1} = \alpha + \beta * \mathrm{HVM}_t + \gamma' \mathrm{X}_t + \varepsilon_{t+1}, \quad (1)$$

where the dependent variable y_t is the monthly growth rate of U.S. industrial production, the predictive variable HVM is the value- or equal-weighted aggregate measure of abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq, and the control variable set X_t includes the excess stock market returns (MKT), the size premium (SMB), the value premium (HML), the liquidity measure of Pastor and Stambaugh (2003) (LIQ), the illiquidity measure of Amihud (2002) (ILQ), four market condition variables [dividend-price ratio (DP), term premium (TERM), default premium (DEF), and the three-month Treasury bill rate (TB)], and a macro-index (CATFIN) that measures the aggregate level of risk taking in the financial sector (Allen, Bali, and Tang, 2012). The sample covers the period from July 1963 to December 2016.
Each entry in the table is the point estimates of coefficient β and γs. Numbers in parentheses are HAC-adjusted t-statistics. Constant terms (αs) are omitted to save space. The adjusted R^2s are in percentage.

Predictive variables	Model specifications							
	Value-weighted volume measure				Equal-weighted volume measure			
	I	II	III	IV	I	II	III	IV
HVM	−0.673	−0.720	−0.736	−0.665	−0.711	−0.900	−0.935	−0.848
	(−2.950)	(−3.280)	(−3.072)	(−3.133)	(−2.448)	(−3.120)	(−2.880)	(−2.933)
MKT		0.011	0.018			0.011	0.018	
		(1.135)	(1.760)			(1.128)	(1.756)	
SMB		0.012	0.014			0.016	0.019	
		(1.014)	(1.191)			(1.387)	(1.533)	
HML		0.006	0.006			0.008	0.009	
		(0.407)	(0.459)			(0.580)	(0.633)	
LIQ		0.018				0.018		
		(2.912)				(2.927)		
ILQ			−0.010				−0.010	
			(−0.636)				(−0.673)	
DP				−0.083				−0.088
				(−1.310)				(−1.370)
DEF				−0.314				−0.310
				(−3.265)				(−3.193)
TERM				0.225				0.229
				(5.318)				(5.351)
TB				0.067				0.043
				(3.217)				
CATFIN				−0.015				−0.015
				(−4.414)				(−4.508)
Adj-R^2	1.45	4.57	2.82	16.26	0.74	4.15	2.41	15.81

Table A11 Multivariate regressions of the high volume return premium as predictors of three macroeconomic indicators

The table summarizes the results of the following predictive regression

$$y_{t+3} = \alpha + \beta * \text{HVPVW}_t + \gamma' \text{X}_t + \varepsilon_{t+3}, \quad (1)$$

where the dependent variable y_t is the Chicago Fed National Activity Index (CFNAI), the growth rate of aggregate corporate earnings (ERN), and nonfarm payroll employment (PAYROLL), the predictive variable HVPVW is the value-weighted high volume return premium based on two independent sorts on size and the abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq, and the control variable set X_t includes a macro-index (CATFIN) that measures the aggregate level of risk taking in the financial sector (Allen, Bali, and Tang, 2012), and four market condition variables [dividend-price ratio (DP), term premium (TERM), default premium (DEF), and the three-month Treasury bill rate (TB)]. The sample covers the period from July 1963 to December 2016. The start date of CATFIN is January 1973. The start date of all other variables is July 1963. The end date of all of the variables is December 2016.

Each entry in the table is the point estimate of coefficient β for the volume premium or γ for other control variables. Numbers in parentheses are the associated HAC *t*-statistics. Constant terms (αs) are omitted to save space. The adjusted R^2s are in percentage.

Predictive variables	Economic indicators								
	Economic activity index (CFNAI)			Corporate earnings (ERN)			Nonfarm payroll employment (PAYROLL)		
	I	II	III	I	II	III	I	II	III
HVPVW	−21.92	−16.81	−12.96	−0.924	−0.706	−0.704	−0.040	−0.028	−0.019
	(−2.348)	(−3.005)	(−2.278)	(−3.026)	(−2.532)	(−2.586)	(−2.856)	(−2.091)	(−1.432)
DP		11.71	7.649		0.899	0.994		0.147	0.130
		(0.361)	(0.246)		(1.912)	(2.078)		(3.485)	(2.604)
DEF		−291.5	−237.9		−4.747	−4.249		−0.795	−0.660
		(−5.242)	(−5.757)		(−1.354)	(−1.284)		(−6.761)	(−5.720)
TERM		87.67	99.16		3.458	3.531		0.091	0.125
		(3.834	(4.531)		(4.060)	(4.258)		(2.624)	(3.370)
TB		24.92	29.61		−0.012	−0.011		0.022	0.035
		(2.122)	(2.715)		(−0.024)	(−0.023)		(1.141)	(1.767)
CATFIN			−8.816			−0.099			−0.016
			(−6.296)			(−0.843)			(−5.171)
Adj-R^2	2.04	22.02	37.81	0.53	3.902	3.69	1.43	31.54	39.70

Table A12 Returns of stocks sorted on abnormal trading volume in combination with shocks to (il)liquidity and idiosyncratic volatility

The table reports average monthly excess returns of value-weighted portfolios formed by bivariate sorts on size, abnormal trading volume, shocks to Amihud's (2002) measure of illiquidity (UILQ), shocks to Fong, Holden, and Trzcinka's (2017) measure of liquidity (ULIQ), and (shocks to) idiosyncratic volatility (IVOL and UIVOL) of stocks traded in NYSE, Amex, and Nasdaq. Also reported are Fama-French (2015) five-factor alphas of the return differences between portfolios sorted on one of these five stock characteristics. The sample spans the period of July 1963-December 2016. Numbers in parentheses are HAC *t*-statistics.
Idiosyncratic volatility of month *t* is the properly scaled sum of recent 17 daily squared returns controlling for Fama-French three factors (market, size, and value). The sample size is chosen to represent about one-third of 50 trading days used to estimate the high volume return premium. Shocks to idiosyncratic volatility are defined as the difference between this volatility estimate and that based on returns of the remaining two-thirds of the 50 trading days. Shocks to illiquidity (UILQ) are similarly defined. Fong, Holden, and Trzcinka's (2017) measure of liquidity is estimated using within-month daily returns. Shocks to liquidity (ULIQ) are defined as the difference between current month liquidity and the average of the previous 12-month's estimates.

	Volume-sorted portfolios							
	Average excess returns				Fama-French 5-factor alphas			
	1 Low	2	3 High	(High – Low)	1 Low	2	3 High	(High – Low)
	Panel A. Portfolios sorted on abnormal trading volume & shocks to illiquidity (UILQ)							
UILQ 1 (Low)	0.480	0.860	1.171	0.691	–0.203	0.179	0.495	0.698
	(2.280)	(4.039)	(5.493)	(7.626)	(–2.813)	(2.568)	(6.109)	(6.898)
2	0.315	0.567	0.706	0.391	–0.127	0.113	0.181	0.308
	(1.646)	(3.116)	(3.648)	(3.973)	(–2.297)	(2.138)	(2.363)	(3.105)
UILQ 3 (High)	0.002	0.238	0.466	0.464	–0.614	–0.416	–0.247	0.367
	(0.008)	(1.091)	(2.134)	(5.021)	(–5.553)	(–4.050)	(–2.170)	(4.062)
(Low – High)	0.478	0.623	0.705		0.411	0.595	0.742	
	(4.123)	(5.464)	(6.021)		(3.247)	(4.011)	(4.828)	
	Panel B. Portfolios sorted on abnormal trading volume & shocks to liquidity (ULIQ)							
ULIQ 1 (Low)	0.226	0.640	0.900	0.675	–0.349	0.065	0.244	0.593
	(1.032)	(2.963)	(4.164)	(7.002)	(–4.591)	(0.843)	(3.500)	(6.445)
2	0.319	0.520	0.568	0.249	–0.147	0.075	0.039	0.186
	(1.724)	(2.968)	(3.185)	(2.762)	(–2.619)	(1.665)	(0.578)	(1.922)
ULIQ 3 (High)	0.323	0.568	0.737	0.414	–0.187	–0.008	0.139	0.326
	(1.697)	(2.960)	(3.739)	(3.969)	(–2.199)	(–0.111)	(1.726)	(2.843)
(Low – High)	–0.097	0.072	0.163		–0.162	0.073	0.105	
	(–0.853)	(0.647)	(1.458)		(–1.384)	(0.631)	(1.009)	
	Panel C. Portfolios sorted on abnormal trading volume & idiosyncratic volatility (IVOL)							
IVOL 1 (Low)	0.381	0.544	0.713	0.332	–0.199	0.055	0.133	0.332
	(2.277)	(3.528)	(4.428)	(3.573)	(–2.881)	(1.131)	(2.307)	(3.518)
2	0.446	0.689	0.845	0.400	–0.016	0.172	0.257	0.273
	(1.864)	(3.010)	(3.634)	(3.539)	(–0.175)	(2.215)	(2.862)	(2.139)

IVOL 3 (High)	–0.068	0.170	0.230	0.298	–0.415	–0.273	–0.222	0.192
	(–0.211)	(0.528)	(0.711)	(1.797)	(–2.629)	(–2.432)	(–1.644)	(0.931)
(Low – High)	0.449	0.374	0.483		0.215	0.328	0.355	
	(1.806)	(1.579)	(2.019)		(1.299)	(2.589)	(2.392)	
	Panel D. Portfolios sorted on abnormal trading volume & shocks to idiosyncratic volatility (UIVOL)							
UIVOL 1 (Low)	0.329	0.499	0.838	0.509	–0.065	0.046	0.303	0.368
	(1.308)	(2.051)	(3.317)	(3.511)	(–0.501)	(0.499)	(2.500)	(2.107)
2	0.321	0.560	0.752	0.431	–0.181	0.094	0.203	0.383
	(1.824)	(3.448)	(4.379)	(4.415)	(–2.825)	(2.025)	(3.104)	(3.795)
UIVOL 3 (High)	0.276	0.514	0.602	0.327	–0.151	0.030	0.069	0.221
	(1.217)	(2.364)	(2.742)	(2.521)	(–1.441)	(0.339)	(0.721)	(1.932)
(Low – High)	0.054	–0.015	0.236		0.086	0.016	0.233	
	(0.385)	(–0.112)	(1.608)		(0.526)	(0.116)	(1.448)	

Table A13 The predictability of the mimicking portfolio for future industrial production growth

This table reports the estimation results of the following regression:

$$IP_t = a + b^*BASE_{t-1} + c_1^*DP_{t-1} + TERM_{t-2} + c_2^*DEF_{t-2} + c_4^*TB_{t-1} + \varepsilon_t, \qquad (A2)$$

where IP_t is industrial production growth over month $(t-1)$ to t, the base assets (BASE) include ten industry portfolios and two fixed income portfolios, TERMR and DEFR, where TERMR is the return difference between long-term government bonds and short-term Treasury bill rates and *DEFR* is the difference between the return on long-term corporate bonds and long-term government bonds. Excess returns to the ten industry portfolios are derived from Kenneth French's website. DP is the CRSP dividend-price ratio. TERM is the difference between the ten-year government bond yield and the three-month Treasury bill rate. DEF is the yield spread between Moody's BAA and AAA corporate bonds. TB is the risk-free rate. The sample spans from July 1963 to December 2016. The numbers in parentheses are *t*-values that are adjusted for heteroskedasticity and autocorrelation (HA) using the Newey and West (1987) estimator. "F stat." reports *F* test-statistic for the null hypothesis that all slope coefficients are jointly zeros. "Adj. *F* Stat." is the same statistic that also adjusts for HA in the variance estimator.

Variable names		Parameter estimates	
		W/O Control Variables	With Control Variables
	Constant	0.002	0.004
		(4.840)	(2.641)
Base Assets	NoDur	0.006	0.012
		(0.363)	(0.742)
	Durbl	0.017	0.019
		(1.781)	(2.329)
	Manuf	−0.013	−0.021
		(−0.873)	(−1.459)
	Enrgy	0.013	0.0145
		(2.463)	(2.714)
	HiTec	0.006	0.008
		(0.894)	(1.310)
	Telcm	0.002	0.000
		(0.232)	(0.018)
	Shops	−0.014	−0.006
		(−0.991)	(−0.519)
	Hlth	−0.015	−0.015
		(−1.494)	(−1.612)
	Utils	−0.008	−0.009
		(−0.829)	(−0.961)
	Other	0.011	0.003
		(0.657)	(0.218)
	DEFR	−0.065	−0.047
		(−2.462)	(−1.928)
	TERMR	−0.042	−0.041
		(−2.408)	(−2.955)
Control Variables	DP		−0.039

		(−0.582)
DEF		−0.509
		(−4.570)
TERM		0.207
		(2.489)
TB		0.059
		(2.490)
Adj. R^2 (%)	3.22	13.01
F stat.	2.775	6.991
p-value	0.001	0.000
Adj. F stat.	3.845	4.922
p-value	0.000	0.000

References (those already included in the paper are not listed here):

Breeden, D.T., M.R. Gibbons, and R. Litzenberger, 1989. Empirical tests of the consumption-oriented CAPM. Journal of Finance 44, 231-262.

Campbell, J., 1996. Understanding risk and return. Journal of Political Economy 104, 298-345.

Chen, J., and H. Hong, and J. Stein. 2001. Forecasting Crashes: Trading Volume, Past Returns and Conditional Skewness in Stock Prices. Journal of Financial Economics 61(3), 345-381.

Cochrane, J.H., 2001. *Asset Pricing*. Revised version. Princeton University Press.

Kandel, E., and N.D. Pearson. 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831-872.

Lamont, O., 2001. Economic tracking portfolios. Journal of Econometrics 105, 161-184.