The High-Volume Return Premium and Economic Fundamentals

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ABSTRACT

Extending Kaniel, Ozoguz, and Starks (2012, *J. Financ. Econ.*) and many others, we present first empirical evidence that indicates the high volume return premium is linked to economic fundamentals. The volume premium has strong predictive power for future industrial production growth and other macroeconomic indicators with or without controls for common equity pricing factors and business cycle variables. However, only a small portion of the volume premium can be attributed to its co-movement with equity return factors and economic risk factors. Mispricing-based factor models also fail to adequately explain the return anomaly.

JEL Classification: G12, E44

Keywords: High volume return premium, Economic fundamentals, Rational and mispricing-based asset pricing models

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1. Introduction

It has long been recognized stocks that recently receive a substantial positive volume shock receive excess market-adjusted returns (Gervais, Kaniel, and Mingelgrin, 2001; Kaniel, Ozoguz, Starks, 2012).[1] Based on U.S. data from July 1963 to December 2016, we show that an investment strategy that goes long stocks that have recently experienced abnormally high trading volume and short stocks that have experienced abnormally low trading volume earns a size-adjusted average monthly premium of 0.53% on a value-weighted basis and 0.68% on an equal-weighted basis. Both estimates of the high volume return premium (or HVP) are statistically significant.[2] A spread between the top and bottom deciles of volume-sorted portfolios, as initially constructed by Kaniel, Ozoguz, Starks (2012), produces similar rates of return.

The leading explanation for the high volume return premium is that it manifests Merton's (1987) investors recognition hypothesis (Gervais, Kaniel, and Mingelgrin, 2001; Lerman, Livnat, and Mendhall, 2008; Kaniel, Ozoguz, and Starks, 2012; Israeli, Kaniel, and Sridharan, 2018). According to this hypothesis, in a market with incomplete information, positive shocks to the trading activity of a stock increase stock visibility that gives rise to subsequent demand and price for that stock. Similarly, Bali, Peng, Shen, and Tang (2014) explain the premiums related to liquidity shocks by investor inattention and illiquidity. Many studies in the microstructure literature that examine trading volume and return relation invoke the mispricing explanation. For example, Gervais and Odean (2001) and Statman, Thorley, and Vorkink (2006) view that trading volume describes investors' learning curves leading to overconfidence and further affects future stock returns. Barber and Odean (2008) and Hou,

[1] A large body of the microstructure literature has investigated contemporaneous and dynamic relationships between trading volume and returns. But, it is Gervais, Kaniel, and Mingelgrin (2001) who first propose and study the high volume return premium that represents a new dimension of studying the volume-return relation and makes it possible to also examine the issue from a standard asset pricing perspective as we do in this paper.
[2] If winsorized at the lower 5th and upper 95th percentiles, the value-weighted volume premium has an average of 0.49%. If winsorization is only applied on the upper end, the average is 0.44% and is still highly significantly different from zero.

Xiong, and Peng (2009) argue that trading volume is related to investor attention and reflects how investors react to the news of the firm.

Extending the previous papers, this study investigates whether the significant positive cross sectional correlation between abnormal trading volume and future stock returns is linked to fundamental economic risks. More broadly, we are interested in whether the volume premium can be explained by existing factor asset pricing models. In particular, as an alternative/complement to the prevailing mispricing explanation, we explore whether a risk-based explanation is possible, at least partially, for the volume premium.[3] Motivated by Fama's (1991) conjecture of an explicit link between the cross sectional and time series stock return predictability, we hypothesize that if the volume premium constructed from the cross section of stocks is indeed connected to economic fundamentals, then it helps predict the time variation of future real economic activities. At the same time, factors proxying for economic risks help to explain the cross sectional variation of returns to stocks sorted on abnormal trading volume.

To test these hypotheses, we adopt two complimentary empirical modeling strategies, each of which has been used by different authors to study the economic content of return factors including the size premium, the value premium, momentum, investment-related return anomalies, and liquidity. We first investigate whether the volume premium helps to predict future real economic activities within the framework of predictive regressions. We provide both in- and out-of-sample evidence that the volume premium contains information that is useful for predicting industrial production growth up to nine months. Quantitatively, a one-standard-deviation increase in the volume premium predicts a 9.2-basis-point decrease in industrial production growth in the coming month, which is about half of the average

[3] Unless otherwise indicated or clear from the context, throughout the paper, we often simply use trading volume in place of abnormal trading volume. Depending upon the context, we also call it shocks to trading volume to mirror the concept of shocks to (il)liquidity. In addition, we use the high volume return premium and the volume premium interchangeably.

economic growth rate during the sample period. The volume premium also exhibits similar predictive power for three other macroeconomic indicators: the Chicago Fed National Activity Index (CFNAI), aggregate corporate earnings, and nonfarm payroll employment.[4]

We then investigate, within the asset pricing framework, to what extent the volume premium can be explained by common risk factors in stock returns and macroeconomic factors. Because the common return factors do not fully account for the high volume return premium, we explore whether economic risk factors carry additional explanatory power. In a seven-factor model that includes Fama and French's (2015) five factors, a liquidity factor, and returns of a mimicking portfolio that tracks news about future industry production growth, we find that the economic risk factor is priced.[5] However, these factors only account for about one-third of the volume premium.

In addition, we study how much of the average return spread between low and high volume portfolios can be accounted for by their exposures to systematic risk, as measured by the loadings on Chen, Roll, and Ross' (1986) five macroeconomic factors. The results suggest that high volume stocks load more than low volume stocks on economic risk related to industrial production and the term premium. Intuitively, some stocks experience a hike in volume partly because the growth prospects of this type of stocks are more sensitive than other stocks to information about the future economy and the news of fundamentals must be priced through trading. Nevertheless, the spreads in factor loadings

[4] Ying (1966) studies the price effect of trading volume and is also the first to indicate that trading volume affects the level of economic activities (p. 677). In Section A of the Internet Appendix, we replicate the main results of Ying (1966) using CRSP data from July 1, 1963 to December 31, 2016. Overall, we find evidence of trading volume leading price changes. In Section B of the Appendix, we complement the above analysis with time series regressions within the framework of the Granger non-causality test. The results suggest that daily trading volume predicts stock price changes and economic activities that are proxied by the daily business conditions index of Aruoba, Diebold, and Scotti (2009).

[5] Our finding that risk related to industrial production growth drives a portion of the volume premium is not surprising. In explaining the driving force for the momentum premium, Liu and Zhang (2008) demonstrate that winners have temporarily higher loadings than recent losers on the growth rate of industrial production. Cooper and Priestley (2011) also provide evidence that the investment growth effect can predict industrial production.

are narrow and the five economic factors in total can only predict a small portion of the volume premium.

Overall, we find time series evidence of the link between the high volume return premium and economic fundamentals. However, the evidence from bivariate cross-sectional analysis at both stock and portfolio levels is somewhat weaker. In particular, while risk plays a role in driving the volume premium, the predicted amount is too small. A large component of the volume premium cannot be accounted for by the common return factors and our measures of economic risks. We also find that the two mispricing-based factor models, Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019), fail to explain the observed volume premium. Therefore, the sources of the return anomaly remain open to debate from the asset pricing perspective.

To the best of our knowledge, this is the first paper to connect the volume premium to macroeconomic fundamentals and examine the volume effect within the asset pricing framework.[6] There is increasing research interest in examining the relationship between the volume effect and firm fundamentals. Akbas (2016) finds that stocks experiencing unusually low trading volume over the week prior to earnings announcements tend to have more unfavorable earnings surprises. Israeli, Kaniel, and Sridharan (2018) demonstrate, in great detail, that unexpected increases in a stock's trading volume are associated with higher corporate investment and financing cash flows in the coming year. Han and Huang (2018) find that negative liquidity shocks lead to lower stock prices in the short run, but higher prices in the long run. They explain the effects by changes in firm level fundamentals and information uncertainty. Our contributions differ from these studies in an important way. While the above studies examine the volume/liquidity effect at the firm level, this paper focuses on the

[6] Hou, Xue, and Zhang (2015) and Harvey, Liu, and Zhu (2016) look into exhaustive lists of return anomalies, including those related to trading volume and liquidity. However, they do not study the high volume return premium.

monthly market aggregate and macroeconomic data. Our research interest is to evaluate the connection between high volume return premiums and economic fundamentals.

Our paper relates to a number of other papers that also interpret the volume-related return premium as compensation for risk. However, their definitions of risk are not the same as what we study here. For example, Garfinkel and Sokobin (2006) use abnormal volume around the earnings announcement as an indicator of investor opinion divergence, and view opinion divergence as a risk. Similarly, Schneider (2009) argues that high volume implies low information quality and, as such, greater uncertainty. Banerjee and Kremer (2010) take a similar stand. Gallmeyer, Hollifield, and Seppi (2009) suggest that large volume signals an unusual degree of uncertainty regarding investor demand for a stock. In comparison, we study whether a direct link exists between the volume premium and common risk factors.

Our paper is also closely related to a large literature regarding the predictive power of firm- and market-wide (il)liquidity for future stock returns. The key difference between this paper and the liquidity literature is that we make different use of trading volume information. Many previous studies examine the impact of trading volume (turnover, or order flow) in its levels form (Brennan, Chordia, and Subrahmanyam, 1998; Chordia and Swaminathan, 2000; Statman, Thorley, and Vorkink, 2006, Lo and Wang, 2010). Another line of the literature measure liquidity (or trading costs) based on the level-form trading volume and study its impact on contemporaneous and future price changes or economic activity (Amihud, 2002; Pastor and Stambaugh, 2003; Næs, Skjeltorp, and Ødegaard, 2011; Lou and Shu, 2017; Chen, Eaton, and Paye, 2018). Some recent work has focused on shocks to liquidity (Bali et al., 2014; Han and Huang, 2018). In contrast, we study economic content and the predictive power of trade by shocks to trading volume alone. Our classification of a stock as high/low volume is relative to its own recent trade history. The measurement of trading volume and liquidity is not trivial. Amihud

(2002) and Acharya and Pedersen (2005) argue that lower levels of liquidity should result in higher predicted future returns. Alternatively, Bali et al. (2014) and Han and Huang (2018) empirically show that stocks experiencing negative liquidity shocks carry a negative premium.

In a recent study, Lou and Shu (2017) demonstrate that pricing of Amihud's (2002) illiquidity measure is not attributable to the construction of the return-to-volume ratio that is intended to capture price impact (or trading costs), but entirely due to the trading volume component.[7] We later demonstrate that, while related, shocks to trading volume capture information that is not common to traditional measures of liquidity or shocks to liquidity. In addition, the volume premium predicts real economy better than liquidity-related measures. In explaining why liquidity is a better economic indicator than stock returns, Næs, Skjeltorp, and Ødegaard (2011) argue that stock returns contain a more complex mix of information that makes the signals more blurred. We conjecture that a similar argument could be made for the performance of the volume premium relative to the liquidity premium.

Another difference between our paper and the liquidity literature is that, when forming portfolios of abnormally high/low volume stocks, we follow Gervais, Kaniel, and Mingelgrin (2001) and Kaniel, Ozoguz, Starks, 2012) and explicitly exclude stocks whose earnings announcements are on or around the portfolio formation day. Stocks are also excluded if their high volume is caused by news about other corporate events such as mergers, acquisitions, and delisting. These types of volume changes probably relate more to firm fundamentals and do not directly relate to macroeconomic fundamentals. On the contrary, because price and volume changes are often concentrated around announcements of such events, many other studies either focus on volume/price effects of these events

[7] Brennan, Huh, and Subrahmanyam (2013) propose to decompose the Amihud (2002) measure into elements that correspond to positive (up) and negative (down) return days. They find that in general, only the down-day element commands a return premium.

or do not distinguish between trading volumes of different causes (Næs, Skjeltorp, and Ødegaard, 2011; Akbas, 2016).

The remainder of the paper proceeds as follows. In the next section we develop testable hypotheses and describe empirical models to test these hypotheses. Section 3 discusses the data. Section 4 presents the main results of the predictive regressions. We pursue risk-based explanations for the volume premium in Section 5 and test mispricing-based explanations in Section 6. Section 7 summarizes the main findings and discusses some limitations of this study.

2. Testable hypotheses and research methodology

Market microstructure theory suggests that both trading volume and price changes are related to the arrival of information to the market. Cochrane (2013, p.41) put it more bluntly, "much trading …is clearly aimed at bringing information to the market." Trading volume indicates how investors trade on individual stocks to share risk or speculate on private information that further induces different subsequent reversal or continuation patterns (Llorente, Michaely, Saar, and Wang, 2002). Wang (1994) develops an equilibrium model of stock trading in which investors have rational expectations but are heterogeneous in their information and private investment opportunities. Lo and Wang (2010) develop an intertemporal equilibrium model of asset market in which the trading process is determined endogenously by two motives, liquidity needs and risk-sharing.

Guided by these theoretical results, we assess whether the high volume return premium captures information that predicts real economy and whether and how it relates to the common economic and equity risk factors. If the answer is yes, then we may interpret the volume premium as having a component that captures the risk-sharing motive of trade. Those who are willing to bear the economic risk by holding abnormally high volume stocks are rewarded with higher expected returns. To reach this objective, we develop two complementary hypotheses.

H1: The high volume return premium helps to predict future economic growth. Fama (1981) and Liew and Vassalou (2000) find that the market risk premium and the value and size premiums all predict GDP growth. Cooper and Priestley (2011) present similar evidence regarding the ability of the investment factor to predict real economic activities. If the high volume return premium (HVP) also proxies for fundamental economic risk, we would expect the volume premium to necessarily contain information useful for predicting future economic activities. To test this hypothesis, we adopt the following standard predictive regression model:

$$y_{t+h} = \alpha + \beta * \mathrm{HVP}_t + \gamma' \mathrm{X}_t + \varepsilon_{t+h}, \tag{1}$$

where y_{t+h} is the growth rate of economic indicators between period (t) and ($t + h$), the vector of X_t is the set of control variables described in detail in later sections. The null hypothesis is that $\beta = 0$, meaning that the volume premium captures no additional information for predicting the economy.

H2: The cross section of average returns to portfolios sorted on abnormal trading volume can be explained by common risk factors and linked to macroeconomic factors. Complementing Hypothesis 1 that examines the link between the volume premium and future economic growth from the aggregate time series perspective, Hypothesis 2 further tests the economic content of the volume premium from the empirical asset pricing perspective. To implement the test, we use the following standard time-series regressions:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} f_{j,t} + \varepsilon_{i,t}, \quad \text{for } i = 1, \ldots, 10,\ t = 1, 2, \ldots, T, \tag{2}$$

where the test assets are ten volume-sorted portfolios, $R_{i,t}$ is the excess return on asset i at the end of period t, $f_{j,t}$ is factor j ($j = 1, \ldots, K$), and K is the number of factors. Model (2) can be used to evaluate both risk- and mispricing-based factor models as we do in Sections 5.3 and 6. To test the joint significance of the alphas, we implement the GRS test in a seemingly unrelated regression (SUR) system of the ten time-series regressions to adjust for heteroskedasticity and autocorrelation when estimating the covariance matrix for the model parameters.

3. Data

We consider all NYSE, Amex, and Nasdaq non-financial common stocks with share codes 10 or 11 for the period of July 1, 1963 through December 31, 2016. They are obtained from CRSP stock securities files and events files. Compustat merged annual and quarterly data files provide firms' accounting information. We construct two types of volume-sorted portfolios. Closely following Gervais, Kaniel, and Mingelgrin (2001) and Kaniel, Ozoguz, Starks (2012), in the first set, we form ten portfolios by one sort on abnormal trading volume. These portfolios will be used as test assets in our cross sectional analysis. A stock is defined as a low (high) volume stock in month *t* if its trading volume on the last trading day of the month is among the lowest (highest) 10% of its 50 daily volumes prior to the formation day (inclusive) (Section C of the Internet Appendix provides more information on the portfolio construction and results with a three-day formation period).

Earlier studies indicate that the trading volume effect is likely to be intertwined with the firm size effect (Blume, Easley, and O'Hara, 1994; Cooper, 1999). To obtain an estimate of the high volume return premium that explicitly controls for the firm size effect, all qualified stocks are ranked according to their market equity. Next, these stocks are categorized as small and large using the median ranked values solely based on NYSE-traded stocks as the breakpoints. In another separate sort, the stocks are divided into three groups, one low volume group with the lower three volume classifications (i.e., lowest to the third deciles), one neutral group with the fourth to seventh deciles of portfolios, and a high volume group with three highest classifications. All stocks are then assigned into six portfolios as the intersections of the two size groups and the three volume groups. The value-weighted high volume return premium (HVPVW) is the difference between the simple average value-weighted returns of the two high volume portfolios and the simple average value-weighted returns of the two low volume portfolios. The equal-weighted high volume return premium (HVPEW) is similarly defined.

Following Liu and Zhang (2008) and Cooper and Priestley (2011), in our benchmark analysis, we use the growth rate of monthly industry production (IP) as the dependent variable in predictive Regression (1). The monthly US total industrial production index is from the Federal Reserve Bank of Saint Louis. As robustness checks, the predictive power of the volume premium is studied for three other macroeconomic indicators. The first is the Chicago Fed National Activity Index (CFNAI) that determines overall economic activity and inflationary pressure. The start date of the index is March, 1967. The two other indicators, the growth rates of real aggregate corporate earnings (ERN) and nonfarm payroll employment (PAYROLL), are more focused. However, Cooper and Priestley (2011) and Allen, Bali, and Tang (2012), respectively, have studied them. The monthly aggregate corporate earnings are from Professor Robert Shiller's web site at Yale University. The nonfarm payroll series is available from the Bureau of Labor Statistics.

In studying the economic content of the volume premium through predictive Regression (1), we use five conditional variables. The first four are common business cycle variables that track economic and business conditions. They are the dividend-price ratio (DP), the default premium (DEF), the term premium (TERM), and the three-month Treasury bill rate (TB). The fifth control variable is a macro-index of systemic risk (CATFIN) of Allen, Bali, and Tang (2012). CATFIN measures the aggregate level of risk taking in the financial sector. As shown in Allen, Bali, and Tang (2012), CATFIN has strong predictive power for economic downturns and uncertainty as measured by financial market volatility. We downloaded the updated index from Professor Turan Bali's personal website at https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers.

Another set of control variables used in Model (1) are Fama and French's (2015) five factors (hereafter also FF five factors) and the momentum factor (UMD) of Carhart (1997). The FF five factors include the excess market returns (MKT), the size premium (SMB), the value premium (HML), the profitability factor (RMW), and the investment factor (CMA). These variables are downloaded from Professor Kenneth French's website. To control for known liquidity effects on stock returns, we calculate and use three illiquidity-related measures based on Amihud's (2002) illiquidity ratio. They are the aggregate illiquidity measure (ILQ), the liquidity premium based on the firm-level illiquidity measure (IML), and the liquidity premium based on shocks to illiquidity (UIML).[8] As part of the robustness checks, we use two measures of stock market-wide liquidity of Pástor and Stambaugh (2003) that are available from CRSP. Finally, because the literature indicates that investor sentiment may be related to investors' trading behavior (Garcia, 2013), we also consider as a control variable investors' sentiment of Baker and Wurgler (2006, 2007) that is available on Professor Jeffery Wurgler's website at NYU.

Panel A of Table 1 reports summary statistics of the monthly value- and equal-weighted high volume return premiums (HVPVW and HVPEW).[9] The average value-weighted HVP is 0.53%, which

[8] In estimating the firm-level and aggregate illiquidity measure of ILQ, we use the same data filtering rules as we use for estimating the high volume return premium. We compute the corresponding liquidity premium (or liquidity factor, IML) as the return of the top tercile portfolio (illiquid) minus that of the bottom tercile portfolio (liquid). In obtaining the IML estimate, we do not control for the size of the stocks since the number of stocks classified as most illiquid and large is small. Other studies have adopted similar approaches. The construction of the liquidity factor UIML is similar, but based on shocks to the illiquidity measure.

[9] Additional descriptive statistics and discussion are given in Section C of the Internet Appendix for the two series, as well as the aforementioned other portfolio returns and economic and financial variables. Panel A of Table 6 reports the returns and Fama and French (2015) five-factor alphas of the six size and volume portfolios, from which the value-weighted volume premium is derived. The panel shows that, while the volume premium is greater in small cap stocks, it averages 0.30% in large stocks which is significantly different from zero.

is only lower than the returns to the momentum portfolios (UMD) of 0.66%, but higher than the FF five factors. The equal-weighted volume premium is higher at 0.68%. The volume premiums also demonstrate strong cyclical patterns. The average value-weighted premium is 1.02% during the 83 months of economic recessions. The average is lower at 0.46% in the expansionary periods.

Panel B of Table 1 reports the summary statistics for the ten one-way volume-sorted portfolios. The returns generally increase from low to high deciles, with a spread of 0.48%. The alphas of the FF five factors show similar patterns. It is clear that the return anomaly comes from both long and short legs of the arbitrage portfolio. In the Internet Appendix Table A7, we report the summary statistics for the equal-weighted volume portfolio returns. The estimated high minus low spread is 1.26% and is reasonably close to the 20-day holding period returns of 1.12% for similarly constructed portfolios by Kaniel, Ozoguz, and Starks (2012, Table 2).

Chordia and Swaminathan (2000) attribute the volume-return relation in daily and weekly data to the differential speed of adjustment by individual stocks to market-wide information. Unlike Chordia and Swaminathan (2000), we examine shocks to trading volume. We also measure the high volume return premium at a monthly frequency which should mitigate the short-run cross-autoregression effect on which Chordia and Swaminathan (2000) focus. To confirm this, we plot in Figure 1 the post-formation daily cumulative return differences between the top and bottom deciles of the volume portfolios. Most of the return spread occurs in the first seven days of the month subsequent to the portfolio formation. The spread remains largely the same without evidence of vanishing through the end of the month. This result suggests that the differential speed of adjustment hypothesis does not hold well for returns related to shocks to the trading volume.

4. The predictive power of the high volume return premium for economic activities

In this section, we examine whether the high volume return premium (HVP) contains information that is related to future industrial production growth and three other economic indicators using the predictive Regression (1) with and without controlling for other predictive variables.

4.1 Univariate regression results

Panel A of Table 2 reports the results of Regression (1) for the growth rate of industrial production. The only predictive variable used in this part of the analysis is the high volume return premium (HVP). Each entry in the table is the point estimate of the coefficient associated with the lagged HVP (β) and its HAC t-statistic when the predictive horizon h is equal to one or Hodrick's (1992) adjusted-t statistic for $h > 1$.

In the first step of our investigation in Panel A, we study the volume premium's one-step-ahead predictive power ($h = 1$). The results indicate that the value-weighted volume premium (HVPVW) is a strong predictor of future industrial production growth. The relationship is highly significant. The point estimate of −0.052 implies that a one-standard-deviation increase in the volume premium (1.75% from Table 1) in the current month is associated with a decrease of 9.2 basis points of industrial production growth in the next month. This effect is not trivial as it is equivalent to 45% of the average growth rate of industrial production during the sample period (i.e., 0.21%). The volume premium continues to hold significant predictive power for industrial production growth up to nine months. The second column indicates a similar pattern for the predictive power of the equal-weighted volume premium for all horizons considered.

We also evaluate the predictive power of the volume premium using a sub-sample that ends in December 2007. By excluding observations from the recent financial crisis and the ensuing great economic recession, we investigate whether the above findings remain robust in the pre-crisis period. The unreported results are very similar to the full-sample estimates.

4.2. Multivariate regression results

Previous studies have found a number of economic and financial variables to have predictive power for future economic activities. In this subsection, we investigate whether the predictive power of the high volume return premium for industrial production can be captured by these known variables. Table 3 summarizes the results of various specifications of Regression (1) for the value-weighted return premium (HVPVW). For ease of comparison, the univariate regression results are reproduced in the first column of Table 3 and named as Specification I.

In Specification II, we control for the effects of Fama and French's (1993) three factors (MKT, SMB, and HML) and Carhart's (1997) momentum factor (UMD). Griffin, Nardari, and Stulz (2007) present strong evidence of many stock markets exhibiting a significant positive relation between turnover and past returns. By including the momentum factor, we control for any possible confounding effect of this dynamic relationship on detecting the predictive power of the volume premium. Clearly, the addition of the four equity factors into the predictive regression does not change the results reported under the univariate Specification I. The results also indicate that the market portfolio (MKT) and the size premium SMB predict economic growth.

In Specification III, the predictive power of the volume premium is evaluated by controlling for Fama and French's (1993) three factors and the liquidity factor (premium) UIML. The predictive power of the volume premium remains as strong as in Specifications I and II. In contrast, the liquidity factor does not have any incremental predictive power. Note, that in unreported results, we also find UIML to have no significant predictive power in a univariate regression. When replacing UIML in

Specification III with the other liquidity premium IML, we find that the point estimate for the alternative liquidity effect IML is 0.024 with a *t*-value of 1.12. In unreported results, unlike UIML, IML is a significant predictor in a univariate regression. Overall, the result of IML is largely consistent with Næs, Skjeltorp, and Ødegaard (2011) who find that an increase in market-wide illiquidity predicts future economic growth. To further evaluate the similarity or lack thereof between the volume premium and the liquidity effect, we also estimate the predictive power of two other measures of liquidity, the liquidity measure of Pástor and Stambaugh (2003) (LIQ) and innovations in LIQ (ULIQ). Table A8 of the Internet Appendix summarizes the results. Briefly, unlike UIML, both liquidity measures of Pástor and Stambaugh (2003) show significant predictive power. Nonetheless, the inclusion of these two measures does not fully capture the predictive power of the volume premium.

The set of control variables in Model Specification IV of Table 3 is the FF five factors. The results indicate that the information captured in the FF five factors is largely orthogonal to what is captured in the volume premium for the purpose of predicting industrial production growth.

The controls in Specification V include the set of four popular business cycle variables: the dividend-price ratio (DP), the default premium (DEF), the term spread (TERM), and the short-term interest rate (TB). Three of the four business cycle variables, DEF, TERM, and TB, show strong predictive power. The adjusted-R^2 increases by 6% over the previous specifications. Interestingly, despite the strong effects of the control variables, the volume premium still retains valuable information for predicting industrial production growth. The point estimate of β is −0.041 and the associated *t*-value is −2.58. The controls in Model Specification VI are the same as those of V except that we further include a macro-index (CATFIN) of Allen, Bali, and Tang (2012). Noticeably, CATFIN shows strong predictive power for industrial production growth. The R^2 of the augmented model increases by almost 6% over Specification V. It appears that the inclusion of CATFIN does not significantly replace the predictive power of the four business cycle variables. It does, however, capture some economic content of the volume premium. The coefficient of HVPVW decreases to −0.036 with a *t*-value of −2.30.

In the last column of Table 3 (Specification VII), we control the effects of the FF five factors, the four business cycle variables, and the systemic risk factor CATFIN. The predictive power of the volume premium is very similar to that in Specification VI.

Internet Appendix Table A9 summarizes the performance of the equal-weighted high volume return premium. In all of the comparable model specifications, the equal-weighted premium exhibits predictive power very similar to that of the value-weighted premium. Overall, we find predictive power of the high volume return premium for future industrial production growth which persists in different model specifications. The predictive power of the volume premium is largely independent of the six other popular portfolio returns. In comparison, it is more linked to that of the four business cycle variables and the Allen, Bali, and Tang's (2012) financial systemic risk factor.

4.3. Additional results from multivariate regressions

In addition to the results presented in Table 3, we also consider three other variables that previous studies have found to predict stock returns. These three variables are Baker and Wurgler's (2006, 2007) investors sentiment (INV_SNT), the realized monthly variance of excess returns to the aggregate stock market portfolio (MKT_VAR) defined as the sum of squared daily returns in a month, and market volatility (MKT_VOL) expressed as the square root of the market variance. The results are reported in the lower half of Table A8 of the Internet Appendix. The point estimate and its estimation precision of the predictive power of HVP is not affected when the index of investors sentiment is used as a control variable. In addition, when modeled together with the realized market variance or market volatility, the volume premium loses about one third of its predictive power. The HAC *t*-statistic also reduces to 2.28 and 2.23, respectively, in the two bivariate predictive regressions.

As previously mentioned, in specifying Regression (1) to study the predictive power of the high volume return premium HVP, we have closely followed the literature (Liew and Vassalou, 2000; Cooper and Priestley, 2011). However, the volume premium may reveal predictive power for industrial production growth (IP) for two different reasons. First, the dependent variable IP is serially correlated with a coefficient of 0.33 (see Table A6). HVP_{t-1} helps predict IP_t because HVP and IP are contemporaneously correlated and HVP_{t-1} simply picks up the lagged effect of IP (i.e., IP_{t-1}). Second, HVP_{t-1} contains information to predict IP_t that is independent of IP_{t-1}. To distinguish between these two hypotheses, we examine the volume premium's predictive power in the standard Granger causality framework by including a lagged term of the dependent variable in the predictive Regression (1). The coefficient associated with the value-weighted HVP_{t-1} remains significant at the 2% level, although the point estimate reduces from the benchmark −0.052 to −0.041 in the augmented model. The point estimate for the equal-weighted HVP reduces from the benchmark −0.064 to −0.048. But, again, the estimate is still significant with a *p*-value of 0.014.

As mentioned earlier in Section 3, the average volume premiums are higher in the recessionary months than in the expansionary months of the business cycles. In a variant of the univariate model (Specification I in Table 3), the predictive power of the volume premium is separately evaluated for the two different stages of business cycles. In the recession periods, the point estimate of β is −0.085, which is larger in magnitude than the benchmark pooled regression estimate of −0.052. In contrast, β is much smaller (−0.011) and statistically insignificant in the expansion months.

Throughout the paper, we examine the predictive power of the abnormally high volume effect by the volume premium. Motivated by Akbas, Genc, Jiang, and Koch (2017), we also compute an aggregate measure of abnormal trading volume and evaluate its predictive power for industrial production. The Internet Appendix Section D and Table A10 summarize the main results. We find that all of the results in Tables 2-3 remain intact when the volume premium is replaced with the aggregate measure of abnormal trading volume.

4.4. Out-of-sample evidence

To evaluate predictive power of the volume premium for industrial production growth using out-of-sample regressions, we obtain one-step-ahead forecasts from four specifications of Regression (1): R, U, R+Z, and U+Z. The first model considered is one with a constant (the R model). The U model includes one-period lagged volume premium. The other two models, (R+X) and (U+X), are obtained by augmenting R and U with the set of four business cycle variables, DP, TERM, DEF, and TB.[10] In Panel A of Table 4, we consider a rolling sample size of 20 years. The ratio of post-sample predictions over in-sample observations (O/I) is 1.7. The root mean squared forecast errors (RMSFE) are normalized by those of the restrictive model R. A value below one indicates that the model produces smaller forecast errors than the benchmark R model. The panel indicates that the U model including past volume premium generates smaller forecast errors. Going beyond simple RMSFE measures, we make formal statistical inferences by implementing Clark and McCracken's (2001) ENC-NEW encompassing test. The null hypothesis, that forecasts generated by the R model encompass those of the U model, is rejected. Therefore, the current volume premium contains information that is useful for forecasting the future growth rate of industrial production. When the business cycle variables are controlled in both the R and U models, the restricted (R+X) model has smaller average forecast errors than the unrestricted (U+X) model. However, the encompassing test results suggest that the volume premium still captures valuable information even after the common business cycle variables are conditioned on. Because model estimation and out-of-sample forecasts

[10] In all cases, one-period lagged dependent variable is included which significantly improves out-of-sample forecasting performances of all four models.

may be sensitive to the choice of initial sample sizes, the analysis in Panel A is repeated in Panel B with the in-sample size increased to half of the entire sample so that the O/I ratio is one. The two encompassing tests indicate that the volume premium contains important information for forecasting industrial production growth whether or not the four business cycle variables are controlled for in the regressions.

4.5 The predictive power of the volume premium for other economic indicators

This study has focused on the growth rate of industrial production as the indicator of economic activities. Here, we briefly report the results of the volume premium's predictive power for three other indicators, the Chicago Fed National Activity Index (CFNAI) and the growth rates of aggregate corporate earnings (ERN) and nonfarm payroll employment (PAYROLL). Panels B, C, and D of Table 2 present the univariate regression results. The evidence is generally consistent with that in Panel A of the table for industrial production (IP). The volume premium predicts CFNAI at the 10% level when $h = 1$. The significance level improves to 5% at $h = 3$. However, the predictive power is no longer significant even at the 10% level at the 12-month horizon. The evidence of predictability is more marginal for corporate earnings and nonfarm payroll employment when $h = 1$. However, the volume premium shows significant predictive power for both indicators at the longer horizons.

We also investigate to what extent the predictive power of the volume premium can be explained by the other control variables. The results of the multivariate regressions are reported in Table A11 for $h = 3$ when the volume premium indicates significant predictive power for all three indicators in the univariate regressions. Given the evidence in Table 3 for industrial production and to save space, we only report two model specifications for each indicator, one including HVPVW and the four business cycle variables, and the other further including Allen, Bali, and Tang's (2012) systemic risk factor CATFIN. Note that CFNAI is standardized to have zero mean and unit variance. Thus, we use the simple sum of values at month (t + 1), (t + 2), and (t + 3) for y_{t+3} in the regressions, which is equivalent to using the three-month moving average index reported by the Chicago Fed. Two results are worth mentioning. First, the volume premium retains statistically significant, although quantitatively smaller, predictive power for the overall economic activity index CFNAI and aggregate corporate earnings (ERN) after either the set of four variables and/or the systemic risk factor CATFIN are controlled for in the regressions. In addition, in the same regressions, CATFIN demonstrates strong additional predictive power for both CFNAI and PAYROLL, but not for ERN.

5. Testing risk-based explanations

After demonstrating the time series evidence on the predictive power of the high volume return premium for economic activities, we further test whether a risk-based explanation is possible for the premium. We first examine whether abnormal trading volume (shocks to trading volume) is cross-sectionally correlated with many well-known stock/firm characteristics that also forecast cross-sectional stock returns. We then study, within the framework of bivariate portfolio analysis, whether the volume effect is related to the price effects of liquidity and the idiosyncratic volatility of individual stocks, as well as their exposure to market risk, changes in market volatility, default spread, and macroeconomic uncertainty. In the third subsection, using standard factor regressions, we test whether the volume premium can be explained within a rational asset pricing framework and whether the cross section of the volume premium is connected to macroeconomic factors.

5.1. Cross-sectional relation between abnormal trading volume and stock characteristics

We study the following stock-level cross-sectional regression model:

$$\tau_{i,t} = \gamma_{0,t} + \gamma_{1,t} Z_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where $\tau_{i,t}$ is stock i's abnormal trading volume percentile at the end of month t over its previous 50-trading days, and $Z_{i,t}$ is a set of firm/stock-specific characteristics observable at t that can also predict future cross-sectional returns. Following Bali, Brown, and Tang (2017) and many others, we include in $Z_{i,t}$ the market beta (β^{MKT}), exposure of stocks to change in aggregate stock market volatility that is proxied by CBOE's VXO (β^{VXO}), the size (SIZE), the book-to-market ratio (BM), momentum (MOM), the short-term reversal (REV), the coskewness measure of Harvey and Siddique (2000) (COSK), the annual growth rates of total assets (IAg) and the operating profitability (REQ). Details are provided regarding the construction of these characteristic variables in Section E of the Internet Appendix.

Model (3) is estimated for each month t. Table 5 summarizes the time series averages of the slope coefficients. The result in Column (1) suggests that the average of the slope estimates associated with the market beta (β^{MKT}) is negative, but statistically insignificant. Since higher volume predicts greater returns in the next month, the negative sign between volume and β^{MKT} implies that stocks with lower (higher) market beta perform better (worse) in the next month. The latter result has been reported by Frazzini and Pedersen (2014) and Bali, Brown, and Tang (2017). Column (2) indicates that the slope estimate for stocks' exposure to change in market volatility (β^{VXO}) is positive, suggesting that market volatility is priced positively. Similarly, the average slope on idiosyncratic volatility (IVOL) is positive and statistically significant (Column 9) suggesting that stocks with high idiosyncratic volatility tend to be high volume stocks and have higher expected returns. The positive relationship between IVOL and future returns is consistent with the finding of Fu (2009) and Huang, Liu, Rhee, and Zhang (2010). As reported in Columns (3) and (4), firms of small caps or high book/market ratios tend to experience high volume and expect to perform better in the next month. The results are consistent with the finding in the literature (Fama and French, 1993). However, only the book/market effect is statistically significant.

Both momentum (Column 5) and short-term reversal (REV in Column 6) are negatively correlated with abnormal trading volume over the sample period. The illiquidity (ILQ) of a stock is also negatively correlated with trading volume in line with our later findings regarding the relationship between the high volume return premium and the illiquidity premium (Table 8). The average slope estimate on coskewness (COSK in Column 8) is negative and significant suggesting that returns of stocks experiencing abnormally high volume shocks are more likely to be negatively skewed. Because high volume stocks generate higher future returns, the result on coskewness is consistent with the central findings of Harvey and Siddique (2000) that stocks with high coskewness with the market generate lower future returns.

The negative slope on total asset growth (IAg) in Column 10 indicates that high volume stocks also tend to be stocks whose book assets grow slowly. This empirical result is potentially in agreement with earlier findings that low asset growth stocks generate high expected returns (Berk, Green, and Naik, 2004). The negative slope on quarterly profitability (REQ) implies that stocks in the high volume categories are more likely to report lower operating profits in past quarters. It is worth noting that we exclude stocks from the volume-sorted portfolios if the portfolio formation days fall in the three-day windows of the earnings announcement.

Finally, all of the above risk factors and stock characteristics are included in the regression of volume percentiles. The results are reported in the last column of the table. While the signs and magnitude of most slope estimates are similar to their univariate counterparts, there are some noticeable changes. The slope on the market beta turns statistically significant. The slope estimate of

SIZE switches sign but remains statistically insignificant. After controlling for other firm characteristics, coskewness and operating profitability are no longer significant.

5.2. Bivariate portfolio-level analysis on abnormal trading volume and other stock return predictors

As a compliment to the above stock-level regression analysis, we conduct a bivariate portfolio-level analysis on the relationship between abnormal volume and future returns while controlling for other stock return predictors. The advantage of portfolio-level analysis is that it does not impose a functional form on the relationship we seek to uncover (Bali, Brown, and Tang, 2017). We first examine what roles, if any, the price effects of liquidity and idiosyncratic volatility play in explaining the volume premium. Because investors can trade for different reasons, and hence liquidity has many dimensions. It can be argued that, although the high volume return premium and the traditional liquidity premium are likely correlated with each other as both are related to the volume of trade, they may each capture different aspects of the price information of trade.

Panel B of Table 6 reports the monthly returns to nine portfolios based on two independent sorts on shocks to Amihud's (2002) measure of illiquidity (UILQ) and abnormal trading volume (recall from Footnote 3 that the measure of trading volume is actually a measure of shocks to volume). Noticeably, the volume effect is present within each liquidity category. Also importantly, there is no monotonic relation between the size of the volume premium and the size of UILQ. The FF five-factor alphas are smaller than the raw returns but remain strongly significant. The last row of Panel B suggests a negative relationship between shocks to illiquidity and future returns in all three trading volume categories, consistent with the findings of Bali et al. (2014) and Han and Huang (2018).

Previous studies have suggested that trading volume could relate to volatility (Campbell, Grossman, and Wang, 1993). Thus, we assign stocks into nine portfolios by two independent sorts on abnormal trading volume and idiosyncratic volatility (IVOL). Idiosyncratic volatility is estimated as the properly scaled sum of within-month squared daily returns filtered by Fama and French's (1993) three factors. Panel C in Table 6 reports that after controlling for idiosyncratic volatility, the volume premium becomes smaller in all three IVOL categories than the unconditional estimate of 0.53%. Nevertheless, the volume effect exists in all three cases. Furthermore, it tends to be higher in stocks experiencing low or neutral volatility shocks and lower in stocks experiencing large and positive volatility shocks. The FF five-factor alphas display similar patterns.

The last row of Panel C Table 6 indicates that price effects of idiosyncratic volatility persist after controlling for the volume effect. In particular, stocks with low idiosyncratic volatility, on average, have higher future returns than stocks with high idiosyncratic volatility consistent with the findings of Ang, Hodrick, Xing, and Zhang (2006). In Panel D, we examine the relationship between trading volume and shocks to idiosyncratic volatility (UIVOL), where UIVOL is the difference between the current month IVOL estimate and the average of the estimates for the previous 12 months. Similar to the findings in Panel C for different levels of idiosyncratic volatility, the volume premium also decreases with shocks to idiosyncratic volatility UIVOL. Overall, the results in Table 6 suggest that the volume effect and the volatility effect are distinct. So are the volume effect and the liquidity effect. As robustness checks, we also study another measure of liquidity (Fong, Holden, and Trzcinka, 2017) and other measures of (shocks to) idiosyncratic volatility. The results are reported in the Internet Appendix Section F and Table A12, which show that our main results from Table 6 still hold.

In Table 7, we further investigate whether the high volume premium persists after controlling for some other cross-sectional return predictors through bivariate portfolio-level analysis. Specifically, at the end of each month, stocks are assigned into nine portfolios with two sorts on abnormal trade volume and one of the following four beta measures: market beta (β^{MKT}), market volatility beta (β^{VXO}), the default spread beta (β^{DEF}), and the macroeconomic uncertainty beta (β^{UNC}). We use the common macro uncertainty index (UNC) of Jurado, Ludvigson, and Ng (2015) as a proxy for macroeconomic uncertainty that uses information in hundreds of macroeconomic and financial indicators. Market beta (β^{MKT}) has been defined earlier. The three other betas are estimated from the following bivariate regression that also controls for the market factor:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \beta_i^X X_t + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ is excess returns to stock i on time t and $R_{M,t}$ is excess returns to the market, $X_t \in \{\Delta VXO_t, DEF_t, UNC_t\}$. β^{VXO} is estimated with within-month daily data while β^{DEF} and β^{UNC} are both estimated using 60 monthly observations.

For the purpose of comparison, in Panel A of Table 7, the FF five-factor alphas of three portfolios sorted solely on abnormal trading volume are tabulated. In addition, the alphas are estimated for three sample periods to match the availability of VXO and UNC. Panel B of Table 7 reports the alphas for the nine value-weighted portfolios formed by two sorts on abnormal volume and market beta. Within each market beta category, the alphas increase from negative to positive. Noticeably, the alphas of the portfolios with low and medium market betas are both statistically significant and close to each other in magnitudes. In contrast, the alpha of stocks with large positive market beta is smaller. This latter result is consistent with the earlier findings based on stock-level regressions in Table 5. Fama (1996) also argues that the sign of the market risk premium in the intertemporal CAPM (ICAPM) world can be negative if the market portfolio serves as a hedge against state variable risk. The last row of Panel B reports the FF five-factor alphas for the three volume-sorted portfolios averaged across the market beta (β^{MKT}) terciles (mean absolute alphas, or m.a.a). Compared to the results in Panel A, controlling for market beta reduces the alphas of the medium and high volume portfolios, but increases that of the low volume portfolio.

In Panel C, the stocks are sorted by abnormal trading volume and market volatility beta (β^{VXO}). The last column "(H – L)" of the panel indicates that the alphas of the volume premiums increase with the market volatility beta suggesting the high volume premium captures some of the cross-sectional return predictive power of market volatility. Nevertheless, it is worth noting that these estimates are based on a much shorter sample period and none of the three alphas are statistically significant at the 5% level.

As robustness checks, in bivariate analysis, we replace the control factor market volatility with default spread (DEF) to follow Bali (2008) and with macro uncertainty (UNC) to follow Bali, Brown, and Tang (2017). Panel D reports the results for portfolios sorted on trading volume and DEF beta. The alphas of the "(H – L)" strategies are similar for the low and medium DEF beta stocks. Both are larger than that of the high β^{DEF} stocks. However, there is no clear link between the high volume premium and exposure to default risk as the average alphas in the bottom row are larger than their counterparts in Panel A. The results in Panel E indicate that, while the alpha spread between high and low volume stocks is smaller for the high uncertain beta stocks than for the low β^{UNC} stocks, it is the largest for stocks with medium uncertain betas. However, controlling for exposure to the macro uncertainty risk does reduce the alphas to various degrees for the three volume portfolios.

5.3. Factor regressions of the volume premium on common risk factors and the macroeconomic factors

5.3.1 The volume premium and common (risk) factors

Panel A of Table 8 presents the factor regression results regarding the relationship between the high volume return premium and common risk and equity return factors. We begin with a one-factor model quantifying the relationship between the volume premium and the liquidity premium IML. As noted earlier, IML is based on portfolios formed on levels of the illiquid measure of Amihud (2002). The results demonstrate that the liquidity premium is weakly correlated with the volume premium in that the loading $\hat{\beta}_{IML}$ is significant at the 10% level. In the second one-factor model (Model II), we estimate the explanatory power of the other measure of the liquidity premium UIML which is based on shocks to illiquidity. UIML performs better than IML in explaining the volume premium. The coefficient of UIML is strongly significant at the 1% level. However, the alternative measure of liquidity premium UIML only accounts for a fraction of the variation of the volume premium with an R^2 of 3.39%. The unexplained component of the volume premium (alpha) is 0.45% which is smaller than the total volume premium (0.53% from Table 1) by a small margin of 0.09%. The results from the two one-factor models suggest that the volume premium captures additional information that is not shared by the liquidity premiums. These results are consistent with earlier findings reported in Table 6 based on intuitive bivariate portfolio sorting.

Because neither of the two liquidity premiums, IML and UIML, can fully explain the benchmark value-weighted volume premium and UIML performs better than IML, in the rest of this subsection, we investigate whether the volume premium can be explained by other common equity return factors in addition to UIML. The first multi-factor model considered is Carhart's (1997) four-factor model. The results under "Model III" in Table 8 indicate that the alpha is large (0.53%) implying that the four-factor model also fails to account for the volume premium. In the next two multivariate regressions, we augment the better performing UIML with FF five factors in Model IV and Hou, Xue, and Zhang's (2015) four factors in Model V. The unexplained component of the volume premium becomes smaller in both cases, but remains statistically significant. The alpha is 0.38% in Model IV, and 0.42% in Model V.

Lastly, in Model VI, we include the FF five factors, the liquidity premium UIML, and returns to a mimicking portfolio (MPR). The mimicking portfolio tracks news related to future industrial production growth and can be interpreted as the industrial production risk factor. This new variable is motivated by the results in Section 4 that the volume premium predicts industrial production growth independent of many other factors. To form the mimicking portfolio, we closely follow Vassalou (2003) who employs the approach when examining the economic content of the value and size premiums.[11] Section G of the Internet Appendix provides details regarding the portfolio construction and a qualification test of the mimicking portfolio as a proxy for news related to future industrial production growth (Table A13).

By including the industrial production risk factor MPR, Model VI in Table 8 has an adjusted-R^2 of 10.2% that is noticeably higher than the 6.4% of the six-factor Model IV. However, the improvement is minimal in terms of alpha. The alpha estimate slightly decreases from Model IV's 0.381% to 0.367% and continues to be significantly different from zero. Quantitatively, this seven-factor model only explains about one-third of the total volume premium. Finally, from the last column of Table 8, the volume spread loads significantly on the IP risk factor MPR, UIML, SMB, HML, and RMW, but not MKT and CMA.

5.3.2. The volume premium spread and Chen, Roll, and Ross' (1986) factors

Given that the common risk factors cannot satisfactorily explain the volume premium, in this section, we explore a slightly different issue. The investigation examines whether a set of macroeconomic factors are able to describe the volume return spread. Following Liu and Zhang (2008) and Cooper and Priestley (2011), we use five Chen, Roll, and Ross's (1986) (CRR) factors as proxies for the macroeconomic factors. The five CCR factors include the growth rate of industrial production (IP), unexpected inflation (UI), the change in expected inflation (DEI), the term premium (TERM), and

[11] Engle, Giglio, Lee, Kelly, and Stroebel (2019) recently use a similar mimicking portfolio approach based on a large panel of equity returns to build climate change hedge portfolios that extract innovations from climate news. In Section 5.3.2, we consider another implementation of the mimicking portfolio approach.

the default premium (DEF). Because using factor-mimicking portfolios delivers sharper estimates of factor loadings than the five macro factors themselves, following Cooper and Priestley (2011) and references therein (especially Eckbo, Masulis, and Norli, 2000), we study the pricing power of the five portfolios mimicking these five macro factors. To form the mimicking portfolios for the five CRR factors, 40 equity portfolios are used as base assets including 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. Section G of the Internet Appendix provides a description of the construction of the five mimicking portfolios.

Panel A of Table 9 reports the adjusted-R^2 for each of the ten deciles of the volume-sorted portfolios. In all cases, the R^2s are higher than 90% with an average of 94%.[12] Panel B tabulates the loadings of the ten equal-weighted portfolios with respect to the five mimicking portfolios. The ten time series regressions are jointly estimated in the form of a seemingly unrelated regression (SUR) so that the covariance of the loadings across deciles is available for use later in Table 10.[13] The loadings on the IP factor generally increase from the low to high volume deciles with a range between 0.29 and 0.34. The upward trend is also evident in loadings on unexpected inflation (UI), the term premium, and the default premium. In contrast, loadings on the change in expected inflation (DEI) decrease from the low to high volume deciles.

In Panel A of Table 10, we estimate risk premiums for the five CCR factors using Fama and MacBeth's (1973) two-step procedure. The test assets are the above 40 equity portfolios. As before, the

[12] However, as Lewellen, Nagel, and Shanken (2010) note, asset pricing tests as commonly practiced can be misleading because apparently strong explanatory power (such as high R^2) provides only weak support for a model.
[13] Unlike the predictive analysis in the previous section, here we focus on the equal-weighted volume portfolios where the volume effect manifests itself more clearly than in the value-weighted portfolios. As expected, both loadings on the economic factors and their spreads across the volume deciles are smaller for the value-weighted portfolios.

mimicking portfolios rather than the economic factors themselves are used in the estimation. We use full sample observations to estimate the factor loadings in the first stage regressions. The five factor risk premiums estimated from the second stage cross-sectional regressions are provided in Panel A of Table 10 along with their Shanken's (1992) corrected *t*-values.[14] The estimates for the IP, TERM, and DEF factors have the same signs and the same order of magnitude as in Table 4 of Cooper and Priestley (2011). Briefly, the premiums are positive for IP and the term spread, but negative for the default spread. The factor premiums are negative for both inflation related factors although the estimate for the change in expected inflation (DEI) is only marginally significant. Next, in Panel B, we calculate the expected returns of the lowest and the highest deciles attributable to each of the five CCR factors. The expected returns are computed as the product of the loadings (from Table 9) and the corresponding factors' risk premiums. The predicted returns to the first and the tenth deciles due to their exposure to the industrial production factor are 0.40% and 0.48%, respectively. The spread is 0.08% or about 1% per annum with an HAC-adjusted *t*-value of 1.41.[15] Exposure to the two other factors, changes in expected inflation and the term spread, also go the right way in driving positive premium spreads between the high and low volume deciles. Quantitatively, they predict positive volume spreads of 0.04% and 0.08%, respectively. In contrast, the predicted spreads are negative (both at −0.06%) due to the portfolios' exposure to the unexpected inflation (UI) and the default spread (DEF). Overall, exposure to the five CCR economic factors combines to predict a mere 0.08% of the monthly return spread, much smaller than the observed spread of 1.26% in Panel B of Table A7.

[14] Since the five mimicking portfolios are all tradable assets, the simple estimates of the factor risk premiums are the sample averages of the portfolio returns: 1.48%, −0.15%, −0.04%, 1.00%, and −0.34%. Here, we follow Cooper and Priestley (2011) and estimate the factor risk premiums using Fama and MacBeth's (1973) two-step procedure. Note that the estimated risk premiums reported in Table 10 are, in general, close to the simple sample averages.

[15] The risk premiums of the five CCR factors and the loadings of the volume deciles on the factors are estimated separately from two systems. In estimating the variance of the premium spread, *dif* in the third row of Panel B in Table 10), it is assumed that the two estimates are independent. By ignoring a covariance term, the variance estimates are likely to be biased. The direction of the bias depends upon the sign of the correlation between the risk premium and the loadings.

6. Testing behavior/mispricing explanations

As previously discussed, earlier studies provide explanations for the volume effect along the lines of mispricing and investor recognition/attention. In this section, we evaluate this alternative hypothesis. Specifically, we examine whether the high volume return premium reduces after controlling for the mispricing factors of Stambaugh and Yuan (2017) and the behavioral factors of Daniel, Hirshleifer, and Sun (2019).

By combining information across 11 prominent anomalies, Stambaugh and Yuan (2017) construct two factors, MGMT and PERF. The former captures common elements of mispricing in net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. PERF arises from five other anomalies: distress, O-score, momentum, gross profitability, and return on assets. Professor Robert Stambaugh's website at Wharton provides these two factor returns and a stock-level mispricing measure we use later. The two behavioral factors of Daniel, Hirshleifer, and Sun (2019) are PEAD and FIN. The post-earnings announcement drift anomaly (PEAD) captures short horizon mispricing, while the financing factor FIN, based on share issuance, captures long horizon mispricing. The two behavior factors are available at Professor Kent Daniel's personal website http://www.kentdaniel.net/data.php. The sample start date is July 1972.

Panel B of Table 8 summarizes the time series regressions of the high volume return premium on the factors studied in the above four- and three-factor models. Noticeably, the volume premium loads positively and significantly on MGMT, but not on the other mispricing factor PERF. This result is not surprising. MGMT arises from anomalies including investment and PERF from anomalies including gross profitability. As shown earlier in Model VI of Table 8, it is the investment factor, not the profitability factor that relates to the volume premium. There is also some evidence that the volume premium loads on FIN, but not on the other behavioral factor PEAD. Overall, both non-risk-based models generate large and strongly significant alphas, 0.45% and 0.48% (recall that the volume premium is 0.53%). Their performances are poorer than those of the augmented Hou, Xue, and Zhang (2015) model and the two variants of Fama and French's (2015) model in Panel A of Table 8.

In the last three columns of Panel B in Table 1, we report alphas of the ten volume sorted portfolios relative to Fama and French's (2015) five-factor model, Stambaugh and Yuan's (2017) four-factor model (MKT, SMB, MGMT, and PERF), and Daniel, Hirshleifer, and Sun's (2019) three-factor model (MKT, PEAD, and FIN). Noticeably, the FF alphas are significant at both legs of the arbitrage portfolios, which rules out the possibility that costly arbitrage (or illiquidity) can explain the high volume return premium. The Stambaugh and Yuan (SY) alphas and Daniel, Hirshleifer, and Sun (DHS) are negative but statistically insignificant for Decile 1 while they are positive and economically and statistically significant for Decile 10. Hence, the SY and DHS alphas suggest that trading volume related return predictability is mainly driven by the long leg of the arbitrage portfolio. This evidence casts further doubt on the importance of the behavioral explanation for the high-volume return premium.[16]

To shed more light on the mispricing based explanation, we investigate whether the high-volume premium in underpriced stocks is different than that in overpriced stocks by forming portfolios based on a bivariate sort on abnormal trading volume and the mispricing measure (MISP) of Stambaugh, Yu, and Yuan (2015). According to Stambaugh, Yu, and Yuan (2015), at the end of each month stocks are ranked independently based on the above-mentioned 11 return anomalies where a

[16] Hou, Xue, and Zhang (2019) investigate 452 equity market anomalies and find that most of these anomalies are significant due to microcaps. In responses to their findings, we repeat the exercises in Tables 1 and 8 using a subsample of stocks whose market capitalizations are larger than the 20th NYSE size percentile. We find that removing microcap stocks does not significantly reduce the high volume return premium. The new value-weighted volume premium is 0.496% with a *t*-value of 6.717. The FF, SY, and DHS alphas are 0.410%, 0.390%, and 0.429%, respectively. The associated *t*-statistics are 5.776, 4.844, and 3.917, respectively. The impact is also small on the alpha spreads for the ten one-way volume sorted portfolios. The FF, SY, and DHS alpha spreads between Deciles 10 and 1 are 0.375%, 0.405%, and 0.446%, respectively. The associated *t*-values are all bigger than two.

higher rank is assigned to the value of the anomaly variable associated with lower one-month-ahead stock returns. The mispricing measure (MISP) is then defined as the arithmetic average of the ranks of the 11 anomalies. Under this definition, higher (lower) MISP score indicates a stronger overvaluation (undervaluation). Therefore, if mispricing drives the high-volume premium, we expect that the alpha spreads of the volume sorted portfolios vary across stocks of different mispricing scores. The results in Table 11 do not support this prediction. In Panel A, the volume-sorted return spread is 0.43% in low MISP stocks and 0.48% in high MISP stocks. The difference is 0.05% per month with a *t*-statistic of only 0.34. The spread is smaller in medium MISP stocks. However, the unreported *t*-tests suggest that it is not statistically different from the two other spreads. Panels B, C, and D show that the FF, SY, and DHS alpha spreads between high and low volume portfolios are also similar in the low and high MISP stocks. The differences are 0.09%, 0.03%, and 0.04% with associated *t*-statistics of 0.60, 0.15, and 0.25, respectively.

When compared to institutional investors, retail investors are likely to pay less attention to individual stocks due to their lack of expertise and economies of scale in gathering information (Barber and Odean, 2008; Bali et al., 2014). Thus, the mispricing or investor-attention based explanation of the high volume premium would imply that the volume effect is larger in stocks that are largely held by individual investors. To test this hypothesis, we use institutional ownership as an alternative proxy for investor attention and form 15 value-weighted bivariate portfolios of the abnormal trading volume and institutional ownership. To measure a stock's institutional ownership, we define a monthly variable INST as the percentage of total shares outstanding that are owned by 13F institutions investors. Thomson Reuters Institutional Holdings (13F) database provides institutional holdings data that are available since 1980. Since institutional holdings are filed with the SEC on a quarterly basis, we use the last calendar quarter values for the next three months. Following the literature (Cremers and Nair, 2005; Bali et al., 2014; Bali, Brown, Murray, and Tang, 2017), missing values of the variable INST are replaced with zero.

Table 12 provides the summarized results. The high volume return premium is the largest in stocks with the lowest institutional ownership and smallest in stocks with the highest percentage of institutional ownership. This result is consistent with the investor-attention based hypothesis. However, the table also indicates that the FF five-factor alphas of the spreads in the last column remain large in magnitude and statistically significant for both the low and high tercile portfolios sorted on the institutional ownership. In addition, overall, the mean absolute pricing errors in the bottom of the table are not smaller than their counterparts in Panel B obtained from a one-way sort on abnormal trading volume for the same period. Thus, differences in the institutional ownership between stocks do not fully explain their differences in the volume effect.

7. Concluding remarks

The prevailing explanation for the volume effect is that it is a manifestation of Merton's (1987) investor recognition hypothesis and signals market inefficiency. Complementing the published research that has primarily focused on firm-level evidence, this study provides the first empirical evidence of the link between the volume premium and macroeconomic fundamentals. Motivated by its strong predictive power for real economy, we also evaluate a risk-based explanation for the volume premium through the lens of empirical asset pricing. A summary of the main findings follows.

First, the high volume return premium contains information that helps to predict future industrial production growth in and out of samples. A one-standard-deviation increase in the volume premium, on average, predicts a 9.2 basis-point decrease in industrial production growth in the coming month amounting to 45% of the average economic growth rate during the sample period. This basic result stands up in the face of various controls for common equity return factors and a host of business cycle variables. The volume premium does lose some predictive power in the presence of a systemic risk factor constructed by Allen, Bali, and Tang (2012).

In addition, we find some cross-sectional evidence that is potentially consistent with the risk interpretation of the volume premium. A factor tracking news related to industrial production growth contains information for pricing volume-sorted portfolios that is incremental to the common risk factors. High volume stocks are risker and command higher premiums because they load more than low volume stocks on three economic factors: industrial production, change in expected inflation, and the term premium.

However, a seven-factor model, which includes Fama and French's (2015) five factors, a liquidity factor, and the industry production risk factor, explains only one-third of the volume premium. A model of Chen, Roll, and Ross' (1986) five macroeconomic factors also performs poorly.

Overall, this study makes some progress toward providing a risk-based explanation for the high volume return premium. However, the evidence assembled in the paper is admittedly limited in that a large chunk of the volume premium cannot be explained by its co-movement with economic risk factors and equity return factors. In addition, the two mispricing-based factor models of Stambaugh and Yuan (2017) and Daniel, Hirshleifer, and Sun (2019) also fail to account for the volume premium. Identifying the sources of this return anomaly remains a great challenge from an asset pricing perspective and warrants much further research.

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Fig. 1.

Post-formation cumulative returns

This exhibit plots post-formation daily cumulative return differences between the top and bottom deciles of the volume portfolios summarized in Table 2. The ten volume portfolios are formed on abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq. The sample spans July 1963-December 2016.

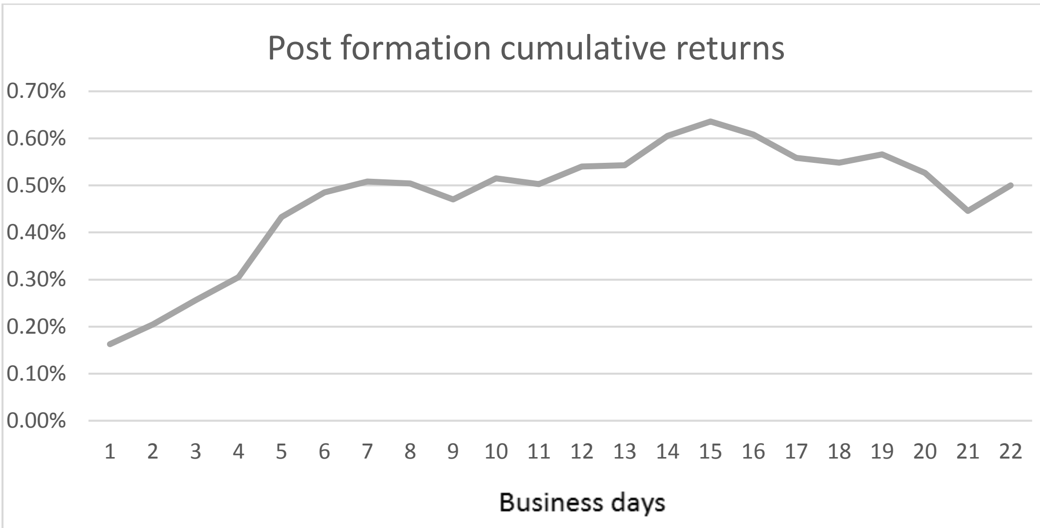

Table 1

Summary statistics of the high volume return premium and ten volume-sorted portfolio returns

The table reports the summary statistics of the monthly value-weighted high volume return premium (HVPVW), equal-weighted high volume return premium (HVPEW), and the excess returns to ten value-weighted portfolios sorted on abnormal trading volume. The two premium series are constructed based on two independent sorts on size and abnormal trading volume of stocks traded in NYSE, Amex, and NASDAQ. The means and standard deviations are both in percentage form. AR(1) is the first-order autoregression and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the Ljung-Box Q-statistic for the null hypothesis that there is no autocorrelation up to order one. "FF5" refers to Fama and French's (2015) market, size, book-to-market, investment, and profitability factors. "SY4" refers to the four factors used by Stambaugh and Yuan (2017) including market, size, and two mispricing factors (MGMT and PERF) that are constructed from a set of 11 prominent anomalies. DHS3 refers to the three factors used by Daniel, Hirshleifer, and Sun (2019) that includes market and two behavioral factors (PEAD and FIN) that capture short- and long-horizon mispricing. The significance levels of the alphas are adjusted for heteroskedasticity and autocorrelation (HAC). The sample start dates are January 1972 for investment and profitability factors, July 1972 for PEAD and FIN, and July 1963 for the remaining variables. The end dates are all December 2016.

	Mean	Std. dev.	Skew.	AR(1)	FF5 alpha	SY4 alpha	DHS3 alpha
			Panel A. The high volume return premium				
HVPVW	0.535	1.753	1.731	0.018			
HVPEW	0.683	1.548	2.445	−0.030			
			Panel B. Portfolios sorted on abnormal trading volume				
Lo 10	0.309	5.200	−0.332	0.078**	−0.173*	−0.165	−0.144
2-Dec	0.272	4.954	−0.685	0.070*	−0.179**	−0.155*	−0.159
3-Dec	0.380**	4.819	−0.581	0.113***	−0.084	−0.079	−0.084
4-Dec	0.462**	4.862	−0.685	0.074*	0.009	0.004	0.013
5-Dec	0.545***	4.622	−0.322	0.052	0.049	0.059	0.021
6-Dec	0.598***	4.699	−0.468	0.065	0.164**	0.182*	0.185*
7-Dec	0.509***	4.718	−0.465	0.054	0.073	0.061	0.012
8-Dec	0.579***	4.781	−0.501	0.047	0.064	0.082	0.097
9-Dec	0.755***	4.923	−0.070	−0.003	0.176*	0.208**	0.287*
Hi 10	0.787***	4.764	−0.092	0.028	0.269***	0.307**	0.378***
(High – Low)	0.478***	3.336	0.742	0.020	0.442***	0.472**	0.522**

Table 2

Univariate regressions of the high volume return premium as predictors of economic activities

The table summarizes results of the following predictive regression

$y_{t+h} = \alpha + \beta * \text{HVP}_t + \gamma' \text{X}_t + \varepsilon_{t+h}$,

where the dependent variable y_t is the monthly growth rate of US industrial production, the Chicago Fed National Activity Index (CFNAI), and the growth rates of aggregate corporate earnings (ERN) and nonfarm payroll employment (PAYROLL). The predictive variables HVPVW and HVPEW are the value- and equal-weighted high volume return premiums based on two independent sorts on size and the abnormal trading volume of stocks traded in NYSE, Amex, and Nasdaq. X_t is an empty set in this table. The start date of CFNAI is March 1967. The start date of all other variables is July 1963. The sample end date is December 2016. The prediction horizons are h = 1, 3, 9, and 12 months. Each entry in the table is the point estimate of coefficient β. Numbers in parentheses are the associated HAC t-statistics for regressions with h = 1 and Hodrick (1992) adjusted t-statistics for h > 2. Constant terms are omitted to save space.

	Panel A. Predictability of industrial production		Panel B. Predictability of economic activity index (CFNAI)	
Horizon (h)	Predictive variable		Predictive variable	
	HVPVW	HVPEW	HVPVW	HVPEW
1	−0.052	−0.057	−7.510	−7.891
	(−2.760)	(−2.795)	(−1.876)	(−1.715)
3	−0.115	−0.110	−21.92	−21.52
	(−3.584)	(−3.003)	(−2.348)	(−2.101)
9	−0.125	−0.169	−28.73	−30.70
	(−2.372)	(−2.944)	(−1.789)	(−2.035)
12	−0.084	−0.138	−29.70	−32.91
	(−1.297)	(−1.840)	(−1.532)	(−1.862)

	Panel C. Predictability of corporate earnings		Panel D. Predictability of nonfarm payroll employment	
Horizon (h)	Predictive variable		Predictive variable	
	HVPVW	HVPEW	HVPVW	HVPEW
1	−0.235	−0.290	−0.010	−0.013
	(−1.306)	(−1.686)	(−1.400)	(−1.560)
3	−0.924	−1.228	−0.040	−0.043
	(−3.026)	(−3.301)	(−2.856)	(−2.823)
9	−3.749	−5.676	−0.067	−0.079
	(−4.816)	(−4.997)	(−3.259)	(−3.689)
12	−3.027	−5.158	−0.080	−0.095
	(−5.267)	(−12.51)	(−3.303)	(−3.777)

Table 3

Multivariate regressions of the high volume return premium as predictors of industrial production growth

The table summarizes results of the following predictive regression

$y_{t+1} = \alpha + \beta$ *HVPVW$_t$ + γ'X$_t$ + ε_{t+1},

where the dependent variable y_t is the monthly growth rate of U.S. industrial production, the predictive variable HVPVW is the value-weighted high volume return premium based on two independent sorts on size and abnormally high 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) of Allen, Bali, and Tang (2012), and four business cycle variables [dividend-price ratio (DP), term premium (TERM), default premium (DEF), and three-month Treasury bill rate (TB)]. The start date of CATFIN is January 1973. The start date for 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 the 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	Model specifications						
variables	I	II	III	IV	V	VI	VII
HVPVW	−0.052	−0.054	−0.057	−0.054	−0.041	−0.036	−0.037
	(−2.760)	(−2.539)	(−2.666)	(−2.535)	(−2.457)	(−2.297)	(−2.174)
MKT		0.016	0.016	0.013			−0.001
		(2.272)	(2.263)	(1.782)			(−0.060)
SMB		0.018	0.017	0.019			0.016
		(1.829)	(1.646)	(1.831)			(1.261)
HML		0.013	0.011	0.020			−0.005
		(1.157)	(1.046)	(1.421)			(−0.248)
UMD		0.005					
		(0.746)					
UIML			−0.009				
			(−0.764)				
RMW				0.003			0.008
				(0.228)			(0.651)
CMA				−0.021			−0.006
				(−0.996)			(−0.246)
DP					−0.013	−0.077	−0.077
					(−0.320)	(−1.213)	(−1.197)
DEF					−0.495	−0.305	−0.320
					(−6.756)	(−3.185)	(−3.219)
TERM					0.175	0.229	0.225
					(4.993)	(5.461)	(5.600)
TB					0.044	0.073	0.073
					(2.782)	(3.444)	(3.485)
CATFIN						−0.014	−0.013
						(−4.450)	(−3.548)
Adj-R^2	1.40	2.57	2.57	2.51	9.48	15.37	15.04

Table 4

Out-of-sample forecasting performance of the volume premium for U.S. industry production

The table summarizes the out-of-sample forecasting results of the following predictive regression

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

where the dependent variable y is the monthly growth rate of U.S. industrial production, the predictive variable HVPVW is the value-weighted high volume return premium based on two independent sorts on size and abnormal trading volume of stocks traded in NYSE, Amex, and NASDAQ, and the control variable set X_t includes four market condition variables, dividend price ratio (DP), term premium (TERM), default premium (DEF), and three-month Treasury bill rate (TB). The sample covers the period from July 1963 to December 2016. We evaluate four model specifications: a restricted model with a constant (R), a model with a constant and the volume premium HVPVW (U), a model with a constant and the set of control variables X (R + X), and a model with a constant, HVPVW, and X (U + X). In all cases, a one-period lag of the dependent variable (y_t) is included to control for autocorrelation. O/I is the ratio of the number of in-sample observations over the post-sample predictions. Root mean squared forecast errors (RMSFE) of all of the models are expressed as a ratio to that of the C model. ENC-NEW is the encompassing test statistic of Clark and McCracken (2001) in which the associated null hypothesis is that forecasts from the model in the first column (H_o) encompass those from the model in the second row (H_A). Under the null hypothesis, the H_o model is preferred to H_A. The critical values of the ENC-NEW test are obtained (in the case of P/R = 1) or linearly interpolated (in the case of P/R = 1.7) from the unpublished appendix of Clark and McCracken (2001). The symbols ** and *** denote significance at the 5% and 1% levels, respectively.

H_o Models	H_A Models			H_A Models		
	U	R+X	U+X	U	R+X	U+X
	Panel A. Rolling scheme, O/I = 1.7			Panel B. Rolling scheme, O/I = 1		
	RMSFE (RMSFE_R = 1)			RMSFE (RMSFE_R = 1)		
	0.9986	0.9937	0.9959	0.9979	1.0033	1.0029
	Encompassing test statistic			Encompassing test statistic		
R	3.551**	33.50***	38.97***	4.686***	60.20***	66.56***
R + X			2.896**			3.946***

Table 5

Average stock characteristics of volume-sorted portfolios

This table reports the time-series averages of the intercepts and slope coefficients of the following regressions of the volume percentiles on the stock-level characteristics and risk factors

$$\tau_{i,t} = \gamma_{0,t} + \gamma_{1,t} Z_{i,t} + \varepsilon_{i,t},$$

where $\tau_{i,t}$ is stock i's trading volume percentile at the end of month t over its previous 50 trading days, and $Z_{i,t}$ is a set of firm/stock-specific characteristics observable at t for stock i that includes the market beta (β^{MKT}), exposure to change in aggregate stock market volatility VXO (β^{VXO}), size (SIZE), the book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), the illiquidity measure of Amihud (2002) (ILQ), a coskewness measure (COSK), idiosyncratic volatility (IVOL), the annual growth rate of total assets (IAg), and operating profitability (REQ). The above cross-sectional regression is estimated on a monthly basis. The start date is January 1986 for VXO, January 1972 for IAg and REQ, and July 1963 for the remaining variables. All sample end dates are December 2016. Numbers in parentheses are HAC t -statistics. The constant terms are not reported. They are all strongly significant.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
β^{MKT}	−0.187												−1.223
	(−1.292)												(−9.933)
β^{VXO}		3.832											3.975
		(3.338)											(3.614)
Size			−0.083										0.089
			(−1.073)										(0.831)
BM				0.401									0.533
				(4.825)									(8.413)
MOM					−1.887								−1.169
					(−8.273)								(−4.921)
REV						−7.740							−3.777
						(−10.21)							(−5.320)
ILIQ							−0.325						−0.796
							(−5.362)						(−7.862)
COSK								−0.526					−0.263
								(−2.254)					(−1.202)
IVOL									2.529				2.046
									(13.78)				(17.21)
IAg										−0.407			−0.504
										(−3.628)			(−6.380)
REQ											−2.939		−0.327
											(−2.678)		(−1.219)

Table 6

Returns of stocks sorted on abnormal trading volume in combination with size, shocks to illiquidity, and shocks to idiosyncratic volatility

The table reports average monthly excess returns of value-weighted portfolios formed by bivariate sorts on size, abnormally high trading volume, shocks to Amihud's (2002) measure of illiquidity (UILQ), 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 return differences between portfolios sorted on one of these five stock characteristics. The sample spans the period July 1963-December 2016. Numbers in parentheses are HAC *t*-statistics. Idiosyncratic volatility is estimated using within-month daily returns after controlling for Fama-French three factors (market, size, and value). Shocks to idiosyncratic volatility are defined as the difference between current month volatility and the average of the previous 12-month's estimates. Shocks to illiquidity are similarly defined.

	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 abnormal trading volume & size							
Size (Small)	0.334	0.788	1.105	0.771	–0.369	0.025	0.334	0.703
	(1.374)	(3.258)	(4.626)	(10.55)	(–5.621)	(0.509)	(5.988)	(9.199)
Size (large)	0.326	0.520	0.625	0.299	–0.091	0.107	0.119	0.211
	(1.761)	(3.009)	(3.441)	(3.056)	(–1.621)	(2.552)	(1.706)	(2.108)
(Small – Large)	0.008	0.268	0.480		–0.278	–0.082	0.215	
	(0.058)	(2.046)	(3.688)		(–3.240)	(–1.307)	(3.393)	
	Panel B. Portfolios sorted on abnormal trading volume & shocks to illiquidity (UILQ)							
UILQ 1 (Low)	0.712	1.077	1.217	0.505	0.097	0.426	0.522	0.425
	(3.356)	(4.863)	(5.462)	(5.353)	(1.105)	(4.189)	(5.764)	(4.831)
2	0.451	0.672	0.760	0.309	–0.110	0.112	0.133	0.242
	(2.334)	(3.535)	(3.979)	(3.972)	(–1.832)	(2.086)	(2.123)	(3.223)
UILQ 3 (High)	–0.134	0.134	0.387	0.521	–0.714	–0.488	–0.263	0.451
	(–0.629)	(0.649)	(1.847)	(5.788)	(–6.556)	(–4.440)	(–2.208)	(4.579)
(Low – High)	0.846	0.943	0.830		0.810	0.914	0.784	
	(5.857)	(6.263)	(5.264)		(5.11)	(5.046)	(4.235)	
	Panel C. Portfolios sorted on abnormal trading volume & idiosyncratic volatility (IVOL)							
IVOL 1 (Low)	0.370	0.569	0.756	0.386	–0.159	0.078	0.179	0.338
	(2.220)	(3.713)	(4.486)	(3.731)	(–2.458)	(1.637)	(2.318)	(3.181)
2	0.415	0.601	0.823	0.408	–0.087	0.090	0.241	0.328
	(1.798)	(2.766)	(3.799)	(3.642)	(–0.935)	(1.226)	(2.649)	(2.601)
IVOL 3 (High)	0.033	0.222	0.291	0.258	–0.303	–0.207	–0.201	0.102
	(0.104)	(0.721)	(0.990)	(1.603)	(–2.307)	(–1.902)	(–1.663)	(0.631)
(Low – High)	0.336	0.347	0.465		0.144	0.285	0.380	
	(1.410)	(1.560)	(2.240)		(1.038)	(2.236)	(2.642)	

	Panel D. Portfolios sorted on abnormal trading volume & shocks to idiosyncratic volatility (UIVOL)							
UIVOL 1 (Low)	0.268	0.727	0.986	0.718	–0.149	0.221	0.401	0.550
	(1.011)	(2.837)	(3.759)	(4.958)	(–1.287)	(1.878)	(3.470)	(3.123)
2	0.332	0.514	0.695	0.362	–0.178	0.057	0.141	0.319
	(1.854)	(3.066)	(3.977)	(3.859)	(–2.654)	(1.132)	(2.205)	(3.043)
UIVOL 3 (High)	0.286	0.502	0.608	0.322	–0.089	0.035	0.093	0.182
	(1.279)	(2.406)	(2.822)	(2.415)	(–0.988)	(0.378)	(0.976)	(1.509)
(Low – High)	–0.018	0.225	0.378		–0.060	0.185	0.308	
	(–0.118)	(1.539)	(2.442)		(–0.405)	(1.133)	(2.107)	

Table 7

Fama-French five-factor alphas of portfolios sorted on trade volume with and without control for other stock return predictors

Each entry in the table is the alphas of the value-weighted portfolios relative to Fama and French's (2015) five factors (the market, size, book-to-market, profitability, and investment). These portfolios are formed either on a one-way sort on abnormal trading volume (Panel A) or on a bivariate sort on abnormal trading volume and one of the following four beta measures in Panels B-E: market beta (β^{MKT}), market volatility beta (β^{VXO}), default beta (β^{DEF}), and macroeconomic uncertainty beta (β^{UNC}). The market beta is estimated using previous 60 monthly returns. The three other betas are estimated from the following bivariate regression that also controls for the market factor:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \beta_i^X X_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is excess returns to stock *i* on time *t*, $R_{M,t}$ is excess returns to the market, $X_t \in \{\Delta VXO_t, DEF_t, UNC_t\}$, and *VXO* is CBOE's market volatility index, DEF is the yield spread between Moody's BAA and AAA corporate bonds, and *UNC* is macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015). β^{VXO} is estimated with within-month daily data for the period of February 1986 through December 2016 when VXO is available. β^{MKT}, β^{DEF}, and β^{UNC} are all estimated using 60 monthly observations. The sample start period is July 1965 for β^{UNC}, and July 1963 for β^{MKT} and β^{DEF}. The end date of all three samples is December 2016. Portfolios in each panel are estimated in one system to allow for correlated errors. The numbers in parentheses are *t*-values that are adjusted for heteroskedasticity and autocorrelation (Newey and West, 1987). The mean absolute alphas (m.a.a.) is the average of alphas (in absolute values) across the three portfolios with the same volume classification.

Panel A. Portfolios formed by one-sort on trading volume

Sample	1 Low volume	2	3 High volume	(H – L)
07/63-12/16	-0.134	0.092	0.146	0.280
	(-2.402)	(2.353)	(2.213)	(2.919)
02/86-12/16	-0.124	0.099	0.095	0.219
	(-1.570)	(1.928)	(1.057)	(1.600)
07/65-12/16	-0.130	0.081	0.150	0.280
	(-2.272)	(2.046)	(2.204)	(2.831)

Panel B. Portfolios formed by two-sort on trading volume and market beta

Portfolios	1 Low volume	2	3 High volume	(H – L)
1 Low β^{MKT}	–0.194	0.026	0.133	0.327
	(–1.653)	(0.259)	(1.410)	(2.669)
2	–0.307	–0.086	0.067	0.374
	(–4.310)	(–1.396)	(0.951)	(4.079)
3 High β^{MKT}	–0.133	0.003	0.048	0.181
	(–0.976)	(0.025)	(0.322)	(1.036)
m.a.a.	0.211	0.038	0.083	

Panel C. Portfolios formed by two-sort on trading volume and market volatility beta

Portfolios	1 Low volume	2	3 High volume	(H – L)
1 Low β^{VXO}	–0.091	0.021	0.118	0.170
	(–0.651)	(0.205)	(0.794)	(1.108)
2	–0.084	0.123	0.130	0.213
	(–1.021)	(2.078)	(1.567)	(1.673)
3 High β^{VXO}	–0.335	0.017	–0.038	0.297
	(–2.018)	(0.131)	(–0.232)	(1.460)
m.a.a.	0.170	0.054	0.095	

Panel D. Portfolios formed by two-sort on trading volume and DEF beta

Portfolios	1 Low volume	2	3 High volume	(H – L)
1 Low β^{DEF}	0.059	0.253	0.365	0.307
	(0.444)	(2.120)	(2.528)	(2.128)
2	–0.185	0.070	0.131	0.317
	(–2.782)	(1.316)	(1.776)	(3.054)
3 High β^{DEF}	–0.225	–0.111	–0.008	0.217
	(–2.145)	(–0.904)	(–0.077)	(1.698)
m.a.a.	0.156	0.145	0.168	

Panel E. Portfolios formed by two-sort on trading volume and macro uncertainty beta

Portfolios	1 Low volume	2	3 High volume	(H – L)
1 Low β^{UNC}	–0.018	–0.003	0.142	0.160
	(–0.162)	(–0.023)	(0.887)	(0.995)
2	–0.183	0.092	0.136	0.319
	(–2.394)	(1.595)	(1.916)	(3.172)
3 High β^{UNC}	–0.022	0.126	0.100	0.122
	(–0.197)	(1.145)	(0.967)	(0.901)
m.a.a.	0.074	0.074	0.126	

Table 8

Time series regressions of the high volume return premium on various risk-based and mispricing factors

This table reports estimation results for the following time series regression

$$R_t = \alpha + \sum_{j=1}^{K} \beta_j f_{j,t} + \varepsilon_t, \quad t = 1, 2, \ldots, T,$$

where R_t is the value-weighted high volume return premium and $f_{j,t}$ is the jth factor. The volume premium is estimated from portfolios formed on two independent sorts on size and abnormal trading volume of stocks traded in NYSE, Amex, and NASDAQ. IML and UIML are two liquidity premium measures based on portfolios sorted on Amihud's (2002) illiquidity ratio and shocks to illiquidity, respectively. MKT, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors used in Fama and French (1993) (FF3) and Fama and French (2015) (FF5). ROE and I/A are the return on equity and investment factors of Hou, Xue, and Zhang (2015) (HXZ4). UMD is the momentum factor of Carhart (1997). MPR is mimicking portfolio returns that we construct to proxy for news related to future industrial production growth. MGMT and PERF are Stambaugh and Yuan's (2017) (SY) two mispricing factors that are constructed from a set of 11 prominent anomalies. PEAD and FIN are Daniel, Hirshleifer, and Sun's (2019) two behavioral factors (DHS) that capture short- and long-horizon mispricing. The sample start dates are January 1972 for ROE and I/A, July 1972 for PEAD and FIN, and July 1963 for the remaining factors. The end dates are all December 2016. Numbers in parentheses are HAC t-statistics.

	Panel A. Liquidity and other common return factors						Panel B. Mispricing factors		
	I. Single-factor IML	II. Single-factor UIML	III. FF3 + UMD	IV. FF5 + UIML	V. HXZ4 + UIML	VI. FF5 + UIML+MPR		VII. SY 4-factor	VIII. DHS 3-factor
Adj-R^2	1.60	3.39	3.56	6.37	4.12	10.20	*Adj-R*^{2}	3.09	2.31
$\hat{\alpha}$	0.518	0.448	0.526	0.381	0.417	0.367	$\hat{\alpha}$	0.446	0.483
	(7.739)	(5.923)	(6.769)	(4.743)	(4.620)	(4.378)		(5.837)	(4.802)
$\hat{\beta}_{IML}$	0.066						$\hat{\beta}_{MKT}$	–0.008	–0.011
	(1.744)							(–0.280)	(–0.347)
$\hat{\beta}_{UIML}$		–0.124		–0.113	–0.102	–0.099	$\hat{\beta}_{SMB}$	0.080	
		(–3.201)		(–2.432)	(–2.036)	(–2.154)		(2.165)	
$\hat{\beta}_{MKT}$			–0.032	–0.003	–0.025	0.002	$\hat{\beta}_{MGMT}$	0.107	
			(–1.248)	(–0.110)	(–0.988)	(0.075)		(2.697)	
$\hat{\beta}_{SMB}$			0.064	0.060	0.039	0.079	$\hat{\beta}_{PERF}$	–0.008	
			(1.752)	(1.809)	(0.993)	(2.266)		(–0.250)	
$\hat{\beta}_{HML}$			0.080	0.070		0.089	$\hat{\beta}_{PEAD}$		0.005
			(2.132)	(1.519)		(1.973)			(0.060)
$\hat{\beta}_{UMD}$			–0.032				$\hat{\beta}_{FIN}$		0.073
			(–0.752)						(1.621)
$\hat{\beta}_{RMW}$				0.084	0.030	0.064			

$(\hat{\beta}_{ROE})$	(2.083)	(0.904)	(1.669)
$\hat{\beta}_{CMA}$	0.049	0.083	0.037
$(\hat{\beta}_{I/A})$	(0.672)	(1.854)	(0.505)
$\hat{\beta}_{MPR}$			2.244
			(2.560)

Table 9

Macroeconomic exposure for portfolio returns formed on trading volume

This table reports loadings with respect to mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) economic factors for ten equal-weighted portfolios formed on abnormally high trading volume of stocks traded in NYSE, Amex, and NASDAQ. The sample spans from July 1963 to December 2016. The five CCR factors are defined as follows. IP is the growth rate of industrial production, UI is unexpected inflation, DEI is the change in expected inflation, TERM is the term spread, and DEF is the default spread. We use 40 equity portfolios as base assets to estimate the mimicking portfolio returns. The base assets include ten equal-weighted size portfolios, ten equal-weighted book/market portfolios, ten equal-weighted profitability portfolios, and ten value-weighted momentum portfolios. The numbers in parentheses are *t*-values that are adjusted for heteroskedasticity and autocorrelation (Newey and West, 1987). The ten portfolios are estimated in one system to allow for correlated errors.

Factors	Lo 10	2-Dec	3-Dec	4-Dec	5-Dec	6-Dec	7-Dec	8-Dec	9-Dec	Hi 10
					Panel A. Adjusted R^2					
	90.7	93.1	94.6	94.7	95.2	95.4	95.5	94.8	94.6	93.4
					Panel B. Loadings on the economic factors					
IP	0.29	0.30	0.29	0.31	0.31	0.33	0.35	0.34	0.34	0.34
	(10.06)	(12.07)	(11.49)	(14.92)	(12.16)	(13.20)	(15.53)	(12.57)	(13.82)	(15.58)
UI	−1.59	−1.60	−1.58	−1.67	−1.53	−1.46	−1.43	−1.43	−1.29	−1.20
	(−13.61)	(−14.98)	(−19.96)	(−20.71)	(−18.56)	−18.42)	(−22.12)	(−16.51)	(−15.40)	(−13.24)
DEI	4.12	3.93	4.11	4.22	3.96	3.67	3.91	3.73	3.27	3.13
	(10.45)	(12.54)	(13.82)	(13.66)	(11.24)	(9.77)	(12.63)	(10.44)	(9.96)	(9.68)
TERM	0.49	0.51	0.51	0.52	0.53	0.53	0.53	0.53	0.55	0.55
	(18.51)	(31.42)	(26.12)	(35.34)	(38.36)	(44.04)	(49.95)	(53.81)	(52.50)	(31.43)
DEF	0.71	0.74	0.75	0.76	0.78	0.80	0.74	0.79	0.80	0.83
	(10.71)	(15.14)	(16.44)	(18.14)	(19.54)	(22.40)	(19.70)	(21.84)	(24.44)	(18.60)

Table 10

Predicted return spread for portfolios formed on abnormally high trading volume

Panel A of this table reports the risk premium estimates for the five Chen, Roll, and Ross (1986) (CRR) economic factors. They are estimated from a Fama and MacBeth (1973) regression of 40 test assets on the mimicking portfolios for the five CRR factors, where the full sample is used in the first-stage regressions. The 40 test assets include ten equal-weighted size portfolios, ten equal-weighted book/market portfolios, ten equal-weighted profitability portfolios, and ten value-weighted momentum portfolios, all obtained from Kenneth French's website. Panel B reports the return components of the lowest and highest equal-weighted volume deciles predicted by their exposure to the CRR factors. They are calculated as the product of the loadings from regressing the monthly returns of the deciles on the mimicking portfolio returns (reported in Table 9) and the factor premiums from Panel A. The row entitled *dif* provides the difference in the predicted premiums between the highest and the lowest deciles of the volume portfolios (namely, Hi 10 − Lo 10). Numbers in parentheses are Shanken (1992) corrected *t*-values. The ten volume portfolios are formed on one-way sort on abnormally high trading volume of stocks traded in NYSE, Amex, and Nasdaq from July 1963 to December 2016.

	Intercept	IP	UI	DEI	TERM	DEF
			Panel A. factor premiums			
$\hat{\gamma}$	−0.09	1.40	−0.15	−0.04	1.39	−0.46
$t_{\hat{\gamma}}$	(−0.41)	(6.95)	(−2.35)	(−1.66)	(2.71)	(−4.35)
			Panel B. Predicted premiums for the volume deciles			
Lo 10		0.40	0.23	−0.16	0.69	−0.32
Hi 10		0.48	0.18	−0.12	0.76	−0.39
dif		0.08	−0.06	0.04	0.08	−0.06
t_{dif}		(1.41)	(−2.21)	(1.59)	(1.38)	(−1.27)

Table 11

Returns of stocks sorted on abnormal trading volume and mispricing scores

Panel A of the table reports average monthly excess returns for value-weighted portfolios formed by a bivariate sort on abnormal trading volume and the mispricing measure (MISP) of Stambaugh, Yu, and Yuan (2015) of stocks traded in NYSE, Amex, and Nasdaq. Panels B, C, and D are Fama and French (2015) five-factor alphas, Stambaugh and Yuan (2017) four-factor alphas, and Daniel, Hirshleofer, Sun (2019) three-factor alphas of these portfolios. The sample spans from July 1965 to December 2016. A stock's mispricing measure (MISP) is defined as the arithmetic average of the ranks of the 11 return anomalies from which Stambaugh and Yuan's (2017) two mispricing factors are constructed. The mean absolute alphas (m.a.a.) are the average of alphas (in absolute values) across three MISP-sorted portfolios within each volume tercile. The numbers in parentheses are *t*-values which are adjusted for heteroskedasticity and autocorrelation (Newey and West, 1987).

	Volume 1 (Low)	2	Volume 3 (High)	(High – Low)	Volume 1 (Low)	2	Volume 3 (High)	(High – Low)
	Panel A Average excess returns				Panel B Fama-French 5-factor alphas			
MISP 1 (Low)	0.428	0.745	0.855	0.427	–0.120	0.245	0.237	0.357
	(2.125)	(4.186)	(4.602)	(3.554)	(–1.371)	(3.911)	(3.071)	(2.926)
2	0.399	0.480	0.691	0.291	–0.042	0.082	0.150	0.192
	(1.806)	(2.404)	(3.464)	(2.562)	(–0.633)	(1.062)	(1.823)	(1.857)
MISP 3 (High)	–0.143	0.117	0.335	0.478	–0.542	–0.332	–0.094	0.448
	(–0.548)	(0.461)	(1.397)	(3.471)	(–4.953)	(–3.406)	(–0.761)	(3.090)
m.a.a.					0.235	0.220	0.160	
	Panel C Stambaugh and Yuan (2017) 4-factor alphas				Panel D. Daniel, Hirshleofer, and Sun (2019) 3-factor alphas			
MISP (Low)	–0.305	0.095	0.081	0.386	–0.183	0.089	0.219	0.402
	(–3.458)	(1.291)	(0.961)	(2.733)	(–1.659)	(1.249)	(2.068)	(2.257)
2	0.007	0.139	0.230	0.223	–0.015	0.159	0.228	0.243
	(0.107)	(1.901)	(2.631)	(1.993)	(–0.191)	(1.768)	(2.399)	(1.948)
MISP 3 (High)	–0.163	–0.027	0.249	0.412	–0.200	–0.043	0.158	0.358
	(–1.579)	(–0.333)	(2.213)	(2.310)	(–1.692)	(–0.386)	(1.113)	(2.026)
m.a.a.	0.158	0.087	0.187		0.132	0.097	0.202	

Table 12
Returns of stocks sorted on abnormal trading volume and institutional ownership

The table reports average monthly excess returns and Fama and French's (2015) five-factor alphas of value-weighted portfolios formed by a one-way sort on abnormal trading volume and by a bivariate sort on volume and institutional ownership (INST) of stocks traded in NYSE, Amex, and Nasdaq. The sample spans from January 1980 to December 2016. A stock's institutional ownership (INST) is defined as the percentage of total shares outstanding that are owned by 13F institutions investors. Thomson Reuters Institutional Holdings (13F) database provides institutional holdings data. The mean absolute alphas (m.a.a.) are the average of alphas (in absolute values) across three INST-sorted portfolios within each volume quintile. The numbers in parentheses are *t*-values which are adjusted for heteroskedasticity and autocorrelation (Newey and West, 1987). Portfolios in each panel are estimated in one system to allow for correlated errors.

Portfolios	1 Low volume	2	3	4	5 High volume	(H – L)
	Panel A. Average excess returns (one-way sort on volume)					
	0.384	0.568	0.747	0.606	0.759	0.375
	(1.496)	(2.341)	(3.331)	(2.641)	(3.287)	(2.562)
	Panel B. FF 5-factor alphas (one-way sort on volume)					
	–0.226	–0.056	0.168	0.019	0.106	0.332
	(–2.105)	(–0.879)	(2.221)	(0.237)	(0.945)	(2.033)
	Panel C. Average excess returns (two-way sort on volume & institutional ownership)					
1 Low INST	0.169	0.426	0.582	0.341	0.685	0.516
	(0.602)	(1.647)	(2.384)	(1.337)	(2.753)	(2.587)
2	0.237	0.595	0.776	0.580	0.659	0.422
	(0.872)	(2.199)	(2.999)	(2.415)	(2.653)	(1.984)
3 High INST	0.654	0.598	0.780	0.660	0.949	0.294
	(2.289)	(2.301)	(3.117)	(2.628)	(3.565)	(1.721)
	Panel D. FF 5-factor alphas (two-way sort on volume & institutional ownership)					
1 Low INST	–0.365	–0.114	–0.026	–0.197	0.090	0.455
	(–2.107)	(–1.07)	(–0.207)	(–1.452)	(0.549)	(2.096)
2	–0.316	–0.069	0.306	0.074	–0.084	0.232
	(–2.021)	(–0.508)	(1.655)	(0.521)	(–0.572)	(0.995)
3 High INST	–0.149	–0.132	0.038	–0.072	0.237	0.386
	(–1.014)	(–1.466)	(0.369)	(–0.669)	(2.089)	(2.020)
m.a.a.	0.277	0.105	0.123	0.114	0.137	