Rivals' Returns

Abstract

Roll R^2 (1988) concludes that our ability to explain the information content of stock returns is modest. Since then, despite advances in priced factors, stock return volatility determinants and stock return predictors identification, regressions of stock returns on contemporaneous variables still leave a dominant share of stock return movements unexplained. Using Hoberg and Phillips (2010) similarity scores to identify firm's rivals, we show that direct interactions between firms matter. Five firms among the ten closest rival firms in the product market space explain firm returns by the same order of magnitude than the Fama and French (2015) five factors model. Using Brogaard et al. (2022) stock return variance decomposition model, we show in addition that the rivals' return based competitive information component amounts to at least one sixth of the firm-specific public information component in regular time and close to four times more when focusing on most extreme rival news arrival.

Keywords: Stock Return, Information, Rivals' Interactions

"Our ability to explain stock price changes is modest" is Roll's (1988) conclusion after regressing firm level stock returns on a combination of priced factors and an industry peers index. The generated average adjusted R^2 was in the order of twenty percent using daily observations (thirty-five percent using monthly returns), even controlling for firm specific news reported in the financial press. To the best of our knowledge, this surprising evidence remains largely unchallenged thirty years later and the finance literature still provides little guidance to explain the information content of seventy percent of daily stock price changes[1]. We explore whether direct interactions between rival firms help to shed light on this conundrum and quantity the contribution of rivals' returns to the information content of daily stock returns.

Several streams of contributions in the finance literature appear close to our research question. The quest for priced factors comes first into mind (eg., Fama and French, 1993 and 2015, among the numerous contributions in this field). The search has been so intensive that biased inferences due to specification search and data mining, practices collectively referenced as *p*-hacking, has become a key issue (Harvey et al., 2016; Harvey, 2017). As an example, Jensen et al. (2021) assemble a new data set gathering 153 factors across 93 countries in order to assess the replicability of previous studies uncovering priced factors. While identifying the set of priced factors is a central topic in finance, as these factors drive the equity premium, information incorporated in stock prices forms a broader set. Firm level idiosyncratic information that affects stock prices can indeed be diversified away by investors and is (or should be) therefore not priced. Idiosyncratic information is still potentially relevant to explain stock returns.

A second set of contributions target determinants of stock return volatility. For example, Campbell et al. (2001) reports an increase in individual stocks idiosyncratic volatility and suggest several possible explanations of this trend (the decline of conglomerates, the rise of equity issuances by younger firms, changes in executive compensations, shocks to investors' discount rates, etc.). Uncovering determinants of stock returns volatility is certainly one another topic of importance but again doesn't target the information content of stock returns as such.

A third set of contributions focuses on variables useful to predict future stock returns, a notoriously difficult but potentially highly rewarding task. For example, McLean and Pontiff (2016) identify 97 variables in previous academic studies that help to predict the cross-section of stock

[1] Two notable exceptions are Savor and Wilson (2014) and Boudoukh et al. (2018). Savor and Wilson (2014) investigate the behavior of asset pricing models around scheduled macroeconomic news announcements and report that the positive relation between return and systematic risk get better empirical support during days of announcements. Boudoukh et al. (2018) use textual analysis to identify fundamental information in news and show that this information accounts for four times more idiosyncratic volatility overnight than during trading hours. Revisiting Roll (1988) results, the authors show that firm level time series adjusted R^2 from pricing models are much lower (not higher) on so-called identified news days (days of news arrival with identified and value-relevant topic), deepening even more our conundrum.

returns and study their out-of-sample and post-publication prediction performance. Stock return prediction is undoubtedly one of the holy grails of the finance profession. Our focus is however on variables explaining the information content of contemporaneous stock returns, not forecasting future ones.

Our explorations start from a simple observation: information on rivals should affect firm stock returns. Not only direct interactions between rival firms have indeed investment and cash-flow implications (Frésard and Valta, 2016) but peers' valuation matters for firm's investment (Foucault and Frésard, 2014). As a typical example, on July 2021 the sixth, the Pentagon announced the cancellation of the USD 10 billion JEDI cloud contract awarded to Microsoft[2]. That day, the Amazon stock registered a 4.69 percent return. This Microsoft specific news was indeed a very good news for Amazon. The Amazon Web Services platform is a direct competitor to the Microsoft Azure cloud platform and thanks to this cancellation, Amazon was again in the race to deliver cloud services to the Pentagon. Not all rivals' interactions are as easy to pinpoint however. When Apple announced officially in June 2020 a shift to Apple's own silicon for its future Mac computers, this was clearly bad news for Intel, which heretofore has supplied Apple with its Core processor family. But Intel stock price didn't appear to react around that announcement. This lack of move is explained by Apple's shift being largely anticipated by industry analysts. In this specific case, capturing stock prices implications of such rivals' interaction and quantifying its importance therefore requires pinpointing the specific days during which rumors and/or information leakages reached the market. While this could conceivably be done for a limited sample of strategic decisions affecting rival firms in a few industries (assuming absence of insiders trading on private information), such data collection effort is out of reach on a large scale and over a long period. But hopefully, if good news for some firms is bad news for the others (or if good news for some is good news for others in the case of cooperation), there should be evidence in return correlations.

Our empirical method is designed to test as cleanly as possible whether interactions between rival firms help to explain stock returns. We face two challenges: identifying rivals and controlling for rival common shocks. The Hoberg and Phillips (2010) (H&Ph henceforth) database[3] helps to meet the former. Using product descriptions collected in Security Exchange Commission (SEC henceforth) filings 10K, H&Ph compute similarity scores (SS henceforth) between firm pairs for the whole Compustat universe, year by year, over the period 1988-2019. This provides a large cohort of listed firms over more than thirty years. Moreover, SS are measures of distance in the product market space that should correlate with the degree of direct competitive interactions between firms. Using H&Ph SS, we

[2] See https://www.cnbc.com/2021/07/06/pentagon-cancels-10-billion-jedi-cloud-contract.html

[3] http://hobergphillips.tuck.dartmouth.edu/industryclass.htm.

collect for each firm-year the ten nearest neighbors in the product market space to form the set of rivals.

Our second challenge is to control for shocks common to the firm and its rivals that generate positive correlation between their returns (e.g., due to an increase in industry product demand). To control for this phenomenon, we augment the priced factors usually included in empirical asset pricing models with an equally-weighted portfolio formed by a subset of firm rivals (in our baseline specification, we select the five even ranked among the ten highest SS-ranked rivals). This portfolio of rivals plays the role of an industry index with the benefit of being dynamically recomputed for each firm-year observation. We finally estimate, year by year using daily returns, adjusted R^2 of regressions of firm returns on priced factors, the rival's industry index returns and with and without rivals' idiosyncratic returns not included in the industry index (firm level time-series regressions henceforth). The increase in adjusted R^2 between these two regressions, if any, should be informative about the importance of rival interactions to explain the information content of daily stock returns.

To assemble our cohort of firms, we proceed in two steps. First, we start from the H&Ph universe, match the provided GVKEY (Compustat identifier) to PERMNO (CRSP identifier) and apply the usual filters (such as dropping penny stocks and stocks with unreported number of shares). Next, we select the subsample of firms that rank within the CRSP universe one thousand largest firms by market capitalization end of May of each year. This procedure leads to a sample close to the Russell 1,000 index that should shelter us from producing results contaminated by infrequent trading issues, representing 84% of the H&Ph sample in market values.

Over the period 1988 to 2019, the average R^2 from firm level time-series regression using the market portfolio excess return as unique explanatory variable (the market model) is 24.75%. The first twenty years of this period witnessed a significant rise in the market model explanatory power, with its average R^2 reaching a peak close to 55% in 2011. Since then however, we observe a progressive decline, the average R^2 reverting close to its pre-internet bubble episode level. This marked pattern has already been noted and analyzed in the literature (Parsley and Poper, 2020). On average, adding the Fama and French (1993) size and value factors add 3.01pp (pp stands for percentage points) to the firm level time-series regression adjusted R^2. The additional contribution of the Fama and French (2015) profitability and investment factors is a more modest 1.40pp. Our industry index contributes to an additional 3.80pp. And, finally, the set of five selected product market closest rivals idiosyncratic returns adds 4.55pp, as much as the size, value, profitability and investment factors together and more than the industry index. To obtain an alternative measure of the importance of rivals information, we use the Brogaard et al. (2022) structural vector auto-regression (VAR) based model of daily stock return variance decomposition. This model identifies market-wide information, firm-specific private information, firm-specific public information and noise components. The rivals' return based competitive information component amounts to at least one sixth of the firm-specific public information component in regular time and close to four times more when focusing on most extreme rival news arrival, confirming the importance of rivals' interactions to understand the source of stock price variations.

We check in depth the robustness of our results. Replicating our analyses on a sample composed of all U.S. listed firms belonging the CRSP universe generates comparable conclusions. A placebo test confirms that the increase in adjusted R^2 generated by rival idiosyncratic returns is not a mechanical consequence of the increase in the number of independent variables included in the firm level time-series regression (as expected because the adjusted R^2 is designed to control for this effect). An alternative product market rival selection strategy (the five closest rivals in the product market space in place of the five odd ranked ones among the ten closest rivals) produces similar increase in adjusted R^2. Controlling for asynchronous trading using the Scholes and Williams (1977) procedure confirms again our base result, as the use of asymmetric betas (Ang et al., 2006), that control for differential responses to good and bad news affecting rivals. Jensen et al. (2021) identify 153 factors that are potentially priced. Therefore, we also check whether our results are driven by missing priced factors. To this end, we replace the Fama and French (2015) five factors by the ten first components generated by a principal component analysis (PCA) of firm level daily returns, an agnostic approach to control for most potential common factors. The increase in adjusted R^2 thanks to rival idiosyncratic returns is this time more limited (3.21pp), yet highly statistically significant. Our results are not driven by unobserved priced factors.

We next undertake investigations to identify determinants the contribution of rival interactions to the information content of stock returns. First, using the average SS of the ten product market closest neighbors as measure of competition intensity, we observe that the contribution of rival idiosyncratic returns to the adjusted R^2 is weaker in a less competitive environment. This result is moreover confirmed at the Fama and French 49 industry classification level. This is to be expected: the tougher the competition, the stronger the impact of rivals' interactions on firm cash-flows, the more stock returns should interact. Next, using the Amihud (2002) price impact measure of liquidity, we uncover that the contribution of rival idiosyncratic returns to the adjusted R^2 is driven by the most liquid stocks. Our results are therefore not a side effect of the presence of illiquid assets in the stock market and, on the contrary, driven by efficient incorporation of new information in stock prices. The importance of rivals' interactions in explaining the information content of stock returns is a pervasive phenomenon that holds across industries.

We investigate also which firm and industry characteristics appear to explain the contribution of rival idiosyncratic returns to the price discovery process. To this end, we assemble a long list of potential explanatory variables, collecting information in the CRSP and Compustat databases and in the K. French Data Library and H&Ph one. The contribution of rivals' idiosyncratic returns to the information content of stock returns appears more important in more dynamic product market environment, for more profitable and growing firms, exposed to more active trading of their stocks. These results shed light on drivers of the price discovery process.

Finally, to some extent by curiosity, we test whether the rival idiosyncratic returns, taken collectively, represent a priced factor. Our test follows Jegadeesh et al. (2019), who introduce an instrumental variable based procedure that allows the use of individual stocks as test assets (in place of portfolios used in the classic approach) while fighting the error-in-variables bias. Our results don't deliver statistically significant results (at least according to Harvey (2017) recommendations).

The main take-away from our analysis is that rivalry among firms generate information that is incorporated into stock returns. Moreover, this source of information is significant when compared to the classic set of priced factors. We are still far away to be in position to provide a comprehensive painting of variables that drive stock returns but we make headway along that road.

We start by describing our empirical design. In Section 2, we present our main results. We next turn successively to robustness checks (Section 3), additional investigations (Section 4), determinants (Section 5) and priced factor (Section 6) analyses. We finally conclude.

1. Empirical Design

This section introduces our econometric approach. It then describes the estimation sample and provides the variable definitions.

1.1. Method

To test whether competitive interactions between firms helps explain the information content of stock returns, we compute firm level time-series regressions of the following general form:

$$r_{it} = \alpha + \boldsymbol{F}'_{\boldsymbol{it}}\,\boldsymbol{\beta} + \boldsymbol{rr}'_{\boldsymbol{it}}\,\boldsymbol{\gamma} + \epsilon_{it} \qquad (1)$$

where i is the firm subscript, t is the time subscript, $\boldsymbol{F}_{\boldsymbol{it}}$ is a vector of factors known to influence stock returns and $\boldsymbol{rr}_{\boldsymbol{it}}$ represents the idiosyncratic returns of a selection of firm $i's$ rivals, obtained after controlling for priced factors and an industry index; (throughout, vectors or matrices are indicated in bold face.)

The identification of firm rivals is challenging, as indicated already by Eckbo (1983). Eckbo tests whether horizontal mergers have collusive effects using merging parties' rivals abnormal return around transaction announcements and regulatory authorities' intervention dates. Given the importance of a precise identification of merging parties' rivals for the statistical power of the proposed test of the market power hypothesis, Eckbo starts from Standard Industrial Classification (SIC henceforth) codes and adds a fifth or a six digit, to precisely identify firm rivals. By hands rivals identification can however hardly be undertaken for large cohort of firms and long periods. The use of SIC codes (or other broad industry classifications) suffers from severe limitations, such as infrequent updates, classification criteria focusing more on technology than product market competition and miss-classification of diversified firms. These limitations are probably responsible for a disappointing ability to explain stock return comovements and/or to form group of firms with similar characteristics (Bhorja et al., 2003).

To alleviate this first problem, we take advantage of the Hoberg and Phillips (2010) similarity scores (H&Ph SS) for identify clusters of rival firms. H&Ph collect in SEC 10K filings firm product descriptions. The authors first build a dictionary of relevant words used in this textual source of information. Next, product descriptions are coded into vectors of binary variables indicating the presence of specific words in the firm product description. The final step is to measure the distance between firm pairs in the product market space as the cosinus distance between the obtained vectors. The resulting SS are bounded between zero and one, zero indicating that the two firms share no words in their product description and one that they are perfectly similar. SS display attractive features to track firm rivals in our case: this distance measure focuses on product similarities, the relevant dimension to capture competitive interactions between firm pairs. SS are updated annually, taking into account the dynamic nature of firm competitive environment. Finally, H&Ph provide SS over the 1988 to 2019 period, for the whole sample of Compustat firm pairs. These features provide us the opportunity to track a large cohort of U.S. listed firms over a period of more than 30 years and, for each of them, to identify their product market closest rivals. In so doing, we follow H&Ph (2010) and collect, for each firm-year observation, the list of the ten nearest neighbors (10NN) in the product market space.

A second challenge that must be addressed to estimate Equation 1 is to untangle firm pairs competitive interactions ($\boldsymbol{rr_{it}}$) from common shocks affecting their returns ($\boldsymbol{F_{it}}$). These common shocks may originate from two sources: changes in the global economic environment that affect all firms and industry level transformations, such a technological change and/or supply chain disruptions, that shift the product demand and/or supply at the industry level.

Global economic forces, to the extent to which they are undiversifiable, represent priced factors. The hunt for priced factors has been intensive in the empirical asset pricing literature during these last forty years, leading to fears of biased inference due to *p*-hacking as pointing out in Harvey (2017). We control for these general sources of stock price variations by the inclusion of the Fama and French (2015) five factors in our baseline specification: the market excess return (*mktrf*), size (*smb*), value (*hml)*, profitability (*rmw*) and investment (*cma*) factors[4]. Fama and French (2016) show indeed that this five factors specifications help to solve several pricing anomalies, an indication of their relevance.

Controlling for industry level shocks is more challenging. One may think that the solution is to include in the return regression specification some classic industry index but this would expose us to the same pitfalls as for the identification of firm rivals. The alternative may appear to use the list of ten firm rivals identified thanks to the H&Ph SS to form a firm specific industry portfolio. But adding such industry portfolio to Equation 1 into $\boldsymbol{F_{it}}$ would let little room to capture the potential contribution of direct firm competitive interactions thanks to $\boldsymbol{rr_{it}}$ to explain stock prices variations. The ten rivals would indeed already be included into the industry portfolio and adding them again to the regression would be mostly redundant[5]. To solve this issue, we form the industry portfolio by selecting even ranked rivals in the list of ten product market rivals and include odd ranked rivals in the return regression specification[6]. These choices lead to an Equation 1 specification that takes the following form:

$$r_{it} = \alpha_0 + \alpha_1 \times mktrf_t + \alpha_2 \times smb_t + \alpha_3 \times hml_t + \alpha_4 \times rmw_t + \alpha_5 \times cma_t \\ + \alpha_6 \times NN_{it}^{\{2,4,6,8,10\}} + \sum_{j \in \{1,3,5,7,9\}} \beta_j \times rr_{jt} + \epsilon_{it} \tag{2}$$

where $NN_{it}^{\{2,4,6,8,10\}}$ is the firm i industry portfolio composed of even ranked rivals ranked by SS and rr_{jt} for $j \in \{1,3,5,7,9\}$ are the list of odd ranked rivals contemporaneous returns.

To obtain a quantitative measure of the contribution of rivals' idiosyncratic returns (the $\sum_{j \in \{1,3,5,7,9\}} \beta_j \times rr_{jt}$ term in Equation 2), we follow Roll (1988) and use the adjusted R^2:

[4] Jensen et al. (2021) identify 153 factors that are potentially priced. Therefore, in a robustness check, we provide also results obtained using the ten first components coming from a PCA of stock returns, an alternative approach agnostic about the economic sources of comovements.

[5] "Mostly" is important here because, using an equally weighted industry portfolio, the rival return coefficients in the industry portfolio are constrained to a constant while they are unconstrained if included individually.

[6] In a robustness check, we use the rivals ranked from six to ten in the list of ten firm product market rivals to form the industry portfolio and include rivals ranked from one to five in the return regression specification.

$$\text{Adjusted } R_i^2 = 1 - \frac{T-1}{T-k-1} \times \frac{SSR_i}{TSS_i} \quad (3)$$

where T is the number of observations for firm i, k is the number of coefficients in the regression equation, SSR is the residuals sum of squares ($SSR = \sum_{t=1}^{T} e_{it}^2$, e_{it} being the regression residuals) and TSS_i is the dependent variable total sum of squares. Using the adjusted R^2 allows to control for the mechanical increase in R^2 due to the addition of variables to a regression specification. As emphasize in Stock and Watson (2020), adding a regressor has indeed two opposite effects on the adjusted R^2: on the one side, the residuals sum of square (SSR) decreases and on the other side, the term $\frac{T-1}{T-k-1}$ increases. The net effect depends on which of these two effects dominates.

The contribution of rivals' idiosyncratic returns to the information content of stock returns is then simply obtained as the difference of adjusted R^2 from estimating Equation 2 with and without the $\sum_{j\in\{1,3,5,7,9\}} \beta_j \times rr_{jt}$ term. We run Equation 2 regression at the firm level, year by year, using daily observations.

1.2. Sample

Because the identification of firm rivals, a key element of our empirical design, relies on H&Ph, we start from the firm universe in the H&Ph database. We use the so-called "entire" Text based Network Industry Classification (TNIC) database that contains SS for all firm pairs[7]. These data are based "on all publicly traded firms (domestic firms traded on either NYSE, AMEX, or NASDAQ) for which we (H&Ph) have Compustat and CRSP data" (see the readme file describing the complete TNIC database). Table 1 provides sample descriptive statistics. In Column 1, the number of unique firms by year in the H&Ph database is reported while Column 2 reports the corresponding aggregated market value[8]. The peak number of firms is registered in 1996 (7,541 unique firms) and, from there, declines regularly to reach 4,031 unique firms in 2019, an impressive fall of 46.5%. The sharp decline in the number of U.S. listed firms has already been noticed in the finance literature, giving rise to worries about a U.S. listing gap phenomenon (Doidge et al., 2017). In market value, a first peak is reached in 1999, that corresponds to the internet bubble episode (from 1996 to 1999, the aggregate market value doubled, a trend that generated suspicions of over-valuation), and second peak was in 2019, the last year of our analysis period. It is noteworthy that, from 1996 to 2019, while the number of listed firms

[7] Available for free download at http://hobergphillips.tuck.dartmouth.edu/tnic_poweruser.htm.

[8] In Column 2, market values are obtained by summing end of fiscal year firm level market values computed as price close (prcc_c field) times common shares outstanding (csho field), these fields being collected in the CRSP/Compustat merged Fundamentals Annual database.

is cut in half, the aggregate market is almost multiplied by four (a direct effect of the irresistible ascension of the GAFAM - Google, Amazon, Facebook, Apple and Microsoft - companies).

To assemble our cohort of firms, we match the H&Ph sample to the CRSP database, converting GVKEY (the Compustat identifier) to PERMNO (the CRSP identifier) and apply the usual data filters[9]. Next, we select the subsample of firms that rank within the CRSP universe one thousand largest firms by market capitalization end of May of each year. This procedure allows us to recompose a sample close to the Russell 1,000 index and to shelter our results from infrequent trading contamination. The result of this matching and filtering is reported in Columns 3 to 6 of Table 1: Column 3 displays the number of unique firms by year[10], Column 4 the corresponding percentage with respect to the original H&Ph sample, Column 5 the aggregate market value[11] and Column 6 the corresponding percentage again with respect to the original H&Ph sample. On average, our sample match 18% of the H&Ph unique firms. This translates to an average coverage in market value of 84% because of our focus on largest firms, mostly stable through the analyzed period.

1.3. Variables

Appendix 1 provides the detailed definitions and data sources of all variables. Most of our analyses estimate Equation 2, the firm level time-series regression. The dependent variable is simply the firm stock return in daily frequency collected in the CRSP database, denoted r_{it}. The firm idiosyncratic returns are the residuals obtained running Equation 1 regression, denoted $Idio\ r_{it}$. Table 2 Panel A provides descriptive statistics. The daily average r_{it} is 0.065%, displays a high dispersion, skewness and kurtosis, features reported as early as Fama (1965). The idiosyncratic component of returns displays similar features, except that they are mechanically centered around zero. Rivals idiosyncratic returns are denoted rr_{it} in Equation 2.

As indicated in Equation 2, we include the five Fama and French (2015) factors (*mktf*, *smb*, *hml*, *rmw* and *cma*) to control for priced sources of comovements. These variables are obtained from the K. French Data Library and descriptive statistics are provided in Table 2 Panel A[12]. Equation 2 also controls for an industry index denoted $NN_{it}^{\{2,4,6,8,10\}}$. The set of rivals composing this index are

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[9] We keep only ordinary U.S. shares (share class 10 and 11 in the CRSP database), drop penny stocks, drop observations with either missing shares outstanding ("shrout" CRSP field) or closing price ("prc" CRSP field) and firm-year observations with less than 90 daily returns in a given year.

[10] Note that our sample encompasses less than 1,000 unique firms by year because not all firms ranking in the 1,000 largest market capitalization each year survive to our data filtering process.

[11] In Column 5, market values are obtained using end of December market values collected in the CRSP database, computed as the product of the price by the number of shares outstanding, respectively "prc" and "shrout" CRSP fields.

[12] Fama and French (2015) use monthly returns and therefore, we can't compare directly our descriptive statistics to that of the authors.

collected using the H&Ph SS to identify the five even ranked closest neighbors in the product market space. Their returns are equally weighted. The diversification effect of portfolio composition is apparent in Table 2 Panel A descriptive statistics: with respect to firm level returns, the standard deviation shrinks by 40%. To replicate Brogaard et al. (2022) daily stock return variance decomposition (see Section 2.2), we also use the raw market return (r_{mt}), the signed dollar volume (x_{it}), computed as the product of price, volume and sign of daily returns and the arithmetic average of the idiosyncratic returns of the 10 ten nearest neighbor firms in the product market space, denoted avg_{it}^{rr}. One another market based variable that we use to characterize stock liquidity is the Amihud (2002) price impact ratio (pi_{it}), defined as the absolute value of daily return divided by the dollar value of trading volume and computed using data collected in the CRSP database. Table 2 Panel A provides also summary statistics for these variables.

Hoberg and Phillips (2010) similarity scores are not used directly as variables in Equation 2 but they play a central role in our empirical strategy. We indeed use them to identify firm rivals, beneficiating from a measure that is updated each year and focuses on the product market dimension. Table 2 Panel B provides a set of descriptive statistics. We use the Complete 10-K TNIC Industry Data available in the Hoberg and Phillips Data Library. This data provides SS for 120,135,355 firm-year pairs, after matching provided GVKEY (Compustat identifier) to PERMNO (CRSP identifier) and restricting the sample of firms that belong to the CRSP universe one thousand largest firms ranked by market capitalization. The corresponding average SS is 0.018. Remembering that SS is bounded between 0 and 1, this may appear to be a low figure but out of the 120,135,355 firm year pairs SS, 61,730,377 SS (51 %) are equal to zero (unreported). Table 2 Panel B reports also statistics for average SS of portfolios composed by the ten nearest neighbors in the product market space ($NN_{10}SS$) and various subsamples of these (the five odd ranked closest by SS – NN_{odd} *SS*, the five even ones – NN_{even} *SS*, the five first ones – NN_{first} *SS* and the five last ones – NN_{last} *SS*), that will be used throughout our analyses. The NN_{10} *SS* average SS is 0.186, ten times higher than the average SS, a mechanical consequence of selection the ten closest neighbors in the product market space, to be compared to 0.201 reported in H&Ph. Averages SS of the portfolios formed by subsamples of the ten nearest neighbors behave as expected: NN_{odd} *SS* and NN_{even} *SS* display comparable average SS and NN_{first} *SS* average SS is 20% higher than NN_{last} *SS*.

In additional investigations, we use a set of firm and industry level characteristics. Firm characteristics (Table 2 Panel C) include total assets in logarithm form (*Total Assets*), leverage (*Leverage*), cash (*Cash*), intangibles (*Intang*), research and development expenses (*R&D*), return on assets (*ROA*) and book to market (*B/M*) financial ratios (all winsorized at the one and ninety-nine percentiles), sales based market share computed at the ten nearest neighbors in product market space level (*MarkShare*) and H&Ph (2014) product market self-fluidity measure (*SelfFluid*). Reported descriptive statistics are comparable with previous contributions using a comparable sample. For example, H&Ph (2014) report an average self-fluidity of 21.043 (Table IV Panel B), while we obtain 21.091 with our sample. To characterize the industry (Table 2 Panel D), we use the sales based Herfindahl-Hirschman index (*HHI)*, defined at the TNIC industry level, as well as two indicator variables, that identifies industry leaders (*Leader*) and industry laggards (*Laggard*): industry leaders are firms with sales and return on assets above the industry median values and industry laggards, the ones with sales and return on assets below these thresholds.

2. The Contribution of Rivals' Idiosyncratic Returns to the Information Content of Stock Returns

2.1. The Increase in Adjusted R^2

We start by reporting results of the Equation 2 estimation in Tables 3 and 4 and in Figure 1. Table 3 provides average results over the whole 1988 to 2019 period. The five columns report adjusted R^2 statistics for the five estimated factor specifications. In Column 1, only the market factor (*mktrf*) is included; in Column 2, the size (*size*) and value (*hml*) factors are added; in Column 3, we add the profitability (*rmw*) and investment (*cma*) ones; in Column 4, our industry index (NN_{even}) is included and finally, the full Equation 2 specification is reported in Column 5. Model specifications are given in the bottom part of the table. For each specification, we provide the number firm-year observations and a set of firm level adjusted R^2 sample statistics: the arithmetic average (*Mean*), its standard error (*Std Mean*), skewness (*Skewness*), Kurtosis (*Kurtosis*), the increase in adjusted R^2 thanks to the addition of factors from column to column (*Diff Mean*) and the corresponding Student statistics (*t-stat*). Table 4 reports the corresponding adjusted R^2 evolution year by year. The factor specifications are denoted similarly to Table 3. *Cont* is the percentage point increase in adjusted R^2 and *% Cont*, the percentage of adjusted R^2 increase relative to the market model (Column 1). Figure 1 provide a graphical representation of Table 4 Columns 1, 2, 4, 6 and 8, using similar notations to specify estimated models.

On average, the market model explains 24.75% of firm level stock price changes. As clearly apparent in Figure 1 and Table 4 Column 1, this explanatory power undergoes a significant time variation during the analyzed period, ranging from a minimum of 8.12% in 1995 to a maximum of 55.01% after the 2008 financial crisis. This time variation has been reported previously (Parsley and Poper, 2020) and is clearly driving the global shape of Figure 1. Since 2011, the market model average R^2 appears to slowly revert to its historical average, the 2008 financial crisis being an exceptional episode.

The addition of the size and value factors increases the average firm level adjusted R^2 by 3.01pp. This increase witnesses itself a significant time variation, with a minimum of 1.41pp in 2003 and a maximum of 6.66pp at the peak of the internet bubble. The average adjusted R^2 contribution relative to the market model R^2 appears to be particularly important in the end of the nineties (reaching 48.86% in 2000), but this is mostly due to the low explanatory power of the market alone during that period (in 1995, the average market model R^2 is only 8.12%).

The profitability and investment factors add on average a more modest 1.40pp to the firm level adjusted R^2. This contribution remains limited over the whole period, as clearly apparent in Figure 1 and exceeds 3pp only in 2001 (with a contribution of 3.40pp). The average relative contribution of these two additional factors is one half of the size and value factors' one.

Adding our industry index increases the average firm level adjusted R^2 by more than twice as much as the profitability and investment factors, with an average contribution of 3.80pp. Moreover, this contribution displays a clearly growing trend: from less than 4pp in the nineties to regularly more than 4pp afterwards). Investigating the determinants of this evolution is not the focus of our analysis but is perhaps an interesting path for future research.

The addition of rivals' idiosyncratic returns (the $\sum_{j \in \{1,3,5,7,9\}} \beta_j \times rr_{jt}$ term in Equation 2) provides an additional 4.55pp firm level average adjusted R^2 increase, in the same order of magnitude as the cumulated contribution of the size, value, profitability and investment factors and surpassing the contribution of the industry factor. This contribution is moreover markedly growing through time, from 1.02pp in 1988 to more than 4pp during the years 2000 to 2013 and above 6pp from 2014 and onwards, a trend highly apparent in Figure 1. With a corresponding Student statistic of 27.95, the rival interactions explanatory power appears strongly significant.

2.2 Daily Stock Return Variance Decomposition

Is the increase in adjusted R^2 obtained thanks to the addition of rivals' idiosyncratic returns economically significant? We have already shown in the previous section that it is in the order of magnitude of the cumulated contribution of the size, value, profitability and investment factors, a striking figure. In this section, we investigate further this issue adopting the daily stock return variance decomposition approach introduced in Brogaard et al. (2022)[13].

Brogaard et al. (2022) develop a variance decomposition model to identify the importance of market-wide information, private firm-specific information revealed through trading, public firm-specific information and noise. To this end, the authors first estimate the following structural vector auto-regression (VAR) model:

[13] We really thank the authors for providing us assistance and a replication code implementing their structural VAR model estimation and variance components identification.

$$r_{mt} = \sum_{l=1}^{5} a_{1l}\, r_{mt-l} + \sum_{l=1}^{5} a_{2l}\, x_{it-l} + \sum_{l=1}^{5} a_{3l}\, r_{it-} \; + \epsilon_{r_{mt}} \tag{4}$$
$$x_{it} = \sum_{l=0}^{5} b_{1l}\, r_{mt-l} + \sum_{l=1}^{5} b_{2l}\, x_{it-l} + \sum_{l=1}^{5} b_{3l}\, r_{it-l} + \epsilon_{x_{it}}$$
$$r_{it} = \sum_{l=0}^{5} c_{1l}\, r_{mt-l} + \sum_{l=0}^{5} c_{2l}\, x_{it-l} + \sum_{l=1}^{5} c_{3l}\, r_{it-l} + \epsilon_{r_{it}}$$

where r_{mt} is the market return at day t, x_{it} the signed dollar volume of firm i (proxied by the product of price, volume and the sign of stock's daily return) and r_{it} is the stock return of firm i. The lag structure of market returns accounts for non-synchronous trading, the one of signed dollar volume for persistence in order flow and the one of return for short-term momentum and reversals driven by temporary price impact of trading. The permanent return responses to market return shocks, signed dollar volume shocks and stock return shocks identify the market-wide information component, the firm-specific private information component and firm-specific public information component respectively. The noise component is the net transitory return from these three sources of shocks[14]. The variance component shares are calculated separately for each stock in each year and then averaged across stocks.

To identify the share of information driven by rivals idiosyncratic information (the competitive information component), we augment Brogaard et al. (2022) structural VAR with an additional endogenous variable, namely either the standard deviation of the idiosyncratic returns of the 10 ten nearest neighbor firms in the product market space, denoted sd_{it}^{rr}, or its signed extremum (the minimum or maximum, whatever is the highest in absolute value), denoted $extr_{it}^{rr}$ [15]. Taking the case of sd_{it}^{rr}, we obtain the following specification:

$$r_{mt} = \sum_{l=1}^{5} a_{1l}\, r_{mt-l} + \sum_{l=1}^{5} a_{2l} x_{it-l} + \sum_{l=1}^{5} a_{3l}\, sd_{it-l}^{rr} + \sum_{l=1}^{5} a_{4l}\, r_{it-l} + \epsilon_{r_{mt}} \tag{5}$$
$$x_{it} = \sum_{l=0}^{5} b_{1l}\, r_{mt-l} + \sum_{l=1}^{5} b_{2l} x_{it-l} + \sum_{l=1}^{5} b_{3l}\, sd_{it-l}^{rr} + \sum_{l=1}^{5} b_{4l}\, r_{it-l} + \epsilon_{x_{it}}$$
$$sd_{it}^{rr} = \sum_{l=0}^{5} c_{1t}\, r_{mt-l} + \sum_{l=0}^{5} c_{2t}\, x_{it-l} + \sum_{l=1}^{5} c_{3t}\, sd_{it-l}^{rr} + \sum_{l=1}^{5} c_{4t}\, r_{it-l} + \epsilon_{x_{it}}$$
$$r_{it} = \sum_{l=0}^{5} d_{1l}\, r_{mt-l} + \sum_{l=0}^{5} d_{2l}\, x_{it-l} + \sum_{l=0}^{5} d_{3l}\, sd_{it-l}^{rr} + \sum_{l=1}^{5} d_{4l}\, r_{it-l} + \epsilon_{r_{it}}$$

Here, rival idiosyncratic returns are the residuals from a factor model including the five Fama and French 2015 factors (*mktrf*, *smb*, *hml*, *rmw* and *cma,* for market, size, value, profitability and investment factors respectively) as well as an industry index (the value weighted average return of the ten nearest neighbor firms in the product market space), to control for known priced factors as well

[14] Note that the authors choose to label information impounded into prices through trading as private information consistently with empirical microstructure models but acknowledge that the distinction between public and private information can at time be blurred.
[15] The addition of stock returns of each identified rival as in Equation 2 is impracticable because of the number of parameters that this would add to the structural VAR.

industry specific information. The standard deviation of rival idiosyncratic returns sd_{it}^{rr} captures therefore the intensity of competitive public information arrival in regular time while the corresponding signed extremum $extr_{it}^{rr}$ picks most extreme shocks.

Results are reported in Table 5. In Column 1, we provide the Brogaard et al. (2022) estimates for reference (see online appendix, Section 2, equally weighted averages). These are obtained over the period 1960 to 2015 for a sample encompassing all NYSE, AMEX and NASDAQ listed stocks (4,362 stocks per year on average). The share of the firm-specific public information component amounts to 34.70% over that period. In Column 2, we report the results of a replication exercise on our analyzed period (from 1988 to 2019). We obtain information shares close to Brogaard et al. (2002). Columns 3 to 6 reports results relative to our four components model (Equation 5). In Columns 3 and 4, the competitive information component is measured using the standard deviation of rival idiosyncratic returns sd_{it}^{rr}, for the sample all listed firms (Column 3) and for the sample of 1,000 largest listed firms (Column 4). The rival information component amounts to 6.02% and 5.01% of the total information flow respectively, information shares that represent approximately one sixth of the firm-specific public information component. When focusing of the most extreme rival information arrival ($extr_{it}^{rr}$), the share of the competitive information component skyrockets and reaches 37.78% (Column 5) and 33.99% (Column 6) of the total information flow for respectively the all firms and the 1,000 largest firms samples. This is close to four times more than the firm-specific public information component. Rivals' idiosyncratic returns clearly matter to explain the information content of stock prices changes.

3. Robustness checks

3.1. All CRSP universe firms

Results reported in tables 3 and 4 and in Figure 1 rest on a subsample composed of the firms who belong to the one thousand largest listed firms by market capitalization in the CRSP universe. Do these results generalize to the whole CRSP universe of listed firms? We check whether this is the case by replicating Table 3 analyses on a cohort of firms assembled following the same set of criteria as for our main sample (see Section 1.2) but dropping the market capitalization filter. We match this time 77% of H&Ph universe unique firms (unreported), the sample covering 92% of the H&Ph sample in market value (unreported).

Results obtained with this all CSP universe firms sample are reported in Table 6 Panel A, under the same organization as in Table 3 (in particular, each column reports results from the corresponding specification in Table 3). The inclusion of rivals' idiosyncratic returns leads an increase in adjusted R^2 of 2pp (with a corresponding Student statistic of 25.61), to be compared this time to 2.58pp for the size and value factors, 0.62pp for the profitability and investment factors and 1.44pp for the industry index, the average adjusted R^2 of the market model being 11.89%. The inclusion of several thousands of small firms to our sample generates a general decline in average adjusted R^2 of the tested factor models, most probably a consequence of infrequent trading, but the contribution of rivals' idiosyncratic returns remains strong, both in level and in statistical significance.

3.2. Placebo Test

We interpret the contribution to the adjusted R^2 from the inclusion of rivals returns in Equation 2 as consistent with the importance of rival interactions to explain the information content of stock price changes. But is it really interactions among rivals that matter or would we obtain a comparable increase in adjusted R^2 by adding any randomly drawn set of five listed firm returns?

We implement a placebo test to investigate this. In this test, the five rivals included in Equation 2 are randomly drawn in the H&Ph universe for each firm, while our industry index is still composed by selecting even ranked rivals in the list of ten product market space closest rivals.

Results are reported in Table 6 Panel B, under the same organization as in Table 3. We are in the present case interested in Columns 4 and 5 results. The addition of the five randomly drawn rivals' idiosyncratic returns in Equation 2 increases the firm level adjusted R^2 by 0.49pp (with an associated Student statistic of 3.01), in contrast to the increase of 4.55pp in Table 3 (with a Student statistic of 27.95). Selecting close rivals in the product market space clearly matters. Note moreover that one should not be surprised to observe some increase in adjusted R^2 due to the inclusion of five randomly drawn rivals' idiosyncratic returns in Equation 2 because the process of random drawing may (and probably do) select from time to time close rivals. Moreover, H&Ph SS are themselves estimated constructs and therefore subject to error-in-variables.

3.3. Rivals Selection

Our baseline strategy to select rivals while controlling for industry level information is to keep even ranked rivals in the list of ten product market space closest rivals to form the industry index and to include odd ranked rivals' idiosyncratic returns as additional variables in Equation 2. As an alternative, we include the five closest rivals' idiosyncratic returns and keep rivals ranked from sixth to tenth to form the industry portfolio. This leads to the following specification:

$$r_{it} = \alpha_0 + \alpha_1 \times mktrf_t + \alpha_2 \times smb_t + \alpha_3 \times hml_t + \alpha_4 \times rmw_t + \alpha_5 \times cma_t \\ + \alpha_6 \times NN_{it}^{\{6,7,8,9,10\}} + \sum_{j \in \{1,2,3,4,5\}} \beta_j \times rr_{jt} + \epsilon_{it} \quad (6)$$

where notations are identical to notations used for Equation 2. Results obtained with this alternative specification are reported in Table 6 Panel C, still under the same organization as in Table 3. We observe this time an increase in adjusted R^2 of 5.52pp, superior to the increase reported in Table 3 (4.55pp in Column 5), with an associated Student statistic of 32.41 (with a corresponding Student statistic of 27.95 in Table 3 Column 5). The increase in adjusted R^2 brought by adding rivals' idiosyncratic returns to the firm level time-series regressions is higher thanks to the selection of closer rivals in the product market space. This confirms that the more the firm are in interaction in the product market space, the more these interactions contribute to the information content of stock returns.

3.4. Asynchronous Trading

Even if our results are obtained tracking a cohort composed of the one thousand largest U.S. listed firms by market capitalization, one may still legitimately worry that results might be affected by asynchronous trading. Scholes and Williams (1977) introduce a procedure to control for this issue. Adopting this procedure, Equation 2 becomes:

$$r_{it} = \alpha_0 + \alpha_1 \times mktrf_t + \alpha_2 \times smb_t + \alpha_3 \times hml_t + \alpha_4 \times rmw_t + \alpha_5 \times cma_t + \alpha_6 \times NN_{it}^{\{2,4,6,8,10\}} + \sum_{j \in \{1,3,5,7,9\}} \left(\left(\beta_j^{t-1} \times rr_{jt-1} \right) + \left(\beta_j^{t} \times rr_{jt} \right) + \left(\beta_j^{t+1} \times rr_{jt+1} \right) \right) + \epsilon_{it} \quad (7)$$

where notations are again identical to notations used in Equation 2, except that the superscript in β coefficients indicates whether returns are lagged by one day ($t-1$), contemporaneous (t) or leaded by one day ($t+1$). Results are reported in Table 6 Panel D, with the same presentation as in Table 3. The inclusion of the rivals' idiosyncratic returns increases the adjusted R^2 by 4.45pp (with a corresponding Student statistic of 26.13), as in our baseline analysis. Our results are not affected by infrequent trading, a conclusion that could have been anticipated in the light of results obtained with the all CRSP universe firms sample (Section 3.1).

3.5. Asymmetric Beta

Another route that has been explored in the finance literature is the possibility that stock returns react asymmetrically to good and bad news, motivating the inception of asymmetric betas (Ang et al., 2006). We follow also this path to check whether the importance of rival interactions to explain stock returns is strengthened when discriminating between positive and negative comovements across rivals' idiosyncratic returns. This leads us to adapt Equation 2 as follows:

$$r_{it} = \alpha_0 + \alpha_1 \times mktrf_t + \alpha_2 \times smb_t + \alpha_3 \times hml_t + \alpha_4 \times rmw_t + \alpha_5 \times cma_t$$
$$+\alpha_6 \times NN_{it}^{\{2,4,6,8,10\}} + \sum_{j\in\{1,3,5,7,9\}} \left(\left(\beta_j^p \times rr_{jt} \times D_{jt} \right) + \left(\beta_j^n \times rr_{jt} \times (1 - D_{jt}) \right) \right) + \epsilon_{it} \tag{8}$$

where we keep the same notations as in Equation 2, D_{jt} is equal to 1 if $rr_{jt} \geq 0$ and β_j^p stands for positive β and β_j^n for negative β. Results are reported in Table 6 Panel E, following the same presentation as in the previous panels. The average firm level adjusted R^2 contribution from the addition of asymmetric rivals' idiosyncratic returns (the last term of Equation 8), is 4.89pp (with a Student statistic of 30.04), to be compare to 4.55pp reported in Table 3 Column 5 (with a Student statistic of 27.95). Taking into account explicitly asymmetric interactions between firm rivals seems to bring at best a marginal improvement in the explanation of the information content of stock returns.

3.6. Principal Components Factors

The Fama and French (2015) five factors model that we use in Equation 2 is a well-accepted benchmark in the academic community. However, the quest for priced factors during the last thirty years (or so) has been intensive, in fact so intensive that it has generated fears of biased inferences due to *p*-hacking (Harvey, 2017). To address this issue and test the replicability of existing studies on priced factors, Jensen et al. (2021) assemble a new data set containing 153 factors over 93 countries. To check the robustness of our results to the specification of the factor model, we adopt an agnostic approach and, as in Roll (1988), use the principal component analysis (PCA) algorithm to extract from the stock return matrix the ten first components. These should absorb most priced factors, whatever they are. We therefore replace the Fama and French (2015) five factors in Equation 2 by these ten first components. The components' extraction is performed on a yearly frequency, using daily returns, to be consistent with our adjusted R^2 contribution estimation procedure. Equation 2 becomes:

$$r_{it} = \alpha_0 + \sum_{f=1}^{10} \alpha_f \times comp_{ft} + \alpha_{11} \times NN_{it}^{\{2,4,6,8,10\}} + \sum_{j\in\{1,3,5,7,9\}} \beta_j \times rr_{jt} + \epsilon_{it} \tag{9}$$

where we keep Equation 2 notations and $comp_{ft}$ stands for component f. Results are presented in Table 6 Panel F, with this time model specifications provided below the table. With respect to Table 3, columns 4 to 6 display results obtained using the new PCA factor model: in Column 4, only the principal components are included ($\sum_{f=1}^{10} \alpha_f \times comp_{ft}$ term in Equation 9), in Column 5 we add our industry index and in Column 6, the rivals' idiosyncratic returns. With respect to Fama and French (2015) five factors model, using the ten first PCA components increases the firm level average adjusted

R^2 by 6.36pp, a significant jump. The industry index adds another 1.48pp to the average adjusted R^2. Finally, rivals' idiosyncratic returns increase the average adjusted R^2 by another 3.21pp (with a Student statistic of 18.92), to be compared to a 4.55pp increase reported in Table 3 Column 5 (with a Student statistic of 27.95). Even using the ten first components obtained thanks to a PCA as factors, rival interactions continue to contribute significantly to the explanation of the information content of stock returns. The relative decline in adjusted R^2 contribution is however noteworthy and indicate that the ten PCA factor model capture probably part of rival interactions.

4. Additional Investigations

Having established that stock prices react to rival interactions, we investigate whether the intensity of competition, stock price liquidity and industry belonging are significant factors modulating this relation.

4.1. Competition

At the heart of our empirical design is the use of H&Ph SS to identify the closest rivals in the product market space. The increase in firm level average adjusted R^2 obtained when selecting the five closest rivals in place of the odd ranked ones (Section 3.3) is a first indication that the intensity of competition potentially affects the relation between rival interactions and the information content of stock return. We undertake here a more systematic exploration along this path.

We characterize the firm competitive environment using the average H&Ph SS of the ten closest rivals in the product market space as in Hoberg and Phillips (2010), denoted $NN_{10}SS$ henceforth. Next, each year of our analyzed period, we affect firm-year observations to quartiles of the $NN_{10}SS$ distribution, firms belonging to the first (fourth) quartile being in the least (most) competitive environment. We finally compute the average adjusted R^2 contribution of rivals' return (term $\sum_{j\in\{1,3,5,7,9\}} \beta_j \times rr_{jt}$ in Equation 2) by quartile of competition intensity.

Grand average results are reported in Table 7 Panel A and corresponding yearly ones in Figure 2. Table 7 Panel A provides, by quartile, the average adjusted R^2 contribution (Column 1), its standard error (Column 2), the corresponding Student statistic (Column 3) and *p*-value (Column 4) as well as the 95% confidence interval (Columns 5 and 6). The rivals' return adjusted R^2 contribution is at its lowest in quartile 1 (least competitive environment), with an average of 3.24pp, significantly below the grand average contribution reported in Table 3 Column 5 (4.55pp). In the next three quartiles, the average adjusted R^2 contribution oscillates between 4.42pp and 5.30pp, without displaying a specific trend from quartile to quartile. This provides indication that the contribution of rival interactions to information content of stock returns only weakens when rivals become really distant. Figure 2, that displays the time-series of firm level average adjusted R^2 contribution by quartile of competition intensity, confirms this diagnostic: in each quartile, the adjusted R^2 time-series presents an increasing trend but, in quartile one, over the whole period, its level is lower than in the three other quartiles.

Figure 3 provides another view at the role of competition by reporting averages at the Fama and French 49 industries level[16]. To obtain this figure, we compute, for each Fama and French 49 industries, the average of the firm level time-series regression adjusted R^2 contribution of rival idiosyncratic returns (vertical axis) and the average of the firm level product market space ten nearest neighbors similarity scores (horizontal axis) over the 1988 to 2019 period[17]. A clear positive correlation between these industry averages emerges, highlighted by the positive slope of the sur-imposed regression line (the univariate correlation is 0.31, highly statistically significant).

4.2. Liquidity

We have already shown that our results are robust to switching to the all CRSP universe firms sample, that incorporate several thousands of small firms in our baseline sample, and to the Scholes and Williams (1977) correction for infrequent trading. In this section, we dig deeper and investigate whether our results pertain more to liquid or illiquid stocks. The response to this question is less obvious than it may seem at first sight. On the one side, we expect naturally liquid stocks to react faster to relevant information and, in particular, to rival interactions, driving up the firm level average adjusted R^2 contribution from rival returns in Equation 2. But, on the other side, liquid stocks are often those of larger and more diversified firms, less exposed to competitive pressures and therefore, potentially less impacted by specific rival movements.

We follow the same empirical strategy as for the investigation of the role of competition in Section 4.1, using the Amihud (2002) price impact to characterize the degree of stock liquidity. More specifically, for each year of our period of investigation, we construct the firm level price impact distribution and allocate firm-year observations to quartiles of this distribution. The first quartile gathers the most liquid stocks (lowest price impact) and the fourth one, the less liquid ones (highest price impact).

Grand average results are reported in Table 7 Panel B, presented like competition investigations (Table 7 Panel A), and Figure 4 displays the corresponding time-series of firm-level average adjusted R^2 contribution by quartile. Table 3 results are clearly driven by more liquid stocks: for most liquid stocks (quartile 1), the average adjusted R^2 contribution turns out to be an impressive 5.77pp (twenty seven percent more than the grand average contribution reported in Table 3 Column 5), while for the

[16] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[17] The industry "precious metal" (industry code 27) is excluded because it amounts to only 77 firm/year observations out of 29,498 and is an outlier.

least liquid ones (quartile 4), it is 3.24pp (close to thirty percent less). We note however that, even for the least liquid stocks, the average adjusted R^2 contribution remains highly statistically significant. Figure 4 confirms these conclusions.

5. The Determinants of Rivals' Idiosyncratic Returns Contribution to the Information Content of Stock Return

After having tested the robustness of our results and investigated whether (and the extent to which) they depend on competition, liquidity and industry, we undertake an analysis of the firm level time-series regression adjusted R^2 determinants. The dependent variable in each estimated specification is the adjusted R^2 contributions of rivals' idiosyncratic returns inclusion in Equation 2 (the $\sum_{j\in\{1,3,5,7,9\}} \beta_j \times rr_{jt}$ term). We collect a set of industry and firm characteristics, namely the ten product market nearest neighbor average similarity score (*NN_{10} SS*), a measure of competition intensity in the firm environment, the corresponding standard deviation (*Std_{10} SS*), a measure of the heterogeneity of the product offering by firm rivals, several classic financial ratios (the natural logarithm of total assets (*log Total Assets*), the leverage (*Leverage*), cash (*Cash*), intangibles (*Intang*) and research and development expenses (*R&D*) , return on assets (*ROA*), book to market (*B/M*)), the firm sales based market share (*MarkShare*), that inform us about the firm market power, the product market self-fluidity (*SelfFluid*), introduced in Hoberg and al. (2014) to characterize the firm product dynamic, the sales based Herfindahl-Hirschman concentration index (*HHI*), a classic measure of industry concentration, and indicator variables identifying industry leaders (*Leader*) and laggards (*Laggard*), that depict the firm position in its industry. Our analysis has no causal interpretation ambition but should be useful to identify firm and industry level characteristics correlated with the rivals' idiosyncratic returns contribution to the information content of stock returns.

Results are reported in Table 8. In Columns 1 and 2, we use the ordinary least square estimator (OLS) with only year fixed effects, while in Columns 3 and 4, we introduce firm and year fixed effects to control for firm level time constant latent factors and to focus on within firm time varying determinants. In Columns 1 and 3, we report univariate results and in Columns 2 and 4, multi-variates ones. This strategy aims to control for multicollinearity and also for the bad control issue (Angrist and Pischke, 2009), that arises when including control variables that are themselves outcome of the variable of interest. Yet to check for potential strong multicollinearity between control variables, we report in Colum 5 variance inflation factors (VIF). Standard errors are clustered at the firm level in all cases.

We start by noting that no one VIF coefficients cross the usual threshold that signal a potential issue of multicollinearity[18]. We next comment results stable across univariate and multi-variate specifications fixed effect estimators that controls for latent factors constant through time. The heterogeneity of rivals' product offering (*Std₁₀ SS*), and firm profitability (*ROA*) are positively correlated with the rivals' idiosyncratic returns contribution to the adjusted R^2. The positive relation with profitability may be rooted in quasi-monopoly rents being more sensitive to rivalry. The mechanism explaining the higher importance of rivals' idiosyncratic returns contribution in more heterogenous industries is at this stage unclear and deserve additional analyses. The relation between the rivals' idiosyncratic returns contribution to the adjusted R^2 and the book to market ratio is negative, indicating that higher growth opportunities are correlated with higher importance of rival interactions to explain stock price changes. This is consistent with the positive coefficient association with profitability and confirm that higher (anticipations of) quasi-monopoly rent increases sensitivity of stock returns to rivalry. The coefficient of market share (*MarkShare*) is negative: a higher market share apparently isolates firms from rivals. The industry concentration (*HHI*) displays a negative coefficient in all specification. This provides additional evidence that firms operating in less competitive environment are less sensitive to rival interactions. Note finally that *Std₁₀ SS*, *ROA*, *MarkShare* and *HHI* coefficient signs and statistical significances are stable with and without firm fixed effects, indicating that latent factors constant through time do not interfere significantly with these variables.

To summarize, Table 8 results confirm that the contribution of rival interactions to the adjusted R^2 of firm level time-series regressions displays significant firm and industry level heterogeneity, being amplified by the rivals' product offering heterogeneity, profitability and growth opportunities. Stock returns of firms active in more concentrated industries and holding larger market shares appear less sensitive to rivals' idiosyncratic information.

6. Asset Pricing Test

The quest for priced factors has been intensive during the last thirty years in the finance literature, so intensive in fact that fears of results driven by *p*-hacking[19] have been raised (Harvey, 2017). Nevertheless, curiosity leads us to investigate whether the contribution of rival interactions to the information content of stock returns is priced. Our ex-ante expectation is that there is no economic reason that suggests this should be the case: partial correlations between rivals' idiosyncratic returns

[18] Belsley et al. (1980) recommend to use a value between 10 and 20 as threshold.
[19] Gu et al. (2020), for example, use machine learning algorithms to perform extensive specification search in measuring asset risk premiums.

can be negative (good news for the ones are bad news for the others when firms compete for the same product market) but also positive in case of cooperation (joint-ventures institutionalize these rivals interactions and the concept of coopetition appeared as early as in the beginning of the twenty century). Rational investors should therefore be able to diversify away rival interactions as a source of risk when composing their portfolios.

We adopt the Jegadeesh et al. (2019) procedure to test for the presence of a priced factor. The authors introduce an instrumental variable based procedure that allows the use of individual stocks as test assets (in place of portfolios in the classic approach) while fighting the error-in-variables bias. We implement this procedure as follows:

- We first estimate firm level time-series regressions on daily returns over a three years rolling window to obtain the factor loadings;
- We next estimate cross-sectional regressions on monthly returns using the lagged estimated factor loadings to obtain risk premia;
- For the instrumental variable based approach, we use factor loadings estimated on odd months as instruments for factor loadings estimated on even months and proceed with the two stage least square estimator (2SLS);

Our rival's returns priced factor candidate is however specific in that it is composed by five rival stock returns (the term $\sum_{j\in\{1,3,5,7,9\}} \beta_j \times rr_{jt}$ in Equation 2) and testing if each of them is individually priced doesn't make sense. We are indeed interested in knowing whether they jointly form a priced factor, beyond the five Fama and French (2015) factors. We implement therefore a classic Fisher test of joint significance of the β coefficients associated with the five rivals' idiosyncratic returns included in Equation 2. This test captures that, the higher the absolute value of their coefficients, the more sensitive are the firm returns to rival interactions, the source of risk that we want to isolate.

Results are reported in Table 9. Column 1 displays coefficients obtained using OLS, while Column 2 reports IV based estimates. Our rivals' idiosyncratic returns factor is labelled *Fisher Rivals*. The estimated risk premium is close to zero in both cases. Our results don't support the notion that rival interactions are priced by investors. We note also that our industry rival portfolio (denoted $NN_{even}\, r_{it}$) is associated with a positive risk premium but again, while statistical significance is achieved at the usual levels of confidence, they remain far from Harvey (2017) recommendations.

7. Conclusion

We started this inquiry by noting that the information drivers of stock returns remain somewhat of a partial mystery. Regressions of daily stock returns on a large set of contemporaneous priced factors and other control variables seldom display adjusted R^2 above twenty-five percent, leaving seventy-five percent unexplained. We suggest that taking into account explicitly interactions between rivals could help to untangle this conundrum. Our empirical strategy is designed to address two challenges: identifying the correct set of rivals and controlling for industry level information.

Our results confirm that rivals' idiosyncratic returns matter: including a set of five rivals' idiosyncratic returns as additional explanatory variables in firm level time-series stock return regressions increase the average adjusted R^2 by close to five percentage points, after controlling for the Fama and French (2015) five factors and an industry index. This result is robust to many specifications, driven by most (not least) liquid stocks. A four to five percentage points adjusted R^2 increase is in the same order of magnitude as the Fama and French size, value, profitability and investment factors taken together. Moreover, the rivals' return contribution to the adjusted R^2 is strongly rising through time, at least doubling over the last 30 years. Using Brogaard et al. (2022) daily stock return variance decomposition, we show in addition that the rivals' return based competitive information component amounts to a significant fraction of the firm-specific public information component. Additional analyses reveal that this increase in adjusted R^2 is driven by firms active in more heterogenous industries, more profitable and with higher growth opportunities. Firms active in more concentrated industries and holding larger market shares appear less sensitive to competitive interactions. We finally show that Rivals' idiosyncratic returns are not a priced factor.

There is no doubt that a large fraction of stock returns remains unexplained. Yet taking account of rival interactions improves significantly our understanding of their information content.

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Figure 1 – Firm Level Time-Series Regression Adjusted R^2 – Baseline Specification

Figure 1 displays yearly average adjusted-R^2 from firm level time-series regressions. *1F* is for a specification with only the market factor (*mktrf*) included, *3F* with the size (*smb*) and value (*hml*) factors in addition, *5F* with the profitability (*rmw*) and investment (*cma*) in addition, *5F+Ind* with the industry portfolio (NN_{even}) formed by the even ranked five product market space nearest neighbors in the set of ten product market space nearest neighbors in addition and, finally, *5F+Ind+RR* with the rivals idiosyncratic returns in addition (see Equation 2). Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

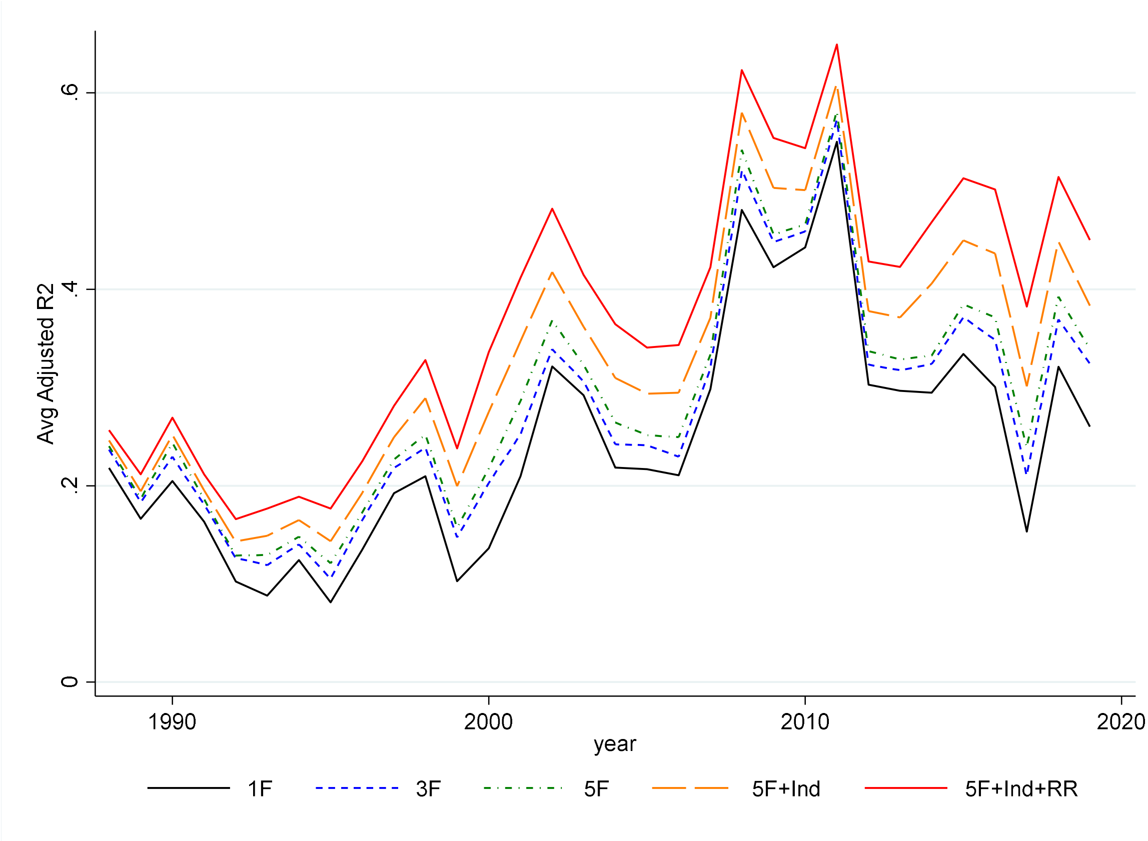

Figure 2 –Rivals' Idiosyncratic Returns Contribution to Firm Level Time-Series Regression Adjusted-R^2 by Quartile of Competition Intensity

Figure 2 presents yearly average contributions of rivals' idiosyncratic returns to firm level time-series regression adjusted-R^2 by quartile of ten product market space nearest neighbors average SS (*NN₁₀ SS*), a measure of competition intensity (Hoberg and Phillips, 2010). Contributions refer to the difference between the average adjusted R^2 of a model including the Fama and French (2015) five factors, an industry portfolio formed by the five even ranked product market space nearest neighbors in the set of ten product market space nearest neighbors and the rivals' idiosyncratic returns (see Equation 2), denoted *5F+Ind+RR* in Figure 1, and the corresponding specification without the rivals' idiosyncratic returns, denoted *5F+Ind* in Figure 1. Quartile 1 is the quartile with the smallest average NN_{10} *SS* (least competitive environment) and quartile 4, the quartile with the highest average NN_{10} *SS* (most competitive environment). Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

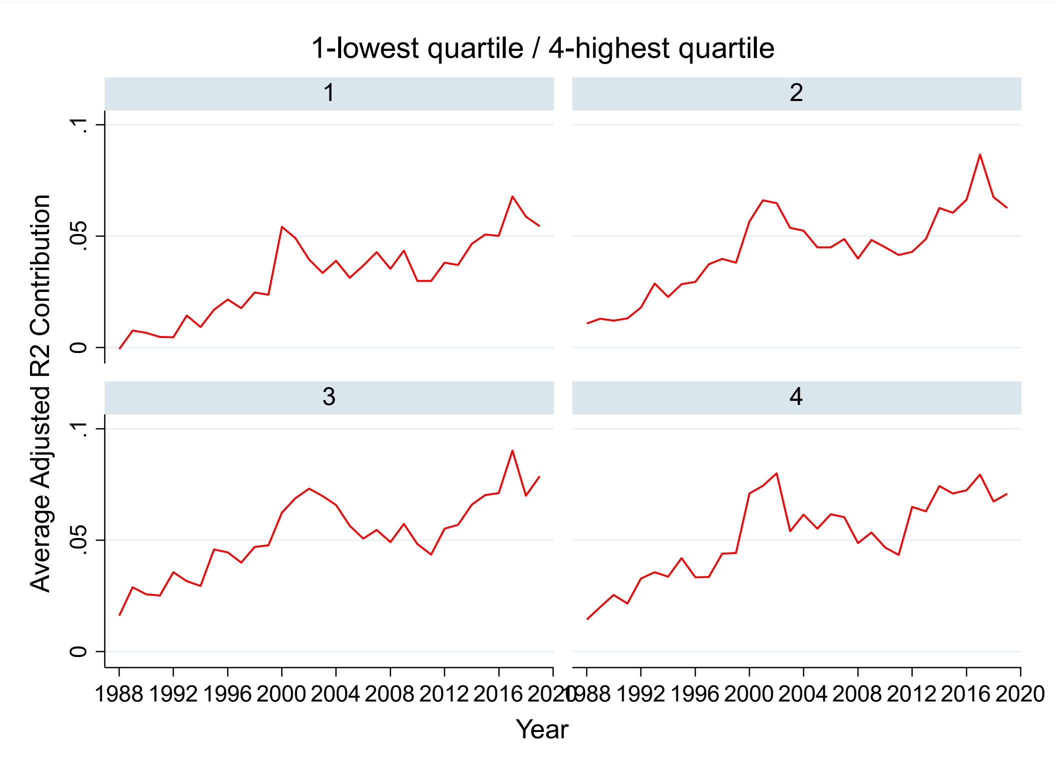

Figure 3 – Rivals' Idiosyncratic Returns Contribution to Adjusted R^2 versus Industry Average Similarity Score

Figure 3 displays average adjusted-R^2 contribution from rivals' idiosyncratic returns (see Equation 2) to firm level time-series regressions (vertical axis) versus the average ten product market space nearest neighbors similarity score by Fama and French 49 industries (horizontal axis). The blue line is obtained running an univariate regression of industry average adjusted-R^2 contributions on industry average similarity scores and the greyed area corresponds to the 95% confidence interval. The industry "precious metal" (industry code 27) is excluded because it amounts to only 77 firm/year observations out of 29,498 and is an outlier. Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

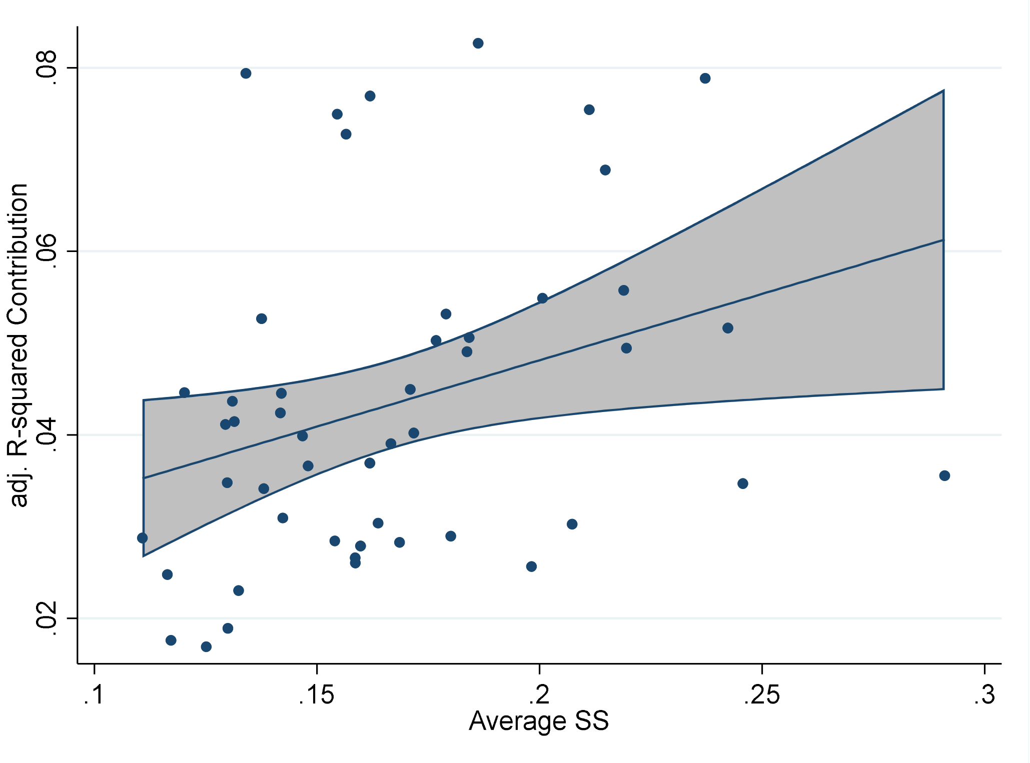

Figure 4 –Rivals' Idiosyncratic Returns Contribution to Firm Level Time-Series Regression Adjusted-R^2 by Quartile of Price Impact

Figure 4 presents yearly average contributions of rivals' idiosyncratic returns to firm level time-series regression adjusted-R^2 by quartile of Amihud (2002) price impact. Contributions refer to the difference between the average adjusted R^2 of a model including the Fama and French (2015) five factors, the industry portfolio formed by the five even ranked product market space nearest neighbors in the set of ten product market space nearest neighbors and the rivals' idiosyncratic returns (see Equation 2), denoted *5F+Ind+RR* in Figure 1, and the corresponding specification without the rivals' idiosyncratic returns, denoted *5F+Ind* in Figure 1. Quartile 1 is the quartile with the smallest average price impact (most liquid assets) and quartile 4, the quartile with the highest average price impact (less liquid assets). Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

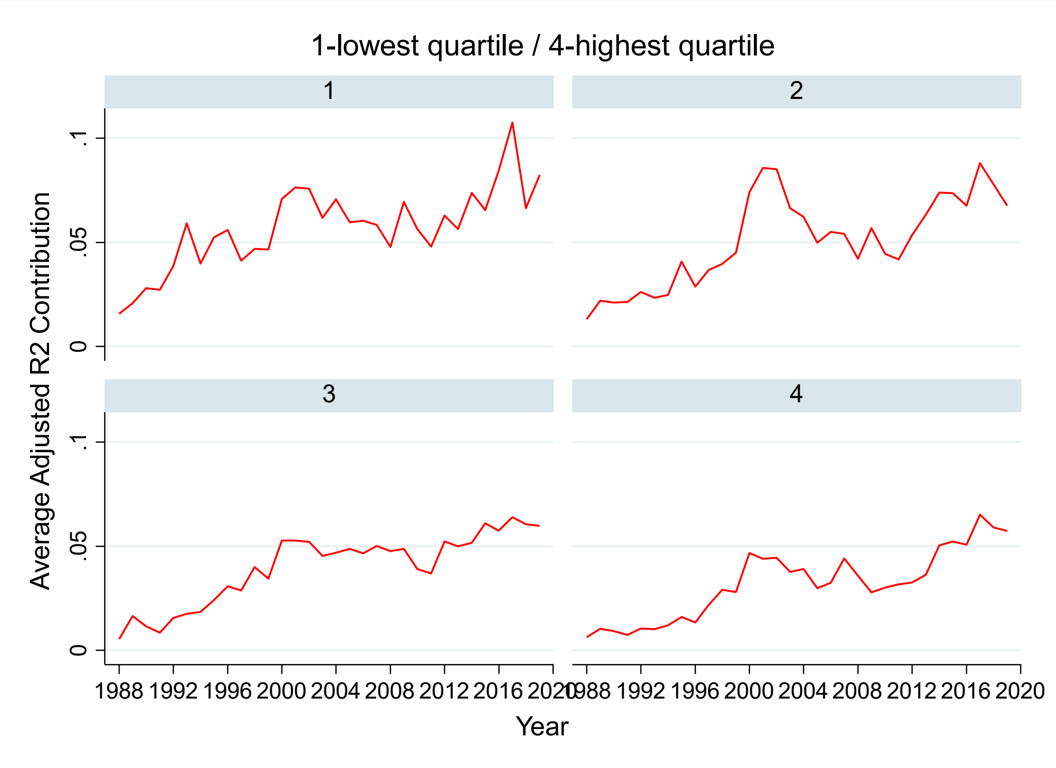

Table 1 – Sample Descriptive Statistics

Table 1 displays comparative descriptive statistics between the Hoberg and Phillips (2010) sample and our sample that is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year. Columns 1 and 2 provide the Hoberg and Phillips number of unique firms by year and their aggregated market values collected in Compustat. Columns 3 and 5 report the corresponding statistics for our sample of firms, market values being collected in the CRSP database (in USD billions), and columns 4 and 6 the corresponding percentages.

	Hoberg & Phillips Sample		Rivals' Return Sample			
Year	**Number**	**Market Value**	**Number**	**%**	**Market Value**	**%**
	(1)	(2)	(3)	(4)	(5)	(6)
1988	3,663	2.1	697	19%	1.8	88%
1989	5,405	2.9	862	16%	2.6	89%
1990	5,480	2.7	898	16%	2.4	87%
1991	5,525	3.6	901	16%	3.1	87%
1992	5,611	3.8	873	16%	3.3	86%
1993	6,148	4.5	895	15%	3.7	83%
1994	6,604	4.5	912	14%	3.8	83%
1995	6,880	6.2	921	13%	5.1	82%
1996	7,541	7.8	939	12%	6.3	80%
1997	7,519	9.9	910	12%	8.3	83%
1998	7,324	12.2	900	12%	10.5	86%
1999	7,110	15.6	908	13%	13.3	85%
2000	6,754	14.3	905	13%	12.5	87%
2001	6,171	13.0	920	15%	11.1	85%
2002	5,710	10.1	951	17%	8.7	87%
2003	5,336	13.3	952	18%	11.3	85%
2004	5,201	15.0	956	18%	12.4	83%
2005	5,095	15.5	932	18%	12.9	83%
2006	5,027	17.5	946	19%	14.3	82%
2007	4,947	17.6	931	19%	14.6	83%
2008	4,691	10.6	933	20%	9.0	85%
2009	4,453	13.6	955	21%	11.4	84%
2010	4,306	15.6	960	22%	13.0	83%
2011	4,179	15.3	951	23%	12.8	84%
2012	4,076	17.1	961	24%	14.3	84%
2013	4,139	22.5	962	23%	18.5	82%
2014	4,281	24.7	960	22%	20.2	82%
2015	4,248	23.5	946	22%	19.1	81%
2016	4,104	25.0	925	23%	20.5	82%
2017	4,062	29.2	935	23%	24.2	83%
2018	4,048	26.3	929	23%	22.3	85%
2019	4,031	33.1	932	23%	28.2	85%
Average	5,302	14.0	921	18%	11.7	84%

Table 2 – Descriptive Statistics

Table 2 reports descriptive statistics for the set of variables used in our regression specifications. Panel A focuses on Returns (*r*, *Idio r*, $NN^{\{2,4,6,8,10\}}$, r_m), signed dollar volume (*x*), arithmetic average of idiosyncratic returns of the ten nearest neighbor firms in the product market space (avg^{rr}), Fama and French factors (*mktrf, smb, hml, rmw, cma*) and Amihud price impact (*pi*), Panel B on Hoberg and Phillips similarity scores (*SS*, NN_{10} *SS*, NN_{odd} *SS*, NN_{even} *SS*, NN_{first} *SS*, NN_{last} *SS*), Panel C on firm characteristics (*Total Assets*, *Leverage*, *Cash*, *Intang*, *R&D*, *ROA*, *B/M*, *MarkShare*, *SelfFluid*) and Panel D on industry characteristics (*HHI*, *Leader*, *Laggard*). Column 1 the arithmetic average, Column 2 the standard deviation, Columns 3 and 4 the skewness kurtosis coefficients respectively. All variable definitions and data sources are provided in Appendix 1. Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

	Mean	**Std**	**Skewness**	**Kurtosis**
	(1)	(2)	(3)	(4)
A. Returns, Factors and Price Impact				
r	0.0652%	2.4912%	0.728	57.441
Idio r	0.0033%	2.0409%	0.918	92.549
$NN^{\{2,4,6,8,10\}}$	0.0034%	1.4035%	1.429	61.507
r_m	0.0470%	1.0492%	-0.231	11.605
X (thousands)	755.38	135,068	-2.090	3,198.670
avg^{rr}	2.6524%	1.8884%	6.378	235.065
mktrf	0.0351%	1.0830%	-0.179	11.393
smb	0.0033%	0.5623%	-0.153	6.503
hml	0.0078%	0.5833%	0.447	11.958
rmw	0.0168%	0.4373%	0.300	10.795
cma	0.0100%	0.4008%	-0.452	14.650
pi (E06)	0.010	0.050	40.104	2144.726
B. Similarity Scores				
SS	0.018	0.035	3.556	21.967
NN_{10} *SS*	0.186	0.068	0.896	3.911
NN_{odd} *SS*	0.192	0.071	0.911	3.884
NN_{even} *SS*	0.181	0.067	0.928	4.006
NN_{first} *SS*	0.203	0.074	0.909	3.980
NN_{last} *SS*	0.169	0.066	0.952	4.002
C. Firm Characteristics				
Total Assets	23,606	109,113	14	251
Leverage	0.243	0.170	0.532	2.918
Cash	0.078	0.095	2.291	10.274
Intang	0.153	0.192	1.338	3.883
R&D	0.023	0.049	3.665	22.945
ROA	0.133	0.096	-0.834	12.578
B/M	0.526	0.404	2.681	21.190
MarkShare	0.120	0.203	2.457	8.737
SelfFluid	21.091	16.675	1.876	7.259
D. Industry Characteristics				
HHI	0.206	0.199	1.650	5.487
Leader	0.641	0.480	-0.589	1.347
Laggard	0.039	0.193	4.767	23.727

Table 3 – Firm Level Time-Series Regression Adjusted-R^2 – Baseline Specification

Table 3 presents adjusted R^2 descriptive statistics for firm level time-series regressions. In Column 1 (*1F*), only the market factor (*mktrf*) is included in the regression specification. In Column 2 (*3F*), the size (*smb*) and value (*hml*) factors are added. In Column 3 (*5F*), the profitability (*rmw*) and investment (*cma*) are in turn added. In Column 4 (*5F+Ind*), we add the industry portfolio (NN_{even}) formed by the even ranked five product market space nearest neighbors in the set of ten product market space nearest neighbors. Finally, in Column 5 (*5F+ind+RR*), the rivals idiosyncratic returns are included (see Equation 2). *Mean* is the arithmetic average, *Std Mean* is the corresponding standard error, *Skewness* and *Kurtosis* are respectively the skewness and kurtosis coefficients. *Diff Mean* is the difference of means between successive columns and *t-stat* is corresponding Student statistic. *Yes* indicates that the corresponding factor is included in the time-series model specification and *No* that it is excluded. Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

	1F	**3F**	**5F**	**5F+Ind**	**5F+Ind+RR**
	(1)	(2)	(3)	(4)	(5)
Firm-year count	29,438	29,438	29,438	29,438	29,438
Adjusted R^2					
Mean	24.75%	27.76%	29.16%	32.96%	37.51%
Std Mean	0.10%	0.10%	0.10%	0.11%	0.12%
Skewness	0.6923	0.6420	0.5905	0.4662	0.2915
Kurtosis	2.8013	2.7051	2.6231	2.3956	2.1632
Diff Mean		3.01%	1.40%	3.80%	4.55%
t-stat		21.28	9.90	25.56	27.95
Model Specification					
mktrf	Yes	Yes	Yes	Yes	Yes
smb	No	Yes	Yes	Yes	Yes
hml	No	Yes	Yes	Yes	Yes
rmw	No	No	Yes	Yes	Yes
cma	No	No	Yes	Yes	Yes
NN_{even}	No	No	No	Yes	Yes
Rivals Returns	No	No	No	No	Yes

Table 4 – Absolute and Relative Firm Level Time-Series Regression Adjusted-R^2 Contribution

Table 4 presents adjusted R^2 for firm level time-series regressions by year. In Column 1 (*1F*), only the market factor (*mktrf*) is included in the regression specification. In Columns 2 and 3 (*3F*), the size (*smb*) and value (*hml*) factors are added. In Columns 4 and 5 (*5F*), the profitability (*rmw*) and investment (*cma*) are in turn added. In Columns 6 and 7 (*5F+Ind*), we add the industry portfolio (NN_{even}) formed by the even ranked five product market space nearest neighbors in the set of ten product market space nearest neighbors. Finally, in Columns 8 and 9 (*5F+Ind+RR*), the rivals idiosyncratic returns are included (see Equation 2). *Cont.* is for contribution, the percentage point increase in adjusted R^2 thanks to the addition of corresponding factors (Columns 2, 4, 6 and 8) and *% Cont*. is for relative contribution, the percentage of adjusted R^2 increase relative to the market model R^2 (Column 1). Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

Year	1F	3F		5F		5F+Ind		5F+Ind+RR	
		Cont.	% Cont.	Cont.	% Cont.	Cont.	% Cont.	Cont.	% Cont.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1988	21.81%	1.87%	8.56%	0.35%	1.62%	0.60%	2.74%	1.02%	4.67%
1989	16.63%	1.70%	10.21%	0.36%	2.19%	0.73%	4.39%	1.74%	10.47%
1990	20.46%	2.48%	12.11%	1.40%	6.86%	0.82%	4.02%	1.75%	8.56%
1991	16.35%	1.75%	10.73%	0.55%	3.36%	0.89%	5.42%	1.62%	9.88%
1992	10.24%	2.40%	23.42%	0.24%	2.37%	1.43%	13.92%	2.28%	22.22%
1993	8.82%	3.10%	35.17%	1.02%	11.60%	1.96%	22.20%	2.76%	31.34%
1994	12.41%	1.62%	13.06%	0.77%	6.19%	1.70%	13.68%	2.38%	19.18%
1995	8.12%	2.40%	29.55%	1.57%	19.32%	2.25%	27.75%	3.34%	41.08%
1996	13.49%	3.00%	22.21%	0.78%	5.78%	1.99%	14.74%	3.22%	23.90%
1997	19.24%	2.55%	13.28%	0.87%	4.54%	2.26%	11.73%	3.21%	16.70%
1998	20.95%	2.91%	13.91%	1.31%	6.25%	3.72%	17.77%	3.89%	18.57%
1999	10.28%	4.45%	43.27%	1.01%	9.82%	4.21%	40.93%	3.85%	37.48%
2000	13.62%	6.66%	48.86%	1.47%	10.78%	5.76%	42.30%	6.11%	44.81%
2001	20.95%	4.27%	20.37%	3.40%	16.23%	6.08%	29.01%	6.47%	30.87%
2002	32.14%	1.76%	5.49%	2.94%	9.14%	4.91%	15.28%	6.44%	20.05%
2003	29.20%	1.41%	4.84%	1.66%	5.67%	3.90%	13.35%	5.28%	18.08%
2004	21.86%	2.35%	10.74%	2.22%	10.14%	4.53%	20.75%	5.47%	25.02%
2005	21.68%	2.43%	11.21%	1.04%	4.78%	4.22%	19.46%	4.70%	21.68%
2006	21.07%	1.89%	8.98%	1.98%	9.41%	4.53%	21.50%	4.86%	23.07%
2007	29.81%	2.08%	6.99%	1.43%	4.80%	3.75%	12.59%	5.17%	17.33%
2008	48.06%	4.05%	8.44%	2.07%	4.30%	3.80%	7.91%	4.33%	9.01%
2009	42.25%	2.55%	6.03%	0.77%	1.82%	4.75%	11.25%	5.07%	12.01%
2010	44.24%	1.63%	3.68%	0.73%	1.64%	3.50%	7.91%	4.25%	9.60%
2011	55.01%	2.21%	4.02%	0.88%	1.61%	2.84%	5.16%	3.96%	7.20%
2012	30.27%	2.05%	6.76%	1.39%	4.59%	4.08%	13.47%	5.03%	16.62%
2013	29.65%	2.10%	7.09%	1.11%	3.73%	4.28%	14.42%	5.14%	17.35%
2014	29.47%	2.92%	9.92%	0.87%	2.95%	7.32%	24.84%	6.24%	21.17%
2015	33.41%	3.74%	11.20%	1.31%	3.91%	6.52%	19.51%	6.31%	18.90%
2016	30.05%	4.79%	15.93%	2.29%	7.64%	6.51%	21.67%	6.51%	21.65%
2017	15.32%	5.70%	37.18%	2.89%	18.90%	6.20%	40.46%	8.11%	52.97%
2018	32.11%	4.83%	15.04%	2.29%	7.12%	5.60%	17.43%	6.60%	20.55%
2019	26.00%	6.43%	24.72%	1.51%	5.82%	4.39%	16.87%	6.67%	25.67%

Table 5 – Daily Stock Return Variance Decomposition

Table 5 reports daily return variance decompositions obtained using Brogaard et al. (2022) structural VAR model expanded to identify the competitive public information component. The variance component shares are calculated separately for each stock in each year and then averaged across stocks. The stock return variance is decomposed into market-wide information (*MktInfoShare*), private firm-specific information (*PrivateInfoShare*), competitive public information component (*RivalInfoShare*) (in Columne 3 to 6), public firm-specific information (*PublicInfoShare* and noise (*NoiseShare*). In Column 1, Brogaard et al. (2022) estimates are reported for reference (see Internet Appendix, Section 2, equally weighted average). In Column 2, we report our Brogaard et al. (2022) replication for the period 1988 to 2019. In Columns 3 to 6, we add the competitive public information component. Columns 3 and 5 report results of the sample of all listed firms on the NYSE, AMEX and NASDAQ, while Columns 4 and 6 focus on the 1,000 largest ones by market value. The measures of the competitive public information component is based on idiosyncratic returns of the ten nearest neighbor firms in the product market space. Idiosyncratic returns are residuals from a factor models including the five Fama and French (2015) factors (*mktrf*, *smb*, *hml*, *rmw*, *cma*) augmented with an industry index (the value-weighted average return of the ten nearest neighbor firms in the product market space). In Columns 3 and 5, we use the standard deviation of rivals' idiosyncratic returns to estimate the competitive information component, while in Columns 5 and 6, we use the signed extremum of rivals' idiosyncratic returns.

	Brogaard et al.	**Replication**	**Rivals' Returns**	**Rivals' Returns**	**Rivals' Returns**	**Rivals' Returns**
	1960/2015	1988/2019	1988/2019	1988/2019	1988/2019	1988/2019
	All Firms	All firms	All Firms	1,000 Largest Firms	All Firms	1,000 Largest Firms
			Std Dev	Std Dev	Signed Extremum	Signed Extremum
	(1)	(2)	(3)	(4)	(5)	(6)
Information shares						
MktInfoShare	13.16%	12.34%	10.94%	19.83%	3.88%	7.28%
PrivateInfoShare	27.75%	27.69%	25.31%	25.45%	7.41%	8.44%
RivalInfoShare			6.02%	5.01%	37.78%	33.99%
PublicInfoShare	34.70%	36.00%	31.06%	28.87%	8.61%	9.67%
NoiseShare	25.19%	23.94%	26.64%	20.81%	42.28%	40.59%

Table 6 - Firm Level Time-Series Regression Adjusted-R^2 – Robustness checks

Table 6 replicates Table 3 for various robustness checks. Each panel is organized like Table 3 and presents adjusted-R^2 descriptive statistics for firm level time-series regressions. In Column 1 (*1F*), only the market factor (*mktrf*) is included in the regression specification. In Column 2 (*3F*), the size (*smb*) and value (*hml*) factors are added. In Column 3 (*5F*), the profitability (*rmw*) and investment (*cma*) are in turn added. In Column 4 (*5F+Ind*), we add the industry portfolio (NN_{even}) formed by the five even ranked product market space nearest neighbors in the set of ten product market space nearest neighbors. Finally, in Colum 5 (*5F+ind+RR*), the rivals idiosyncratic returns are included (see Equation 2). *Mean* is the arithmetic average, *Std Mean* is the corresponding standard error, *Skewness* and *Kurtosis* are respectively the skewness and kurtosis coefficients. *Diff Mean* is the difference of means between successive columns and *t-stat* is corresponding Student statistic. Panel A reports results for a sample composed of all CRSP universe firms for which needed data are available). Panel B reports results of a placebo test where rivals idiosyncratic returns are from firms randomly selected in our sample of U.S. listed firms (see Section 3.1). In Panel C, an alternative strategy for rivals selection is used: the industry portfolio is composed of the five rivals ranked sixth to tenth by decreasing SS in the product market space and rivals idiosyncratic returns by returns from firms ranked one to fifth (see Section 3.2). Panel D presents results controlling for asynchronous trading using the Scholes and Williams (1977) correction (see Section 3.3). In Panel E, we control for the potential effects of asymmetric betas (see Section 3.4) and in Panel F, we test a factor specification based on the ten first components from a principal component analysis in place of the Fama and French five factors (see Section 3.5). Model specifications for Panel F are provided below the panel because they differ from Table 3. *Yes* indicates that the corresponding factor is included in the time-series model specification and *No* that it is excluded. Except in Panel A, our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

Panel A – All CRSP universe firms

	1F	3F	5F	5F+Ind	5F+Ind+RR
	(1)	(2)	(3)	(4)	(5)
Firm-year count	131,456	131,456	131,456	131,456	131,456
Adjusted R^2					
Mean	11.89%	14.47%	15.09%	16.53%	18.53%
Std Mean	0.04%	0.05%	0.05%	0.05%	0.06%
Skewness	1.5337	1.3371	1.2881	1.2369	1.1466
Kurtosis	4.8889	4.1738	4.0008	3.7626	3.4454
Diff Mean		2.58%	0.62%	1.44%	2.00%
t-stat		40.29	8.77	20.36	25.61

Panel B – Placebo Test

	1F	3F	5F	5F+Ind	5F+Ind+RR
	(1)	(2)	(3)	(4)	(5)
Firm-year count	29,432	29,432	29,432	29,432	29,432
Adjusted R^2					
Mean	24.76%	27.76%	29.17%	32.96%	33.45%
Std Mean	0.10%	0.10%	0.10%	0.11%	0.12%
Skewness	0.6920	0.6417	0.5903	0.4665	0.4593
Kurtosis	2.8018	2.7053	2.6234	2.3963	2.4451
Diff Mean		3.00%	1.41%	3.79%	0.49%
t-stat		21.21	9.97	25.49	3.01

Panel C – Rival Selection

	1F	3F	5F	5F+Ind	5F+Ind+RR
	(1)	(2)	(3)	(4)	(5)
Firm-year count	29,431	29,431	29,431	29,431	29,431
Adjusted R^2					
Mean	24.75%	27.76%	29.16%	32.40%	37.92%
Std Mean	0.10%	0.10%	0.10%	0.11%	0.13%
Skewness	0.6924	0.6421	0.5906	0.4889	0.2747
Kurtosis	2.8017	2.7056	2.6238	2.4308	2.1372
Diff Mean		3.01%	1.40%	3.24%	5.52%
t-stat		21.28	9.90	21.79	32.41

Panel D – Asynchronous Trading

	1F	3F	5F	5F+Ind	5F+Ind+RR
	(1)	(2)	(3)	(4)	(5)
Firm-year count	29,438	29,438	29,438	29,438	29,438
Adjusted R^2					
Mean	24.75%	27.76%	29.16%	32.96%	37.41%
Std Mean	0.10%	0.10%	0.10%	0.11%	0.13%
Skewness	0.6923	0.6420	0.5905	0.4662	0.2231
Kurtosis	2.8013	2.7051	2.6231	2.3956	2.1805
Diff Mean		3.01%	1.40%	3.80%	4.45%
t-stat		21.28	9.90	25.56	26.13

Panel E – Asymmetric Beta

	1F	3F	5F	5F+Ind	5F+Ind+RR
	(1)	(2)	(3)	(4)	(5)
Firm-year count	29,438	29,438	29,438	29,438	29,438
Adjusted R^2					
Mean	24.75%	27.76%	29.16%	32.96%	37.85%
Std Mean	0.10%	0.10%	0.10%	0.11%	0.12%
Skewness	0.6923	0.6420	0.5905	0.4662	0.2698
Kurtosis	2.8013	2.7051	2.6231	2.3956	2.1570
Diff Mean		3.01%	1.40%	3.80%	4.89%
t-stat		21.28	9.90	25.56	30.04

Panel F – Principal Components Factors

	1F	3F	5F	PCA	PCA+Ind	PCA+Ind+RR
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-year count	29,438	29,438	29,438	29438	29,438	29,438
Adjusted R^2						
Mean	24.75%	27.76%	29.16%	35.52%	37.00%	40.21%
Std Mean	0.10%	0.10%	0.10%	0.12%	0.12%	0.12%
Skewness	0.6923	0.6420	0.5905	0.3845	0.3370	0.2040
Kurtosis	2.8013	2.7051	2.6231	2.3011	2.2490	2.1367
Diff Mean		3.01%	1.40%	6.36%	1.48%	3.21%
t-stat		21.28	9.90	40.72	8.72	18.92
Model Specification						
mktrf	Yes	Yes	Yes	No	No	No
smb	No	Yes	Yes	No	No	No
hml	No	Yes	Yes	No	No	No
rmw	No	No	Yes	No	No	No
cma	No	No	Yes	No	No	No
PCA10	No	No	No	Yes	Yes	Yes
NN_{even}	No	No	No	No	Yes	Yes
Rivals Returns	No	No	No	No	No	Yes

Table 7 - Firm Level Time-Series Regression Adjusted R^2 – Additional Investigations

Table 7 displays results of three additional investigations that explore the role of competition (Panel A) and liquidity (Panel B) in explaining the increase in adjusted R^2 thanks to taking into account rivals' idiosyncratic returns. In Panel A, firm-year observations are ranked by quartile of competition intensity, using the Hoberg and Phillips (2010) ten nearest neighbors average similarity scores (see Section 4.1) and in Panel B, firm-year observations are ranked by quartile of liquidity, using the Amihud (2002) price impact measure (see Section 4.2). *Mean* (Column 1) stands for arithmetic average and is the average increase in adjusted R^2 thanks to the addition of rivals' idiosyncratic returns to the Fama and French five factors models augmented with an industry index. *SE* (Column 2) is the corresponding standard error, *t-Stat* (Column 3) the Student statistics, *p*-Value (Column 4) the associated probability and *95% Conf. Int.* (Columns 5 and 6) the 95% confidence level interval. Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1).

Panel A – Competition

					95% Conf. Int.	
	Mean	**SE**	**t-Stat**	**p-Value**	**Lower**	**Upper**
Quartile	(1)	(2)	(3)	(4)	(5)	(6)
1	3.24%	0.08%	40.38	0.00	3.08%	3.40%
2	4.42%	0.08%	55.04	0.00	4.27%	4.58%
3	5.30%	0.08%	65.91	0.00	5.14%	5.45%
4	5.23%	0.08%	65.04	0.00	5.07%	5.39%

Panel B – Liquidity

					95% Conf. Int.	
	Mean	**SE**	**t-Stat**	**p-Value**	**Lower**	**Upper**
Quartile	(1)	(2)	(3)	(4)	(5)	(6)
1	5.77%	0.08%	72	0.00	5.61%	5.92%
2	5.14%	0.08%	64.16	0.00	4.99%	5.30%
3	4.04%	0.08%	50.45	0.00	3.89%	4.20%
4	3.24%	0.08%	40.35	0.00	3.08%	3.39%

Table 8 – Determinants of Rivals Idiosyncratic Returns Contributions to Firm Level Time-series Regression adjusted R^2

Table 8 reports results of univariate (Columns 1 and 3) and multivariate (Columns 2 and 4) regressions specified to investigate the determinants of rivals' idiosyncratic returns contributions to firm level time-series regression adjusted R^2. In each case, the dependent variable is the percentage point increase of adjusted R^2 between a firm level time-series regression specification that includes rivals' idiosyncratic returns (see Equation 2) and a specification that exclude them, respectively reported in Columns 5 and 4 of Table 3. Columns 1 and 2 provides results obtained using the classic ordinary least square estimator (*Pooled*) and Columns 3 and 4, the panel data fixed effects estimator (*Fixed Effects*). The set of investigated determinants include the ten product market nearest neighbor average similarity score ($NN_{10}SS$), the corresponding standard deviation ($Std_{10}SS$), the natural logarithm of total assets (*log Total Assets*), the leverage (*Leverage*), cash (*Cash*), intangibles (*Intang*), research and development (*R&D*), return on assets (*ROA*), book to market (*B/M)* financial ratios, the firm sales based market share (*MarkShare)*, the Hoberg et al. (2014) product market self-fluidity (*SelfFluid*), the sales based Herfindahl-Hirschman concentration index (*HHI*) and indicator variables identifying industry leaders (*Leader*) and laggards (*Laggard*). Variable definitions and data sources are provided in Appendix 1.). Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1). R^2 and adjusted R^2 are respectively the R-squared and the adjusted R-squared. *Fisher* is the Fisher test of joint significance of the coefficients. *Num Obs* is the number of firm-year observations. Student statistics are reported bellow coefficient estimates, between parentheses. * stands for statistically significant at the 10% confidence level, ** at the 5% confidence level and *** at the 1% confidence level. *VIF* is the variance inflation factor, provided in Column 5.

	Pooled		Fixed Effects		VIF
	(1)	(2)	(3)	(4)	(5)
NN_{10} SS	0.0959***	-0.0584***	0.0352	-0.1133***	2.19
	(6.85)	(-2.94)	(1.54)	(-4.26)	
Std_{10} SS	0.3418***	0.3713***	0.2284***	0.2873***	1.10
	(5.65)	(5.23)	(4.78)	(4.66)	
log Total Assets	0.0061***	0.0056***	-0.0017	-0.0001	1.74
	(8.33)	(5.97)	(-1.04)	(-0.07)	
Leverage	0.0348***	0.0262***	0.0075	0.0095	1.19
	(6.58)	(4.41)	(1.09)	(1.11)	
Cash	-0.0539***	-0.0010	0.0047	-0.0002	1.51
	(-6.14)	(-0.09)	(0.53)	(-0.02)	
Intang	-0.0161***	-0.0145**	-0.0065	0.0016	1.30
	(-2.61)	(-2.23)	(-0.87)	(0.17)	
R&D	-0.1499***	-0.0703***	0.0260	0.0358	1.38
	(-9.04)	(-3.74)	(1.15)	(1.41)	
ROA	0.0182**	0.0644***	0.0448***	0.0347***	1.59
	(2.24)	(5.80)	(4.24)	(2.78)	
B/M	0.0118***	0.0007	-0.0081***	-0.0068**	1.53
	(4.91)	(0.25)	(-3.31)	(-2.42)	
MarkShare	-0.0194***	-0.0103*	-0.0184***	-0.0134***	2.22
	(-4.72)	(-1.81)	(-4.68)	(-2.75)	
SelfFluid	-0.0001	-0.0001**	-0.0001***	-0.0001***	1.10
	(-1.44)	(-2.25)	(-3.41)	(-2.94)	
HHI	-0.0365***	-0.0386***	-0.0176***	-0.0137***	2.56
	(-9.43)	(-6.23)	(-4.04)	(-2.58)	
Leader	-0.0009	-0.0022	0.0018	0.0001	1.32
	(-0.59)	(-1.26)	(1.53)	(0.08)	
Laggard	-0.0087***	-0.0047	-0.0024	-0.0026	1.12
	(-3.03)	(-1.45)	(-0.86)	(-0.82)	
Year FEs	Yes	Yes	Yes	Yes	
Firm FEs	No	No	Yes	Yes	
R^2		0.115		0.486	
adjusted R^2		0.114		0.415	
Fisher		28.65		19.67	
Num Obs		25,086		25,086	

Table 9 – Asset Pricing Test

Table 9 reports results obtained using the Jegadeesh et al. (2019) procedure to test whether rivals' idiosyncratic returns are priced. The test is implemented over the 1988 to 2019 period. Firm level time-series regression are estimated using daily returns over a three years rolling window in order to obtain factor loadings. Next, cross-sectional regressions on monthly returns are estimated using lagged factor loadings to obtain risk premia. Column 1 displays results of estimation by ordinary least square (*OLS*) while Column 2 results use factor loadings estimated on even months as instruments for factor loadings on odd months (*IV*). *cons* stands for constant, *mktrf* for market factor, *smb* for size factor, *hml* for value factor, *rmw* for profitability factor, *cma* for investment factor, $NN_{even}\ r_{it}$ for industry factor and *Fisher Rivals* for rivals' idiosyncratic returns factor (see Equation 2). All variables are defined in Appendix 1. Our sample is composed of firms that are present in Hoberg and Phillips universe, fulfill data requirements and belong to the one thousand largest CRSP universe firms ranked by market capitalization end of May of each year (see Table 1). Student statistics are reported bellow coefficient estimates, between parentheses. * stands for statistically significant at the 10% confidence level, ** at the 5% confidence level and *** at the 1% confidence level.

	(1)	(2)
cons	0.0032	0.0007
	(1.57)	(0.22)
mktrf	0.0116***	0.0138***
	(3.43)	(2.97)
smb	0.0048***	0.0072***
	(2.82)	(2.57)
hml	-0.0010***	-0.0120***
	(-5.32)	(-4.64)
rmw	-0.0017	--0.0012
	(-0.90)	(-0.43)
cma	-0.0054***	-0.0055**
	(-4.05)	(-2.37)
$NN_{even}\ r_{it}$	0.0120***	0.0168***
	(2.80)	(2.91)
Fisher Rivals	0.0000	0.0000
	(0.16)	(0.29)

Appendix 1 – Variable Definitions and Data Sources

	Definition	Data Source
	(1)	(2)
A. Returns, Factors and Price Impact		
r	Stock returns	CRSP Database
Idio r	Idiosyncratic return obtained from a regression on the Fama and French (2015) five factors model	CRSP Database - K. French Data Library
rr	Rival idiosyncratic stock returns	CRSP Database
r_m	Market return	CSRP Database
x	Signed dollar volume (product of price, volume and sign of return)	CRSP Database
avg^{rr}	Arithmetic average of idiosyncratic returns of the ten nearest neighbor firms in the product market space	CRSP Database - K. French Data Library - Hoberg and Phillips Data Library
$NN^{\{2,4,6,8,10\}}$	Equally weighted industry portfolio return obtained using the five even ranked product market space nearest neighbors in the set of ten product market space nearest neighbors	CRSP Database - K. French Data Library - Hoberg and Phillips Data Library
mktrf	Market factor	K. French Data Library
smb	Size factor	K. French Data Library
hml	Value factor	K. French Data Library
rmw	Profitability factor	K. French Data Library
cma	Investment factor	K. French Data Library
Fisher Rivals	Rivals Idiosyncratic Returns Factor	CRSP Database - Hoberg and Phillips Data Library
pi	Amihud (2002) price impact	CRSP Database
B. Similarity Scores		
SS	Product market similarity score	Hoberg and Phillips Data Library
NN_{10} *SS*	10 product market space nearest neighbors average SS	Hoberg and Phillips Data Library
Std_{10} *SS*	10 product market space nearest neighbors SS standard deviation	Hoberg and Phillips Data Library
NN_{odd} *SS*	Five odd ranked product market space nearest neighbors in the set of ten product market space nearest neighbors average SS	Hoberg and Phillips Data Library
NN_{even} *SS*	Five even ranked product market space nearest neighbors in the set of ten product market space nearest neighbors average SS	Hoberg and Phillips Data Library
NN_{first} *SS*	5 first ranked product market spcace nearest neighbors in the set of ten product market space nearest neighbors average SS	Hoberg and Phillips Data Library
NN_{last} *SS*	5 last ranked product market space nearest neighbors in the set of ten product market space nearest neighbors average SS	Hoberg and Phillips Data Library

C. Firm Characteristics

Total Assets	Book value of total assets	Compustat
Leverage	Long term debt total plus debt in current liabilities divided by total assets	Compustat
Cash	Cash divided by total assets	Compustat
Intang	Intangible assets total divided by total assets	Compustat
R&D	Research and development expenses divided by total assets	Compustat
ROA	Operating income before depreciation divided by total assets	Compustat
B/M	Book to market value of equities, computed as in Davis et al. (2000), divided by the market value of equities	Compustat
MarkShare	Hobert and Phillips TNIC sales based market shares	Compustat
SelfFluid	Product Market Self-Fluidity from Hoberg et al., 2014	Hoberg and Phillips Data Library

D. Industry Characteristics

HHI	Sales based Herfindahl-Hirschman Index	Compustat
Leader	Dummy variable equal to one if the firm sales and ROA are above the median firm sales and ROA in the corresponding TNIC industry	Compustat
Laggard	Dummy variable equal to one if the firm sales and ROA are below the median firm sales and ROA in the corresponding TNIC industry	Compustat