CATERING THROUGH NOMINAL SHARE PRICES REVISITED

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ABSTRACT

Finance research suggests that firms cater to investors' time-varying preference for low-priced stocks by managing nominal share prices. We show that the existing empirical tests of such catering use highly persistent data that may lead to finding significant relations between variables that are actually independent (spurious regression bias). We revisit the catering hypothesis applying five estimation techniques that reduce the effects of data persistence. Adjusted for persistence, the data offer little evidence that stock splits respond to catering incentives. There is some, although mixed, evidence that catering incentives affect the firms' choice of the post-split prices and the IPO prices.

Introduction

Baker, Greenwood, and Wurgler (2009) (hereafter, BGW) propose that investors have a time-varying preference for low-priced stocks; in some years such stocks trade at a premium to stocks with relatively high prices. BGW suggest that firms recognize this preference and cater to investors by managing nominal share prices. Specifically, in years when the preference for low-priced stocks is high, more firms choose to split their shares, splitting firms choose lower post-split prices, and IPO firms choose to list at lower prices. Time series and panel data tests used by BGW confirm the main implications of the catering hypothesis.

BGW's results fully replicate in our tests. We show however that the time series variables used in obtaining these results are highly persistent, i.e., exhibit high levels of autocorrelation.[1] When used in levels, highly persistent variables may cause the spurious regression bias that leads researchers to report significant relations between variables that are in fact independent (e.g., Granger, Hyung, and Jeon, 2001).[2]

Given that the spurious regression bias may result in finding empirical support for the catering hypothesis even if firms do not actually respond to catering incentives, we revisit the results using five alternative techniques that reduce the bias concerns. Specifically, we (i) reduce persistence by examining the changes in variables instead of levels (first differencing), (ii) apply the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1980, 1997), (iii) use corrected critical values for t-statistics (Phillips, 1986), (iv) use multi-period differencing, and (v) use alternative data dimensions such as panel data.

[1] In addition to finding high persistence, we cannot reject the presence of unit roots in many of the regression variables.
[2] Granger and Newbold (1974) and Phillips (1986) establish that the spurious regression bias arises when non-stationary unit root processes are used in regressions. Granger et al. (2001) find that this bias may arise even if regression variables are stationary, as long as these variables are persistent. Ferson, Sarkissian, and Simin (2003) and Novy-Marx (2013) confirm these results when studying return predictability.

The first of the abovementioned techniques, first differencing, is perhaps the most commonly used. Despite its popularity, the technique is sometimes criticized for reducing data variation and leading to information losses, the problem known as *over-differencing* (e.g., Greenwood, Hanson, and Stein, 2010; Cochrane, 2012). Mindful of the over-differencing concern, we use caution when interpreting the results obtained via first differencing. We note that this concern is significantly mitigated, or does not apply, to the other four of the abovementioned techniques. For instance, King and Rebelo (1993) show that the HP filter reduces persistence of time series data while preserving substantially more information content than first differencing. Because of this property, the filter is often viewed as a compromise between regressions in levels and in first differences (Cochrane, 2012). The third alternative, using corrected critical values for the regression t-statistics, keeps the data in levels and therefore does not affect their information content. The fourth alternative, multi-period differencing, deals with the concern that some variables may change too slowly to remain meaningful after one-period differencing (e.g., Greenwood et al., 2010). Finally, using alternative data dimensions (panel data) allows for perhaps the most robust look at the hypothesis as it bypasses some of the concerns associated with time series modelling.

The results obtained when we use the five alternative techniques show that the effect of catering incentives on firm behavior is more nuanced than the initial results suggest. Specifically, we find little evidence of catering as a motive for firms to split their shares. In the meantime, the evidence that firms manage IPO prices and the post-split prices in response to catering incentives is preserved in some tests, yet weakens or disappears in others.

From the economic standpoint, the nuanced nature of the effect of catering incentives may be rooted in the costs of carrying out a stock split. Angel (1997) and Weld, Michaely, Thaler, and

Benartzi (2009) report that these costs are substantial and include administrative/legal expenditures, the cost of getting a split approved by the shareholders, the additional per-share listing and maintenance fees levied by some stock exchanges, and the per-share franchise taxes levied by some states of incorporation. Also notable are higher trading costs and lower liquidity in the post-split months that may have adverse effects on the cost of capital (e.g., Conroy, Harris, and Benet, 1990; Kadapakkam, Krishnamurthy, and Tse, 2005). Our results are consistent with the notion that the perceived benefits from catering via nominal share prices do not usually exceed these costs; however, once the decision to split has been made (perhaps for reasons other than catering), catering considerations may influence the less costly choice of the post-split price.[3] Relatedly, it is possible that catering considerations may affect a relatively low-cost choice of the IPO price.

We note that we cannot fully eliminate a possibility, however small, that the results of our alternative tests are falsely rejecting the true hypothesis that splitting activity responds to investor preferences. Nevertheless, our findings show that the assessment of catering via stock splits has to rely more strongly on the readers' priors than the results in levels would suggest. More generally, we propose that studies that use highly persistent time series data should supplement results in levels with results that account for the possible effects of the spurious regression bias. Results that only hold in levels are not to be discarded; however, the issues raised by such studies should not be considered settled until additional supportive evidence is found.

The remainder of the study is organized as follows. In Section I, we discuss the data and the variables of interest. In Section II, we replicate the original BGW results in levels and analyze

[3] Aside from catering, finance literature has put forward several hypotheses to explain firms' split decisions. Among these, most often discussed are signaling (e.g., Grinblatt, Masulis, and Titman, 1984; Brennan and Copeland, 1988), price range (e.g., Baker and Gallagher, 1980; Angel, 1997), and norms (Weld et al., 2009).

the time series properties of the variables. In Section III, we discuss techniques that reduce (or account for) data persistence and the effect of using these techniques on the support for the catering hypothesis. Section IV concludes.

I. Data and main variables

When selecting our sample and constructing the variables, we follow the procedure described by BGW word for word and obtain a sample virtually identical to theirs. To track stock splits, we retrieve 44 years (1963-2006) of CRSP data for common stocks (CRSP share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ (CRSP exchange codes 1, 2, and 3). For each stock, we identify splits as the distribution events with the CRSP event code 5523. We exclude reverse splits and stock dividends identified as distribution events with the split factor less than or equal to 0.25. The resulting sample contains the same number of splits as BGW report.

BGW propose that firms split their stock to cater to investors' price level and company size preferences. To proxy for these preferences, they define three premiums: (i) the low-price premium, P^{CME}, where *CME* stands for *cheap minus expensive*; (ii) the small-cap premium, P^{SMB}, where *SMB* stands for *small minus big*, and (iii) the split announcement premium, A. P^{CME} is the log difference of the average market-to-book (MB) ratios of low- and high-priced stocks. P^{SMB} is the log difference of the average MB ratios of small and large stocks. The split announcement premium, A, is the abnormal return from the day before a split announcement through ten days after the effective split date, scaled by the standard deviation of returns. In the tests reported in the next section, we use the yearly P^{CME}, P^{SMB}, and A estimates reported by BGW and refer to them as the *catering premiums*.[4]

BGW use four variables to measure price management: (i) s_t – the number of splits by all firms in year t expressed as a percentage of the total number of firms, (ii) m_t – an aggregate measure of split activity computed as the cross-sectional average of the log difference between the actual stock price and the beginning-of-year stock price grown at the stock return excluding dividends, (iii) p_t^{IPO} – the log of the average IPO price in year t, and (iv) p_t – the log of the average post-split stock price in year t. We use the same variables.

II. Results in levels and persistence tests

II.A. Catering tests

BGW use yearly time series regressions that model firms' price management activities as a function of the catering premiums:

$$depvar_t = a + bP_{t-1}^{CME} + cP_{t-1}^{SMB} + dA_{t-1} + ep_{t-1}^{EW} + fr_t^{EW} + u_t, \qquad (1)$$

where $depvar$ is s, m, p_{IPO}, or p as defined previously; P_{t-1}^{CME} and P_{t-1}^{SMB} are the low-price and small-stock premiums in year $t-1$ (either equal-weighted or value-weighted), A_{t-1} is the split announcement premium, p_{t-1}^{EW} is the log equal-weighted average stock price, and r_t^{EW} is the log equal-weighted return excluding distributions in year t. BGW report that the catering premiums are statistically significant in almost all of their tests, corroborating the hypothesis that firms respond to investor preferences for small and cheap stocks by managing their share prices.

We report estimation results for eq. 1 in the left-hand side sections of Table I. The right-hand side sections report the results in first differences that we will discuss shortly. The estimated

[4] As a robustness exercise, we also reconstruct these premiums closely following BGW's procedure. Our reconstructed premiums and BGW's original premiums are numerically similar with a correlation coefficient of 0.95. The results do not change if we use our reconstructed premiums instead of the premiums reported by BGW.

eq. 1 coefficients are numerically similar to the ones reported by BGW. The t-statistics are also similar.[5] Overall, our results in levels are consistent with the premise that catering incentives have a significant effect on price management by firms.

II.B. Persistence

In this section, we ask if any of the variables in eq. 1 are persistent, i.e., exhibit a lack of mean reversion. In time series plots, persistence is observed as stretches of several consecutive observations above or below the mean. At first glance, yearly realizations of P^{CME} and P^{SMB}, both equal-weighted (EW) and volume-weighted (VW), appear rather persistent (Figure 1, Panel A). Further, the presence of a persistent trend is observed when we use the HP filter in Panels B through E.[6] Once the trend is removed (plots labeled *de-trended*), the P^{CME} and P^{SMB} series have non-persistent patterns. We note that the split announcement premium A is not as persistent as the other catering proxies (Panel F). We return to this premium shortly.

Next we formally examine the persistence levels of the variables by estimating their autocorrelation (AC) and partial autocorrelation (PAC) functions.[7] Panel A of Figure 2 reports ACs and PACs for a simulated unit root series, which we use as a benchmark for comparison with the variables in eq. 1.[8] The first AC and PAC for the simulated series are large (0.85), and the autocorrelation function decreases very slowly. The only partial autocorrelation significantly

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[5] We note that while our results are similar to BGW's, we are not able to replicate their coefficients exactly. For instance, in Panel A, with s as dependent variable, our coefficient on $VW\ P_{t-1}^{CME}$ is 1.24 (t-statistic = 2.43), while their estimate is 1.33 (t-statistic = 2.84). We obtain the data for these regressions directly from BGW's published paper. We believe that the discrepancies between our coefficients and theirs may be driven by the fact that we use data with only two decimals (as in the published paper), and BGW use more decimals.

[6] The filter is a standard method of removing a persistent trend in the business cycle literature (e.g., Kydland and Prescott, 1990; Backus and Kehoe, 1992). The idea behind the HP filter is to model persistent series as the sum of a cyclical component and a persistent trend component. In a subsequent section, we describe the estimation methods and benefits of the HP filter in more detail.

[7] We provide a detailed discussion of the AC and PAC functions in the appendix.

[8] We simulate the process $y_t = y_{t-1} + \varepsilon_t$, where ε_ts are randomly selected from a standard normal distribution.

different from zero is the first one. These are common characteristics of a unit root series.

Next, we turn our attention to the regression variables in eq. 1. Panels B through E show that the first ACs and PACs for both P^{CME} and P^{SMB} (both equal-weighted and value-weighted) are larger than or equal to 0.82. The autocorrelation functions decrease slowly, and even at the third lag (representing three years) the ACs generally lay outside of critical bounds represented by the vertical lines and as such are significant at the 5% level. As in the simulated unit root series, the first PACs are significantly different from zero. Moreover, we reject the null hypothesis that all ACs are insignificant up to any number of lags (see the p-value columns). The split announcement premium A is less persistent than P^{CME} and P^{SMB} (Panel F). The control variable p^{EW} (Panel G) is highly persistent, and the control variable r^{EW} (Panel H) is not persistent. Finally the dependent variables m, p_{IPO}, and p are highly persistent, whereas s is also persistent but to a lower degree than the other dependent variables (Panels I through L).

As shown by Granger et al. (2001), persistence levels similar to those reported in Figure 2 may lead researchers to incorrectly conclude that there is a relation between variables that are actually independent. In their simulations, a true null hypothesis of independence is rejected at the 5% significance level more than 20% of the time for sample sizes and time series properties similar to those of our data. The high likelihood of rejecting true hypotheses when using highly persistent time series is also discussed by Novy-Marx (2013).[9]

With high levels of persistence in some of the variables used in eq. 1, it may be of interest to test if these variables are non-stationary.[10] To formally examine non-stationarity, we use several

[9] In the appendix, we ask if the persistent yet economically unrelated variables used by Novy-Marx (2013, 2014) have a significant relation to the price management proxies in a setting similar to that of eq. 1. We find that in 24% of cases Novy-Marx's variables appear related to price management at the 5% significance level, corroborating the notion that finding significant relations between unrelated variables is far too easy when the variables are persistent

[10] Butler, Grullon, and Weston (2006) analyze the effects of non-stationarity caused by structural breaks in time series regressions and find that this type of non-stationarity leads to spurious results.

tests: the Augmented Dickey-Fuller (ADF), Phillips and Perron (1988) (PP), Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS), and Elliot, Rothenberg, and Stock (1996) (ERS). Upon running these tests, we cannot reject the null hypothesis of non-stationarity of the catering premiums.[11] We note that non-stationarity is not a necessary condition for the spurious regression bias. The bias exists even if regression variables are stationary as long as these variables are highly persistent (Granger et al., 2001).

III. Alternative techniques

III.A. First differencing

Our discussion so far suggests that the results obtained from eq. 1 may be subject to the spurious regression bias. Recognizing the possibility of such bias, researchers often report time series results in both levels and first differences and downplay the results that are not robust in differences (e.g., Graham, Leary, and Roberts, 2014). Using first differences to reduce persistence was originally proposed by Granger and Newbold (1977) and Plosser and Schwert (1978). Intuitively, if the level of catering incentives influences firms' price management in a given year, one may expect that changes in catering incentives should also have an effect on price management, as follows:

$$\Delta depvar_t = a + b\Delta P_{t-1}^{CME} + c\Delta P_{t-1}^{SMB} + dA_{t-1} + e\Delta p_{t-1}^{EW} + fr_t^{EW} + u_t, \qquad (2)$$

where $\Delta depvar_t = depvar_t - depvar_{t-1}$, $\Delta P_{t-1}^{CME} = P_{t-1}^{CME} - P_{t-2}^{CME}$, and ΔP_{t-1}^{SMB} and Δp_{t-1}^{EW} are defined in a similar manner. As previously, $depvar$ takes values of s, m, p_{IPO}, or p. We include variables A_{t-1} and r_t^{EW} in their original form since they are not persistent. Note that in eq. 2, the

[11] Details of these non-stationarity tests are in the appendix.

control variables r_t^{EW} and Δp_{t-1}^{EW} represent, respectively, this year's return and the price change in the previous year, i.e., previous year's return.

We report estimation results for eq. 2 along the results for eq. 1 in Table I. The estimated coefficients for eq. 2 show that support for the catering hypothesis noticeably weakens when we use first differences. In Panels A and B, when we estimate eq. 2 for s and m, dependent variables P^{CME} and P^{SMB} are insignificant in all specifications. Notably, the significance of A also goes away, although A is not persistent, likely because eq. 2 adjusts for persistence of prices. The results for p^{IPO} are mixed, with $VW\ P^{CME}$ significant at the 5% level, $VW\ P^{SMB}$ significant at the 10% level, and $EW\ P^{CME}$ and $EW\ P^{SMB}$ not significant (Panel C).[12] The only price management proxy that remains discernibly dependent on catering incentives is the post-split price, for which all catering proxies other than A are significant (Panel D).[13]

In summary, the tests that use first differences provide mixed support for the nominal price management hypothesis. Although the data contain some evidence that firms make price level decisions based on catering considerations, there is no strong evidence that these considerations affect the firms' decisions to initiate stock splits. This said, we note that although first differencing is a popular method to reduce variable persistence, it may significantly reduce data variation and lead to information losses. In what follows, we report the results from a series of alternative tests that deal with persistent variables while preserving the information content of the data.

III.B. The Hodrick-Prescott filter

[12] In Panel C, we use IPO first-day closing prices. In the appendix, we report the results using IPO offering prices and the midpoints of the pre-IPO filing range – two additional variables used by BGW. Results for the IPO offering prices resemble those for the first-day closing prices; in differences, only two variables, $VW\ P^{CME}$ and $EW\ P^{SMB}$, are significant at the 5% and 10% levels, respectively. When we use midpoints of the pre-IPO filing range, all catering variables are insignificant.

[13] In the appendix, we discuss possible reasons for A not being significant in this specification.

King and Rebelo (1993) show that the HP filter reduces persistence while largely preserving the low-frequency content. This property may be observed in Panels B through E of Figure 1 where the de-trended (filtered) series maintain most of the time series variation found in the original data. The HP filter models a persistent series as the sum of its cyclical component and its trend component. Specifically, for the data series $y_t = (y_1, \ldots, y_T)'$, the persistent trend component $\hat{\tau}_T = (\hat{\tau}_{T1}, \hat{\tau}_{T2}, \ldots, \hat{\tau}_{TT})'$ is derived by minimizing the following function over τ:

$$\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}(\tau_{t+1} - 2\tau_t + \tau_{t-1})^2, \tag{3}$$

where T is the sample size, and λ is a smoothing parameter.[14] Once the persistent trend component is computed, the cyclical component (or the de-trended series) is obtained as the difference between the original series and the estimated trend: $\hat{c}_{Tt} = y_t - \hat{\tau}_{Tt}$.

Upon applying the HP filter to the variables identified earlier as persistent, we compute new autocorrelation functions (reported in the appendix) to examine if there is any reduction in the level of persistence. The functions confirm that the filtered variables are not persistent. Notably, once high levels of persistence are removed, the catering proxies lose explanatory power, in levels, for s and m – the two variables that capture the firms' decisions to split (Table II). One exception is the A proxy that remains marginally significant at the 10% level for s. When we examine the IPO and post-split prices, the HP filter results are mixed. As with differencing, two out of five catering proxies are significant in the p^{IPO} specification, and four out of five proxies are significant in the p specification.[15]

[14] Since our data are yearly, we set $\lambda = 6.25$ following Ravn and Uhlig (2002). As a robustness check, we also use $\lambda = 100$ suggested by Backus and Kehoe (1992) and obtain similar results.
[15] To save space, in Table II, we report only the coefficients of interest. In the appendix, we report the complete set of tables that use HP-filtered variables.

III.C. Corrected critical values for t-statistics

An alternative way to obtain reliable results in regressions with persistent variables is to correct the critical levels of the t-statistics. Phillips (1986) finds that for the case of 50 non-stationary observations, the appropriate critical value of the t-statistic is close to 15 instead of 1.96 commonly used for stationary data. When we apply Phillips' criterion to eq. 1, which contains 44 observations, the critical value for the t-statistic is close to 13. None of the t-statistics in Table I, including the t-statistics in the post-split price specification, crosses this critical value.

Phillips's corrected t-statistics are computed assuming that the regression variables are non-stationary unit root processes. As we mention earlier, we cannot reject the null hypothesis of non-stationarity for most of the variables in eq. 1 using the ADF, PP, KPSS, and ERS tests. Nevertheless, to stay on the conservative side we next obtain alternative corrected t-statistics for highly persistent variables without assuming non-stationarity.

To do so, we follow a simulation procedure similar to those used by Phillips (1986) and Granger et al. (2001). First, we randomly generate an independent catering proxy following an autoregressive process of order one with the autocorrelation of 0.82 as in Figure 2. Then, we use the simulated proxy and the original data for s, m, p^{IPO}, p, p^{EW}, and r^{EW} to estimate eq. 1. We proceed to test the null hypothesis that the simulated proxy is significant at 1%, 5%, and 10% levels with standard errors robust to heteroskedasticity and autocorrelation up to three lags. We repeat this process 10,000 times and compute the number of times the true null hypothesis of independence is rejected (size of the test). As expected, when we use the critical values from the t-distribution we over-reject the true null hypothesis. As such, we increase the critical values until we obtain the correct rejection rates (1%, 5%, and 10%). The resulting corrected critical values are reported in Table III.

The results reported in Table III vary depending on the level of desired statistical significance. At the 10% significance level, 40% of s specifications, no m specifications, 80% of p^{IPO} specifications, and no p specifications contain evidence consistent with catering via nominal price management. At the 1% significance level, only the p^{IPO} specifications (80% of them) contain evidence consistent with such catering.

III.D. Multi-period differencing

It is sometimes argued that certain economic variables may change too slowly to retain meaningful information after one-period differencing. To address this issue, researchers use multi-period differencing (e.g., Greenwood et al., 2010). We note that there are no objective criteria to deem a time series slow-moving. As such, we leave the final judgement on whether the catering proxies are slow-moving to the reader. With this in mind, in Table IV we ask if using multi-period differences changes the results. We report coefficients from regressions of the following form:

$$\Delta_k depvar_t = a + b\Delta_k P_{t-1}^{CME} + c\Delta_k P_{t-1}^{SMB} + d\bar{A}_{t-1} + e\Delta_k p_{t-1}^{EW} + f\bar{r}_t^{EW} + u_t, \quad (4)$$

where all variables are as previously defined, and s, m, p^{IPO}, p, P^{CME}, P^{SMB}, and p^{EW} are differenced over $k \in \{2, \ldots, 5\}$ years. We average the stationary variables $\bar{A}$ and $\bar{r}^{EW}$ over k years. The results offer mixed support for the catering hypothesis. First, all catering proxies are insignificant in all s specifications. Second, only 5 out of 20 coefficients in the m specifications are significant. In the meantime, multi-year differencing notably improves statistical significance in the p^{IPO} specifications.[16] In the post-split price specifications, A continues to be insignificant.

[16] Multi-year differencing improves significance of the IPO first-day closing price proxy (reported in Table IV) and the offering price proxy (reported in the appendix). For the midpoint of the pre-IPO price range proxy, also reported in the appendix, the results are only significant in 5 out of 20 specifications. We note that multi-year differencing of the IPO variables is based on relatively small sample sizes of 22-25 observations. As such, the IPO results should be interpreted with an added degree of caution.

III.F. An alternative data dimension: firm-level tests

An additional way to evaluate the results of regressions with persistent variables is to use alternative data dimensions. In corporate finance research, the availability of panel data often offers an attractive alternative to the time series tests. This is also the case in our setting. We posit that a true determinant of firms' behavior should not only explain this behavior in aggregate, but also explain decisions by individual firms. We begin by replicating BGW's panel results focusing on P^{CME} as do BGW. Our results are similar when we use the other catering premiums. Table V contains the coefficients from the following pooled probit regression that controls for the catering incentives and for the known determinants of stock splits:

$$depvar_{i,t} = a + bP_{t-1}^{CME} + ep_{i,t-1} + fr_{i,t} + gNYSED_{i,t} + h\sigma_{i,t-1} \tag{5}$$
$$+jp_{i,t-1}^{Industry} + kp_{i,t-1}^{LastSplit} + u_{i,t},$$

where $depvar_{i,t}$ is either $\Pr(s_{i,t} = 1)$ – an indicator variable equal to 1 if firm i declares a split in year t and equal to zero otherwise, or $m_{i,t}$ – a summary measure of splitting activity equal to the log of the ratio of the stock price p for firm i at year-end t to the stock price p for firm i at year-end $t-1$ grown at the stock return r for firm i in year t excluding dividends, or $p_{i,t}$ – the log month-end price for a stock i that splits in month t; P_{t-1}^{CME} is the value-weighted low-price premium as previously defined; $p_{i,t-1}$ is stock i's log price; $r_{i,t}$ is the log of (1 plus stock i's return in year t); $NYSED_{i,t}$ is the NYSE market capitalization decile for firm i in year t; $\sigma_{i,t-1}$ is volatility based on the previous year's daily returns; $p_{i,t-1}^{Industry}$ is the log average price in the matched Fama and French (1997) industry; and $p_{i,t-1}^{LastSplit}$ is the log of the post-split price from the most recent split by firm i. In specifications that use $p_{i,t}$ as the dependent variable, we follow BGW and replace $p_{i,t-1}$ with $p_{i,t-1}^{LastSplit}$ and $r_{i,t}$ with $r_{i,t}^{LastSplit}$.[17]

The set of controls in eq. 5 contains a number of conventional split determinants. As argued by Lakonishok and Lev (1987), firms with high nominal prices are likely to lower their prices by splitting. Often, such firms use the industry price or their own previous post-split price as a benchmark. Split decisions are also conditional on recent price runups captured by the r_t variable and on company size, with larger companies often opting for higher nominal prices (Nayak and Prabhala, 2001). Finally, volatile firms may be less likely to split given a higher chance of reaching a low price anyway.

In columns 1 through 3 of Table V, we re-estimate the base case, the industry control, and the last split control specifications reported by BGW. Our results are similar to theirs and appear to corroborate the notion that catering incentives influence individual firms' decisions to split their shares (Panels A and B) and the firms' choices of the post-split price (Panel C). Having confirmed BGW's panel result, we turn our attention to measuring the explanatory power of catering incentives.

We begin by estimating a univariate model, in which P^{CME} is the only explanatory variable (column 4). With $\Pr(s_{i,t} = 1)$ as the dependent variable (Panel A), the marginal effect of P^{CME} is 0.83 and is statistically significant at 5%, consistent with catering incentives affecting the probability of a stock split. Notably however, the pseudo-R^2 is 0.00 causing us to question the explanatory power of catering incentives. Adding to our curiosity is the result for the m specification in Panel B that has an insignificant P^{CME} coefficient. We note however that in the post-split specification (Panel C), the P^{CME} coefficient is statistically significant, and the R^2 is relatively high (0.06).

[17] We do not have access to the IPO panel data, therefore we are unable to estimate eq. 5 for individual IPOs.

To shed additional light on the explanatory power of P^{CME}, we re-estimate eq. 5 excluding it. The results reported in columns 5 through 7 are similar to the results in columns 1 through 3. We note that the pseudo-R^2 in Panel A does not decrease by more than 0.01 when P^{CME} is excluded.[18] In the meantime, adjusted R^2s in Panels B and C do not change at all when P^{CME} is excluded. These results confirm that the low-price premium has low explanatory power.

To further examine this issue, we ask: How many splits does P^{CME} explain? To find the answer, we use the *percent correctly explained* measure that counts the number of splits that are explained by P^{CME} by comparing the explanatory power of eq. 5 to its equivalent that excludes P^{CME}. We begin by estimating the fitted in-sample probabilities of a split using these two equations. Then, we use these probabilities to explain $s_{i,t}$ as follows: if the fitted probability is higher than a given threshold value (L), then $\hat{s}_{i,t} = 1$; otherwise, $\hat{s}_{i,t} = 0$. The percentage of times the predicted $\hat{s}_{i,t}$ matches the actual $s_{i,t}$ is the percent correctly explained. We use the unconditional probability of a split in our sample, 0.06, as a threshold value for L.[19]

In Table VI, we report the results for three specifications: the base case, the industry control, and the last split control. The base case model without P^{CME} correctly explains 11,345 out of 12,856 split events, which corresponds to 88.25% of all split events.[20] This model also correctly explains 68.63% of non-split events. When we add P^{CME} to the model, the number of correctly explained events increases by 62, a rather trivial number. For non-split events, including P^{CME} increases the percent of correctly explained events from 68.63% to 69.42%. The two alternative

[18] Similarly to R^2s, pseudo-R^2s automatically increase when more regressors are added to the model.
[19] Cramer (1999) shows that when the proportion of ones is significantly lower than the proportion of zeros (as in our case), the optimal choice of L is the sample proportion of ones (i.e. the unconditional probability of a split in our sample). Using L=0.5 as suggested by Wooldridge (2002) does not change our conclusions. In the appendix, we report the ROC (Receiver Operating Characteristic) curves that are consistent with the results reported here.
[20] Our initial sample contains 13,354 splits – the same number as BGW report. In the multivariate tests, not all controls are available for every firm-year, reducing the number of splits to 12,856.

specifications show similar patterns, and the explanatory power of P^{CME} is even lower. Specifically, in the industry (last split) control specifications, adding P^{CME} helps explain 56 (36) additional splits. Overall, the increase in explanatory power from adding P^{CME} is rather small.

As discussed so far, our results are somewhat puzzling. For instance, the base case coefficient on P^{CME} when $\Pr(s_{i,t} = 1)$ is the dependent variable is 0.60 (column 1, Panel A, Table V). This estimate is quite significant economically, implying an increase in the split probability by 0.6% – an important increase given the unconditional split probability of 6%. Yet Table VI shows that P^{CME} has very low explanatory power. It is therefore important to understand how P^{CME} may have an economically large coefficient and low explanatory power. We address this issue next.

Earlier, we discussed the spurious regression bias that may arise when highly persistent variables are used in time-series tests. We note that high persistence or non-stationarity do not lead to the spurious regression bias in pooled panels. Still, persistence may result in inconsistent and therefore unreliable coefficients and standard errors. To obtain reliable regression results, a pooled probit model must be dynamically complete. In the setting of eq. 5, dynamic completeness requires an assumption that past values of the dependent and independent variables do not influence the probability of a stock split. Such assumption seems too strong to be true. First, the probability of a split is likely to be smaller if the firm went through a split in the previous year. Second, as our earlier results indicate, a number of control variables are highly persistent. We formally test for dynamic completeness of the models in eq. 5 following Wooldridge (2002) and reject the null hypothesis that the models are dynamically complete.

A common way to ensure that a model is dynamically complete, and the estimated parameters are consistent is to use changes in variables instead of levels. Similarly to our earlier argument, if the level of catering incentives in the previous year influences price management, then changes in catering incentives should also have an effect on price management by individual firms. In Panel A of Table VII, we report coefficients estimated from eq. 5 using yearly changes in P^{CME}. All other explanatory variables are the same as in Table V. Notably, ΔP^{CME} is not statistically significant for either $\Pr(s_{i,t} = 1)$, or $m_{i,t}$, or the two multivariate $p_{i,t}$ specifications (Panels A, B, and C).

We note that concerns with potential over-differencing remain in the panel specifications. As such, we view the results in Table VII as only suggestive. The results that are not subject to over-differencing concerns are those in Tables V and VI. These results indicate that catering incentives do not have much power to explain firms' decisions to split their shares. Still, catering incentives may play a notable role in the firms' choice of the post-split price.

IV. Conclusion

We revisit the findings of Baker et al. (2009) (BGW), who propose that firms cater to investors' time-varying preferences for low-priced stocks by managing their nominal share prices. More specifically, BGW suggest that when the preference for low-priced stocks is high, firms will split more and to lower prices, and IPO firms will choose to list at lower prices.

BGW derive their results from time series and panel regressions, in which the variables are used in levels. These results fully replicate in our tests. We are however concerned that some of the regression variables are highly persistent and may therefore lead to the spurious regression bias when used in levels. This bias often results in finding significant relations between variables that are actually independent. Upon adjusting for persistence using five different techniques, we find little evidence that stock splits and catering incentives are related. In the meantime, the evidence that catering considerations matter in the firms' choice of IPO prices and post-split prices becomes mixed.

The nuanced nature of these results may be attributed to the costs of carrying out a stock split. These costs are usually substantial and include administrative and legal expenditures, additional listing and maintenance fees, franchise taxes, and increased liquidity costs. Our results imply that although the perceived benefits from catering may not exceed these costs, once a split decision has been made, perhaps for reasons other than catering (e.g., signaling, price range, and/or norms), firms may take catering into account in their choice of the new nominal price.

In addition to shedding new light on the catering hypothesis, our work adds to the ongoing discussion on the proper treatment of persistent variables in finance research. We discuss the pros and cons of the commonly used first differencing approach, and discuss four alternative methods of dealing with persistent time series. Among these methods are the Hodrick-Prescott filter, corrected critical values for the regression t-statistics, multi-period differencing, and alternative data dimensions. We suggest that studies that use highly persistent time series data should supplement results in levels with results that account for the possible effects of the spurious regression bias. Results that only hold in levels are perhaps not to be discarded; however, the issues raised by such studies should not be considered settled until additional supportive evidence is found.

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Table I. Time series regressions of price management and catering incentives

Description: The table reports coefficient estimates for the following models in levels and differences:

$$depvar_t = a + bP_{t-1}^{CME} + cP_{t-1}^{SMB} + dA_{t-1} + ep_{t-1}^{EW} + fr_t^{EW} + u_t \text{ and}$$
$$\Delta depvar_t = a + b\Delta P_{t-1}^{CME} + c\Delta P_{t-1}^{SMB} + dA_{t-1} + e\Delta p_{t-1}^{EW} + fr_t^{EW} + u_t,$$

where $depvar$ is either s – the number of splits by all firms in year t expressed as percentage of the total number of firms (Panel A), or m – a summary measure of splitting activity in year t equal to the log of the ratio of the actual average stock price to the $t-1$ stock price grown at the stock return excluding dividends (Panel B), or p_{IPO} – the log of the average IPO first-day closing price in year t, or p – the log of the average post-split stock price in year t. Among regressors, P^{CME} and P^{SMB} are the low-price and small-stock premiums, A is the split announcement premium, p^{EW} is the log equal-weighted average stock price, and r^{EW} is the log equal-weighted return excluding distributions. We use equal- and value-weighted (EW and VW) measures of the low-price and small-stock premiums. First differences are defined as follows: $\Delta depvar_t = depvar_t - depvar_{t-1}$; $\Delta P_{t-1}^{CME} = P_{t-1}^{CME} - P_{t-2}^{CME}$. ΔP_{t-1}^{SMB} and Δp_{t-1}^{EW} are defined in a similar manner. All right hand side variables are standardized to unit variance as in BGW, and t-statistics in parentheses are computed from standard errors robust to heteroskedasticity and autocorrelation up to three lags. Asterisks ***, **, and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Interpretation: When used in levels, catering variables appear to explain firms' price management behavior. Yet when used in first differences to reduce bias-inducing persistence, catering incentives only explain the post-split prices and, to a lesser degree, the IPO prices.

Panel A: Split %

	s					Δs				
$VW\ P_{t-1}^{CME}$	1.24**					-0.28				
	(2.43)					(-0.43)				
$EW\ P_{t-1}^{CME}$		1.30***					-0.01			
		(2.98)					(-0.01)			
$VW\ P_{t-1}^{SMB}$			1.37**					0.10		
			(2.69)					(0.28)		
$EW\ P_{t-1}^{SMB}$				1.56***					0.21	
				(4.32)					(0.36)	
A_{t-1}					1.69***					0.09
					(4.45)					(0.24)
p_{t-1}	1.05***	0.87**	0.91***	0.76**	0.94***	1.63***	1.63***	1.60***	1.53***	1.59***
	(3.13)	(2.39)	(2.92)	(2.50)	(3.69)	(2.92)	(2.72)	(2.85)	(2.36)	(3.10)
r_t	0.39	0.33	0.41	0.33	0.19	3.84*	3.87*	3.82	3.74	3.82*
	(1.45)	(1.24)	(1.61)	(1.35)	(0.73)	(1.82)	(1.74)	(1.63)	(1.48)	(1.76)
N	44	44	44	44	44	43	43	43	43	43
Adj. R^2	0.18	0.22	0.24	0.33	0.37	0.31	0.30	0.31	0.31	0.30

Panel B: Splitting activity

	m					Δm				
$VW\ P_{t-1}^{CME}$	-0.98**					0.06				
	(-2.38)					(0.20)				
$EW\ P_{t-1}^{CME}$		-0.90*					-0.24			
		(-1.79)					(-1.04)			
$VW\ P_{t-1}^{SMB}$			-0.98**					-0.03		
			(-2.18)					(-0.19)		
$EW\ P_{t-1}^{SMB}$				-0.89					-0.30	
				(-1.64)					(-1.52)	
A_{t-1}					-0.82					-0.11
					(-1.68)					(-0.56)
p_{t-1}	-0.47	-0.30	-0.33	-0.20	-0.28	-0.45	-0.39	-0.44	-0.31	-0.41
	(-1.24)	(-0.72)	(-0.86)	(-0.49)	(-0.97)	(-1.59)	(-1.38)	(-1.54)	(-1.05)	(-1.53)
r_t	-1.69	-1.48	-1.74*	-1.50	-1.21	-2.35**	-2.36**	-2.34**	-2.16*	-2.29**
	(-1.55)	(-1.26)	(-1.72)	(-1.34)	(-1.31)	(-2.20)	(-2.09)	(-2.13)	(-1.84)	(-2.18)
N	44	44	44	44	44	43	43	43	43	43
Adj. R^2	0.12	0.11	0.14	0.11	0.08	0.16	0.19	0.16	0.20	0.17

Panel C: IPO price

	p_{IPO}					Δp_{IPO}				
$VW\ P_{t-1}^{CME}$	-0.17***					-0.10**				
	(-8.74)					(-2.70)				
$EW\ P_{t-1}^{CME}$		-0.16***					-0.07			
		(-6.81)					(-1.66)			
$VW\ P_{t-1}^{SMB}$			-0.16***					-0.08*		
			(-7.92)					(-2.01)		
$EW\ P_{t-1}^{SMB}$				-0.18***					-0.06	
				(-6.70)					(-1.06)	
A_{t-1}					-0.14**					-0.08
					(-2.24)					(-1.68)
p_{t-1}	0.09***	0.17***	0.15***	0.20***	0.24**	-0.03	-0.01	-0.01	-0.01	-0.03
	(2.96)	(5.79)	(7.91)	(8.30)	(2.60)	(-0.78)	(-0.31)	(-0.21)	(-0.29)	(-0.67)
r_t	0.05**	0.06**	0.07***	0.08***	0.12***	0.14	0.16	0.22	0.19	0.25
	(2.17)	(2.72)	(3.13)	(3.40)	(3.67)	(1.45)	(1.47)	(1.42)	(1.42)	(1.50)
N	27	27	27	27	27	26	26	26	26	26
Adj. R^2	0.81	0.73	0.82	0.75	0.45	0.33	0.13	0.22	0.06	0.10

Panel D: Post-split price

	p					Δp				
$VW\ P_{t-1}^{CME}$	-0.12***					-0.08***				
	(-4.00)					(-2.81)				
$EW\ P_{t-1}^{CME}$		-0.09***					-0.06***			
		(-2.77)					(-2.84)			
$VW\ P_{t-1}^{SMB}$			-0.12***					-0.08***		
			(-4.51)					(-3.81)		
$EW\ P_{t-1}^{SMB}$				-0.09***					-0.06***	
				(-3.10)					(-2.79)	
A_{t-1}					-0.07**					-0.04
					(-2.61)					(-1.35)
p_{t-1}	0.14***	0.16***	0.15***	0.17***	0.17***	0.07***	0.08***	0.09***	0.09***	0.08***
	(-7.21)	(-7.13)	(-8.31)	(-7.56)	(-10.84)	(3.77)	(3.73)	(4.40)	(4.03)	(3.34)
r_t	0.09	0.11*	0.08*	0.11*	0.13	0.12**	0.13**	0.17***	0.17**	0.16**
	(-1.66)	(-1.99)	(-1.82)	(-2.01)	(-1.68)	(2.41)	(2.44)	(3.02)	(2.58)	(2.32)
N	44	44	44	44	44	43	43	43	43	43
Adj. R^2	0.79	0.7	0.8	0.69	0.62	0.46	0.35	0.46	0.32	0.24

Table II. Time series regressions with the Hodrick-Prescott filter

Description: The table contains estimation results from the following levels model:

$$depvar_t = a + bP_{t-1}^{CME} + cP_{t-1}^{SMB} + dA_{t-1} + ep_{t-1}^{EW} + fr_t^{EW} + u_t,$$

where all variables are defined as in Table I. Before running the regression, we apply the Hodrick-Prescott filter to s, m, p_{IPO}, p, P^{CME}, P^{SMB} (both equal- and value-weighted), and p^{EW} to address persistence. t-Statistics in parenthesis are computed from standard errors robust to heteroskedasticity and autocorrelation up to three lags. In this table, we only report the coefficients of the catering variables. The full set of coefficient estimates is available in the appendix. Asterisks ***, **, and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Interpretation: When the Hodrick-Prescott filter is used to adjust for data persistence, there is no evidence that the catering incentives are related to stock split activity. There is however some evidence that firms account for the catering incentives when choosing the IPO prices and especially the post-split prices.

$depvar$	$VW\ P_{t-1}^{CME}$	$EW\ P_{t-1}^{CME}$	$VW\ P_{t-1}^{SMB}$	$EW\ P_{t-1}^{SMB}$	A_{t-1}
s	-0.23	-0.13	-0.02	-0.07	0.25*
	(-0.82)	(-0.45)	(-0.13)	(-0.24)	(1.63)
m	0.06	-0.08	0.00	-0.11	-0.07
	(0.49)	(-0.73)	(0.04)	(-1.10)	(-0.84)
p_{IPO}	-1.23**	-0.81	-1.16**	-0.88	-1.32
	(-2.65)	(-1.69)	(-2.52)	(-1.58)	(-1.41)
p	-0.06***	-0.05***	-0.06***	-0.05***	-0.02
	(-4.68)	(-3.74)	(-5.09)	(-3.12)	(-1.04)

Table III. Corrected critical values for t-statistics

Description: The table reports corrected critical values for the eq. 1 t-statistics and the percentage of Table 1 coefficients, in levels, that are significant using the corrected critical values. To obtain the critical values, we replicate the simulation procedure used by Phillips (1986) and Granger et al. (2001). First we randomly generate an independent catering proxy following an autoregressive process of order one with autocorrelation levels reported in Figure 2. Then, using original data for the regression variables s, m, p^{IPO}, p, p^{EW}, and r^{EW} as well as the simulated catering proxy we estimate eq. 1. Then we test the null hypothesis that the simulated proxy is significant at 1, 5, and 10% significance levels with standard errors robust to heteroskedasticity and autocorrelation up to three lags. We repeat this process 10,000 times and compute the number of times the null hypothesis is rejected (size of the test). The critical values that produce the correct size of the test are reported here.

Interpretation: Adjusting the critical values of the t-statistics to reduce the effects of data persistence shows the following. Catering incentives are related (i) to the aggregate level of splitting in 0%, 40%, and 40% of cases, at the 1%, 5%, and 10% significance levels, respectively; (ii) to the overall price management in no cases, (iii) to the IPO prices in 80% of cases, and (iv) to the post-split prices in no cases.

	1%		5%		10%	
	critical val.	% signif.	critical val.	% signif.	critical val.	% signif.
s	5.5	0	4.1	40	3.2	40
m	6.8	0	5.0	0	4.1	0
p^{IPO}	5.5	80	4.4	80	3.7	80
p	7.8	0	5.8	0	4.8	0

Table IV. Time series regressions with multi-year differencing

Description: The table reports coefficients from multi-year differenced regressions of the following form:

$$\Delta_k depvar_t = a + b\Delta_k P^{CME}_{t-1} + c\Delta_k P^{SMB}_{t-1} + d\bar{A}_{t-1} + e\Delta_k p^{EW}_{t-1} + f\bar{r}^{EW}_t + u_t,$$

where all variables are defined as in Table I, and s, m, p^{IPO}, p, P^{CME}, P^{SMB}, and p^{EW} are differenced, with k denoting the number of years used to compute the differences. Variables with low persistence levels: $\bar{A}$ and $\bar{r}^{EW}$ are averaged over k years. t-Statistics in parentheses are computed from standard errors robust to heteroskedasticity and autocorrelation up to three lags. Asterisks ***, **, and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Interpretation: Multi-year differencing offers support for the relation between catering and (i) the aggregate splitting activity in 0% of cases; (ii) price management in 25% cases; (iii) IPO prices in 95% of cases, and (iv) post-split prices in 80% of cases.

Panel A: Dependent variable is $\Delta_2 s_t$

	$VW\ \Delta_k P^{CME}_{t-1}$	$EW\ \Delta_k P^{CME}_{t-1}$	$VW\ \Delta_k P^{SMB}_{t-1}$	$EW\ \Delta_k P^{SMB}_{t-1}$	$_k A_{t-1}$
$\Delta_k s_t, k=2$	0.05	0.19	0.23	0.33	0.31
	(0.12)	(0.42)	(0.70)	(0.71)	(0.70)
$\Delta_k s_t, k=3$	0.06	0.27	0.27	0.41	0.40
	(0.13)	(0.54)	(0.60)	(0.72)	(0.73)
$\Delta_k s_t, k=4$	-0.10	0.27	0.05	0.25	0.50
	(-0.23)	(0.50)	(0.14)	(0.47)	(1.05)
$\Delta_k s_t, k=5$	0.05	0.34	0.10	0.34	0.11
	(0.10)	(0.57)	(0.21)	(0.54)	(0.18)
$\Delta_k m_t, k=2$	-0.12	-0.39**	-0.18	-0.49***	-0.17
	(-0.85)	(-2.46)	(-1.45)	(-2.77)	(-0.72)
$\Delta_k m_t, k=3$	-0.23	-0.57***	-0.30	-0.69**	-0.11
	(-1.11)	(-2.79)	(-1.34)	(-2.47)	(-0.32)
$\Delta_k m_t, k=4$	-0.09	-0.57*	-0.18	-0.61	-0.27
	(-0.34)	(-1.87)	(-0.83)	(-1.67)	(-0.52)
$\Delta_k m_t, k=5$	-0.27	-0.75	-0.28	-0.84	0.02
	(-0.83)	(-1.63)	(-0.80)	(-1.46)	(0.03)
$\Delta_k p^{IPO}{}_t, k=2$	-0.16***	-0.14***	-0.16***	-0.16***	-0.15
	(-4.70)	(-3.03)	(-4.70)	(-2.90)	(-1.54)
$\Delta_k p^{IPO}{}_t, k=3$	-0.18***	-0.17***	-0.20***	-0.20***	-0.17*
	(-5.68)	(-3.56)	(-8.38)	(-3.77)	(-1.96)
$\Delta_k p^{IPO}{}_t, k=4$	-0.20***	-0.20***	-0.22***	-0.25***	-0.20***
	(-6.28)	(-4.47)	(-6.06)	(-5.05)	(-3.04)
$\Delta_k p^{IPO}{}_t, k=5$	-0.23***	-0.24***	-0.25***	-0.31***	-0.25**
	(-8.00)	(-5.54)	(-8.16)	(-7.48)	(-2.80)
$\Delta_k p_t, k=2$	-0.14***	-0.12***	-0.14***	-0.15***	-0.07
	(-5.61)	(-4.12)	(-6.87)	(-4.81)	(-1.35)
$\Delta_k p_t, k=3$	-0.15***	-0.13***	-0.17***	-0.17***	-0.06
	(-5.47)	(-4.01)	(-9.26)	(-5.44)	(-1.25)
$\Delta_k p_t, k=4$	-0.15***	-0.13***	-0.16***	-0.18***	-0.04
	(-8.55)	(-5.72)	(-9.42)	(-8.61)	(-1.07)
$\Delta_k p_t, k=5$	-0.19***	-0.17***	-0.20***	-0.25***	-0.02
	(-7.44)	(-4.36)	(-9.34)	(-8.82)	(-0.40)

Table V. Firm-level panel regressions

Description: The table reports estimation results for the following regression model:

$$depvar_{i,t} = a + bP_{t-1}^{CME} + ep_{i,t-1} + fr_{i,t} + gNYSED_{i,t} + h\sigma_{i,t-1} + jp_{i,t-1}^{Industry} + kp_{i,t-1}^{LastSplit} + u_{i,t},$$

where $depvar$ is either $\Pr(s_{i,t} = 1)$, with $s_{i,t}$ being an indicator variable equal to 1 if firm i declares a split in year t and equal to zero otherwise (estimated using probit, Panel A), or $m_{i,t}$ – a summary measure of splitting activity equal to the log of the ratio of the stock price p for firm i at year-end t to the stock price p for firm i at year-end $t-1$ grown at the stock return r for firm i in year t excluding dividends (OLS pooled panel estimation, Panel B), or $p_{i,t}$ – the log month-end price for a stock i that splits in month t (OLS cross-section, Panel C); P_{t-1}^{CME} is the lagged value-weighted low-price premium defined previously; $p_{i,t-1}$ is stock i's log price in year $t-1$; $r_{i,t}$ is the log of (1 plus return on stock i in year t); $NYSED_{i,t}$ is the NYSE market capitalization decile for firm i in year t; $\sigma_{i,t-1}$ is lagged volatility based on the previous year's daily returns; $p_{i,t-1}^{Industry}$ is the log average price in the matched Fama and French (1997) industry; and $p_{i,t-1}^{LastSplit}$ is the log of the post-split price from the most recent split by firm i. In Panel C, we follow BGW and replace $p_{i,t-1}$ with $p_{i,t-1}^{LastSplit}$ and $r_{i,t}$ with $r_{i,t}^{LastSplit}$. In Panel A, the coefficients represent the marginal effects. t- and z-statistics in parentheses are clustered by year. Asterisks ***, **, and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Interpretation: In a panel regression setting, the catering variable P^{CME} has negligible explanatory power when used to explain firms' individual decisions to split and individual price management activities. The variable has explanatory power when used to explain individual firms' post-split prices.

	with P_{t-1}^{CME}				without P_{t-1}^{CME}		
	Base case	Industry control	Last split control	Univariate	Base case	Industry control	Last split control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: dependent variable $\Pr(s_{i,t} = 1)$							
P_{t-1}^{CME}	0.60***	0.52***	0.92***	0.83**			
	(3.31)	(2.98)	(3.00)	(2.15)			
p_{t-1}	4.06***	4.11***	10.56***		4.12***	4.17***	10.64***
	(28.18)	(32.57)	(26.50)		(30.44)	(33.82)	(27.44)
r_t	3.12***	3.02***	6.89***		3.28***	3.14***	7.11***
	(12.50)	(12.42)	(12.69)		(12.42)	(12.32)	(11.81)
$NYSED_{i,t}$	-0.37***	-0.37***	-0.53***		-0.40***	-0.39***	-0.56***
	(-14.95)	(-16.53)	(-9.41)		(-15.65)	(-16.70)	(-10.30)
σ_{t-1}	32.65***	30.69***	110.76***		28.34***	26.47***	93.71***
	(6.15)	(5.89)	(6.69)		(5.24)	(4.93)	(5.40)
$p_{t-1}^{Industry}$		-0.67***				-0.89***	
		(-4.84)				(-5.71)	
$p_{t-1}^{LastSplit}$			-5.20***				-5.49***
			(-17.27)				(-16.51)
N	211,256	211,256	71,781	229,865	211,256	211,256	71,781
pseudo-R^2	0.25	0.25	0.25	0.00	0.24	0.24	0.25

	with P_{t-1}^{CME}				without P_{t-1}^{CME}		
	Base case	Industry control	Last split control	Univariate	Base case	Industry control	Last split control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: dependent variable $m_{i,t}$							
P_{t-1}^{CME}	-0.90**	-0.75*	-0.74*	-0.18			
	(-2.08)	(-1.78)	(-1.70)	(-0.60)			
p_{t-1}	-7.87***	-8.14***	-11.99***		-7.72***	-8.05***	-11.89***
	(-15.61)	(-16.00)	(-15.55)		(-15.30)	(-15.78)	(-15.38)
r_t	-7.24***	-7.24***	-8.99***		-7.32***	-7.31***	-9.05***
	(-10.61)	(-10.62)	(-12.22)		(-10.69)	(-10.65)	(-11.87)
$NYSED_{i,t}$	1.07***	1.07***	0.80***		1.07***	1.07***	0.81***
	(11.32)	(11.30)	(10.60)		(11.29)	(11.25)	(10.83)
σ_{t-1}	-16.38	-15.48	-147.91***		-9.27	-9.61	-137.25***
	(-1.38)	(-1.29)	(-4.75)		(-0.74)	(-0.74)	(-4.33)
$p_{t-1}^{Industry}$		1.87***				2.12***	
		(6.46)				(7.41)	
$p_{t-1}^{LastSplit}$			5.18***				5.32***
			(13.50)				(12.84)
N	211,256	211,256	71,781	211,730	211,256	211,256	71,781
Adj. R^2	0.12	0.13	0.15	0.00	0.12	0.13	0.15
Panel C: dependent variable $p_{i,t}$							
P_{t-1}^{CME}	-0.03***	-0.02***		-0.16***			
	(-3.68)	(-2.95)		(-6.13)			
$p_{t-1}^{LastSplit}$	0.62***	0.62***			0.63***	0.62***	
	(21.94)	(21.67)			(21.97)	(21.78)	
$r_t^{LastSplit}$	0.56***	0.56***			0.57***	0.56***	
	(23.36)	(22.81)			(22.26)	(22.01)	
$NYSED_{i,t}$	0.04***	0.04***			0.04***	0.04***	
	(11.70)	(11.81)			(11.64)	(11.78)	
σ_{t-1}	0.67	0.91**			1.26**	1.41***	
	(1.63)	(2.33)			(2.19)	(2.75)	
$p_{t-1}^{Industry}$		0.05***				0.06***	
		(4.10)				(5.62)	
N	13,299	13,299		13,308	13,299	13,299	
Adj. R^2	0.76	0.76		0.06	0.76	0.76	

Table VI. Explanatory power of P^{CME}

Description: The table reports percent of correctly explained split and non-split events based on the estimates obtained from the following two models, with all variables defined in Table V:

$$\Pr(s_{i,t} = 1) = a + bP_{t-1}^{CME} + ep_{i,t-1} + fr_{i,t} + gNYSED_{i,t} + h\sigma_{i,t-1} + jp_{i,t-1}^{Industry} + kp_{i,t-1}^{LastSplit} + u_{i,t}$$

$$\Pr(s_{i,t} = 1) = a + ep_{i,t-1} + fr_{i,t} + gNYSED_{i,t} + h\sigma_{i,t-1} + jp_{i,t-1}^{Industry} + kp_{i,t-1}^{LastSplit} + u_{i,t}$$

We report the number of and the percent of correctly explained events using the threshold value *L*=0.06. The results are similar when we use *L*=0.50, and when we use P_{t-1}^{SMB} or A_{t-1} instead of P_{t-1}^{CME}.

Interpretation: When added to the base model for individual firms' split decisions, P^{CME} improves explanatory power by less than 1%.

	correctly explained, without P_{t-1}^{CME}		correctly explained, with P_{t-1}^{CME}		increase in explanatory power
	# of events	% of events	# of events	% of events	%
Base Case					
split events	11,345	88.25	11,407	88.73	0.48
non-split events	136,166	68.63	137,730	69.42	0.79
all events	147,511	69.83	149,137	70.60	0.77
Industry Control					
split events	11,350	88.29	11,406	88.72	0.43
non-split events	136,778	68.94	138,131	69.62	0.68
all events	148,128	70.12	149,537	70.78	0.66
Last Split Control					
split events	6,640	91.01	6,676	91.50	0.49
non-split events	45,919	59.75	46,357	60.32	0.57
all events	52,559	62.46	53,033	63.02	0.56

Table VII. Firm-level differenced panel regressions

Description: We report regression estimates from the following model:

$depvar_{i,t} = a + b\Delta P^{CME}_{t-1} + ep_{i,t-1} + fr_{i,t} + gNYSED_{i,t} + h\sigma_{i,t-1} + jp^{Industry}_{i,t-1} + kp^{LastSplit}_{i,t-1} + u_{i,t}$,

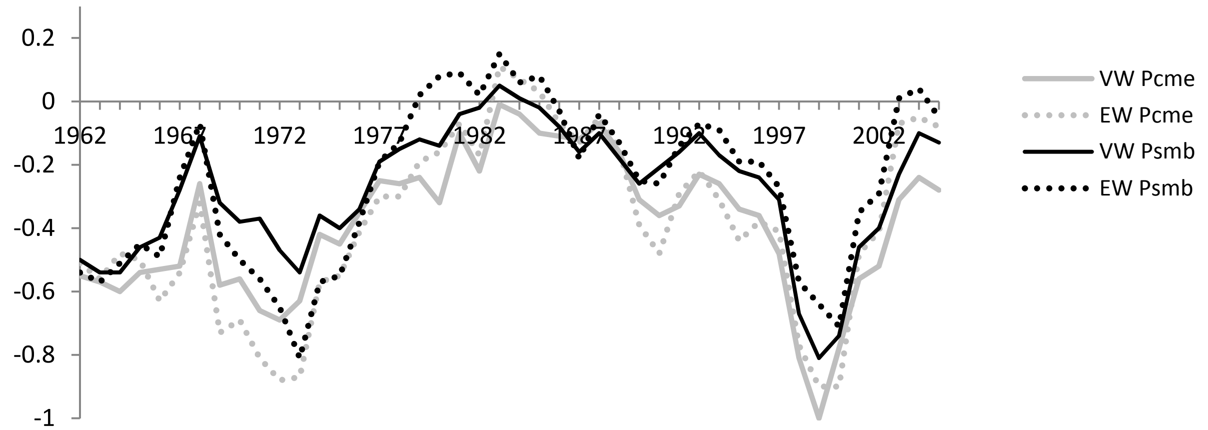
where we use changes in P^{CME}, and all other variables, coefficient estimates, and statistics are as defined in Table V. The dependent variable in Panel A is $\Pr(s_{i,t} = 1)$, the dependent variable in Panel B is $m_{i,t}$, and in Panel C is $p_{i,t}$. Asterisks ***, **, and * denote statistical significance at 0.01, 0.05, and 0.10 levels, respectively.

Interpretation: When first differences are used in the panel setting to adjust for data persistence, P^{CME} is not a significant determinant of firms' individual decisions to split and their price management. The evidence linking P^{CME} to the firms' choice of the post-split prices is considerably weakened when first differences are used.

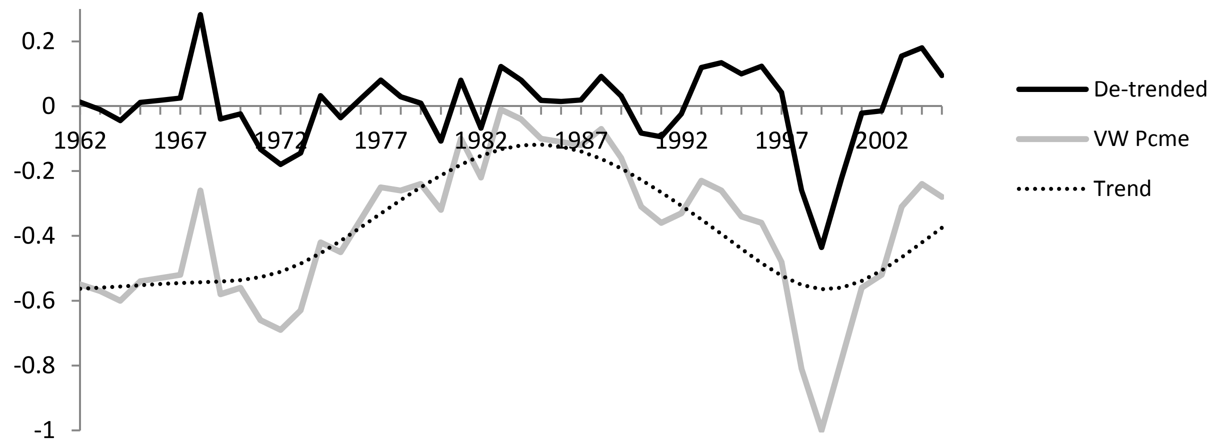
	Univariate	Base case	Industry control	Last split control
Panel A: $\Pr(s_{i,t} = 1)$ regressions using changes in P^{CME}				
ΔP^{CME}_{t-1}	-0.57	-0.17	-0.18	-0.33
	(-1.55)	(-0.99)	(-1.15)	(-1.12)
p_{t-1}		4.11***	4.17***	10.60***
		(30.78)	(34.10)	(27.93)
r_t		3.27***	3.12***	7.08***
		(12.63)	(12.52)	(11.83)
$NYSED_{i,t}$		-0.40***	-0.40***	-0.56***
		(-15.85)	(-17.02)	(-10.49)
σ_{t-1}		27.52***	25.63***	91.56***
		(5.36)	(5.10)	(5.75)
$p^{Industry}_{t-1}$			-0.89***	
			(-5.68)	
$p^{LastSplit}_{t-1}$				-5.45***
				(-16.78)
N	227,797	209,275	209,275	84,148
pseudo-R^2	0.001	0.238	0.243	0.240
Panel B: $m_{i,t}$ regressions using changes in P^{CME}				
ΔP^{CME}_{t-1}	0.38	0.26	0.31	0.54
	(1.12)	(0.76)	(0.98)	(1.68)
p_{t-1}		-7.73***	-8.06***	-11.87***
		(-15.32)	(-15.77)	(-15.89)
r_t		-7.33***	-7.32***	-9.01***
		(-10.76)	(-10.74)	(-11.76)
$NYSED_{i,t}$		1.07***	1.07***	0.81***
		(11.21)	(11.18)	(11.12)
σ_{t-1}		-8.51	-8.82	-136.58***
		(-0.70)	(-0.71)	(-4.58)
$p^{Industry}_{t-1}$			2.14***	
			(7.71)	
$p^{LastSplit}_{t-1}$				5.26***
				(12.70)
N	209,749	209,275	209,275	71,712
pseudo-R^2	0.00	0.12	0.13	0.15

Panel C: $p_{i,t}$ regressions using changes in P^{CME}			
ΔP_{t-1}^{CME}	-0.09*	-0.01	-0.01
	(-1.75)	(-1.21)	(-1.25)
$p_{t-1}^{LastSplit}$		0.63***	0.62***
		(22.19)	(21.93)
$r_t^{LastSplit}$		0.56***	0.56***
		(23.09)	(22.69)
$NYSED_{i,t}$		0.04***	0.04***
		(11.56)	(11.71)
σ_{t-1}		1.08**	1.25***
		(2.43)	(3.08)
$p_{t-1}^{Industry}$			0.06***
			(5.36)
N	13,251	13,242	13,242
pseudo-R^2	0.02	0.76	0.76

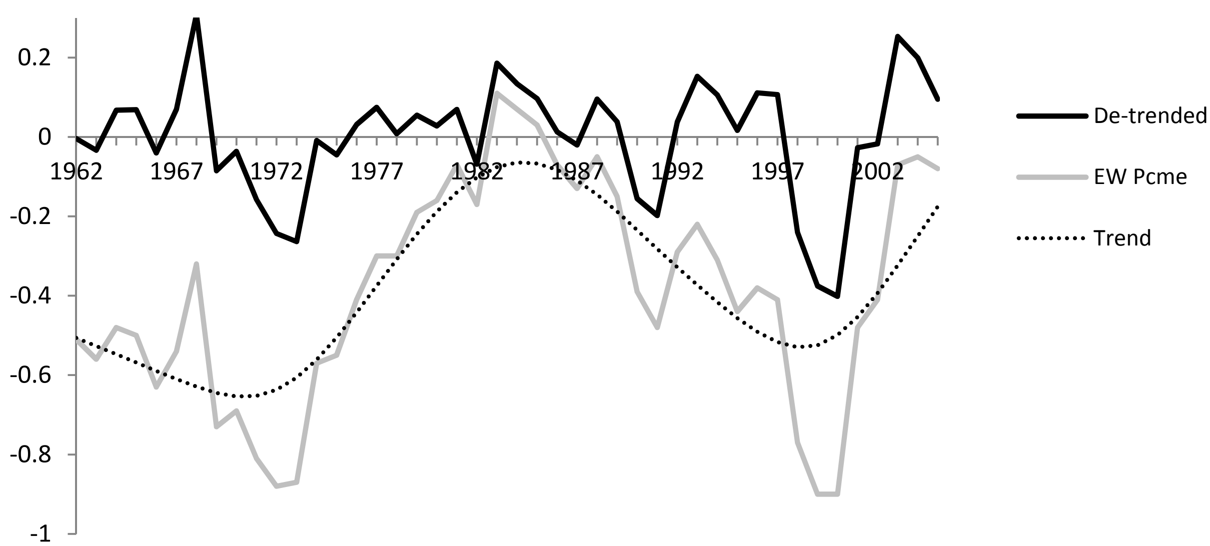
Panel A: Levels



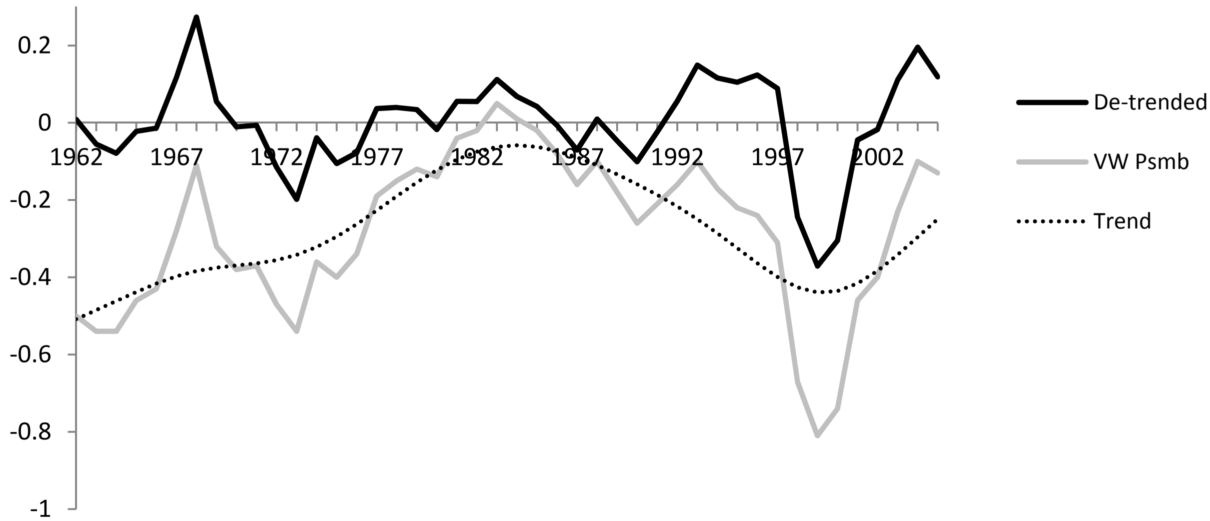
Panel B: HP filter for VW P^CME



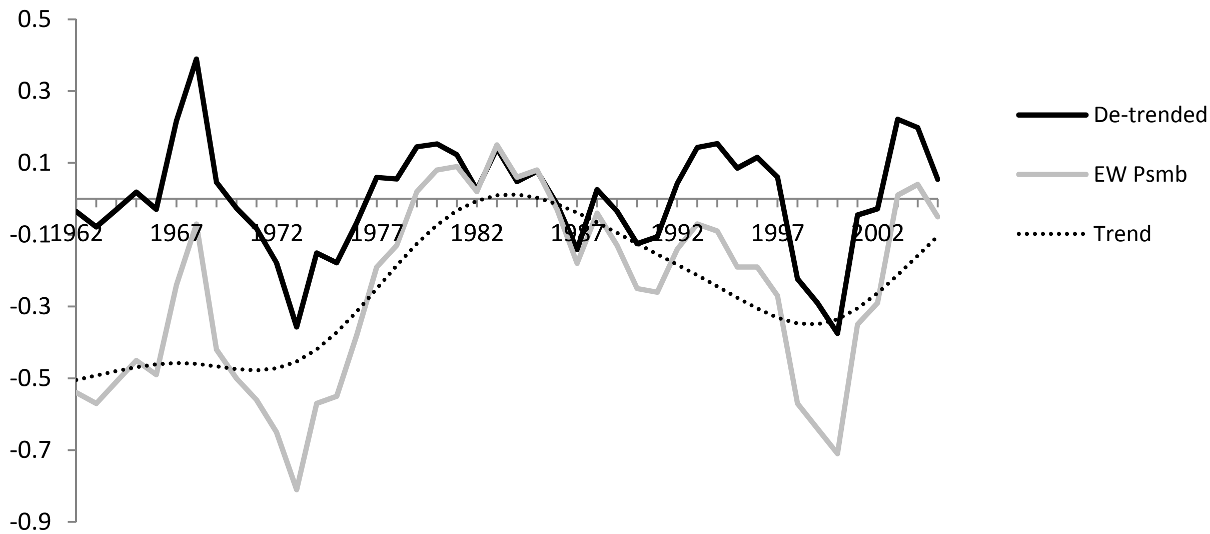
Panel C: HP filter for EW P^CME



Panel D: HP filter for VW P^{SMB}



Panel E: HP filter for EW P^{SMB}



Panel F: HP filter for A

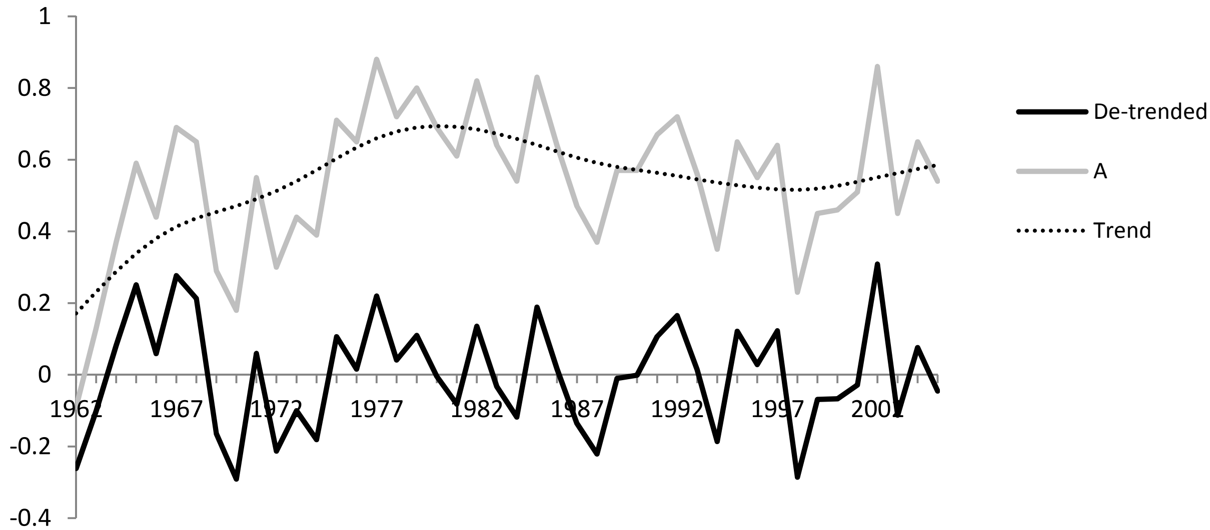


Figure 1. Catering proxies in levels and after Hodrick-Prescott filtering (de-trending)

Description: Panel A plots catering proxies P^{CME} and P^{SMB} (both equal-weighted (EW) and value-weighted (VW)) in levels as reported by Baker et al. (2009). The solid lines represent the value-weighted proxies, and the dotted lines represent the equal-weighed proxies. Panel B displays $VW\ P^{CME}$ in levels (solid grey line), the non-stationary trend (dotted line), and the Hodrick-Prescott filtered (de-trended) series (solid black line). Panels C, D, E, and F report similar de-trending results for, respectively, the levels of $EW\ P^{CME}$, $VW\ P^{SMB}$, $EW\ P^{SMB}$ and A.

Interpretation: When plotted in levels, most catering proxies appear very persistent. The Hodrick-Prescott filter confirms existence of a non-stationary trend in the data.

Panel A: Generated Unit root series

Autocorrelation	Partial Correlatio...	LAG	AC	PAC	p-value
		1	0.85	0.85	0.00
		2	0.71	-0.03	0.00
		3	0.57	-0.12	0.00
		4	0.42	-0.10	0.00
		5	0.29	-0.05	0.00
		6	0.19	0.02	0.00
		7	0.11	0.00	0.00
		8	0.13	0.30	0.00
		9	0.17	0.06	0.00
		10	0.20	-0.03	0.00

Panel B: $VW\ P^{CME}$

Autocorrelation	Partial Correlatio...	LAG	AC	PAC	p-value
		1	0.82	0.82	0.00
		2	0.63	-0.12	0.00
		3	0.43	-0.18	0.00
		4	0.26	-0.01	0.00
		5	0.15	0.02	0.00
		6	0.11	0.13	0.00
		7	0.14	0.11	0.00
		8	0.10	-0.23	0.00
		9	0.03	-0.14	0.00
		10	-0.10	-0.19	0.00

Panel C: $VW\ P^{SMB}$

Autocorrelation	Partial Correlatio...	LAG	AC	PAC	p-value
		1	0.83	0.83	0.00
		2	0.57	-0.38	0.00
		3	0.34	-0.02	0.00
		4	0.12	-0.15	0.00
		5	-0.04	-0.01	0.00
		6	-0.06	0.28	0.00
		7	-0.00	0.00	0.00
		8	0.04	-0.10	0.00
		9	0.05	-0.07	0.00
		10	0.02	-0.15	0.00

Panel D: $EW\ P^{CME}$

Autocorrelation	Partial Correlatio...	LAG	AC	PAC	p-value
		1	0.82	0.82	0.00
		2	0.62	-0.15	0.00
		3	0.42	-0.12	0.00
		4	0.28	0.04	0.00
		5	0.12	-0.18	0.00
		6	0.06	0.19	0.00
		7	0.04	0.02	0.00
		8	0.01	-0.12	0.00
		9	-0.04	-0.05	0.00
		10	-0.18	-0.39	0.00

Panel E: $EW\ P^{SMB}$

Autocorrelation	Partial Correlatio...	LAG	AC	PAC	p-value
		1	0.82	0.82	0.00
		2	0.60	-0.24	0.00
		3	0.36	-0.17	0.00
		4	0.15	-0.07	0.00
		5	-0.02	-0.07	0.00
		6	-0.05	0.27	0.00
		7	-0.01	0.07	0.00
		8	0.01	-0.16	0.00
		9	0.03	-0.02	0.00
		10	-0.02	-0.23	0.00

Panel F: A

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.36	0.36	0.01
		2	0.21	0.09	0.02
		3	0.06	-0.05	0.04
		4	0.06	0.04	0.07
		5	-0.05	-0.09	0.11
		6	0.03	0.07	0.18
		7	0.13	0.14	0.20
		8	0.04	-0.08	0.27
		9	-0.02	-0.06	0.35
		10	0.16	0.22	0.32

Panel G: p^{EW}

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.82	0.82	0.00
		2	0.66	-0.06	0.00
		3	0.52	-0.02	0.00
		4	0.36	-0.14	0.00
		5	0.19	-0.17	0.00
		6	0.09	0.11	0.00
		7	0.04	0.03	0.00
		8	0.03	0.13	0.00
		9	0.01	-0.11	0.00
		10	0.01	0.03	0.00

Panel H: r^{EW}

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	-0.01	-0.01	0.94
		2	-0.25	-0.25	0.22
		3	0.05	0.04	0.37
		4	0.22	0.17	0.23
		5	-0.20	-0.20	0.16
		6	-0.25	-0.19	0.08
		7	-0.06	-0.18	0.12
		8	0.15	0.05	0.11
		9	-0.14	-0.11	0.12
		10	-0.05	0.03	0.17

Panel I: s

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.33	0.33	0.02
		2	0.24	0.15	0.02
		3	0.24	0.14	0.01
		4	-0.07	-0.24	0.02
		5	-0.15	-0.17	0.03
		6	-0.16	-0.07	0.03
		7	-0.19	-0.01	0.03
		8	-0.29	-0.17	0.01
		9	-0.20	-0.07	0.01
		10	-0.15	-0.03	0.01

Panel J: m

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.78	0.78	0.00
		2	0.70	0.24	0.00
		3	0.60	-0.01	0.00
		4	0.40	-0.31	0.00
		5	0.30	-0.02	0.00
		6	0.09	-0.28	0.00
		7	-0.00	0.07	0.00
		8	-0.08	0.04	0.00
		9	-0.16	0.07	0.00
		10	-0.11	0.19	0.00

Panel K: p^{IPO}

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.66	0.66	0.00
		2	0.35	-0.14	0.00
		3	0.34	0.31	0.00
		4	0.28	-0.13	0.00
		5	0.13	-0.04	0.00
		6	0.09	0.04	0.00
		7	0.04	-0.11	0.00
		8	-0.03	-0.00	0.00
		9	-0.08	-0.07	0.00
		10	-0.11	-0.06	0.00

Panel L: p

Autocorrelation	Partial Correlation	LAG	AC	PAC	p-value
		1	0.78	0.78	0.00
		2	0.57	-0.10	0.00
		3	0.51	0.24	0.00
		4	0.45	-0.04	0.00
		5	0.37	0.02	0.00
		6	0.27	-0.13	0.00
		7	0.15	-0.08	0.00
		8	0.04	-0.14	0.00
		9	-0.03	-0.02	0.00
		10	-0.12	-0.15	0.00

Figure 2. Autocorrelation functions for the regression variables

Description: The figure displays, autocorrelograms and partial autocorrelograms for all variables in eq. 1 up to 10 lags (LAG). Panel A contains the simulated unit root series. Panels B through F contain the catering proxies VWP^{CME}, VWP^{SMB}, $EW\ P^{CME}$, EWP^{SMB} and A. Panels G and H are for p^{EW}– the log equal-weighted average stock price, and r^{EW}– the log equal-weighted return excluding distributions. Panels I through L contain the dependent variables s, m, p^{IPO}, and p. We report autocorrelation coefficients (AC), partial autocorrelation coefficients (PACs), and p-values for the null hypothesis that all ACs up to a given lag are equal to zero. The two vertical lines in the autocorrelation graphics represent critical bounds for the null hypotheses that the ACs or PACs are equal to zero at the 5% significance level.

Interpretation: Autocorrelation tests confirm that many of the regression variables have high levels of persistence.