Small-size public companies and aggregate fluctuations

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Abstract

This paper empirically examines the hypothesis that the stock price of publicly traded companies serves as a common signal to privately held firms and contribute to aggregate fluctuations by creating commonalities among private firms. Using data from Korea for the period of 2000-2015, we find evidence for the hypothesis with industry-level aggregate volatility and the stock price of small-size public companies. Specifically, a positive cross-sectional relation exists between the volatility of an industry and the presence of small—but not large—public firms in the industry. Further, the positive relation is attributable to the commonality in private firms' growth around the stock price of small—but not large—public industry peers. We also find that the industry volatility that is related to the stock price of small public firms is the one that is unique to the industry and unrelated to market-wide movements. Our results suggest that small-size public companies play a unique role in aggregate fluctuations by making private firms cohesive within an industry but distinct across industries. In short, small-size public companies serve as a counterbalance to larger public firms who impose market-wide shocks across companies in different industries.

Keywords: Aggregate fluctuation; Private firms; Public peers; Firm size; Industry; Stock price

JEL classification: G14; G31; G32

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1. Introduction

In this paper, we empirically examine whether the stock price of publicly traded companies serves as a common signal to privately held firms and contribute to aggregate fluctuations by creating commonalities among the private firms. In doing so, we pay particular attention to the difference between large, flagship public companies and smaller-size ones in their role as a benchmark for private firms. While existing theories stress the role of big firms in aggregate fluctuations (e.g., Gabaix 2011; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi 2012), small-size public companies may also play a non-trivial role due to their comparability to private firms. Using data from Korea in which a large number of private firms are required to provide financial information for external auditing purposes,[1] we find evidence that small public companies play a unique role in aggregate fluctuations.

We first fix our idea. The idea arises from the finding of a recent study, namely, that publicly traded companies improve the informational environments of private firms by producing and disclosing a variety of information whose industry- and market-wide components are useful to private firms (Badertscher, Shroff, and White 2013). We note that such an externality has an implication for aggregate fluctuations. Specifically, the readily available industry- and market-wide information may lead private firms to co-move and increase aggregate volatility. Given its salience and visibility, the stock price of public companies seems to be particularly suited to create such commonalities among private firms and contribute to aggregate fluctuations; hence, our hypothesis.

Certainly, testing this hypothesis is not straightforward, as a variety of econometric and inferential issues will mask the true relation among private firms, public companies, and aggregate

[1] In 1981, the Korean government had required both private and public companies whose total assets are worth at least 3 billion Korean won (KRW) to be externally audited and to make their financial information publicly available. The size criterion has increased gradually since then and, in 2009, it was raised to 10 billion Korean won (approximately 10 million U.S. dollars). This cutoff level corresponds to the bottom 0.5-percentile total assets of all publicly traded companies in Korea at the start of 2009.

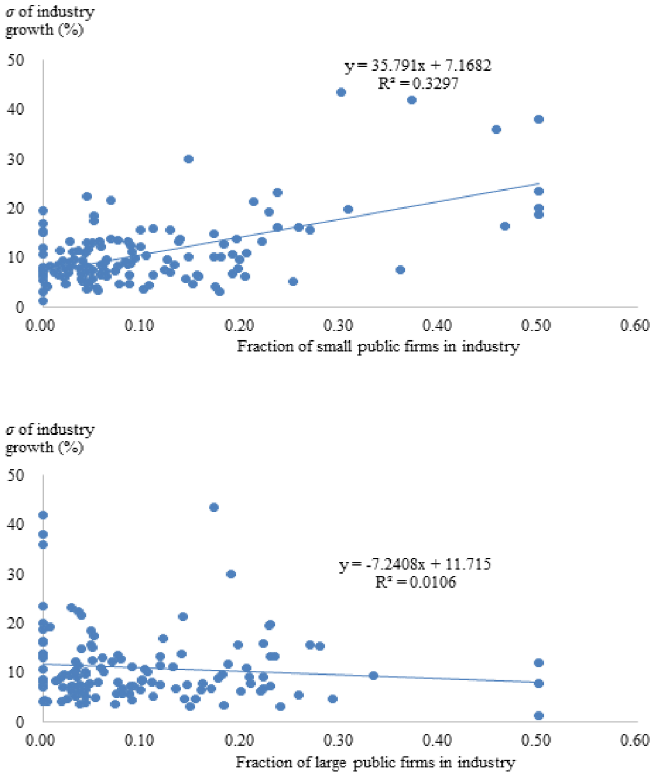
fluctuations. Mindful of those issues, however, we begin with the simplest possible approach.[2] Specifically, we choose industry as the aggregation level, and measure aggregate fluctuations by the standard deviation of the industry's annual asset growth. We then estimate a cross-sectional regression of the industry's asset-growth volatility on the log numbers of private firms, of large public companies, and of small public companies in the industry. Not a perfect measure of the price signal from public companies, the number of public firms can still quantify the strength of such price signals. (Shortly, we report the results based on a direct measure of stock price signal.)

As shown below, the coefficient on the log number of small public companies is significantly positive, whereas the log number of large public companies is negative and insignificant. (Numbers in brackets are *t*-statistics.)

$$\text{industry volatility} = \alpha + \underset{[-5.04]}{\underset{-2.840}{\beta_1 \text{*n(private)}}} + \underset{[-1.13]}{\underset{-0.660}{\beta_2 \text{*n(large public)}}} + \underset{[3.72]}{\underset{2.311}{\beta_3 \text{*n(small public)}}} + \varepsilon$$

To ensure that the observed coefficients are not spurious, we create a scatter plot between the industry volatility and the number of public companies (as a fraction of the number of all firms in the industry). With small-size public firms, the relationship is undeniably positive with an R^2 of 32.9%, while the one with larger public firms is negative and insignificant.

[2] If nothing comes up in a simple setting, it would be difficult to justify more sophisticated estimation methods. However, a potentially promising pattern observed in a preliminary exploration would certainly warrant a more serious look at the data.



No doubt that the above results are contaminated by the confounding effects and endogenous factors. Still, given that the results are vastly different between small and large public companies and those with small firms are consistent with our hypothesis, a more careful look at the data seems to be warranted. Below, we explain how we attempt to tease out the true relationship among size-sorted public companies, private firms, and aggregate fluctuations.

The immediate question is how we distinguish between small and large public companies. Data from Korea facilitate this distinction, as companies are listed either on an exchange for large, flagship companies (KOSPI) or on the one designed for small, fast-growing firms (KOSDAQ). The average firm size of the two exchanges compares at the ratio of approximately 10 to 1, and the small-size public companies in the results above are those listed on KOSDAQ while the larger ones are KOSPI-listed companies. When we instead sort public firms by the median total assets (each year), we obtain a very similar result.

Another—and a lot more critical—question is whether we are simply picking up the pattern of some industries being more volatile than others and those volatile industries having more KOSDAQ-listed (or small-size) public companies. It is a plausible scenario given that KOSDAQ was introduced to facilitate listings of small but fast-growing companies (in technology-related industries). The growth of small firms is also known to be more volatile. Thus, one may not be surprised by the positive cross-sectional relationship between the aggregate volatility of an industry and the presence of small firms in the industry. In a similar vein, the negative (albeit insignificant) relationship between industry volatility and large public companies could simply be due to stable industries tending to have more mature public firms.

We address this endogeneity issue in the following two ways. First, we employ industry-year observations in panel regressions. Specifically, we estimate a regression of the annual industry volatility (as measured by the absolute value of the annual industry growth rate) on the log numbers of small-size public companies and of larger ones in the industry at the beginning of the year, along with control variables including industry fixed effects. Consistent with the earlier results, the log number of small public companies enters the regression with a significant and positive coefficient while that of larger ones is negative and insignificant. That is, for a given industry, the aggregate volatility increases with the presence of small public companies, but not with that of larger ones. When we alternatively use the log number of small public firms at the end of the year, it is no longer significant. The log number of large public firms, measured at year-end, remains insignificant as well.

Second, we utilize firm-level data. Specifically, we estimate a panel regression of the annual asset growth rate of private firms on the equally weighted average q ratio—measured at the start of the year—of small or of large public companies in the same industry, along with control variables including firm fixed effects.[3] The q ratio of public companies is a direct measure of the stock price signal that is available to the private firms in the same industry. We find a positive coefficient for the q ratio with both groups of public firms, meaning that there is a commonality in private firms' growth in relation to the stock price of the public industry peers. However, the magnitude of the coefficient is greater when the q ratio is averaged only over small public firms.

More importantly, the q ratio of small public firms is most significant—both economically and statistically—when the industry is most volatile. We obtain this result by estimating the panel regression for each of the sub-samples sorted by the industry volatility (i.e., the y-axis variable in the graphs above). That is, industries are grouped into high-, mid-, or low-volatility sub-sample based on their own time-series volatility of annual asset growth rate, and we find the q ratio of small firms to be most significant in the sub-sample of the highest volatility. To the contrary, the q ratio of large firms does not line up with the volatility of sub-samples.

Could the results be attributable to different degrees of common fundamentals across industries? More precisely, could it be that the industries with more small public firms have greater common fundamentals and thus show greater aggregate fluctuations than the industries with fewer small-size public companies? Similarly, could it be that the degree of common fundamentals among same-industry firms is unrelated to the presence of large public companies in the industry? To verify these scenarios, we examine a set of sub-samples that are sorted by the cash flow correlation between private and public firms in the same industry. We find that the q ratio of small public peers is most significant when the cash flow correlation is lowest, whereas the q ratio of large public peers is most significant when the correlation is highest. These results indicate, at a minimum, that the earlier-found comovement among private firms' growth in relation to the public-peer stock price is not spuriously stemming from common fundamentals.

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[3] The value-weighted average q ratio yields similar but *weaker* results, which again confirm the role of small-size public companies.

Another important—and potentially more interesting—question is whether the industry-level aggregate volatility contributes to the market-level fluctuations. In order to answer this question, we decompose the industry volatility (i.e., the y-axis variable in the graphs above and the sorting variable for the volatility sub-samples) into the industry-specific volatility and the rest. It turns out that the small-peer q ratio is most significant when the industry-specific volatility is the highest and, conversely, when the industry's market-related volatility is the lowest. Interestingly, the q ratio of large public companies shows the exact opposite pattern: it is most significant when the industry's contribution to market-level volatility is the highest.

All the preceding q regressions are focused on the changes in total assets, but it is instructive to examine how those changes are funded. We expect the asset changes financed by retained earnings to be different from those funded by newly contributed capital, since the latter involves outside capital providers who may themselves engage in benchmarking private firms against their public industry peers. To verify this issue, we substitute various changes in the right-hand side of balance sheet for the total-asset changes in firm-level panel regressions. We find that the private-firm commonality around the public-peer stock price is least pronounced with retained earnings. With the stock price of small public peers, in particular, the commonality is most pronounced with newly contributed equity capital and non-financial liabilities. With the stock price of large public peers, changes in non-financial and financial liabilities show the greatest commonality.

In sum, our findings are consistent with the notion that the stock price of small public companies serves as a common signal to private firms and contribute to the industry-level aggregate fluctuations by creating commonalities among the private firms. Interestingly, this externality does not seem to go beyond the industry boundary. More precisely, our results suggest that the stock price of small public companies makes private firms in the industry more cohesive within the industry but more distinct from companies in other industries. Hence, the two size-sorted groups of public companies in an industry serve different purposes for the private firms in the same industry: large-size public companies provide private firms with market-wide information, but it is the smaller-size public firms in the same industry that the private firms are benchmarked against. Indeed, small-size public companies seem to serve as a counterbalance to larger public firms in terms of aggregate fluctuations.

We are agnostic about whether the observed commonalities among private firms—in relation to the public-peer stock price—are an act of irrational herding or a rational response to valid information. While prior studies suggest that better-performing and more sophisticated economic agent herd less (e.g., Alevy, Haigh, and List 2007; Foucault and Fresard 2014), we simply have no criterion to judge the observed comovement. Similarly, it is difficult—if not impossible—to tell whether aggregate fluctuations are beneficial or detrimental. After all, volatility can be associated with both noise and information (e.g., Lee and Liu 2011). Regardless, however, aggregate fluctuations mean that there exist common movements across different entities, which constitute an important observation to which a theory needs to fit. By reporting a unique commonality in private firms' growth around the stock price of small public firms, our paper shows that small-size public companies need to be taken seriously in the analysis of aggregate fluctuations.

This paper proceeds as follows. Section 2 describes our sample and data. Section 3 reports the empirical results and Section 4 concludes the paper.

2. Sample and data

To construct the sample, we begin with all non-financial firms covered by FnGuide, a Korean database following both public and private companies. The dataset includes companies that were delisted at some point in the past and thus causes no survivorship bias. We then drop the firm-year observations whose total assets are missing or negative during the 1999-2015 period. We also drop the firm-year observations when the company goes public (IPO). We further screen the sample by dropping firms with no corporation identification code, firms whose industry classification is missing, and firms whose industry code is "K" (financials & insurance companies), "O" (Public administration, national defense, & social security administration), or "Q" (Public health & social welfare). We also clean up duplicate observations for a given firm-year. As a result, we obtain 240,401 firm-year observations for the period from 2000 to 2015. Of those firm-year observations, approximately 90% (217,398) are private firms. To conduct the analysis, we require a private firm to have at least one public industry peer, with an industry defined by the 3-digit Korean SIC codes. This requirement reduces the private-firm observations down to 200,631. During the sample period, 34,726 private firms are in the sample at least once and the sample contains 1,437 unique public firms.

Table 1 reports the snapshots of our final sample vis-à-vis the original (i.e., unscreened) database. The first row shows that, in a given year, both the original dataset and our sample have a much larger number of private firms than publicly traded companies. Between the two public exchanges, KOSDAQ houses a larger number of firms than KOSPI. Then second and third rows then show that private firms are much smaller than public companies. The average asset size of a private firm is about one tenth of a public firm (one fifth by the median). Due to the larger number in the economy, however, private firms are comparable to public firms as a whole. In the original dataset, the aggregate assets under the management of private firms is approximately 879 trillion Korean wons (KRWs), whereas the assets under the control of public firms is 1,028 trillion KRWs. Similar statements can be made for corporate investment: while a given private firm invests much less than a typical public firm, the aggregate investment by private firms is comparable to the investment of public firms as a whole.

Breaking public companies by their listing venues, a typical KOSDAQ-listed firm is in fact closer to a private company, both in terms of firm size and corporate investment, than to a KOSPI-listed public company. In other words, companies listed on the two exchanges, KOSPI and KOSDAQ, are strikingly different from each other. While not tabulated, the industry distribution in our sample is not so different between private and public firms and between KOSPI- and KOSDAQ-listed companies.[4] The majority of private and public firms are in the manufacturing sector (industry sector code "C"), followed by the service sector.[5] In terms of the number of companies, the two sectors combined account for more than 80% of the sample private firms and over 90% of the sample public firms.

3. Empirical results

This section reports the empirical results. We begin with the analysis with industry-year observations and proceed to analyze firm-year observations.

3.1. Industry volatility and public companies – within-industry analysis

The graphs in the introduction motivate us to take a closer look at the relation between the industry-level aggregate volatility and the presence of public firms in the industry. Based on the cross-industry pattern, however, the graphs only allow for limited inferences. Thus, we now examine the time-series pattern within industry. Specifically, we estimate the following equation:

$$\sigma_{i,t} = \alpha + \sum_{k=1,2,3} \ln(nfirms_{i,k,t-1}) + \ln(A_{i,t-1}) + I_i + \varepsilon_{i,t}, \qquad (1)$$

where $\sigma_{i,t}$ is the volatility of industry i in year t, $nfirms_{i,k,t-1}$ is the number of firms belonging to firm group k in industry i at the end of the year t-1, and $A_{i,t-1}$ is the total assets of industry i at the end of year t-1. Finally, I_i is a set of industry fixed effects. The three firm groups are private firms, small

[4] In the original dataset, the real estate management sector is almost entirely composed of private firms. In other sectors, however, private firms coexist with public firms.

[5] The service sector is defined passively by excluding agriculture, forestry, and fishing ("A"), manufacturing ("C"), construction ("F"), and transportation ("H"). More than a quarter of the service sector is from the retail and wholesale industry ("G").

public companies, and large public companies. As a measure of $\sigma_{i,t}$, we use the absolute value of the industry i's total asset growth rate during year t. The presence of industry fixed effects makes the coefficients be determined by the time-series, within-industry variation in variables.

Table 2 reports the regression results. Consistent with the regression result and the graphs in the introduction, the log number of small public companies enters the regression with a significant and positive coefficient (Model (1)). This result is also robust to using the balance panel—i.e., the one with the industries that are in the sample during the entire sample period (Model (2)). Also consistent with the earlier results, the log number of large public companies is negative and insignificant, both in Models (1) and (2). Thus, the interpretation is that an industry experiences greater aggregate volatility as it has more small-size public companies.

Note that the two models include only the industry-year observations where the natural log of firm $nfirms_{i,k,t-1}$ is defined. In other words, we drop the industry-year observation where any of the three firm groups is missing. To avoid any loss of information, we reintroduce those observations by re-defining $nfirms_{i,k,t-1}$ as the number of firms belonging to firm group k in industry i at the end of the year t-1 plus one. That way, even if an industry has, say, no small-size public firms, it will be given a value of zero (i.e., ln(0+1)=0) and this industry-year observation remains in the data for regressions. Models (3) and (4) in Table 2 show that the significant positive coefficient for the number of small public companies is robust to using this re-definition. The coefficient for the number of large public companies also continues to be negative and insignificant.

3.2. Panel regressions with firm-year observations

We now more directly examine the comovement among private firms in relation to the stock price signal from their public industry peers. This analysis utilizes the firm-year observations of private firms as in the following equation:

$$\Delta A_{i,t} = CF_{i,t-1} + \ln(A_{i,t-1}) + Q_{peer,t-1} + CF_{peer,t-1} + \ln(A_{peer,t-1}) + f_i + y_t + \varepsilon_{i,t}\,, \qquad (2)$$

where $\Delta A_{i,t}$ is the total asset growth rate of private firm i during year t, $CF_{i,t\text{-}1}$ is the cash flow (i.e., operating income plus depreciation) of private firm i at the end of year t-1, and $A_{i,t\text{-}1}$ is the total assets of private firm i at the end of year t-1. The variables for "peer", such as $Q_{peer,t\text{-}1}$, are the equally weighted average values across the small- or large-size public industry peers. The q ratio is computed as the ratio of: total assets minus book value of equity plus market value of equity, to total assets. Finally, f and y are respectively firm and year fixed effects.

Summary statistics on the regression variables are reported in Table 3 and the regression results are in Table 4. We find that the average q-ratio of public industry peers is significantly and positively related to the asset growth of private firms. The coefficient is 0.0.0225 for the equally weighted average q-ratio of large-size public industry peers and 0.0.0290 for that of small public peers. A one-standard deviation changes in those q-ratios correspond to 14% and 29% of the typical annual asset growth of private firms, respectively. In an unreported result, we substituted the valued-weighted average q ratio and found that the coefficients are smaller in magnitude but continue to be significant statistically. In sum, there is strong evidence that private firms comove around the stock price of their public industry peers. Certainly, this commonality might be spuriously stemming from the common economic fundamentals among same-industry firms. We will address this issue in Section 3.4.1.

Besides the q-ratio, other regression variables carry the usual signs. Specifically, the coefficient for the own-cash flow is positive, while that of the own-size variable is negative. Their signs are very typical of this type of q regression (e.g., Fazzari, Hubbard, and Petersen 1988). Interestingly, the average cash flow of small-size public industry peers is negative but it is statistically insignificant and thus we no further pursue the meaning of this finding.

3.3. Volatility-sorted sub-samples

Thus far, we have reported two main results. First, we have documented a positive cross-sectional relation between an industry's aggregate volatility and the presence of small public companies in the industry. Second, we have shown that private firms in an industry comove in conjunction with the stock price of small-size public companies in the same industry. We now see whether the two results are related. One way of checking the link between the two is to see whether the comovement of private firms around the public-peer stock price is different between volatile industries and stable ones. According to our hypothesis, the comovement should be more pronounced in volatile industries. That is, the q ratio of small-size public industry peers should be more significant in volatile industries. On these grounds, we construct three sub-samples by sorting the sample industries by their volatility (i.e., the y-axis variable of the graphs in the introduction). We then estimate Eq. (2) within each sub-sample.

Table 5 shows that the q ratio of small public companies is most significant in the sub-sample of the highest volatility. The coefficient is 0.0581 and it is more than twice as large as the full-sample estimate (0.0290). At the other end of the spectrum (i.e., the sub-sample of the lowest volatility), the coefficient is 0.0151 and is thus nearly half of the full-sample estimate. While endogeneity needs addressing, the result is consistent with the notion that the commonality among private firms around the public-peer stock price contributes to the industry-level aggregate volatility.

In contrast, the q ratio of large-size public companies shows the exact opposite pattern. Across the sub-samples, the coefficient for the q ratio shows no monotonic pattern. Moreover, it is the lowest-volatility sub-sample that shows the most significant coefficient for the q ratio. Again, while the endogeneity problems remain to be addressed, the result with large public peer is not consistent with notion that the commonality among private firms around the public-peer stock price contributes to the industry-level aggregate volatility.

3.4. Robustness

3.4.1. Fundamental correlation

At least two issues exist in the preceding analysis and its results. One is that the industry-level aggregate volatility is an increasing function of common fundamentals among same-industry firms. If other things are equal, the industries with stronger common fundamentals would have greater aggregate fluctuations because the common fundamentals would make companies move in the same direction. Hence, a positive relation between private-firm growth and public-peer q is not surprising.

To address this issue, we construct another set of sub-samples that are sorted by the cash flow correlation among same-industry companies. Specifically, each year we calculate the average cash flows of the size-sorted public industry peers within industry. We then compute the time-series correlation between the average cash flows of an industry's sized-sorted public peers and the cash flows of a private firm in the same industry. Finally, we average those cash flow correlations within industry and assign the sample industries into three sub-samples based on the average cash flow correlation assign the private firms into one of the three sub-samples based on their cash flow correlation.

Table 6 reports the results. The regression coefficients across the sub-samples are inconsistent with the claim that the q ratio of public industry peers is significant because of the high fundamental correlation between private firms and their public industry peers. Specifically, the q ratio of small public industry peers is most significant in the sub-sample of the lowest cash flow correlation. Interestingly, the q ratio of large public industry peers is the opposite: it is most significant when the cash flow correlation is the highest. At a minimum, the results indicate that our earlier finding—namely, the commonality among private firms around the stock price of small public industry peers is not attributable to common fundamentals among those same-industry companies.

3.4.2. Industry-specific vs. market-related volatility

The other issue with regard to the results in Section 3.3 is whether the industry-level aggregate volatility contributes to market-wide fluctuations or it is diversified across industries. To answer this question, we regress the annual industry asset growth rates on the market-level asset growth rates, and use the volatility of the regression residuals as a measure of industry-specific volatility. As a measure of the market-level asset growth, we use either the average growth rate across industries or the growth rate of the aggregate (i.e., the sum across industries) total assets. Three sub-samples are then constructed by the industry-specific volatility.

As shown in Table 7, the q ratio of small public companies is most (least) significant in the sub-sample of the highest (lowest) industry-specific volatility. This pattern is robust between the two measures of market-level volatility. The results suggest that the stock price of small public industry peers makes private firms more cohesive within an industry but more distinct from other firms in different industries. Put differently, the small-size public industry peers serve as a source of information that is purely industry-specific. The q ratio of large public companies does not show any monotonic pattern across the sub-samples. However, it is least significant in the sub-sample of the highest industry-specific volatility. Thus, the stock price of large public companies seems to play the opposite role: it mostly provides market-wide information.

Another way of gauging the different roles of small and large public companies in providing market-wide and industry-specific information is to include a market-level q ratio in the regression. Specifically, we compute a q ratio that is averaged over all sample industries' large-firm q ratios, and add it to Eq. (2). Similarly, we add the average q ratio over the industries' small-firm q ratios and include it in the regression when the small-firm q ratio is used.

Table 8 shows that the market-level q ratio of large public companies is much more pronounced than their industry-specific q ratio. Specifically, the coefficient for the market-level q ratio is 0.156 whereas the industry-specific q ratio has a coefficient of 0.022. In contrast, the market-average q ratio of small public companies enters the regression with a coefficient of 0.023, which is smaller than that of the industry-level q ratio—i.e., 0.037.

3.5. Financing of asset growth

Thus far, we have examined asset changes at the industry level (Section 3.1) and at the individual firm level (Sections 3.2 through 3.4). In this section, we examine how those asset changes are funded. Broadly speaking, asset changes are funded either internally (i.e., retained earnings) or externally (i.e., newly contributed capital) and the rest should be financed by non-financial liabilities—i.e., accruals. Our goal in this section is to see which type of financing shows particularly strong commonalities among private firms in relation to the stock price of public industry peers. What we expect to see is that the asset changes funded externally show a greater commonality. It is because outside capital providers may well engage in benchmarking behavior. In other words, besides the private-firm management who makes asset-changing decisions, outside financiers may also refer to the public industry peers and their stock prices in making the funding decisions.

To this end, we estimate the following equation:

$$\Delta F_{i,t} = CF_{i,t-1} + \ln(A_{i,t-1}) + Q_{peer,t-1} + CF_{peer,t-1} + \ln(A_{peer,t-1}) + f_i + y_t + \varepsilon_{i,t}\,, \qquad (3)$$

where $\Delta F_{i,t}$ is private firm i's change in a certain balance-sheet item (detailed short) during year t, scaled by the total assets at the end of year t-1. Similar to Chen and Chen (2012), we specifically consider the annual changes in: financial liabilities (i.e., debt capital), non-financial liabilities, equity capital, and cumulative retained earnings. All other variables are defined in the same way as in Eq. (2).

Table 9 shows the results. Consistent with our conjecture, the commonality among private firms' growth around the public-peer stock price (i.e., the coefficient for the q ratio) is most pronounced in external funding. Specifically, the q ratio of small public companies is most significant for equity financing, while the q ratio of large public firms shows most significance for debt financing. Conversely, both q ratios are least significant for the internally generated funds (i.e., changes in cumulative retained earnings).

4. Conclusions

This paper empirically examines a hypothesis, namely, that the stock price of publicly traded companies serves as a common signal to privately held firms and contribute to aggregate fluctuations by creating commonalities among the private firms. In doing so, we are particularly interested in seeing whether there is any difference between large, flagship public companies and smaller-size ones in their role as a benchmark for private firms. Our results—based on the data from Korea for the period of 2000-2015—tell starkly contrasting stories for the two groups of public companies. Large public companies serve as a source of market-wide information for private firms, whereas small-size public companies provide private firms with industry-level information. As a consequence, small public companies contribute to aggregate fluctuations by making private firms in an industry cohesive with one another but distinct from companies in different industries. In short, the results suggest that small-size public companies serve as a counterbalance to larger public firms who impose market-wide shocks across companies in different industries.

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Table 1. Characteristics of Korean companies – public and private

The table presents basic properties of the unscreened and screened datasets. The dataset consists of all nonfinancial, publicly traded or privately-held companies in Korea. Public companies are further divided into "large" and "small" groups, by the exchange on which they are listed. The companies on the KOSPI exchange are defined as "large", while those listed on the KOSDAQ exchange are denoted as "small." The sample also contains the private companies that are required to provide financial information for external auditing purposes. The sample period is from 2000 to 2015. The firm-year observations without total assets or corporate registration number are dropped from the sample. Besides financial industry, the following industry sectors are excluded: public administration and defense, compulsory social security, and human health and social work activities. Our final sample further requires the firm-year observations to have the key variables for our analysis available. Numbers below are in billion Korean wons, except for the number of firms.

	Unscreened dataset				Screened sample dataset			
	Private	Public			Private	Public		
		all	large	small		all	large	small
Average # of firms	13,587	1,438	630	808	12,539	1,437	629	808
Firm size								
average	61.7	695.9	1,482.2	95.9	61.7	696	1,482.2	95.9
median	19.7	95.6	247.3	59.5	19.8	95.6	247.2	59.5
aggregate	879,297	1,027,622	946,502	81,119	808,217	1,027,330	946,259	81,071
Investment								
average	3.2	37.2	78.8	5.5	3.1	37.2	78.8	5.5
median	0.3	2.6	5	1.8	0.3	2.6	5	1.8
aggregate	43,336	54,473	50,127	4,345	39,880	54,442	50,105	4,337

Table 2. Industry panel regression

The table presents the estimates for the panel regressions using industry-year observations. Industry is based on the KSIC 3-digit industry classifications. The dependent variable is the absolute value of the industry-level aggregate asset growth rate at annual frequencies. The regressors include $nfirms_k$, which is the log number of firm group k in the industry at the start of the year (models (1) and (2)) or the log of: the number of firms in firm group k in the industry at the start of the year plus one (models (3) and (4)). Balanced panel in models (2) and (4) include only the industries that are present during the entire sample period of 2000-2015. We require the industry to have at least one public company. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	nfirms is natural log of # of firms		*nfirms* is natural log of (# of firms+1)	
	Unbalanced panel (1)	Balanced panel (2)	Unbalanced panel (3)	Balanced panel (4)
$nfirms_{private}$	-0.0074	0.0035	0.0080	0.0143
	[0.015]	[0.016]	[0.012]	[0.012]
$nfirms_{large\ public}$	-0.0014	-0.0036	0.0130	0.0083
	[0.012]	[0.012]	[0.015]	[0.016]
$nfirms_{small\ public}$	0.0235**	0.0246**	0.0312***	0.0295**
	[0.011]	[0.012]	[0.010]	[0.011]
ln(lagged assets)	-0.0110	-0.0193	-0.0260**	-0.0296***
	[0.013]	[0.013]	[0.011]	[0.011]
Constant	0.3397	0.4844**	0.5767***	0.6402***
	[0.233]	[0.225]	[0.191]	[0.191]
Observations	1,309	1,245	1,999	1,710
N of industries	101	92	138	114
Industry FE	YES	YES	YES	YES
Adj. R^2	0.006	0.007	0.0133	0.0134

Table 3. Descriptive Statistics

The table shows summary statistics on firm-level panel regression variables. Statistics for private companies at the individual firm level and those for public industry peers are at the portfolio level. ΔA_i is the annual change in total assets for private firm i, CF_i is private frim i's the cash flows that are calculated as the operating income plus depreciation, scaled by total assets. $\ln(A_i)$ is the natural log of private frim i's total assets. Q_k is the equally weighted average q ratio over the public industry peers belonging to group k, where k is either "large peers" (i.e., those listed on KOSPI) or "small peers" (i.e., those listed on KOSDAQ). CF and $\ln(A)$ for peers are defined similarly. We winsorize all variables at the 1st and 99th percentiles of the pooled observations.

	Mean	Median	StdDev	Min	Max
	Private firms (N=200,631)				
ΔA_i	0.089	0.035	0.339	-0.746	1.784
CF_i	0.075	0.068	0.105	-0.283	0.417
$\ln(A_i)$	16.998	16.768	0.955	15.303	20.268
	EW portfolio of large public industry peers (N=10,075)				
$Q_{large\ peers}$	1.022	0.878	0.547	0.360	3.831
$CF_{large\ peers}$	0.069	0.069	0.077	-0.223	0.287
$\ln(A_{large\ peers})$	19.493	19.248	1.502	16.684	23.846
	EW portfolio of small public industry peers (N=12,921)				
$Q_{small\ peers}$	1.341	1.069	0.884	0.463	5.891
$CF_{small\ peers}$	0.056	0.068	0.115	-0.406	0.304
$\ln(A_{small\ peers})$	17.860	17.833	0.882	15.888	20.288

Table 4. Panel regressions of private-firm asset growth on public-industry-peer q ratio

The table presents the estimates for the panel regressions using firm-year observations. The dependent variable is the annual asset growth rate of a private firm (ΔA_i). The regressors include the private firm's own cash flows (CF_i) and firm size ($\ln(A_i)$). The variables for the private firm's public industry peers (Q_{peers}, CF_{peers}, and $\ln(A_{peers})$) are also included in the regression as the equally weighted average across small or large public peers. An intercept is in the regression but its coefficient is not reported here. Detailed information about those variables are in the caption for Table 3. The estimation period is from 2000 to 2015. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ΔA_i	
	Only with ***large*** public industry peers	Only with ***small*** public industry peers
$CF_{i,\,t\text{-}1}$	0.2871^{***}	0.2996^{***}
	[0.015]	[0.015]
$\ln(A_{i,\,t\text{-}1})$	-0.3264^{***}	-0.3307^{***}
	[0.004]	[0.004]
$Q_{peers,\,t\text{-}1}$	0.0225^{***}	0.0290^{***}
	[0.003]	[0.003]
$CF_{peers,\,t\text{-}1}$	0.0514^{***}	-0.0227
	[0.018]	[0.021]
$\ln(A_{peers,\,t\text{-}1})$	0.0355^{***}	0.0490^{***}
	[0.004]	[0.004]
Observations	186,476	192,751
N of firms	32,414	33,360
Firm FE	YES	YES
Year FE	YES	YES
Adj. R^2	0.177	0.179

Table 5. Panel regressions by sub-samples sorted by industry volatility

The table presents the estimates for the panel regressions using firm-year observations, which are estimated for each of the sub-samples sorted by the industry-level aggregate volatility. The industry volatility is the time-series standard deviation of the industry's annual asset growth rate. The regression variables are the same as those in Table 4. An intercept is in the regression but its coefficient is not reported here. The estimation period is from 2000 to 2015. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ΔA_i					
	Only with ***large*** public industry peers			Only with ***small*** public industry peers		
	Low-volatility sub-sample	Medium-volatility sub-sample	High-volatility sub-sample	Low-volatility sub-sample	Medium-volatility sub-sample	High-volatility sub-sample
$CF_{i,\,t\text{-}1}$	0.2817***	0.2336***	0.3918***	0.2830***	0.2542***	0.4218***
	[0.022]	[0.026]	[0.032]	[0.021]	[0.026]	[0.032]
$\ln(A_{i,\,t\text{-}1})$	-0.3215***	-0.3310***	-0.3424***	-0.3181***	-0.3414***	-0.3495***
	[0.006]	[0.007]	[0.010]	[0.006]	[0.007]	[0.010]
$Q_{peers,\,t\text{-}1}$	0.0367***	0.0082	0.0207***	0.0151***	0.0212***	0.0581***
	[0.005]	[0.007]	[0.006]	[0.004]	[0.006]	[0.007]
$CF_{peers,\,t\text{-}1}$	-0.0769***	0.3923***	0.0488	-0.1687***	0.0218	0.0865**
	[0.021]	[0.043]	[0.070]	[0.030]	[0.038]	[0.043]
$\ln(A_{peers,\,t\text{-}1})$	0.0947***	-0.0016	-0.0194*	0.0508***	0.0380***	0.0394***
	[0.006]	[0.005]	[0.011]	[0.005]	[0.008]	[0.008]
Observations	92,110	62,949	31,417	97,345	64,167	31,239
N of firms	16,008	11,000	5,406	16,742	11,134	5,484
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.173	0.180	0.201	0.170	0.185	0.203

Table 6. Panel regressions by sub-samples sorted by cash flow correlation within industry

The table presents the estimates for the panel regressions using firm-year observations, which are estimated for each of the sub-samples sorted by the cash flow correlation within industry. The cash flow correlation is first computed between a private firm in an industry and an equally weighted portfolio of its public industry peers (small or large). The resulting correlations are then averaged across private firms within industry. The regression variables are the same as those in Table 4. An intercept is in the regression but its coefficient is not reported here. The estimation period is from 2000 to 2015. Numbers in brackets the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ΔA_i					
	Only with ***large*** public industry peers			Only with ***small*** public industry peers		
	Low-correlation sub-sample	Medium-correlation sub-sample	High-correlation sub-sample	Low-correlation sub-sample	Medium-correlation sub-sample	High-correlation sub-sample
$CF_{i,\,t\text{-}1}$	0.1894***	0.3372***	0.3613***	0.3277***	0.2561***	0.3354***
	[0.026]	[0.025]	[0.025]	[0.028]	[0.023]	[0.025]
$\ln(A_{i,\,t\text{-}1})$	-0.3560***	-0.3159***	-0.3100***	-0.3348***	-0.3410***	-0.3197***
	[0.008]	[0.007]	[0.007]	[0.009]	[0.007]	[0.007]
$Q_{peers,\,t\text{-}1}$	0.0067	0.0281***	0.0877***	0.0328***	0.0250***	0.0170**
	[0.005]	[0.006]	[0.010]	[0.005]	[0.004]	[0.007]
$CF_{peers,\,t\text{-}1}$	0.0149	0.4327***	0.1645***	-0.0406	-0.1852***	0.1047***
	[0.022]	[0.056]	[0.054]	[0.035]	[0.038]	[0.036]
$\ln(A_{peers,\,t\text{-}1})$	0.0514***	0.0097*	0.0546***	0.0303***	0.0444***	0.0888***
	[0.006]	[0.005]	[0.009]	[0.007]	[0.005]	[0.009]
Observations	66,952	60,485	58,994	44,375	79,406	68,828
N of firms	12,613	10,626	9,151	7,482	14,435	11,342
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.185	0.172	0.187	0.195	0.178	0.176

Table 7. Panel regressions by sub-samples sorted by industry-specific volatility ("induvol")

The table presents the estimates for the panel regressions using firm-year observations, which are estimated for each of the sub-samples sorted by the industry-specific volatility ("induvol"). To obtain industry-specific volatility, we regress the industry's annual asset growth rate on the market-level asset growth rate, and compute the time-series standard deviation of the regression residuals. The market-level asset growth rate is either the average asset growth rate across the sample industries (Panel A) or the growth rate of the aggregate—i.e., the sum across the sample industries—assets (Panel B). The regression variables are the same as those in Table 4. An intercept is in the regression but its coefficient is not reported here. The estimation period is from 2000 to 2015. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ΔA_i					
	Only with ***large*** public industry peers			Only with ***small*** public industry peers		
	Low-induvol sub-sample	Medium-induvol sub-sample	High-induvol sub-sample	Low-induvol sub-sample	Medium-induvol sub-sample	High-induvol sub-sample
Panel A. "induvol" against average asset growth rate across sample industries						
$CF_{i,\,t\text{-}1}$	0.3065***	0.2000***	0.3875***	0.3023***	0.2249***	0.4011***
	[0.020]	[0.029]	[0.031]	[0.020]	[0.029]	[0.031]
$\ln(A_{i,\,t\text{-}1})$	-0.3207***	-0.3343***	-0.3479***	-0.3183***	-0.3457***	-0.3488***
	[0.006]	[0.008]	[0.010]	[0.006]	[0.008]	[0.010]
$Q_{peers,\,t\text{-}1}$	0.0271***	0.0323***	0.0121**	0.0137***	0.0248***	0.0558***
	[0.005]	[0.007]	[0.006]	[0.004]	[0.006]	[0.007]
$CF_{peers,\,t\text{-}1}$	-0.0497**	0.3941***	0.0486	-0.1322***	0.0594	0.0225
	[0.021]	[0.046]	[0.066]	[0.030]	[0.039]	[0.043]
$\ln(A_{peers,\,t\text{-}1})$	0.0914***	0.0045	-0.0207**	0.0483***	0.0339***	0.0452***
	[0.006]	[0.005]	[0.010]	[0.005]	[0.009]	[0.008]
Observations	102,605	51,839	32,032	107,617	50,727	34,407
N of firms	17,498	9,339	5,577	18,206	9,140	6,014
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.175	0.183	0.194	0.173	0.185	0.197

Table 7. cont.

	Dependent variable: ΔA_i					
	Only with ***large*** public industry peers			Only with ***small*** public industry peers		
	Low-induvol sub-sample	Medium-induvol sub-sample	High-induvol sub-sample	Low-induvol sub-sample	Medium-induvol sub-sample	High-induvol sub-sample
Panel B. "induvol" against growth rate of market-wide aggregate assets						
$CF_{i,\,t\text{-}1}$	0.2618***	0.2684***	0.3978***	0.2580***	0.3023***	0.4115***
	[0.019]	[0.033]	[0.031]	[0.019]	[0.032]	[0.031]
$\ln(A_{i,\,t\text{-}1})$	-0.3215***	-0.3410***	-0.3415***	-0.3208***	-0.3569***	-0.3488***
	[0.005]	[0.009]	[0.010]	[0.005]	[0.010]	[0.010]
$Q_{peers,\,t\text{-}1}$	0.0299***	0.0302***	0.0107*	0.0139***	0.0375***	0.0558***
	[0.005]	[0.007]	[0.006]	[0.004]	[0.006]	[0.007]
$CF_{peers,\,t\text{-}1}$	0.0252	0.1285***	0.0427	-0.0557**	-0.0786*	0.0320
	[0.021]	[0.046]	[0.069]	[0.028]	[0.045]	[0.043]
$\ln(A_{peers,\,t\text{-}1})$	0.0736***	0.0052	-0.0142	0.0542***	0.0245***	0.0450***
	[0.006]	[0.005]	[0.010]	[0.005]	[0.009]	[0.008]
Observations	118,624	36,741	31,111	122,878	37,029	32,844
N of firms	20,640	6,439	5,335	21,159	6,461	5,740
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.171	0.195	0.195	0.170	0.202	0.200

Table 8. Industry average q ratio vs. market average q ratio

The table presents the estimates for the panel regressions using firm-year observations. The regression specification is the same as the one in Table 4, except that the market-level q ratio of public peers is additionally included. The market-level q ratio, denoted as $mktQ_{peers}$, is the equally weighted average of the q ratios of the public industry peers (Q_{peers}). An intercept is in the regression but its coefficient is not reported here. Detailed information about those variables are in the caption for Table 3. The estimation period is from 2000 to 2015. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: ΔA_i	
	Only with ***large*** public industry peers	Only with ***small*** public industry peers
$CF_{i,\,t\text{-}1}$	0.2641***	0.2810***
	[0.015]	[0.014]
$\ln(A_{i,\,t\text{-}1})$	-0.3152***	-0.3221***
	[0.004]	[0.004]
$Q_{peers,\,t\text{-}1}$	0.0220***	0.0371***
	[0.003]	[0.003]
$CF_{peers,\,t\text{-}1}$	0.0572***	-0.1432***
	[0.018]	[0.020]
$\ln(A_{peers,\,t\text{-}1})$	0.0606***	0.0810***
	[0.003]	[0.003]
$mktQ_{peers,\,t\text{-}1}$	0.1561***	0.0233***
	[0.008]	[0.004]
Observations	186,476	192,751
N of firms	32,414	33,360
Firm FE	YES	YES
Year FE	YES	YES
Adj. R^2	0.169	0.170

Table 9. Decomposition of assets growth

The table presents the estimates for the panel regressions using firm-year observations. The dependent variable is a private firm's annual rate of changes in one of the following four variables: financial liabilities (*△Debt*), non-financial liabilities (*△Non-financial Liability*), equity capital and capital surplus (*△Equity*), and retained earnings (*△Retained Earnings*). The regressors are the same as those in Table 4. An intercept is in the regression but its coefficient is not reported here. Panel A is for the results with large public industry peers and Panel B for small public industry peers. The definitions of small and large public industry peers are in the caption of Table 1. The estimation period is from 2000 to 2015. Numbers in brackets are the cluster-robust standard errors. *, **, and *** indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Only with ***large*** public industry peers

	Dependent variable:			
	△Debt	*△Non-debt liabilities*	*△Equity*	*△Retained Earnings*
$CF_{i,\,t\text{-}1}$	0.1341***	-0.0715***	-0.0230***	0.2293***
	[0.009]	[0.007]	[0.003]	[0.007]
$\ln(A_{i,\,t\text{-}1})$	-0.1227***	-0.0940***	-0.0226***	-0.0309***
	[0.002]	[0.002]	[0.001]	[0.002]
$Q_{peers,\,t\text{-}1}$	0.0058***	0.0063***	0.0039***	0.0033**
	[0.002]	[0.002]	[0.001]	[0.001]
$CF_{peers,\,t\text{-}1}$	0.0304***	-0.0115	-0.0023	0.0306***
	[0.011]	[0.009]	[0.004]	[0.007]
$\ln(A_{peers,\,t\text{-}1})$	0.0165***	0.0124***	0.0009	-0.0014
	[0.002]	[0.002]	[0.001]	[0.001]
Observations	186,476	186,476	186,476	186,476
N of firms	32,414	32,414	32,414	32,414
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0714	0.0554	0.0296	0.0403

Table 9. cont.

Panel B. Only with ***small*** public industry peers

	Dependent variable:			
	△Debt	*△Non-debt liabilities*	*△Equity*	*△Retained Earnings*
$CF_{i,\,t\text{-}1}$	0.1352***	-0.0636***	-0.0240***	0.2305***
	[0.009]	[0.007]	[0.003]	[0.007]
$\ln(A_{i,\,t\text{-}1})$	-0.1223***	-0.0953***	-0.0230***	-0.0330***
	[0.002]	[0.002]	[0.001]	[0.001]
$Q_{peers,\,t\text{-}1}$	0.0044***	0.0071***	0.0096***	0.0024**
	[0.002]	[0.001]	[0.001]	[0.001]
$CF_{peers,\,t\text{-}1}$	0.0037	-0.0323***	-0.0137***	0.0144*
	[0.013]	[0.010]	[0.005]	[0.008]
$\ln(A_{peers,\,t\text{-}1})$	0.0197***	0.0099***	0.0035***	0.0067***
	[0.002]	[0.002]	[0.001]	[0.001]
Observations	192,751	192,751	192,751	192,751
N of firms	33,360	33,360	33,360	33,360
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0698	0.0558	0.0352	0.0409