Tobin's *q* and the Signaling Effect of Filing Lag in Explaining Firm Performance

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Abstract:
This paper examines filing lag, measured as the number of days from fiscal period end to the filing date of either the 10-K or 10-Q report, as a signal of firm operational capabilities. With Spence's (1973) signaling theory, we show that filing lag fulfills the requirements of being a signal of operational capabilities and ultimately firm performance. Furthermore, using Compustat, EDGAR, and US Census data on NYSE and NASDAQ firms, we empirically confirm a robust negative relationship between filing lag and the market-based measure of firm performance, Tobin's q: On average, all other things equal, firms with a one day shorter average filing lag experience 1.3 percent higher q ratios and decreasing the filing lag average with one day increases a firm's q ratio with 0.6 percent. Additionally, we identify several other industry and firm characteristics (industry, industry concentration, firm size, advertising expenditure, R&D expenditure, firm auditor, and filing class) that explain parts of Tobin's q.

Key Words:
Filing Lag, 10-K and 10-Q Reports, Signaling, Firm Performance, Tobin's q

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Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

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1. Introduction

Executives prefer to issue debt over equity to avoid communicating that their equity is overvalued (Myers & Majluf, 1984). Producers issue long and extensive warranties to convey the high quality of their product. Programmers show up to coding job interviews looking sloppy to illustrate that their life is spent behind a computer screen. Each of these examples illustrates how one party can alleviate information asymmetries by signaling their underlying quality to another. In this paper, we provide evidence on the signaling relationship between filing lag and firm performance. We define filing lag as the number of days from the fiscal period end to the filing date of either the 10-K or 10-Q report, and measure firm performance using Tobin's q.

More specifically, we investigate the research question: Is filing lag a signal of firm operational capabilities? We believe that fast filing can be a way for high performing firms to credibly convey their superior operational capabilities, in accordance with contract theory's signaling perspective. We define operational capabilities as more efficient internal processes within a firm. In turn, we believe that these operational capabilities can be captured in measures of firm performance.

Using Standard and Poor's Compustat dataset, the U.S. Securities and Exchange Commission's (SEC) EDGAR database, and U.S. Census Bureau data, we estimate the relative importance of industry related factors, firm specific factors, and filing lag in explaining firm performance. The empirical approach is based upon a research tradition started by Lindenberg and Ross (1981), where stock market data, captured by Tobin's q, is used to explore a variety of firm characteristics and their contribution to firm performance: (a) similar to Schmalensee (1985) and Wernerfelt and Montgomery (1988), we find that firm sector is significant in explaining firm performance; (b) similar to Lindenberg and Ross (1981), we find that industry concentration is significant in explaining firm performance; (c) similar to Bharadwaj, Bharadwaj, and Konsynski (1999), we find that firm size is significant in explaining firm performance; (d) similar to Amit and Wernerfelt (1990) and Bharadwaj et al. (1999), we find that advertising intensity is significant in explaining firm performance; (e) similar to Bracker and Ramaya (2011), we find that research and development intensity is significant in explaining firm performance; and (f) we find that filing lag is significant in explaining firm performance.

1.1 Section Overview

It is our belief that filing lag is a signal of the operational capabilities of a firm. Firm operational capabilities should contribute to firm performance. Firm performance is captured by Tobin's q. In order to provide evidence on this relationship, we first present theoretical arguments based upon Spence's (1973) signaling theory to show that filing lag fulfills the requirements of being a signal of operational capabilities. These operational capabilities should, in turn, affect firm performance. Second, we provide evidence from the finance literature that Tobin's q is the preferable way to measure firm performance. Finally,

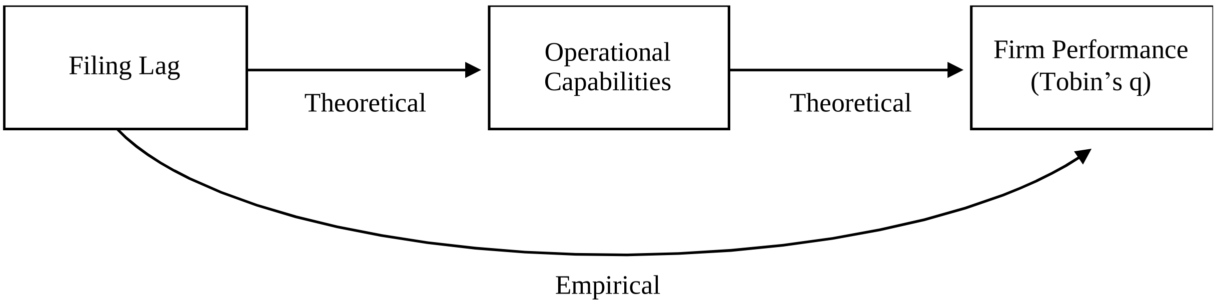

Figure 1. The filing lag and firm performance relationship.

we confirm the signaling effect empirically by regressing filing lag on Tobin's q with adequate control variables. This relationship is illustrated in **Figure 1**.

Spence (1973) specify, in his seminal work on labor markets, two criteria that define credible signals: They must be subjected to manipulation by the signaling entity and negatively correlated with the signaling entity's productive capabilities. Filing lag is subjected to manipulation by firms since they are free to file their 10-K or 10-Q reports to the SEC any date within the deadline. Furthermore, it is reasonable to assume that the marginal cost of faster filing is lower for firms with a more efficient filing process. Therefore, filing lag should be negatively correlated with a firm's operational capabilities. Additionally, the efficiency of the filing processes can be interpreted as a reflection of the efficiency of other processes within a firm as well. Therefore, we conclude that filing lag can be interpreted with signaling theory as a signal of firm operational capabilities.

In the finance and economics literature, the limitations of using accounting based measures to capture firm performance are well-known. Measures such as return on assets and return on equity are associated with a number of issues: They are backward looking, not adjusted for risk, and distorted by temporary disequilibrium effects. Instead, we use the market based measure Tobin's q as a measure of firm performance. Tobin's q, defined as the capital market value of the firm divided by the replacement value of its assets, is forward-looking, risk-adjusted, and less susceptible to changes in accounting practices (Montgomery & Wernerfelt, 1988). Furthermore, there is a wealth of research using Tobin's q to investigate firm characteristics' individual effects on firm performance, and the use of Tobin's q in this paper further connects our findings to the larger literature. We approximate Tobin's q in accordance with Chung and Pruitt's (1994) method.

With a dataset of 39,222 observations based on Standard and Poor's Compustat database with added variables from the SEC's EDGAR database and U.S. Census Bureau data, we investigate whether filing lag can explain parts of a firm's q ratio. In the main model, we regress Tobin's q on the following independent variables: (a) industry, (b) industry concentration, (c) total sales, (d) the logarithm of the number of employees, (e) advertising expenditure, (f) R&D expenditure, (g) auditor, (h) filing class, and (i) filing lag. The R^2 of the main model is 43.9 percent and the filing lag variable is significant at the 1 percent level with a coefficient of -0.013. The results are robust to controlling for autocorrelation and heteroskedasticity. Additionally, we find that the filing lag variable remains negative and significant at the 1 percent level when adding firm specific fixed effects.

The remainder of the paper is organized as follows: In part 2, we present the theoretical framework as to why filing lag should be a signal of firm operational capabilities through the concept of signaling theory. Additionally, we provide a basis for the argument that filing lag should represent firm performance and discuss the use of Tobin's q as a measure of firm performance. Finally, we clearly define the filing lag variable and explain how our research differs from existing. In part 3, we present the dataset and describe the data cleaning process. We then present the identification strategy and the models used in empirically identifying filing lag as a signal of operational capabilities. In part 4, we present the results of the empirical analysis. In part 5, we conclude our findings, acknowledge the limitations of our research, and present directions for future research.

2. Literature Review

2.1 Filing Lag and Signaling Theory

Signaling theory is the concept of one party reducing information asymmetry through credibly conveying information to another party. Spence (1973) illustrates this phenomenon through labor markets: In most labor markets an employer cannot be certain of the productive capabilities of a job applicant. In order to discern the best applicant, the employer will look at a plethora of personal attributes. Of these personal attributes, some are immutably fixed while others are alterable. The alterable personal attributes, referred to as signals, are possible to subject to manipulation by the applicants, however, frequently at some cost. Education, for example, is costly. These types of costs are referred to as signaling costs and are assumed to be negatively correlated with productive capability. Notice that an individual is not necessarily aware of their signaling. An applicant will acquire signals, although costly, as long as the signaling costs are less than the expected profits. Because of different levels of productivity, however, the optimal signals will differ among individuals, allowing for credible signaling of their underlying productive capabilities. An employer can therefore base their hiring decision on these signals.

Much like the labor market, financial markets are inhabited by information asymmetry. Management is better informed about the productive capabilities of their firms and wants to credibly convey these characteristics to the market. In this research paper, we evaluate firms as the signaling entity and filing lag as the signal. It is reasonable to assume that the marginal cost of faster filing is lower for firms with a more efficient filing process. Therefore, filing lag is associated with a signaling cost that is negatively correlated with a firm's filing ability. Furthermore, we can infer that filing lag is subjected to manipulation by firms as they are able to impact the timeliness of their reporting. Moreover, it is reasonable to assume that a firm that is efficient in their filing process will apply the same level of commitment in their core business. Especially since there are no apparent benefits of filing faster than required by SEC regulations. Therefore, we believe that the efficiency of the filings process can be interpreted as a reflection of the efficiency of other processes within a firm as well. Finally, it is natural to assume that more efficient internal processes are associated with increased firm performance. To conclude, filing lag credibly signals the efficiency of the filing process. The efficiency of the filing process can be interpreted as a reflection of the efficiency of other internal processes within a firm. More efficient internal processes increase firm performance. Therefore, filing lag can be interpreted as a signal of firm operational capabilities and the management of productive firms can use filing lag to credibly convey their superior productivity to the market.

2.2 Firm Performance and Tobin's q

Created by James Tobin in 1969, Tobin's q is the ratio between a firm's market value and its replacement value. The q ratio is used to measure and explain a variety of phenomena. For example: (a) evaluate capitalized value of monopoly rents (Lindenberg & Ross, 1981, Salinger, 1984, Smirlock, Gilligan, & Marshall, 1984, and Montgomery & Wernerfelt, 1988), (b) evaluate differences in gains from tender offers (Lang, Stulz, & Walkling, 1989), (c) analyze firms' decisions to expand capital stock (Blundell, Bond, Devereux, & Schiantarelli, 1992), and (d) evaluate the relationship between takeover gains and targets and bidders (Servaes, 1991).

Additionally, Tobin's q can be used as a market based measure of firm performance (Chen & Lee, 1995). Accounting measures of firm performance is criticized in the finance literature, and in particular accounting rates of return (Fisher & McGowan, 1983, and Benston, 1985). Accounting rates of return suffer from distortion effects due to their failure to consider differences in systematic risks when comparing firms. Additionally they suffer from effects such as different accounting conventions for R&D and advertising expenditures. Altogether these properties make comparisons between firms based upon accounting measures difficult. The q ratio, being a market based measure, addresses the limitations of accounting measures of performance. Lubatkin and Shrieves (1986) summarize the presumed advantages of market based measures: (a) stock prices are the only direct measure of stockholder value, (b) stock prices are believed to reflect all relevant information aspects of performance, (c) stock prices are readily available for all publicly traded firms, (d) stock prices are reported objectively, (e) stock prices have been shown to "see through" managers' attempts to manipulate reported accounting measures, (f) stock prices can be adjusted for general market movements, inflation, and the firm's market risk, and (g) stock prices provide a basis for evaluating investors' assessment of the impact of managerial decisions. Together these benefits make a comparison of firm performance based on the q ratio more accurate than accounting measures.

Because of its ability to more accurately represent firm performance, Tobin's q is also frequently used in investigating the importance of different firm characteristics in explaining firm performance. This research tradition was started by Lindenberg and Ross in 1981. Since then, Tobin's q has been used in evaluating, among other things: (a) firm diversification (Wernerfelt & Montgomery, 1988, and Lang & Stulz, 1994), (b) IT investments (Bharadwaj et al., 1999), (c) advertising investments (Wu & Bjornson, 1996), (d) research and development investments (Cockburn & Griliches, 1988), and (e) intellectual capital (Hejazi, Ghanbari, & Alipour, 2016). Similar to the studies above, we evaluate the effect of filing lag on firm performance, measured as Tobin's q.

2.3 Defining Types of Reporting Lag

Before presenting existing research on filing lag, we must first briefly state the financial report release process and clearly define the filing lag that we evaluate. All listed public firms on US markets are required to report their financial results to the United States Securities and Exchange Commission (SEC) four times during the year; three quarterly reports covering the firm's first, second and third fiscal quarter, and one annual report after the fourth quarter. The annual reports are known as 10-K filings and provide a comprehensive overview of the firm's business and financial condition, including audited financial statements. The 10-K deadline is 60 days for large accelerated filers (public float larger than $700 million), 75 days for accelerated filers (public float larger than $75 million), and 90 days for non-accelerated filers (public float less than $75 million). The quarterly reports are known as 10-Q filings and contain unaudited financial statements. The 10-Q deadline is 40 days for large accelerated filers and accelerated filers, and 45 days for non-accelerated filers (SEC, 2009). To evaluate the signaling effect of reporting lag we define the 10-K and 10-Q filing lag as the number of days from fiscal period end to the filing of the respective report.

Filing lag is attractive as an independent variable due to the availability of data and the standardized requirements for all filers. All SEC filings are available in the EDGAR database provided by the SEC. Furthermore, since the 10-K and 10-Q filings are strictly regulated by the SEC, all firms are required to supply the same amount and quality of financial information. This is important from a signaling point of view as all firms facing the same requirements makes the signal of faster filing more credible.

The 10-K and 10-Q filing lag is not to be confused with the closely related earnings announcement lag and audit report lag. Earnings announcement lag is commonly defined as the number of days from fiscal period end to the public release of earnings figures in financial journals. Audit report lag is commonly defined as the number of days from fiscal period end to the audit report release of a financial statement. Filing lag as a reporting lag variable is preferable to these alternatives because earnings announcement lag and audit report lag contain noise. We regard earnings announcement lag to be inferior because some firms release their complete earnings announcements in conjunction with their 10-K and 10-Q filings, while others release less detailed announcements of various lengths prior to the filings. Therefore, evaluating firm performance and operational capabilities via earnings announcement lag becomes less efficient as the work put in by the firms to produce the announcements varies greatly. Furthermore, earlier research regarding earnings announcement lag has found a wealth of evidence for earnings announcement release strategies of various kinds. Audit report lag also includes noise as the variable emphasizes the time it takes for independent audit firms to complete their audits. By using filing lag, not only do all reports contain the same quantity and quality of information, but we also ensure that the reporting lag variable is not greatly impacted by the efficiency of the audit firm.

2.4 Existing Reporting Lag Research

There is little research on the determinants of 10-K and 10-Q filing lag, however, there is a wealth of research on the determinants of earnings announcement lag and audit report lag. We apply earlier research in these fields together with research on determinants of Tobin's q when evaluating relevant control variables for the models. Abernathy, Barnes, Stefaniak, and Weisbarth (2017) summarize the extant literature on reporting lag and find five firm specific factors affecting earnings announcement lag and audit report lag: (a) firm size, measured as the logarithm of sales volume or firm total assets, is negatively correlated with reporting lag (Givoly & Palmon, 1982, Carslaw & Kaplan, 1991, and Soltani, 2002); (b) longer audit delays negatively affect earnings quality (Asthana, 2014), and early research on the topic shows that poor performers produce less timely reports, using net income as an indicator of performance (Courtis, 1976, and Kross, 1981); (c) audit complexity, measured as the presence of extraordinary items in the income statement, is positively correlated with longer reporting lag (Ng & Tai, 1994, and Leventis, Weetman, & Caramanis, 2005); and (d) firm industry classification is correlated with reporting lag (Ashton, Graul, & Newton, 1989, Newton & Ashton, 1989, Carslaw & Kaplan, 1991, Bamber, Bamber, & Schoderbek, 1993, Schwartz & Soo, 1996, and Givoly & Palmon, 1982).

2.5 Conclusion of Literature Review

Courtis (1976) and Kross (1981) document a negative relationship between earnings announcement lag and firm performance, using the sign of net income as a measurement of firm performance. Their findings support our belief that filing lag is related to firm performance. Apart from our critique on the use of earnings announcement lag as a variable, we argue against Courtis' and Kross' use of accounting based measures to measure firm performance. In this paper, we propose the use of 10-K and 10-Q filing lag as the reporting lag variable and Tobin's q as the measure of firm performance. It is our belief that filing lag signals the operational capabilities of a firm which are captured by the q-ratio which in turn explains firm performance. We hypothesize that the relationship between filing lag and Tobin's q should be negative according to Spence's (1973) theory of signaling costs.

3. Data and Methodology

To conduct the research, we primarily use parts of Standard and Poor's Compustat database accessed through Wharton. The Compustat database contains a wide range of financial and accounting data on more than 84,000 firms gathered primarily through SEC filings (Wharton, n.d.). Compustat data is commonplace in financial, economic, and accounting research because of its availability and comprehensiveness. The initial exported dataset contains approximately 500,000 quarterly observations dated from 1987 to 2017. The variables exported are manually selected to test the research question. Among these are: (a) industry identification codes such as GIC and NAICS, (b) reporting data such as firm fiscal year, (c) accounting data such as total assets, and (d) financial data such as market value of equity. Quarterly Compustat data is unavailable for the variables liquidation value of preferred stocks, advertising expenses, R&D expenses, and firm auditor, and annual data is used instead. To keep the quarterly structure of the data, we assume that the liquidation value of preferred stocks remains constant during the year and apply the same figures to all quarters. Furthermore, we spread out the annual expenses evenly over the quarters. Finally, we assume that firm auditor is not changed during the year and apply the annual audit firm to each quarter.

A recent study by Jan Kiel (2017) criticizes the estimation of the Herfindahl index with Compustat data. Kiel proves that the correlations between the popular Herfindahl index approximation from Compustat and Herfindahl indices calculated from more comprehensive U.S. Census Bureau data are alarmingly low. Therefore, we calculate the Herfindahl index from U.S. Census data provided by Jan Kiel. Furthermore, 10-K and 10-Q filing dates for firms in the Compustat dataset are retrieved from SEC's EDGAR database through their masterindex files. The EDGAR database contains automatically collected data from companies and others who are required by law to file forms with the SEC (SEC, 2010).

We limit the dataset with two criteria: (a) we only keep observations from the two largest stock exchanges, the New York Stock Exchange and NASDAQ, ensuring similar regulatory requirements between firms, and (b) we only keep observations between 2006 and 2017 in order to isolate more current results. Furthermore, *make-or-break* firms, such as biotech-, pharmaceutical-, and oil and gas exploration firms, have high q-values due to their large potential but lack of current assets and have on average few employees and low sales. These firms bias the sample and we therefore limit the research with two additional criteria: (c) we only observe firms with more than 100 employees, and (d) we only observe firms with more than $10 million in quarterly sales.

The dataset list missing values, especially for advertising expenditure and R&D expenditure. We follow the convention of past Tobin's q studies, replacing the missing values for the advertising and R&D variables with their corresponding industry average (Bharadwaj et al., 1999, and Wernerfelt & Montgomery, 1988). We then remove all observations with missing data on variables of interest, using listwise

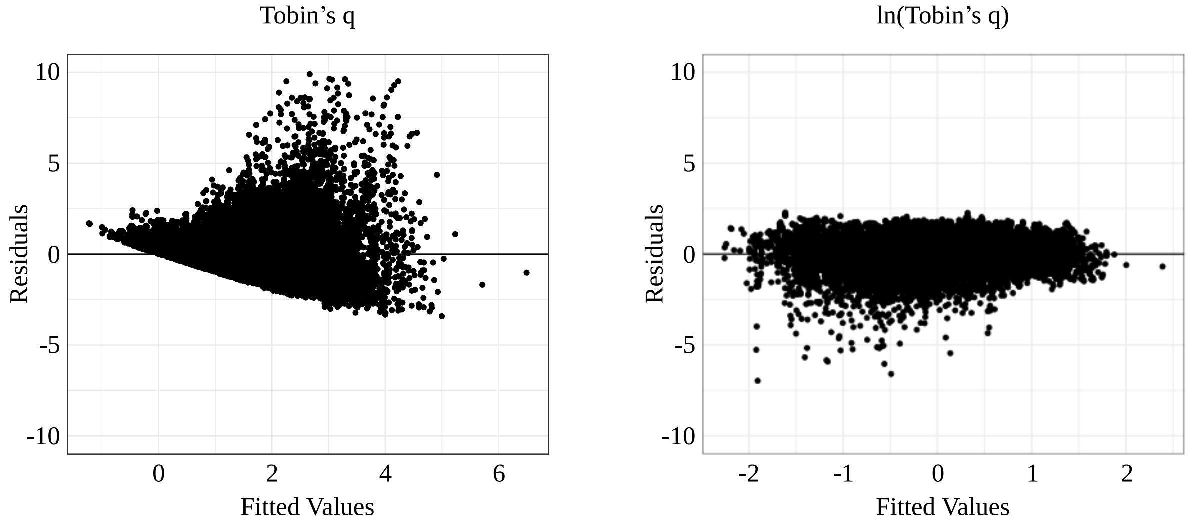

Figure 2. Heteroskedasticity test of Tobin’s q

deletion. An analysis of the data removed and the data kept in the sample shows that there are some systematic differences (see **Appendix 1**). The mean and standard deviation of the filing lag variable in the final dataset are 42.4 and 6.3 respectively compared to 42.9 and 5.8 in the data removed. The q ratio mean and standard deviation in the final dataset are 1.5 and 1.4 respectively compared to 1.3 and 1.4 in the data removed. A comparison of the other variables produce similar results, revealing that there are some systematic differences between the datasets. However, since the differences are small, we do not find the resulting bias large enough to warrant any large concern for the robustness of the results. Through the use of cook's distance, we identify a few outliers. This process results in the elimination of three uniquely influential firms from the data that adversely bias the results of the regressions.

We test the main model for heteroskedasticity with a Breusch Pagan test using studentized residuals. We find that the hypothesis of constant variance can be discarded at the 1 percent level. A visual observations of the residuals confirms the existence of heteroskedasticity in the data (see Tobin’s q, **Figure 2**). The q ratio variance is higher for firms with high q ratios than for firms with low q ratios. We therefore replace the q ratio dependent variable with the logarithm of the q ratio. With the new dependent variable, the Breusch Pagan test can still be discarded at the 1 percent level. However, a visual inspection of the residuals confirms that the bias has been greatly reduced (see ln(Tobin’s q), **Figure 2**). The heteroskedasticity is still of some concern. To avoid skewed results we use robust standard errors in all regressions as an extra precaution. We test the main model for multicollinearity by calculating the variance inflation factors (see **Appendix 2**). No variance inflation factor is above the 3.5 threshold and we can therefore conclude that multicollinearity is not an issue in the model.

Table 1. Summary Statistics of Sample Data

				Correlation Among Variables						
Variables	N	Mean	SD	1	2	3	4	5	6	7
(1) Tobin's q	39 222	1.486	(1.363)	1.00						
(2) Industry Conc.	39 222	0.048	(0.039)	-0.02***	1.00					
(3) Total Sales	39 222	1.198	(3.441)	-0.02***	0.20***	1.00				
(4) Employees	39 222	15.663	(43.112)	0.01**	0.12***	0.52***	1.00			
(5) Adv. (Ratio)	39 222	0.022	(0.038)	0.15***	0.02**	0.00	0.00	1.00		
(6) R&D (Ratio)	39 222	0.076	(0.180)	0.20***	0.02***	-0.04***	-0.06***	0.05***	1.00	
(7) Filing lag	39 222	42.441	(6.281)	-0.15***	-0.10***	-0.27***	-0.26***	0.00	-0.01	1.00

* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

The final sample comprises 1,356 firms and 39,222 observations spanning 10 years. The average market value of the firms in the sample is $7.7 billion and the average number of employees is 15,663. The mean Tobin's q over the sample period is 1.5 and the 3 year rolling average filing lag is 42.4 days. Additional summary statistics for the sample are provided in **Table 1**.

3.1 Dependent and Independent Variables

The dependent variable in this study is Tobin's q. We approximate the q ratio using Chung and Pruitt's (1994) method, which only requires basic financial and accounting data, readily available in the Compustat database. Chung and Pruitt find that their approximated q ratio, utilizing 10 years of data from 1978 to 1987, can explain at least 96.6 percent and at most 99.3 percent of the variability in the more theoretically correct Tobin's q computed by Lindenberg and Ross (1981). In accordance with Chung and Pruitt, we define Tobin's q as:

$$q_i = \frac{MVE_i + PS_i + DEBT_i}{TA} \quad (1)$$

Equation 1. Where:
q_i = Tobin's q of firm *i*
MVE_i = Market value of equity of firm *i*
PS_i = Liquidation value of outstanding preferred stock of firm *i*
$DEBT_i$ = Value of short-term liabilities net of short term assets plus book value of long-term debt of firm *i*
TA_i = Book value of total assets of firm *i*

The key independent variable in this study is 10-K and 10-Q filing lag, calculated as the three-year rolling average. To populate the years 2007 to 2009 with filing lag data, the variable is calculated before limiting the dataset to the years 2007 to 2016. We use a three-year rolling average for the filing lag variable since a firm needs to be able to consistently produce faster filings than their counterparts in order to signal higher efficiency.

We choose control variables by drawing upon the existing literature in finance, economics, and accounting. We identify three criteria to determine the relevant control variables for the models: (a) the variable is proven or reasonably expected to be significant in explaining Tobin's q, (b) the variable is proven or reasonably expected to affect filing lag, and (c) the variable is readily available and the inclusion of the variable does not require the removal of a large number of observations. Two industry related and six firm specific control variables are included in the main model. We also include a specific year fixed effect control variable to remove any time effects impacting the q ratio. Additionally, we test the robustness of the main model by adding firm specific fixed effects.

3.2 Industry Control Variables

There is a wealth of research in finance and economics documenting the impact of industry characteristics on firm performance (Schmalensee, 1985, and Wernerfelt & Montgomery, 1988). We use two control variables to represent industry effects: Industry specific fixed effects using 8-digit GIC code dummy variables and industry concentration using the Herfindahl index.

The industry specific fixed effects are included to account for the industry effects, apart from industry concentration, that affects the q ratio. Theoretically, the inclusion of industry specific fixed effects should account for the industry effect completely. Therefore, unlike earlier studies, we will not be able to map which underlying industry effects that affect the q ratio. However, we include industry specific fixed effects to ensure that there are no unobserved industry effects correlated with filing lag that could potentially bias the results of the regressions. The industry dummy variables are created at the 8-digit GIC sub-industry level in order to capture as many industry effects as possible.

Industry concentration should affect the q ratio of firms by allowing for higher profits in high concentration industries. Lindenberg and Ross (1981) study the relationship between monopoly rents and firms' q ratios in their thought provoking paper *Tobin's Q and Industrial Organization*. They find that firms with more market power tend to be placed at the higher end of the q ratio spectrum. We therefore include industry concentration, using the Herfindahl index, as a control variable. If Lindenberg and Ross' (1981) findings are applicable to our sample, the effect of industry concentration on Tobin's q is likely to be positive.

3.3 Firm Control Variables

The six firm specific control variables included in the models are: Total sales, the logarithm of the number of employees, advertising ratio, R&D ratio, firm auditor, and filing class.

We use two variables to control for firm size: The logarithm of the number of employees and total sales. The logarithm of the number of employees in a firm, measured in thousands, is shown by Bharadwaj et al. (1999) to be significant in explaining Tobin's q. Additionally, Givoly and Palmon (1982), Carslaw and Kaplan (1991), and Soltani (2002) prove that firm size has a large effect on reporting lag, indicating the importance of controlling for firm size. Therefore, we include an additional firm size control variable; total sales, measured as quarterly total sales in $1 billion. The correlation between the logarithm of the number of employees and the total sales variables is 0.4, indicating that both control variables contain unique information. In line with prior research, we hypothesize that the logarithm of the number of employees will be negatively correlated with Tobin's q. We make no prediction about the sign of total sales relationship with Tobin's q.

There is a wealth of research documenting the relationship between advertising expenditure and firm performance as well as R&D expenditure and firm performance. Wernerfelt and Montgomery (1988), Amit and Wernerfelt (1990), and Bharadwaj et al. (1999) include versions of advertising expenditure and R&D expenditure as control variables when modelling Tobin's q. Similarly, we choose to include advertising and R&D expenditure as control variables. Furthermore, we follow the convention set by these studies and transform the expenditures into ratios by dividing the expenditures with total sales, both measured in $1 million. This procedure should remove the effect of larger firms having larger expenditures. In line with Amit and Wernerfelt (1990) and Bharadwaj et al. (1999), we hypothesize that the advertising ratio will have a positive relationship with Tobin's q. Similarly, in line with Bracker and Ramaya (2011), we hypothesize that the R&D ratio will have a positive relationship with Tobin's q.

The 10-K filing contains audited financial information. Therefore, it is natural to assume that the audit firm used in the filing process will be correlated with the filing lag variable. To reduce the risk of omitted variable bias, we control for firm auditor using dummy variables for the most common audit firms. We make no prediction about the dummy variables' relationship with the q ratio.

Finally, we include dummy variables to account for the different 10-K and 10-Q filing deadlines for large accelerated filers, accelerated filers, and non-accelerated filers. Due to a lack of data, we use market cap to approximate public float. We increase the cutoff points for the classifications by about 25 percent to account for all shares not being publicly traded. We define large accelerated filers as firms with a market cap greater than $1000 million, accelerated filers as firms with a market cap greater than $100 million, and non-accelerated filers as firms with a market cap smaller than $100 million.

Additional to the industry related and firm specific control variables, we include time fixed effects by including dummy variables for each observed year. The dummy variables should account for natural changes in Tobin's q due to time as well as macroeconomic shocks.

3.4 Statistical Analyses

In line with prior research, we use ordinary least-squares regressions (OLS) to estimate the relationship between filing lag and Tobin's q. Furthermore, we isolate the explanatory power of the filing lag variable with hierarchical regressions. Initially, we estimate the main model (**Model 1**):

$$\ln(q) = \beta_0 + \beta_1 Ind. + \beta_2 Conc. + \beta_3 Sales + \beta_4 \ln(Emp.) + \beta_5 Ad. + \beta_6 RD. + \beta_7 Audit + \beta_8 Class + \beta_9 Year + \varepsilon \quad \text{(A)}$$

$$\ln(q) = \beta_0 + \beta_1 Ind. + \beta_2 Conc. + \beta_3 Sales + \beta_4 \ln(Emp.) + \beta_5 Ad. + \beta_6 RD + \beta_7 Audit + \beta_8 Class + \beta_9 Year + \beta_{10} Flag + \varepsilon \quad \text{(B)}$$

Model 1. Where:
q = Tobin's q
Ind. = Industry specific dummy variables
Conc. = Industry concentration
Sales = Quarterly total sales
Emp. = Number of employees
Ad. = Advertising ratio
RD = R&D ratio
Audit = Audit firm dummy varaibles
Class = Filing class dummy variables
Year = Annual time dummy variables
Flag = 10-K and 10-Q filing lag
ε = Error term with zero mean

Model 1 consists of two regressions: Regression A, which tests the relationship between industry related and firm specific control variables and q, and Regression B which adds the filing lag variable to examine the incremental variance explained. Furthermore, we estimate models for each filing class separately in **Model 2**, **3**, and **4**:

$$\ln(q) = \beta_0 + \beta_1 Ind. + \beta_2 Conc. + \beta_3 Sales + \beta_4 \ln(Emp.) + \beta_5 Ad. + \beta_6 RD + \beta_7 Audit + \beta_8 Year + \varepsilon \quad \text{(A)}$$

$$\ln(q) = \beta_0 + \beta_1 Ind. + \beta_2 Conc. + \beta_3 Sales + \beta_4 \ln(Emp.) + \beta_5 Ad. + \beta_6 RD + \beta_7 Audit + \beta_8 Year + \beta_9 Flag + \varepsilon \quad \text{(B)}$$

Model 2, 3, and 4.

Model 2, 3 and 4 are similar to Model 1 but investigate non-accelerated filers, accelerated filers, and large accelerated filers respectively. Naturally, these models do not include the filing class dummy variables.

3.5 Firm Fixed Effects

Additionally, to test the robustness of the results, we add firm specific fixed effects to the main model in **Model 5**:

$$\ln(q) = \beta_0 + \beta_1 Conc. + \beta_2 Sales + \beta_3 \ln(Emp.) + \beta_4 Ad. + \beta_5 RD + \beta_6 Audit + \beta_7 Class + \beta_8 Year + \beta_9 Firm + \varepsilon \quad \text{(A)}$$

$$\ln(q) = \beta_0 + \beta_1 Conc. + \beta_2 Sales + \beta_3 \ln(Emp.) + \beta_4 Ad. + \beta_5 RD + \beta_6 Audit + \beta_7 Class + \beta_8 Year + \beta_9 Firm + \beta_{10} Flag + \varepsilon \quad \text{(B)}$$

Model 5. Where:
Firm = Firm specific dummy variables

Firm specific fixed effects allows us to control for unobserved firm characteristics which reduces the risk of omitted variable bias. However, adding firm fixed effects to the model excludes cross-sectional variation between firms, reducing the statistical power of the regressions. Therefore, Model 5 only compares changes in filing lag within a firm and their effect on the firm's Tobin's q, rather than comparing the filing lag and Tobin's q of different firms with one another. Furthermore, due to firm industry being constant, industry specific fixed effects are removed from Model 5. The same procedure is repeated and firm specific fixed effects are added to the separated filers models in **Model 6**, **7**, and **8**:

$$\ln(q) = \beta_0 + \beta_1 Conc. + \beta_2 Sales + \beta_3 \ln(Emp.) + \beta_4 Ad. + \beta_5 RD + \beta_6 Audit + \beta_7 Year + \beta_8 Firm + \varepsilon \quad \text{(A)}$$

$$\ln(q) = \beta_0 + \beta_1 Conc. + \beta_2 Sales + \beta_3 \ln(Emp.) + \beta_4 Ad. + \beta_5 RD + \beta_6 Audit + \beta_7 Year + \beta_8 Firm + \beta_9 Flag + \varepsilon \quad \text{(B)}$$

Model 6, 7, and 8.

Table 2. Descriptive Statistics of Models

	All Filers (Model 1, 5)		Non-Accelerated[1] (Model 2, 6)		Accelerated[2] (Model 3, 7)		Large Accelerated[3] (Model 4, 8)	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Tobin's q (Log)	0.062	(0.870)	-0.905	(1.038)	-0.145	(0.839)	0.368	(0.682)
Industry Conc.	0.048	(0.039)	0.043	(0.041)	0.042	(0.033)	0.054	(0.043)
Total Sales	1.198	(3.441)	0.050	(0.113)	0.163	(0.236)	2.128	(4.515)
Employees (Log)	1.278	(1.699)	-0.560	(1.068)	0.378	(1.259)	2.225	(1.442)
Adv. (Ratio)	0.022	(0.038)	0.017	(0.031)	0.021	(0.039)	0.024	(0.039)
R&D (Ratio)	0.076	(0.180)	0.052	(0.082)	0.078	(0.170)	0.078	(0.198)
Filing lag	**42.441**	**(6.281)**	**50.013**	**(5.466)**	**44.474**	**(5.239)**	**39.745**	**(5.481)**
Sample Size	39 222		3 405		14 966		20 851	

[1] Sample reduced to estimated non-accelerated filer firms (market value less than $100 million)
[2] Sample reduced to estimated accelerated filer firms (market value greater than $100 million)
[3] Sample reduced to estimated large accelerated filer firms (market value greater than $1 billion)

Table 3. Pooled OLS Regression Results[1]

	All Filers (Model 1)		Non-Accelerated[1] (Model 2)		Accelerated[2] (Model 3)		Large Accelerated[3] (Model 4)	
Variables	A	B	A	B	A	B	A	B
Industry Conc.	-0.189	-0.222	-1.334	-1.263	0.634	0.616	-0.314	-0.363
	(-1.6)	(-1.9)	(-1.8)	(-1.7)	(3.0)**	(2.9)**	(-2.4)*	(-2.8)**
Sales	0.016	0.014	0.107	0.127	-0.376	-0.403	0.014	0.012
	(15.0)***	(13.6)***	(0.5)	(0.6)	(-11.6)***	(-12.0)***	(13.4)***	(11.7)***
Employees (Log)	-0.145	-0.157	-0.171	-0.167	-0.145	-0.153	-0.127	-0.141
	(-38.9)***	(-41.2)***	(-6.9)***	(-6.7)***	(-18.8)***	(-19.8)***	(-29.3)***	(-31.7)***
Advertising	1.220	1.171	4.305	4.215	0.317	0.281	1.076	0.966
(Ratio)	(8.4)***	(8.0)***	(6.0)***	(5.8)***	(1.2)	(1.1)	(6.0)***	(5.4)***
R&D (Ratio)	0.111	0.100	0.691	0.736	0.071	0.041	0.102	0.099
	(4.8)***	(4.4)***	(2.9)**	(3.1)**	(1.5)	(0.8)	(3.9)***	(3.8)***
Accelerated Filers	0.948	0.905						
(Dummy)	(49.1)***	(46.1)***						
Large Accelerated	1.697	1.626						
Filers (Dummy)	(80.3)***	(75.0)***						
Filing Lag		**-0.013**		**0.006**		**-0.014**		**-0.015**
		(-17.5)* **		**(1.4)**		**(-10.9)*** **		**(-20.9)*** **
R^2	0.435	0.440	0.350	0.351	0.348	0.354	0.400	0.411
Adj. R^2	0.434	0.439	0.330	0.330	0.343	0.349	0.396	0.407
Δ Adj. R^2		**0.005**		**0.005**		**0.006**		**0.011**
F-Value	239.3	242.1	17.3	17.2	65.5	66.6	119.0	123.5
Sample Size	39 222	39 222	3 405	3 405	14 966	14 966	20 851	20 851

[1] Standardized regression coefficients are reported, with t-values in paranthesis
[2] Sample reduced to estimated non-accelerated filer firms (market value less than $100 million)
[3] Sample reduced to estimated accelerated filer firms (market value greater than $100 million)
[4] Sample reduced to estimated large accelerated filer firms (market value greater than $1 billion)
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

4. Results

4.1 Descriptive Statistics

The basic features of the samples for each model are provided in **Table 2**. We observe that the mean logarithm of Tobin's q increases with filing class and the standard deviation decreases. This suggests that smaller firms on average experience lower q ratios than larger firms. Similarly, both the advertising and R&D ratios increase with filing class as well, implying that larger firms tend to invest more heavily in both advertising and R&D. We can confirm the validity of the R&D ratio as the average is similar to the one found by Bracker and Ramaya (2011). In the main model, we can observe that the mean three-year rolling average filing lag is 42.4 days. The filing lags for the separated filing classes are 50.0, 44.5, and 39.7 days respectively. Compared to the expected three-year filing deadlines, 56.25, 48.75, and 45[1], we observe that the average filing is submitted four to six days prior to the deadline in all filing classes.

4.2 Industry Control Variables

The regression results of Model 1-4 are presented in **Table 3**.

In total, we generate 95 industry specific dummy variables, of which 78 are significant in the main model: four at the 10 percent level, six at the 5 percent level, and 68 at the 1 percent level. Examining the incremental increase in variance explained of the industry specific fixed effects, we find that they contribute 13.8 percent of the variance explained in the main model (see **Appendix 3**). The large incremental increase confirms Schmalensee's (1985) and Wernerfelt and Montgomery's (1988) findings that firm sector is significant in explaining firm performance.

The coefficient of the industry concentration variable is negative and not significant in the main model. As we expect the relationship to be significant and positive in line with Lindenberg and Ross' (1981) research, the result is surprising. However, when testing the incremental variance explained of the industry specific fixed effects, we observe that the industry concentration variable is significant at the 1 percent level. Therefore, we believe that the industry specific fixed effects capture the effect of industry concentration, making the industry concentration variable superfluous in the main model.

4.3 Firm Control Variables

Firm specific control variable results are in most cases consistent with prior research.

The coefficient of the firm size control variable total sales is positive and significant in the main model. The positive coefficient suggests that firms with higher sales, all other things equal, on average experience higher q ratios. The results for Model 2-4 are inconsistent. In Model 1-4, the second firm size control variable, the logarithm of the number of employees, has

[1] Calculation of expected filing deadlines:
Non-accelerated filers $= (45 \times 3 + 90)/4 = 56.25$
Accelerated filers $= (40 \times 3 + 75)/4 = 48.75$
Large accelerated filers $= (40 \times 3 + 60)/4 = 45.00$

negative coefficients and is significant at the 1 percent level. These results are in line with Bharadwaj et al.'s (1999) findings and suggest that firms that have fewer employees, all other things equal, experience higher q ratios.

The coefficients of the advertising and the R&D ratio variables are significant at the 1 percent level in the main model. Additionally, the coefficients of the variables are positive in Model 1-4, implying that the relationship between the advertising ratio variable and Tobin's q as well as the R&D ratio variable and Tobin's q is positive. Analogous to Amit and Wernerfelt (1990) and Bharadwaj et al. (1999), we can confirm that advertising is positively correlated with the q ratio. Similarly, analogous to Bracker and Ramaya (2011), we can confirm that R&D is positively correlated with the q ratio.

We generate firm auditor dummy variables for the auditors included in the Compustat database. The procedure produces 16 dummy variables, of which 14 are significant at least at the 5 percent level in the main model. The *big four* audit firms have coefficients and t-values similar to one another and are all significant.

The filing class dummy variables are the most significant independent variables in the main model. The accelerated filers and large accelerated filers dummy variables have large, positive coefficients: 0.905 and 1.626 respectively. Therefore, we can conclude that on average, large accelerated filers have the highest q ratios, and accelerated filers have higher q ratios than non-accelerated filers but lower than large accelerated filers, in line with the findings from Table 2.

We generate time fixed effects dummy variables for the years 2007 to 2016. The procedure produces 9 dummy variables which all have negative coefficients and are significant at the 1 percent level in the main model. The negative coefficients indicate that the annual average q ratios in the sample are less than the average q ratio of the base year 2007. Furthermore, we can observe that the coefficients of the variables are increasing, indicating that the annual average q ratios have been growing after the drop in 2008. The pattern indicates that firm q ratios were greatly affected by the 2008 Financial Crisis.

4.4 Filing Lag

The hierarchical regression analysis shows that the inclusion of the filing lag variable increases the variance explained in Tobin's q for all samples. The incremental increase in the variance explained is 0.5 percent in the main model, illustrating that filing lag presents unique information in explaining the variance in Tobin's q. The coefficient of the filing lag variable is negative, as hypothesized and in accordance with Spence's (1973) signaling theory. The -0.013 coefficient can be interpreted as: Firms with one day shorter average filing lag have 1.3 percent higher Tobin's q values on average, all other things equal. Furthermore, the t-value of -17.5 proves the significance of the filing lag variable. Given adequate control variables, we can be reasonably certain that the effect we see in the filing lag variable is an isolation of the signaling effect. In the separate models, the incremental variance explained and the significance of the filing lag variable increases from non-accelerated filers to large accelerated filers, suggesting that the

Table 4. Fixed Effects Regression Results[1]

	All Filers (Model 5)		Non-Accelerated[2] (Model 6)		Accelerated[3] (Model 7)		Large Accelerated[4] (Model 8)	
Variables	A	B	A	B	A	B	A	B
Industry Conc.	1.010	1.052	1.179	0.679	2.151	2.144	0.649	0.702
	(3.4)***	(3.5)***	(0.4)	(0.2)	(4.0)***	(4.0)***	(1.7)	(1.9)
Sales	0.002	0.002	-1.664	-1.673	-0.130	-0.123	0.002	0.002
	(1.3)	(1.2)	(-3.1)**	(-3.1)**	(-2.6)**	(-2.4)*	(1.3)	(1.1)
Employees (Log)	-0.084	-0.088	0.170	0.181	-0.029	-0.032	-0.133	-0.137
	(-8.2)***	(-8.7)***	(2.6)*	(2.7)**	(-1.5)	(-1.6)	(-11.9)***	(-12.3)***
Advertising (Ratio)	0.892 (3.2)**	0.924 (3.3)**	2.333 (1.7)	2.330 (1.7)	0.837 (1.9)	0.866 (2.0)*	0.643 (2.7)**	0.657 (2.8)**
R&D (Ratio)	-0.118	-0.118	-0.637	-0.609	-0.211	-0.212	-0.095	-0.094
	(-2.5)*	(-2.6)*	(-1.4)	(-1.4)	(-3.3)**	(-3.3)**	(-2.2)*	(-2.2)*
Accelerated Filers (Dummy)	0.774 (39.5)***	0.771 (39.3)***						
Large Accelerated Filers (Dummy)	1.234 (56.6)***	1.228 (56.2)***						
Filing Lag		**-0.006**		**0.006**		**-0.003**		**-0.008**
		(-5.9)***		**(0.9)**		**(-1.6)**		**(-8.1)*****
R^2	0.785	0.785	0.659	0.659	0.744	0.744	0.832	0.832
Adj. R^2	0.777	0.777	0.620	0.620	0.727	0.727	0.824	0.825
Δ Adj. R^2		**0.000**		**0.000**		**0.000**		**0.001**
F-Value	99.7	99.8	17.0	16.9	46.3	46.3	109.9	110.3
Sample Size	39 222	39 222	3 405	3 405	14 966	14 966	20 851	20 851

[1] Standardized regression coefficients are reported, with t-values in paranthesis
[2] Sample reduced to estimated non-accelerated filer firms (market value less than $100 million)
[3] Sample reduced to estimated accelerated filer firms (market value greater than $100 million)
[4] Sample reduced to estimated large accelerated filer firms (market value greater than $1 billion)
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)

signaling effect is more prevalent in larger firms.

4.5 Firm Fixed Effects

Finally, to evaluate the robustness of the results, we add firm fixed effects to the regressions. The regression results of Model 5-8 are presented in **Table 4**.

The coefficient of the industry concentration variable is positive and significant at the 1 percent level in Model 5. The positive coefficient suggests that, all other things equal, increases in the concentration of a firm's operating industry increases the firm's q ratio. In contrast to the results of the main model, these results are expected and in line with Lindenberg and Ross' (1981) research. In contrast to the results of the main model, the coefficient of the total sales variable is not significant in Model 5. The absence of significance is likely an effect of the reduced statistical power of firm fixed effects. The coefficient of the second firm size control variable, the logarithm of the number of employees, is negative and significant at the 1 percent level in Model 5. Adding to the findings of the main model, we can conclude that on average, all other things equal, firms with fewer employees experience higher q ratios and firms reducing the number of employees experience increases in their q ratio.

In Model 5, the advertising ratio coefficient is positive and significant at the 5 percent level. Additionally, the coefficients of the variable are also positive in Model 6-8, implying that firms that increase their advertising ratio on average experience a higher q ratio, all other things equal. These findings support our earlier finding that, all other things equal, firms with higher advertising ratios on average experience higher q ratios. Moreover, the coefficient for the R&D ratio variable is negative and significant at the 10 percent level in Model 5. The coefficients are also negative in Model 6-8, implying that on average, all other things equal, firms experience lower q ratios when increasing their R&D ratio. This relationship is also found by Bracker and Ramaya (2011). Adding to the findings of the main model, we can conclude that on average, all other things equal, firms with higher R&D ratios experience higher q ratios while increasing the R&D ratio decreases a firm's q ratio.
The auditor dummy variables are significant at the 1 percent level in Model 5. We can observe that the coefficients of the *big four* audit firms have similar coefficients and t-values, indicating that switching from one *big four* auditor to another has little impact on firm performance.

The addition of firm fixed effects reduces the incremental variance explained by the filing lag variable in Model 5-8. The coefficient of the filing lag variable is negative and significant at the 1 percent level in Model 5. Furthermore, the -0.006 coefficient can be interpreted as a one day decrease in the filing lag variable on average increases Tobin's q of a firm with 0.6 percent, all other things equal. Adding to the findings of the main model, we can conclude: On average, all other things equal, firms with a one day shorter average filing lag experience 1.3 percent higher q ratios and decreasing the filing lag average with one day increases a firm's q ratio with 0.6 percent. The consistent negative and significant relationship between the filing lag variable and Tobin's q supports our hypothesis that filing lag is a signal of firm operational capabilities.

4.6 Conclusion of Results

To conclude, we find that: (a) firm sector is significant in explaining firm performance similar to Schmalensee (1985) and Wernerfelt and Montgomery (1988); (b) firm industry concentration is significant in explaining firm performance in accordance with Lindenberg and Ross (1981); (c) the logarithm of the number of employees is negatively correlated with firm performance, similar to Bharadwaj et al. (1999); (d) advertising is positively correlated with firm performance similar to Amit and Wernerfelt (1990) and Bharadwaj et al. (1999); (e) R&D is significant in explaining firm performance similar to Bracker and Ramaya (2011); and (f) filing lag is significant in explaining firm performance and the coefficient is negative in accordance with Spence's (1973) signaling theory.

5. Implications and Conclusions

We demonstrate the negative relationship between Tobin's q and filing lag. This relationship is robust to controlling for industry related factors (industry specific fixed effects and industry concentration), firm specific factors (sales, log of employees, advertising ratio, R&D ratio, firm auditor, and filing class), and time fixed effects, which have the potential to impact Tobin's q and may be correlated with filing lag. Additionally, the relationship is robust to controlling for firm fixed effects. We believe that these variables serve as adequate controls to reduce omitted variable bias, isolating the signaling effect. The results of the regressions supports the hypothesis of a signaling effect in the filing lag of 10-K and 10-Q reports that can be captured by the q ratio. Firms credibly convey their operational capabilities by filing their 10-K and 10-Q reports faster. The observed constant negative and significant relationship between filing lag and Tobin's q and our ability to confirm earlier findings in the regressions increases the robustness of the results. The occurrence of a signaling effect emphasizes that providing timely filings is of great importance to firms and managers. Furthermore, filing lag can serve as a determinant of the q ratio, contributing to the finance literature on Tobin's q.

The use of Tobin's q as a measure of firm performance leads to limitations in the research. Since the q ratio is a market based measurement, it relies on the efficient market hypothesis which is a heavily debated subject in the finance literature. Burton Malkiel (2003), summarizes the critique against the efficient market hypothesis which shows that the market incorporates: (a) short term momentum, (b) long-run return reversals, (c) seasonal and day-of-the-week patterns, and (d) bubbles and irrational pricing. Inefficiencies in the market would create noise in the q ratio as a measurement of firm performance and cast doubt on any results obtained.

Furthermore, we cannot empirically prove that the observed relationship between filing lag and Tobin's q is a signaling effect. The relationship between filing lag and Tobin's q is empirically proven, but the mechanism through which filing lag affects firm performance is only theoretical: Filing lag fulfills the requirements for being a signal of the operational capabilities of a firm and firm operational capabilities should contribute to firm performance. It is possible that filing lag is correlated with a variable, that is unaccounted for, that affects Tobin's q. Future research into the mechanisms behind the filing lag and Tobin's q relationship is needed to provide additional empirical support for the signaling effect. Additionally, future research should study if this signaling effect has implications for stock performance.

6. References

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Appendix 1

A comparison of the final dataset and the data removed is provided in **Table 5**. Additional to the variables used in Model 1, the variable market cap is examined to confirm that the dataset does not greatly vary from the data removed.

Table 5. Descriptive Statistics of Data Removed

	Dataset		Removed Data	
Variables	Mean	Standard Deviation	Mean	Standard Deviation
Tobin's q (Log)	1.501	(1.440)	1.332	(1.387)
Industry Conc.	0.048	(0.039)	0.039	(0.037)
Total Sales	1.196	(3.439)	1.527	(6.080)
Employees (Log)	1.275	(1.700)	0.890	(1.822)
Adv. (Ratio)	0.022	(0.038)	0.022	(0.035)
R&D (Ratio)	0.076	(0.180)	0.059	(0.145)
Market Cap	7.654	(26.325)	7.287	(25.568)
Filing Lag	**42.441**	**(6.278)**	**42.928**	**(5.791)**
Sample Size	39 288		41 717	

Appendix 2

The multicollinearity of the variables in Model 1 are evaluated in **Table 6**. None of the squared comparable generalized variance inflated factors exceed the 3.5 rule of thumb for multicollinearity.

Table 6. Multicollinearity[1]

Variables	GVIF	DF	CGVIF	$CGVIF^2$
Industry	32.489	94	1.019	1.038
Industry Conc.	1.653	1	1.286	1.654
Total Sales	1.787	1	1.337	1.788
Employees (Log)	3.251	1	1.803	3.251
Adv. (Ratio)	2.275	1	1.508	2.274
R&D (Ratio)	1.662	1	1.289	1.662
Filing Lag	1.721	1	1.312	1.721
Auditor	4.006	16	1.044	1.090
Filing Class	2.732	2	1.286	1.654
Year	1.135	9	1.007	1.014

[1]Where:
GVIF = Generalized variance inflation factor
DF = Degrees of freedom
CGVIF = GVIF^(1/(2*DF)), comparable generalized variance inflation factor
$CGVIF^2$ = CGVIF^2

Appendix 3

In order to measure the incremental variance explained by the industry specific fixed effects, we estimate **Model 9**:

$$\begin{aligned}\ln(q) = \; & \beta_0 + \beta_1 Conc. + \beta_2 Sales + \beta_3 \ln(Emp.) + \beta_4 Ad. + \beta_5 RD. + \\ & \beta_6 Audit + \beta_7 Class + \beta_8 Year + \beta_9 Flag + \varepsilon\end{aligned} \tag{A}$$

$$\begin{aligned}\ln(q) = \; & \beta_0 + \beta_1 Ind. + \beta_2 Conc. + \beta_3 Sales + \beta_4 \ln(Emp.) + \beta_5 Ad. + \\ & \beta_6 RD. + \beta_7 Audit + \beta_8 Class + \beta_9 Year + \beta_{10} Flag + \varepsilon\end{aligned} \tag{B}$$

Model 9. Where:
q = Tobin's q
Ind. = Industry specific dummy variables
Conc. = Industry concentration
Sales = Quarterly total sales
Emp. = Number of employees
Ad. = Advertising ratio
RD = R&D ratio
Audit = Audit firm dummy varaibles
Class = Filing class dummy variables
Year = Annual time dummy variables
Flag = 10-K and 10-Q filing lag
ε = Error term with zero mean

Model 9 is tested in **Table 7**.

Table 7. Industry OLS Regression Results[1]

Variables	All Filers (Model 9) A	B
Industry Conc.	-1.286 (-13.2)***	-0.222 (-1.9)
Sales	0.002 (2.2)*	0.014 (13.6)***
Employees (Log)	-0.136 (-37.2)***	-0.157 (-41.2)***
Advertising (Ratio)	2.662 (21.8)***	1.171 (8.0)***
R&D (Ratio)	0.402 (11.3)***	0.100 (4.4)***
Accelerated Filers (Dummy)	0.878 (42.4)***	0.905 (46.1)***
Large Accelerated Filers (Dummy)	1.620 (72.2)***	1.626 (75.0)***
Filing Lag	-0.010 (-13.4)***	**-0.013 (-17.5)*** **
R^2	0.302	0.440
Adj. R^2	0.301	0.439
Δ Adj. R^2		**0.138**
F-Value	512.9	242.1
Sample Size	39 222	39 222

[1] Standardized regression coefficients are reported, with t-values in paranthesis
* Significant at $p \leq 0.10$ (two-tailed test)
** Significant at $p \leq 0.05$ (two-tailed test)
*** Significant at $p \leq 0.01$ (two-tailed test)