# Essays in Security Analysis and Trading

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Submitted by

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St Gallen, January 2020

Alexandru Rif

# Summary

This dissertation lies at the intersection of fundamental and technical investment analysis. In their search for key market signals, which lie at the foundation of investment decisions, both fundamental and technical investors are faced with the challenging task of acquiring and interpreting financial data, with the goal of extracting decision relevant information. Advances in computation technology and data management systems have enabled the surfacing of intra-day algorithmic traders, relying on their fast reaction times and computational power to interpret market signals and identify key investment and divestment signals. On the other hand, the fundamental investor uses financial statements as his primary source of information in order to identify and assess a company's individual value drivers.

**Chapter I** of this dissertation is devoted to investigating stock price overreactions around idiosyncratic crashes on the Nasdaq100. The scope of the analysis is to uncover whether liquidity provision after stock price crashes is beneficial for investors with short reaction times.

**Chapter II** investigates market conditions across individual exchanges in the case of cross-listed securities around a macro-economic event which triggered a concomitant three sigma negative return for 71 Nasdaq100 members. Specifically, this chapter looks into developments in liquidity, trading costs and trading activity across primary, secondary and tertiary exchanges.

**Chapter III** aims at analyzing the effect of segment reporting on analysts' earnings forecast accuracy. Particularly, it investigates the link between EPS forecast errors and the arising profitability "gap" when comparing profitability aggregated from segment reporting and firm profitability as derived from consolidated financial statements.

# Zusammenfassung

Thematisch befindet sich diese Dissertation am Schnittpunkt fundamentaler und technischer Investitionsanalyse. Auf der Suche nach wichtigen Marktsignalen und entscheidungsrelevanten Informationen stehen sowohl fundamentale als auch technische Anleger vor der Herausforderung, Finanzdaten für ihre Anlageentscheidungen erfassen und interpretieren zu können. Fortschritte in der Computertechnologie und in Datenverwaltungssystemen führen zum Einen dazu, dass im täglichen Handel vermehrt Algorithmen zur Interpretation relevanter Marktsignale und zur Identifikation transaktionsauslösender Investitions- und Veräusserungssignale Anwendung finden. Die Algorithmen zielen dabei insbesondere auf schnelle Reaktionszeiten und Rechenleistung ab. Zum Anderen nutzt der fundamentale Investor den Abschluss als primäre Informationsquelle, um die individuellen Werttreiber eines Unternehmens zu identifizieren und zu bewerten.

**Kapitel I** dieser Dissertation befasst sich mit der Untersuchung übertriebener Aktienkursreaktionen im Zusammenhang mit idiosynkratischen Kursstürzen von Nasdaq100-Unternehmen. Im Rahmen der Analyse soll herausgefunden werden, ob die Bereitstellung von Liquidität nach einem Börsencrash für Anleger mit kurzen Reaktionszeiten einen Vorteil bietet.

**Kapitel II** untersucht anhand 71 Nasdaq100-Unternehmen die Marktbedingungen für auf einzelnen Börsen zweitkotierten Wertpapiere im Zusammenhang mit makroökonomischen Ereignissen, die eine Drei-Sigma-Negativrendite auslösten. Dieses Kapitel befasst sich insbesondere mit der Entwicklung der Liquidität, der Handelskosten und der Handelsaktivität an Primär-, Sekundär- und Tertiärbörsen.

**Kapitel III** zielt darauf ab, die Auswirkungen der Segmentberichterstattung auf die Genauigkeit der Gewinnprognosen der Analysten zu analysieren. Insbesondere wird der Zusammenhang zwischen Gewinnerwartungen von Analysten und den Rentabilitätsabweichungen untersucht, die entstehen, wenn die Segmentberichterstattung und nicht der konsolidierte Abschluss zu Prognosezwecken verwendet wird.

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# Chapter I
# Short-term Stock Price Reversals after Extreme Events

Alexandru Rif Sebastian Utz

**Abstract**

We studied the intraday effects of market fragmentation and return overreactions around stock price crashes of Nasdaq100 constituents based on nanosecond data. We analyzed whether market fragmentation and liquidity provision after stock price crashes is beneficial for investors with short reaction time. We found that market fragmentation does not affect the recovery after the crash which we document to be at 31% of the negative one-minute crash interval return in the subsequent trading minute. The relative magnitude of the reversal after crash intervals was particularly high for the 20% most liquid and the 20% smallest firms of our sample.

*JEL classification*: G12, G14, L11.

*Keywords*: Stock price reversal; High-frequency trading; Stock price crash; Market fragmentation.

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# 1. Introduction

The rise of electronic, fully-automated markets resulted in an unprecedented increase in market fragmentation, triggering increased levels of attention from regulators, investors and academic scholars alike. An ardent discussion emerged on whether increased market fragmentation is beneficial or detrimental to financial markets' liquidity. Aitken et al. (2017) found that market fragmentation is associated with improved market quality, while Upson and VanNess (2017) and Bessembinder (2003) argued that competition between exchanges was linked with lower transaction costs and increased liquidity. These studies primarily investigate the effects of market fragmentation in normal trading conditions, while the role of market fragmentation in times of extreme intraday events, remains an open empirical question.

In market microstructure literature, a vivid discussion emerged on the question of whether a new type of investors, so-called high frequency traders (HFTs) provide or detract liquidity on financial markets. HFTs are defined as 'professional traders acting in proprietary capacity' who use 'extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders' by the U.S. Securities and Exchange Commission (SEC). The rise of electronic markets, increased computing power, algorithmic trading and reduced latency have been the primary enabling factors for the emergence of HFTs. Concerning van Kervel and Menkveld (2019), Korajczyk and Murphy (2018), HFTs acted as market makers in a normal market environment (i.e., provided liquidity), but traded in line with the market perception (i.e., detracted liquidity) as soon as they detected a persistent trend. However, the general literature on the impact of HFTs on bid-ask spreads and price efficiency, as well as their contribution to extreme market movements such as the flash crash is mixed. While Hasbrouck and Saar (2013), Chaboud et al. (2014), Hasbrouck (2018) documented a negative correlation between HFT and crashes, Gao and Mizrach (2016), Boehmer et al. (2018), Kirilenko et al. (2017) showed an increased frequency of crashes related to

HFT activities.

This paper investigates short-term price movements in the context of stocks with various degrees of market fragmentation. At least two types of events exist that can trigger large price movements: an update in information and imbalances of trades. While the information contained in news updates results in a rapid adjustment of prices on efficient markets, imbalances of trades push prices away from fundamental values. In recent times, the emergence of extreme transitory price movements, such as the flash crash on May 3, 2010, have attracted significant attention from researchers and regulators alike. While the majority of studies have focused on such systematic events to understand the role played by various automated traders (high-frequency traders, algorithmic traders etc.) from a market liquidity perspective, we aim at investigating differences in market conditions and trading activity around an exogenous price shock.

We analyzed investment returns around stock price crashes. Figure 1 shows an example of such a stock price crash for LBrands on February 23, 2017. The daily return calculated based on open and close price was $-3.1\%$ on this day. However, the development of intraday prices exhibited high volatility, i.e., prices took to reach new market equilibrium. Specifically, by 11:05 AM, LBrands was trading $-5\%$ lower than its open price, exhibiting a steep declining pattern, followed by a period of recovery lasting up until 12:05, at which time LBrands was reporting $-2\%$ return for the day.

Hasbrouck and Saar (2013),Chordia et al. (2008) found that HFTs increase liquidity in such extreme situations, being associated with greater market efficiency (Carrion, 2013; Brogaard et al., 2014; Chaboud et al., 2014). Moreover, Shkilko and Sokolov (2020) associate reduced HFT activity with lower adverse selection and lower trading costs.

Thus, we state the hypothesis that during a price shock, market pricing is inefficient only for a very short period due to overreactions. This situation provides the opportunity to exploit the advantages of low-latency data transfer and increased computational power to trade against the wind, provide short-term liquidity, and gain returns from short-term stock price reversals.

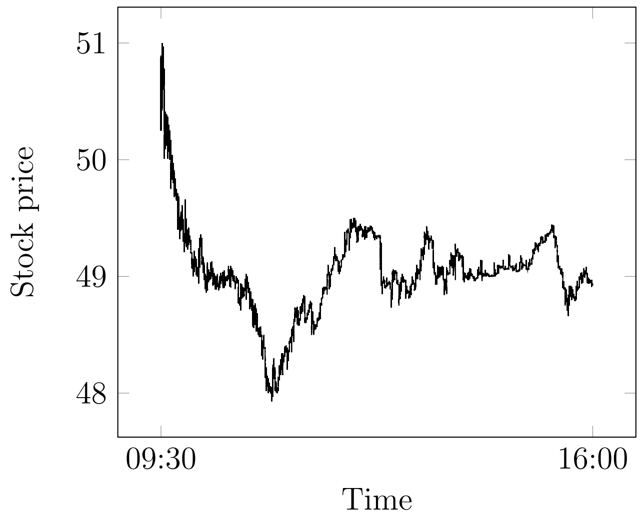


Fig. 1. Intraday price development of LBrands on February 23, 2017.

On the topic of return reversals, a large body of literature addressed the risk-bearing capacity of intermediaries (Kirilenko et al., 2017; Nagel, 2012; Hameed and Mian, 2015). Nagel (2012), So and Wang (2014) showed that providing liquidity during reversals is profitable. Furthermore, Handa and Schwarz (1993) show that placing a network of buy and sell limit order as part of a trading strategy is profitable. HFTs can react marginally faster to market signals, and thus conduct so-called latency arbitrage and stale quote sniping (Foucault et al., 2003; Menkveld and Zoican, 2017; Budish et al., 2015). Brogaard et al. (2017), Brogaard et al. (2018) studied HFTs during a short-sale ban and around extreme price movements. Empirical results (see Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993) highlighted that intraday mean-reversion in inventories, and relatively high trading volume are noticeable characteristics of intermediation, which are categorized as high-frequency traders or high-frequency market makers (Biais et al., 2015; Ait-

Sahalia and Saglam, 2017; Jovanovic and Menkveld, 2016). Concerning the finding of Brogaard et al. (2018), HFTs speed up the reversal process after extreme price movements.

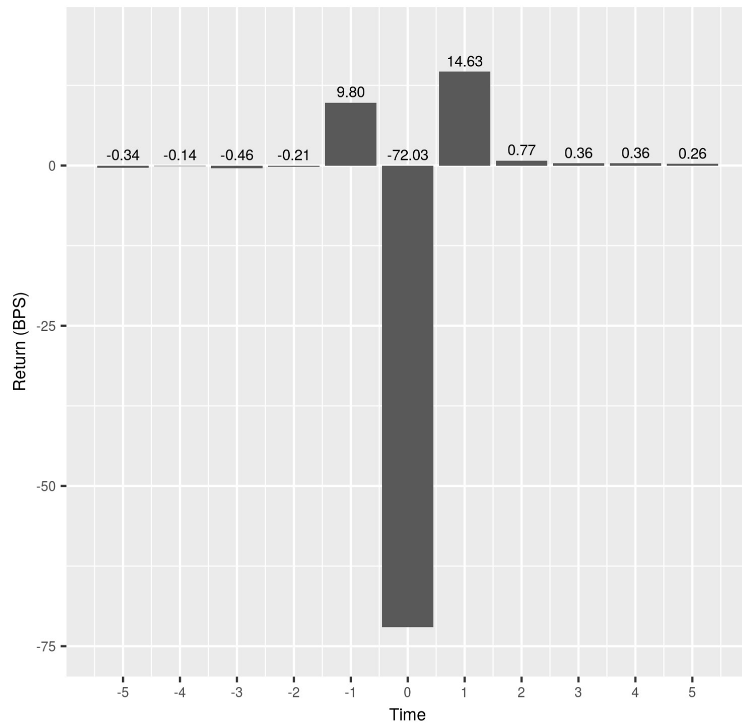


Fig. 2. This figure shows the average return profile across our set of 15,242 identified extreme return intervals. It shows the minute returns during the five individual minutes before and after extreme interval. All returns are expressed in basis points.

Our study investigates the effect of market fragmentation and intraday return patterns around extreme price movements. We analyze a sample of intraday quote and trade data of the Nasdaq100 constituents for the period from January 2014 to January 2019. We divide each trading day into 390 one-minute intervals and clustered intervals according to their returns in the crash and non-crash intervals. Crash intervals exhibit characteristics (such as return and trading activity) significantly different from non-crash intervals.

The one-minute return of a crash interval was 72 basis points lower than the return of a non-crash interval (see Figure 2). Multivariate analyses show the existence of an after-crash reversal, which is about 27% of the crash return, while the reversal has the highest proportion of the crash return for firms with high-liquid stocks and high firm size.

Figure 3 portrays an example of how the algorithmic crash identification approach would flag and label the minute intervals based on an extreme event occurring around $t$, whereby $t-1$, $t$ and $t+1$ represent the cutoff points delimiting fixed minuted intervals. The interval starting at $t-1$ and ending at $t$ would be flagged as a crash interval, while consecutively the interval beginning at $t$ and ending at $t+1$ constitutes the follow-up reversal interval. Consequently, it is important to note, that the algorithmic approach does not take the minimum of a minute interval in calculating the returns, or the crash return respectively, but rather relies on chronological delimiters which are ex-ante defined to be fixed. While this does indeed potentially cause understatements of crash and reversal returns, this approach ensures the robustness and systematic nature of the identification algorithm.

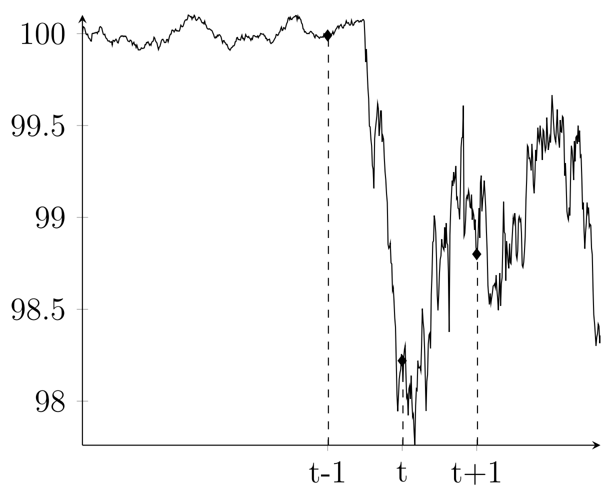


Fig. 3. Generic example of crash interval.

In an event study, whereby 45 Nasdaq100 constituents experienced a concomitant extreme negative price movements, we investigate differences in trade and volume patterns between stocks with different degrees of market fragmentation. On December 1st, 2017, between 11:14 AM and 11:15 AM the market experienced an external shock, reacting to a news release reporting that Michael Flynn pleaded guilty to lying to federal agents in the context of President Trump's Russian election interference investigation. By using a difference-in-differences approach we find no evidence on discrepancies or deviations in trade, volume and return patterns between stocks with an increased volume split across individual exchanges and stocks whose trading volume is concentrated on one single exchange. These results provide evidence that market fragmentation does negatively affect the aforementioned reversal process.

To the best of our knowledge, our study is the first one looking into the role played by market fragmentation around extreme price movements. On the topic of short term return reversals and HFT activity, one related paper is Brogaard et al. (2018), which investigated the role of HFTs around extreme stock price movements, in particular by analyzing quote data. In contrast, our study examines the return structure around extreme return intervals by relying on realized trade prices to capture real investment returns.

Using recent advances and increasing affordability in cloud computing services the analysis included in this paper covers all the constituents in the Nasdaq100 over the period from January 2014 to January 2019, in contrast to the (post-)financial crisis period of 2008 and 2009 covered in Brogaard et al. (2018). Additionally, we focused on downward price movements and characterized the stock price development in an eleven-minute time window around the crash minute. Moreover, we extend the results presented in Upson and VanNess (2017) and Bessembinder (2003), who document a positive effect of volume fragmentation on general market conditions.

The remainder of the paper proceeds as follows. In Section 2, we discuss the data employed in this paper. In Section 3, we present our empirical methodology and results. In Section 4, we conclude.

## 2. Data

We employed intraday trading data from the NYSE Daily Trade and Quote (DTAQ) database available over the WRDS Cloud platform. Specifically, we sourced data from the Daily TAQ files from where we retrieved millisecond-level data from January 1st, 2014, microsecond level data starting from July 27th, 2015, and nanosecond level data starting from October 24th, 2016. The data covers trade, quote, and national best bid and offer (NBBO) data for a basket of the 100 stocks comprising the Nasdaq100. Our observation period ranges from January 2014 to January 2019, yielding a sample of 1,564,388,227 analyzed trades in total.

We restricted our data to trades and quotes posted within the regular trading hours of the NYSE (9:30 a.m to 4:00 p.m.). Concerning the handling of withdrawn quotes and quotes with abnormal conditions, we followed the methodology outlined in Holden and Jacobsen (2014). Namely, we considered crossed quotes (quotes where the bid price is higher than the ask price) if they arose because the ask price was zero while the bid price was non-zero. We excluded quotes with abnormal quote and trade conditions, such as situations where trading has been halted. Further, we focused on trades of common stocks in our sample. In this respect, we dropped any observation for which the quote and trade conditions are listed as A, B, H, K, L, O, R, V, W, and Z*. We also excluded data points where the bid price is greater than the ask price, if listed by the same exchange, or for which either price or quantity was equal to zero. In line with Chordia et al. (2001), we also dropped any data points where the quoted spread was higher than 5 USD.

We corrected the original NBBO daily file considering data from all of the available exchanges following Holden and Jacobsen (2014). Subsequently, we

* Table 8 in the Appendix defines all abnormal trade and quote conditions.

matched trades with corresponding NBBO quotes at the microsecond level. Based on this matched data set, we classified trades as buyer- or seller-initiated trades in line with the classification method proposed by Lee and Ready (1991).

# 3. Methodology and Results

## *A. Crash Intervals and Summary Statistics*

To investigate the reversal returns after stock price crashes, we split each trading day within the matched trade and NBBO quote data into fixed equal one-minute time intervals. Hence, splitting a typical trading day resulted in 390 individual one-minute intervals. One minute intervals may appear very long compared to the time HFT algorithms require in order to re-evaluate a trading strategy. While Brogaard et al. (2018) considered 10-second-intervals, van Kervel and Menkveld (2019) 30-minutes update time stamps. In particular, Brogaard et al. (2018) showed that prices continued to move in the direction of the largest return for several seconds after the first indication for an extreme price movement. In this respect, we decided to use one-minute intervals. In unreported tests, we varied the time horizon from 30 seconds to five minutes. The results stayed qualitatively similar.

For each interval, we then calculated the actual realized interval return based on the recorded trades, the standard deviation of the realized returns based on the within-interval realized trades, the minimum and the maximum realized return within each interval. Additionally, we determined the average quoted spread, the total traded share volume, and the net volume of shares bought or sold within each one-minute interval.

Moreover, we relied on the literature on stock price crashes to identify extreme price changes across the one-minute intervals. Therefore, we assigned the strategy of Brogaard et al. (2018), Hutton et al. (2009) and defined a one-minute interval as a crash interval if the actual return is an event occurring once in a thousand observations, i.e., the 0.1%-quantile. Equation 1 shows the identification rule for crash interval variable $C_{i,t}^{m,k}$:

$$C_{i,t}^{m,k} = \begin{cases} 1 & r_{i,t} \leq \mu_{i,t}^{m,k} + \Phi^{-1}(0.001) \cdot \sigma_{i,t}^{m,k} \\ 0 & r_{i,t} > \mu_{i,t}^{m,k} + \Phi^{-1}(0.001) \cdot \sigma_{i,t}^{m,k} \end{cases}, \tag{1}$$

where $r_{i,t}$ is the actual return of the respective one-minute interval $t$ of firm $i$, $\mu_{i,t}^{m,k}$ is the expected return for firm $i$ in one-minute interval $t$, $\sigma_{i,t}^{m,k}$ is the standard deviation of the expected return for firm $i$ in one-minute interval $t$, and $\Phi^{-1}(0.001) = -3.09$ represents the critical value for the 0.1%-quantile of the standard normal distribution with mean zero and standard deviation one. We specified $\mu_{i,t}^{m,k}$ and $\sigma_{i,t}^{m,k}$ according to two different conceptual procedures ($m = \{1, 2\}$) to identify extreme downward price movements. $k$ refers to the number of historical observations that are used in either procedure.

The first procedure ($m = 1$) considered consecutive $k$ previous one-minute intervals to estimate the expected interval return and its standard deviation. We used a varying number of observations $k$ in Equation 1 corresponding to 5, 15, and 60 previous one-minute intervals, as well as 390 one-minute intervals for one day, 1950 one-minute intervals for one week, 40,950 one-minute intervals for one month, and 122,850 one-minute intervals for one quarter-time spans.

Our second procedure ($m = 2$) used matched time intervals, as opposed to consecutive time intervals. We defined a matched time interval as the interval corresponding to the identical time interval, albeit in a prior trading day. For instance, yesterday‘s first trading minute (9:30:00-9:31:00) served as a matched interval for today‘s first trading minute. The second procedure addressed the significantly different intraday return pattern of large returns in the early morning, which leveled off during the day. Therefore, we assessed whether an interval classifies as a stock price crash by determining the crash variable of Equation 1 based on 5, 21, 63, and 252 matched intervals, corresponding to a week, month, quarter, and one year time spans.

Finally, we defined a crash dummy variable $C_{i,t}$ for each one-minute interval $t$ of a specific firm $i$. The crash dummy equals one if all of the above-mentioned identification methods flag the interval as a crash interval and zero otherwise:

$$C_{i,t} = \begin{cases} 1 & C_{i,t}^{m,k} = 1 \; \forall m, k \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

In total, we identified 15,242 one-minute intervals, which we labeled as crash intervals, while 46,773,469 one-minute intervals show no extreme downward movements (see Table 1). Panel A of Table 1 provides pooled raw descriptive statistics of our data set, contrasting the characteristics of non-crash and crash intervals. The first set of columns reports values for the non-crash intervals. The mean bid-ask spread in a non-crash one-minute interval was 5.72 basis points (bp). This number almost tripled in crash intervals (14.67bp). In particular, the standard deviation of the bid-ask spreads among the one-minute intervals is substantially higher for crash intervals than for non-crash intervals (43.52bp vs 13.24bp). While the return of non-crash one-minute intervals was 0.02bp on average, crash intervals observed an average return of −72.03bp. The standard deviation of the one-minute returns observed for crash intervals was ten times larger than the one observed for non-crash intervals. In a 10th percentile one-minute crash interval, the return was −145.17bp compared to −8.18bp in a non-crash interval.

Moreover, we calculated the minimum and maximum returns between two subsequent trades in each one-minute interval. Non-crash intervals exhibited on average −4.9bp for the minimum and 4.93bp for the maximum. The range from the 10th percentile of the minimum return (−9.6bp) and the 90th percentile of the maximum return (9.63bp) was rather narrow. The respective quantities in crash intervals showed a substantially higher variation in trading returns. While the 10th percentile of the minimum return equaled a return lower than −1%, we also observed high positive returns of 50bp

(90th percentile of the maximum return).

We constructed a momentum indicator that counts the number of successive intervals during which negative (positive) realized returns were observed. I.e., if we obtained negative returns in Intervals $t-3$, $t-2$, and $t-1$, the value of the momentum variable for Interval $t$ is $-3$. Symmetrically, if the series of interval returns were positive, the momentum indicator takes the value of $+3$. Alternatively, if returns in intervals $t-3$ and $t-1$ were negative but positive in the Interval $t-2$, the momentum indicator for Interval $t$ is 0 as a change in sign has been recorded.

The average momentum of non-crash intervals is 0.28, the 10th percentile of the momentum was $-1$, and the 90th percentile of the momentum was 2. These values indicate a market structure with mostly alternating one-minute interval returns with only 10% observations with at least a series of two subsequent negative one-minute interval returns and another 10% observations with at least a series of three subsequent positive one-minute interval returns. Crash intervals, however, occurred on average after two prior one-minute intervals with negative returns. Only 10% of the crash intervals were preceded by a series of at least three one-minute intervals with a negative return.

A fundamental distinction between non-crash and crash intervals was the trading activity in the respective one-minute interval in terms of trading volume and number of trades. While the number of actual trades recorded within an interval increased more than threefold vs a non-crash interval, the average trading volume in the crash intervals was approximately 7.5 times higher. On average, 13,500 shares were traded in a non-crash one-minute interval, while 101,180 shares were traded in a crash one-minute interval. The increased volume was due to a substantially higher number of trades in the respective intervals (215 vs 717). The negative average of the LRQty variable (the LRQty is the number of buyer-initiated trades minus the number of seller-initiated trades) indicated that during crash intervals, a substantially

Table 1: This table reports on pooled raw and standardized descriptive statistics for crash and non-crash minute intervals. Our sample consists of all trades and quotes for the constituents of the Nasdaq100 throughout an observation period ranging from January 2014 to January 2019 aggregated into one-minute intervals. The unit of the reported spread and return quantities is basis points.

| | Non-Crash Intervals (N=46,773,469) | | | | | Crash Intervals (N=15,242) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | $10^{th}$%ile | Median | $90^{th}$%ile | Mean | SD | $10^{th}$%ile | Median | $90^{th}$%ile |
| *Panel A: Raw quantities* | | | | | | | | | | |
| BidAsk | 5.72 | 13.24 | 1.55 | 3.30 | 10.59 | 14.67 | 43.52 | 1.94 | 5.55 | 26.96 |
| Ret | 0.02 | 8.94 | −8.18 | 0.00 | 8.17 | −72.03 | 80.16 | −145.17 | −46.39 | −23.60 |
| MinRet | −4.90 | 9.28 | −9.60 | −3.23 | −1.27 | −44.90 | 86.14 | −106.77 | −17.68 | −4.65 |
| MaxRet | 4.93 | 9.37 | 1.28 | 3.24 | 9.63 | 22.65 | 67.69 | 2.04 | 9.04 | 52.80 |
| SD | 1.84 | 2.70 | 0.55 | 1.20 | 3.56 | 8.92 | 22.50 | 0.98 | 2.93 | 19.22 |
| Mom | 0.26 | 1.67 | −1.00 | 0.00 | 2.00 | −0.88 | 1.44 | −3.00 | 0.00 | 0.00 |
| Vol | 13.50 | 54.63 | 0.51 | 3.99 | 29.35 | 101.18 | 292.14 | 2.30 | 23.80 | 235.63 |
| NrTrd | 215.46 | 381.79 | 20.00 | 95.00 | 504.00 | 717.98 | 1,297.18 | 58.10 | 312.50 | 1,660.00 |
| LRQty | −0.61 | 39.94 | −3.95 | −19.00 | 3.68 | −34.16 | 168.01 | −71.08 | −6.22 | 0.90 |
| *Panel B: Standardized quantities* | | | | | | | | | | |
| BidAsk | −5.84E−4 | 0.99 | −0.64 | −0.14 | 0.70 | 1.82 | 8.38 | −0.40 | 0.22 | 3.71 |
| Ret | 2.66E−3 | 0.97 | −0.93 | −4.54E−4 | 0.93 | −8.16 | 9.39 | −15.98 | −5.16 | −3.04 |
| MinRet | 1.52E−3 | 0.98 | −0.46 | 0.14 | 0.41 | −4.66 | 10.24 | −11.66 | −1.39 | −0.03 |
| MaxRet | −6.56E−4 | 0.99 | −0.41 | −0.14 | 0.46 | 2.01 | 7.87 | −0.28 | 0.44 | 5.55 |
| SD | −9.96E−4 | 0.99 | −0.50 | −0.16 | 0.56 | 3.08 | 9.06 | −0.25 | 0.51 | 7.80 |
| Mom | 2.26E−4 | 1.00 | −0.81 | −0.13 | 1.11 | −0.70 | 0.88 | −1.93 | −0.24 | −0.07 |
| Vol | −8.13E−4 | 0.99 | −0.40 | −0.19 | 0.47 | 2.50 | 5.39 | −0.22 | 0.87 | 6.38 |
| NrTrd | −6.85E−4 | 1.00 | −0.76 | −0.27 | 1.03 | 2.10 | 3.40 | −0.45 | 1.21 | 5.41 |
| LRQty | 4.27E−4 | 1.00 | −0.26 | 4.27E−4 | 0.25 | −1.31 | 4.50 | −3.51 | −0.50 | 0.08 |

higher number of trades were seller-initiated trades compared to non-crash intervals.

Panel B of Table 1 provides the same statistics after a $z$-transformation of the interval statistics. We present these quantities to capture the effect of the difference in absolute values of single firms. For instance, trading volume significantly varies across firms. Even after controlling for firm-specific influences, the summary statistics display a similar relationship between non-crash and crash intervals. Since the average values of all variables in the non-crash sample were almost zero, the average z-scores of the crash sample indicated the significance level of the crash interval variables different from zero (alternative hypothesis). Except for the momentum and the LRQty variables, all other variables were significantly different from zero, and thus from the ones of the non-crash sample.

We continued focusing on the crash interval. We investigated the consecutive one-minute intervals five minutes before and after the crash interval to understand the development of the variables around such an extreme event. Therefore, we structured the bid-ask spread, the return standard deviation (between single trades), the average minimum return, the average maximum return, and the trade volume in event-time and aggregated each variable across the cross-section. Figure 4 exhibits the development of these variables. We observed a gradual increase in the quoted bid-ask spread, peaking in the crash interval followed by a moderate, gradual recovery in the follow-up minute intervals (Subfigure (a)). The recorded trading volume (Subfigure (b)) exhibited a spike pattern, with minimal increases in the five minutes running up to the crash, followed by a more than twofold increase in the actual crash interval. This pattern suggests that traders with a fast reaction could be behind such an increase in trading activity.

Turning to the metrics calculated based on the individual within-interval trades, we observed a similar pattern such as the one of the quoted spread for the standard deviation of realized returns (Subfigure (e)). The average

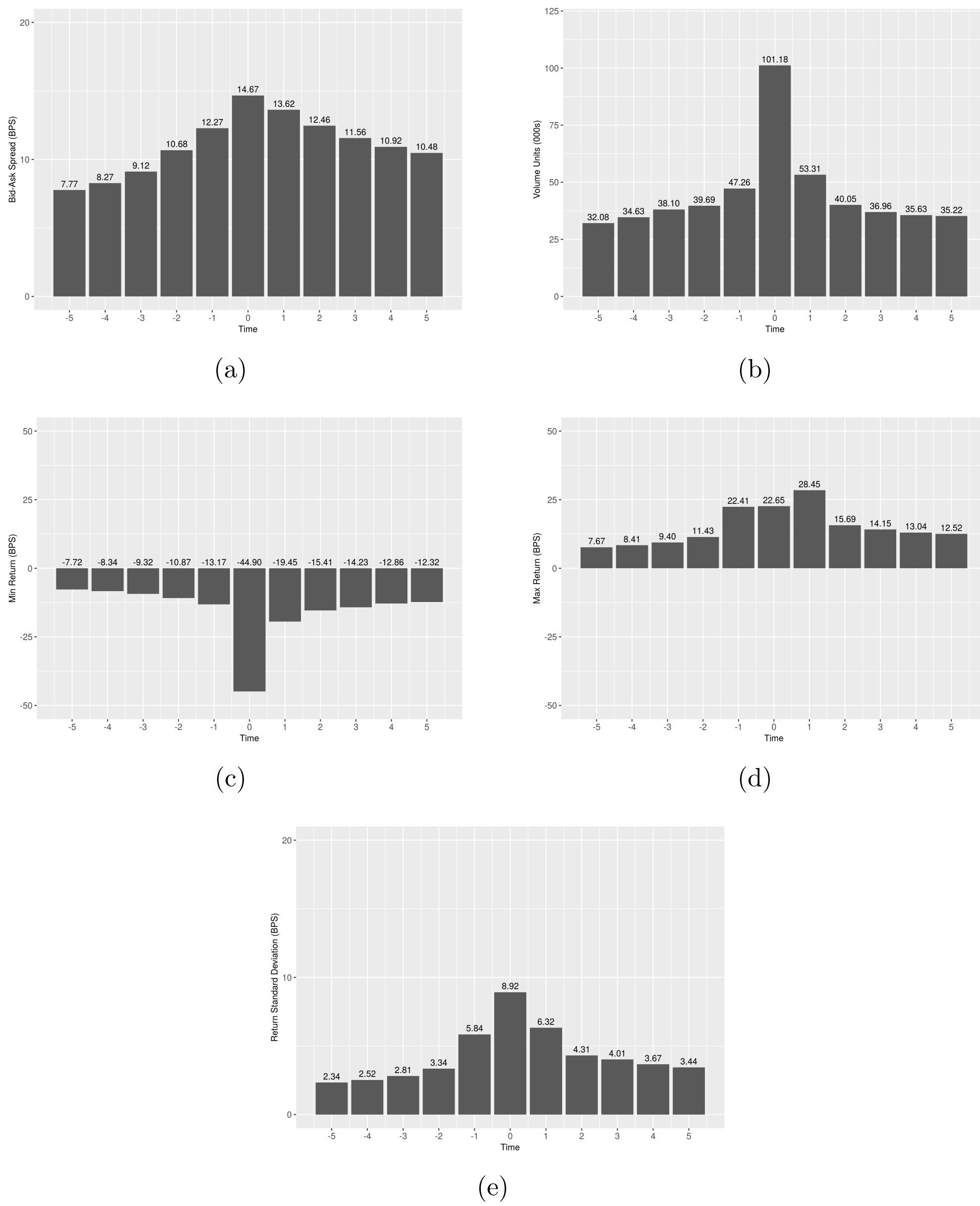


Fig. 4. This figure shows the average developments in (a) Bid-ask spread, (b) Standard deviation between trades, (c) Maximum return, (d) Minimum return and (e) Trade volume across our set of 15,242 identified extreme return intervals. Spread and return figures are expressed in basis points, while volume figures are expressed in thousands of units.

minimum return between two trades showed downward spikes, which were more than three times smaller during the crash minute than in the minutes before the event (Subfigure (c)). Conversely, the average maximum return increased considerably, effectively doubling in $t-1$ and staying at this level in $t$, it reached its peak only in $t+1$, providing preliminary evidence supporting the idea of a trading strategy aimed at capitalizing on a potential overreaction taking place in $t$ and a possible reversal in $t+1$.

## B. *Structure of One-Minute Interval Returns*

We began with an analysis of the one-minute interval returns. Therefore, we ran OLS regression models with firm and year fixed-effects, and clustered standard errors on firm-level (Equation 3):

$$Ret_{i,t} = \beta_0 + \Theta \cdot Controls_i + \alpha_i + u_t + \epsilon_{it} \tag{3}$$

where $\Theta$ is the vector of coefficients of the independent variables, $\alpha_i$ is the firm fixed effect, $u_t$ is the time fixed effect, and $\epsilon_{it}$ is the error term. We estimated nine different model specifications. The dependent variable was the log return (in basis points) of each of our 46 million one-minute interval observations. We organized the data according to the event time and used each one-minute interval as the interval under consideration once, i.e., its index is $t$. We explained the variation of these one-minute interval returns of index $t$ by a set of control variables including crash dummy variable, the log returns observed in the five one-minute intervals before and after the analyzed minute interval $t$, the momentum observed as of $t-1$, as well as the standard deviation of within interval returns, the bid-ask spread, and trading volume recorded across the previous individual five one-minute intervals. Moreover, we include interaction variables between the five lagged and lead returns and the crash dummy to investigate the specific return structure before and after crash intervals. The nine model specifications distinguished by the subset of control variables we included in the estimation. Model specification (9) contains the entire list of control variables.

In the first model specification, we explained the variation of the log returns of the one-minute intervals with the crash dummy variable (see Table 2). According to the estimation, the coefficient of the crash dummy in Model (1) showed that intervals flagged as crash intervals exhibited on average a return which is about 72bp lower when compared to the average returns of non-crash intervals. The coefficient was strongly significant different from zero. We augmented this model specification by lagged and lead returns and their interactions with the crash dummy in model specifications (2) – (7). Although the coefficient of the dummy variable slightly reduced in magnitude, it remained statistically significantly different from zero at a $p < 0.01$ level.

In line with extant literature, we observed and confirmed a negative correlation structure between the returns experienced in the pre- and post-crash intervals. This negative correlation structure remains constant throughout model specifications (2) to (9) with statistically significant and negative coefficients displayed for the four interval returns before the Interval $t$. The strongest effect was observed for Interval $t-1$, where the negative coefficient for $\mathrm{Ret}_{t-1}$ suggests the occurrence of a reversal in $t$, quantifying to roughly 10% of the return recorded in Interval $t-1$. We observed a similar correlation pattern when looking at returns recorded in the four one-minute intervals after $t$ in model specifications (5) to (9). The negative coefficient for $\mathrm{Ret}_{t+1}$ is symmetrical in magnitude and sign to the coefficient reported for $\mathrm{Ret}_{t-1}$ pointing to the existence of a return reversal, which is strongest in $t+1$. This pattern supported an alternating return development in which the current return shows a 10% reversal of the return of the last one-minute interval.

We further noticed that the occurrence of a crash in $t$ has a statistically significant and amplifying effect on the observed return structure. For crash intervals, the reversal pattern was intensified since the coefficient of the in-

Table 2: This table reports on the structure of the one-minute interval returns. Our sample consisted of all trades and quotes for the constituents of the Nasdaq100 throughout an observation period ranging from January 2014 to January 2019 aggregated into minute intervals. We set up nine model specifications and ran corresponding OLS regressions with time and firm fixed effects, and firm clustered standard errors. The dependent variable was the one-minute interval return expressed in basis points in the minute interval $t$. The variable Crash represented a dummy variable which takes the value of 1 when the minute interval was classified as a crash observation using our previously described methodology. The return, standard deviation of within interval returns, and bid-ask spread were expressed in basis points. The trading volume was expressed in thousands of units. $t$ statistics were reported in parentheses. *, **, *** denoted significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | | (7) | | (8) | | (9) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat |
| Crash | −71.9571*** | (−33.08) | | | −70.9252*** | (−34.64) | −66.2842*** | (−38.96) | | | −69.3895*** | (−34.75) | −56.9403*** | (−31.83) | −57.6979*** | (−32.71) | −58.2999*** | (−32.90) |
| $\text{Ret}_{t-1}$ | | | −0.1082*** | (−15.00) | −0.1055*** | (−15.02) | −0.1006*** | (−15.05) | −0.1084*** | (−14.93) | −0.1057*** | (−14.94) | −0.1007*** | (−14.95) | −0.1037*** | (−15.50) | −0.0964*** | (−15.70) |
| $\text{Ret}_{t-2}$ | | | −0.0119*** | (−6.02) | −0.0117*** | (−6.04) | −0.0111*** | (−5.91) | −0.0126*** | (−6.17) | −0.0124*** | (−6.19) | −0.0118*** | (−6.05) | −0.0148*** | (−7.19) | −0.0123*** | (−6.95) |
| $\text{Ret}_{t-3}$ | | | −0.0072*** | (−11.14) | −0.0073*** | (−11.41) | −0.0074*** | (−11.35) | −0.0079*** | (−11.67) | −0.0080*** | (−11.91) | −0.0080*** | (−11.79) | −0.0095*** | (−11.93) | −0.0085*** | (−12.10) |
| $\text{Ret}_{t-4}$ | | | −0.0074*** | (−13.34) | −0.0074*** | (−13.75) | −0.0074*** | (−13.84) | −0.0073*** | (−12.88) | −0.0074*** | (−13.29) | −0.0074*** | (−13.43) | −0.0081*** | (−14.01) | −0.0075*** | (−13.12) |
| $\text{Ret}_{t-5}$ | | | −0.0002 | (−0.27) | −0.0002 | (−0.42) | −0.0004 | (−0.61) | −0.0001 | (−0.24) | −0.0002 | (−0.38) | −0.0003 | (−0.56) | −0.0007 | (−1.14) | −0.0001 | (−0.18) |
| $\text{Ret}_{t-1}$ x Crash | | | | | | | −0.4681*** | (−8.40) | | | | | −0.5050*** | (−9.92) | −0.5280*** | (−10.64) | −0.4883*** | (−10.06) |
| $\text{Ret}_{t-2}$ x Crash | | | | | | | −0.0265 | (−0.36) | | | | | −0.0290 | (−0.39) | −0.1163 | (−1.46) | −0.0074 | (−0.09) |
| $\text{Ret}_{t-3}$ x Crash | | | | | | | 0.0758 | (1.09) | | | | | 0.0876 | (1.24) | 0.0076 | (0.11) | 0.1133* | (1.97) |
| $\text{Ret}_{t-4}$ x Crash | | | | | | | 0.0052 | (0.08) | | | | | 0.0554 | (1.14) | −0.0084 | (−0.17) | 0.0141 | (0.28) |
| $\text{Ret}_{t-5}$ x Crash | | | | | | | 0.2059*** | (3.18) | | | | | 0.1656*** | (2.89) | 0.1223** | (2.17) | 0.0998* | (1.84) |
| $\text{Ret}_{t+1}$ | | | | | | | | | −0.1084*** | (−14.93) | −0.1044*** | (−14.36) | −0.0989*** | (−13.16) | −0.0989*** | (−13.15) | −0.0918*** | (−13.38) |
| $\text{Ret}_{t+2}$ | | | | | | | | | −0.0126*** | (−6.18) | −0.0120*** | (−5.95) | −0.0100*** | (−5.06) | −0.0100*** | (−5.06) | −0.0081*** | (−4.48) |
| $\text{Ret}_{t+3}$ | | | | | | | | | −0.0079*** | (−11.69) | −0.0077*** | (−11.75) | −0.0067*** | (−10.26) | −0.0067*** | (−10.26) | −0.0060*** | (−10.42) |
| $\text{Ret}_{t+4}$ | | | | | | | | | −0.0073*** | (−12.88) | −0.0072*** | (−13.12) | −0.0061*** | (−14.08) | −0.0061*** | (−14.07) | −0.0060*** | (−13.60) |
| $\text{Ret}_{t+5}$ | | | | | | | | | −0.0001 | (−0.23) | −0.0000 | (−0.05) | 0.0005 | (0.89) | 0.0005 | (0.87) | 0.0007 | (1.20) |
| $\text{Ret}_{t+1}$ x Crash | | | | | | | | | | | | | −0.4794*** | (−13.38) | −0.4806*** | (−13.46) | −0.4882*** | (−13.06) |
| $\text{Ret}_{t+2}$ x Crash | | | | | | | | | | | | | −0.3593*** | (−4.37) | −0.3576*** | (−4.35) | −0.3442*** | (−4.08) |
| $\text{Ret}_{t+3}$ x Crash | | | | | | | | | | | | | −0.3188*** | (−4.05) | −0.3194*** | (−4.05) | −0.3438*** | (−4.30) |
| $\text{Ret}_{t+4}$ x Crash | | | | | | | | | | | | | −0.3339*** | (−3.80) | −0.3372*** | (−3.84) | −0.3054*** | (−3.54) |
| $\text{Ret}_{t+5}$ x Crash | | | | | | | | | | | | | −0.1896*** | (−3.56) | −0.1845*** | (−3.43) | −0.2094*** | (−3.44) |
| $\text{Mom}_{t-1}$ | | | | | | | | | | | | | | | 0.0462*** | (5.54) | 0.0444*** | (5.55) |
| $\text{Mom}_{t-1}$ x Crash | | | | | | | | | | | | | | | 3.4767*** | (8.80) | 2.8368*** | (7.42) |
| $\text{SD}_{t-1}$ | | | | | | | | | | | | | | | | | 0.0368*** | (5.68) |
| $\text{SD}_{t-2}$ | | | | | | | | | | | | | | | | | 0.0031 | (1.16) |
| $\text{SD}_{t-3}$ | | | | | | | | | | | | | | | | | 0.0008 | (0.32) |
| $\text{SD}_{t-4}$ | | | | | | | | | | | | | | | | | 0.0022 | (0.89) |
| $\text{SD}_{t-5}$ | | | | | | | | | | | | | | | | | 0.0015 | (0.68) |
| $\text{BidAsk}_{t-1}$ | | | | | | | | | | | | | | | | | −0.0004 | (−0.22) |
| $\text{BidAsk}_{t-2}$ | | | | | | | | | | | | | | | | | −0.0003 | (−0.25) |
| $\text{BidAsk}_{t-3}$ | | | | | | | | | | | | | | | | | −0.0023** | (−2.00) |
| $\text{BidAsk}_{t-4}$ | | | | | | | | | | | | | | | | | 0.0009 | (0.95) |
| $\text{BidAsk}_{t-5}$ | | | | | | | | | | | | | | | | | −0.0000 | (−0.03) |
| $\text{Vol}_{t-1}$ | | | | | | | | | | | | | | | | | 0.0004*** | (2.91) |
| $\text{Vol}_{t-2}$ | | | | | | | | | | | | | | | | | 0.0005*** | (5.94) |
| $\text{Vol}_{t-3}$ | | | | | | | | | | | | | | | | | 0.0003*** | (4.39) |
| $\text{Vol}_{t-4}$ | | | | | | | | | | | | | | | | | 0.0000 | (0.19) |
| $\text{Vol}_{t-5}$ | | | | | | | | | | | | | | | | | −0.0000 | (−0.37) |
| Cons | 0.0271*** | (11.26) | 0.0042* | (1.86) | 0.0273*** | (10.37) | 0.0270*** | (10.75) | 0.0047* | (1.86) | 0.0273*** | (9.48) | 0.0263*** | (9.45) | 0.0095** | (2.44) | −0.0766*** | (−5.82) |
| Year F.E. | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Firm F.E. | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| $N$ | 46,301,174 | | 46,300,676 | | 46,300,674 | | 46,300,674 | | 46,300,674 | | 46,300,175 | | 46,300,175 | | 46,300,175 | | 43,291,019 | |
| adj. $R^2$ | 0.020 | | 0.012 | | 0.031 | | 0.034 | | 0.023 | | 0.042 | | 0.048 | | 0.048 | | 0.044 | |

teraction term of $Ret_{t-1}$ and the crash dummy was about $-0.5$. Specifically, a one basis point increase in $Ret_{t-1}$ is associated, on average, with a crash return which was 0.5bp more negative than the return in a non-crash interval. I.e., if the one-minute interval $t$ was a crash interval, the log return in this interval was $0.5 \cdot Ret_{t-1}$ smaller than for a non-crash interval. Additionally, we observed the return reversal in the one-minute interval after the crash. This effect is symmetrical when looking at the observed coefficients reported for the interaction terms between the crash dummy and the lead five returns reported in model specifications (7), (8), and (9). The log return of a firm experiencing a stock price crash in $t$ showed a stock price reversal in the first minute after the crash which is $48\% \cdot Ret_t$ higher as the reversal after a non-crash interval.

Referring to Model (8), we observed a positive, statistically significant impact of the momentum indicator on the return recorded in Interval $t$. Given the average momentum of 0.2 as computed for non-crash intervals, momentum had a minor impact on the magnitude of the return recorded in $t$ when no crash was recorded. This effect was substantially amplified when looking at crash intervals. Specifically, any unit decrease in momentum was associated with a crash return which was, on average, roughly 3.5bp lower.

The standard deviation of within interval returns and the observed bid-ask spread had a weak and immaterial association with the return in Interval $t$. The reported coefficients in Model (9) were statistically insignificant apart from the coefficient for the bid-ask spread at $t-3$, which nevertheless could be regarded as immaterial given the average size of quoted bid-ask spread. Similarly, while the coefficients of the lagged trading volume were strongly statistically significant, they showed no material association with the return at $t$.

## C. Reversal Return After Crash Intervals

We continued our analysis on the subset of crash one-minute intervals to study the return reversals after a crash. Therefore, we explained the variation of the log returns of the one-minute crash interval one minute after the crash by the crash interval return and further control variables:

$$Ret_{i,t+1} = \beta_0 + \beta_1 \cdot Ret_t + \Gamma \cdot Controls_i + \alpha_i + u_t + \epsilon_{it} \tag{4}$$

where $\Gamma$ is the vector of coefficients of the independent variables, $\alpha_i$ is the firm fixed effect, $u_t$ is the time fixed effect, and $\epsilon_{it}$ is the error term.

The negative and statistically significant coefficients for $\text{Ret}_t$ across all four model specifications showed that indeed, a reversal was present (see Table 3). The magnitude of this reversal, one minute after the crash interval, was about 27% of the size of the log return during the crash interval (see model specification (1)). Furthermore, Model (2) showed that the return of the interval before the crash interval was also associated with the return in the reversal Interval $t+1$. Namely, a positive return of one basis point recorded in the Interval $t-1$ is associated with a 0.2 basis point reduction of the reversal in $t+1$. Model (3) documented a positive and statistically significant association between the return in the reversal interval and the momentum variable before the crash. Specifically, a positive momentum up to the crash interval is linked to a stronger reversal. Each unit increase in the momentum variable was linked to a 1.3 basis point increase in the return observed in the recovery interval.

## D. Firm Characteristics and the Magnitude of the Crash Reversal Return

Given the strong statistical evidence documenting the occurrence of a reversal in Interval $t+1$, we further analyzed the influence of firm characteristics on the size of the reversal. Accordingly, we split our sample of firms

Table 3: This table reports the estimates of the OLS regression model with time and firm fixed effects, and firm clustered standard errors explaining the variation in the one-minute interval return in $t+1$ as a function of a set of independent variables. We estimated four model specifications. The return, standard deviation of within interval returns, and bid-ask spread are expressed in basis points. The trading volume is expressed in thousands of units. $t$ statistics are reported in parentheses. *, **, *** denote significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| | *Dependent variable: post-crash one-minute interval returns ($Ret_{T+1}$)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | | (4) | |
| | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat | Coeff. | $t$-stat |
| $\text{Ret}_t$ | $-0.2682^{***}$ | $(-8.32)$ | $-0.3115^{***}$ | $(-9.03)$ | $-0.3144^{***}$ | $(-9.05)$ | $-0.3060^{***}$ | $(-9.19)$ |
| $\text{Ret}_{t-1}$ | | | $-0.2040^{***}$ | $(-8.42)$ | $-0.2168^{***}$ | $(-8.59)$ | $-0.2312^{***}$ | $(-6.47)$ |
| $\text{Ret}_{t-2}$ | | | 0.0128 | (0.31) | $-0.0247$ | $(-0.57)$ | 0.0018 | (0.04) |
| $\text{Ret}_{t-3}$ | | | $0.0796^{**}$ | (2.10) | 0.0464 | (1.19) | $0.0937^{**}$ | (2.59) |
| $\text{Ret}_{t-4}$ | | | $0.1159^{**}$ | (2.25) | $0.0898^{*}$ | (1.73) | 0.0738 | (1.47) |
| $\text{Ret}_{t-5}$ | | | 0.0554 | (1.33) | 0.0383 | (0.92) | 0.0403 | (0.77) |
| $\text{Mom}_{t-1}$ | | | | | $1.4708^{***}$ | (5.64) | $1.3008^{***}$ | (4.97) |
| $\text{SD}_{t-1}$ | | | | | | | 0.1028 | (0.75) |
| $\text{SD}_{t-2}$ | | | | | | | 0.1756 | (0.67) |
| $\text{SD}_{t-3}$ | | | | | | | 0.5654 | (1.62) |
| $\text{SD}_{t-4}$ | | | | | | | $-0.0928$ | $(-0.20)$ |
| $\text{SD}_{t-5}$ | | | | | | | $1.6303^{**}$ | (2.11) |
| $\text{BidAsk}_{t-1}$ | | | | | | | 0.0395 | (0.89) |
| $\text{BidAsk}_{t-2}$ | | | | | | | $-0.0995$ | $(-0.89)$ |
| $\text{BidAsk}_{t-3}$ | | | | | | | $-0.0453^{*}$ | $(-1.73)$ |
| $\text{BidAsk}_{t-4}$ | | | | | | | 0.0173 | (0.19) |
| $\text{BidAsk}_{t-5}$ | | | | | | | $-0.3130$ | $(-1.31)$ |
| $\text{Vol}_{t-1}$ | | | | | | | 0.0050 | (0.80) |
| $\text{Vol}_{t-2}$ | | | | | | | $-0.0212^{***}$ | $(-3.54)$ |
| $\text{Vol}_{t-3}$ | | | | | | | $-0.0063^{*}$ | $(-1.80)$ |
| $\text{Vol}_{t-4}$ | | | | | | | $-0.0069$ | $(-1.30)$ |
| $\text{Vol}_{t-5}$ | | | | | | | $-0.0231^{***}$ | $(-4.21)$ |
| Cons | $-6.0925^{***}$ | $(-2.72)$ | $-7.3186^{***}$ | $(-3.21)$ | $-8.0047^{***}$ | $(-3.42)$ | $-9.6215^{***}$ | $(-4.14)$ |
| Year F.E. | Yes | | Yes | | Yes | | Yes | |
| Firm F.E. | Yes | | Yes | | Yes | | Yes | |
| $N$ | 15,104 | | 15,102 | | 15,102 | | 14,135 | |
| adj. $R^2$ | 0.141 | | 0.171 | | 0.174 | | 0.196 | |

into quintiles, from smallest to largest, with respect to the observed bid-ask spread, firm size, book to market ratio, and momentum. For each of these sub-samples, we repeated the estimation of the model specification (9) of Equation 3 and model specification (4) of Equation 4.

The results strengthened our previous findings, observing statistically significant reversal coefficients across all sub-samples and all in line with our previous narrative (see Table 4).† We observed that the firms with the largest average bid-ask spread (Quintile 5 in *Panel Bid-Ask*), experienced the steepest crash, which was −76.93bp versus −44.2bp reported for the most liquid firms in Quintile 1. Concurrently, the reversal after the crash was strongest in Quintile 1, where we observed a rebound quantified to 33.05% of the return in the crash interval, as opposed to a recovery of only 19.73% of the crash drop observed for the least liquid companies.

Conversely, we observed a similar pattern when splitting our sample according to firm size measured by market capitalization. The largest firms exhibited the smallest crash returns of −44.59bp, but the strongest reversal of 53.97% in terms of the proportion of the magnitude of the crash return. Moreover, under this specification, we also reported the best model fit with an adjusted $R^2$ of 0.371. Concerning the remaining two panels (book to market ratio and momentum indicator), the results across the quintile groups are not particularly distinctive.

†For the brevity of the reported results, Table 4 contained only the coefficients of the crash dummy and the reversal coefficient for each panel-quintile combination, respectively. We quantified the magnitude of the average unexplained crash return at $t$ and reported the coefficient of the crash dummy variable of Equation 3 in the first column of each panel-quintile combination. The second column in each panel-quintile combination contained the coefficient to quantify the reversal. Therefore, we reran the regression defined under model specification (4) in Equation 4. Additionally, we reported on model characteristics, i.e., the number of observations and the adjusted $R^2$ of the respective model.

Table 4: This table contains regression estimates of our two baseline regressions for different subsamples concerning the bid-ask spread, firm size, book to market ratio and momentum quintiles. The dependent variable in the first column corresponding to each quintile is the return recorded for the interval at $t$ expressed in basis points, while the dependent variable in the second column of each quintile is the return recorded for interval $t+1$ expressed in basis points. The model specifications are similar to those listed under model specification (9) in Table 2 and under model specification (4) in Table 3, respectively. For brevity, we only report the values of the coefficients for the crash dummy and that of the observed return relevant for quantifying the magnitude of the reversal. All returns are expressed in basis points. $t$ statistics are reported in parentheses. *, **, *** denote significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| | (Q1) | | (Q2) | | (Q3) | | (Q4) | | (Q5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $Ret_t$ | $Ret_{t+1}$ | $Ret_t$ | $Ret_{t+1}$ | $Ret_t$ | $Ret_{t+1}$ | $Ret_t$ | $Ret_{t+1}$ | $Ret_t$ | $Ret_{t+1}$ |
| *Panel Bid-Ask* | | | | | | | | | | |
| Crash | −44.2005*** | | −56.2028*** | | −55.6882*** | | −61.5015*** | | −76.9334*** | |
| | (−16.40) | | (−18.47) | | (−24.14) | | (−16.81) | | (−17.77) | |
| $Ret_t$ | | −0.3305*** | | −0.3621*** | | −0.3740*** | | −0.3044*** | | −0.1973*** |
| | | (−3.92) | | (−4.96) | | (−3.85) | | (−5.59) | | (−3.81) |
| N | 9,341,941 | 3,133 | 9,039,894 | 2,798 | 8,800,280 | 2,697 | 8,483,505 | 2,858 | 7,625,399 | 2,649 |
| adj. $R^2$ | 0.049 | 0.196 | 0.033 | 0.219 | 0.038 | 0.368 | 0.040 | 0.224 | 0.066 | 0.097 |
| *Panel Size* | | | | | | | | | | |
| Crash | −64.9713*** | | −65.3170*** | | −61.9671*** | | −60.2931*** | | −41.5934*** | |
| | (−17.99) | | (−20.43) | | (−15.99) | | (−16.97) | | (−17.85) | |
| $Ret_t$ | | −0.1971*** | | −0.2401*** | | −0.3466*** | | −0.2764*** | | −0.5397*** |
| | | (−3.08) | | (−5.38) | | (−5.36) | | (−3.98) | | (−6.40) |
| N | 8,010,362 | 2,403 | 8,698,252 | 2,670 | 9,023,101 | 3,006 | 8,456,767 | 2,971 | 9,102,537 | 3,085 |
| adj. $R^2$ | 0.053 | 0.148 | 0.034 | 0.150 | 0.052 | 0.308 | 0.040 | 0.156 | 0.051 | 0.371 |
| *Panel Book/Mkt* | | | | | | | | | | |
| Crash | −62.3480*** | | −52.6448*** | | −56.5125*** | | −57.8163*** | | −60.5944*** | |
| | (−14.13) | | (−14.68) | | (−15.72) | | (−15.31) | | (−15.55) | |
| $Ret_t$ | | −0.2989*** | | −0.3129*** | | −0.2438*** | | −0.3493*** | | −0.3184*** |
| | | (−3.68) | | (−3.81) | | (−4.34) | | (−4.80) | | (−4.83) |
| N | 9,038,196 | 3,025 | 8,247,436 | 2,499 | 8,930,798 | 2,984 | 8,878,798 | 2,756 | 8,195,791 | 2,871 |
| adj. $R^2$ | 0.046 | 0.186 | 0.054 | 0.282 | 0.038 | 0.138 | 0.040 | 0.173 | 0.046 | 0.279 |
| *Panel Momentum* | | | | | | | | | | |
| Crash | −66.8491*** | | −57.7690*** | | −54.5149*** | | −56.2890*** | | −55.0246*** | |
| | (−15.75) | | (−12.84) | | (−16.17) | | (−15.73) | | (−17.09) | |
| $Ret_t$ | | −0.3479*** | | −0.3038*** | | −0.2798*** | | −0.3351*** | | −0.2460*** |
| | | (−4.45) | | (−5.05) | | (−3.43) | | (−5.41) | | (−3.49) |
| N | 8,823,748 | 2,899 | 8,596,338 | 2,810 | 8,354,803 | 2,558 | 8,866,479 | 2,850 | 8,649,651 | 3,018 |
| adj. $R^2$ | 0.049 | 0.209 | 0.043 | 0.178 | 0.045 | 0.326 | 0.035 | 0.209 | 0.054 | 0.147 |

## *E. Market fragmentation and post-event trading*

The increasing degree of market fragmentation observed throughout the last two decades has attracted attention from scholars and regulators alike. A large number of studies aimed at understanding the effects of market fragmentation have shed light on the effects that market fragmentation has on general market conditions. In fact, Aitken et al. (2017) found that market fragmentation is associated with improved market quality, while Upson and VanNess (2017) and Bessembinder (2003) argued that competition between exchanges was linked with lower transaction costs and increased liquidity. However, the role of market fragmentation in a period of extreme returns remains an open empirical question. This question is particularly important for our setting, since distinct market conditions on different exchanges might impact our results regarding actual achieved reversal returns.

To understand the impact of listing concentration on post-event return reversals, we applied a quasi-natural experiment. We identified December 1st, 2017, as an event day, on which 45 Nasdaq100 constituents (see Table 9) experienced an extreme negative price movement between 11:14 AM and 11:15 AM. The market reacted to a news release reporting that Michael Flynn pleaded guilty to lying to federal agents in the context of President Trump's Russian election interference investigation. In summary, our results show no differences in trade and volume patterns between stocks with an increased volume split across individual exchanges and stocks which are concentrated on one single exchange. Thus, market fragmentation does not affect our earlier results.

In the experiment, we considered the five one-minute intervals before the event, the event minute, and the five one-minute intervals after the event. We split the 45 securities according to their degree of cross-listing across individual exchanges by analyzing the daily trading volume recorded on each of the 17 participating exchanges in the TAQ Daily Files on the date of our selected event, December 1st, 2017. For each security, we ranked the individual exchanges based on their share of reported trading volume. We identified the top three exchanges, by trading volume, for each individual security. Taken together, these three exchanges accounted for over 70% of trading volume, as well as number of trades, recorded for each security covered in our experiment. We then quantified the degree of cross-exchange volume split by computing a Herfindahl-Hirschman Index based on the share of trading volume reported for each security across its top three exchanges by trading volume. By construction, this index ranges from zero to one, whereby securities who score higher on this metric have a higher volume share concentration on the primary exchange. Finally, we split our experiment sample into quintiles according to the values of our calculate Herfindahl-Hirschman Index. Cross-listed securities were those securities falling in the quintile with the highest level of trading volume split across multiple exchanges, while concentrated securities were those securities allocated to the quintile with the highest degree of trading volume concentration on the primary exchange.

On a descriptive level, trading activity sustained similar across all three exchanges for both cross-listed and concentrated securities, in particular when considering the crash minute $t$ and the reversal reported at $t+1$ (see Table 5). Moreover, the recorded trading volume exhibited a similar increasing pattern across all exchanges into the crash minute, which was then followed by a gradual reduction in the post-event minutes. The bid-ask spread results showed a similar pattern, which peaked in the first post-event minute before gradually decreasing in the following minute intervals.

To investigate any differences in market conditions and trading activity between cross-listed and concentrated securities around the crash event, we implemented a difference-in-differences approach similar to Callaway et al. (2018). We denoted as treated, those securities allocated to the quintile containing the highest degree of cross-listing and as non-treated, those securities allocated to the quintile with the highest degree of trading volume concentration on a single exchange. Since we were focusing on the period following

Table 5: This table reports on the developments in minute returns, trading volume, as well as bid-ask spread around the event recorded on December 1, 2017 whereby 45 Nasdaq100 members experienced a crash following the release of negative political news. Cross-listed securities, are those securities falling in the quintile with the highest level of trading volume split across multiple exchanges, while concentrated securities are those securities allocated to the quintile with highest degree of trading volume concentration on the primary exchange. Figures for returns and bid-ask spread are in basis points, trading volume is presented in USD million

| | Cross-listed Securities | | | Concentrated Securities | | |
|---|---|---|---|---|---|---|
| | 1. Exchange | 2. Exchange | 3. Exchange | 1. Exchange | 2. Exchange | 3. Exchange |
| *Panel A: Returns* | | | | | | |
| t−5 | −22.58 | −24.07 | −22.29 | −20.58 | −17.56 | −17.16 |
| t−4 | 4.05 | 3.80 | 5.97 | 7.17 | 3.11 | 0.64 |
| t−3 | −10.73 | −6.71 | −7.62 | −12.01 | −10.64 | −9.59 |
| t−2 | 6.05 | 4.49 | 2.01 | 9.38 | 7.44 | 4.58 |
| t−1 | −13.02 | −16.89 | −15.19 | −16.32 | −13.20 | −10.65 |
| t | −64.38 | −53.05 | −57.93 | −53.66 | −42.28 | −51.83 |
| t+1 | 42.30 | 36.67 | 40.13 | 41.94 | 26.56 | 36.50 |
| t+2 | 3.95 | 1.49 | 1.46 | 3.41 | 2.48 | 4.56 |
| t+3 | 1.08 | −1.35 | −0.64 | −6.66 | −1.78 | −7.26 |
| t+4 | −2.08 | −0.92 | −1.78 | −0.58 | 0.72 | −0.44 |
| t+5 | 2.05 | 3.74 | 3.74 | −1.28 | −2.09 | 2.76 |
| *Panel B: Volume* | | | | | | |
| t−5 | 0.54 | 0.29 | 0.36 | 0.53 | 0.10 | 0.12 |
| t−4 | 0.48 | 0.30 | 0.19 | 0.41 | 0.07 | 0.07 |
| t−3 | 0.35 | 0.22 | 0.12 | 0.31 | 0.06 | 0.05 |
| t−2 | 0.38 | 0.18 | 0.13 | 0.16 | 0.03 | 0.03 |
| t−1 | 0.34 | 0.21 | 0.15 | 0.29 | 0.06 | 0.06 |
| t | 0.70 | 0.41 | 0.41 | 0.81 | 0.11 | 0.13 |
| t+1 | 0.60 | 0.30 | 0.20 | 0.43 | 0.07 | 0.08 |
| t+2 | 0.39 | 0.15 | 0.13 | 0.29 | 0.05 | 0.05 |
| t+3 | 0.39 | 0.16 | 0.12 | 0.24 | 0.03 | 0.04 |
| t+4 | 0.23 | 0.09 | 0.07 | 0.27 | 0.04 | 0.03 |
| t+5 | 0.28 | 0.11 | 0.08 | 0.22 | 0.05 | 0.03 |
| *Panel C: Bid−Ask Spread* | | | | | | |
| t−5 | 6.79 | 8.76 | 13.64 | 8.48 | 80.89 | 24.50 |
| t−4 | 7.53 | 9.97 | 19.25 | 9.50 | 99.04 | 22.60 |
| t−3 | 7.44 | 9.33 | 13.45 | 8.81 | 74.15 | 21.88 |
| t−2 | 7.48 | 9.26 | 13.16 | 9.04 | 66.15 | 23.77 |
| t−1 | 8.05 | 10.93 | 17.79 | 10.02 | 65.25 | 21.27 |
| t | 9.83 | 16.37 | 27.59 | 11.38 | 93.82 | 29.06 |
| t+1 | 13.59 | 25.27 | 52.89 | 13.82 | 120.17 | 33.03 |
| t+2 | 11.78 | 16.90 | 47.83 | 13.16 | 95.52 | 30.51 |
| t+3 | 10.04 | 17.74 | 65.59 | 13.11 | 106.82 | 26.35 |
| t+4 | 10.96 | 18.44 | 62.50 | 11.22 | 105.82 | 23.97 |
| t+5 | 9.21 | 19.16 | 52.72 | 10.57 | 94.94 | 22.42 |

the crash minute interval, we defined the after-period as the minute interval immediately following up after the crash interval. In this respect, we constructed two dummy variables.

Table 6: This table contains the regression estimates of our difference-in-differences approach aimed at investigating differences in trading patterns and general market conditions in cross-listed versus concentrated securities for the minute period after the crash event. All returns are expressed in basis points. Figures referring to trading volume are expressed in units, while figures for the bid-ask spread are expressed in basis points. $t$-statistics are reported in parentheses. *, **, *** denote significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| | 1. Exchange | | 2. Exchange | | 3. Exchange | |
|---|---|---|---|---|---|---|
| | Coeff | $t$-stat | Coeff | $t$-stat | Coeff | $t$-stat |
| *Panel Dependent Variable: Return* | | | | | | |
| after | 1.6365*** | (12.78) | 4.6064*** | (6.17) | 4.4378*** | (8.15) |
| DiD | −0.1635 | (−0.35) | −1.9987* | (−1.74) | −1.7041 | (−1.59) |
| Cons | −0.3759*** | (12.27) | −0.7652*** | (−10.59) | −0.802*** | (−10.65) |
| Firm FE | Yes | | Yes | | Yes | |
| N | 5,152 | | 2,211 | | 2,294 | |
| adj. $R^2$ | 0.0221 | | 0.0392 | | 0.0438 | |
| *Panel Dependent Variable: Volume* | | | | | | |
| after | −16.4158* | (−1.68) | −12.6638 | (−1.11) | −1.8695 | (−0.14) |
| DiD | 113.7954 | (1.31) | 367.8724 | (1.04) | 54.3568 | (0.87) |
| Cons | 228.3605*** | (38.22) | 224.9603*** | (8.21) | 174.8205*** | (39.22) |
| Firm FE | Yes | | Yes | | Yes | |
| N | 5,152 | | 2,211 | | 2,294 | |
| adj. $R^2$ | 0.0012 | | 0.0061 | | 0.0010 | |
| *Panel Dependent Variable: Bid-Ask Spread* | | | | | | |
| after | 3.2893*** | (4.81) | 31.9308 | (1.46) | 8.3940*** | (3.89) |
| DiD | 1.3855 | (1.05) | −20.3471 | (−0.91) | 11.1449 | (1.40) |
| Cons | 9.7203*** | (157.54) | 50.9635*** | (50.28) | 28.3391*** | (80.34) |
| Firm FE | Yes | | Yes | | Yes | |
| N | 11,880,000 | | 11,880,000 | | 11,880,000 | |
| adj. $R^2$ | 0.0858 | | 0.0152 | | 0.0077 | |

The first, took the value of one if the security has been treated (cross-listed security) and zero if the security was non-treated (concentrated security), while the second dummy variable took the value of one if the observation belonged to the minute immediately following after to the crash minute and zero otherwise. Using this experimental setting, we investigated potential differences in observed returns, trading volume, and bid-ask spread patterns between cross-listed and concentrated securities, for each of the three main exchanges.

We observed that throughout all our model specifications the difference-in-differences interaction term had statistically insignificant coefficients at the $p < .05$ level (see Table 6). The panels depicted our dependent variables (i.e., observed returns, trading volume, and bid-ask spread) in our regression equation. Weak evidence existed for different observed returns on the secondary exchange between cross-listed and concentrated stocks after the treatment (at the $p < .1$ significance level). The fact that, in general, the interaction terms were insignificantly different from zero supports the view that the development of market conditions and trading activity around the crash interval is similar for cross-listed and concentrated securities. As an additional robustness check, we reran our regressions after splitting our sample into terciles and found that the difference-in-differences interaction term had statistically insignificant coefficients at the $p < .05$ throughout all model specifications. This finding supports and complements the findings of O'Hara and Ye (2011), who found that market fragmentation does not harm market quality.

# 4. Conclusion

In this paper, we investigated the effects of market fragmentation and the structure of intraday returns around extreme downward price movements. In an event study, whereby following an exogenous external shock 45 Nasdaq100 constituents experienced an extreme concomitant negative price movement, we investigated potential differences in market conditions and trading patterns between cross-listed securities and stocks whose trading volume is concentrated on a single exchange. Using a difference-in-differences approach, our results point towards similarities in trading activity and market conditions of stocks with various degrees of market fragmentation. This finding supports the idea that market fragmentation does not harm market quality.

Furthermore, we analyzed more than 46 million one-minute intervals of the Nasdaq100 constituents in the period ranging from January 2014 to January 2019. We identified 15,242 extreme minute return intervals and furthermore found clear evidence supporting an after crash return reversal, which is about 28% of the crash return.

These findings provided indications of market inefficiency around idiosyncratic stock price crashes. High-frequency traders may exploit such market overreactions by providing short-term liquidity in the minute after the stock price crash occurs.

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# Appendix

Table 7: Complete list of variables and their corresponding description

| Variable Name | Variable Description |
|---|---|
| BidAsk | The average observed bid-ask spread within a minute interval measured in basis points. |
| Crash | Dummy variable which identifies minute intervals with an extreme negative return. The variable takes the value 1 if the condition listed under Equation (1) is fulfilled |
| MaxRet | The maximum return, in basis points, observed between individual trades taking place within the minute intervals. |
| MinRet | The minimum return, in basis points, observed between individual trades taking place within the minute intervals. |
| Mom | The momentum observed up until the start of the current minute interval. It is calculated as the count of successive intervals during which negative (positive) realized returns are observed. For example, if negative returns are observed in intervals t−3, t−2 and t−1, the value of the momentum variable for interval t will be −3. Symmetrically, if the series of interval returns is positive, the momentum indicator will take the value of +3. Alternatively, if we observe negative returns in intervals t−3 and t−1 but a positive return in interval t−2, the momentum indicator for interval $t$ will be 0 as a sign change has been recorded. |
| LRQty | The net number, expressed in thousands of units, of buyer/seller initiated trades. The value is calculated as the number of buyer initiated trades minus the number of seller initiated trades. Trades are categorized using the algorithm presented in Lee and Ready (1991). |
| NrTrd | The number of trades recorded during a defined minute interval. |
| Ret | The return, in basis points, observed in a minute interval, calculated as the natural logarithm of the last trade price divided by the first trade price within a minute interval. |
| SD | The standard deviation, in basis points, of the returns observed between individual trades taking place within the minute intervals. |
| Vol | The number of units, in thousands, of common stock traded during a minute interval. |

Table 8: Description of quote conditions which have been excluded in line with Holden and Jacobsen (2014), as well as the equity symbol suffixes for which observations from the daily trades dataset have not been included in our final sample

| Quote Condition | Description |
|---|---|
| A | This condition indicates that the current offer is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Offer side and can be traded through pursuant to anticipated Regulation NMS requirements |
| B | This condition indicates that the current bid is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Bid side and can be traded through pursuant to anticipated Regulation NMS requirements. |
| H | This condition indicates that the quote is a 'Slow' quote on both the Bid and Offer sides. While in this mode, auto-execution is not eligible on the Bid and Offer sides, and either or both sides can be traded through pursuant to anticipated Regulation NMS requirements. |
| O | This condition can be disseminated to indicate that this quote was the opening quote for a security for that Participant. |
| R | This condition is used for the majority of quotes to indicate a normal trading environment. It is also used by the FINRA Market Makers in place of Quote Condition 'O' to indicate the first quote of the day for a particular security. The condition may also be used when a Market Maker re-opens a security during the day. |
| W | This quote condition is used to indicate that the quote is a Slow Quote on both the Bid and Offer sides due to a Set Slow List that includes High Price securities. While in this mode, auto-execution is not eligible, the quote is then considered Slow on the Bid and Offer sides and either or both sides can be traded through, as per Regulation NMS. |
| Equity Suffix | Description |
| K | Non-Voting Shares |
| L | Miscellaneous situations such as certificates of participation, preferred participation, and stubs |
| V | Denotes a transaction in a security authorized for issuance, but not yet issued. All "when issued" transactions are on an "if" basis, to be settled if and when the actual security is issued. |
| Z | Miscellaneous situations such as certificates of preferred when issued |

Table 9: This table lists the individual Nasdaq100 members for which the event recorded on December 1, 2017 between 11:14 AM and 11:15AM, represented a concomitant crash event. The table shows their respective average trading volume per minute across each of the three individual exchanges, the share of total trading volume broken down on exchange level, as well as their allocated quintile according to cross-exchange volume split. The figures for the average per minute trading volume are expressed in USD million.

| | Average Minute Trading Volume (Mln USD) | | | Average Share of Trading Volume (Percent) | | | Volume Split |
|---|---|---|---|---|---|---|---|
| | 1. Exchange | 2. Exchange | 3. Exchange | 1. Exchange | 2. Exchange | 3. Exchange | Quintile |
| AAL | 0.42 | 0.11 | 0.10 | 0.66 | 0.16 | 0.18 | 4 |
| ALGN | 0.50 | 0.11 | 0.10 | 0.70 | 0.19 | 0.11 | 4 |
| AMGN | 0.58 | 0.14 | 0.16 | 0.63 | 0.18 | 0.19 | 4 |
| AMZN | 6.26 | 2.02 | 2.92 | 0.53 | 0.20 | 0.27 | 2 |
| ATVI | 0.35 | 0.13 | 0.11 | 0.59 | 0.22 | 0.19 | 2 |
| AVGO | 0.98 | 0.40 | 0.34 | 0.58 | 0.22 | 0.20 | 2 |
| BIIB | 0.45 | 0.08 | 0.07 | 0.73 | 0.15 | 0.12 | 5 |
| CA | 0.06 | 0.01 | 0.02 | 0.56 | 0.24 | 0.20 | 3 |
| CDNS | 0.07 | 0.03 | 0.02 | 0.58 | 0.27 | 0.15 | 2 |
| CELG | 0.45 | 0.18 | 0.16 | 0.60 | 0.22 | 0.18 | 2 |
| COST | 1.05 | 0.33 | 0.21 | 0.65 | 0.22 | 0.13 | 4 |
| CSX | 0.66 | 0.23 | 0.29 | 0.54 | 0.21 | 0.25 | 1 |
| CTAS | 0.25 | 0.08 | 0.07 | 0.67 | 0.17 | 0.16 | 3 |
| CTSH | 0.33 | 0.12 | 0.09 | 0.58 | 0.26 | 0.16 | 3 |
| CTXS | 0.24 | 0.12 | 0.05 | 0.62 | 0.25 | 0.13 | 3 |
| EA | 0.46 | 0.09 | 0.08 | 0.72 | 0.15 | 0.13 | 5 |
| FAST | 0.10 | 0.03 | 0.03 | 0.57 | 0.22 | 0.22 | 3 |
| FB | 3.43 | 1.44 | 1.18 | 0.58 | 0.21 | 0.21 | 2 |
| FISV | 0.32 | 0.32 | 0.07 | 0.69 | 0.12 | 0.19 | 2 |
| GILD | 0.76 | 0.51 | 0.28 | 0.53 | 0.30 | 0.17 | 1 |
| GOOG | 8.08 | 1.57 | 1.91 | 0.69 | 0.16 | 0.15 | 4 |
| HOLX | 0.12 | 0.06 | 0.05 | 0.59 | 0.23 | 0.18 | 1 |
| IDXX | 0.09 | 0.03 | 0.05 | 0.53 | 0.15 | 0.32 | 2 |
| ILMN | 0.28 | 0.11 | 0.05 | 0.64 | 0.19 | 0.16 | 3 |
| INTC | 1.72 | 0.58 | 0.60 | 0.58 | 0.21 | 0.21 | 2 |
| INTU | 0.23 | 0.09 | 0.04 | 0.63 | 0.26 | 0.11 | 4 |
| KHC | 0.14 | 0.07 | 0.05 | 0.56 | 0.22 | 0.22 | 1 |
| MAR | 0.38 | 0.19 | 0.11 | 0.54 | 0.30 | 0.16 | 1 |
| MDLZ | 0.28 | 0.02 | 0.07 | 0.75 | 0.06 | 0.19 | 5 |
| MNST | 0.20 | 0.02 | 0.04 | 0.74 | 0.09 | 0.17 | 5 |
| MXIM | 0.14 | 0.01 | 0.02 | 0.81 | 0.07 | 0.12 | 5 |
| NVDA | 3.56 | 1.05 | 0.68 | 0.69 | 0.18 | 0.13 | 4 |
| PAYX | 0.20 | 0.03 | 0.03 | 0.72 | 0.17 | 0.11 | 5 |
| PCAR | 0.18 | 0.06 | 0.05 | 0.64 | 0.21 | 0.15 | 3 |
| PEP | 0.43 | 0.18 | 0.16 | 0.59 | 0.25 | 0.16 | 1 |
| QCOM | 0.83 | 0.47 | 0.39 | 0.52 | 0.26 | 0.22 | 1 |
| SIRI | 0.10 | 0.11 | 0.05 | 0.32 | 0.41 | 0.27 | 1 |
| SNPS | 0.16 | 0.05 | 0.04 | 0.63 | 0.17 | 0.20 | 4 |
| SWKS | 0.39 | 0.14 | 0.22 | 0.55 | 0.19 | 0.26 | 1 |
| SYMC | 0.24 | 0.07 | 0.08 | 0.67 | 0.11 | 0.22 | 3 |
| TXN | 0.80 | 0.17 | 0.13 | 0.71 | 0.17 | 0.12 | 5 |
| VRSK | 0.12 | 0.03 | 0.03 | 0.68 | 0.15 | 0.17 | 4 |
| WBA | 0.49 | 0.05 | 0.10 | 0.76 | 0.09 | 0.15 | 5 |
| XLNX | 0.23 | 0.04 | 0.04 | 0.74 | 0.15 | 0.11 | 5 |
| XRAY | 0.17 | 0.06 | 0.05 | 0.63 | 0.16 | 0.21 | 3 |

# Chapter II
# Market Conditions of Cross-listed Securities around a Macro Event

Alexandru Rif

**Abstract**

This paper investigates the developments in liquidity, trading costs and trading activity within individual cross-listed securities around a macro-economic event which triggered a concomitant three sigma negative return for 71 Nasdaq100 constituents. The results strengthen the position of a security's primary exchange as liquidity forerunner. The share of "trade-through" volume, i.e. trades executed below the national best bid or above the national best ask is higher for stocks with higher volume concentration on a single exchange, suggesting that market fragmentation is associated with increased market efficiency. Moreover, the reported share of "trade-through" volume, calculated using a one-millisecond time window, scrutinizes the current methodology set forth under Rule 611 of the SEC's National Market System Regulation.

*JEL classification*: G10, G12, G14.

*Keywords*: Market Fragmentation, Order Protection Rule, Trade-through Rule.

# List of Figures



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# 1. Introduction

On December 19, 2018 at 14:00, the Federal Open Market Committee (FOMC) of the US Federal Reserve (Fed) released a statement announcing that an interest rate increase will be set in place and furthermore acknowledged the need for increased monitoring of global economic and financial developments in the context of US-China trade frictions. The Federal Reserve's announcement triggered a market-wide, downward price pressure which was observed across all major US equity indexes, whereby the S&P500, Dow Jones Industrial Average dropped 1.5% while the Nasdaq100 reported a 2.2% drop at close. The selling pressure immediately started following up on the news release, which took place at 14:00, and by 14:01 the Nasdaq100 was down about 73 basis points. Developments in general market conditions of cross-listed securities have received substantial attention from academic scholars, who find that cross-listed securities with a higher degree of trading volume split across individual exchanges exhibit increased liquidity and lower transaction costs (Bessembinder, 2003; Upson and VanNess, 2017; Aitken et al., 2017). By analyzing a sample of 71 members of the Nasdaq100 Index, for which the Fed's announcement triggered a negative three sigma event, this paper documents and compares developments in liquidity, trading costs and trading activity across individual exchanges. The results emphasize the robustness in liquidity conditions on the primary exchange and link an increased cross-exchange volume split with lower average "trade-through" volume, i.e. trading volume executed below the national best bid or above national best ask. Calculating "trade-through" volume using a one millisecond time window, as opposed to the one second interval set forth under Rule 611 of the SEC's National Market System Regulation, reveals that more than 30% of trading volume is traded outside the national best bid and ask (offer) (NBBO) vs 0.16% reported in SEC (2015) for February 2014 under the one-second rule. Nevertheless, the results obtained when comparing the individual, exchange-specific distributions of "trade-through" costs support the idea that the US market performs as a unitary, integral market, whereby the individual exchanges serve as access points for market participants.

Patterns in trading activity and developments in market quality have received substantial attention from scholars throughout the evolution of financial markets (Hasbrouck and Schwartz, 1988; Admati and Pfleiderer, 1988; Chordia et al., 2011; Nagel, 2012). Similar to Scholtus et al. (2014) and Erenburg and Lasser (2009), who use macro-economic news to study the effects of algorithmic trading on trading volume, bid-ask spread, volatility and order-book depth, this paper investigates general market conditions and incurred cost inefficiencies in cross-listed securities, observed during and around the Fed's announcement time. The regulatory environment surrounding trade execution in the US is governed by the Securities Exchange Act of 1934, which stipulates clearly the fiduciary duty of broker-dealers to ensure best execution for their clients. In Europe, contemporary efforts in this direction are led by the series of Markets in Financial Instruments Directive (MIFID) regulations, whereby the recent MIFID II directly and more thoroughly addresses this topic, setting stricter rules for monitoring the best execution policy. Specifically, investment firms are required to publish the top five trading venues where client orders are executed, along with an analysis aimed at providing transparency and enable monitoring of actual execution quality. Nevertheless, practices conflicting with set fiduciary duties have been long documented and studied by scholars. To name an example, phenomena like "Cream-skimming", the process of dealers routing retail trading activity to competing venues, have been long documented and studied by scholars (Easley et al., 1996; Battalio, 1997; Bolton et al., 2016). However, such practices remain beyond the scope of this work.

The return recorded in the minute following up to the Fed's announcement constituted a three sigma negative event for 71 of the Nasdaq100 titles, which compose the sample for the analysis included in this paper. High frequency data is sourced from the New York Stock Exchange Trade and Quote (TAQ) daily files. The sample period covers an eleven minute time window, which is divided into two symmetric pre- and post-event periods of five minutes, as well as the one minute event period.

Particularly, this paper compares the spreads and incurred trading costs across the top three public exchanges by daily trading volume for individual stocks, members in the Nasdaq100 Index, which exhibited an extreme downward price movement in the first trading minute (14:00-14:01) following up to the FOMC's public announcement. In line with the findings in Brogaard et al. (2018), sharp increases in trading activity, in particular dollar trading volume and number of trades is reported. Similar to Chordia et al. (2002), a deterioration in liquidity conditions, as measured by the quoted bid-ask spread, is documented across all three covered individual exchanges. Despite an increase of 218% in quoted bid-ask spread versus the pre-event period, the primary exchange outperforms its peers when considering the absolute time it was quoting prices in line with the national best bid or national best ask. Specifically, quoting 69.86% in line with the national best bid and 68.85% of the time with the national best ask, respectively, the primary exchange offered the best buying and selling conditions throughout the event minute. Calculating the percent of total volume executed on an individual exchange, while set exchange was quoting prices below the national best bid or above the national best ask at a 1 millisecond time window, reveals that about 30% of trading volume across all exchanges would be classified as "trade-through" volume vs. 0.16% reported by SEC (2015) for February 2014. Rule 611 of SEC Regulation NMS expressly prohibits such practices, yet, in contrast, classifies a trade as a "trade-through" using a more permissive one-second time window. Kolmogorov-Smirnov tests are performed pairwise in order to compare the individual distributions of incurred trade cost inefficiencies on the individual exchanges. The results support the concept of the US markets comprising a single virtual trading space with individual exchanges acting as access points and complement the findings of O'Hara and Ye (2011), who report that market fragmentation does not hinder general market quality. Moreover, in line with extant crash literature the results document and confirm sharp increases in trading volume, quoted spread and number of executed trades when compared to the five minute pre-event and post-event period (Brogaard et al., 2018).

Given its scope, this paper resides within, and contributes to, two major literature streams covering market fragmentation and crash trading. Considering the current market architecture, which is comprised of multiple single exchanges on which cross-listed stocks are actively traded by market participants, market fragmentation bears fundamental implications on the general market ecosystem and market conditions. Consequently, market fragmentation and, more narrowly, its implications on general market conditions, is a topic that received significant attention by research scholars. Upson and VanNess (2017) investigate the effect of cross-exchange quote competition on national best bid and ask (offer) (NBBO) depth, trade execution, as well as market fragmentation. They report that quote competition erodes NBBO depth on individual exchanges, yet find that increased volume fragmentation has a beneficial effect on both trade execution and general NBBO depth. Aitken et al. (2017) link increasing degrees of fragmentation with improved market quality. Similarly, Bessembinder (2003) show that competition between exchanges is associated with lower transaction costs and increased liquidity.

The paper is structured as follows: Section 2 covers the theoretical framework, Section 3 discusses the sample selection and data, Section 4 reports on the analysis and main results, while Section 5 covers the conclusion.

# 2. Theoretical Framework

## *2.1. The Fed's Announcement*

Chen et al. (1986) where amongst the first scholars to empirically show that stock returns react to macro-economic news announcements. Christiansen and Ranaldo (2007) report a significant impact of macro announcements on correlations between stocks and bonds.

Modern economic theory and a deep field of literature have documented the close relationship between the Federal Reserve's interest rate target and stock market reactions and impact on valuations (Campbell, 1987; Fama, 1981; Elyasiani and Mansur, 1998; Bjørnland and Leitemo, 2009). Rising interest rates are used by market participants as signals of the economic cycle (Chen, 2009), govern portfolio allocations (Boubaker et al., 2018) and trigger higher discounts in company valuations (Flannery and James, 1984). Chen (1991) documents the association between short term interest rates and economic growth. Chuliá et al. (2010) find that a 10bp interest rate increase surprise is associated with a −46bp stock market return. Kontonikas et al. (2013) report that stocks exhibit positive returns when the Fed cuts interest rates, associating a 100bp interest rate cut with a 400bp positive reaction in the S&P500 Index.

At the time of the announcement, the Fed acknowledged the deteriorating financial outlook caused by the escalating trade frictions between the United States and China, and also confirmed in the published FOMC Meeting notes the rising concerns among market participants of a potential economic slowdown.

This event constituted a fundamental economic shock, triggering an immediate negative reaction throughout the US stock markets. Of all the 100 Nasdaq constituents, the event represented a three sigma event for 71 titles. The method used for identifying and cataloging the trading minute following up to the Fed's announcement is in line with the methodology set forth in Rif and Utz (2019). Specifically, two methodologies of identifying extreme returns were used. The first, uses rolling average minute returns and minute return standard deviation, while the second relies on matched average minute returns and minute return standard deviations for identifying extreme negative returns.

The identification procedure is formalized in Equation 1

$$r_t \leq \mu_t - 3.19 \times \sigma_t \tag{1}$$

Various time intervals were used for both identification methodologies, corresponding to one week, one month, one quarter and one year time spans. The selected event minute, was identified concomitantly by both methodologies and across all previously mentioned time spans, as an extreme event for all of the 71 Nasdaq100 titles.

Given its economic implication and magnitude, the Fed's announcement offers a valuable setting for studying the impact of a market wide negative shock on general market conditions.

## *2.2. Market fragmentation*

Increasing market fragmentation is a well documented phenomenon, whereby newly established, highly-automated, electronic exchanges such as BATS are gaining increasing market share (Menkveld, 2013). Figure 1 illustrates the trend towards fragmentation as revealed by a study published by the SEC in 2015. Acting on its tripartite mission to protect investors, maintain fair and orderly efficient markets, as well as to facilitate capital formation, the SEC launched a series of proposals aimed at tackling the potential adverse effects of market fragmentation (Stoll, 2001).

Regulation National Market System (NMS), passed by the SEC and in force since 2005, directly addresses potential issues arising in a multi-exchange set-up. It comprises of four main pillars, targeting fair trade ex-

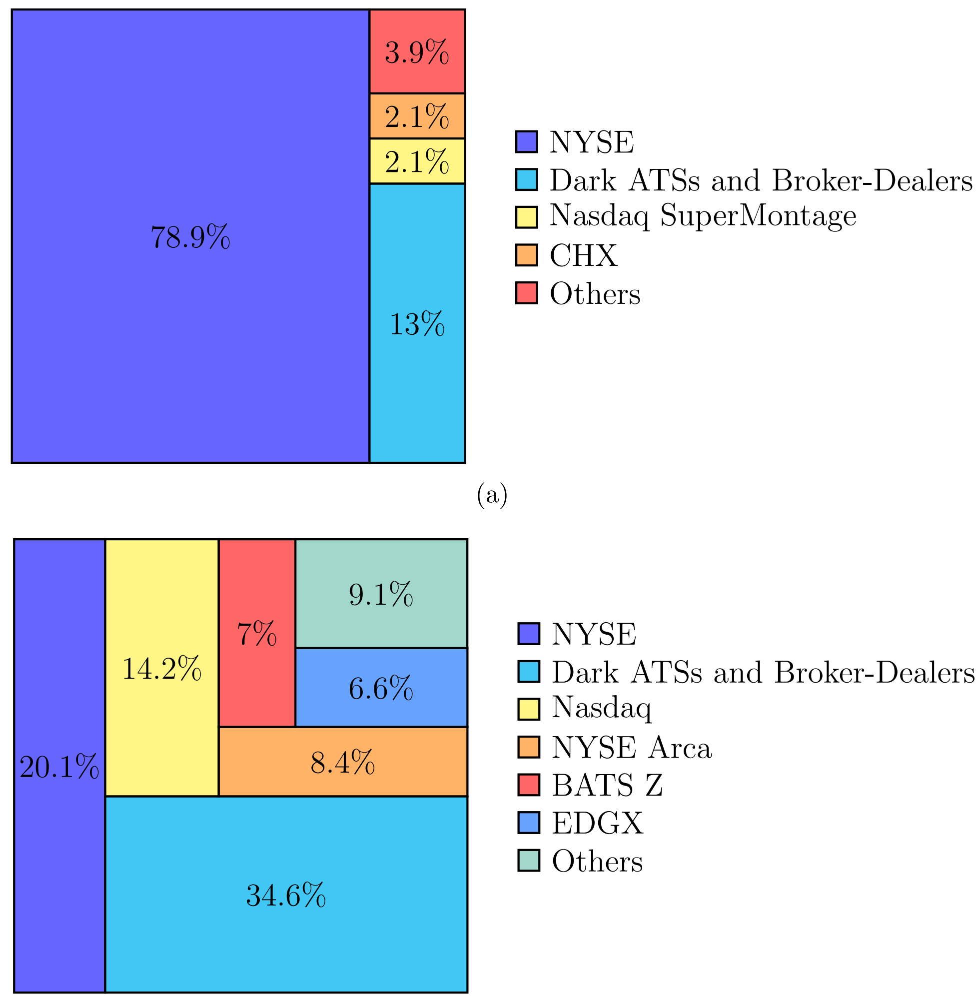


Fig. 1. (a) Trading Volume Split 2004 (b) Trading Volume Split 2014

ecution prices, inter-exchange access, minimum quotation increments and improved market data access (SEC, 2005). Specifically, NMS Rule 611, also referred to as "Order Protection Rule" or "Trade-through Rule" stipulates that no trade is to be executed at prices which are inferior to bid and ask prices readily available and accessible on other exchanges. In essence, the rule effectively prohibits broker-dealers from executing trades on behalf of their clients on a particular exchange, if the price at which the transaction would be executed is below the national best bid or above the national best ask. Nevertheless, exceptions are also stipulated.

Paragraph (b)(8) of Rule 611 provides for an exception in the case of "flickering" quotations. Namely, it exempts from this rule situations, where the exchange on which the potential "trade-through" took place quoted during the previous one-second time window, prices in line with the national best bid or national best ask, which were in line or worse than the transacted price. The disclosed reasoning behind this exception is to provide a so-called "workable" protection system, which is not imposing an excessive burden on the exchange's order routing operations in times of fast changing market prices.(SEC, 2005)

Another important exception concerning Inter-Market Sweep Orders (ISOs) is also foreseen under Paragraphs (b)(5) and (b)(6) of Rule 611. These orders are exempt from the effects of the "Order Protection Rule" and once a qualified ISO is received by an exchange, it is warranted to go ahead and process that order without having the need to check for protected quotations on other exchanges. (SEC, 2005) Moreover, Pargraph (b)(7) of Rule 611 also exempts benchmark orders from the "Order Protection Rule".

A memorandum published in April 2015 by the SEC, presents the impact that Regulations NMS and, specifically, Rule 611 has had on reducing "trade-through" volume. The memorandum shows that, as of February 2014, 0.16% of the total trading volume on the Nasdaq qualified as "trade-through" volume, as opposed to 7.7% in February 2004. A similar pattern is also exhibited in the case of NYSE listed stocks, whereby a decrease from 7.2% in February 2004 to 0.18% in February 2014 is recorded.(SEC, 2015)

### *2.3. General Market Conditions*

Recent advances in algorithmic trading have lead to an increasing share of trading volume attributed to automated traders (Carrion, 2013). Throughout recent times, a special class of automated traders, so called high-frequency traders (HFTs) has emerged, reaping the benefits of increased computing power, exhibiting extremely short reaction times due to high speed, low-latency connections and advanced order routing.

The activity and role of HFTs around macroeconomic events has attracted significant attention from academics. Brogaard et al. (2014) use a proprietary dataset provided by Nasdaq which enables the identification and tracking of HFT activity and show that HFT liquidity supply is greater than HFT liquidity demand. The findings in Foucault et al. (2015) emphasize the importance of speed around news events, whereby traders with lower reaction times benefit from higher expected profits and show that the fraction of trading volume attributable to HFTs is higher around price relevant news.

## 3. Sample Selection and Data

### *3.1. High-frequency Data*

The data employed has been sourced from the New York Stock Exchange Trade and Quote (TAQ) Database, hosted by the Wharton Research Data Services (WRDS) Cloud platform. The analysis uses high frequency trade and quote data covering the 11 minute period, comprised of the five pre-announcement trading minutes (13:55-14:00), prior to the Fed's interest rate hike announcement, the event minute (14:00-14:01) and the five post announcement trading minutes (14:01-14:06). Specifically, the sample covers trade and quote data for a basket of 71 companies included in the Nasdaq100 Index.

The consolidated NYSE TAQ Files contain nanosecond level trade and quote data for each of the 14 participating facilities, as well as reconstructed national best bid and offer data compiled by WRDS, based on the raw quote data. Table 1 summarizes the trading activity in terms of volume and number of trades recorded on December 19, 2018 split by each of the 14 participating facilities.

It is important to note that trade observations for which the exchange identifier refers to the Financial Ind. Regulatory Authority, Inc. are not recorded by an actual exchange, but are trades reported by the FINRA Trade Reporting Facility. For the most part, these are trades that were executed in dark pools, directly between counter-parties or on various other platforms. These observations are not considered, as no bid or ask data is available for these trades, rendering impossible any liquidity related insights or deeper analysis.

In line with the aim of the paper, the analysis focuses on the top three public exchanges, ranked by trading volume, on which the 71 companies are cross-listed. Specifically, the analysis focuses on data reported by Nasdaq Stock Exchange, Bats BZX Exchange and NYSE Arca which together account for 44.69% of the total dollar trading volume (68.19% exclusively considering the public exchanges), as well as for 56.32% of the total number of executed trades (68.56% exclusively considering the public exchanges).

### *3.2. Algorithmic Design*

One of the main challenges when analyzing intra-day data is working with data files of increased size. As an illustrative example, given a typical TAQ Daily Quote file ranges from 30 to 50 gigabytes, screening for extreme intra-day returns over a five year period implies iterating through approximately 50 petabytes or 50 million gigabytes. Implicitly, the magnitude of the resulting

Table 1: This table provides information regarding the trading activity: trading volume and number of trades covering all of the participating reporting entities included in the NYSE TAQ Files. The figures in the table refer to the sample of 71 members of the Nasdaq100 and cover the entire regular hours trading session on December 19, 2018.

| Exchange Name | Symbol | Vol (MM USD) | % Tot Vol (USD) | Nr Trades | % Tot Nr Trades |
|---|---|---|---|---|---|
| Financial Ind. Regulatory Authority, Inc. | D | 23,356.04 | 34.46% | 895,659 | 17.86% |
| Nasdaq Stock Exchange, LLC | Q | 18,796.28 | 27.73% | 1,655,098 | 33.00% |
| Bats BZX Exchange, Inc. | Z | 5,889.06 | 8.69% | 660,316 | 13.16% |
| NYSE Arca, Inc. | P | 5,607.01 | 8.27% | 509,438 | 10.16% |
| Bats EDGX Exchange, Inc. | K | 4,161.94 | 6.14% | 357,776 | 7.13% |
| The Investors' Exchange, LLC (IEX) | V | 2,564.22 | 3.78% | 184,375 | 3.68% |
| Bats BYX Exchange, Inc. | Y | 1,656.97 | 2.44% | 221,570 | 4.42% |
| New York Stock Exchange LLC | N | 1,548.13 | 2.28% | 130,889 | 2.61% |
| Nasdaq OMX BX, Inc. | B | 1,519.15 | 2.24% | 171,357 | 3.42% |
| Bats EDGA Exchange, INC | J | 1,052.59 | 1.55% | 102,923 | 2.05% |
| Nasdaq OMX PSX, Inc. LLC | X | 621.83 | 0.92% | 62,499 | 1.25% |
| National Stock Exchange Inc. (NSX) | C | 502.08 | 0.74% | 50,902 | 1.01% |
| Chicago Stock Exchange, Inc. (CHX) | M | 412.05 | 0.61% | 2,901 | 0.06% |
| NYSE MKT LLC | A | 97.47 | 0.14% | 10,333 | 0.21% |

dataset renders such an analysis impossible to carry out on a traditional workstation. Recent advances in data storage and processing, along with the rise of affordable cloud computing platforms provide a viable solution for performing big data analytics.

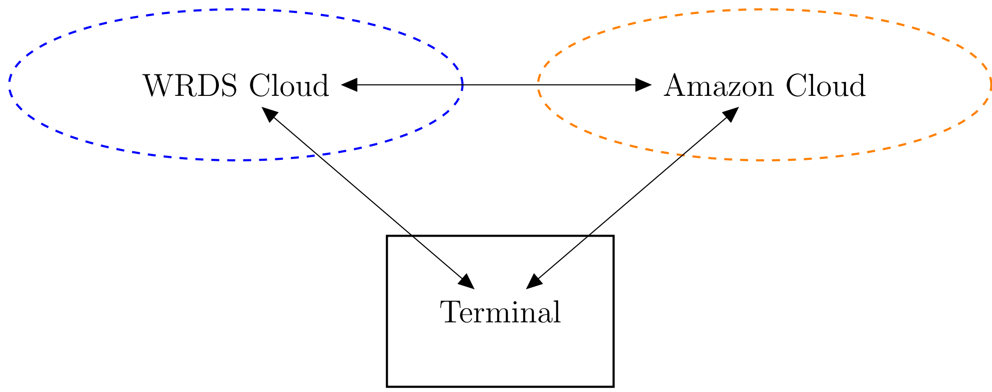


Fig. 2. Computational architecture

Figure 2 provides an overview of the architecture employed for the purpose of running the analysis. Specifically, this paper takes advantage of the resources provided by the WRDS Cloud platform for iterating through the trade and quote data for all 100 constituents of the Nasdaq100 Index for the period starting from 1st of January 2014 and up until 1st of January 2019. Taking advantage of the SAS Studio platform hosted by WRDS offering direct access to the TAQ files, the raw data is cleaned in line with the procedure outlined in Section 3.3 and aggregated at stock-minute level. The resulting intermediate dataset is then transferred to a virtual machine set up on AWS Cloud (Amazon Web Services Cloud Platform) running R, where extreme negative minute-return intervals are identified. A total of 15,242 three sigma events were identified using the procedure defined in Rif and Utz (2019).

Of the identified set of events, the Fed's Announcement on December 19, 2018 published at 14:00 US Eastern Time is the one with the highest number of concomitantly affected stocks, 71 of the 100 Nasdaq100 constituents and serves as the basis for the analysis. As a next step, for each stock's primary, secondary and tertiary exchange nanosecond level trade, quote and best bid and ask data were retrieved for the event minute 14:00-14:01 as well as for the five minute pre- and post-event periods through the WRDS in-house developed Python package. Trade and quote data are matched at exchange level, then snapshots of the top of the order book for each of the three individual exchanges are generated and stored at a one-millisecond interval for each stock. The analysis is then conducted using the resulting dataset.

## *3.3. Data Cleaning*

The sample data is restricted to trades and quotes submitted to the individual exchanges during the time window starting from 13:55 and ending at 14:06. First, any trade observations which are not referring to common stock are excluded from the sample. Specifically, referring to the TAQ Client specifications, any trades with conditions listed as A, B, H, K, L, O, R, V, W, and Z are dropped from the dataset. Quote data is processed in line with the methodology set forth in Holden and Jacobsen (2014) and Rif and Utz (2019). Namely, quotes flagged with irregular trade conditions or any observations for which the bid and ask price stemming from the same reporting venue are crossed are also dropped. Furthermore, observations for which either the bid or the ask quantity are missing or listed as 0 are not considered. Moreover, any trades for which the equity suffixes were listed as K, L , V, or Z were also dropped from the dataset. Quote and trade data are matched according to the procedure introduced in Holden and Jacobsen (2014). A table covering the description of the excluded trade and quote conditions is included in the Appendix.

Table 2 reports general summary statistics showing the individual developments in average minute return, bid-ask spread as well as the minute trading volume split according to individual exchanges and covering the five minute period prior to the Fed's announcement, the event minute, and the five minute period following up the publication of the announcement. All

Table 2: This table provides exchange level descriptive statistics showing the developments during the five pre-event minute periods, the one minute event period and the five post event minute periods. The figures are calculated on a per minute per stock basis and represent average minute return, bid-ask spread and per minute USD trading volume.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| *Minute Return* | | | | | | | | | |
| Mean | 9.23 | -88.59 | -7.34 | 7.45 | -71.55 | -10.12 | 7.05 | -71.43 | -9.96 |
| 10th %ile | -8.95 | -131.16 | -39.42 | -7.50 | -126.85 | -45.56 | -7.82 | -131.03 | -44.02 |
| Median | 7.12 | -83.58 | -8.11 | 4.60 | -71.61 | -8.42 | 3.17 | -73.36 | -7.21 |
| 90th %ile | 33.26 | -41.29 | 27.26 | 27.65 | -10.94 | 26.40 | 27.37 | -5.23 | 23.86 |
| Std Dev | 17.07 | 41.47 | 29.26 | 15.22 | 51.31 | 30.27 | 15.50 | 47.86 | 30.67 |
| *Bid Ask Spread* | | | | | | | | | |
| Mean | 11.40 | 36.30 | 20.27 | 41.03 | 103.87 | 65.89 | 68.39 | 152.85 | 63.12 |
| 10th %ile | 2.37 | 12.71 | 5.22 | 2.68 | 19.29 | 5.57 | 3.88 | 19.07 | 7.24 |
| Median | 7.99 | 31.05 | 16.10 | 11.22 | 64.84 | 21.08 | 16.06 | 77.61 | 23.96 |
| 90th %ile | 25.01 | 69.39 | 39.51 | 93.87 | 207.49 | 107.90 | 209.58 | 362.60 | 144.75 |
| Std Dev | 12.18 | 22.59 | 18.26 | 105.11 | 125.60 | 222.62 | 151.11 | 206.48 | 122.34 |
| *Minute USD Volume (Mln)* | | | | | | | | | |
| Mean | 0.53 | 2.47 | 0.98 | 0.21 | 0.66 | 0.49 | 0.14 | 0.46 | 0.24 |
| 10th %ile | 0.04 | 0.28 | 0.05 | 0.00 | 0.02 | 0.00 | 0.00 | 0.01 | 0.00 |
| Median | 0.20 | 0.76 | 0.31 | 0.06 | 0.15 | 0.09 | 0.04 | 0.13 | 0.06 |
| 90th %ile | 1.13 | 5.74 | 2.50 | 0.49 | 1.55 | 1.22 | 0.30 | 0.99 | 0.60 |
| Std Dev | 1.17 | 5.49 | 2.49 | 0.48 | 1.92 | 1.43 | 0.40 | 1.16 | 0.56 |

figures are calculated based on stock-minute figures.

The first panel, covering the minute returns, shows the magnitude of the Fed announcement's impact, whereby the average minute return across the 71 individual companies is -88.59bp in the case of the primary exchange, while the average minute return within the five minute period prior to the event which is 9.23bp. A similar profile is also displayed when considering the figures for the secondary and tertiary exchanges, where the average return in the pre-event period is 7.45bp and 7.05bp, respectively, while during the event minute the average drop is reported at -71bp, 55bp and -71.43bp respectively, roughly similar to the ratio exhibited on the primary exchange. Similarities across the exchanges are also observed when considering the minute return distributional data, whereby comparable figures are reported for the 10th and 90th decile, as well as for the median and standard deviation. It is important to stress that these figures can very well vary across the individual trading venues, since they are calculated based on actual trade prices as opposed to quoted returns.

Coupling the return data with the volume data reported in the third panel serves as primary indication that market participants are active and exhibit similar trading activity across all three public exchanges. In line with literature linking trading volume to price movements, (Brogaard et al., 2018; Lee and Swaminathan, 2000) we observe that trading volume sharply increased across all three exchanges during the event minute. The primary exchange experiences a fivefold increase in minute-stock dollar trading volume, or \$2.47 Mln per title, when compared with the average minute trading volume during the pre-event period, \$0.53 Mln per title. The secondary and tertiary exchanges experience a threefold increase in minute trading volume during the event minute, reaching \$0.66 Mln and \$0.46 Mln, compared to \$0.21 Mln and \$0.14 Mln in the pre-event period. The minute volume post-event is substantially lower throughout all exchanges and is roughly double to the one recorded in the pre-event levels. The importance of the relatively higher increase in trading volume experienced by the primary exchange, is further augmented by the findings in Eun and Sabherwal (2003), who report a direct link between the share of a cross-listed security's total volume on one exchange and the share of informative trades which augment the price discovery process.

Referring to the second panel, the quoted bid-ask spread, differences in liquidity level, proxied by the bid-ask spread, are observable across the three exchanges throughout all three time periods. The first exchange, as in the case of minute trading volume, exhibits the best trading conditions when benchmarked against the other two exchanges, with the quoted bid-ask spread being throughout all the periods smaller than that reported by the counterparts. Noticeably, the distribution of the bid-ask spread is right-skewed, with the values for the mean being considerably higher than the median throughout all three exchanges and time periods. Nevertheless, even when comparing the median bid-ask spread values for all exchanges, the primary exchange, remains the venue offering the best trading conditions.

A deterioration in trading conditions, i.e. an increase in the quoted spread is exhibited by all three trading venues, whereby the mean bid-ask spread quoted on the primary exchange increases from an average of 11.40bp during the five pre-event minutes to 36.30bp during the event minute , representing a 218% increase and drops to 20.27bp in the post-event period. The secondary and tertiary exchange, exhibit a similar pattern, quoting a mean bid-ask spread of 41.03bp and 68.39bp, respectively for the five minute period prior to the Fed's announcement, while spiking to 103.87bp and 152.85bp, respectively, during the event minute and leveling off at 65.89bp and 63.12bp during the five post event minutes. These reported developments in the quoted bid-ask spread are in line with Chordia et al. (2002) who document a drop in liquidity in times of falling stock prices.

These initial figures stress the importance, for liquidity aware traders, of having access to a security's primary exchange. The following section aims at shedding more light regarding the trading conditions on individual exchanges.

# 4. Analysis and Main Results

## *4.1. Liquidity Conditions*

In order to get a better picture of the liquidity, as proxied by the quoted bid-ask spread, across the individual trading venues, Table 3 provides an overview regarding the quoted bid and ask prices, by exchange, benchmarked versus the national best bid (NBB) and national best ask (offer) price (NBO), as well as benchmarked versus the other two trading venues. Specifically, the figures illustrate the percentage of time during which each exchange was at the national best bid or at the national best ask, across each of the three time periods of focus, as well as the percentage of time during which the individual exchange was deviating from the national best bid or ask, but nevertheless, it was providing superior quotes in comparison to the other two trading venues.

The first panel of Table 3 shows the percentage of time that each of the individual exchanges is matching the national best bid. The figures for the primary exchange confirm the results introduced already by the descriptive statistics, whereby the primary exchange was quoting the most favorable bid-ask spread, and show that the exchange is on average 70.45% of the time matching the national best bid during the pre-event period. The secondary and tertiary exchanges, on the other hand, score substantially lower during the same period, at 47.90% and 38.07% respectively. Similar figures, stressing the superiority of the primary exchange in terms of liquidity during the pre-event period, are also reported in the third panel, the one referring to the time during which an exchange is at the national best ask.

The most interesting development, constituting the main finding and a strong argument for the supremacy of the primary exchange in terms of

Table 3: This table shows the trading conditions across the primary, secondary and tertiary exchanges, split according to the three time periods of the Fed's announcement: the five minute pre-event period, the event minute and the five minute post event period. The results are presented separately for bid and ask prices, in order to highlight any potential effects of high selling or buying pressure across the three different periods of the event. In order to increase transparency and enable a better comparison amongst the three exchanges, the four panels also split the results between time at national best bid or national best ask, versus time below national best bid (above national best ask) but above the best bid (below the best ask) quoted on the other two competing exchanges. All figures are calculated on a per minute-stock average.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| *% of Time at national best bid* | | | | | | | | | |
| Mean | 70.45% | 69.86% | 65.30% | 47.90% | 24.47% | 40.36% | 38.07% | 18.19% | 31.01% |
| 10th %ile | 37.83% | 39.61% | 33.03% | 3.95% | 3.73% | 5.29% | 3.54% | 0.51% | 2.67% |
| Median | 73.64% | 72.28% | 67.62% | 49.97% | 22.75% | 39.23% | 33.67% | 11.65% | 25.22% |
| 90th %ile | 96.56% | 87.11% | 91.91% | 87.77% | 49.87% | 76.15% | 79.34% | 44.38% | 68.50% |
| Std Dev | 22.44% | 18.40% | 22.12% | 29.71% | 17.07% | 25.78% | 27.46% | 18.55% | 24.53% |
| *% of Time below national best bid but above other exchanges* | | | | | | | | | |
| Mean | 7.59% | 12.10% | 8.55% | 2.61% | 1.43% | 3.29% | 1.58% | 1.37% | 1.64% |
| 10th %ile | 0.01% | 1.16% | 0.11% | 0.00% | 0.01% | 0.01% | 0.00% | 0.00% | 0.00% |
| Median | 1.95% | 10.65% | 3.78% | 0.36% | 0.27% | 1.01% | 0.06% | 0.38% | 0.25% |
| 90th %ile | 21.07% | 24.76% | 20.72% | 6.80% | 4.44% | 8.48% | 5.35% | 3.77% | 4.28% |
| Std Dev | 13.31% | 10.74% | 13.06% | 6.86% | 2.35% | 5.89% | 4.17% | 2.58% | 3.95% |
| *% of Time at national best ask* | | | | | | | | | |
| Mean | 67.81% | 68.85% | 63.15% | 44.23% | 18.60% | 34.69% | 33.27% | 19.33% | 24.65% |
| 10th %ile | 34.45% | 42.52% | 31.75% | 3.37% | 0.45% | 3.28% | 2.00% | 0.34% | 1.35% |
| Median | 71.52% | 71.39% | 66.82% | 41.59% | 14.84% | 29.72% | 25.80% | 12.44% | 19.08% |
| 90th %ile | 95.15% | 94.78% | 87.82% | 88.22% | 44.53% | 72.39% | 76.00% | 47.82% | 54.75% |
| Std Dev | 22.93% | 18.23% | 20.89% | 31.38% | 17.11% | 25.31% | 27.96% | 21.32% | 21.76% |
| *% of Time above national best ask but below other exchanges* | | | | | | | | | |
| Mean | 7.86% | 12.30% | 9.16% | 2.96% | 1.65% | 4.13% | 2.70% | 1.60% | 2.27% |
| Mean | 7.86% | 12.30% | 9.16% | 2.96% | 1.65% | 4.13% | 2.70% | 1.60% | 2.27% |
| 10th %ile | 0.01% | 1.69% | 0.18% | 0.00% | 0.00% | 0.01% | 0.00% | 0.01% | 0.01% |
| Median | 1.97% | 10.48% | 4.84% | 0.69% | 0.37% | 1.46% | 0.17% | 0.23% | 0.33% |
| 90th %ile | 22.97% | 22.47% | 23.13% | 9.00% | 5.97% | 10.52% | 8.30% | 5.08% | 6.75% |
| Std Dev | 13.13% | 12.12% | 11.66% | 6.25% | 2.46% | 8.11% | 6.32% | 2.30% | 4.61% |

liquidity during extreme events, refers to the trading conditions, during the event minute. The primary exchange is slightly under 70% of the time at the national best bid and 68.86% of the time at the national best ask, figures which are only marginally below the figures reported by the primary exchange for the pre-event period. In contrast, the magnitude of the deterioration from the pre-event liquidity conditions, to those in the event minute, is significantly higher in the case of the secondary and tertiary exchanges. The percent of time during which these two venues are at the best bid are 24.47% and 18.19%, respectively, which represents a -48.90% and -52.20% relative drop compared to the percent of time during which these exchanges were at the best bid in the pre-event period. Similar developments are also reported when referring to the percent of time during which the secondary and tertiary exchanges are quoting ask prices in line with the national best ask during the event minute. The secondary and tertiary exchanges are, on average 18.60% and 19.33% of the time at the national best ask, representing a -58.01% and -41.89% relative drop, respectively when benchmarked against pre-event levels.

The stark deterioration in quoted spreads on the secondary and tertiary exchanges is further augmented by the figures reported in panels 2 and 4. Specifically, these figures show the percent of time during which an individual exchange is quoting bid or ask prices which are inferior to the national best bid or national best ask, yet better than the other 2 comparable venues. The primary exchange quotes below national best bid yet superior to those on the secondary and tertiary exchange, 7.59% of the time during the pre-event period, while this figure increases up to 12.10% during the event minute. On the other hand and in contrast to the developments on the primary exchange, the secondary and tertiary exchange quote bid prices below the national best bid but superior to their counterparts during 2.61% and 1.58% of the time in the pre-event period, while these figures drop to 1.43% and 1.37%, respectively during the event minute. These developments further show the superior trading conditions exhibited by the primary exchange.

It is important to note, that the developments in the quoted bid prices are of particular interest, given that the event triggered a negative price reaction and a substantial trading volume increase as reported in the previous section. Indeed, the findings suggest, that market participants wishing to close or reduce open positions would be in the best position to do so by having access to the primary exchange. Adding the time during which each exchange is at the national best bid or offer with the time during which the individual exchange is superior to its counterparts further strengthens this argument. Referring again to mean values, the primary exchange is an optimal selling venue during 78.0% of the time during the pre-event period, while this figure experiences an increase during the event minute to 81.96%. On the other hand, the secondary and tertiary exchanges represent optimal selling venues during 50.51% and 39.65% of the time during the pre-event period, while, in contrast to the primary exchange, they experience a deterioration in this metric in the event-period, providing only 25.90% and 19.56% of the time optimal selling conditions.

Similar developments are also observed when focusing on optimal buying conditions, as measured by the sum of time an individual exchange is at the national best ask or, above the national best ask, yet below the ask price quoted by its respective other two counterparts. The primary exchange again dominates in terms of the total time it quotes optimal ask prices: 75.67% of the time during the pre-event period, 81.15% during the event period and 72.31% during the post-event period. In contrast, the secondary and tertiary exchanges, report 47.19% and 35.97% ask price optimality during the pre-event period, 20.25% and 20.93% during the event minute, 38.82% and 26.92% during the post-event period. Consequently, assuming a market participant would wish to open a position after the extreme downward movement, would be best served on the primary exchange.

However, despite the more favorable conditions offered by the primary exchange, as documented above, trades are nevertheless also taking place on the secondary and tertiary exchanges. This introduces the second research question: Are market participants that trade on secondary or tertiary exchanges incurring additional trading costs?

## *4.2. Trade Price Inefficiencies and Trading Activity*

In order to explore the market participant's trading activity and uncover any potential inefficiencies that might arise from a trader executing trades on an exchange that deviates from the national best bid or offer, or on an exchange that quotes inferior bid or ask prices to those on the other two trading venues, we split the sample of 71 stocks into five quintiles, according to their degree of cross-listing.

In line with the approach in Upson and VanNess (2017), who also investigate the effects of cross-venue volume split on general market conditions, the sample split is hereby performed using a Herfindahl index. The index is calculated, per individual stock, based on the share of total trading volume transacted on each of the three exchanges. Equation 2 formalizes the adopted approach.

$$Qty_{Split_k} = \sum_{i=1}^{3} \left( \frac{ExchangeVolume_{i,k}}{TotalStockVolume_k} \right)^2 \text{, where k represents the stock and i the exchange} \tag{2}$$

Consequently, Table 4 shows the corresponding shares of trading volume, split across the individual exchanges. Quintile 1 includes the stocks with the highest split in trading volume across the three exchanges, whereby 52.52% of the trading volume is executed on the first exchange, 29.51% on the secondary exchange and 17.97% on the tertiary exchange. Conversely, Quintile 5 covers the stocks with the highest trading volume concentration on a single venue, with 78.33% of the total volume being handled by the primary exchange, 13.78% and 7.90% by the secondary exchange and tertiary exchange, respectively.

Table 4: This table shows the percentage split in trading volume across the five quintiles corresponding to the different degrees of trading volume split between the exchanges. Quintile 1 refers to stocks with the highest degree of volume split across individual exchanges, while quintile five covers stocks whose trading volume is highly concentrated on the primary exchange.

| | Primary Exchange | Secondary Exchange | Tertiary Exchange |
|---|---|---|---|
| Quintile 1 | 52.52% | 29.51% | 17.97% |
| Quintile 2 | 62.92% | 22.64% | 14.44% |
| Quintile 3 | 66.66% | 17.47% | 15.87% |
| Quintile 4 | 71.19% | 17.35% | 11.45% |
| Quintile 5 | 78.33% | 13.78% | 7.90% |

The methodological approach to calculate the cost inefficiencies for an individual trade executed on a particular exchanges is formalized in Equation 3. By construction, the approach aims at capturing deviations in executed trade prices from the NBB and NBO, while also accounting for the available NBB and NBB quantity.

$$Cost = \begin{cases} \frac{(NBB_t - P_{Trade}) \times Min(Qty_{Trade}, NBB_{Qty})}{TotalTradeValue} & \text{, if } P_{Trade} \leq NBB \\ 0 & \text{, if } NBB \leq P_{Trade} \leq NBO \\ \frac{(P_{Trade} - NBO_t) \times Min(Qty_{Trade}, NBO_{Qty})}{TotalTradeValue} & \text{, if } P_{Trade} \geq NBO \end{cases} \quad (3)$$

Table 5 summarizes the cost inefficiencies, in basis points, incurred by market participants, summarizing them by exchange and across the three distinct time periods during and around the Fed's announcement. The results are presented by contrasting the cost inefficiencies between the stocks which have the highest volume split across the individual exchanges, summarized in the first panel, and stocks which have the highest degree of trading volume concentration, herewith included in the second panel of Table 5.

Table 5: This table shows the costs, in basis points, of inefficiencies incurred by market participants when executing trades on individual exchanges at prices that deviate from the NBB or NBO. The costs are calculated as the difference between the individual trade price and the quoted NBB or NBO quoted for the stock. The results are split by individual exchange and across the three different time periods.The panel labeled Quintile 1 refers to stocks with the highest degree of volume split across individual exchanges, while the panel labeled Quintile 5 covers stocks whose trading volume is highly concentrated on the primary exchange.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| *Quintile 1* | | | | | | | | | |
| Mean | 0.12 | 0.38 | 0.30 | 0.13 | 0.41 | 0.18 | 0.16 | 0.46 | 0.41 |
| Skewness | 6.30 | 8.00 | 17.05 | 7.76 | 6.54 | 10.90 | 6.86 | 5.52 | 15.18 |
| 90th %ile | 0.34 | 1.14 | 0.73 | 0.36 | 1.35 | 0.60 | 0.49 | 1.42 | 0.95 |
| 95th %ile | 0.89 | 2.19 | 1.33 | 0.88 | 2.27 | 1.11 | 1.03 | 2.57 | 1.49 |
| 99th %ile | 2.20 | 5.48 | 3.47 | 2.10 | 6.03 | 2.74 | 3.02 | 6.81 | 4.24 |
| Std Dev | 0.44 | 1.30 | 2.03 | 0.49 | 1.38 | 0.67 | 0.57 | 1.42 | 2.89 |
| N | 3,351 | 2,940 | 6,250 | 2,304 | 1,128 | 5,348 | 1,460 | 1,048 | 2,731 |
| *Quintile 5* | | | | | | | | | |
| Mean | 2.10 | 5.42 | 1.87 | 2.31 | 4.36 | 1.89 | 0.72 | 1.45 | 1.84 |
| Skewness | 4.93 | 2.98 | 5.73 | 5.78 | 3.17 | 6.84 | 7.24 | 5.69 | 7.94 |
| 90th %ile | 6.18 | 20.12 | 3.19 | 6.22 | 11.82 | 2.67 | 0.75 | 1.82 | 1.60 |
| 95th %ile | 13.89 | 40.12 | 13.29 | 13.78 | 40.93 | 10.48 | 2.97 | 4.84 | 3.63 |
| 99th %ile | 40.16 | 63.82 | 32.38 | 60.65 | 57.92 | 37.15 | 14.12 | 36.46 | 99.34 |
| Std Dev | 6.96 | 13.64 | 6.98 | 8.42 | 12.12 | 8.05 | 3.23 | 6.71 | 11.50 |
| N | 1,073 | 649 | 1,239 | 240 | 131 | 429 | 231 | 106 | 324 |

In line with Aitken et al. (2017) who directly link improved market efficiency with increasing degrees of cross-market volume split, the difference between the inefficiencies reported for Quintile 1 versus those documented for Quintile 5 suggests that stocks with a higher degree of cross-listing are traded more efficiently, when compared to their more concentrated counterparts. Taking the case of the primary exchange across the pre-event, event and post-event periods, average costs associated with inefficiencies are about 17, 14 and 6 times higher for concentrated stocks. Moreover, these findings also support the argumentation proposed in Bessembinder (2003), whereby increased competition between individual exchanges results in decreases in costs and general market conditions.

Secondly, comparing the incurred costs across the different time phases of the event, increases in trade cost inefficiencies reported for trades executed during the event minute, relative to those incurred during the pre-event period, become evident. Looking at the mean reported values, it can be observed that the stocks with the highest degree of cross-listing, exhibit an increase from 0.12bp for the primary exchange, 0.13bp and 0.16bp for the secondary and tertiary exchange, respectively, to 0.38bp, 0.41bp and 0.46bp, respectively. This translates into a more than 200% increase in cost inefficiencies, across all exchanges. Increases of similar magnitude are also documented when observing the figures in the second panel. Here, inefficiencies increase from pre-event levels of 2.10bp, 2.31bp and 0.72bp for the primary, secondary and tertiary exchange to 5.42bp, 4.36bp and 1.45bp.

In order to further investigate differences in bid ask spread and trade cost inefficiencies between cross-listed and concentrated securities in a multivariate setting, a series of OLS regressions are run. A dummy variable (Cross-listed), which takes the value of one if a security belongs to the quintile with the highest degree of cross-listing and zero when a security belongs to the quintile with the highest degree of trading volume concentration on a single exchange is included throughout all model specifications. Moreover,

Table 6: This table shows the coefficients of the OLS regressions aimed at investigating the differences in bid-ask spread, as well as in trade cost inefficiencies calculated at a one-millisecond time interval between cross-listed securities and concentrated securities. All model specifications contain minute fixed effects, as well as firm level clustered standard errors. All coefficients for spread and cost metrics are expressed in basis points. $t$-statistics are reported in parentheses. *, **, *** denote significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| | Primary Exchange | | Secondary Exchange | | Tertiary Exchange | |
|---|---|---|---|---|---|---|
| | Coeff | t-stat | Coeff | t-stat | Coeff | t-stat |
| Panel Dependent Variable: Bid-Ask Spread | | | | | | |
| Cross-listed | -12.63*** | -3.41 | 3.72 | 0.09 | -72.26** | -2.38 |
| Constant | 17.07*** | 5.80 | 23.53 | 1.06 | 76.43*** | 2.98 |
| Minute FE | Yes | | Yes | | Yes | |
| N | 20,460,000 | | 20,460,000 | | 20,460,000 | |
| adj. $R^2$ | 0.182 | | 0.023 | | 0.120 | |
| Panel Dependent Variable: Cost Inefficiencies | | | | | | |
| Cross-listed | -2.97** | -2.13 | -2.14** | -2.05 | -1.49 | -1.11 |
| Constant | 2.65** | 2.33 | 2.20** | 2.18 | 1.87 | 1.44 |
| Minute FE | Yes | | Yes | | Yes | |
| N | 15,541 | | 4,079 | | 2,641 | |
| adj. $R^2$ | 0.012 | | 0.008 | | 0.011 | |

all model specifications include minute fixed effects and clustered standard errors at the security level. Table 6 reports on the coefficients for the six model specifications. Referring to the first panel of Table 6, the negative and statistically significant coefficients reported for the Cross-listed dummy imply that on average, cross-listed securities exhibit a smaller bid-ask spread, when looking at a security's primary and tertiary exchange. Specifically, the bid-ask spread is on average -12.63bp smaller for cross-listed securities when compared to concentrated securities on the primary exchange, while the difference increases to -72.26bp, in the case of the tertiary exchange. The negative, statistically significant coefficient for the Cross-listed dummy variable in the second panel of Table 6, suggests that incurred trade costs inefficiencies are indeed lower for cross-listed securities when referring to the cases of the primary and secondary exchanges. Specifically, these incurred costs are -2.97bp and -2.14bp smaller on the primary and secondary exchange, respectively. In this respect these findings provide further evidence supporting the idea that market fragmentation does not harm market quality.

However, the high degree of comparability in recorded cost inefficiencies reported in Table 5 across individual exchanges and across each of the separate event periods suggests that such inefficiencies are uniformly observed across all exchanges. It appears that there is no difference in trading activity across the individual exchanges, supporting the idea of a unified US market with multiple access points (individual exchanges).

In order to compare the individual cost inefficiency distributions, observed on the individual exchanges, a series of two-sample Kolmogorov-Smirnov tests for equality of distributions are performed. The null hypothesis states that the two test samples belong to the same distribution. Specifically, this nonparametric test calculates the distance of the first distribution to its counterpart. The particular advantage of the selected approach is that the Kolmogorov-Smirnov test takes into account both differences in location and in the shape of the cumulative distribution functions corresponding to the two compared samples.

Table 7: This table presents the results of the pairwise performed two-sample Kolmogorov-Smirnov tests for equality of distributions. The null hypothesis of the tests states that the two test samples belong to the same distribution. The test is performed pairwise across all three exchanges.

| Primary vs. Secondary | | | Secondary vs. Tertiary | | | Primary vs. Tertiary | | |
|---|---|---|---|---|---|---|---|---|
| Benchmark | Diff. | P-Value | Benchmark | Diff. | P-Value | Benchmark | Diff. | P-Value |
| Primary | 0.01 | 0.71 | Secondary | 0.01 | 0.92 | Primary | 0.01 | 0.79 |
| Secondary | -0.02 | 0.19 | Tertiary | -0.03 | 0.12 | Tertiary | -0.04 | 0.01 |
| Combined K-S | 0.02 | 0.37 | Combined K-S | 0.03 | 0.23 | Combined K-S | 0.04 | 0.02 |

Table 7 summarizes the results obtained when running two-sample Kolmogorov-Smirnov tests pairwise for the three exchanges. Looking at the reported t-values for the Combined K-S test, we fail to refute the null hypothesis of the Combined K-S test in the case of the first two comparisons, primary vs. secondary and secondary vs. tertiary exchange. Corroborating these results with the summarized costs in Table 5 provides further evidence of the similar pattern trade cost inefficiency throughout the individual exchanges.

Indeed, the Combined K-S t-value, reported when referring to the comparison of the primary vs. tertiary exchange, indicates the rejection of the null hypothesis and therefore suggesting that in fact the cumulative distribution functions of the two trading cost inefficiencies distributions differ. Specifically, the negative difference of -0.04 reported for the tertiary exchange indicates that trading costs on the tertiary exchange are lower than those observed on the primary exchange. Nevertheless, the low difference reported by the test weaken the counter argument. Corroborating these results with the summarized costs in Table 5 provides further evidence of the similar pattern trade cost inefficiency throughout the individual exchanges.

Complementing these results, Table 8 summarizes the percent of per-minute realized trading volume which has been traded in times during which the exchange was deviating from the national best bid or national best offer. Analogous to the case of the incurred cost inefficiencies, we observe

Table 8: This table shows the percent of per-minute trading volume, that occurs on the individual exchanges, in times during which the exchange is not quoting either the national best bid or national best ask. The results are split by individual exchange and across the three different time periods. The panel labeled Quintile 1 refers to stocks with the highest degree of volume split across individual exchanges, while the panel labeled Quintile 5 covers stocks whose trading volume is highly concentrated on the primary exchange.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| *Quintile 1* | | | | | | | | | |
| Mean | 14.26% | 30.02% | 25.66% | 12.39% | 29.17% | 20.00% | 15.10% | 28.70% | 22.68% |
| Median | 12.25% | 32.54% | 23.15% | 7.25% | 32.31% | 21.14% | 6.92% | 30.52% | 19.47% |
| 90th %ile | 28.52% | 43.51% | 52.02% | 35.24% | 46.09% | 36.59% | 45.18% | 45.26% | 52.34% |
| 95th %ile | 38.91% | 45.42% | 67.16% | 48.77% | 59.31% | 40.86% | 52.56% | 45.32% | 54.86% |
| 99th %ile | 72.21% | 45.42% | 100.00% | 59.93% | 59.31% | 100.00% | 66.68% | 45.32% | 100.00% |
| Std Dev | 14.47% | 12.12% | 20.40% | 15.01% | 15.30% | 15.86% | 17.87% | 10.25% | 21.18% |
| *Quintile 5* | | | | | | | | | |
| Mean | 33.14% | 43.09% | 34.75% | 23.53% | 37.53% | 35.94% | 14.39% | 20.66% | 24.55% |
| Median | 18.45% | 27.39% | 28.01% | 0.00% | 14.81% | 25.07% | 0.00% | 16.00% | 17.12% |
| 90th %ile | 100.00% | 86.72% | 97.41% | 100.00% | 89.11% | 100.00% | 59.38% | 33.54% | 84.88% |
| 95th %ile | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |
| 99th %ile | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |
| Std Dev | 34.92% | 29.58% | 31.53% | 37.12% | 37.16% | 37.93% | 29.41% | 26.04% | 29.65% |

evident similarities when comparing the mean values reported for the individual exchanges across the pre-event and event periods for stocks included in Quintile 1. Specifically, 14.26% of the trading volume occurring on the primary exchange during the pre-event period happens when the exchange quotes prices which are either below or above the national best bid or national best ask respectively, versus 12.39% and 15.10% in the case of the secondary and tertiary exchanges. These figures increase to 30.02%, 29.17% and 28.70% for the primary, secondary and tertiary exchanges respectively during the event-minute. Nevertheless, similarities in reported volume patterns disappear when turning to the figures reported for Quintile 5. The primary exchange, which referring back to the figures in Table 4, handles on average 78.33% of the total volume reported by an individual stock, reports that 33.14% of the trading volume took place outside the national best bid or national best ask during the pre-event period, 43.09% during the event minute and 34.75% during the post-event period. The figures for the secondary and tertiary exchange are indeed throughout all time periods lower when benchmarked against the primary exchange. This comes in strong contrast to the developments in the stocks with the highest volume split across individual exchanges, suggesting that decreased inter-exchange competition could in fact cause market participants to bear increased inefficiencies.

Overall, the presented results confirm the findings presented in extant literature covering cross-listed securities, whereby supporting and providing alternative evidence that stocks with an increased split in trading volume across multiple regional exchanges offer better market conditions. Both incurred cost inefficiencies and trading volume outside the national best bid and ask are substantially higher for stocks whose trading volume is concentrated solely on the primary exchange. Nevertheless, when strictly looking at liquidity, as measured by the quoted bid-ask spread, the primary exchange dominates its peers and remains the best trading venue.

# 5. Conclusion

This paper analyzes general market conditions and in particular liquidity and trading activity in times of extreme events such as the one on December 19, 2018, when at 14:00, the Federal Open Market Committee (FOMC), through its regular communication channel, published a press release announcing a 25bp interest rate increase and expressed concerns about potentially deteriorating macro-economic conditions. The event triggered an immediate decline in major US indexes, whereby 71 cross-listed Nasdaq100 index constituents experienced a three sigma negative price movement.

Liquidity conditions deteriorate in the event-period, the minute immediately following up the Fed's announcement, with threefold reported increases in bid-ask spread across all individual exchanges. Trading volume, as well as the number of executed trades increase when compared to the 5-minute pre-event interval. Despite increasing bid-ask spreads, the primary listing exchange remains superior in terms of liquidity across all time event periods. Benchmarked against the secondary and tertiary exchanges, the primary exchange is quoting 81.96% and 81.15% percent of the time bid and ask prices prices which are equally best or superior.

Furthermore, the paper documents an increase in trade cost inefficiencies, measured as trades executed below the national best bid or above national best ask, across all three individual exchanges, in both cross-listed and single exchange concentrated stocks, in the period covering the fist minute after the Fed's decision to increase interest rates when compared to pre-event levels.

Nevertheless, the analysis reports similarities in trade cost inefficiencies and volume patterns when looking at stocks with an increased volume split across individual exchanges, while the opposite is observed in the case for stocks who mainly trade on one exchange.

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# Appendix

Table 9: Complete description of abnormal quote conditions which have been excluded in line with the data cleaning process described in Holden and Jacobsen (2014), as well as the additional equity symbol suffixes for which observations from the daily trades dataset have not been included.

| Quote Condition | Description |
|---|---|
| A | This condition indicates that the current offer is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Offer side and can be traded through pursuant to anticipated Regulation NMS requirements |
| B | This condition indicates that the current bid is in 'Slow' quote mode. While in this mode, autoexecution is not eligible on the Bid side and can be traded through pursuant to anticipated Regulation NMS requirements. |
| H | This condition indicates that the quote is a 'Slow' quote on both the Bid and Offer sides. While in this mode, auto-execution is not eligible on the Bid and Offer sides, and either or both sides can be traded through pursuant to anticipated Regulation NMS requirements. |
| O | This condition can be disseminated to indicate that this quote was the opening quote for a security for that Participant. |
| R | This condition is used for the majority of quotes to indicate a normal trading environment. It is also used by the FINRA Market Makers in place of Quote Condition 'O' to indicate the first quote of the day for a particular security. The condition may also be used when a Market Maker re-opens a security during the day. |
| W | This quote condition is used to indicate that the quote is a Slow Quote on both the Bid and Offer sides due to a Set Slow List that includes High Price securities. While in this mode, auto-execution is not eligible, the quote is then considered Slow on the Bid and Offer sides and either or both sides can be traded through, as per Regulation NMS. |
| Equity Suffix | Description |
| K | Non-Voting Shares |
| L | Miscellaneous situations such as certificates of participation, preferred participation, and stubs |
| V | Denotes a transaction in a security authorized for issuance, but not yet issued. All "when issued" transactions are on an "if" basis, to be settled if and when the actual security is issued. |
| Z | Miscellaneous situations such as certificates of preferred when issued |

Table 10: This table shows the percentage of trade volume per minute interval, which given the rules specified under SEC NMS Regulation - Rule 611 would classify as trade-through volume. Specifically, Inter-market Sweep Orders have been dropped from the dataset. Additionally, a the one-second time window rule has also been applied, prohibiting the classification of a given trade as a trade-through if the exchange at hand had quoted either at the national best bid or national best ask within a one-second time window.

| *Primary Exchange* | | | | | | |
|---|---|---|---|---|---|---|
| Interval | Mean | Skewness | 95th %ile | 99th %ile | Std Dev | Nr. Trades |
| t-5 | 1.43% | 7.53 | 5.11% | 35.31% | 7.42% | 802 |
| t-4 | 0.55% | 6.54 | 2.68% | 22.40% | 2.80% | 990 |
| t-3 | 0.35% | 12.33 | 0.00% | 11.75% | 3.51% | 800 |
| t-2 | 0.71% | 6.55 | 4.15% | 24.46% | 3.70% | 618 |
| t-1 | 1.22% | 9.47 | 1.20% | 30.58% | 8.58% | 1509 |
| t | 0.14% | 13.84 | 0.00% | 2.90% | 1.26% | 3623 |
| t+1 | 0.63% | 13.64 | 0.00% | 23.04% | 5.04% | 1578 |
| t+2 | 0.04% | 9.70 | 0.17% | 0.17% | 0.24% | 1404 |
| t+3 | 0.30% | 10.23 | 0.00% | 14.71% | 2.67% | 1263 |
| t+4 | 0.17% | 10.11 | 0.00% | 4.10% | 1.22% | 2059 |
| t+5 | 0.33% | 9.93 | 1.37% | 13.21% | 2.11% | 1392 |

| *Secondary Exchange* | | | | | | |
|---|---|---|---|---|---|---|
| Interval | Mean | Skewness | 95th %ile | 99th %ile | Std Dev | Nr. Trades |
| t-5 | 0.94% | 7.47 | 6.95% | 37.66% | 4.33% | 333 |
| t-4 | 0.25% | 6.48 | 0.00% | 11.10% | 1.64% | 405 |
| t-3 | 0.22% | 21.28 | 0.00% | 0.00% | 4.68% | 456 |
| t-2 | 0.22% | 5.94 | 0.00% | 8.58% | 1.37% | 421 |
| t-1 | 0.99% | 13.93 | 3.11% | 18.38% | 5.05% | 579 |
| t | 1.26% | 4.22 | 3.50% | 18.85% | 2.82% | 1035 |
| t+1 | 0.95% | 4.28 | 3.50% | 15.52% | 2.83% | 584 |
| t+2 | 0.20% | 9.23 | 0.00% | 13.32% | 1.82% | 624 |
| t+3 | 0.31% | 9.33 | 0.49% | 22.64% | 2.36% | 730 |
| t+4 | 0.19% | 12.67 | 0.00% | 1.06% | 1.92% | 1350 |
| t+5 | 0.25% | 5.85 | 0.00% | 8.94% | 1.46% | 781 |

| *Tertiary Exchange* | | | | | | |
|---|---|---|---|---|---|---|
| Interval | Mean | Skewness | 95th %ile | 99th %ile | Std Dev | Nr. Trades |
| t-5 | 0.26% | 9.61 | 0.00% | 24.99% | 2.55% | 286 |
| t-4 | 0.00% | . | 0.00% | 0.00% | 0.00% | 349 |
| t-3 | 0.21% | 12.90 | 0.15% | 0.15% | 2.56% | 339 |
| t-2 | 0.00% | . | 0.00% | 0.00% | 0.00% | 275 |
| t-1 | 1.43% | 6.11 | 3.91% | 33.31% | 5.51% | 471 |
| t | 1.97% | 7.51 | 7.86% | 87.15% | 9.90% | 877 |
| t+1 | 1.18% | 11.34 | 10.43% | 13.69% | 5.65% | 537 |
| t+2 | 2.12% | 6.87 | 1.04% | 49.97% | 11.56% | 510 |
| t+3 | 1.15% | 7.77 | 0.00% | 16.70% | 6.52% | 369 |
| t+4 | 0.87% | 9.22 | 5.23% | 5.23% | 4.01% | 850 |
| t+5 | 0.86% | 12.36 | 4.67% | 6.02% | 6.69% | 605 |

Table 11: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price above the national best ask. The results are split by individual exchange and across the three different time periods. The panel labeled Quintile 1 refers to stocks with the highest degree of volume split across individual exchanges, while the panel labeled Quintile 5 covers stocks whose trading volume is highly concentrated on the primary exchange.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| Quantile 1 | | | | | | | | | |
| Mean | 9.15% | 9.96% | 10.49% | 8.86% | 7.83% | 9.79% | 10.84% | 6.88% | 7.49% |
| Skewness | 1.41 | 0.15 | 0.71 | 1.81 | 0.25 | 2.44 | 1.74 | 2.18 | 1.95 |
| Median | 6.44% | 11.72% | 9.00% | 4.08% | 7.54% | 8.57% | 2.54% | 4.81% | 3.18% |
| 90th %ile | 22.05% | 22.26% | 24.71% | 25.00% | 15.71% | 21.05% | 41.67% | 16.41% | 19.16% |
| 95th %ile | 25.59% | 22.35% | 29.13% | 34.25% | 20.59% | 30.20% | 51.31% | 35.91% | 26.67% |
| 99th %ile | 51.81% | 22.35% | 31.44% | 57.37% | 20.59% | 69.47% | 66.68% | 35.91% | 50.82% |
| Std Dev | 9.68% | 7.44% | 9.00% | 11.64% | 6.48% | 10.89% | 16.15% | 8.80% | 10.08% |
| Quantile 5 | | | | | | | | | |
| Mean | 22.99% | 22.56% | 13.47% | 19.37% | 27.28% | 15.41% | 12.80% | 2.82% | 11.02% |
| Skewness | 1.39 | 1.09 | 1.54 | 1.62 | 0.97 | 1.78 | 2.35 | 2.70 | 2.73 |
| Median | 3.90% | 8.48% | 6.61% | 0.00% | 10.14% | 0.00% | 0.00% | 0.00% | 0.00% |
| 90th %ile | 100.00% | 70.01% | 43.30% | 100.00% | 87.16% | 61.58% | 50.02% | 9.22% | 34.96% |
| 95th %ile | 100.00% | 82.59% | 59.06% | 100.00% | 100.00% | 87.32% | 100.00% | 27.09% | 58.37% |
| 99th %ile | 100.00% | 82.59% | 70.34% | 100.00% | 100.00% | 100.00% | 100.00% | 27.09% | 100.00% |
| Std Dev | 34.99% | 28.38% | 17.63% | 36.35% | 35.52% | 27.43% | 28.51% | 7.42% | 21.85% |

Table 12: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price below the national best bid. The results are split by individual exchange and across the three different time periods. The panel labeled Quintile 1 refers to stocks with the highest degree of volume split across individual exchanges, while the panel labeled Quintile 5 covers stocks whose trading volume is highly concentrated on the primary exchange.

| | Primary Exchange | | | Secondary Exchange | | | Tertiary Exchange | | |
|---|---|---|---|---|---|---|---|---|---|
| | Pre-event | Event | Post-event | Pre-event | Event | Post-event | Pre-event | Event | Post-event |
| Quantile 1 | | | | | | | | | |
| Mean | 5.24% | 20.11% | 15.55% | 3.53% | 21.34% | 10.21% | 4.25% | 21.81% | 15.22% |
| Skewness | 2.37 | 0.01 | 2.89 | 3.40 | 1.05 | 0.82 | 2.07 | -0.36 | 2.28 |
| Median | 2.71% | 19.55% | 11.95% | 0.00% | 19.44% | 9.25% | 0.00% | 23.21% | 8.53% |
| 90th %ile | 17.01% | 31.56% | 31.07% | 11.47% | 38.23% | 22.65% | 17.69% | 32.76% | 36.08% |
| 95th %ile | 25.35% | 39.70% | 49.42% | 23.00% | 59.31% | 30.53% | 25.01% | 32.83% | 47.34% |
| 99th %ile | 36.80% | 39.70% | 100.00% | 46.12% | 59.31% | 39.16% | 33.36% | 32.83% | 100.00% |
| Std Dev | 8.36% | 9.62% | 18.22% | 7.88% | 13.63% | 9.54% | 8.17% | 8.51% | 19.30% |
| Quantile 5 | | | | | | | | | |
| Mean | 11.04% | 23.85% | 22.25% | 4.94% | 10.25% | 23.05% | 1.59% | 17.84% | 13.53% |
| Skewness | 2.01 | 0.07 | 1.53 | 4.50 | 2.23 | 1.29 | 6.43 | 2.18 | 2.27 |
| Median | 0.00% | 21.04% | 8.06% | 0.00% | 0.00% | 0.00% | 0.00% | 13.87% | 0.00% |
| 90th %ile | 37.36% | 45.06% | 94.81% | 19.75% | 33.27% | 100.00% | 0.50% | 33.54% | 34.83% |
| 95th %ile | 54.86% | 45.33% | 100.00% | 32.72% | 69.28% | 100.00% | 4.86% | 100.00% | 84.96% |
| 99th %ile | 83.40% | 45.33% | 100.00% | 100.00% | 69.28% | 100.00% | 59.38% | 100.00% | 100.00% |
| Std Dev | 17.72% | 13.04% | 31.43% | 15.07% | 18.44% | 35.34% | 8.50% | 26.50% | 25.45% |

Table 13: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price below the national best bid. The results are split by individual exchange and across 11 Minute Intervals.The table covers the stocks included in Quintile 1, referring to stocks with the highest degree of volume split across individual exchanges.

| | Pre-event | | | | | Event | Post-event | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | t-5 | t-4 | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 | t+4 | t+5 |
| Primary Exchange | | | | | | | | | | | |
| Mean | 3.66% | 4.10% | 2.88% | 10.10% | 5.47% | 20.11% | 21.72% | 16.85% | 8.29% | 18.33% | 12.56% |
| Skewness | 1.68 | 3.15 | 0.40 | 1.00 | 2.62 | 0.01 | 2.61 | 2.86 | 0.34 | 1.63 | 1.96 |
| Median | 0.00% | 0.74% | 3.70% | 4.37% | 3.85% | 19.55% | 17.41% | 12.19% | 8.35% | 18.29% | 8.02% |
| 90th %ile | 15.20% | 8.76% | 7.21% | 34.29% | 9.50% | 31.56% | 35.09% | 36.02% | 17.86% | 34.24% | 37.16% |
| 95th %ile | 20.49% | 36.80% | 8.66% | 36.34% | 30.20% | 39.70% | 100.00% | 100.00% | 20.50% | 65.62% | 61.67% |
| 99th %ile | 20.49% | 36.80% | 8.66% | 36.34% | 30.20% | 39.70% | 100.00% | 100.00% | 20.50% | 65.62% | 61.67% |
| Std Dev | 6.11% | 8.81% | 2.82% | 11.99% | 7.03% | 9.62% | 22.20% | 23.10% | 6.29% | 15.25% | 15.86% |
| Secondary Exchange | | | | | | | | | | | |
| Mean | 0.65% | 0.78% | 1.73% | 7.13% | 7.46% | 21.34% | 10.81% | 10.56% | 8.18% | 13.42% | 8.01% |
| Skewness | 2.35 | 1.54 | 1.48 | 2.00 | 1.56 | 1.05 | 0.48 | 0.42 | 0.75 | 0.78 | 1.38 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 3.73% | 19.44% | 9.98% | 9.95% | 6.07% | 11.48% | 8.20% |
| 90th %ile | 4.54% | 2.86% | 5.52% | 28.01% | 23.00% | 38.23% | 21.89% | 23.00% | 17.75% | 29.47% | 19.27% |
| 95th %ile | 5.85% | 4.41% | 9.23% | 46.12% | 33.91% | 59.31% | 30.62% | 30.53% | 25.46% | 39.16% | 34.19% |
| 99th %ile | 5.85% | 4.41% | 9.23% | 46.12% | 33.91% | 59.31% | 30.62% | 30.53% | 25.46% | 39.16% | 34.19% |
| Std Dev | 1.73% | 1.31% | 2.75% | 12.98% | 9.31% | 13.63% | 9.24% | 9.96% | 7.35% | 10.59% | 9.05% |
| Tertiary Exchange | | | | | | | | | | | |
| Mean | 1.61% | 1.80% | 3.06% | 5.86% | 9.28% | 21.81% | 17.95% | 15.00% | 14.14% | 17.89% | 11.14% |
| Skewness | 2.83 | 3.42 | 1.61 | 1.14 | 0.96 | -0.36 | 2.54 | 2.47 | 0.93 | 0.34 | 1.27 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 1.64% | 23.21% | 12.46% | 6.41% | 10.32% | 16.67% | 3.87% |
| 90th %ile | 8.05% | 3.11% | 15.05% | 19.92% | 32.13% | 32.76% | 35.98% | 34.11% | 38.46% | 36.36% | 36.19% |
| 95th %ile | 17.69% | 21.81% | 15.53% | 25.00% | 33.36% | 32.83% | 100.00% | 100.00% | 49.55% | 47.27% | 47.42% |
| 99th %ile | 17.69% | 21.81% | 15.53% | 25.00% | 33.36% | 32.83% | 100.00% | 100.00% | 49.55% | 47.27% | 47.42% |
| Std Dev | 4.58% | 5.26% | 5.22% | 7.94% | 12.54% | 8.51% | 23.67% | 24.79% | 14.96% | 14.41% | 14.97% |

Table 14: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price below the national best bid. The results are split by individual exchange and across 11 Minute Intervals.The table covers the stocks included in Quintile 5, referring to stocks with the lowest degree of volume split across individual exchanges.

| | Pre-event | | | | | Event | Post-event | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | t-5 | t-4 | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 | t+4 | t+5 |
| Primary Exchange | | | | | | | | | | | |
| Mean | 2.30% | 6.49% | 12.96% | 17.00% | 16.46% | 23.85% | 34.48% | 31.90% | 19.29% | 21.85% | 4.53% |
| Skewness | 1.20 | 2.35 | 1.86 | 1.60 | 0.27 | 0.07 | 0.84 | 0.91 | 1.81 | 0.89 | 1.97 |
| Median | 0.00% | 0.00% | 8.31% | 5.74% | 12.46% | 21.04% | 23.33% | 12.29% | 2.59% | 18.58% | 0.00% |
| 90th %ile | 8.34% | 28.77% | 54.86% | 56.07% | 37.86% | 45.06% | 100.00% | 100.00% | 100.00% | 55.80% | 25.19% |
| 95th %ile | 11.12% | 52.24% | 64.94% | 83.40% | 38.06% | 45.33% | 100.00% | 100.00% | 100.00% | 68.53% | 31.13% |
| 99th %ile | 11.12% | 52.24% | 64.94% | 83.40% | 38.06% | 45.33% | 100.00% | 100.00% | 100.00% | 68.53% | 31.13% |
| Std Dev | 3.89% | 14.34% | 19.28% | 23.94% | 15.46% | 13.04% | 36.63% | 37.92% | 33.30% | 20.64% | 9.68% |
| Secondary Exchange | | | | | | | | | | | |
| Mean | 0.00% | 0.19% | 5.87% | 6.84% | 10.79% | 10.25% | 38.97% | 28.82% | 23.75% | 27.94% | 0.50% |
| Skewness | . | 3.18 | 1.81 | 1.33 | 3.01 | 2.23 | 0.60 | 0.96 | 1.07 | 0.95 | 3.33 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 30.48% | 2.04% | 0.00% | 10.10% | 0.00% |
| 90th %ile | 0.00% | 0.00% | 32.72% | 28.97% | 19.98% | 33.27% | 100.00% | 100.00% | 66.56% | 86.99% | 0.00% |
| 95th %ile | 0.00% | 2.53% | 37.73% | 33.34% | 100.00% | 69.28% | 100.00% | 100.00% | 100.00% | 100.00% | 6.96% |
| 99th %ile | 0.00% | 2.53% | 37.73% | 33.34% | 100.00% | 69.28% | 100.00% | 100.00% | 100.00% | 100.00% | 6.96% |
| Std Dev | 0.00% | 0.67% | 13.17% | 12.18% | 25.52% | 18.44% | 38.59% | 42.11% | 33.28% | 34.83% | 1.79% |
| Tertiary Exchange | | | | | | | | | | | |
| Mean | 0.00% | 6.60% | 0.00% | 0.30% | 1.32% | 17.84% | 6.62% | 37.00% | 3.69% | 16.84% | 7.17% |
| Skewness | . | 2.47 | . | 2.27 | 2.29 | 2.18 | 1.11 | 0.57 | 1.94 | 1.87 | 2.43 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 13.87% | 0.00% | 14.00% | 0.00% | 11.15% | 0.00% |
| 90th %ile | 0.00% | 59.38% | 0.00% | 2.44% | 4.86% | 33.54% | 26.02% | 100.00% | 14.96% | 34.83% | 19.39% |
| 95th %ile | 0.00% | 59.38% | 0.00% | 2.44% | 10.53% | 100.00% | 27.55% | 100.00% | 25.69% | 84.96% | 59.53% |
| 99th %ile | 0.00% | 59.38% | 0.00% | 2.44% | 10.53% | 100.00% | 27.55% | 100.00% | 25.69% | 84.96% | 59.53% |
| Std Dev | 0.00% | 18.66% | 0.00% | 0.81% | 3.08% | 26.50% | 10.97% | 42.48% | 8.16% | 22.95% | 17.46% |

Table 15: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price above the national best ask. The results are split by individual exchange and across 11 Minute Intervals.The table covers the stocks included in Quintile 1, referring to stocks with the lowest degree of volume split across individual exchanges.

| | Pre-event | | | | | Event | Post-event | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | t-5 | t-4 | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 | t+4 | t+5 |
| Primary Exchange | | | | | | | | | | | |
| Mean | 4.63% | 9.75% | 5.35% | 7.24% | 18.76% | 9.96% | 12.40% | 8.50% | 7.91% | 7.14% | 16.50% |
| Skewness | 1.18 | 0.32 | 0.76 | 1.35 | 1.17 | 0.15 | 0.56 | 0.89 | 0.03 | -0.04 | -0.10 |
| Median | 3.86% | 8.05% | 1.76% | 5.01% | 16.46% | 11.72% | 10.55% | 5.06% | 8.09% | 6.36% | 18.03% |
| 90th %ile | 13.58% | 21.53% | 16.72% | 17.24% | 28.29% | 22.26% | 30.33% | 24.38% | 16.84% | 12.88% | 30.13% |
| 95th %ile | 17.84% | 24.14% | 18.02% | 30.13% | 51.81% | 22.35% | 30.54% | 25.03% | 17.36% | 14.37% | 31.44% |
| 99th %ile | 17.84% | 24.14% | 18.02% | 30.13% | 51.81% | 22.35% | 30.54% | 25.03% | 17.36% | 14.37% | 31.44% |
| Std Dev | 5.10% | 8.68% | 6.36% | 8.19% | 11.34% | 7.44% | 10.26% | 8.80% | 6.72% | 4.47% | 9.80% |
| Secondary Exchange | | | | | | | | | | | |
| Mean | 6.87% | 9.57% | 3.86% | 10.34% | 13.43% | 7.83% | 9.94% | 13.03% | 10.94% | 6.13% | 8.99% |
| Skewness | 2.67 | 1.02 | 1.10 | 1.55 | -0.17 | 0.25 | 0.17 | 2.22 | 0.92 | 0.68 | 0.26 |
| Median | 0.00% | 7.20% | 0.00% | 3.19% | 14.29% | 7.54% | 9.68% | 8.52% | 7.50% | 3.18% | 9.52% |
| 90th %ile | 25.00% | 22.96% | 14.25% | 39.69% | 25.77% | 15.71% | 21.05% | 36.59% | 30.20% | 16.21% | 22.27% |
| 95th %ile | 57.37% | 34.25% | 15.11% | 46.74% | 26.02% | 20.59% | 22.71% | 69.47% | 34.67% | 18.79% | 23.05% |
| 99th %ile | 57.37% | 34.25% | 15.11% | 46.74% | 26.02% | 20.59% | 22.71% | 69.47% | 34.67% | 18.79% | 23.05% |
| Std Dev | 14.55% | 9.65% | 5.23% | 14.23% | 9.45% | 6.48% | 7.07% | 17.23% | 10.39% | 6.37% | 8.17% |
| Tertiary Exchange | | | | | | | | | | | |
| Mean | 2.64% | 14.27% | 5.16% | 14.36% | 18.10% | 6.88% | 5.86% | 5.57% | 9.11% | 5.21% | 11.71% |
| Skewness | 2.61 | 1.25 | 2.79 | 1.52 | 1.10 | 2.18 | 0.75 | 1.42 | 1.55 | 1.07 | 1.33 |
| Median | 0.00% | 4.57% | 0.00% | 5.64% | 12.54% | 4.81% | 4.30% | 1.18% | 3.63% | 2.11% | 6.88% |
| 90th %ile | 14.05% | 51.31% | 15.49% | 41.67% | 45.46% | 16.41% | 15.30% | 15.32% | 24.34% | 16.40% | 30.66% |
| 95th %ile | 25.24% | 59.49% | 45.18% | 66.68% | 53.52% | 35.91% | 18.17% | 26.56% | 44.47% | 20.66% | 50.82% |
| 99th %ile | 25.24% | 59.49% | 45.18% | 66.68% | 53.52% | 35.91% | 18.17% | 26.56% | 44.47% | 20.66% | 50.82% |
| Std Dev | 6.74% | 18.41% | 11.51% | 18.87% | 16.09% | 8.80% | 5.87% | 7.39% | 12.11% | 6.47% | 14.10% |

Table 16: This table shows the percent of per-minute trading volume, executed on a particular exchange, at a price above the national best ask. The results are split by individual exchange and across 11 Minute Intervals.The table covers the stocks included in Quintile 5, referring to stocks with the lowest degree of volume split across individual exchanges.

| | Pre-event | | | | | Event | Post-event | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | t-5 | t-4 | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 | t+4 | t+5 |
| Primary Exchange | | | | | | | | | | | |
| Mean | 16.32% | 24.41% | 24.48% | 24.21% | 25.54% | 22.56% | 11.73% | 11.93% | 13.48% | 5.69% | 24.42% |
| Skewness | 1.37 | 1.27 | 1.33 | 1.20 | 1.34 | 1.09 | 1.01 | 1.74 | 1.35 | 0.85 | 0.54 |
| Median | 3.90% | 0.58% | 0.00% | 0.00% | 11.67% | 8.48% | 8.39% | 5.88% | 11.42% | 3.20% | 23.61% |
| 90th %ile | 47.49% | 100.00% | 100.00% | 100.00% | 100.00% | 70.01% | 28.54% | 42.00% | 30.14% | 13.73% | 65.78% |
| 95th %ile | 77.36% | 100.00% | 100.00% | 100.00% | 100.00% | 82.59% | 44.93% | 59.34% | 59.06% | 20.49% | 70.34% |
| 99th %ile | 77.36% | 100.00% | 100.00% | 100.00% | 100.00% | 82.59% | 44.93% | 59.34% | 59.06% | 20.49% | 70.34% |
| Std Dev | 23.09% | 38.91% | 38.65% | 37.03% | 33.92% | 28.38% | 13.27% | 16.81% | 16.15% | 6.25% | 24.53% |
| Secondary Exchange | | | | | | | | | | | |
| Mean | 22.25% | 28.16% | 8.44% | 12.35% | 24.34% | 27.28% | 14.19% | 21.42% | 4.53% | 9.16% | 26.70% |
| Skewness | 1.31 | 1.10 | 3.01 | 2.37 | 1.28 | 0.97 | 1.40 | 0.96 | 2.95 | 3.10 | 1.05 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 10.14% | 0.00% | 0.00% | 0.00% | 0.09% | 0.00% |
| 90th %ile | 97.09% | 100.00% | 1.33% | 42.38% | 100.00% | 87.16% | 56.20% | 61.58% | 5.60% | 19.91% | 100.00% |
| 95th %ile | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 66.15% | 87.67% | 48.80% | 87.32% | 100.00% |
| 99th %ile | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 66.15% | 87.67% | 48.80% | 87.32% | 100.00% |
| Std Dev | 38.44% | 40.47% | 27.61% | 28.87% | 39.44% | 35.52% | 22.33% | 29.35% | 13.44% | 21.65% | 36.35% |
| Tertiary Exchange | | | | | | | | | | | |
| Mean | 3.68% | 5.86% | 18.18% | 6.25% | 24.29% | 2.82% | 13.03% | 4.92% | 11.21% | 9.45% | 15.67% |
| Skewness | 2.47 | 1.62 | 1.65 | 2.27 | 1.38 | 2.70 | 2.54 | 2.47 | 0.94 | 2.99 | 1.23 |
| Median | 0.00% | 0.00% | 0.00% | 0.00% | 4.21% | 0.00% | 0.00% | 0.00% | 3.70% | 0.00% | 13.48% |
| 90th %ile | 33.11% | 33.33% | 100.00% | 50.02% | 100.00% | 9.22% | 24.68% | 44.26% | 34.96% | 19.56% | 33.37% |
| 95th %ile | 33.11% | 33.33% | 100.00% | 50.02% | 100.00% | 27.09% | 100.00% | 44.26% | 37.57% | 100.00% | 58.37% |
| 99th %ile | 33.11% | 33.33% | 100.00% | 50.02% | 100.00% | 27.09% | 100.00% | 44.26% | 37.57% | 100.00% | 58.37% |
| Std Dev | 10.40% | 11.44% | 38.57% | 16.54% | 36.16% | 7.42% | 28.47% | 13.91% | 15.00% | 26.65% | 17.19% |

Table 17: This table show the primary, secondary and tertiary exchange corresponding to each individual stock included in the dataset. The ranking is calculated based on the recorded trading volume on 19th December 2018 and covers all trading volume recorded during regular trading hours: 9:30 to 16:00.

| Stock | Primary Exchange | Seconary Exchange | Tertiary Exchange | Stock | Primary Exchange | Seconary Exchange | Tertiary Exchange |
|---|---|---|---|---|---|---|---|
| AAL | Q | P | Z | INCY | Q | P | V |
| ADBE | Q | V | P | INTC | Q | Z | P |
| ADI | Q | V | Z | INTU | Q | V | P |
| ADSK | Q | V | P | ISRG | Q | Z | P |
| ALGN | Q | K | V | JBHT | Q | V | Z |
| ALXN | Q | V | P | JD | Q | Z | P |
| AMAT | Q | Z | P | LRCX | Q | V | P |
| AMZN | Q | P | K | MAR | Q | Z | B |
| ASML | Q | V | Z | MCHP | Q | P | Z |
| ATVI | Q | V | Z | MDLZ | Q | Z | P |
| AVGO | Q | V | K | MSFT | Q | Z | V |
| BIIB | Q | V | K | MU | Q | P | Z |
| BKNG | Q | V | Z | MXIM | Q | Z | V |
| BMRN | Q | V | P | MYL | Q | Z | K |
| CDNS | Q | V | Z | NFLX | Q | P | K |
| CELG | Q | V | P | NVDA | Q | P | K |
| CERN | Q | Z | P | ORLY | Q | Z | V |
| CHKP | Q | V | P | PEP | Q | V | Z |
| CHTR | Q | V | Z | PYPL | Q | P | Z |
| CMCS | Q | Z | Y | QCOM | Q | Z | P |
| COST | Q | Z | P | REGN | Q | V | Z |
| CSCO | Q | Z | P | ROST | Q | V | Z |
| CSX | Q | V | Z | SIRI | Q | Z | V |
| CTRP | Q | V | P | SNPS | Q | V | Z |
| CTXS | Q | V | Z | STX | Q | Z | P |
| DLTR | Q | V | Z | SWKS | Q | P | Z |
| EA | Q | Z | P | SYMC | Q | Z | P |
| EBAY | Q | V | Z | TMUS | Q | V | Z |
| ESRX | Q | Z | P | TSLA | Q | P | V |
| FAST | Q | V | Z | TTWO | Q | P | Z |
| FB | Q | V | P | TXN | Q | V | Z |
| FISV | Q | Z | V | ULTA | Q | Z | K |
| FOX | Q | Z | P | VRSK | Q | V | P |
| FOXA | Q | Z | K | VRTX | Q | V | Z |
| GOOG | Q | V | P | WBA | Q | V | Z |
| HOLX | Q | V | Z | WDAY | Q | V | P |
| HSIC | Q | V | Z | WYNN | Q | P | K |
| IDXX | Q | V | K | XLNX | Q | V | P |
| ILMN | Q | V | Z | XRAY | Q | P | Z |

# Chapter III
# The Shortcomings of Segment Reporting and their Impact on Analysts' Earnings Forecasts

Robert Gutsche Alexandru Rif

**Abstract**

We deliver US-sample based evidence suggesting that segment reporting biases analysts' earnings per share forecasts. We show that the error in EPS forecasts corresponds to a profitability "gap" between profitability aggregated from segment reporting and profitability computed from consolidated financial statements, in particular when segment reporting is overly optimistic. We show that the forecast error is associated with the profitability gap when reported segments lack major profitability components such as assets, revenue, or operating income. Our panel consists of a sample of 591 US listed companies and covers the period 2009 to 2016.

*JEL classification*: M41, M10, M21, G32.

*Keywords*: ASC 280 (SFAS 131), IFRS 8, Forecast accuracy, Segment reporting.

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# 1. Introduction

The necessity of understanding individual business activities and the importance of disaggregated information availability when analyzing companies and forecasting their earnings is long acknowledged and considered to be indispensable (Jenkins Committee, 1962; Association for Investment Management and Research (AIMR), 1993; American Institute of Certified Public Accountants (AICPA), 1994; Epstein and Palepu, 1999). In this respect, segment reporting complements information given in consolidated primary financial statements (balance sheet, income statement, and cash flow statement, equity statement). Without segment reporting, the consolidated financial statements, inherently, provide only limited information on individual business activities (Chen and Zhang, 2003). Accordingly, research documents that segment reporting provides new and useful information to analysts and investors, assists in forecasting earnings (Ettredge et al., 2005; Botosan et al., 2011) and potentially reduces information asymmetries (Kajüter and Nienhaus, 2017).

However, segment reporting may not be useful per se. There are reasonable concerns that segment reporting under the management approach warrants earnings management on segment level and impairs segment reporting quality. Indeed, under the current approach of segment reporting,

- the disclosed segment split (i.e., disaggregation of consolidated financial statement information to report individual business activities as segments),
- the line item granularity (reported line items per segment),
- the use of non-GAAP recognition and measurement principles for segment reporting, and
- the allocation of transactions (i.e., revenue, assets, operating income, etc.) to segments

are highly discretionary. They provide management "leeway" to manage earnings on segment level (Wang and Ettredge, 2015; Berger and Hann, 2007; Givoly et al., 1999; Lail et al., 2014). Coupled with a lack of transparency regarding the actual criteria underlying management's segment reporting decisions, the management approach under ASC 280 (SFAS 131)–which is also adopted by IFRS 8–raises understandability and reliability concerns (e.g., ESMA, 2011; KPMG, 2010).

In this paper, we use the error in annual consensus EPS forecasts as a metric to analyze the usefulness of segment reporting for US-companies, which report segments according to ASC 280 (SFAS 131). We link the EPS forecast error to the "gap" between profitability aggregated from segments and the firms' consolidated profitability. Based on annual reporting data of 591 diversified US listed companies from 2009 to 2016, we find that segments, which lack key profitability components (i.e., revenue, assets, and/or operating income) yield a statistically significant EPS forecast error.

Our findings suggest that analysts neglect segments with incomplete data per segment (transaction allocation) in their EPS forecasts. Analysts seem to focus on those segments with a "full story" (i.e., with a complete set of profitability components per segment). Referring to prior literature that finds that the non-GAAP measurement "gap" between segment and consolidated statements affects stock returns (Wang and Ettredge, 2015; Alfonso et al., 2012), in our research setting, we do not find a statistically significant effect of the use of non-GAAP measures for segment reporting on the accuracy of forecasted EPS. Furthermore, we provide evidence suggesting that an increased segment split (i.e., more information) is not associated with an increase in analyst forecast accuracy. On the contrary, an increased segment split is associated with lower forecast accuracy. This finding might result from the (poor) quality of the segment split disclosed by firms under the management approach, coupled with a trade-off between line item granularity and increases in the actual segment split. (Bugeja et al., 2015; Ettredge et al., 2006; Gotti, 2016).

# 2. Background, Literature and Hypotheses

Diversified companies are a bundle of individual business activities with different risk, return and growth profiles (Krüger et al., 2015). Their assessment is inherently relevant for earnings forecasts and valuation analysis (Chen and Zhang, 2003; Botosan et al., 2011). Hence, unwinding individual business activities of diversified firms is vital for understanding the firm as a whole and underlines the importance of disaggregated information availability. Therefore, information provided in segment reporting should ideally correspond to the individual business activities and their idiosyncratic characteristics (Herrmann and Thomas, 2000; Langdon, 1973; Collins, 1975). For example, analysts perceive segment reporting as more reliable when similar products, rather than dissimilar products are combined in a segment (Maines et al., 1997).

## *2.1. Segment reporting under ASC 280 and IFRS 8*

However, the discussion regarding how segment reporting should be designed–or even whether segment reporting should exist at all–is almost half a century old (Jenkins Committee, 1962) and still a topic of debate and improvement, PIR IFRS (2017). The current approach to segment reporting under ASC 280 (introduced in 1997) and IFRS 8 (introduced in 2006) is the so-called management approach. It addresses the aforementioned idea of splitting primary financial statements into segments based on the managements' perspective on business activities. It aligns external with internal reporting for segments. Analysts favor this congruency of internal and external reporting, since they perceive it as more reliable compared to a segment reporting approach that differs from the firms' perspective on business activities (Maines et al., 1997; Botosan et al., 2011).

The management approach replaced the former risk-reward approach that required segments to be reported according to risk-reward profiles of a firm's individual business or geographical activities and required the reporting of specific line items that had to be consistent with accounting principles used to prepare the primary financial statements. The standard setters expected the management approach to deliver 'more' useful information when compared to the the risk-reward approach. By taking the perspective of the chief operating decision maker on business activities, the management approach is expected to disaggregate consolidated financial statement information based on the risk and rewards that the management thinks is important (Nichols et al., 2013; André et al., 2016). Hence, the internal view of the management is expected to reflect the management's "fair" view on segment performance and segment-related risk (Wang and Ettredge, 2015).

However, the management approach indisputably gives the management leeway to manipulate earnings information at the segment level (Wang and Ettredge, 2015). Research documents that firms shift income between reported segments with the aim of managing segment earnings (Berger and Hann, 2007; Lail et al., 2014). Since revenue and cost allocation requirements are tied to management's discretion and are lacking transparency, managers have incentives to overemphasize or hide segment profitability when agency or proprietary costs avoidance is high (Givoly et al., 1999; Botosan and Stanford, 2005). One example can be traced back to the segment reporting of utility companies, such as electricity providers, who often, in their reporting practice, split their power generating business unit from the power trading business unit. The current lapse regulation can result in lack of transparency between revenue and cost allocation between these two segments, blurring the actual profitability of the generating and trading activities.

We identify the segment split, the line item granularity, the recognition and measurement of segment data, and the allocation of transactions to segments as the primary dimensions for the analysis of the quality of segment reporting. We therefore, briefly discuss these four dimensions and their implications on fundamental analysis and the EPS forecast error metric in order to develop our hypotheses.

### *2.2. Segment Split*

The adoption of the management approach increased the number of reported business segments (Herrmann and Thomas, 2000; Street et al., 2000; Berger and Hann, 2003) and reduced single segment reporting (Botosan and Stanford, 2005). Intrinsically, an increased number of segments increases the available information. It enables diversified firms to report on different individual business activities. This corresponds to the idea of increasing the disclosure on business activities with different idiosyncratic risk-reward characteristic (Herrmann and Thomas, 2000). However, more segment information does not necessarily increase the information value of segment reporting. If understandability is limited, the analysis becomes less reliable (Maines et al., 1997) and analysts will primarily base their forecasts more on the consolidated financial statements which have stricter reporting requirements.

The segment split criteria–whether business activities have or have not been aggregated in segments–are seldom stated by companies in their reports and remain unclear (ESMA, 2011; KPMG, 2010). This lack of transparency is particularly striking, given that firms have full discretion over changing the segment split at any time if justified by the management's view on the business activities. Inconsistencies over time, but also between firms, restrain understandability and reliability of the segment split. Furthermore, there are no strict requirements to allocate (annual and/or quarterly) cost and revenue to segments on a consistent basis. In fact, quarterly segment reporting can deviate from annual segment reporting and must not add up to full year reporting numbers. Therefore, we hypothesize that:

H1: In contrast to the intention of the standard setter, the segment split is positively associated with EPS forecast error.

### *2.3. Line item granularity*

Detailed financial statement data (from line items) flows into the decision making process of market participants (Abarbanell and Bushee, 1997). Profitability, growth and their drivers are linked to stock returns (Akbas et al., 2017; Cooper et al., 2011; Nissim and Penman, 2001). Extant literature emphasizes the importance of profitability metrics, such as operating profit margin and asset turnover and their development over time and cross-sections for market participants in forecasting earnings and future profitability (Fairfield and Yohn, 2001; Soliman, 2008). Hence, in order to facilitate earnings forecasts and valuation tasks the availability of segment line items such as sales, costs and assets and their breakdown (i.e., nature of assets, costs, sales) is indispensable. If line item granularity is high and provided on segment level, it fundamentally assists in forecasting earnings and cash flows of individual business activities. It allows the assessment of overall firm fundamental risk and firm value.

However, line item disclosure is only required for key income statement items and only if the management actively uses these items in their decision-making process (SFAS 131.27, similarly IFRS 8.23), therefore putting segment line item reporting at the full discretion of the management.

In fact, firms appear to be resilient in providing a detailed line item breakdown of their business activities. Documenting the surfacing of a trade-off between line item disclosure and number of reported segments, studies find evidence of an actual reduction of line item disclosure when increasing the segment split following the implementation of the management approach (Bugeja et al., 2015; Ettredge et al., 2006; Gotti, 2016). In particular, key items such as assets per segment and capital expenditure per segment decrease while equity investments/income, income tax or interests expense/income marginally increase (Street et al., 2000; Herrmann and Thomas, 2000).

Furthermore, the reported segment line items do not provide the necessary depth needed to analyze the segment's value drivers. Key line items such as income tax expense, interest revenue, interest expense, R&D expense, and similar, which would allow analysts to disentangle segment earnings into operating results, are only scarcely and selectively reported (Herrmann and Thomas, 2000). Other critical items such as leases, financial assets, or operating liabilities against customers and suppliers (advance payments, or accounts payable) are not required to be reported separately for segments at all, and depend on the discretion of firms to report line items voluntarily.

Hence, line item granularity is helpful, if it is comprehensive and reconcilable. However, given the incomplete and discretionary character of line item reporting per segment and no requirement to reconcile segment line items to the line items in the consolidated statements, firms will provide increased discretionary (as opposed to mandatory) line item granularity in order to avoid agency or proprietary costs (Givoly et al., 1999; Botosan and Stanford, 2005). Ergo, the concept of line item reporting under the management approach potentially distorts the perception of the analyst. Consequently, we hypothesize that:

H2: In contrast to the intention of the standard setter, line item reporting is positively associated with EPS forecast error.

## *2.4. Non-GAAP segment accounting*

Under the management approach, firms are allowed to use internal accounting principles for the recognition and measurement of line items (ASC 280-10-50-27, and similarly IFRS 8.25). However, non-GAAP measures may be difficult to interpret (e.g., IFRS 8, BC12). As a result, the recognition and measurement of segment line items might not add up to the earnings, the financial position or the cash flow presented in consolidated financial statements. The use of internal reporting policies for segment reporting creates indeed a gap and therefore reconciliation is required by the standard setter. However, a full reconciliation that tracks segment data mismatches back to the individual line items of consolidated financial statements is not required. Under the current standard, a mere reconciliation of totals is deemed sufficient (ASC 280-10-50-30, 55-49).

Studies analyzing the aforementioned reconciliation gap find that segment reporting yields aggregated segment earnings in excess of consolidated earnings, a so-called negative gap (Wang and Ettredge, 2015; Alfonso et al., 2012). This suggests an incomplete allocation of expenses or losses to segments. A negative gap exhibits a stronger association with stock returns, as opposed to a positive gap (i.e., consolidated earnings in excess of aggregated segment earnings); recurring and larger gaps are associated with high proprietary and agency costs and, moreover, the gaps are positively associated with surrogates of income items for which managers are unlikely to be held responsible (i.e., corporate intangibles, acquisition activity and special or unusual items) (Wang and Ettredge, 2015). Nevertheless, segment earnings appear to be incrementally useful to investors when measured against stock returns (Wang and Ettredge, 2015; Hollie and Yu, 2012). However, the market appears to be mispricing the non-GAAP metrics, by not acknowledging the informational value of a full reconciliation (Hollie and Yu, 2012), despite evidence suggesting that the gap is value-relevant (Alfonso et al., 2012).

An explanation, as to why this mispricing appears could stem from earnings projections. Hence, it is important and it remains an open empirical question whether this gap is associated with an error in analyst forecast. Following the conceptual approach in the aforementioned studies, we calculate the gap between segment-based and consolidated statement-based "profitability gap" and analyze its association with the forecast error.

Profitability of core business activities, as a key metric for business analysis and valuation, e.g. it is an "anchor" for each valuation exercise. It helps forecasting future earnings of the firm if profitability metrics effectively reveal operating profitability of individual business activities. A key prerequisite for this task, however, is a disaggregation of business activities and a relevant line item reporting on segment level. A blurred picture of segment profitability is a setback that comes at the cost of a proper analysis of segment profitability and its usefulness in evaluating the firm's prospects (Penman, 2013). In fact, prior research also shows that the incremental information value of segment reporting is low and can be attributed to considerable measurement errors in reported segments (Chen and Zhang, 2003; Givoly et al., 1999).

Given the level of discretion allotted to management by anchoring segment reporting to the internal reporting practices, the low reconciliation requirements under ASC 280-10-50-30, 55-49 (and similarly IFRS 8.28, IG4), as well as a lack of transparency and understanding of segment data, we hypothesize that:

H3: The gap between non-GAAP aggregated profitability, derived from segment reporting, versus GAAP consolidated profitability, as obtained from consolidated primary financial statements is positively associated with the EPS forecast error.

### *2.5. Allocation of transactions to segments*

Segment reporting might increase proprietary cost (i.e., managers conceal segments with relatively high abnormal profits to avoid harmful competition) or agency cost (i.e., managers hide segments with relatively low abnormal profits to protect their self-interest) of firms (Berger and Hann, 2007; Wang et al., 2011; Lail et al., 2014; Ettredge et al., 2006; Bugeja et al., 2015; Givoly et al., 1999). This incentivizes management not to accurately reveal segment profitability under the management approach, unless constrained to do so by dependance on external financing (Ettredge et al., 2006). Indeed, under the flexibility of the management approach, firms strategically report segment performance by shifting income between segments (Lail et al., 2014) and firms increased the number of segments under the management approach without revealing significantly more about differences in segment profitability (Ettredge et al., 2006).

In this sense, we introduce a profitability gap metric that aims at capturing the effect arising from segments for which key profitability items are missing. This metric enables us to investigate whether segments with an incomplete set of profitability items, have an effect on the observed forecast error. We calculate the profitability gap between segment reporting and the consolidated financial statements depending on missing profitability components for reported business segments. We hypothesize that

H4: The profitability gap arising from segments with missing profitability components (sales, assets, or/and operating income) is positively associated with the EPS forecast error.

# 3. Research Design

We test our hypotheses by running a set of regressions based on the model formalized under Equation 1:

$$\begin{aligned} F\_Error_{i,t} &= \beta_0 + \beta_1 SplitBS_{i,t} + \beta_2 GranBS_{i,t} + \beta_3 PrftGap_{i,t} + \\ &\quad + \Sigma Controls_{i,t} + IndustryFE + YearFE + \xi_{i,t} \qquad (1) \end{aligned}$$

Where, $F\_Error$ denotes the forecast error, $SplitBS$ stands for our segment business segment split variable, $GranBS$ stands for the business segment line item granularity, $PrftGap$ denotes the profitability gaps resulting from transaction allocation and non-GAAP accounting. Throughout all our different model specifications, we control for industry and year fixed effects, as well as include relevant control variables shown in prior literature to impact analysts' earnings forecast accuracy (Baldwin, 1984; Behn et al., 2008; Hope, 2003). All metrics are explained in the following and additional information is provided in the Appendix. Furthermore, given the nature of our study, we acknowledge the potential limitations caused by endogeneity within our analysis, stemming changes in segment split, segment reporting frameworks, management incentive schemes, etc.

We calculate the forecast error at time t, using the mean of all available analyst earnings forecasts, as:

$$F\_ERROR_{i,t} = \frac{|EPS_{i,t} - EPS\ Forecast_{i,t-1}|}{Price_{i,t}} \tag{2}$$

As an additional check, we recalculate the forecast error by scaling it by book value per share, as well as price at $t-1$ and obtain similar results throughout our analyses. To address our first hypothesis (H1), we investigate the cross-sectional effect of the reported segment split, $SplitBS$, on the forecast error. We measure the degree of business activity aggregation in reported segments at time t by constructing an Herfindahl-Hirschman index based metric with respect to segment business revenue (Berger and Hann, 2007; Kang et al., 2017). We calculate the index as the sum of the squared ratios of individual segment revenue to total firm revenue. Since the Herfindahl-Hirschman index is a concentration metric, we calculate $SplitBS$ then as one minus the Herfindahl-Hirschman index to emphasize the effect of splitting financial information into segments:

$$SplitBS_{i,t} = 1 - \sum_{j}^{n} \left( \frac{BusinessSegmentRevenue_{i,j,t}}{TotalRevenue_{i,t}} \right)^2 \tag{3}$$

Where:

$n$ denotes the number of business segments of firm $i$ at time $t$.

By construction, this metric will range from 0 to below 1, whereby firms with an increased breakdown of business activities, the segment split, will score higher, while firms with a high degree of aggregation of business activities in few segments will score lower on the scale.

As mentioned in the previous section, we expect that the reported segment structure does not mirror actual firm diversification due to the discretionary segment split, income shifting between segments and internal management principles. We specifically control for diversification, in order to mitigate for the possibility that the effect captured by $SplitBS$ on the $F\_ERROR$ is in fact driven by actual firm diversification. Research suggests that more diversified firms have a higher segment split, reporting more segments (Kang et al., 2017). However, as a matter of this study, it makes sense to distinguish between segment split and diversification. The segment split is discretionary, mimicking managements perspective on the firms' activities. Thus, we control for diversification by counting the number of disclosed industry codes obtained from the first two digits of the reported NAICS codes and correspondingly include dummy variables throughout all our model specifications.

To address our second hypotheses (H2), we count the reported line items for each segment and then determine the number of line items each firm typically uses for the reporting of its segments. We conjecture that the most representative number of line items that a firm "typically" discloses is identified as the median number of the line items disclosed per segment for each firm in a given year. We then scale this number of line items for each firm by the highest such observed value on a yearly basis. The resulting metric, ranging from 0 to 1, serves as a means of differentiating companies with various degrees of line item disclosure, with higher values signaling an increased number of line items. We calculate this metric for mandatory line items according to ASC 280 (Compustat items: dps, esubs, ias, ivaeqs, nis, ops, revts) and for discretionary line items (all other Compustat items in the business segment data set with non-missing values) separately.

We approach our third hypotheses (H3) by computing the profitability gap as a result of non-GAAP vs GAAP accounting in segment reports. $ROAGap1$ is the "gap" between aggregated unlevered segment profitability and unlevered firm level profitability as obtained from the end of year financial statements. A similar approach can be found in Wang and Ettredge

(2015), Alfonso et al. (2012), or Hollie and Yu (2012).

$$ROA\ Gap1_{i,t} = \left|ROA_{i,t} - aggROA1_{i,t}\right| \tag{4}$$

Where,

$$aggROA1_{i,t} = \frac{\sum_j^n Op.IncomeSegments(afterTax)_{i,j,t}}{\sum_j^n SegmentAssets_{i,j,t}} \tag{5}$$

And,

$$ROA_{i,t} = \frac{Op.Income(afterTax)ConsolidatedFin.Statements_{i,t}}{TotalAssets_{i,t}} \tag{6}$$

With $i$ denotes the firm, $j$ the segment and $t$ the time period.

We also compute the profitability gap as a levered metric $ROEGap1$.

$$ROEGap1_{i,t} = \left|ROE_{i,t} - aggROE1_{i,t}\right| \tag{7}$$

We reconstruct firm level return on equity from segment level return on assets as follows:

$$\begin{aligned} aggROE1\ _{i,t} \quad &= \quad aggROA1_{i,t} + \frac{TotalDebt}{TotalEquity} \times (aggROA1_{i,t} - \\ &\quad -NetBorrowingCosts_{i,t}) \end{aligned}$$

with $n$ representing the number of segments of firm $i$ at time $t$.

We use as a proxy for net borrowing costs (after taxes) the difference between operating income (before taxes) and net income (after tax) scaled by total debt:

$$NetBorrowingCosts_{i,t} = \frac{OpIncome(beforeTax)_{i,t} - NetIncome_{i,t}}{TotalDebt_{i,t}} \tag{8}$$

Return on equity on firm level is calculated by:

$$ROE_{i,t} = \frac{NetIncome_{i,t}}{TotalEquity_{i,t}} \tag{9}$$

For our fourth hypothesis (H4), we calculate $ROAGap2$, $ROAGap3$ as well as a levered version of the gaps: $ROEGap2$ and $ROEGap3$, similarly as before for $ROEGap1$. However, in the case of $ROAGap2$ we completely exclude all segment profitability components (segment operating income and segment assets) for those segments that do not report segment revenue or assets. When calculating $ROAGap3$ we completely exclude all segment profitability components (segment operating income and segment assets) for those segments that do not report segment revenue or assets or operating income. As a result, the difference between $ROAGap2$ and $ROAGap3$ stems from those segments which do not report segment assets yet report operating income. These particular cases are excluded from aggregated segment profitability when generating $ROAGap3$.

## *3.1. Controls*

In line with accounting quality research, we control for earnings quality by including the accruals amount derived from the cash flow statement as a control variable in our regression model (Hribar and Collins, 2002). This is also in line with forecasting literature, which finds that analysts consistently take into account discretionary accruals when issuing earnings forecasts (Givoly et al., 2011).

Analyst coverage is found to have a positive effect on earnings forecast accuracy (Huang et al., 2017). To account for this in our model, we control for the number of analysts' opinions that flow into the earnings forecast.

Volatile earnings are more difficult to forecast (Dichev and Tang, 2009). We calculate the 5-year earnings volatility for our sample and include it as an additional control in our models.

Larger firms are more likely to have increased press coverage and receive greater analyst attention (Kothari et al., 2009). We use total revenue as a proxy for firm size and control for it throughout our analysis.

We control for leverage, since research has shown that firms relying more heavily on external financing are willing to reveal more information about segment profitability differences (Ettredge et al., 2006).

All our models include firm parameters such as the ratio of accruals, number of analysts' estimates that contribute to the earnings forecast, the standard deviation of the past 5 years' earnings per share, while also controlling industry, year, diversification fixed effects and firm random effects. As a robustness check, we rerun our regressions controlling for firm fixed effects and find similar results.

# 4. Data

Our initial dataset contains 4,411 US listed firms covering the 8-year period from 2009 to 2016. We select 2009 as the starting year for our analysis, as it excludes the financial crisis, yet covers the period of internationally harmonized segment reporting (ASC 280 was adopted in substance by IFRS 8). Furthermore, by exclusively relying on a US sample, we ensure comparability and homogeneity in reporting within our observed firm pool. Nevertheless, due to the strong convergence between IFRS 8 and ASC 280 our results are relevant also for firms reporting under IFRS 8.

Due to the nature of our research question, we restrict our analysis to firms reporting two or more business segments. We also eliminate firms with only 1 geographical segment and for those segments for which the segment type specification is missing. Furthermore, we eliminate firms with missing data, negative book value of equity (since our analysis bases on calculations of also levered profitability gap) and outliers (when the forecast error is greater than 800%). We drop firms which trade at a price below 1 USD, for which no earnings forecast is available, those for which we cannot calculate the past 5 year's earnings standard deviation, as well as those for which no segment level data exists (Akbas et al., 2017). The breakdown of our sample selection procedure and the corresponding firm count is presented in Table 1. We also additionally conducted all our analyses using a winsorised dataset, yielding similar results.

Table 1: This table shows, step-by-step, our sample selection process. Our final sample consists of 591 firms and covers 2,786 firm-year observations. To alleviate the survivorship bias, we do not require firms to have observations for all years, therefore yielding an unbalanced panel

| | |
|---|---|
| 4,411 | – U.S.-listed firms (Compustat) – Initial Sample |
| 1,918 | – after dropping firms with less than 2 business segments |
| 1,141 | – after dropping firms with less than 2 geographical segments |
| 1,137 | – after dropping firms with missing type of segments |
| 1,025 | – after dropping penny stocks |
| 1,007 | – after dropping firms with negative book value |
| 901 | – after dropping outliers in terms of forecast error (F Error >8) |
| 894 | – after dropping firms for which no analyst coverage exists |
| 892 | – after dropping firms which do not have 5-yr earnings history |
| 885 | – after dropping firms with missing accruals |
| 606 | – after dropping firms with no segment profitability metrics |
| 598 | – after dropping firms for which no total debt is disclosed |
| 591 | – after dropping extreme ROE values (ROE >500%) |
| 591 | – Working Sample (2,786 Firm – Years) |

Our final sample consists of 591 firms whith 2,786 firm-year observations. To alleviate the survivorship bias, we do not require firms to have observations in all years, resulting in an unbalanced panel.

Table 2: This table presents descriptive statistics referring to our final sample of 591 firms. A breakdown showing descriptive statistics for each variable on a year by year basis is available in Table 8 in the Appendix.

| | n | m | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| F ERROR | 2,790 | 0.051 | 0.132 | 0.007 | 0.019 | 0.044 |
| F ERROR (Sign) | 2,790 | -0.033 | 0.138 | -0.035 | -0.009 | 0.003 |
| ROA Gap1 | 2,790 | 0.035 | 0.176 | 0.001 | 0.006 | 0.021 |
| ROA Gap2 | 2,790 | 0.049 | 0.086 | 0.009 | 0.027 | 0.058 |
| ROA Gap3 | 2,790 | 0.031 | 0.059 | 0.006 | 0.017 | 0.036 |
| ROA Gap1 (Sign) | 2,790 | 0.019 | 0.178 | -0.004 | 0.000 | 0.009 |
| ROA Gap2 (Sign) | 2,790 | 0.037 | 0.092 | 0.000 | 0.022 | 0.053 |
| ROA Gap3 (Sign) | 2,790 | 0.020 | 0.063 | 0.000 | 0.013 | 0.031 |
| ROE Gap1 | 2,541 | 0.046 | 0.102 | 0.017 | 0.029 | 0.047 |
| ROE Gap2 | 2,541 | 0.035 | 0.047 | 0.012 | 0.024 | 0.043 |
| ROE Gap3 | 2,541 | 0.037 | 0.066 | 0.011 | 0.023 | 0.044 |
| ROE Gap1 (Sign) | 2,541 | -0.058 | 0.391 | -0.109 | -0.057 | -0.023 |
| ROE Gap2 (Sign) | 2,541 | -0.059 | 0.233 | -0.091 | -0.039 | 0.003 |
| ROE Gap3 (Sign) | 2,541 | -0.030 | 0.236 | -0.075 | -0.023 | 0.027 |
| SplitBS | 2,790 | 0.519 | 0.195 | 0.421 | 0.532 | 0.666 |
| SplitGS | 2,790 | 0.467 | 0.227 | 0.300 | 0.491 | 0.657 |
| GranBS_M | 2,790 | 0.725 | 0.152 | 0.571 | 0.857 | 0.857 |
| GranBS_D | 2,790 | 0.427 | 0.119 | 0.368 | 0.421 | 0.474 |
| GranGS_M | 2,790 | 0.364 | 0.183 | 0.167 | 0.417 | 0.500 |
| GranGS_D | 2,790 | 0.331 | 0.075 | 0.276 | 0.345 | 0.345 |
| ACCRUALS | 2,790 | 0.040 | 0.026 | 0.026 | 0.035 | 0.047 |
| NESTIMATES | 2,790 | 0.215 | 0.154 | 0.098 | 0.176 | 0.314 |
| EPS_STDEV | 2,790 | -0.080 | 1.174 | -0.841 | -0.170 | 0.519 |
| MARKET CAP | 2,790 | 8,315 | 23,338 | 757 | 2,082 | 5,676 |
| ASSETS | 2,790 | 9,491 | 39,627 | 764 | 2,255 | 5,957 |
| REVENUE | 2,790 | 7,263 | 18,161 | 744 | 1,960 | 5,012 |
| DEBT TO EQUITY | 2,790 | 0.835 | 1.587 | 0.180 | 0.481 | 0.880 |
| NSEGBUS | 2,790 | 4.318 | 1.669 | 3 | 4 | 5 |
| NSEGGEO | 2,790 | 4.767 | 3.496 | 3 | 4 | 6 |
| NNAICSBUS | 2,790 | 4.007 | 2.029 | 3 | 4 | 5 |
| NNAICSGEO | 2,790 | 1.853 | 0.399 | 2 | 2 | 2 |

# 5. Empirical Results

In this section we empirically investigate the relationship between segment reporting and analyst's earnings forecast error. It is important to note, that by construction, the forecast error throughout our analysis is depicted as a delta Earnings-to-Price ratio. To get a benchmark for the magnitude of the reported forecast errors, as well as to help in interpreting our results, one might consider a normal Price-to-Earnings Ratio of 10, which translates to Earnings-to-Price ratio of 0.1. While looking at Table 2, we report the interquartile range for the forecast error at 0.044-0.007 or 0.037, which in turn translates to 37% of a normal Earnings-to-Price ratio. Given this observed magnitude, a better understanding of the drivers of earnings forecast errors is of importance for all market participants, in particular to those who heavily rely on earnings multiples for valuation or investment purposes.

## *5.1. Descriptive Statistics and Univariate Analysis*

Table 2 reports the descriptive statistics for our working sample. We report the correlation matrix in Tables 3 a and 3 b. For a complete description of our variables and data sources please refer to Table 9 in the Appendix.

**Forecast Error (denoted as delta earnings-to-price ratio)**: The mean (median) absolute forecast error $F\_ERROR$ scaled by price at time t is 0.051 (0.019). If the sign of the forecast error is considered, the mean (median) value of the forecast error of the $F\_ERROR(Sign)$ is -0.033 (-0.009). Table 4, Panel A splits and ranks the different profitability gap variables according to the forecast error quintiles. We observe that the higher quintiles of $F\_ERROR$ correspond to higher mean (median) profitability gaps, suggesting that EPS forecasts might indeed be influenced by segment reporting. However, the standard deviation of the profitability gaps is relatively high when the profitability gaps are split and ranked according the $F\_ERROR$ and $F\_ERROR$ $(Sign)$. We analyze this relationship further in a multivari-

Table 3 a: This table covers the correlations between our selected variables. Spearman (Pearson) correlations are reported below (above) the diagonal, while bold entries denote significance at $p < .05$

| | F ERROR | F ERROR (Sign) | ROA Gap1 | ROA Gap2 | ROA Gap3 | ROA Gap1 (Sign) | ROA Gap2 (Sign) | ROA Gap3 (Sign) | ROE Gap1 | ROE Gap2 | ROE Gap3 | ROE Gap1 (Sign) | ROE Gap2 (Sign) | ROE Gap3 (Sign) | SplitBS | SplitGS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| F ERROR | 1 | **-0.336** | 0.028 | **0.074** | **0.115** | **-0.069** | **-0.138** | **-0.117** | **0.117** | **0.302** | **0.250** | -0.006 | 0.035 | 0.010 | 0.016 | 0.005 |
| F ERROR (Sign) | **-0.573** | 1 | -0.026 | **-0.068** | **-0.111** | **0.068** | **0.145** | **0.123** | **-0.104** | **-0.269** | **-0.221** | 0.009 | -0.018 | 0.009 | -0.025 | -0.021 |
| ROA Gap1 | **0.188** | **-0.165** | 1 | **0.398** | **0.486** | **0.930** | **0.110** | **0.204** | **0.709** | **0.227** | **0.183** | **0.738** | **0.049** | 0.033 | **0.048** | 0.008 |
| ROA Gap2 | 0.031 | 0.032 | **0.314** | 1 | **0.781** | **0.216** | **0.521** | **0.480** | **0.216** | **0.342** | **0.599** | **0.160** | **0.176** | **0.301** | 0.027 | 0.012 |
| ROA Gap3 | **0.088** | -0.057 | **0.473** | **0.885** | 1 | **0.354** | **0.462** | **0.621** | **0.305** | **0.447** | **0.433** | **0.285** | **0.267** | **0.291** | **0.055** | 0.025 |
| ROA Gap1 (Sign) | -0.033 | 0.050 | **0.118** | **0.217** | **0.201** | 1 | **0.467** | **0.535** | **0.612** | **0.051** | **0.021** | **0.773** | **0.097** | **0.096** | **0.044** | 0.018 |
| ROA Gap2 (Sign) | **-0.097** | **0.153** | **0.117** | 0.778 | **0.625** | **0.234** | 1 | **0.804** | **-0.071** | **-0.130** | **-0.141** | **0.163** | **0.301** | **0.529** | 0.021 | **0.039** |
| ROA Gap3 (Sign) | -0.069 | **0.088** | **0.122** | **0.671** | **0.694** | **0.336** | **0.893** | 1 | -0.035 | **-0.092** | **-0.053** | **0.277** | **0.435** | **0.497** | 0.037 | **0.048** |
| ROE Gap1 | **0.133** | 0.018 | **0.210** | 0.059 | 0.036 | **-0.204** | **-0.123** | **-0.199** | 1 | **0.690** | **0.548** | **0.438** | **-0.045** | **-0.067** | 0.037 | -0.023 |
| ROE Gap2 | **0.129** | -0.030 | **0.166** | 0.049 | 0.042 | **-0.144** | **-0.152** | **-0.212** | **0.513** | 1 | **0.790** | 0.008 | **-0.093** | **-0.122** | 0.035 | -0.031 |
| ROE Gap3 | **0.171** | **-0.092** | **0.191** | **0.181** | **0.209** | -0.0527 | -0.025 | -0.035 | **0.391** | **0.773** | 1 | 0.013 | -0.030 | **-0.050** | 0.013 | **-0.043** |
| ROE Gap1 (Sign) | **0.240** | **-0.240** | **0.212** | 0.066 | **0.182** | **0.450** | **0.185** | **0.334** | **-0.464** | **-0.291** | **-0.156** | 1 | **0.833** | **0.682** | 0.017 | 0.014 |
| ROE Gap2 (Sign) | **0.236** | **-0.243** | **0.168** | **0.337** | **0.457** | **0.317** | **0.474** | **0.631** | **-0.445** | **-0.335** | **-0.097** | **0.495** | 1 | **0.903** | -0.012 | 0.018 |
| ROE Gap3 (Sign) | **0.204** | **-0.162** | **0.153** | **0.537** | **0.512** | **0.334** | **0.676** | **0.693** | **-0.385** | **-0.337** | **-0.100** | **0.430** | **0.928** | 1 | -0.005 | 0.021 |
| SplitBS | -0.039 | 0.033 | 0.069 | 0.011 | 0.0311 | 0.081 | 0.051 | 0.074 | 0.022 | -0.053 | -0.046 | 0.014 | -0.001 | -0.001 | 1 | **0.140** |
| SplitGS | 0.001 | -0.014 | **0.084** | -0.027 | -0.038 | **0.099** | 0.010 | 0.023 | -0.054 | -0.059 | **-0.083** | 0.005 | -0.039 | -0.043 | **0.165** | 1 |
| GranBS_M | -0.030 | 0.047 | 0.018 | **0.139** | **0.132** | **-0.094** | **0.124** | **0.106** | -0.071 | **-0.088** | **-0.085** | -0.0183 | **0.103** | **0.109** | **-0.150** | **-0.224** |
| GranBS_D | -0.023 | 0.009 | **-0.109** | 0.048 | 0.054 | 0.064 | **0.109** | **0.138** | -0.021 | -0.058 | -0.039 | -0.0203 | 0.045 | 0.06 | **-0.129** | **-0.139** |
| GranGS_M | 0.039 | -0.004 | -0.051 | -0.023 | -0.023 | -0.081 | 0.022 | 0.020 | -0.046 | **-0.130** | **-0.138** | 0.064 | **0.119** | **0.098** | -0.070 | **-0.201** |
| GranGS_D | -0.069 | 0.063 | **-0.147** | -0.060 | **-0.082** | -0.077 | 0.006 | -0.021 | **0.091** | -0.011 | -0.040 | **-0.152** | **-0.097** | -0.057 | -0.031 | **0.086** |
| ACCRUALS | **0.146** | **-0.206** | 0.058 | 0.0558 | 0.053 | -0.011 | 0.019 | -0.008 | -0.034 | -0.014 | 0.008 | **0.104** | **0.156** | **0.159** | **-0.118** | **-0.102** |
| NESTIMATES | **-0.186** | 0.0603 | 0.044 | -0.003 | -0.057 | **0.115** | 0.004 | -0.012 | 0.043 | 0.059 | 0.068 | **-0.180** | **-0.208** | **-0.156** | **0.212** | **0.286** |
| EPS_STDEV | **0.212** | -0.078 | **0.110** | **0.097** | **0.096** | **0.140** | **0.102** | **0.097** | 0.048 | **0.104** | **0.130** | **0.111** | **0.107** | **0.121** | **0.092** | 0.074 |
| MARKET CAP | **-0.349** | **0.203** | 0.069 | 0.014 | -0.047 | **0.140** | 0.051 | 0.011 | 0.040 | 0.027 | -0.025 | **-0.257** | **-0.293** | **-0.236** | **0.166** | **0.384** |
| ASSETS | **-0.151** | **0.084** | 0.080 | -0.067 | **-0.108** | **0.130** | -0.042 | -0.064 | **0.194** | **0.146** | **0.102** | **-0.241** | **-0.294** | **-0.261** | **0.176** | **0.360** |
| REVENUE | **-0.197** | **0.140** | 0.080 | 0.008 | -0.054 | **0.125** | 0.024 | -0.024 | **0.271** | **0.158** | **0.095** | **-0.323** | **-0.356** | **-0.285** | **0.160** | **0.282** |
| DEBT TO EQUITY | 0.040 | **-0.091** | 0.007 | -0.054 | -0.065 | 0.008 | -0.015 | -0.046 | **0.206** | **0.158** | **0.167** | **-0.324** | **-0.213** | **-0.163** | 0.023 | 0.025 |
| NSEGBUS | -0.015 | **0.120** | 0.143 | **0.163** | **0.162** | **0.112** | **0.198** | **0.183** | 0.035 | -0.032 | -0.024 | -0.001 | 0.019 | 0.057 | **0.653** | **0.144** |
| NSEGGEO | 0.057 | **-0.089** | **0.104** | 0.012 | -0.041 | **0.115** | 0.048 | 0.013 | **-0.089** | -0.036 | -0.056 | **0.106** | 0.035 | 0.051 | **0.194** | **0.727** |
| NNAICSBUS | 0.049 | -0.060 | 0.044 | **-0.085** | **-0.122** | **0.107** | -0.015 | -0.049 | -0.060 | **-0.123** | **-0.099** | 0.047 | 0.008 | 0.030 | **0.107** | 0.068 |
| NNAICSGEO | -0.035 | -0.024 | -0.010 | -0.018 | -0.073 | 0.080 | 0.029 | -0.023 | -0.079 | **-0.084** | -0.054 | 0.060 | 0.003 | 0.040 | -0.010 | 0.077 |

Table 3 b: This table covers the correlations between our selected variables. Spearman (Pearson) correlations are reported below (above) the diagonal, while bold entries denote significance at $p < .05$

| | GranBS_M | GranBS_D | GranGS_M | GranGS_D | ACCRUALS | NESTIMATES | EPS_STDEV | MARKET CAP | ASSETS | REVENUE | DEBT TO EQUITY | NSEGBUS | NSEGGEO | NNAICSBUS | NNAICSGEO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| F ERROR | -0.030 | 0.008 | -0.021 | -0.034 | 0.139 | **-0.064** | **0.125** | **-0.075** | -0.031 | **-0.047** | **0.047** | 0.001 | **0.043** | **-0.059** | 0.001 |
| F ERROR (Sign) | 0.003 | -0.020 | -0.007 | **0.038** | **-0.123** | 0.014 | **0.085** | **0.048** | 0.017 | 0.032 | **-0.037** | -0.014 | **-0.066** | **0.038** | -0.004 |
| ROA Gap1 | **-0.122** | -0.022 | -0.033 | -0.025 | -0.018 | **0.045** | -0.004 | 0.014 | 0.002 | 0.021 | -0.002 | **0.101** | -0.003 | **0.039** | 0.013 |
| ROA Gap2 | -0.003 | **-0.071** | 0.006 | **-0.061** | 0.018 | 0.035 | 0.006 | -0.009 | -0.027 | **-0.049** | **-0.046** | **0.051** | 0.009 | -0.029 | -0.028 |
| ROA Gap3 | -0.010 | -0.033 | 0.001 | **-0.084** | **0.044** | -0.006 | 0.006 | -0.016 | -0.021 | **-0.042** | -0.019 | **0.091** | 0.031 | -0.018 | -0.044 |
| ROA Gap1 (Sign) | **-0.129** | -0.008 | **-0.044** | -0.004 | -0.029 | **0.053** | -0.001 | 0.022 | -0.001 | 0.031 | 0.002 | **0.095** | 0.002 | **0.048** | 0.020 |
| ROA Gap2 (Sign) | 0.028 | -0.013 | 0.014 | -0.001 | -0.019 | 0.020 | 0.015 | -0.001 | -0.032 | -0.031 | -0.028 | **0.040** | 0.001 | -0.006 | 0.063 |
| ROA Gap3 (Sign) | 0.001 | 0.016 | -0.006 | -0.024 | 0.001 | -0.013 | 0.017 | -0.015 | **-0.042** | -0.033 | -0.011 | **0.058** | 0.025 | -0.023 | -0.024 |
| ROE Gap1 | **-0.111** | **-0.045** | -0.021 | -0.012 | -0.021 | 0.029 | 0.002 | -0.001 | 0.034 | **0.062** | 0.023 | 0.106 | -0.018 | **0.052** | -0.027 |
| ROE Gap2 | **-0.071** | **-0.069** | **-0.044** | **-0.063** | **0.040** | 0.032 | 0.001 | 0.016 | **0.076** | **0.095** | **0.049** | **0.064** | 0.002 | 0.018 | **-0.083** |
| ROE Gap3 | **-0.041** | **-0.064** | -0.020 | **-0.071** | **0.052** | 0.020 | -0.001 | -0.003 | **0.061** | **0.045** | 0.029 | 0.038 | -0.006 | -0.016 | **-0.104** |
| ROE Gap1 (Sign) | **-0.071** | -0.020 | 0.002 | -0.028 | 0.022 | -0.018 | 0.011 | -0.038 | -0.029 | -0.035 | **-0.208** | **0.054** | 0.019 | 0.022 | 0.062 |
| ROE Gap2 (Sign) | **0.068** | -0.024 | **0.066** | **-0.040** | **0.091** | **-0.112** | 0.028 | **-0.098** | **-0.068** | **-0.117** | **-0.354** | -0.004 | **0.056** | **-0.039** | 0.043 |
| ROE Gap3 (Sign) | **0.073** | **-0.039** | **0.066** | -0.030 | **0.095** | **-0.090** | 0.027 | **-0.087** | **-0.055** | **-0.117** | **-0.281** | -0.001 | **0.045** | -0.028 | **0.082** |
| SplitBS | **-0.130** | **-0.072** | **-0.129** | -0.026 | **-0.069** | **0.141** | 0.011 | **0.162** | **0.134** | **0.041** | 0.024 | **0.722** | **0.083** | **0.471** | -0.001 |
| SplitGS | **-0.135** | **-0.089** | **-0.195** | **0.041** | **-0.076** | **0.115** | -0.002 | **0.093** | **0.046** | -0.005 | -0.019 | **0.069** | **0.464** | 0.035 | **0.085** |
| GranBS_M | 1 | **0.207** | **0.623** | 0.008 | **-0.057** | **-0.218** | 0.011 | **-0.102** | **-0.122** | **-0.158** | **-0.047** | **-0.186** | -0.032 | **-0.078** | 0.028 |
| GranBS_D | **0.324** | 1 | 0.034 | **0.148** | 0.026 | **-0.043** | -0.016 | -0.007 | -0.013 | -0.035 | 0.035 | **-0.073** | **-0.082** | -0.010 | **0.092** |
| GranGS_M | **0.632** | 0.033 | 1 | **0.147** | -0.021 | **-0.265** | 0.022 | **-0.133** | **-0.126** | **-0.182** | **-0.056** | **-0.178** | **-0.145** | **-0.106** | -0.010 |
| GranGS_D | 0.005 | **0.119** | 0.071 | 1 | **-0.053** | 0.034 | -0.020 | 0.019 | -0.031 | 0.035 | -0.001 | -0.002 | **-0.166** | 0.0351 | -0.026 |
| ACCRUALS | 0.042 | 0.001 | 0.053 | 0.001 | 1 | -0.005 | 0.012 | **-0.070** | **-0.061** | **-0.087** | **0.179** | **-0.046** | -0.029 | **-0.137** | 0.057 |
| NESTIMATES | **-0.309** | **-0.088** | **-0.353** | 0.036 | **-0.128** | 1 | **-0.080** | **0.456** | **0.297** | **0.462** | **0.055** | 0.157 | 0.015 | **0.166** | 0.064 |
| EPS_STDEV | **-0.089** | 0.031 | 0.030 | 0.012 | 0.023 | -0.008 | 1 | **-0.037** | -0.024 | -0.035 | -0.013 | -0.008 | -0.024 | **-0.037** | 0.020 |
| MARKET CAP | **-0.277** | -0.064 | **-0.343** | **0.106** | **-0.181** | **0.808** | -0.016 | 1 | **0.769** | **0.708** | **0.060** | 0.223 | 0.011 | **0.351** | 0.043 |
| ASSETS | **-0.326** | -0.041 | **-0.370** | **0.120** | **-0.166** | **0.774** | **0.094** | **0.916** | 1 | 0.687 | **0.091** | 0.232 | 0.005 | **0.358** | 0.036 |
| REVENUE | **-0.290** | -0.065 | **-0.326** | **0.177** | **-0.150** | **0.706** | **0.110** | **0.855** | **0.907** | 1 | **0.057** | 0.186 | -0.035 | **0.337** | 0.058 |
| DEBT TO EQUITY | **-0.121** | 0.046 | **-0.117** | 0.043 | **0.103** | **0.092** | 0.065 | **0.127** | **0.257** | **0.221** | 1 | 0.003 | **-0.037** | 0.030 | 0.026 |
| NSEGBUS | **-0.131** | **-0.153** | **-0.096** | -0.028 | -0.076 | **0.167** | 0.070 | **0.185** | **0.165** | **0.176** | 0.004 | 1 | **0.062** | **0.630** | 0.022 |
| NSEGGEO | **-0.163** | -0.075 | **-0.199** | -0.081 | -0.034 | **0.303** | **0.091** | **0.299** | **0.267** | **0.223** | -0.075 | **0.148** | 1 | 0.009 | **0.094** |
| NNAICSBUS | -0.006 | 0.027 | 0.016 | -0.062 | **0.178** | **0.106** | 0.013 | 0.039 | 0.048 | 0.061 | 0.028 | **0.166** | **0.139** | 1 | **0.467** |
| NNAICSGEO | 0.040 | **0.103** | 0.013 | -0.041 | **0.100** | **0.094** | 0.043 | 0.061 | 0.062 | 0.041 | 0.004 | 0.044 | **0.123** | **0.592** | 1 |

ate setting in Section 5.2.

Moreover, Table 4 Panel A reveals that the standard deviation of 0.132 (and similar 0.138 for $F\_ERROR(Sign)$) is primarily driven by the fifth quintile, which is the one with the largest forecast error. The negative values reported for the mean of $F\_ERROR(Sign)$ across quintiles one two and three indicate that a substantial proportion of the firms included in our sample exhibit overly optimistic (pessimistic) earnings forecasts corresponding to the profitability gaps, whereby actual EPS figures undershoot (overshoot) analysts' expectations.

**Profitability Gap (between aggregated profitability from segments and firm profitability)**: The mean (median) absolute unlevered profitability gaps $ROAGap1$, $ROAGap2$, $ROAGap3$ are reported at 0.035 (0.006), 0.049 (0.027), 0.031 (0.017). The mean (median) levered profitability gaps denoted by $ROEGap1$, $ROEGap2$, $ROEGap3$ are 0.046 (0.029), 0.035 (0.024), 0.037 (0.023). Considering also the direction (sign) of the gap, the mean (median) reported unlevered profitability gaps $ROAGap1(Sign)$, $ROAGap2(Sign)$, $ROAGap3(Sign)$ and the mean (median) levered profitability gaps $ROEGap1(Sign)$, $ROEGap2(Sign)$, $ROEGap3(Sign)$ are 0.019 (0.000), 0.037 (-0.022), 0.020 (-0.013) and -0.058 (-0.057), -0.059 (-0.039), -0.030 (-0.023), respectively. These results provide initial evidence that the aggregated profitability from segments is higher than the profitability from the consolidated financial statements, which suggests that if analysts rely too much on segments reporting their EPS estimates might overestimate the profitability of assets, equity, as well as the firm's earnings. Again the standard deviation is high, further analysis is carried out in a multivariate setting (see section regression analysis).

Table 4, Panel B splits and ranks the unlevered profitability gap according to the forecast error when the sign of the forecast error $F\_ERROR(Sign)$ is also taken into account. The figures in the reported quintiles suggest that overly optimistic (pessimistic) EPS estimates correspond to observations where segment aggregated profitability is indeed higher (lower) than consolidated profitability. Further evidence is also provided when considering the Spearman (Pearson) correlations reported in Table 3 a. Specifically, the Spearman (Pearson) between the absolute forecast error $F\_ERROR$ and the levered (ROE) profitability gap metrics $ROEGap1$, $ROEGap2$, $ROEGap3$ is 0.133 (0.117), 0.129 (0.302) and 0.171 (0.250), while if the sign is also taking into account, then the correlations are: 0.240 (-0.006), 0.236 (0.035) and 0.204 (0.010), respectively.

**Segment Split**: The mean (median) business segment split variable $SplitBS$ is 0.519 (0.532), while geographical segment split variable $SplitGS$ is 0.467 (0.491).

**Line Item Granularity**: The mean (median) business segment granularity of mandatory $GranBS\_M$ and discretionary line items $GranBS\_D$ are 0.725 (0.857) and 0.427 (0.421), respectively. The mean (median) geographical segment granularity covering mandatory $GranGS\_M$ and discretionary line items $GranGS\_D$ are 0.364 (0.417) and 0.331 (0.345), respectively.

**Number of segments and industries**: The mean (median) number of business segments, denoted as $NSEGBUS$, is 4.318 (4.0) with a standard deviation of 1.669, while the mean (median) number of geographical segments, $NSEGGEO$, is 4.767 (4.0) with a standard deviation of 3.496. The mean (median) reported number of NAICS per company across business segments, denoted as $NNAICSBUS$, is 4.007 (4.0) with a standard deviation of 2.029, while in the case of geographical segments, $NNAICSGEO$, the mean (median) is 1.853 (2.0) with a standard deviation of 0.399.

Table 5 Panel A splits and ranks the segment split variables: $SplitBS$, $SplitGS$ and the line item granularity variables: $GranBS\_M$, $GranBS\_D$, $GranGS\_M$, and $GranGS\_D$ according to the calculated forecast error quintiles of $F\_ERROR$. Based on the correlation tables and contrary to the common expectation that an increased split would increase valuable information on business activities and facilitate the forecast of earnings, we find

Table 4: This table splits and ranks the six profitability gap variables according to the ranked quintiles of the absolute forecast error (Panel A), as well as the raw forecast error (Panel B). The figures in the reported quintiles suggest that overly optimistic (pessimistic) EPS forecasts correspond to observations where segment aggregated profitability is indeed higher (lower) than consolidated profitability.

Panel A: Absolute forecast error

| | F_ERROR | | | ROA Gap1 | | ROA Gap2 | | ROA Gap3 | | ROE Gap1 | | ROE Gap2 | | ROE Gap3 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | n | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd |
| 1 | 558 | 0.002 | 0.001 | 0.028 | 0.222 | 0.050 | 0.084 | 0.027 | 0.046 | 0.036 | 0.076 | 0.027 | 0.032 | 0.028 | 0.041 |
| 2 | 558 | 0.009 | 0.002 | 0.036 | 0.218 | 0.048 | 0.064 | 0.027 | 0.037 | 0.041 | 0.095 | 0.028 | 0.027 | 0.029 | 0.035 |
| 3 | 558 | 0.019 | 0.004 | 0.038 | 0.181 | 0.051 | 0.105 | 0.033 | 0.093 | 0.043 | 0.078 | 0.031 | 0.030 | 0.032 | 0.033 |
| 4 | 558 | 0.038 | 0.008 | 0.028 | 0.093 | 0.045 | 0.064 | 0.029 | 0.042 | 0.046 | 0.129 | 0.032 | 0.029 | 0.035 | 0.038 |
| 5 | 558 | 0.189 | 0.251 | 0.043 | 0.127 | 0.053 | 0.105 | 0.039 | 0.056 | 0.065 | 0.120 | 0.056 | 0.084 | 0.063 | 0.127 |
| Total | 2790 | 0.051 | 0.132 | 0.035 | 0.176 | 0.049 | 0.086 | 0.031 | 0.059 | 0.046 | 0.102 | 0.035 | 0.047 | 0.037 | 0.066 |

Panel B: Forecast error considering the sign

| | F_ERROR(Sign) | | | ROA Gap1 (Sign) | | ROA Gap2 (Sign) | | ROA Gap3(Sign) | | ROE Gap1 (Sign) | | ROE Gap2 (Sign) | | ROE Gap3 (Sign) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | n | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd |
| 1 | 558 | -0.172 | 0.199 | -0.011 | 0.080 | 0.012 | 0.115 | 0.008 | 0.068 | -0.060 | 0.225 | -0.026 | 0.217 | -0.014 | 0.243 |
| 2 | 558 | -0.028 | 0.008 | 0.019 | 0.094 | 0.037 | 0.062 | 0.022 | 0.043 | -0.047 | 0.242 | -0.039 | 0.179 | -0.011 | 0.195 |
| 3 | 558 | -0.009 | 0.004 | 0.032 | 0.201 | 0.050 | 0.114 | 0.027 | 0.095 | -0.041 | 0.410 | -0.055 | 0.210 | -0.022 | 0.221 |
| 4 | 558 | 0.002 | 0.003 | 0.023 | 0.221 | 0.043 | 0.078 | 0.022 | 0.045 | -0.087 | 0.457 | -0.089 | 0.257 | -0.056 | 0.251 |
| 5 | 558 | 0.045 | 0.170 | 0.034 | 0.230 | 0.044 | 0.074 | 0.022 | 0.046 | -0.052 | 0.529 | -0.083 | 0.284 | -0.048 | 0.260 |
| Total | 2790 | -0.033 | 0.138 | 0.019 | 0.178 | 0.037 | 0.092 | 0.020 | 0.063 | -0.058 | 0.391 | -0.059 | 0.233 | -0.030 | 0.236 |

Table 5: Panel A of this table splits and ranks the segment split variables and the line item granularity variables according to the absolute forecast error quintiles. Panel B splits and ranks the variables referring to the number of business segments, business NAICS, mandatory and discretionary line item granularity according to segment split quintiles.

Panel A

| | | F_ERROR | | SplitBS | | SplitGS | | GranBS_M | | GranBS_D | | GranGS_M | | GranGS_D | | SplitBS | | NNAICSBUS | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | n | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd |
| 1 | 558 | 0.002 | 0.001 | 0.530 | 0.195 | 0.467 | 0.223 | 0.733 | 0.150 | 0.439 | 0.118 | 0.317 | 0.157 | 0.207 | 0.052 | 0.530 | 0.195 | 4.172 | 2.179 |
| 2 | 558 | 0.009 | 0.002 | 0.518 | 0.196 | 0.457 | 0.221 | 0.725 | 0.151 | 0.424 | 0.110 | 0.312 | 0.155 | 0.201 | 0.041 | 0.518 | 0.196 | 4.199 | 2.302 |
| 3 | 558 | 0.019 | 0.004 | 0.518 | 0.197 | 0.483 | 0.223 | 0.728 | 0.156 | 0.419 | 0.112 | 0.314 | 0.155 | 0.198 | 0.041 | 0.518 | 0.197 | 3.973 | 1.914 |
| 4 | 558 | 0.038 | 0.008 | 0.515 | 0.202 | 0.465 | 0.235 | 0.718 | 0.156 | 0.425 | 0.121 | 0.317 | 0.157 | 0.200 | 0.045 | 0.515 | 0.202 | 3.927 | 1.973 |
| 5 | 558 | 0.189 | 0.251 | 0.514 | 0.185 | 0.462 | 0.234 | 0.720 | 0.149 | 0.428 | 0.131 | 0.302 | 0.159 | 0.195 | 0.046 | 0.514 | 0.185 | 3.763 | 1.696 |
| Total | 2790 | 0.051 | 0.132 | 0.519 | 0.195 | 0.467 | 0.227 | 0.725 | 0.152 | 0.427 | 0.119 | 0.312 | 0.157 | 0.200 | 0.045 | 0.519 | 0.195 | 4.007 | 2.029 |

Panel B

| | | SplitBS | | NSEGBUS | | NNAICSBUS | | GranBS_M | | GranBS_D | | GranGS_M | | GranGS_D | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quintile | n | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd | m | sd |
| 1 | 558 | 0.209 | 0.110 | 2.944 | 0.825 | 3.043 | 1.076 | 0.751 | 0.141 | 0.439 | 0.152 | 0.337 | 0.157 | 0.205 | 0.048 |
| 2 | 558 | 0.448 | 0.033 | 3.312 | 0.788 | 3.152 | 1.089 | 0.751 | 0.140 | 0.435 | 0.104 | 0.329 | 0.151 | 0.195 | 0.055 |
| 3 | 558 | 0.538 | 0.035 | 3.975 | 0.930 | 3.525 | 1.509 | 0.712 | 0.166 | 0.423 | 0.122 | 0.313 | 0.155 | 0.200 | 0.036 |
| 4 | 558 | 0.647 | 0.024 | 4.805 | 0.891 | 4.486 | 1.844 | 0.711 | 0.153 | 0.420 | 0.103 | 0.310 | 0.166 | 0.204 | 0.042 |
| 5 | 558 | 0.754 | 0.045 | 6.552 | 1.650 | 5.828 | 2.672 | 0.699 | 0.153 | 0.418 | 0.105 | 0.273 | 0.147 | 0.197 | 0.043 |
| Total | 2790 | 0.519 | 0.195 | 4.318 | 1.669 | 4.007 | 2.029 | 0.725 | 0.152 | 0.427 | 0.119 | 0.312 | 0.157 | 0.200 | 0.045 |

no apparent relationship between these metrics, at least based on this analysis. A possible explanation might be that the increased segment split is actually reflecting more diversified firms and offsets the information value of a greater segment split. However, the number of NAICS, $NNAICSBUS$, is quasi-constant throughout all quintiles, close to 4, with only a slight decrease in the mean and standard deviation when considering the 5 quintiles of $F\_ERROR$. Moreover, the correlation matrix does not suggest a strong association between diversification and the forecast error,while the correlation between the forecast error and the number of reported NAICS is negligibly low, as well as showing an inconclusive sign 0.049 (-0.059).

Segment split is often used as a proxy for (or confused with) diversification (e.g., Kang et al., 2017), despite the discretionary character of the actual segment split. To display the relationship between segment split, number of business segments and number of industries reported for business segments, Table 5, Panel B splits and ranks number of segments and the number of line items and NAICS against our segment split variable. Table 6 shows the number of NAICS for business segments and the number of segments and segment split for the corresponding firms. It reveals that a striking 71.4 percent of the firms operate in one, two, three or four industries but report, on average, in all cases only about the same number of segments and the same segment split. Moreover, in line with this argumentation, the increase in the average segment split from 0.209 to 0.538, as depicted in Table5 in Panel B, referring to quintiles one to three (covering 60% of all firms) corresponds to firms having three to four business segments and reporting approximately three business NAICS.

Furthermore, when looking at the relation between the forecast error and the number of business segments, we find similar results, namely a correlation of -0.015 (0.001). Given a mean (median) of business segments and NAICS of about 4, the correlation between the segment split variable and the number of business segments is 0.653 (0.722); however, the correlation between the

Table 6: This table provides an overview of the number of business NAICS that firms in our data-set report and relates this number to the number of reported business segments and segment split.

| NNAICS BUS | | | | NSEGBUS | | SplitBS | |
|---|---|---|---|---|---|---|---|
| Nr. | Firms | Perc. | Cum. | m | sd | m | sd |
| 1 | 95 | 3.4 | 3.4 | 3.621 | 0.121 | 0.455 | 0.022 |
| 2 | 480 | 17.2 | 20.6 | 3.567 | 0.060 | 0.435 | 0.008 |
| 3 | 765 | 27.4 | 48.0 | 3.566 | 0.042 | 0.448 | 0.007 |
| 4 | 653 | 23.4 | 71.4 | 4.044 | 0.050 | 0.499 | 0.007 |
| 5 | 296 | 10.6 | 82.0 | 5.091 | 0.065 | 0.610 | 0.008 |
| 6 | 185 | 6.6 | 88.7 | 5.627 | 0.105 | 0.659 | 0.009 |
| 7 | 139 | 5.0 | 93.7 | 5.957 | 0.092 | 0.699 | 0.008 |
| 8 | 78 | 2.8 | 96.5 | 5.705 | 0.141 | 0.681 | 0.009 |
| 9 | 40 | 1.4 | 97.9 | 7.225 | 0.233 | 0.698 | 0.023 |
| 10 | 27 | 1.0 | 98.9 | 7.481 | 0.386 | 0.767 | 0.010 |
| 11 | 16 | 0.6 | 99.4 | 8.938 | 0.536 | 0.808 | 0.019 |
| 12 | 5 | 0.2 | 99.6 | 8.800 | 0.200 | 0.833 | 0.020 |
| 13 | 2 | 0.1 | 99.7 | 9.500 | 0.500 | 0.851 | 0.005 |
| 14 | 2 | 0.1 | 99.8 | 10.500 | 0.500 | 0.854 | 0.010 |
| 15 | 4 | 0.1 | 99.9 | 10.750 | 0.250 | 0.864 | 0.010 |
| 16 | 1 | 0.0 | 99.9 | 9.000 | . | 0.819 | . |
| 17 | 2 | 0.1 | 100.0 | 15.000 | 0.000 | 0.916 | 0.001 |
| Total | 2790 | 100 | | 4.317 | 0.072 | 0.519 | 0.008 |
| Sub Group of NNAICSBUS 1 to 4: | | | | 3.726 | 0.053 | 0.462 | 0.008 |
| Sub Group of NNAICSBUS 5 to 17: | | | | 5.794 | 0.119 | 0.662 | 0.010 |

segment split and the number of NAICS is 0.107 (0.471), a substantially lower value by comparison, supporting our understanding that it is important to distinguish between segment split and diversification.

The analysis in Table 5, Panel B also provides evidence that an increased number of segments results in a decreased number of reported line items when the segment split increases, particularly for the quintiles 4 and 5, which is in line with the finding in prior studies ((Bugeja et al., 2015; Ettredge et al., 2006; Gotti, 2016). Also, when looking at the correlation figures in Table 3 a, the segment split, mandatory and discretionary line items are not linked to a reduction in the forecast error in this univariate setting -0.039, -0.030, -0.023 (0.016, -0.030, 0.008).

**Size**: The mean (median) size as measured through market capitalization $MARKET\_CAP$ is 8,315 (2,082) million USD with a standard deviation of 23,338, asset size $ASSETS$ is 9,491 (2,255) million USD with a standard deviation of 39,627 and revenue $REVENUE$ is 7,263 (1,960) million USD with a standard deviation of 18,161.

There is a slight negative correlation between the accounting quality variable $ACCRUALS$ and the business segment split $SplitBS$ of -0.118 (-0.069), whereby the higher the split, the lower the number of disclosed mandatory line items -0.150 (-.130). A similar picture is documented when looking at the negative correlation between the geographical segment split and mandatory line items granularity -.224 (-0.195), implying that an increased segment split is correlated with a reduction in line items (Bugeja et al., 2015; Ettredge et al., 2006; Gotti, 2016). Conversely, when looking at discretionary line items, the opposite can be observed.

Larger companies, as measured by market cap, total assets or revenue benefit from increased analyst coverage as evidenced by correlations between 0.706 and 0.808 (0.297 and 0.462).

The forecast error positively correlates with standard deviation of last five years of EPS 0.212 (0.125). In contrast to existing findings referring to the impact of leverage on information availability (Dhaliwal et al., 2011), the debt-to-equity ratio does not correlate with the forecast error 0.040 (0.047), nor with the segment split -0.039 (0.016) in this univariate setting.

## *5.2. Regression Analysis*

Table 7 depicts the results of our regression analysis. Panel A and Panel B of Table 7 document and quantify the effect of the profitability gaps on the forecast error. All of the 4 regressions address the relationship between the profitability gap from "no-full-story" segments, for which profitability reporting is incomplete, i.e. segments that do not report revenue or assets: $ROA\_Gap2$, $ROE\_Gap2$, or segments lacking revenue, assets or operating income: $ROA\_Gap3$ and $ROE\_Gap3$ and its effect on the forecast error. We find and document a statistically significant (coefficient for the levered metric is 0.797 for $ROE\_Gap2$) positive association with the forecast error. This comes to support our fourth hypothesis (H4). This finding suggests that analysts' earnings forecasts are biased towards firm profitability as derived from segments, for which a complete set of profitability-related data items (assets, revenues or operating earnings) is disclosed, the "full-story" segments. Moreover, this finding is significantly tied to the amount and even the sign of the earnings forecast error–statistically and economically significant coefficients of $PrftGap(SegPrft > ConsPrft)$, R-squared of 0.46, reported in Panel B of Table 7. $PrftGap(SegPrft > ConsPrft)$ captures the case, where the aggregated segment reporting profitability is more optimistic than the profitability based on consolidated financial statements. However, in the opposite case, this is not the case. This implies that if aggregated segment profitability (from "full-story" segments) is higher than the consolidated profitability, then analysts are inclined to issue overly optimistic earnings forecasts.

This suggests that the attention of analysts might be directed to those segments where performance metrics are readily available. Our findings complement prior research which shows that the discretion of segment reports and usefulness of actual segment data is exploited by management, suggesting that companies manage segment profitability through the allocation of business activities when aggregating them into reported segments (Berger and Hann, 2007) and inter-segment income shifting (Lail et al., 2014; You, 2014).

Referring to the non-GAAP vs GAAP topic, given the lack of a complete reconciliation requirement between aggregated segments and firm level reporting, as well as the leeway provided by the low reporting requirements, coupled with the internal measurement principle, we tested if the existence of a discrepancy between segment aggregated profitability and firm level profitability explains the forecast error $ROA\_Gap1$, $ROE\_Gap1$. However, the evidence for a profitability gap that results from non-GAAP accounting (internal recognition and measurement principles for reported segments in contrast to the U.S.-GAAP for consolidated financial statements) is weak and only supports H3 in the case of the levered metric, $ROE\_Gap1$, contrasting the findings in Wang and Ettredge (2015) who report a value relevant relationship with this gap. This could result from the firms' use of external accounting principles for their internal and segment reporting, facilitating the preparation of segment reporting and internal reports as it is readily available (Crawford et al., 2012; Nichols et al., 2012).

Throughout all of our different model specifications we find statistically significant evidence that the segment split is positively associated with the forecast error. To make sure that the findings are not driven by the level of firm diversification, we control for firm diversification by creating dummies for the number of business NAICS of a firm. The finding directly supports our first hypothesis (H1) and strengthens the idea that an increased segment split under the loose and permissive regulatory framework in defining and aggregating business activities into reporting business segments does not serve as a catalyst for forecasting purposes.

Referring to the coefficients of $GranBS\_M$ and $GranBS\_D$, we find that

Table 7: This table reports the results of our regression analysis. The dependent variable across all model specifications is the EPS forecast error. Panel A and Panel B document and quantify the effect of the different profitability gaps on the forecast error. *, **, *** denote significance at the $p < .1$, $p < .05$ and $p < .01$ levels.

| Panel A: Regression of forecast error on profitability gaps, segment split and line item granularity | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excluding incomplete segments when aggregating segment profitability | | | | | | | | | | | | PrftGap from non-Gaap accounting | | | | | |
| | Gap2 (unlevered, ROA) | | | Gap2 (levered, ROE) | | | Gap3 (unlevered, ROA) | | | Gap3 (levered, ROE) | | | Gap1 (unlevered, ROA) | | | Gap1 (levered, ROE) | | |
| Independent Variable | Coeff | RSE | t | Coeff | RSE | t | Coeff | RSE | t | Coeff | RSE | t | Coeff | RSE | t | Coeff | RSE | t |
| Business Segment Variables | | | | | | | | | | | | | | | | | | |
| PrftGap | 0.170 ** | 0.068 | 2.51 | 0.797 *** | 0.123 | 6.50 | 0.252 * | 0.151 | 1.67 | 0.445 *** | 0.160 | 2.79 | 0.027 | 0.017 | 1.63 | 0.130 * | 0.069 | 1.89 |
| SplitBS | 0.044 *** | 0.012 | 3.71 | 0.032 *** | 0.012 | 2.63 | 0.040 *** | 0.012 | 3.39 | 0.038 *** | 0.012 | 3.04 | 0.042 *** | 0.012 | 3.61 | 0.043 *** | 0.013 | 3.20 |
| GranBS_M | -0.040 * | 0.020 | -1.93 | -0.020 | 0.022 | -0.89 | -0.038 * | 0.021 | -1.86 | -0.026 | 0.022 | -1.16 | -0.034 | 0.021 | -1.60 | -0.022 | 0.024 | -0.92 |
| GranBS_D | 0.066 * | 0.035 | 1.89 | 0.068 * | 0.039 | 1.74 | 0.063 * | 0.035 | 1.79 | 0.065 | 0.040 | 1.63 | 0.061 * | 0.035 | 1.75 | 0.060 | 0.040 | 1.50 |
| Controls | | | | | | | | | | | | | | | | | | |
| ACCRUALS | 0.586 *** | 0.200 | 2.93 | 0.538 ** | 0.228 | 2.35 | 0.559 *** | 0.199 | 2.81 | 0.567 ** | 0.233 | 2.43 | 0.574 *** | 0.200 | 2.87 | 0.625 *** | 0.231 | 2.70 |
| NESTIMATES | 0.185 *** | 0.037 | 5.03 | 0.156 *** | 0.040 | 3.92 | 0.185 *** | 0.037 | 5.06 | 0.164 *** | 0.040 | 4.06 | 0.187 *** | 0.036 | 5.11 | 0.190 *** | 0.039 | 4.83 |
| EPS_STDEV | 0.013 *** | 0.005 | 2.61 | 0.012 ** | 0.006 | 2.24 | 0.013 *** | 0.005 | 2.62 | 0.013 ** | 0.005 | 2.43 | 0.013 *** | 0.005 | 2.59 | 0.014 ** | 0.006 | 2.44 |
| SIZE | -0.038 *** | 0.004 | -10.58 | -0.034 *** | 0.004 | -9.04 | -0.037 *** | 0.004 | -10.49 | -0.036 *** | 0.004 | -8.97 | -0.038 *** | 0.004 | -10.67 | -0.039 *** | 0.004 | -10.03 |
| DEBT TO EQUITY | 0.004 *** | 0.002 | 2.75 | 0.003 * | 0.001 | 1.81 | 0.004 *** | 0.002 | 2.67 | 0.003 ** | 0.001 | 2.19 | 0.004 ** | 0.001 | 2.45 | 0.003 ** | 0.001 | 2.14 |
| SplitGS | 0.047 *** | 0.016 | 2.87 | 0.049 *** | 0.018 | 2.66 | 0.043 *** | 0.016 | 2.65 | 0.052 *** | 0.018 | 2.84 | 0.045 *** | 0.016 | 2.74 | 0.049 *** | 0.018 | 2.70 |
| Year Fixed Effects | | Yes | | | Yes | | | Yes | | | Yes | | | Yes | | | Yes | |
| Industry Fixed Effects | | Yes | | | Yes | | | Yes | | | Yes | | | Yes | | | Yes | |
| R-squared | | 0.10 | | | 0.17 | | | 0.10 | | | 0.14 | | | 0.08 | | | 0.10 | |
| Observations | | 2,790 | | | 2,541 | | | 2,790 | | | 2,541 | | | 2,790 | | | 2,541 | |
| No. Of Groups | | 592 | | | 548 | | | 592 | | | 548 | | | 592 | | | 548 | |
| Panel B: Regression coefficients for sub-samples of positive and negative sign of the PrftGap variable | | | | | | | | | | | | | | | | | | |
| PrftGap (SegPrft>ConsPrft) | 0.627 ** | 0.291 | 2.15 | 0.067 * | 0.038 | 1.75 | 1.301 *** | 0.132 | 9.83 | -0.094 ** | 0.045 | -2.08 | -0.027 | 0.017 | -1.63 | -0.130 * | 0.069 | -1.89 |
| R-squared | | 0.38 | | | 0.12 | | | 0.46 | | | 0.15 | | | 0.08 | | | 0.10 | |
| Observations | | 629 | | | 1,876 | | | 751 | | | 1,610 | | | 2,790 | | | 2,541 | |
| No. Of Groups | | 276 | | | 459 | | | 316 | | | 423 | | | 592 | | | 548 | |
| PrftGap (SegPrft<ConsPrft) | 0.020 | 0.025 | 0.81 | -0.061 | 0.055 | -1.10 | -0.012 | 0.024 | -0.49 | -0.005 | 0.033 | 0.16 | -0.001 | 0.004 | -0.17 | 0.017 | 0.013 | 1.33 |
| R-squared | | 0.06 | | | 0.15 | | | 0.06 | | | 0.13 | | 0.19 | | | | 0.31 | |
| Observations | | 2,161 | | | 665 | | | 2,039 | | | 931 | | 1,437 | | | | 408 | |
| No. Of Groups | | 526 | | | 255 | | | 517 | | | 315 | | 483 | | | | 195 | |

increased mandatory line item granularity (H2) is associated with a decrease in the forecast error, while increased discretionary disclosure is associated with increases in the forecast error. This finding provides further evidence suggesting that the leeway and discretion under the current standard might be impeding the work of outside analysts, yielding less accurate forecasts.

# 6. Conclusion

Indisputably, segment reporting is a powerful tool for the firm in its communication with analysts and investors. However, segment reporting provides valuable information if it reliably reveals current performance of major business activities. In so doing, it provides a benchmark for the future guidance of the firm's management and it assists analysts in their forecasts and investors in their investment decision-making. Poor segment reporting, in turn, bears the risk of misinforming analysts and investors.

In this study, we argue, that discretion with regard to the segment split, allocation and granularity of segment data, coupled with shortcomings in matching and reconciling segment data with data from primary financial statements, impedes an effective analysis of reported segments and hence the evaluation of the company's prospects. In particular, over-reliance by analysts on the (incomplete) data presented for segments bears the risk of resulting in a systematic forecast error, while the lack of key line items amplifies the discretionary nature of segment reporting.

Under ASC 280 (SFAS 131) and similarly IFRS 8, segment reporting aims at presenting financial information disaggregated into reporting segments, with the goal of enabling users to analyze individual business activities of the company and evaluate its prospects as a whole (ASC 280-10-1, IFRS 8.1). This is in line with research that suggests that disclosure on individual business activities (aggregated in segments) leads to an increased permeability of earnings forecasts into stock returns (Ettredge et al., 2005) and contributes to market efficiency in general (Hossain, 2008; Park, 2011).

With this study, we contribute to the existing segment reporting literature by investigating the usefulness of segment reporting with respect to EPS forecasting and EPS forecast accuracy. We address this question by a bottom up approach, aiming to reconcile firm level profitability by aggregating individual segment level profitability.

We provide evidence that there is a positive association between segment reporting profitability and earnings forecasts accuracy, which suggests that analysts might be biased in their earnings forecast. We document a statistically (and economically) significant relationship between the identified discrepancy and the forecast error, also when considering the sign of the error. We show the existence of a profitability gap between segment-aggregated profitability and (consolidated) firm level profitability and provide evidence that this gap is positively associated with the analysts' earnings per share forecast error. In particular, our findings suggest that exclusively relying on segments with a full set of profitability variables (revenue, assets, income) the "full-story" segments while ignoring segments for which such variables are missing drives the forecast error. Specifically, if segment profitability is larger than consolidated profitability, analysts are inclined to issue overly optimistic earnings forecasts. Analysts will potentially use the segment data as input in their models to forecast segment and then firm profitability. However, in contrast to prior literature which finds that the non-GAAP measurement "gap" between segment and consolidated statements affects stock returns (Wang and Ettredge, 2015; Alfonso et al., 2012), we find that the non-GAAP vs. GAAP measurement effect is neglectable. The relevant effect comes from segments overly optimistic profitability figures.

Our findings suggest that analyst forecasts might be influenced by the firms' allocation and measurement of segment data, the reported line item granularity and segment split, which directs analyst attention primarily to those segments that allow for profitability calculations, leaving out segments, which do not report components of profitability metrics.

Moreover, we find that companies with less segments have a lower forecast error–after controlling for the level of firm diversification. Indeed, low segment split company forecasts are even more accurate when the discrepancy of segment and consolidated profitability is high, signaling that analysts might ignore segment data when a mismatch is obvious. Greater disaggregation across reported segments is not helping analysts in their exercise of forecasting earnings. This finding suggests that the split of firm level data into reported segment data does not correspond to individual business activities and their idiosyncratic risk characteristics and therefore systematically contributes to the analyst forecast error. It also suggests that granularity of line item disclosure and the leeway to shuffle relevant line item information between segments play a key role in the assessment of the firm's business activities.

Our findings are in line with previous research that finds that current segment reporting fails to provide an adequate split according to a diversified firm‘s individual business profitability, risk and growth dimensions. We attribute our findings to the reporting requirements of segment data under the "management approach". This includes (1) reporting financial data that is used for internal management purposes and that may not be fully or at all be in line with GAAP coupled with little to no reconciliation needs, (2) aggregation of business activities to reportable segments based on the management's internal view, and (3) aggregation and reallocation of assets, costs and sales if justified by internal reporting principles without any transparency or consistency requirements.

Discretionary disaggregation coupled with limited disclosure of key line items (such as a breakdown between operating and financial assets) do not facilitate an accurate understanding, i.e. a breakdown of current profitability into its core drivers, which in turn would serve as a basis for forecasting future profitability. Furthermore, the discretionary character of segment reports is amplified by the fact that reported segment data under both standards, US-GAAP and IFRS, is neither required to match with data provided in primary financial statements, nor is a full reconciliation required that tracks segment data mismatches back on the line item of financial statements. As a result, segment reporting lacks important information that is necessary for profitability analysis and forecasting. Nevertheless, the analyst's exercise of analyzing segment profitability to understand a company's risk, return and growth characteristics with the ultimate aim of forecasting sustainable future earnings requires a clear view on core profitability metrics from the business activities and their development, as well as an understanding of the underlying accounting.

We interpret our results as triggering evidence for the fact that the status-quo of segment reporting falls short of disclosing vital information, which is relevant for analysts in their forecasting of future earnings. Surpassed in terms of disclosure amount and scope by end of year reporting, which offers a relatively good basis for assessing profitability, growth and risk, segment reporting falls short of delivering the vital value added needed by analysts when forecasting future earnings. Consequently, we see that for firms whose consolidated end of year reported numbers, disclosed in the more detailed firm level reporting and therefore closely resembling those of the concentrated segment, forecast errors are lower.

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# Appendix

Table 8: This table provides a breakdown of the descriptive statistics covering our data-set on a yearly basis. A full description for each of our variables is provided in Table 9 in the Appendix

| | 2009 | | | 2010 | | | 2011 | | | 2012 | | | 2013 | | | 2014 | | | 2015 | | | 2016 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | n | m | sd | n | m | sd | n | m | sd | n | m | sd | n | m | sd | n | m | sd | n | m | sd | n | m | sd |
| F ERROR | 284 | 0.095 | 0.280 | 324 | 0.042 | 0.073 | 343 | 0.041 | 0.087 | 384 | 0.057 | 0.138 | 387 | 0.037 | 0.068 | 386 | 0.036 | 0.077 | 363 | 0.075 | 0.155 | 319 | 0.037 | 0.059 |
| F ERROR (Sign) | 284 | -0.051 | 0.291 | 324 | -0.001 | 0.085 | 343 | -0.016 | 0.095 | 384 | -0.042 | 0.143 | 387 | -0.024 | 0.074 | 386 | -0.028 | 0.080 | 363 | -0.066 | 0.159 | 319 | -0.032 | 0.062 |
| ROA Gap1 | 284 | 0.033 | 0.074 | 324 | 0.058 | 0.331 | 343 | 0.028 | 0.065 | 384 | 0.039 | 0.184 | 387 | 0.054 | 0.250 | 386 | 0.028 | 0.111 | 363 | 0.021 | 0.118 | 319 | 0.013 | 0.032 |
| ROA Gap2 | 284 | 0.064 | 0.140 | 324 | 0.058 | 0.091 | 343 | 0.049 | 0.074 | 384 | 0.051 | 0.115 | 387 | 0.047 | 0.059 | 386 | 0.044 | 0.067 | 363 | 0.045 | 0.066 | 319 | 0.041 | 0.051 |
| ROA Gap3 | 284 | 0.040 | 0.076 | 324 | 0.033 | 0.053 | 343 | 0.029 | 0.044 | 384 | 0.034 | 0.107 | 387 | 0.031 | 0.039 | 386 | 0.028 | 0.037 | 363 | 0.028 | 0.037 | 319 | 0.027 | 0.034 |
| ROA Gap1 (Sign) | 284 | -0.006 | 0.081 | 324 | 0.039 | 0.334 | 343 | 0.014 | 0.070 | 384 | 0.024 | 0.186 | 387 | 0.038 | 0.252 | 386 | 0.018 | 0.113 | 363 | 0.013 | 0.119 | 319 | 0.007 | 0.034 |
| ROA Gap2 (Sign) | 284 | 0.021 | 0.153 | 324 | 0.040 | 0.101 | 343 | 0.041 | 0.079 | 384 | 0.043 | 0.119 | 387 | 0.037 | 0.066 | 386 | 0.039 | 0.070 | 363 | 0.039 | 0.070 | 319 | 0.037 | 0.054 |
| ROA Gap3 (Sign) | 284 | 0.008 | 0.085 | 324 | 0.018 | 0.060 | 343 | 0.021 | 0.049 | 384 | 0.025 | 0.109 | 387 | 0.021 | 0.046 | 386 | 0.023 | 0.040 | 363 | 0.023 | 0.041 | 319 | 0.023 | 0.036 |
| ROE Gap1 | 257 | 0.057 | 0.090 | 286 | 0.062 | 0.155 | 310 | 0.049 | 0.052 | 351 | 0.046 | 0.056 | 347 | 0.052 | 0.186 | 350 | 0.037 | 0.052 | 338 | 0.039 | 0.081 | 302 | 0.029 | 0.025 |
| ROE Gap2 | 257 | 0.052 | 0.090 | 286 | 0.039 | 0.044 | 310 | 0.041 | 0.046 | 351 | 0.036 | 0.034 | 347 | 0.028 | 0.032 | 350 | 0.028 | 0.035 | 338 | 0.033 | 0.049 | 302 | 0.026 | 0.025 |
| ROE Gap3 | 257 | 0.061 | 0.158 | 286 | 0.042 | 0.053 | 310 | 0.043 | 0.055 | 351 | 0.036 | 0.040 | 347 | 0.030 | 0.038 | 350 | 0.027 | 0.034 | 338 | 0.036 | 0.058 | 302 | 0.029 | 0.030 |
| ROE Gap1 (Sign) | 257 | -0.076 | 0.204 | 286 | -0.020 | 0.558 | 310 | -0.089 | 0.336 | 351 | -0.035 | 0.474 | 347 | -0.007 | 0.429 | 350 | -0.059 | 0.364 | 338 | -0.096 | 0.391 | 302 | -0.086 | 0.199 |
| ROE Gap2 (Sign) | 257 | -0.055 | 0.210 | 286 | -0.058 | 0.151 | 310 | -0.075 | 0.308 | 351 | -0.056 | 0.243 | 347 | -0.044 | 0.133 | 350 | -0.059 | 0.208 | 338 | -0.070 | 0.333 | 302 | -0.053 | 0.198 |
| ROE Gap3 (Sign) | 257 | -0.034 | 0.248 | 286 | -0.023 | 0.182 | 310 | -0.043 | 0.276 | 351 | -0.029 | 0.247 | 347 | -0.021 | 0.148 | 350 | -0.029 | 0.229 | 338 | -0.039 | 0.315 | 302 | -0.025 | 0.194 |
| SplitBS | 284 | 0.502 | 0.198 | 324 | 0.504 | 0.204 | 343 | 0.519 | 0.208 | 384 | 0.537 | 0.197 | 387 | 0.528 | 0.191 | 386 | 0.529 | 0.190 | 363 | 0.523 | 0.184 | 319 | 0.501 | 0.188 |
| SplitGS | 284 | 0.457 | 0.222 | 324 | 0.459 | 0.233 | 343 | 0.470 | 0.234 | 384 | 0.475 | 0.226 | 387 | 0.473 | 0.225 | 386 | 0.475 | 0.231 | 363 | 0.456 | 0.229 | 319 | 0.467 | 0.216 |
| GranBS_M | 284 | 0.725 | 0.140 | 324 | 0.713 | 0.156 | 343 | 0.720 | 0.156 | 384 | 0.727 | 0.153 | 387 | 0.716 | 0.166 | 386 | 0.719 | 0.161 | 363 | 0.738 | 0.142 | 319 | 0.742 | 0.137 |
| GranBS_D | 284 | 0.312 | 0.125 | 324 | 0.399 | 0.110 | 343 | 0.428 | 0.109 | 384 | 0.441 | 0.103 | 387 | 0.444 | 0.106 | 386 | 0.448 | 0.114 | 363 | 0.454 | 0.110 | 319 | 0.464 | 0.115 |
| GranGS_M | 284 | 0.357 | 0.186 | 324 | 0.360 | 0.189 | 343 | 0.376 | 0.191 | 384 | 0.373 | 0.182 | 387 | 0.370 | 0.181 | 386 | 0.360 | 0.180 | 363 | 0.358 | 0.179 | 319 | 0.357 | 0.176 |
| GranGS_D | 284 | 0.299 | 0.091 | 324 | 0.322 | 0.079 | 343 | 0.344 | 0.085 | 384 | 0.339 | 0.074 | 387 | 0.333 | 0.064 | 386 | 0.334 | 0.067 | 363 | 0.338 | 0.067 | 319 | 0.334 | 0.065 |
| ACCRUALS | 284 | 0.042 | 0.027 | 324 | 0.039 | 0.027 | 343 | 0.041 | 0.033 | 384 | 0.039 | 0.026 | 387 | 0.038 | 0.025 | 386 | 0.038 | 0.024 | 363 | 0.039 | 0.022 | 319 | 0.040 | 0.025 |
| NESTIMATES | 284 | 0.193 | 0.134 | 324 | 0.206 | 0.152 | 343 | 0.214 | 0.154 | 384 | 0.213 | 0.150 | 387 | 0.218 | 0.156 | 386 | 0.219 | 0.154 | 363 | 0.226 | 0.163 | 319 | 0.223 | 0.158 |
| EPS_STDEV | 284 | 2.346 | 9.428 | 324 | 2.762 | 9.488 | 343 | 3.262 | 10.496 | 384 | 3.112 | 11.429 | 387 | 3.285 | 12.766 | 386 | 2.916 | 13.377 | 363 | 2.859 | 15.434 | 319 | 3.704 | 21.960 |
| MARKET CAP | 284 | 5,635 | 14,871 | 324 | 6,473 | 16,476 | 343 | 6,614 | 18,299 | 384 | 7,038 | 19,665 | 387 | 8,950 | 24,949 | 386 | 10,091 | 26,990 | 363 | 10,079 | 28,098 | 319 | 11,014 | 30,202 |
| ASSETS | 284 | 8,949 | 48,070 | 324 | 8,851 | 45,060 | 343 | 9,379 | 42,968 | 384 | 8,979 | 39,216 | 387 | 9,814 | 41,065 | 386 | 9,696 | 37,930 | 363 | 10,050 | 32,501 | 319 | 10,082 | 28,687 |
| REVENUE | 284 | 6,338 | 16,575 | 324 | 6,520 | 16,902 | 343 | 7,145 | 17,627 | 384 | 7,255 | 18,197 | 387 | 7,191 | 18,743 | 386 | 7,905 | 20,063 | 363 | 8,083 | 19,585 | 319 | 7,354 | 16,487 |
| DEBT TO EQUITY | 284 | 0.732 | 1.289 | 324 | 0.628 | 1.002 | 343 | 0.839 | 2.339 | 384 | 0.704 | 0.965 | 387 | 0.672 | 0.964 | 386 | 0.861 | 1.404 | 363 | 1.031 | 1.677 | 319 | 1.231 | 2.357 |
| NSEGBUS | 284 | 4.088 | 1.413 | 324 | 4.238 | 1.627 | 343 | 4.455 | 1.967 | 384 | 4.523 | 1.886 | 387 | 4.432 | 1.686 | 386 | 4.425 | 1.664 | 363 | 4.264 | 1.551 | 319 | 4.000 | 1.308 |
| NSEGGEO | 284 | 4.408 | 2.718 | 324 | 4.608 | 2.832 | 343 | 4.787 | 3.397 | 384 | 4.948 | 3.460 | 387 | 4.899 | 3.845 | 386 | 4.972 | 3.971 | 363 | 4.744 | 3.687 | 319 | 4.630 | 3.586 |
| NNAICSBUS | 284 | 3.880 | 2.061 | 324 | 3.978 | 2.124 | 343 | 3.980 | 2.214 | 384 | 4.065 | 2.119 | 387 | 4.013 | 1.968 | 386 | 4.075 | 1.973 | 363 | 4.058 | 1.934 | 319 | 3.959 | 1.831 |
| NNAICSGEO | 284 | 1.800 | 0.403 | 79 | 1.861 | 0.348 | 343 | 1.869 | 0.395 | 384 | 1.885 | 0.407 | 387 | 1.832 | 0.404 | 386 | 1.862 | 0.408 | 363 | 1.851 | 0.428 | 319 | 1.839 | 0.413 |

Table 9: This table provides a complete description and the computation method of our variables

| Variable | Description | Calculation |
|---|---|---|
| F_ERROR | The absolute of the difference between the earnings per share before extraordinary items as reported by the firm (Compustat Fundamental Database) and the forecasted earnings per share before extraordinary items for T as of T-1 (Thomson Reuters I/B/E/S Database) scaled by the market share price at the end of fiscal year T (Baldwin, 1984; Behn, Choi, & Kang, 2008; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012; O. K. Hope, 2003). | $F\_ERROR_{i,t} = \frac{\lvert EPS_{i,t} - EPS\ Forecast_{i,t}\rvert}{Price_{i,t}}$ |
| F_ERROR(Sign) | The difference between the earnings per share before extraordinary items as reported by the firm (Compustat Fundamental Database) and the forecasted earnings per share before extraordinary items for T as of T-1 (Thomson Reuters I/B/E/S Database) scaled by the market share price at the end of fiscal year T (Baldwin, 1984; Behn, Choi, & Kang, 2008; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012; O. K. Hope, 2003). | $F\_ERROR(Sign)_{i,t} = \frac{EPS_{i,t} - EPS\ Forecast_{i,t}}{Price_{i,t}}$ |
| ROA Gap1 | The absolute of the difference between the return on assets as derived from the company's business segments (Compustat Segment Database) and return on common equity as derived from company's financial statements (Compustat Fundamental Database) scaled by the market share price at the end of fiscal year T (Compustat Funadamental Database). The metric is calculated with respect to year T. This metrcis contains the difference due to non-gaap accounting in segment reports. | $ROAGap1_{i,t} = \lvert ROA_{i,t} - aggROA1\ _{i,t} - \rvert$ <br> $aggROA1_{i,t} = \frac{\sum_j^n OperatingIncomefromSegmentsafterTax)_{i,j,t}}{\sum_j^n SegmentAssets_{i,j,t}}$ <br> $ROA_{i,t} = \frac{OperatingIncome\,(after\ Tax)\ fromConsolidatedFinancialStatememts_{i,t}}{TotalAssets_{i,t}}$ |
| ROA Gap2 | Same metric as ROA Gap1, but completely excludes all segment metrics (segment operating income and segment assets) for those segments that do not report segment revenue or assets. | |
| ROA Gap3 | Same metric as ROA Gap1, but completely excludes all segment metrics (segment operating income and segment assets) for those segments that do not report segment revenue, assets, or operating income. | |

Table 9 Continued: This table provides a complete description and the computation method of our variables

| Variable | Description | Calculation |
|---|---|---|
| ROAGap1(Sign) | The calculation is similar to that of ROA Gap 1 but additionaly also taking into account the direction (+/-) of the profitability gap. | $ROAGap1_{i,t} = ROA_{i,t} - aggROA1\ _{i,t}$ |
| ROAGap2(Sign) | Same metric as ROA Gap 1 (sign) based on aggROA2, taking into account the direction (+/-) of the profitability gap. | |
| ROAGap3(Sign) | Same metric as ROA Gap 1 (sign) based on aggROA3 taking into account the direction (+/-) of the profitability gap. | |
| ROEGap1 | Levered version of ROA Gap 1. | $ROEGap1_{i,t} = \lvert ROE_{i,t} - aggROE1_{i,t} \rvert$<br>$aggROE\ _{i,t} = aggROA_{i,t} + \frac{TotalDebt}{TotalEquity} \times (aggROA_{i,t} - NetBorrowingCosts_{i,t})$<br>$NetBorrowingCosts_{i,t} = \frac{OperatingIncome(beforeTax)\ _{i,t} - NetIncome_{i,t}}{TotalDebt_{i,t}}$<br>$ROE_{i,t} = \frac{NetIncome_{i,t}}{TotalEquity_{i,t}}$ |
| ROEGap2 | Levered version of ROA Gap 2. | |
| ROEGap3 | Levered version of ROA Gap 3. | |
| ROEGap1(Sign) | Same metric as ROE Gap 1 but taking into account the direction (+/-) of the profitability gap. | |
| ROEGap2(Sign) | Same metric as ROE Gap 2 but taking into account the direction (+/-) of the profitability gap. | |
| ROEGap3(Sign) | Same metric as ROE Gap 3 but taking into account the direction (+/-) of the profitability gap. | |
| SplitBS | Business segment aggregation index computed as 1 minus the Herfindahl-Hirschman approach, calculated as the sum of the squared revenue shares of the company's individual business segments. (Cho, 2015; O. K. Hope, Kang, Thomas, & Vasvari, 2008; O.-K. Hope, Kang, Thomas, & Vasvari, 2009; Lang & Stulz, 1994) | $SplitBS_{i,t} = 1 - \sum_{j}^{n} \left( \frac{BusinessSegmentRevenue_{i,j,t}}{TotalRevenue_{i,t}} \right)^2$ |

Table 9 Continued: This table provides a complete description and the computation method of our variables

| Variable | Description | Calculation |
|---|---|---|
| SplitGS | Business segment aggregation index computed as 1 minus the Herfindahl-Hirschman approach, calculated as the sum of the squared revenue shares of the company‘s individual business segments. (Cho, 2015; O. K. Hope, Kang, Thomas, & Vasvari, 2008; O.-K. Hope, Kang, Thomas, & Vasvari, 2009; Lang & Stulz, 1994) | $SplitGS_{i,t} = 1 - \sum_{j}^{n} \left( \frac{GeographicalSegmentRevenue_{i,j,t}}{TotalRevenue_{i,t}} \right)^2$ |
| GranBS_M GranBS_D | Median per firm and year of the count of the reported mandatory line items per segment divided by the highest such observed value of all firms per year. Mandatory line items: compustat items: dps, esubs, ias, ivaeqs, nis, ops, revts; discretionary line items: all other compustat items in the business segment data set with non-missing values. | |
| GranGS_M, GranGS_D | Same metric as GranBS_M, GranBS_D but calculated for geographical segments. | |
| ACCRUALS | Ratio between depreciation and amortization as reported in the cash flow statement (Compustat Fundamental Database) scaled by the firm‘s total assets (Compustat Fundamental Database). The metric is calculated with respect to year T, (Dechow, Sloan, & Sweeney, 1995; Francis, LaFond, Olsson, & Schipper, 2005; Hribar & Collins, 2002) | |
| NESTIMATES | Natural logarithm of the number of analysts‘ estimates that flow into the earnings per share before extraordinary items forecast in year T | |
| EPS_STDEV | Natural logarithm of the standard deviation of the firm‘s earnings per share before extraordinary items (Compustat Fundamental Database) in the most recent 5 fiscal years, from year T-5 to T (Dichev & Tang, 2009) | |
| SIZE | Natural logarithm of the total revenue as reported by the firm in year T(Compustat Fundamental Database) | |
| MARKET CAP | Natural logarithm of the total revenue as reported by the firm in year T(Compustat Fundamental Database) | |
| ASSETS | Total Assets (Compustat Fundamental Database) | |
| REVENUE | Total Revenue(Compustat Fundamental Database) | |
| DEBT TO EQUITY | Debt-to-equity ratio (Compustat Fundamental Database) | |
| NSEGBUS | Number of business segments reported by the firm in year T (Compustat Segment Database) | |
| NSEGGEO | Number of geographical segments reported by the firm in year T (Compustat Segment Database) | |
| NNAICSBUS | Number of NAICS (North American Industry Classification System) codes that the company reports in year T allocated to a firms business segments. | |
| NNAICSGEO | Number of NAICS (North American Industry Classification System) codes that the company reports in year T allocated to a firms geographical segments. | |

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|---|---|
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| Nationality | Romania |
| Date of birth | 28 July 1989 |
| Gender | Male |
| **Education and training** | |
| **2016-present** | **Ph.D. in Finance (PiF)**<br>University of St.Gallen (HSG), St.Gallen Switzerland |
| **2012-2014** | **Master in Banking and Finance (MBF)**<br>University of St.Gallen (HSG), St.Gallen, Switzerland |
| **2010-2014** | **Bachelor in Economics**<br>Bocconi University, Milan, Italy |
| **2008-2010** | **Bachelor in Business Administration**<br>CEU Business School, Budapest, Hungary |
| **2004-2008** | **High-School Diploma in Mathematics and Computer Programming**<br>"Grigore Moisil" high-school, Timisoara, Romania |
| **Work experience** | |
| **2016-present** | **Institute for Operations Research and Computational Finance (ior/cf-HSG)** |
| Occupation or position held | Research and Teaching Assistant |
| Main activities and responsibilities | -Provided support and development for the HSG Trading Room project<br>-Developed equity analysis tools (CC Security Analysis) |
| **2015-2016** | **Roland Berger Strategy Consultants** |
| Occupation or position held | Junior Consultant |
| Main activities and responsibilities | -Provided support for various active projects |
| **2014-2015** | **Goldman-Sachs (Synthetic Products Group)** |
| Occupation or position held | Analyst |
| Main activities and responsibilities | -Assisted the trading desk in various risk and controlling tasks<br>-Primarily responsible with controlling Emerging Markets Accounts |

## Personal skills and competences

Mother tongue: Romanian.

Other languages

| Self-assessment | Understanding | | Speaking | | Writing |
|---|---|---|---|---|---|
| *European level (*)* | Listening | Reading | Spoken interaction | Spoken production | |
| **English** | Fluent | Fluent | Fluent | Fluent | Fluent |
| **German** | Fluent | Fluent | Fluent | Fluent | Fluent |
| **Italian** | Intermediate | Intermediate | Intermediate | Intermediate | Intermediate |

*(*) Common European Framework of Reference for Languages*

Computer Skills: C/C++, Python, R, Stata,SAS, Microsoft Office

## Conference Participation & Presentations

**2017** American Accounting Association (AAA) Annual Meeting, San Diego USA

**2018** European Accounting Association (EAA) Annual Meeting Milan, Italy

**2019** European Financial Management Association (EFMA), Annual Meeting Ponta Delgada, Portugal