Data-Driven Decision-Making in Sales: Can Marketing Analytics Enhance Sales Performance?

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Abstract

Marketing analytics is increasingly used to aid sales force decision making. However, there is little empirical understanding of how the adoption of marketing analytics tools can affect sales performance. Using data from a global B2B information technology company, we find that on average the adoption of a new marketing analytics tool improved sales quota attainment rate by 14%. The reasons behind this increased attainment rate vary by type of sales agents. High performers using marketing analytics won more sales opportunities and performed better relative to quota with inactive customers (customers with no recent transactions). These high performers, however, reduced sales to active accounts. In contrast, compared to high performers, low performers using marketing analytics worked with more marketing-initiated leads and achieved more sales to active accounts. Overall, we interpret this to suggest that marketing analytics can empower the more-skilled sales agents to reach a more balanced account portfolio and help the less-skilled sales agents to seize opportunities that might have been missed.

Keywords: Data-driven decision-making, marketing analytics, marketing and sales interface, sales force management, B2B sales

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1 Introduction

Recent technological developments in the collection, storage, and processing of data have generated rapid progress in analytics. We empirically investigate how analytics can affect decisions in the context of the launch of a marketing analytics tool at the marketing-sales interface in a global business-to-business (B2B) network supplier. Sales force is a critical function in many industries. Approximately 15 million people in the United States are involved in sales and sales-related occupations, making it 10% of total employment and the second largest occupational group (Bureau of Labor Statistics, 2018). Improving sales productivity is thus a top priority for many companies. In the United States alone, companies have invested over $800 billion per year in their sales forces (Zoltners et al., 2008).

Better alignment between marketing and sales is often believed to be an opportunity to improve productivity (Kotler et al., 2006; Sabnis et al., 2013). In most B2B companies, marketing generates leads for the sales force to convert into orders and revenues. However, in practice, marketing is often neglected by sales, with more than 70 percent of leads generated by marketing never pursued (Marcus, 2002). Salespeople tend to ignore marketing-initiated leads due to the lack of trust in marketing's knowledge of customer needs, and marketing is often asserted to "play no role" in developing sales-initiated leads (Kotler et al., 2006).

In this paper, we study whether and how marketing analytics may improve marketing-sales alignment and increase sales productivity. Our data set comes from a global network supplier whose main products include switches, routers, and security. In our empirical setting, the company invested in developing a marketing analytics tool with advanced capabilities in capturing customer engagement activities and predicting sales potential. This analytics tool served two purposes. First, it aimed to improve the quality of new sales leads generated by marketing, and second, it aimed to provide information about the leads generated by the sales agents.[1] Like any major investment,

[1]The firm we study uses the terms sales agents, salespeople, agents, and account executives interchangeably. In this paper, we use the term 'sales agent' whenever possible.

perhaps the most critical question from management is the benefit of marketing analytics to the firm: does marketing analytics indeed enhance the performance of sales agents? If yes, how?

Our setting is useful for measuring the impact of analytics on business output because there is a clear set of decision-makers, an analytics tool that supports each decision-maker, and a performance measure specific to each decision-maker. To estimate the effect of marketing analytics on sales productivity, we use a difference-in-differences approach (before and after the launch, between adopters and non-adopters). Many sales agents did not adopt the new tool in the first two years likely due to the cost of adoption (Jones et al., 2005; Widmier et al., 2002). We control for agent- and time-specific fixed effects with several time-varying controls. The core identification assumption is that there are no systematic differences in the trend of sales performance between adopters and non-adopters. To support this assumption, we document parallel trends conditional on these controls before adoption. These parallel trends exist across high and low performers and across a large number of alternative definitions of the dependent variable.

We find an overall positive effect of marketing analytics adoption on sales performance: after the launch of marketing analytics, on average the adopter group enhanced their quota attainment rate (i.e., the cumulative percent of annual quota attained) by 14%. Further investigation with respect to sales agent and customer account characteristics reveals that marketing analytics supported different types of sales agents in different ways.

For sales agents who achieved their assigned sales quotas before the launch of marketing analytics (who we label the ‘high performers’), after adoption they increased their sales quota attainment from inactive customer accounts (i.e., those with no transactions over the past year). Compared to the high performers, for sales agents who did not achieve their sales quota prior to the launch of marketing analytics (‘low performers’), the adoption of marketing analytics is associated with an increase in sales quota attainment from active customer accounts (those with transactions in the past year).

This result suggests that marketing analytics may serve a different purpose for high and low performers. It may help high performers refine their customer account portfolio and help low performers find more cross-selling opportunities that they might have neglected in the past year. To explore this hypothesis, we examine the sales process by looking at different stages of the sales funnel.

In the early lead qualification stage of the sales funnel, sales agents select promising leads as sales opportunities to convert. While we did not observe any significant change in the lead acceptance for the high performers, for the low performers, the marketing analytics tool resulted in a significantly higher marketing-initiated lead acceptance rate (the fraction of the leads generated by marketing accepted as sales opportunities) in active customer accounts. Thus, in the lead qualification stage, marketing analytics supplied high-quality leads missed by the low performers.

In the later lead conversion stage of the sales funnel, when sales agents convert opportunities into sales, marketing analytics led to a higher conversion rate (which we label the 'sales winning rate'). Consistent with the results on quota attainment, for high performers, the increase in the sales winning rate occurred mainly with inactive accounts. This suggests that marketing analytics provided valuable information on customer needs that helped the high performers win these accounts. In contrast, low performers significantly increased their sales winning rate in active accounts. This suggests that the marketing analytics tool enabled the low performers to close warm leads more effectively.

Overall, our results suggest that marketing analytics, a new data-based technology to aid sales decision-making, significantly enhanced sales productivity at the firm we study. Within the sales process, the specific tasks (i.e., generating leads, qualifying leads, and converting leads) where we observed a significant boost in performance varied by a sales agent's skill level (high vs. low performers) and the activeness of customer accounts.

The findings from different stages of the sales funnel suggest how marketing analytics supports high- and low-performing groups differently. For lead generation and qualification, marketing analytics can substitute for human skill. Therefore, low performers accept more marketing-initiated leads, and low performers who use analytics select more highly-promising leads. The analytics tool provides low performers with the kind of information high performers likely already had. In contrast, at the lead conversion stage, marketing analytics appears to be a complement to human skill. The complementarity effect is driven by enabling the conversion of inactive accounts. It appears to provide information to high performers that enables them to convert relatively difficult accounts.

Combined, our results indicate that both low performers and high performers benefit from analytics, but in different ways. After adopting marketing analytics, overall, the sales agents significantly improved sales winning rates at their inactive accounts. However, the effect on sales conversion for the active accounts is mixed, likely due to the company's incentive structure and the nature of multitasking: we observe a slight reduction in the sales winning rate for high performers while we observe a positive coefficient on the sales winning rate for the low performers. The high performers were already skilled enough to exceed the sales quota, and the company offered little incentive to exceed the quota by a large amount. In response to the increased productivity with inactive accounts, high performers shifted some effort away from active accounts. Consequently, we observe a small dip in winning sales at active accounts. This result implies a need for the company to adjust the incentive plans in line with the changes brought by marketing analytics.

1.1 Related Literature

Our paper primarily contributes to two streams of research: sales force management and the effect of information technology (IT) on business performance. First, our paper is directly related to the empirical literature that examines effort in salespeople's decisions and performance (e.g. Kim et al. (2019b)). Sabnis et al. (2013) study sales performance along the sales funnel, including prequalification, qualification, and conversion. Our paper adopts similar measures. However, unlike their paper which uses self-reported survey data, we use a company's internal records and the launch of a new marketing analytics tool to enable a causal interpretation.

An extensive part of sales force research studies the compensation plans for salespeople (e.g., Chung et al. 2014; Kalra et al. 2003; Kim et al. 2019a; Misra and Nair 2011). In our empirical setting, the sales agents were compensated according to a regressive quota-based plan. Although the present paper does not directly study the effect of such compensation plans on salespeople's behavior, our results are consistent with the existing literature (Chung et al., 2014; Misra and Nair, 2011). For instance, the high performers, who were already skilled enough to achieve the quota, were not as motivated to increase overall sales as the low performers who were still striving to achieve the quota. Similarly, although we do not explicitly examine a sales agent's multi-task decisions, the results are consistent with the literature (Kim et al., 2019a). After the adoption of marketing analytics improved the productivity of selling to the inactive accounts, we observe a slight dip in the efforts that the high performers put into the active accounts.

In B2B contexts, prior work has focused on pricing, branding, and other marketing activities and addressed their impact on company-level outcomes (Bruno et al., 2012; Homburg et al., 2013; Kotler and Pfoertsch, 2007; Zhang et al., 2014). Our paper provides new insights on how a B2B company may improve marketing-sales coordination by reducing the long-standing conflicts between marketing and sales. The lack of follow-up of marketing-initiated leads has been a recurring problem for B2B companies (Kotler et al., 2006; Sabnis et al., 2013). Our paper demonstrates that using new technologies like marketing analytics, which enhances the value of marketing efforts to the sales agents at the entire spectrum of skill levels, can effectively improve the coordination between two functional divisions.

This paper also directly contributes to the literature investigating the effect of IT on firm performance. Our paper identifies a positive impact of a particular IT adoption decision on sales performance, with the magnitude of effects varying according to account and agent types. Our results add new evidence to an extensive literature examining the relationship between IT and productivity (Bertschek and Kaiser, 2004; Bresnahan et al., 2002; Brynjolfsson and Hitt, 1996), and IT and medical outcomes (Miller and Tucker, 2011). A common theme in the literature is that IT adoption is beneficial on average, but the average hides important differences over time and across groups. Our results are consistent with this theme.

Our specific IT application relates to marketing analytics and the use of what is often called 'big data'. Thus, the findings build on the existing knowledge of data-driven decision-making. Brynjolfsson and McElheran (2016) investigate the adoption of data-driven decision-making and its impact on manufacturing productivity. By investigating plant-level survey data across industries, the authors show heterogeneity in adoption across the size and the age of the firms, along with evidence of the importance of complementary processes. Our paper builds on this literature, but with a focus on individual-level effects in a specific sales context.

Finally, at the intersection of technology and sales, existing research has explored the decision to adopt sales-related technology (Ryan and Tucker, 2012; Tucker, 2008), the role of sales training (Atefi et al., 2018; Chung et al., 2021), the feasibility of sales automation (Syam and Sharma, 2018; Karlinsky-Shichor and Netzer, 2019), and the effect of IT on sales performance (Ahearne et al., 2004, 2008). Our paper is particularly close to Ahearne et al. (2004) and Ahearne et al. (2008); however, while those studies examine the effect of customer relationship management (CRM) software, we examine a technology on lead management.

The rest of the paper proceeds as follows. We describe the empirical background in Section 2 and explain the data in Section 3. Section 4 presents empirical results on the effect of marketing analytics in three measures: sales performance in quota attainment, lead acceptance rate, and sales winning rate. Finally, in Section 5, we conclude with the main results and directions for future research.

2 Empirical Setting

Our data set comes from a company that provides switches, routers, security, and related IT products to large enterprises in a wide range of industries including global financial institutions, IT giants, telecommunications, educational institutions, and medical centers. As typical in B2B markets, the company relies on the sales force to manage customer relationship and conduct sales transactions. The sales force consists of a team of sales agents, each assigned an exclusive set of customers defined by industry, geographic location, and/or business scale. For small business clients, the company sells products via their partner companies, not directly via their sales agents. The exclusive account assignment guides the company in routing each new prospect or sales lead to a specific sales agent. The company compensates each sales agent with a salary and a quota-based sales commission. The company assigns an annual sales quota to each sales agent and awards a commission for the sales amount above the sales agent's sales quota. To calculate the amount of commission, the company follows a two-level regressive commission in its compensation structure: a regular commission rate applied to the sales achieved between 100% and 200% of sales quota, followed by a lower commission rate for the sales amount exceeding 200% of sales quota.

Next, we provide detailed descriptions for four areas of sales practice: the sales funnel, sales performance measures, account and sales categorization, and marketing analytics for sales leads.

2.1 Sales Funnel

A typical sales process in the company follows the sales funnel depicted in Figure 1. The sales funnel consists of three stages: lead generation/prequalification, lead qualification, and lead conversion. A sales funnel starts with lead generation/prequalification and can be initiated either by marketing or by the sales agents. In conventional practice, marketing generates sales leads by collecting information of prospective customers via various marketing activities such as trade shows, product seminars, direct mail, and cold-calling. The information is filed as a lead, containing contact details and several scores summarizing customer activities such as trade show attendance, seminar registration, frequency of interactions, and categories of products that customers have shown interest in. If a lead's overall score reaches a certain threshold, the lead passes the prequalification stage and is assigned to the sales agent responsible for the account.

In the second stage, the sales agent conducts further research and analysis to determine if the lead is worth pursuing. Leads that have passed the sales agent's qualification are accepted as opportunities for further pursuit.

Sales agents can also obtain sales leads directly, either from their existing customers or through referrals (Godes, 2012; Jolson, 1988; Sabnis et al., 2013). We label the leads generated and prequalified by marketing as marketing-initiated leads and those by sales as sales-initiated leads respectively. Unlike marketing-initiated leads which are recorded and tracked for marketing-sales communications, sales-initiated leads are not recorded in the company's internal system until the second stage of the sales funnel. When the sales agents discover sales leads promising enough to pass their own prequalification, they manually input these leads into the internal system (provided by salesforce.com). Like the marketing-initiated leads, the sales-initiated leads that have passed the qualification stage are called sales opportunities.

In the third stage of the sales funnel, labeled as lead conversion, the sales agents engage in sales activities to convert the opportunities into transactions. Common conversion activities include communicating with the stakeholders, working with engineers to create customized product solutions, writing proposals, negotiating the prices and payment terms, and completing sales orders. Depending on a sales agent's sales skill and the product-need fit, some opportunities are won (i.e., converted into actual sales) while others are lost. Successfully converted opportunities result in actual sales that are added to the sales performance.

We define leads at the customer level.[2] For example, if a customer is interested in purchasing both routers and gateways within the same fiscal quarter, we treat this as one lead, rather than two separate leads, from the customer. Customers typically prefer to purchase multiple products together for the benefit of product compatibility and bargaining power. Moreover, during the sales conversion stage, sales agents communicate with the customers to find out their needs (e.g., constructing a new data center) and propose solutions covering a range of products of potential

[2]When defining the appropriate level of customers, we refer to Data Universal Numbering System (DUNS), a widely used standard identifier for business entities.

Figure 1: A Sales Funnel with Outcome Measures in Different Sales Stages

Index	Outcome measures	Descriptions
For sales performance		
(1)	Quota Attainment Rate (QAR)	$\frac{\text{\$Sales attained (annual cumulative)}}{\text{\$One's annual quota}}$
(2)	Sales Winning Rate (SWR)	$\frac{\text{\#Opportunities won}}{\text{\#Opportunities}}$
For sales-marketing interactivity		
(3)	Lead Acceptance Rate (LAR)	$\frac{\text{\#Marketing-initiated opportunities}}{\text{\#Marketing-initiated leads}}$

interest to the customers. Given the various common conversion activities with considerable time,[3] they are unlikely to be handled separately.

2.2 Sales Performance Measures

The company uses the quota attainment rate, which is the ratio of a sales agent's annual sales and annual sales quota, as its primary performance measure. The quota attainment rate is regarded as a reliable and accurate measure for performance because the sales quota controls for territory- and account-specific factors such as territory size, territory-specific industries, and economic conditions (Ahearne et al., 2008).

Figure 1 shows two intermediate performance measures in the sales funnel. First, the lead acceptance rate is the number of marketing-initiated opportunities as a fraction of total marketing-initiated leads (Gopalakrishna and Lilien, 1995; Smith et al., 2006). The lead acceptance rate measures the level of alignment between sales and marketing within the company, representing the contribution of marketing to sales performance.

Second, the sales winning rate is the number of opportunities won as a fraction of the total number of opportunities. Sales winning rate, which measures a sales agent's ability to successfully convert sales opportunities into transactions, is another common sales productivity measure (Jasmand et al., 2012; Jolson, 1988). In addition to the overall sales winning rate, we further measure the sales winning rate for marketing-initiated and sales-initiated opportunities separately.

[3] In our data, among the opportunities won by the company, on average the third stage took 51.14 days (with a standard deviation of 66.28 days) for an opportunity's status to move from "pursuit" to "won". Among all the opportunities, on average it took 113 days (with a standard deviation of 863.89 days) to move from "pursuit" to "closed", where "closed" including winning and losing the deals.

2.3 Account and Sales Categorization

We categorize customer accounts into active and inactive accounts. Active accounts are defined as customer accounts with at least one recorded sale in the past year, and inactive accounts are those without any sales in the past year. Following this definition, in order to sort customer accounts each year, we need prior-year observations and hence we have to sacrifice the first-year observation (the year 2014) in the analyses. In the sales process analysis, we provide the sales performance measures for active and inactive accounts separately.

Relatively speaking, the sales agents have established a closer relationship and enjoyed a higher level of trust with active accounts. As a result, given the same selling efforts, active accounts are commonly recognized as easier to convert than the inactive ones (Jolson, 1988). Moreover, since sales agents are less familiar with inactive accounts, it requires additional effort to learn the needs and internal process of inactive accounts. Thus, qualifying the leads of inactive accounts often involves more effort and greater uncertainty.

We categorize sales agents into two groups based on their pre-analytics sales performance. Specifically, as noted above, we call those who attained the annual sales quota prior to the arrival of the analytics tool at the company as 'high performers', and others as 'low performers'. This categorization is based on the company's annual audited report which contains information on each sales agent's annual performance. The company sets the sales quota for each sales agent according to the account potential. The level of quota attainment, which is performance adjusted by account characteristics, reflects a sales agent's skill and selling effort. Although the company's compensation system has two levels of commission rates, corresponding to 100% and 200% of quota attainment respectively, only 2.47% (14 out of all 444) of sales agents in our data exceeded 200% of the quota. Since the 200% quota achievers as a group were too small for a meaningful analysis, we combine the 100% and 200% quota achievers into the high performers group.[4]

[4] We also take an average of all pre-analytics quota attainment rates (not just one year) when categorizing the sales agents into high and low performers. The result shows that only 6 sales agents are sorted differently (4 from high to low and 2 from low to high performers), which is 1.4% of the total 444 sales agents who had at least one pre-analytics

2.4 Marketing Analytics for Sales Leads

The marketing analytics tool was intended to improve the quality of lead generation and prequalification in the sales funnel. One may expect the significance of improvement to depend on sales agent and account characteristics. For instance, between the types of accounts, it is easier for an agent to assess and qualify leads with active accounts, but more difficult with inactive accounts due to lack of familiarity and trust. The marketing analytics tool, by collecting and synthesizing the customer's product-related activities, can potentially bridge the information gap with inactive accounts. Active accounts, however, have regular contact with the sales agents and thus the information provided by marketing analytics may overlap with the knowledge of sales agents. As a result, the effect of marketing analytics for active accounts may be low. The findings of Jolson (1988) suggest that marketing analytics can also be useful for converting leads from inactive accounts in the final stage of the sales funnel.

The effect of marketing analytics on sales productivity may also vary between high- and low-performing sales agents. The findings of Sujan et al. (1988) suggest that analytics might support the low performers most. The low-performing sales agents may be less capable of qualifying leads and less skilled in converting opportunities into sales. Marketing analytics, by improving the quality of lead prequalification, may significantly improve the lead selection of low-performing sales agents. We summarize the above hypotheses on how marketing analytics affect a sales agent's sales productivity in Table 1.

Table 1: Possible Effects of Marketing Analytics on Improving Sales

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Account Characteristics</td></tr>
<tr><td>Active Accounts</td><td>Inactive Accounts</td></tr>
<tr><td rowspan="2">Agent Characteristics</td><td>High performers</td><td>Low</td><td>High</td></tr>
<tr><td>low performers</td><td>High</td><td>High</td></tr>
</table>

While the previous literature suggests a clear direction of which account or agent type would

quota attainment record (i.e., excluding those sales agents who joined the company later). We replicated the main analysis using this categorization and found the results to be robust.

expect a stronger effect from each relevant dimension alone, when combining the two dimensions together it is not clear how they would interact. The magnitudes and directions of the effects will depend on the marginal impact of improving conversions in inactive accounts and the changes in incentives to allocate effort across accounts. For example, while we expect marketing analytics to support low-performing sales agents and to provide useful information about inactive accounts, low-performing sales agents may get the greatest benefit of marketing analytics by receiving pertinent information about active accounts. If the low performers put more effort into active accounts, then the effect of marketing analytics on inactive accounts may be dampened. Our empirical investigation can help to find a clear answer.

3 Data

Our dataset is an unbalanced panel with 566 sales agents and 4,867 quarterly observations from the year 2014 to 2018. We have access to the quarterly sales records reported by the sales agents upon the occurrence of each sales order. We also have the company's annual audited reports of the commissions obtained by each sales agent after auditing all sales and real transaction records at the end of each year.

Although the company introduced the marketing analytics tool in the second quarter of 2017, they did not start recording individual login activity until April 18, 2018. Before that, the system recorded only the cumulative number of logins for each user. As an example, consider a sales agent who viewed the marketing analytics tool for the first time at the beginning of the third quarter of 2017 and then viewed it once at the beginning of each subsequent quarter. For this sales agent, we would observe four logins as of April 17, 2018, and then one login in the third and fourth quarter of 2018.

We consider the first four quarters before the detailed tracking in April 2018 as the implementation period. The company had a global sales network with more than 100 physical offices, and marketing did not have the full information that maps sales agents to the assigned customer accounts. During the implementation period, the mappings were gradually completed with the assistance of field marketing units, and therefore the value of marketing analytics was realized gradually within the organization.

Given the gradual implementation and the cumulative nature of login activity measures during the period, we consider two different indicators for the adoption status of a sales agent (denoted by i) at quarter t and illustrate them in Figure 2.

- $EventuallyAdopted_{it} (= EventualAdopters_i \times After_t)$ covers the entire observation period. This indicator is a product of two dummy variables, $EventualAdopters_i$ and $After_t$. $EventualAdopters_i$ indicates whether sales agent i belongs to the adopter group measured at the end of our observation period and $After_t$ indicates whether quarter t is after the launch of marketing analytics. Together, $EventuallyAdopted_{it}$ equals one from the second quarter of the year 2017 to the fourth quarter of the year 2018 for adopters and zero otherwise.

- $HasAdopted_{it}$ skips the implementation period. This dummy variable indicates whether sales agent i had already used marketing analytics by period t, computed based on tracked login activities.

Figure 2: Timeline of the Datasets and Adoption Measures

	2014				2015				2016				2017				2018			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Notable Events														Logins Cumulated				Logins Tracked		
Dataset																				
Eventually Adopted *(EA)*	Pre-analytics													Post-analytics						
Has Adopted *(HA)*	Pre-analytics													Implementation				Post-analytics		

Note:

- Under $HasAdopted$ measure (HA, $HasAdopted_{it}$), adoption is defined as the (trackable) moment of adoption.
- Under $EventuallyAdopted$ measure (EA, $EventualAdopter_i \times After_t$), adoption is defined by assuming all adopters started using the marketing analytics tool since its introduction to the company (from the second quarter of the year 2017).

The first measure, $EventuallyAdopted$, assumes those who have ever used marketing analytics started using the tool from the beginning when it was first implemented (i.e., the second quarter of 2017). Under this definition, late adopters who logged into the system in 2018 are treated as if they have used the analytics software since the last year. Hence, $EventuallyAdopted$ is a less accurate measure of adoption and can be interpreted as a lower-bound (or, an upper-bound if the adoption has a negative effect) of the effect of the marketing analytics. Although $HasAdopted$ captures the exact time of the adoption, we achieve the precision at the expense of the length of after-analytics observations. To estimate a conservative adoption effect and to use the entire time series of the data, we use the $EventuallyAdopted$ measure for our main analyses, and demonstrate robustness to the $HasAdopted$ measure in the appendix.

To categorize the high-performing and low-performing sales agents, we use sales records from the annual audited report in the year 2016. For a small number of sales agents missing the year 2016 records, we use the most recent year's annual report prior to the introduction of marketing analytics.

Table 2 and Table 3 provide descriptive statistics. We use the quota attainment rate as a dependent variable for sales performance.[5] As mentioned earlier, we aggregate sales leads to the customer account level. Hence, all the intermediate performance measures including the number of leads, the number of opportunities, and the number of opportunities won indicate the number of unique customers within each quarter. We observe that most of the opportunities were sales initiated, i.e., generated by the sales agents. The sales winning rate of sales-initiated opportunities is greater than that of marketing-initiated opportunities. Regarding the customer account types, both the sales winning rate and the lead acceptance rate of active accounts are greater than those of inactive accounts.

Our core explanatory variable of interest is an indicator for the adoption of the marketing

[5]The max quota attainment rate of 41.47 is a sales agent who joined in 2016 and had a poor performance. The agent improved in 2017 and then closed several large deals in 2018 (surpassing quota by a factor of 40). In an interview with us, the agent noted that some of the success can be traced to the marketing analytics tool.

Table 2: Summary Statistics of the Main Dataset: Variables Related to Outcome Measures

Statistic	N[a]	Mean	St. Dev.	Min	Median	Max
Quota Attainment Rate (QAR, (1)/(2))[b]	4,867	0.66	1.17	0.00	0.49	41.47
(1) Sales (cumulative, in millions)	4,867	8.21	17.58	0.00	4.00	342.23
(2) Sales quota (set annually, in millions)	4,867	19.05	36.79	0.67	8.04	398.47
QAR from active[c] accounts	3,874	0.46	1.24	0.00	0.27	41.31
Sales (cumulative, in millions) from active accounts	3,874	6.41	17.62	0.00	2.28	340.89
QAR from inactive[c] accounts	3,874	0.20	0.41	0.00	0.03	6.58
Sales (cumulative, in millions) from inactive accounts	3,874	1.95	6.49	0.00	0.30	164.47
Sales Winnning Rate (SWR, (3)/(4))[d]	4,867	0.59	0.34	0.00	0.67	1.00
(3) Number of opportunities[e] won	4,867	6.75	8.71	0	4	76
(4) Number of opportunities	4,867	10.92	14.93	0	6	156
SWR from active accounts	3,874	0.56	0.42	0.00	0.68	1.00
Number of active opportunities won	3,874	3.50	5.29	0.00	1.00	46.00
Number of active opportunities	3,874	4.84	7.59	0.00	2.00	61.00
SWR from inactive accounts	3,874	0.45	0.37	0.00	0.50	1.00
Number of inactive opportunities won	3,874	3.79	5.85	0.00	2.00	56.00
Number of inactive opportunities	3,874	7.01	10.33	0.00	3.00	90.00
SWR from sales-initiated[f] accounts	4,867	0.59	0.35	0.00	0.67	1.00
Number of sales-initiated opportunities won	4,867	5.80	7.39	0	3	76
Number of sales-initiated opportunities	4,867	9.04	11.91	0	5	93
SWR from sales-initiated active accounts	3,874	0.54	0.43	0.00	0.67	1.00
SWR from sales-initiated inactive accounts	3,874	0.46	0.38	0.00	0.50	1.00
SWR from marketing-initiated[g] accounts	4,867	0.23	0.37	0.00	0.00	1.00
Number of marketing-initiated opportunities won	4,867	0.95	2.33	0	0	30
Number of marketing-initiated opportunities	4,867	1.88	4.62	0	0	75
SWR from marketing-initiated active accounts	3,874	0.18	0.36	0.00	0.00	1.00
SWR from marketing-initiated inactive accounts	3,874	0.13	0.29	0.00	0.00	1.00
Lead Acceptance Rate (LAR, (5)/(6))[h]	4,867	0.29	0.39	0	0	1
(5) Number of marketing-initiated opportunities	4,867	1.76	4.03	0	0	53
(6) Number of marketing-initiated leads	4,867	3.04	7.51	0	1	279
LAR from active accounts	3,874	0.22	0.38	0.00	0.00	1.00
Number of marketing-initiated active opportunities	3,874	0.86	2.25	0.00	0.00	28.00
Number of marketing-initiated active leads	3,874	1.35	2.89	0.00	0.00	45.00
LAR from inactive accounts	3,874	0.20	0.36	0.00	0.00	1.00
Number of marketing-initiated inactive opportunities	3,874	0.96	2.52	0.00	0.00	25.00
Number of marketing-initiated inactive leads	3,874	1.79	5.83	0.00	0.00	234.00

[a] The observations (subscript it) are quarterly (subscript t) observations per sales agent (i).
[b] Quota attainment rate represents cumulative sales of a year relative to the annual quota that is assigned to each sales agent.
[c] (In)Active accounts refer to the accounts with(out) sales records in the prior year. Statistics are based on four-year data (N = 3,874) as the first year (2014) is consumed to classify customer account types.
[d] Sales winning rate represents the percentage of opportunities pursued in each quarter that were converted into sales orders.
[e] Opportunities refer to accounts that are qualified by corresponding sales agents (See Figure 1).
[f] Leads that were generated by sales agents, recorded as opportunities (4) from the beginning by skipping the prequalification stage.
[g] Leads that are originally generated by marketing (6) and assigned to sales agents.
[h] Lead acceptance rate represents the percentage of marketing-initiated leads qualified by sales agents

analytics tool. For our main measure of adoption ($EventuallyAdopted$) the average adoption is 11%. In the pre-analytics sales performance, on average, the sales agents achieved sales just above their annual sales quota (1.084). There were about the same number of high performers and low performers. New agents are a group of sales agents who joined the company after the year 2017 and hence did not have any sales records before the company introduced the markeing analytics tool. We include the new agents group in the analysis as a control, but do not interpret the coefficients associated with the new agents as causal because this group does not have pre-analytics observations.

Table 3: Summary Statistics of the Main Dataset: Covariates

Statistic	N[a]	Mean	St. Dev.	Min	Median	Max
Adoption ($EventuallyAdopted$)	4,867	0.11	0.31	0	0	1
Adoption ($HasAdopted$)	4,867	0.05	0.22	0	0	1
Tenure	4,867	5.69	3.67	0	5	19
Grade level	4,867	7.85	0.64	5	8	10
Previous sales forum pageviews	4,867	43.53	54.45	0	25	520
Previous voluntary training sessions	4,867	1.51	2.59	0	0	32
Pre-analytics sales performance[b]	4,382	1.08	0.41	0.12	1.03	3.71
High performers (N(%))	216 (38%)					
Low performers (N(%))	228 (40%)					
New agents (N(%))	122 (22%)					

[a] The observations (subscript it) are quarterly (subscript t) observations per sales agent (i).
[b] The groups are classified by the last annual quota attainment from annual audited reports before marketing analytics.

Based on the previous literature in technology adoption and data-driven decision-making, we add multiple control variables that may affect the adoption and the impact of adoption on sales performance: tenure, grade level, sales forum page views, voluntary training sessions, and sales status. Previous research suggests a positive relation between sales experience and sales performance (Churchill Jr et al., 1985) and a negative relation between tenure and the adoption of data-driven decision-making (Brynjolfsson and McElheran, 2016). The sales agents who have worked at the company longer may have established stronger customer relationship and/or developed sales tactics effective in this industry; these sales agents may find marketing analytics less valuable.

Some sales agents started their careers in the company with a higher grade level than others, typically due to their credentials and experience at other companies. Thus, the grade level is another measure of overall sales experience.

The company has a sales forum website where the sales agents can find information about the company's products, post questions to others, and share sales tactics. We use the number of sales forum page views as a measure of technology preferences across sales agents and over time. Some may prefer to gather information by viewing digital webpages and communicate with colleagues through the web forum while others prefer to ask and communicate in real person. We expect sales agents with more sales portal activities to be more likely to adopt marketing analytics (Keillor et al., 1997). In addition, we use the number of training sessions voluntarily taken by each sales agent over time to measure tendency to spend time learning. Unlike the core and mandatory sales-related training, the contents in voluntary training sessions are not necessarily related to sales activities. We expect that those who are more open to learning new things are more likely to try the new marketing analytics tool. We take the lagged value for both the technology preference and openness to learning variables.

We also use each sales agent's quota attainment at the end of the previous quarter (i.e., lagged dependent variable resets annually) as a measure for the current sales status. Sales agents with lower quota attainment rates when they start a quarter may be more desperate and consequently both the value of adopting marketing analytics and the impact of marketing analytics on sales may be greater.

We further control for unobservable heterogeneity associated with the sales agents with individual dummy variables. We control for time effects using quarterly dummy variables. Details of how we construct each variable are provided in Table 4.

Table 4: Notation and Description of Variables

Variable	Notation	Description
Dependent Variables		
Quota Attainment Rate	QAR_{it}	The cumulative sum of sales quota attained by quarter t divided by the annual sales quota assigned to sales agent i.
Sales Winning Rate	SWR_{it}	The ratio of the number of opportunities won to the number of opportunities for sales agent i in quarter t.
Lead Acceptance Rate	LAR_{it}	The ratio of the number of marketing-initiated opportunities to the number of marketing-initiated leads for sales agent i in quarter t.
Independent Variables		
Adoption ($EventuallyAdopted$)	$EventuallyAdopted_{it}$	A multiplied combination of two dummy variables indicate whether sales agent i is an eventual adopter (1) ($EventualAdopters_i$) and whether the marketing analytics tool was available to agents (1) in quarter t ($After_t$).
Adoption ($HasAdopted$)	$HasAdopted_{it}$	A dummy variable indicates whether sales agent i has ever used (1) the marketing analytics tool by the end of quarter t.
Pre-analytics Sales Performance	$LowPerformers_{i,pre}$ $NewAgents_{i,pre}$	A categorical variable based on the previous year's quota attainment (actual sales at the end of the previous year ($y - 1$) divided by the year's annual sales quota) of sales agent i. (baseline: $HighPerformers_{i,pre}$)
Control Variables		
Sales Status	$SalesStatus_{it-1}$	The quota attainment rate of sales agent i at the end of the previous quarter ($t - 1$) that resets annually, representing a current year sales status at the beginning of quarter t.
Tenure	$Tenure_{it}$	An integer representing the number of years has passed since sales agent i took the current position at quarter t.
Grade Level	$GradeLevel_{it}$	An integer representing the grade level of sales agent i during quarter t.
Previous Sales Forum Pageviews	$SalesforumViews_{it-1}$	An integer representing the number of sales forum page views of sales agent i during the previous quarter ($t - 1$).
Previous Voluntary Traning Sessions	$VoluntaryTraining_{it-1}$	An integer represents the number of voluntary training sessions that sales agent i took at the previous quarter ($t - 1$).

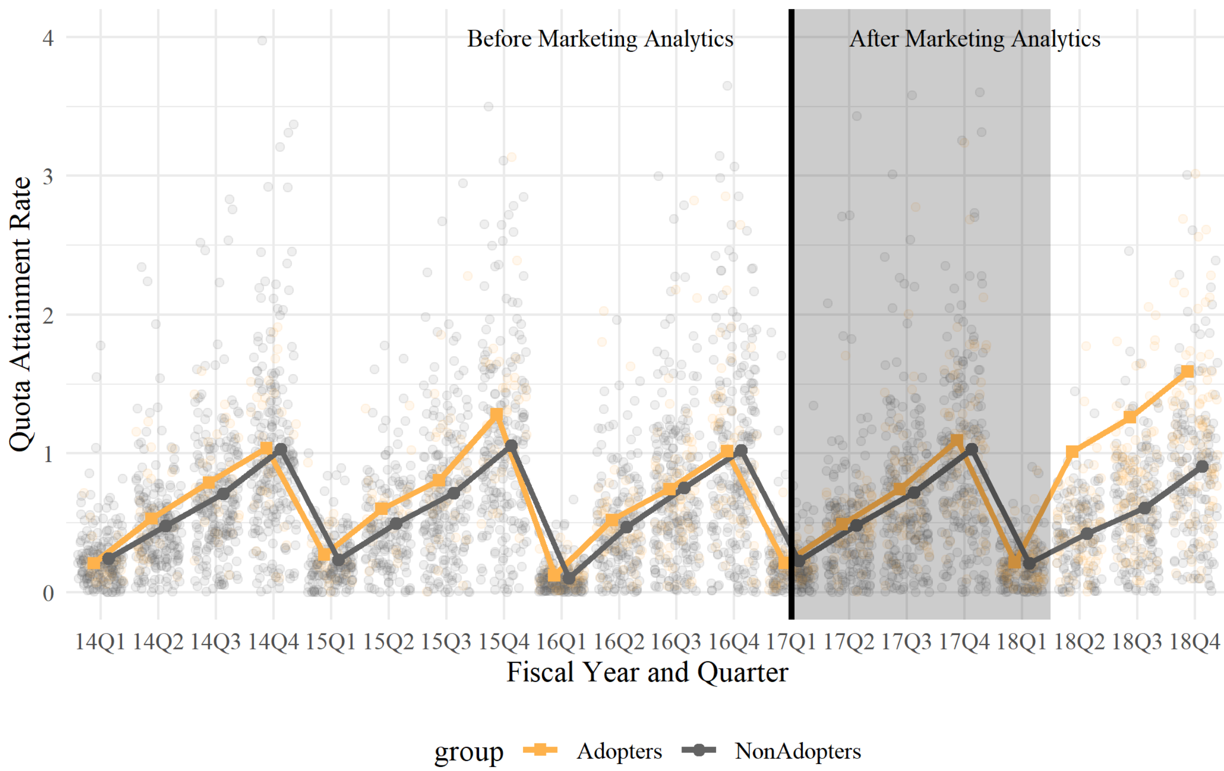
Note: The company updates the tenure and changes in grade level (if any) annually in the middle of June. Hence, given that a sales agent maintained the same position, the sales agent had the same number of years as the tenure in the first and second quarters, and the tenure increased by one in every third and fourth quarter.

4 Empirical Analysis and Results

4.1 Marketing Analytics and Sales Performance

The two lines in Figure 3 show the average quarterly quota attainment rates for the adopter and non-adopter groups. The black vertical line indicates when the marketing analytics tool was launched, and the shaded area represents the implementation period. The figure shows that the gap between the two groups increases after the launch of marketing analytics. While we observe only a slight increase during the first year with marketing analytics, the increase in the gap is substantial during the second year. The significantly smaller effect in the first year is likely due to a combination of gradual implementation mentioned earlier in Section 3 and the long selling cycle with the company (four months on average with a high variance).

Figure 3: Average Quota Attainment Rate for Adopters and Non-Adopters



Note: Scattered dots represent sales agents' quarterly quota attainment rate. 21 dots with a rate over 4 are omitted due to space limitation. The shaded area in the early post-analytics period indicates the implementation period.

We also compare the groupwise mean quota attainment rates between the adopters and non-adopters and test the statistical significance of the differences in Table 5. We first compare the quota attainment rate between the fourth quarter of the pre- and post-analytics period. We observe that both adopters and non-adopters had the same average quota attainment rate before implementing marketing analytics. After the launch of marketing analytics, the adopters' quota attainment rate increased substantially, leading to a significant gap in quota attainment rate between the adopters and non-adopters. We also expand the analysis to periodic average comparison and find similar results: no pre-analytics difference in quota attainment rate between adopter and non-adopters, but the difference becomes statistically significant ($p < 0.05$) in the post-analytics period.

Table 5: Groupwise Differences in the Quota Attainment Rate

	Before Marketing Analytics			After Marketing Analytics		
	Adopters	Non-Adopters	t-test (p-value)	Adopters	Non-Adopters	t-test (p-value)
Point-of-time Comparison[a]						
Quota Attainment Rate	1.02 (0.57)	1.02 (0.84)	0.964	1.59 (4.20)	0.90 (0.54)	0.038
Quota Attainment Rate (excluding new agents)	1.02 (0.57)	1.02 (0.84)	0.964	1.89 (5.23)	0.92 (0.51)	0.060
Periodic Average Comparison[b]						
Quota Attainment Rate	0.56 (0.29)	0.56 (0.44)	0.877	0.94 (1.82)	0.64 (0.51)	0.019
Quota Attainment Rate (excluding new agents)	0.58 (0.27)	0.58 (0.43)	0.968	1.06 (2.25)	0.68 (0.53)	0.044

[a] This panel compares two single-period observations: the fourth quarter of the year 2016 (before) vs. the fourth quarter of the year 2018 (after).
[b] This panel computes an individual average per sales agent and compares the average across sales agents: quarters before the marketing analytics (until the first quarter of the year 2017) and after.

So far, we have shown that we observe a similar trend on the quota attainment rate, as well as no groupwise mean differences between the adopters and non-adopters before the introduction of the marketing analytics tool. Next, we turn to regression analysis. Under the parallel trends assumption, we use a difference-in-differences identification strategy with fixed effects to estimate the average effect of marketing analytics adoption on the quota attainment rate. Our base specification is shown below in Equation 1, and an augmented specification that allows the treatment to be heterogeneous across different types of agents is presented in Equation 2 (results are shown in columns 3 and 4 respectively of Table 6):

$$
\begin{aligned}
QuotaAttained_{it} =& \alpha + \beta EventuallyAdopted_{it} + \\
& \gamma_0 LowPerformers_{i,pre} + \gamma_1 NewAgents_{i,pre} + \delta Z_{it-1} + \theta Z_{it} \\
& \textstyle\sum_{i=2}^{I} \kappa_i I_i + \sum_{t=2}^{T} \tau_t I_t + \epsilon_{it}^{D},
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
QuotaAttained_{it} =& \alpha + \beta EventuallyAdopted_{it} + \\
& \gamma_0 LowPerformers_{i,pre} + \gamma_1 NewAgents_{i,pre} + \\
& \gamma_2 EventuallyAdopted_{it} \times LowPerformers_{i,pre} + \\
& \gamma_3 EventuallyAdopted_{it} \times NewAgents_{i,pre} + \delta Z_{it-1} + \theta Z_{it} \\
& \textstyle\sum_{i=2}^{I} \kappa_i I_i + \sum_{t=2}^{T} \tau_t I_t + \epsilon_{it}^{D}.
\end{aligned} \tag{2}
$$

In Equation 1, the main coefficient of interest is β, which is the coefficient measuring the effect of marketing analytics adoption. In addition, Z represents multiple controls, including lagged controls with coefficients δ (sales forum page views, number of voluntary training sessions taken, and lagged quota attainment rate) and the same time period controls with coefficients θ (tenure and grade level). We also include individual and time period fixed effects. In Equation 2, we add interaction terms between marketing analytics adoption and pre-analytics performance in quota attainment: as we set the base group as high performers, coefficient β in Equation 2 captures the adoption effect of high performers, while the coefficients γ_2 and γ_3 capture the relative adoption effect of low performers and new agents from the baseline, respectively. Considering that our data provider is a global company that has local offices around the world, it is possible that the errors could be correlated between sales agents in the same department.[6] To address this concern, we cluster standard errors at the department level (Cameron and Miller, 2015). In the online appendix, we demonstrate robustness to a number of alternative specifications, including measuring sales outcomes by total sales rather than quota attainment, using different time frames, using information on logins to identify the timing of adoption, propensity score matching of adopter and non-adopter samples, excluding outliers, and dropping adopters who only used the marketing analytics tool once.

Our main identification assumption is that after we control for individual and time fixed effects and differences that drive tenure, grade level, sales forum views, voluntary training, and lagged quota attainment rate, there is no systematic difference between the adopters and non-adopters in the trend of their propensity to successfully generate sales after the launch of marketing analytics relative to before the launch.[7] As in any difference-in-difference analysis, it is possible that adoption is correlated with unobserved trends. For example, sales agents may change their effort over time for unobserved reasons, and as part of their change in efforts, become more likely to adopt the software. Their increase in effort can result in an increase in sales, which is coincident with adoption but not caused by adoption. Another example is that salespeople might anticipate increased customer demand and adopt the software to better serve the demand. Again, in this instance, the increase in sales would be coincident with adoption but not caused by adoption. We do not think these explanations are likely because they do not explain the difference between high and low sales agents, which is central to our results. In addition, these explanations also did not arise in qualitative interviews with sales agents.

The estimation results are shown in Table 6. Based on the main-effect model, Equation 1, (column 3 of results in Table 6), we find that on average the adoption of marketing analytics is

[6]The company allocates local marketing budget to each department. There are on average 3 sales agents (with a median of 2) in a department. Hence, by clustering errors within each department, we expect to control model errors that come from region-based characteristics and department-level sales quota assignments for sales agents in the same department.

[7]Voluntary training and other controls are likely endogenous to the impact of analytics. As we show in the appendix, our qualitative results are robust to a large number of alternative specifications.

correlated with a 14.3% increase in quota attainment rate.[8] Considering the difference in pre-analytics sales performance among the sales agents (column 4 in Table 6), we find a positive coefficient for adoption in high performers (5%, $p = 0.03$). For low performers, we do not see the significantly positive relative adoption coefficient to the high-performing group but find a slight overall positive relationship (by adding the interaction coefficient to the base group, high performers, 24.9%, $p = 0.09$). The economically large and positive coefficients suggest that the marketing analytics tool improves overall sales productivity.

We also estimate the main model specification with separate coefficients estimated for each quarter. Figure 4 represents quarterly adoption coefficients of linear regression with individual fixed effects and standard errors clustered by department. We use the last quarter before the launch of marketing analytics (the first quarter of the year 2017) as a base and obtain each time-specific coefficient relative to the base (Kearney and Levine, 2015). In the regression model, we use quarterly time (t) dummy variables to control for time-specific market conditions. Here, given the objective to construct the time trends of adoption coefficients for adopters and non-adopters, we drop the quarterly dummy variables and add time-specific adoption dummy variables.

The first plot in Figure 4 shows the changes of the time-specific coefficient over time. We find significant changes in the quarterly coefficients after the launch of marketing analytics with a peak in the second quarter of the year 2018.[9] The remaining plots in Figure 4 correspond to the interaction coefficients between adoption and pre-analytics sales performance. Again, we observe a slight increase for high performers with significance and a drastic increase for low performers with huge standard error bars.

In Figure 4, we observe a surge in quote attainment and a drop in the low-performing group between the second and the third quarter of the year 2018. The shape is driven by 12% of adopters

[8]It is worth noting that the result tells us the benefit of technology of the treated group, the adopters. Given that those who benefit from adoption may be more likely to adopt, we would expect non-adopters' benefit of adoption to be smaller than that of the adopters.

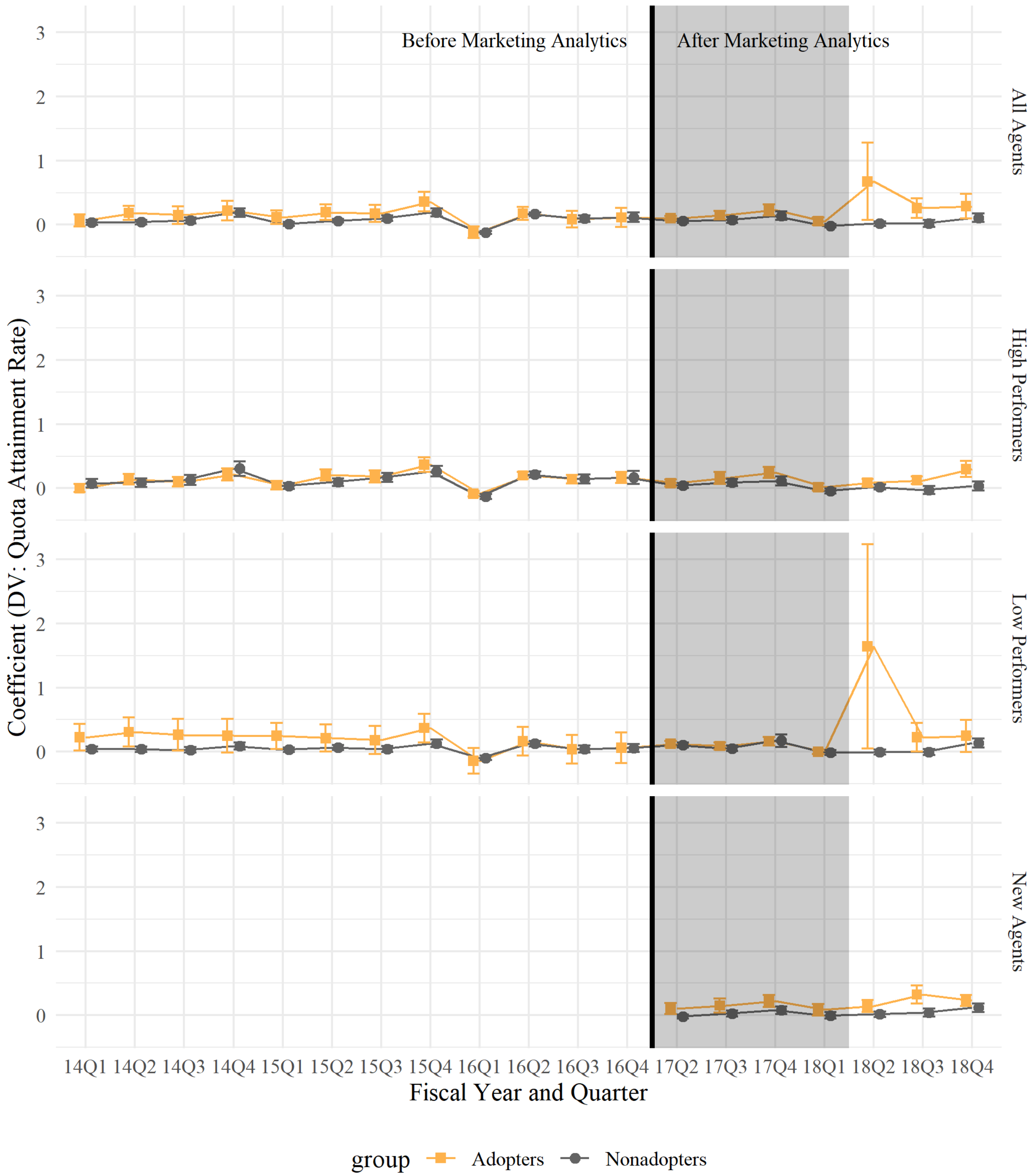
[9]The same pattern appears in a number of other analyses of the quota attainment rate, including Figures 5 and 6 comparing active and inactive accounts and several robustness checks in the online appendix.

Table 6: Adoption of Marketing Analytics and Sales Performance (Quota Attainment Rate): Linear Fixed Effect Regression Results

	DV: Quota Attainment Rate			
Agent Characteristics	Main	Interaction	Main	Interaction
Account Characteristics	Overall	Overall	Overall	Overall
	(1)	(2)	(3)	(4)
Adoption (EA)	0.287**		0.143**	
	(0.141)		(0.063)	
Adoption (EA): Base		0.044		0.051**
		(0.054)		(0.024)
Adoption × low performers		0.528		0.198
		(0.366)		(0.153)
Adoption × new agents		0.035		0.076
		(0.167)		(0.061)
SalesStatus			0.921***	0.920***
			(0.069)	(0.068)
Tenure			0.008	0.008
			(0.007)	(0.007)
GradeLevel			0.015	0.016
			(0.026)	(0.026)
SalesforumViews			-0.0004	-0.0004
			(0.0003)	(0.0003)
VoluntaryTraining			0.001	0.001
			(0.001)	(0.001)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	566	566	566	566
Departments (Cluster)	211	211	211	211
Observations	4,867	4,867	4,867	4,867
R-squared	0.341	0.344	0.737	0.738
Adjusted R-Squared	0.251	0.253	0.701	0.701
F Statistic	56.43***	52.33***	496.20***	495.36***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Figure 4: Quota Attainment Rate Over Time: Overall Accounts



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

(3 out of 26 sales agents) who achieved their sales quota by the end of the second quarter of the year. It appears that after achieving the sales quota in the second quarter, these adopters' sales activities decreased in the remaining sales quarters, perhaps to avoid the increase in sales quota in the next year (often referred to as the "ratcheting" Misra and Nair, 2011; Weitzman, 1980). Consistent with these results, in appendix Figure A.1 we confirm that the proportion of previously low-performing sales agents who achieved the annual sales quota among low-performing adopters increased at the same time.

While we can observe overall positive adoption effects, interaction coefficients with respect to the different types of sales agents in Table 6 and Figure 4 suggest that adoption impacts high performers and low performers differently. To examine whether and how the different types of sales agents use the tool differently to enhance their performance, we incorporate a second dimension: customer account characteristics (see Table 1). For example, to achieve their sales quota, some sales agents may prioritize customer accounts that they have actively interacted with, while other sales agents may allocate greater effort to the customer accounts to which they have not sold any products recently. Such decisions can vary by the adoption of marketing analytics as the analytics tool provides more information to the agents about their customer accounts.

We split the quota attainment rate into the proportion that comes from customers with recent transactions (i.e., contribution to quota attainment rate from active accounts) and that without recent sales records (i.e., contribution to quota attainment rate from inactive accounts). For each sales agent, we use previous year ($y - 1$) observations to classify whether the account is active in year y. The first year of the data (the year 2014) is therefore dropped from the analysis. This leaves four years of data for the quota attainment rate from active and inactive accounts, totaling 3,874 observations.

Table 7 presents the results by agent and account types. Overall, for high performers, we observe a positive adoption coefficient on the quota attainment rate from inactive accounts, while the sign from active accounts is the opposite. For low performers, compared to the base (i.e., high performers), analytics adoption is positively associated with the quota attainment rate from active accounts while the sign from inactive accounts is negative. Figure 5 and Figure 6 show that the increase in the quota attainment rate that is observed in the earlier figure (see Figure 4) is driven by active accounts for low performers and inactive accounts for high performers. Combining both results, this is consistent with high performers shifting some of their effort to inactive accounts with the assistance from the marketing analytics tool and low performers identifying new cross-selling opportunities from active accounts that they might have missed in the past year.

So far, our results have shown that marketing analytics likely enhanced sales productivity. However, our hypotheses on the underlying reason for the increased productivity remain speculative. To examine why the analytics tool appears to have a positive impact on performance, and a differential impact across high and low performers, we next explore the impact of marketing analytics through the sales funnel.

4.2 Impact of Marketing Analytics in Sales Process

In the sales funnel shown in Figure 1, the quota attainment rate depends on two intermediate conversion measures, namely, lead acceptance rate and sales winning rate. Considering the differences in sales efforts on conversion and the value of marketing analytics between different types of customer accounts, we present both conversion rates (lead acceptance rate and sales winning rate) with three different categories: overall conversion, the conversion rate of active accounts, and the conversion rate of inactive accounts.

Marketing Analytics and Lead Acceptance Rate

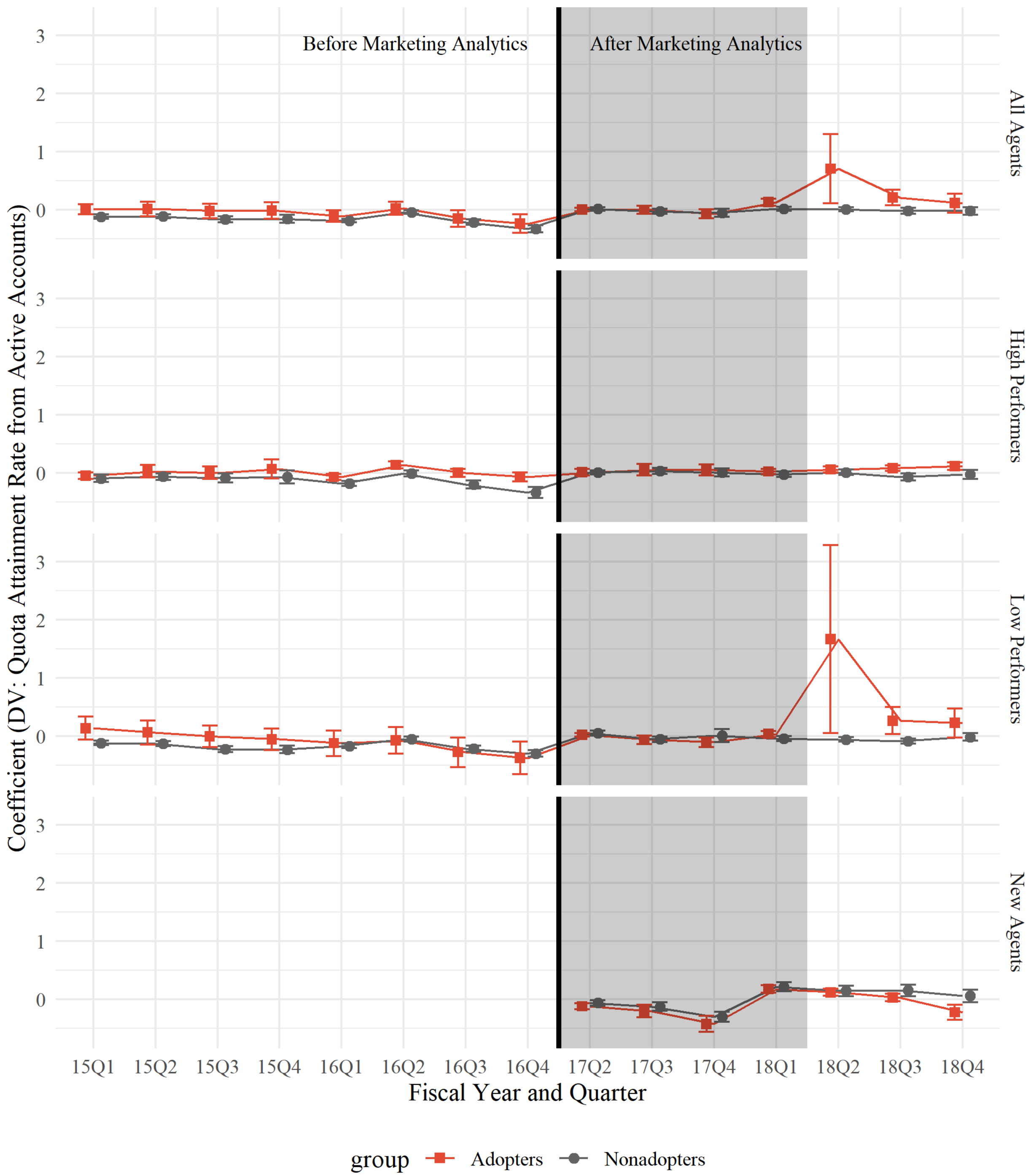
The lead acceptance rate – the percentage of marketing-initiated leads accepted as opportunities – measures the marketing analytics tool's ability to generate high-quality leads not discovered by the sales agent. A common reason for the low acceptance by the sales agent is the perceived poor quality of marketing-initiated leads (Smith et al., 2006). Marketing analytics could improve the lead

Table 7: Adoption of Marketing Analytics and Sales Performance (Quota Attainment Rate) by Agent and Account Type: Linear Fixed Effect Regression Results

	DV: Quota Attainment Rate			
Agent Characteristics	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Active	Inactive	Active	Inactive
	(1)	(2)	(3)	(4)
Adoption (EA) : Base	-0.104	0.120***	-0.086**	0.127***
	(0.065)	(0.041)	(0.044)	(0.040)
Adoption × low performers	0.717*	-0.089	0.341*	-0.107
	(0.409)	(0.084)	(0.184)	(0.082)
Adoption × new agents	-0.058	0.122	-0.018	0.103
	(0.122)	(0.086)	(0.060)	(0.084)
SalesStatus			0.881***	0.034
			(0.044)	(0.036)
Tenure			0.012*	0.004
			(0.007)	(0.005)
GradeLevel			-0.017	0.030
			(0.041)	(0.029)
SalesforumViews			-0.0003	-0.0002
			(0.0005)	(0.0002)
VoluntaryTraining			-0.004	0.005**
			(0.003)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	499	499	499	499
Departments (Cluster)	198	198	198	198
Observations	3,874	3,874	3,874	3,874
R-squared	0.306	0.499	0.697	0.505
Adjusted R-Squared	0.199	0.422	0.650	0.429
F Statistic	33.09***	17.79***	203.66***	17.08***

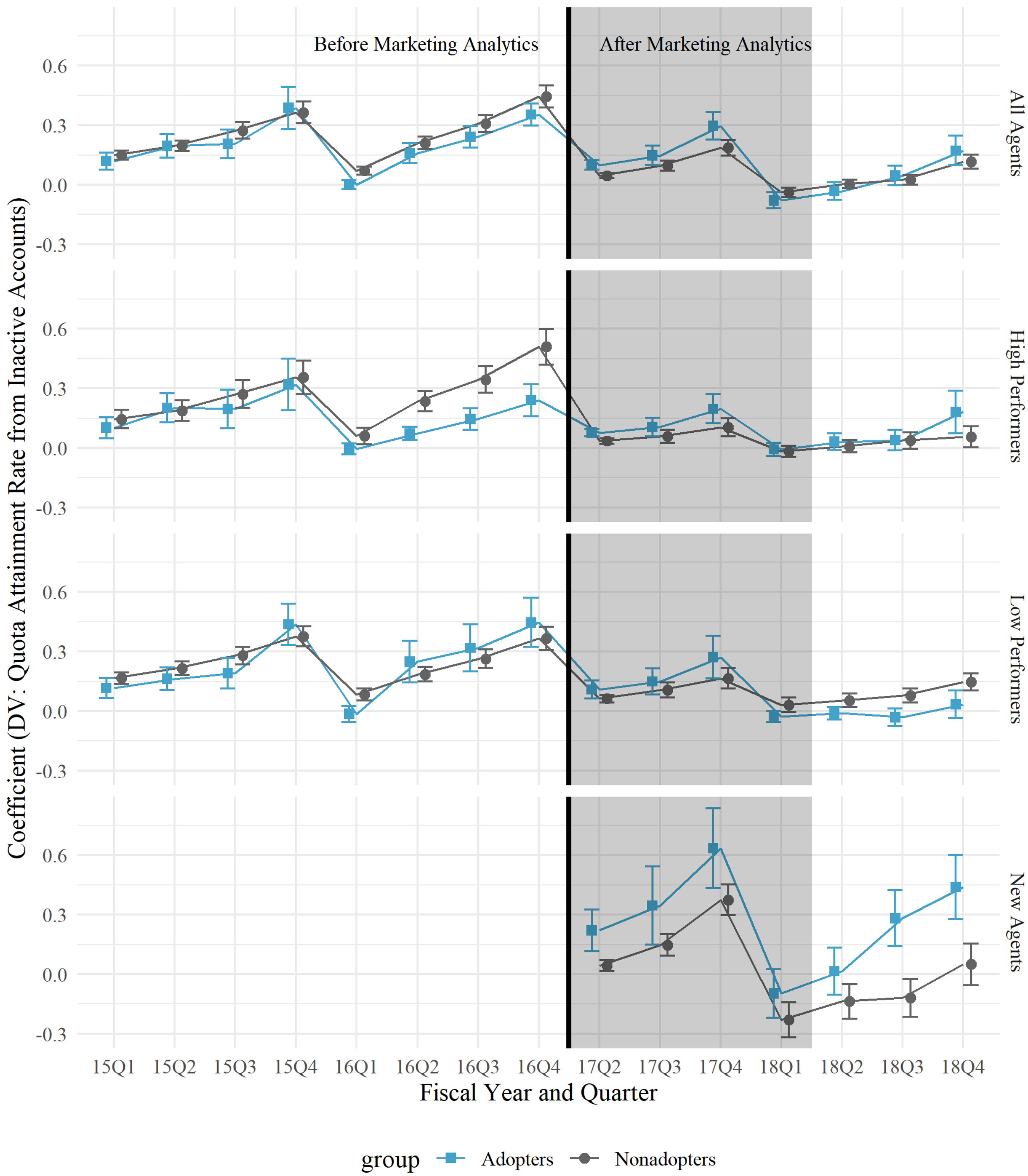
Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Figure 5: Quota Attainment Rate Over Time: Active Accounts



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure 6: Quota Attainment Rate Over Time: Inactive Accounts



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

acceptance rate by capturing more leads and by providing better engagement level measures with data-based evidence. Column 2 of Table 8 shows that after the adoption of marketing analytics, compared to the high performers, the lead acceptance rate slightly increased for low performers. Importantly, the increase in the lead acceptance rate for low performers from active accounts is significant and substantial (11.0%, $p = 0.022$, column 3 in Table 8 by adding the interaction coefficient to the base group, high performers).

The results demonstrate that marketing analytics helped the company generate more high-quality marketing-initiated leads for low performers. The low-performing agents are likely less capable of identifying leads, across both active and inactive accounts. The marketing analytics tool may have helped the low performers identify new cross-selling opportunities in their active accounts. Moreover, the increase in the lead acceptance rate suggests that the sales agents' distrust of marketing-initiated leads can be resolved by providing data-based evidence through marketing analytics.

On the other hand, for high performers, marketing analytics had no significant relation with the acceptance rate. High-performing agents, who were skilled at identifying and converting cross-selling opportunities in active accounts and at identifying promising inactive accounts, would likely find marketing analytics more valuable later in the funnel.

Marketing Analytics and Sales Winning Rate

The sales winning rate – the percentage of opportunities converted into successfully closed sales – depends on the quality of leads pursued and the sales agent's ability and effort in closing the deals. The results of first two columns in Table 9 suggest that the adoption of marketing analytics enhanced the overall sales winning rate by 7.5%, which is strongly driven by the baseline group, the high performers (8.5%), followed by the low performers (6.6%, $p < 0.01$). We then split the accounts into active and inactive groups and conduct the analysis separately (see column 3 and 4 of Table 9). For high performers, after adopting marketing analytics, the sales winning rate among

Table 8: Adoption of Marketing Analytics and Sales Conversion (Lead Acceptance Rate) by Agent and Account Types: Linear Fixed Effect Regression Results

	DV: Lead Acceptance Rate			
Agent Characteristics	Main	Interaction	Interaction	Interaction
Account Characteristics	Overall	Overall	Active	Inactive
	(1)	(2)	(3)	(4)
Adoption	0.013			
	(0.033)			
Adoption (EA): Base		-0.032	-0.049	0.014
		(0.040)	(0.039)	(0.045)
Adoption × low performers		0.085*	0.159***	0.044
		(0.051)	(0.056)	(0.061)
Adoption × new agents		0.340	0.183	0.402***
		(0.224)	(0.259)	(0.087)
SalesStatus	-0.001	-0.002	0.007	-0.003
	(0.002)	(0.002)	(0.005)	(0.002)
Tenure	0.016*	0.016*	0.026***	0.041***
	(0.009)	(0.009)	(0.003)	(0.011)
GradeLevel	0.019	0.019	-0.007	0.013
	(0.021)	(0.021)	(0.032)	(0.026)
SalesforumViews	-0.00003	-0.00003	-0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.0007	0.0005	-0.0005	0.003
	(0.002)	(0.002)	(0.002)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	566	566	499	499
Departments (Cluster)	211	211	198	198
Observations	4,867	4,867	3,874	3,874
R-squared	0.526	0.527	0.499	0.508
Adjusted R-Squared	0.460	0.461	0.421	0.431
F Statistic	5.64***	5.84***	6,745.78***	5.19***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

the active accounts fell by 10.1%, but the sales winning rate among the inactive accounts increased by 15.0%. In contrast, for low performers, we find a positive adoption effect on the sales winning rate in active accounts compared to the base, the high performers.

The results suggest that the information from marketing analytics helped high performers increase the sales winning rate among inactive accounts substantially, but the sales winning rate became lower among active accounts. Consistent with our results, Sujan et al. (1988) suggest that high performers (i.e., *above average performers*) tend to have richer information about their active customers than low performers. Thus, since the high-performing sales agents already knew their active customer accounts quite well, the value of the information from marketing analytics is low for active accounts but can still be high for inactive customer accounts. In contrast, with marketing analytics, the low performers improved their sales winning rate and this improvement was mainly in active accounts. The results suggest that the low performers could seize more high-quality opportunities, some of which would have been missed otherwise. The plots of quarterly adoption coefficients of two linear regressions (corresponding to column 3 and column 4 in Table 9) show consistent results (See appendix A.2 and A.3).

Overall, the results support our hypotheses about the different benefits of marketing analytics between the high and low performers. By using marketing analytics, high performers increased the quota attainment rate and sales winning rate from inactive accounts. Interestingly, the coefficients of marketing analytics on high performer's sales winning rate in active and inactive accounts have opposite signs (column 3 and 4 in Table 9). This may be due to the sales agents' reallocation of effort in a multi-task environment (Kim et al., 2019a,b). Each sales agent is responsible for a portfolio of accounts, including active and inactive accounts. A sales agent allocates the (limited) available time and resources to accounts with higher expected sales. Since it takes more time and effort to (re)connect to inactive customer accounts, the sales agents have the tendency to focus more effort (than desired by the company) on the leads with active accounts. Marketing analytics tools, by reducing the uncertainty of sales leads, make the inactive accounts more attractive for the high performers to pursue. Limited time and resource availability then lead these sales agents to spend less effort on the active accounts. As a result, when we split the quota attainment rate by whether the accounts are active, we observe the increased (decreased) contribution to quota attainment rate from inactive (active) accounts for high performers (see Table 7). It is worth noting that companies often find it challenging in motivating the sales force to work on inactive accounts in order to broaden the customer base. While the common approach is to offer special incentives for acquiring new customers or activating inactive accounts, this result suggests potential for an alternative solution by empowering the sales agents through marketing analytics.

On the other hand, low performers increased their quota attainment rate by about 25% ($p < 0.1$) and sales winning rate by about 7% by using marketing analytics. The findings suggest that the low performers achieve more sales by improving the sales winning rate. Given their low sales performance at the conversion stage,[10] the result suggests that marketing analytics supplements their low sales skills to enhance the sales winning rate. In addition, compared to the high performers, the increase is notable among active accounts. The findings suggest that marketing analytics enabled the low performers to seize cross-selling opportunities, resulting in increased revenues from the active accounts.

To further understand the effect of marketing analytics, we examine the sales winning rates for sales- and marketing-initiated leads separately (see Figure 1). The overall results for marketing analytics discussed earlier, by whether the account is active and by pre-analytics performance, are all valid with sales-initiated leads (column 5 and 6 in Table 9). However, the results for marketing-initiated leads, while in the same direction, have higher p-values.[11]

To summarize, our results suggest that marketing analytics enhanced marketing's supporting role in sales productivity. In addition, the results suggest that the marketing analytics tool helps high

[10]In the year 2016, a year before the marketing analytics, among 150 high performers and 144 low performers, the average sales winning rate was 0.71 for high performers and 0.60 for low performers (groupwise difference is statistically significant at p=0.001).

[11]The weak statistical significance may be due to a small number of non-zero observations. According to Table 2, on average less than two (1.881) marketing-initiated leads were accepted, and among them, less than one lead (0.945) resulted in sales.

and low performers differently: the enhancement occurred in inactive accounts but not in active accounts for previously high-performing agents, while the improvement occurred relatively more in active accounts but less in inactive accounts for low-performing agents. Such improvements are consistent throughout the sales process, reflecting a higher level of alignment between marketing and sales. As one sales agent at the company put it in an interview with us, "more deals are marketing-influenced after the marketing analytics."

Table 9: Adoption of Marketing Analytics and Sales Conversion (Sales Winning Rate) by Agent and Account Types: Linear Fixed Effect Regression Results

	DV: Sales Winning Rate							
	All Sources (Both Sales- and Marketing-initiated)				*Sales-initiated*		*Marketing-initiated*	
Agent Characteristics	Main	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Overall	Active	Inactive	Active	Inactive	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adoption	0.075***							
	(0.018)							
Adoption (EA): Base		0.085***	-0.101**	0.150***	-0.087**	0.124**	-0.042	0.013
		(0.020)	(0.042)	(0.050)	(0.041)	(0.053)	(0.044)	(0.029)
Adoption × low performers		-0.019	0.147**	-0.015	0.129**	0.006	0.078	-0.058
		(0.023)	(0.071)	(0.063)	(0.062)	(0.066)	(0.050)	(0.051)
Adoption × new agents		-0.082	0.305*	-0.126	0.267*	-0.066	0.056	-0.191
		(0.095)	(0.158)	(0.085)	(0.148)	(0.084)	(0.279)	(0.203)
SalesStatus	0.002	0.002	0.005	0.005*	0.007	0.005*	0.003	0.0003
	(0.003)	(0.003)	(0.008)	(0.003)	(0.009)	(0.003)	(0.006)	(0.002)
Tenure	-0.074***	-0.074***	0.010	-0.011*	0.002	-0.008	0.012**	-0.004
	(0.027)	(0.027)	(0.006)	(0.006)	(0.007)	(0.006)	(0.005)	(0.011)
GradeLevel	0.026	0.026	-0.029	0.033	-0.035	0.022	-0.027	0.020
	(0.019)	(0.019)	(0.039)	(0.039)	(0.042)	(0.040)	(0.033)	(0.022)
SalesforumViews	0.0001	0.0001	0.0004	0.00002	0.0003	0.0001	0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)
VoluntaryTraining	0.0002	0.0003	0.009***	-0.002	0.009***	-0.002	-0.0010	-0.002
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	566	566	499	499	499	499	499	499
Departments (Cluster)	211	211	198	198	198	198	198	198
Observations	4,867	4,867	3,874	3,874	3,874	3,874	3,874	3,874
R-squared	0.712	0.712	0.608	0.493	0.570	0.487	0.455	0.419
Adjusted R-Squared	0.672	0.672	0.547	0.415	0.503	0.407	0.370	0.328
F Statistic	5.08***	4.81***	30.47***	42.34***	89.05***	5.79***	24.99***	4.11***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

5 Concluding Remarks

The development of technology has enabled advanced data-driven marketing analytics to support sales agents' decision-making. Using data from a global B2B information technology company, we investigate the impact of the adoption of marketing analytics on sales force's performance. We find that the adoption of a marketing analytics tool significantly enhanced the sales quota attainment rate. To the best of our knowledge, this is the first paper that quantifies the value of data-based marketing analytics for sales performance. As each sales agent can decide whether to adopt marketing analytics, we measure the impact of an adoption decision on performance at the individual decision-makers level.

We further examine the effect of marketing analytics by looking into three sales performance measures, by pre-analytics sales performance (high performers and low performers), and by customer account types (active and inactive accounts). For the high performers, the adoption of marketing analytics increased quota attainment rate and sales winning rate from inactive accounts, but small decreases in contribution to quota attainment rate and sales winning rate from active accounts. Compared to the high performers, low performers significantly increase lead acceptance rate and sales winning rate from active accounts, resulting in an increased percentage contribution to quota attainment rate from active accounts.

The results suggest a different role for the marketing analytics tool between different sales performance groups. While high-performing sales agents harness marketing analytics to achieve more sales conversions with inactive customer accounts, low-performing sales agents utilize the information from marketing analytics to seize high-quality opportunities with active customer accounts.

For high-performing agents, they were likely more skilled at identifying and converting leads in active accounts. The customer engagement data available from the company's marketing analytics tool provided useful insights into the needs of inactive customer accounts and enabled these salespeople to better qualify the leads and convert the opportunities with these inactive accounts.[12] With the improved productivity for the inactive accounts, the high-performing agents likely shifted some efforts away from the active accounts.

On the other hand, for low-performing agents, the marketing analytics tool not only appears to provide new and high-quality leads for active accounts but it also appears to help convert the opportunities into sales. With marketing analytics providing data-based evidence, both sales and marketing may be more confident in the quality of marketing-initiated leads, drawing out more leads from the so called "sales lead black hole" (Hasselwander, 2006).

This paper focuses on identifying and demonstrating the effect of marketing analytics on sales performance. We note that despite the significant benefits, the adoption rate was still low: only 36.5% of sales agents had adopted marketing analytics almost two years after the launch. This low adoption rate suggests that there may be barriers to adoption which could be examined in future research: for instance, how did the sales agents perceive the benefit or cost of using marketing analytics? (Dietvorst et al., 2015) Moreover, what types of interventions such as incentives, communications, and training sessions could the company consider in promoting the adoption of marketing analytics? Our results also imply that companies should follow different approaches to motivating their sales agents at different skill levels.

Our results can also motivate another path for future research: a possibility for the company to redesign sales compensation plans after the introduction of marketing analytics. First, the analytics tool, by capturing additional leads and making customer needs more transparent, is expected to change sales productivity. As a result, the current commission rate may no longer be optimal. Second, the basis of incentives can directly affect the sales agents' intentions to adopt the marketing analytics. For instance, offering an incentive for sales realized by converting marketing-initiated leads may enhance the probability of adoption. Third, although there is a slight overall sales increase for the high-performing group of sales agents, the results seem to be driven by these agents shifting their focus between accounts. We observed that they achieved a substantial improvement in

[12]A sales agent who adopted the marketing analytics tool indicated during an interview the value of marketing analytics as being "armed with sales battle cards".

success with inactive accounts but a significant decrease in sales from active accounts. We suspect that this decrease could be due to the lack of monetary motivation: the commission rate above the 200% of sales quota was much lower than the regular commission rate. Moreover, most of the high performers already knew how to exceed 100% of the assigned quota, but the chance of exceeding 200% of the quota was low even with the help of the marketing analytics tool. As evidence, we observe only 5.9% of observations exceeding 200% of the annually assigned quota during the pre-analytics period and the proportion did not increase (even decreased to 5.1%) after the introduction of marketing analytics.[13] Future research may develop a structural model to estimate the sales agents' decision rules and use counterfactual analysis to investigate the optimal incentive design.

Overall, marketing analytics appears to provide information that complements the sales agent's own knowledge for all types of accounts. The results suggest that the value of marketing analytics for high-performing agents is primarily in serving inactive accounts. Given that they have already exploited the main opportunities from active accounts in the past year, high performers seem to pursue more inactive accounts. In contrast, previously low-performing agents seem to utilize information mainly from active accounts, as active accounts are easier to convert due to their previously-established relationship.

[13]For pre-analytics, we have 48 out of 807 annual observations before the year 2017 exceeding 200% of the annual quota. For post-analytics, we have 28 out of 554 annual observations.

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Online Appendix

A Additional Plots for the Main Dataset

In this section, we provide more plots of the pattern in outcomes over time. Our definition of adoption in this section remains $EventuallyAdopted$. Later in this appendix we explore robustness to other definitions. First, we further explore the "surge and drop" of the adoption coefficients in the low-performing sales agents between the second and third quarter of the year 2018 (See Figure 4). Based on the definition, the low-performing group did not achieve their sales quota before the marketing analytics, not having received any additional commission. The Figure A.1 shows the proportion of sales agents who achieve their quota by quarter. At the second quarter of the year, we observe that 12% of low-performing adopters had already achieved their sales quota of the year (i.e., 100%). This proportion is even greater than that of high-performing sales agents (10%). Combined with the common sales phenomenon that sales agents reduce sales activities when they achieve their sales goal of a year to avoid increase in sales quota in the next year (also known as ratcheting), it suggests that the low performers who achieved or were close to achieving their sales quota had incentives to reduce their sales activities after the second quarter.

Next, we show coefficient plots (from Figure A.2 to Figure A.5) with respect to two outcome measures (i.e., sales winning rate and lead acceptance rate) by different types of sales agents within each figure and by different types of accounts with separate figures: active accounts and inactive accounts.

Figure A.1: Proportion of Sales Agents who Achieved their Quota over Time

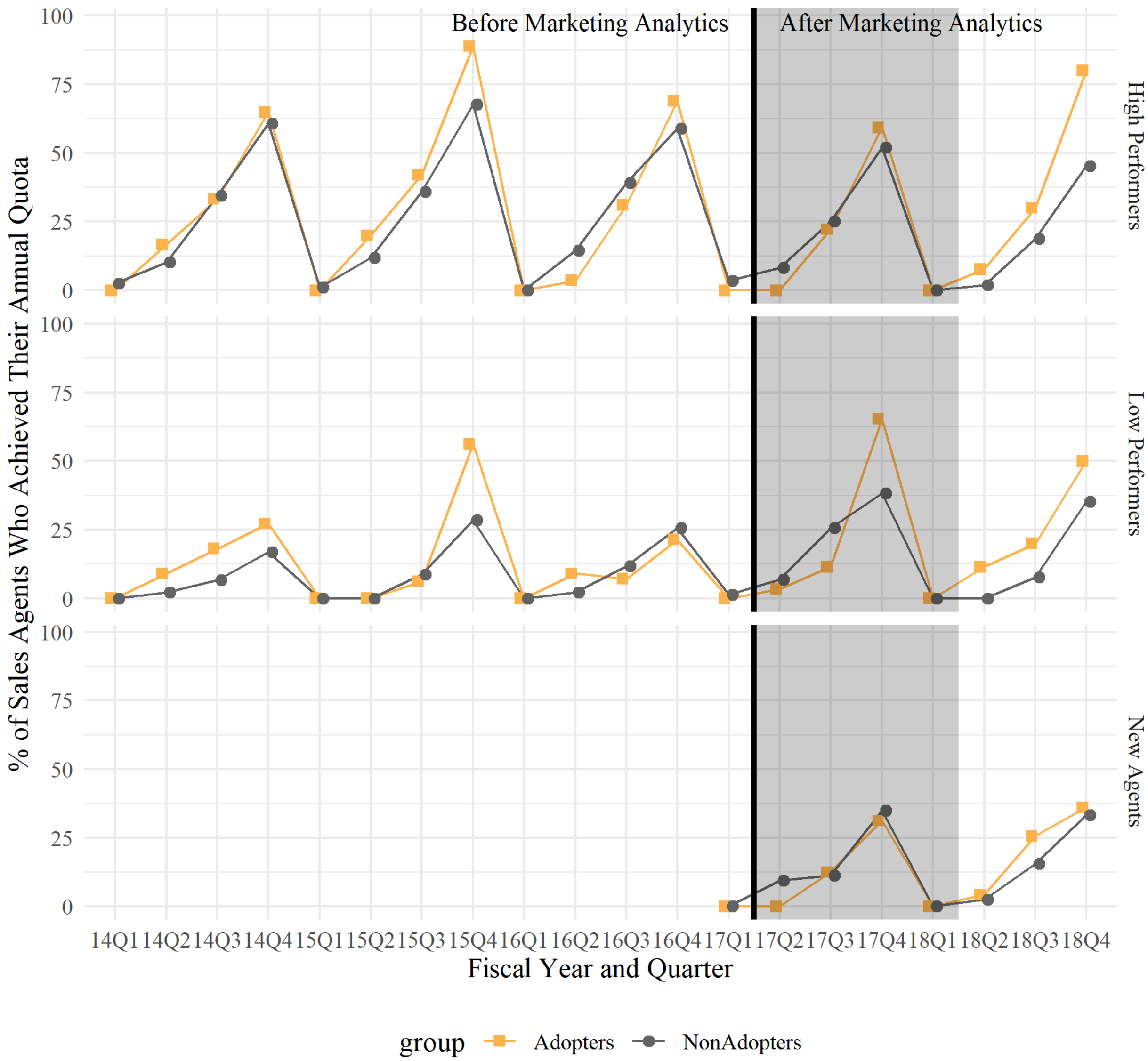
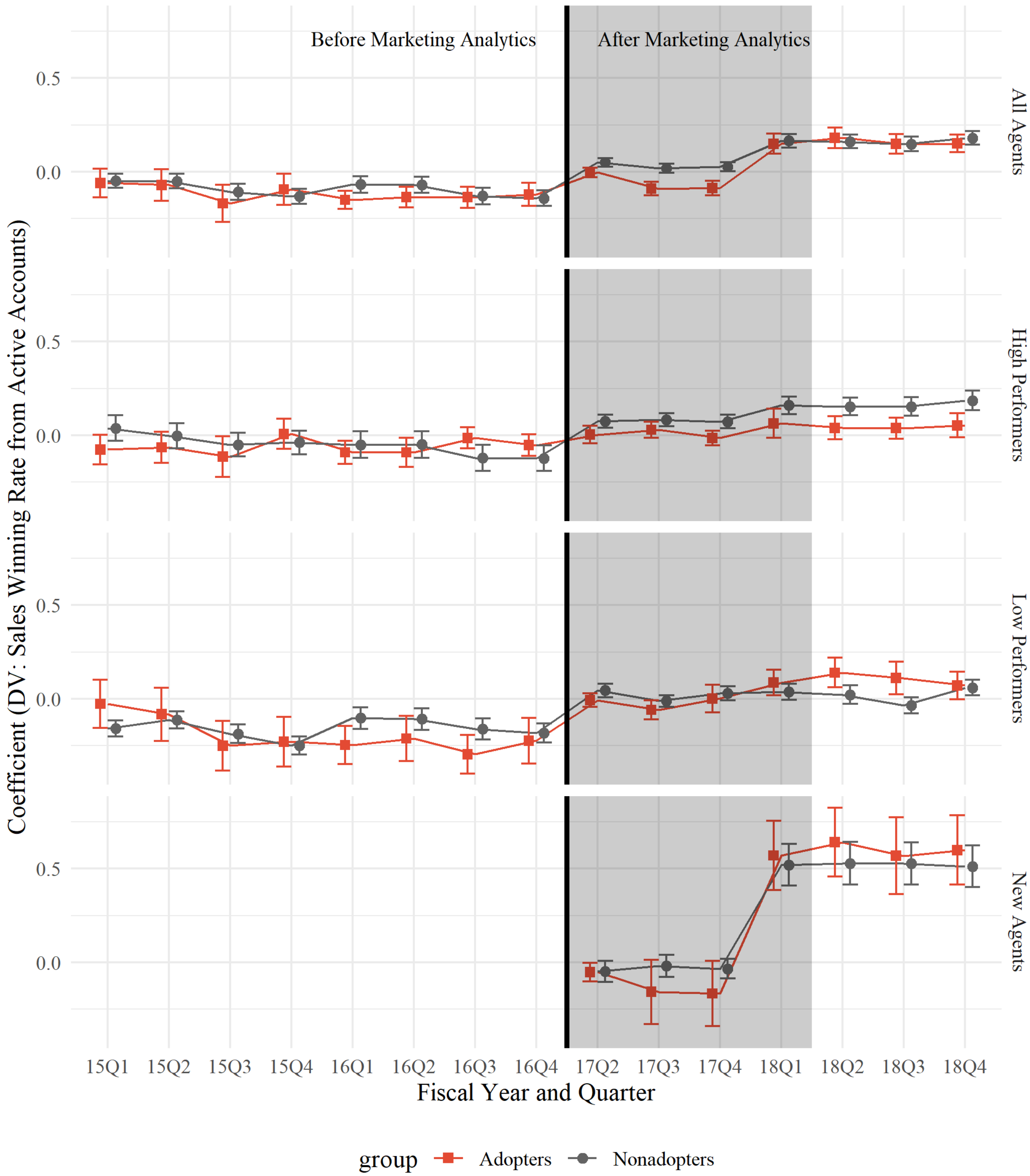
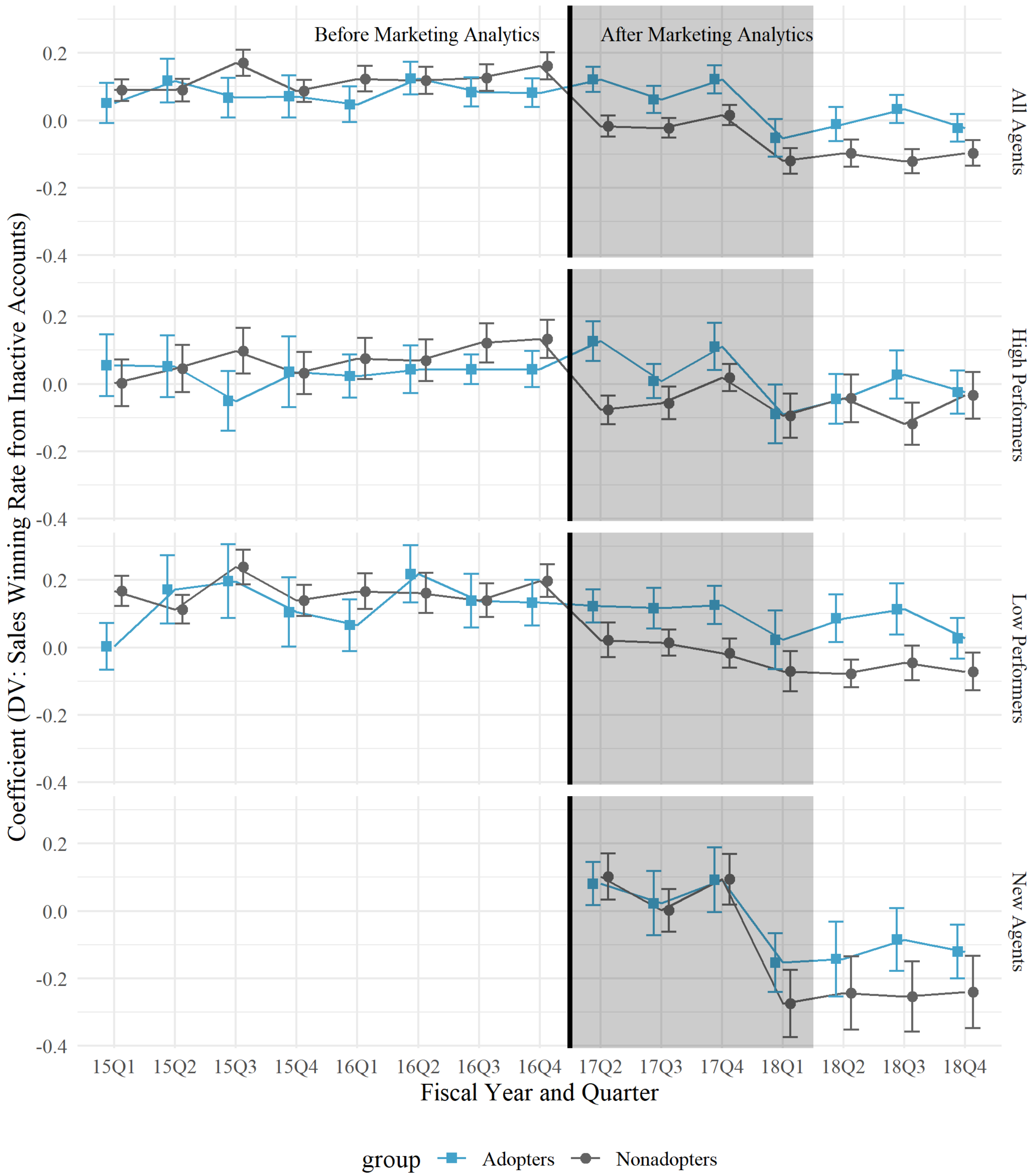


Figure A.2: Sales Winning Rate Over Time: Active Accounts



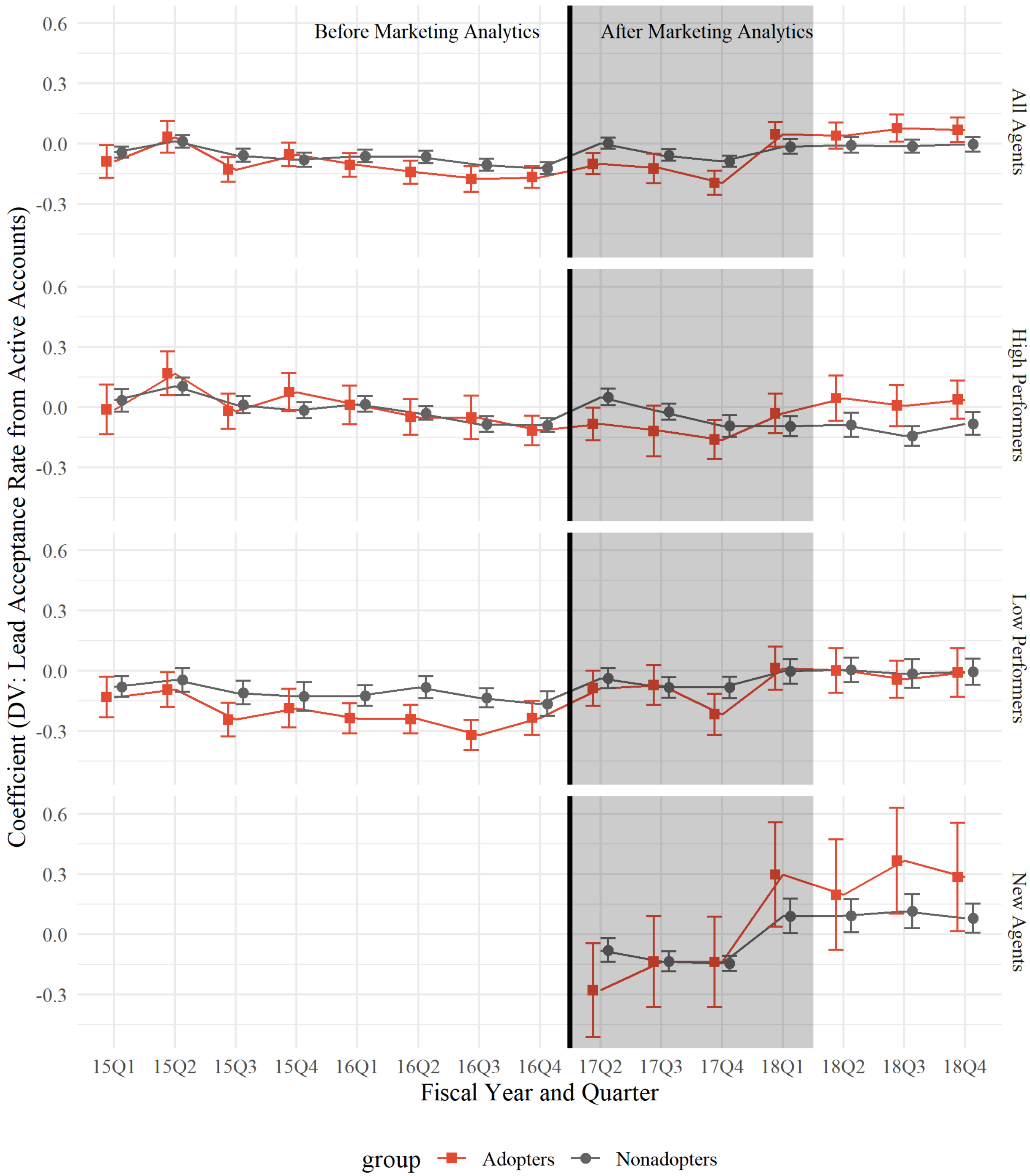
Note: The first graph coefficients are from main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure A.3: Sales Winning Rate Over Time: Inactive Accounts



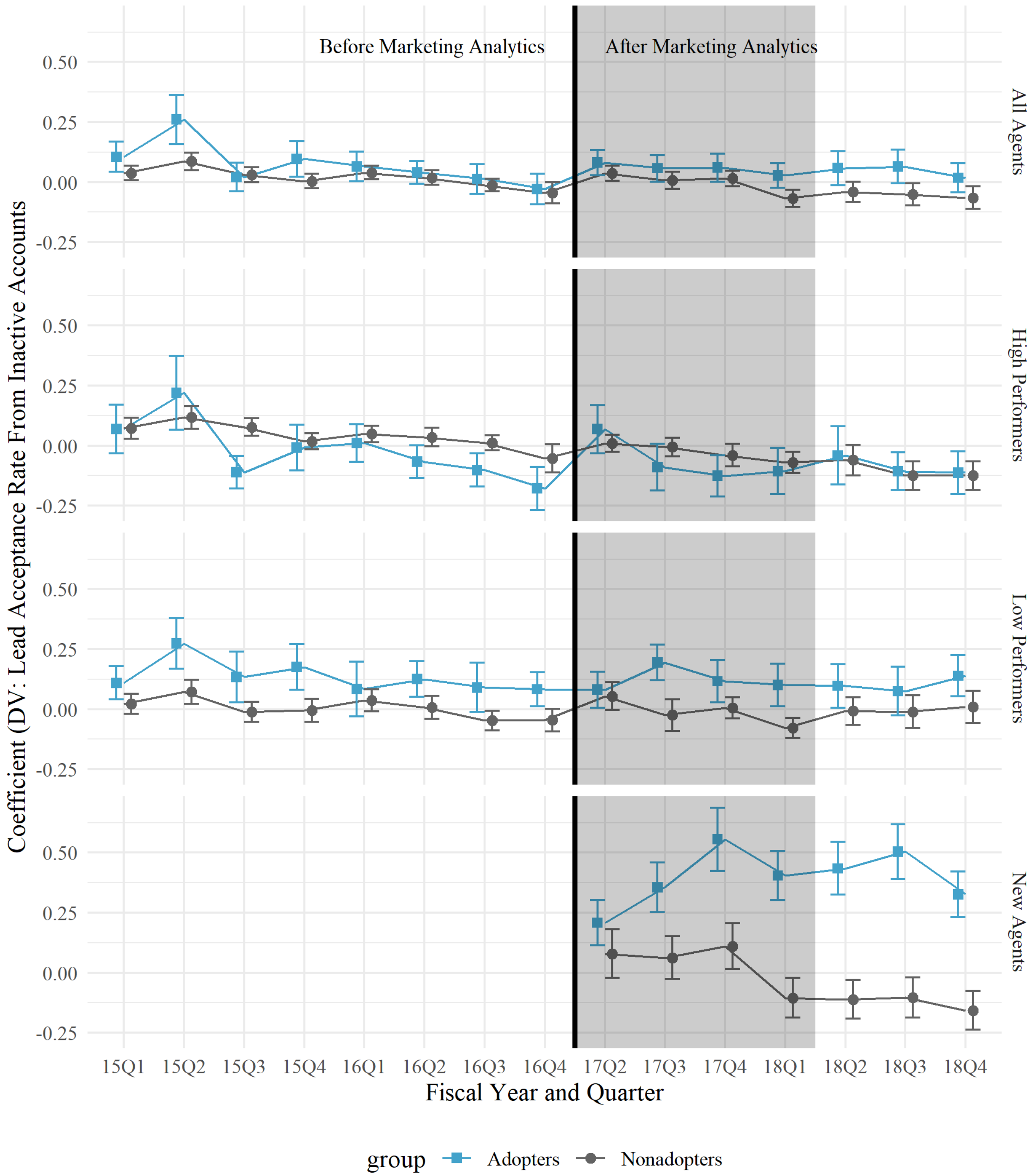
Note: The first graph coefficients are from main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure A.4: Lead Acceptance Rate Over Time: Active Accounts



Note: The first graph coefficients are from main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure A.5: Lead Acceptance Rate Over Time: Inactive Accounts



Note: The first graph coefficients are from main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

B Exploring Robustness

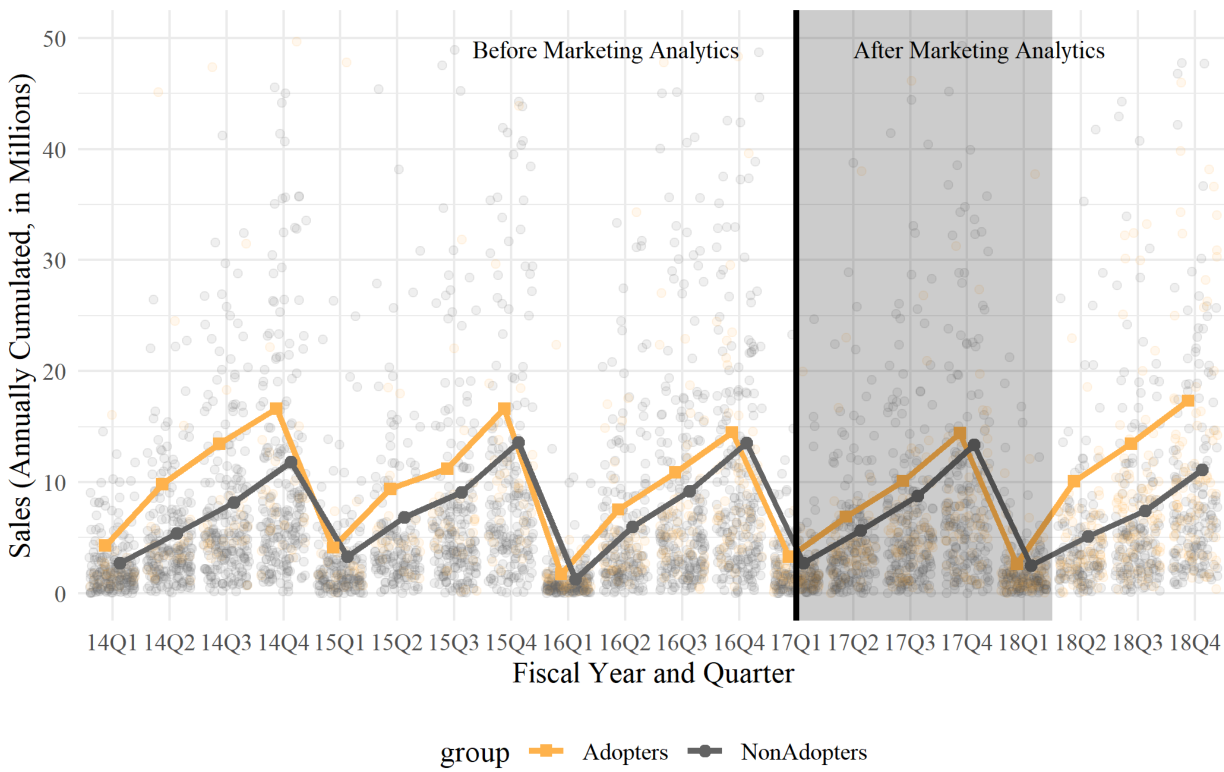
In this section, we check the robustness of our results by alternative performance measures, alternative time frames, alternative sample constructions for adopters and non-adopters, excluding outliers, and excluding one-time users of the marketing analytics tool. Across a wide variety of specifications, we find the qualitative results are robust. The signs of the coefficients of interest are consistent. While some results lose significance, the following core results hold: (i) high performer sales to inactive accounts increase, (ii) low performer sales to active accounts increase, (iii) high performer sales winning rate increases for inactive accounts, and (iv) low performer sales winning rate and lead acceptance rate increase for active accounts.

B.1 Alternative Measure of Sales Outcome

While the quota attainment rate measures sales relative to sales quota, one may be interested in the changes in the absolute amount of sales that are brought by marketing analytics. We further explore the sales amount as our outcome measure to ensure the robustness of our findings. Figure B.1 shows the annual cumulative sales for adopters and non-adopters at each sales quarter. We can observe that the average cumulative sales for adopters was similar to that for non-adopters in the latest pre-analytics year (i.e., the year 2016) and the first post-analytics year, but the gap between the two groups increases after the implementation period (i.e., after the first quarter of the year 2018). Table B.1 compares the groupwise mean difference of cumulative sales between the adopters and non-adopters. Whether we compare the point-of-time average or periodic average, in both cases, we cannot reject the null hypothesis that the means of two groups are equal before the launch of marketing analytics. While we can observe greater average cumulative sales among adopters than that of non-adopters in post-analytics periods, the means of two groups do not show statistically significant differences (i.e., $p < 0.05$).

In line with the preceding result, we do not observe significant positive adoption effects on cumulative sales in the main and interaction models (columns 1 and 2 in Table B.2). However,

Figure B.1: Average Annual Cumulative Sales for Adopters and non-adopters Over Time



Note: Scattered dots represent sales agents' annual cumulative sales amounts per quarter. 82 observations with a ratio over 50 million are not shown but included in group averages. The shaded area in the early post-analytics period indicates the implementation period.

Table B.1: Groupwise Differences in Sales Amount

	Before Marketing Analytics			After Marketing Analytics		
	Adopters	Non-Adopters	t-test (p-value)	Adopters	Non-Adopters	t-test (p-value)
Point-of-time Comparison[a]						
Sales (cumulative, in millions)	14.50	13.55	0.783	17.34	11.13	0.058
	(31.29)	(21.03)		(38.08)	(13.81)	
Sales (cumulative, in millions)	14.50	13.55	0.783	20.94	12.32	0.085
(excluding new agents)	(31.29)	(21.03)		(46.58)	(15.29)	
Number of sales agents	57	232		96	167	
Number of new agents (N(%))	0	0		36	63	
	(0%)	(0%)		(38%)	(38%)	
Periodic Average Comparison[b]						
Sales (cumulative, in millions)	7.77	6.82	0.568	11.13	7.76	0.058
	(16.61)	(11.61)		(21.73)	(11.12)	
Sales (cumulative, in millions)	8.25	7.03	0.487	12.96	8.98	0.123
(excluding new agents)	(17.05)	(11.83)		(25.60)	(12.83)	
Number of sales agents	64	402		96	254	
Number of new agents (N(%))	4	18		36	86	
	(6.2%)	(4.5%)		(38%)	(34%)	

[a] This panel compares two single-period observations: the fourth quarter of the year 2016 (before) vs. the fourth quarter of the year 2018 (after).

[b] This panel computes an individual average per sales agent and compares the average across sales agent: quarters before the marketing analytics (until the first quarter of the year 2017) and after.

when we take into account different agent and account types, we observe similar results to our main findings: marketing analytics adoption coefficients are associated with the increases in cumulative sales from inactive accounts for high performers and active accounts for low performers.

Table B.2: Adoption of Marketing Analytics and Sales (Cumulative, in millions) by Agent and Account Types: Linear Fixed Effect Regression Results

	DV: Cumulative Sales			
Agent Characteristics	Main	Interaction	Interaction	Interaction
Account Characteristics	Overall	Overall	Active	Inactive
	(1)	(2)	(3)	(4)
Adoption (EA)	0.073			
	(1.008)			
Adoption (EA) : Base		0.037	-1.659**	1.767***
		(1.127)	(0.773)	(0.621)
Adoption × low performers		0.128	3.585**	-2.635**
		(1.756)	(1.806)	(1.230)
Adoption × new agents		-1.403	-0.926	-0.474
		(1.427)	(1.120)	(0.697)
SalesStatus	7.413***	7.412***	7.167***	0.210
	(0.461)	(0.463)	(0.351)	(0.217)
Tenure	0.153	0.153	0.400**	-0.094**
	(0.116)	(0.116)	(0.181)	(0.046)
GradeLevel	2.852**	2.852**	3.127**	1.091**
	(1.121)	(1.121)	(1.394)	(0.514)
SalesforumViews	0.003	0.003	0.006	-0.005
	(0.006)	(0.006)	(0.007)	(0.004)
VoluntaryTraining	-0.046	-0.045	-0.048	0.026
	(0.049)	(0.048)	(0.066)	(0.049)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	566	566	499	499
Departments (Cluster)	211	211	198	198
Observations	4,867	4,867	3,874	3,874
R-squared	0.707	0.707	0.700	0.516
Adjusted R-Squared	0.666	0.666	0.653	0.440
F Statistic	117.23***	112.22***	48.13***	19.14***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

As mentioned earlier, we use the quota attainment rate as a sales performance measure because the sales quota controls for unobservable characteristics that are territory- and account-specific. Hence, sales relative to the sales quota is a reliable measure of sales performance (Ahearne et al., 2008). Like past literature, the underlying assumption of using this measure is that sales quota is set by considering each sales agent's territory and customer accounts, and therefore the quota can be used as a reference point to evaluate whether the sales agent has performed well relative to expectations.

The construction of the sales quota suggests endogeneity concerns about the interaction between the quota and marketing analytics adoption, due to "ratcheting" (Misra and Nair, 2011; Weitzman, 1980). That is, if a sales agent achieved the quota in year 1, the sales agent's next sales quota may be increased in year 2, making it harder to achieve the next year's quota. Therefore, we explore the difference in sales quota between a year and the previous year. Table B.3 shows that although the increase (decrease) in sales quota after an (under)achievement of the previous sales quota does not always happen, it is more likely to happen than the opposite scenario in many cases. Hence, we further explore the robustness of our findings by fixing the sales quota to the average sales quota per sales agent and to the first year sales quota per sales agent in our data.

Table B.4 shows the linear fixed effects regression results by using a fixed sales quota as a denominator of the dependent variable (rather than the annual sales quota). When we use the average sales quota per sales agent, we observe a consistent adoption effect with the overall models (columns 1 and 2 in Table B.4). In the interaction models with different types of accounts, while the sign of the coefficients is consistent, the results for active accounts are insignificant (column 3 in Table B.4). Yet, the impact of adoption on inactive accounts remains consistent (column 4 in Table B.4). When we use the first annual quota in our observations, we find insignificant results in the first two columns (columns 5 and 6 in Table B.4). Yet, the results in interaction models with different account types (columns 7 and 8 in Table B.4) are significant and consistent with our main findings.

Considering that our data provider is a global company, market- and time-specific factors

Table B.3: Differences in Sales Quota between Sales Agents who Achieved the Previous Year's Quota vs. Those that Did Not

		Number of Sales Agents	
	Total	Increased Sales Quota in year y (N (%))	Decreased Sales Quota in year y (N (%))
Achieved sales quota in year $(y-1)$			
Year 2015	96	64 (67%)	32 (33%)
Year 2016	92	74 (80%)	18 (20%)
Year 2017	111	79 (71%)	32 (29%)
Year 2018	110	85 (77%)	25 (23%)
Did not achieve sales quota in year $(y-1)$			
Year 2015	89	37 (42%)	52 (58%)
Year 2016	76	40 (53%)	36 (47%)
Year 2017	109	41 (38%)	68 (62%)
Year 2018	94	50 (53%)	44 (47%)

Note: The difference of annual sales quota is calculated as sales quota assigned to each sales agent in year y minus sales quota assigned to the sales agent in year $(y-1)$. Among 566 sales agents, 368 sales agents are in this analysis (190 sales agents that have only one-year observations and 8 sales agents that have only two discontinuous years of observations are excluded for we are unable to compute the difference).

can be substantially different. Moreover, the way the opportunity is given to each sales agent can vary across years. Also, a specific year's quota may not be very reliable to understand one's sales performance over years: the first annual quota may be set too low (or too high). Despite the deficiencies of the alternative measures, we can observe the signs of coefficients are the same for almost all measures, and especially the coefficients from heterogeneity results with respect to different agent and account types are very consistent.

Table B.4: Adoption of Marketing Analytics and Sales with Fixed Sales Quotas by Agent and Account Types: Linear Fixed Effect Regression Results

	DV: Quota Attainment Rate (fixed sales quota at average)[a]				*DV: Quota Attainment Rate (fixed sales quota at the first year)*[b]			
Agent Characteristics	Main	Interaction	Interaction	Interaction	Main	Interaction	Interaction	Interaction
Account Characteristics	Overall	Overall	Active	Inactive	Overall	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adoption (EA)	0.143**				0.103			
	(0.063)				(0.087)			
Adoption (EA) : Base		0.051**	-0.021	0.062***		-0.032	-0.097**	0.060***
		(0.024)	(0.027)	(0.018)		(0.041)	(0.042)	(0.018)
Adoption × low performers		0.198	0.276	-0.041		0.287	0.381*	-0.043
		(0.153)	(0.169)	(0.032)		(0.191)	(0.214)	(0.040)
Adoption × new agents		0.076	0.070	0.014		0.212*	0.186*	0.041
		(0.061)	(0.058)	(0.035)		(0.117)	(0.102)	(0.042)
SalesStatus	-0.079	-0.080	-0.084	-0.002	-0.113	-0.115	-0.116	-0.003
	(0.069)	(0.068)	(0.066)	(0.002)	(0.081)	(0.081)	(0.080)	(0.003)
Tenure	0.008	0.008	0.012**	0.003	0.004	0.004	-0.020***	-0.011***
	(0.007)	(0.007)	(0.005)	(0.003)	(0.014)	(0.014)	(0.008)	(0.003)
GradeLevel	0.015	0.016	-0.005	0.017	0.064	0.065	0.076	-0.013
	(0.026)	(0.026)	(0.034)	(0.014)	(0.060)	(0.060)	(0.076)	(0.032)
SalesforumViews	-0.0004	-0.0004	-0.0003	-0.0002*	-0.0002	-0.0002	-0.0002	-0.0003
	(0.0003)	(0.0003)	(0.0005)	(0.0001)	(0.0005)	(0.0005)	(0.0007)	(0.0002)
VoluntaryTraining	0.001	0.001	-0.0003	0.002	-0.004*	-0.004**	-0.007**	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	566	566	499	499	566	566	499	499
Departments (Cluster)	211	211	198	198	211	211	198	198
Observations	4,867	4,867	3,874	3,874	4,867	4,867	3,874	3,874
R-squared	0.136	0.137	0.128	0.351	0.161	0.163	0.155	0.274
Adjusted R-Squared	0.017	0.017	-0.008	0.250	0.046	0.047	0.024	0.162
F Statistic	20.93***	19.50***	14.37***	12.13***	10.91***	10.56***	227.00***	8.72***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.
Quota Attainment Rate is computed as quarterly sales (i.e., time-variant numerator) divided by a fixed sales quota (i.e., time-invariant denominator) for each sales agent: [a] Average annual quota per sales agent; [b] Each sales agent's first year sales quota that is observed in the data.

B.2 Alternative Time Frames

Next, we explore the robustness of our findings by estimating the model with different choices of the time period. Considering that our data covers the five-year periods from the year 2014 to 2018, we rerun the model by taking three different time frames: two pre- and post-analytics years (2015 - 2018), one pre-analytics, one implementation, and one post-analytics years (2016 - 2018), and one pre- and post-analytics year (2016, 2018). Table B.5 shows the main adoption effect of four different time frames, including our original model in the first column. While we consistently have positive and significant adoption coefficients for all cases, we can observe the greater adoption coefficients with the shorter time periods.

For the last three time frames [14], we further check the interaction model (Equation 2) with different types of customer accounts. In Table B.6, B.7, and B.8, we observe consistent results: positive overall adoption effect on quota attainment rate and sales winning rate (column 1 and 4 in each table), positive adoption effect on all outcome measures in active accounts for low-performing sales agents (column 2, column 5, column 8 in each table), and positive adoption effect on quota attainment rate and sales winning rate in inactive accounts for high-performing sales agents (column 3 and column 6 in each table). Again, we observe greater adoption coefficients with the shorter observation time, closer to the adoption.

[14]While our main model for overall accounts covers the five-year period (2014 - 2018), we used the year 2014 to classify whether an account was active, and therefore we cannot compute interaction models with different account types (active, inactive) for the five-year time frame.

Table B.5: Adoption of Marketing Analytics and Sales Performance: Different Choices of the Time Period

	DV: Quota Attainment Rate			
	2014 - 2018	*2015 - 2018*	*2016 - 2018*	*2016, 2018*
Agent Characteristics	Main	Main	Main	Main
Account Characteristics	Overall	Overall	Overall	Overall
	(1)	(2)	(3)	(4)
Adoption	0.143**	0.152**	0.187**	0.365*
	(0.063)	(0.071)	(0.082)	(0.202)
SalesStatus	0.921***	0.916***	0.912***	0.839***
	(0.069)	(0.067)	(0.066)	(0.169)
Tenure	0.008	0.015**	-0.257	-0.262
	(0.007)	(0.006)	(0.186)	(0.166)
GradeLevel	0.015	0.013	0.019	-0.009
	(0.026)	(0.032)	(0.038)	(0.036)
SalesforumViews	-0.0004	-0.0005	-0.0009	-0.002
	(0.0003)	(0.0005)	(0.0006)	(0.001)
VoluntaryTraining	0.001	0.002	0.001	0.005
	(0.001)	(0.002)	(0.003)	(0.004)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	566	499	423	404
Departments (Cluster)	211	198	182	172
Observations	4,867	3,874	3,009	1,997
R-squared	0.737	0.733	0.730	0.744
Adjusted R-Squared	0.701	0.692	0.684	0.677
F Statistic	496.20***	450.22***	503.02***a	286.78***a

Note: a. F Statistics are manually computed by using the number of parameters.
Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B.6: Adoption of Marketing Analytics and Sales Outcome Measures: Years 2015 to 2018

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (EA): Base	0.041*	-0.086**	0.127***	0.072***	-0.101**	0.150***	-0.051	-0.049	0.014
	(0.022)	(0.044)	(0.040)	(0.020)	(0.042)	(0.050)	(0.044)	(0.039)	(0.045)
Adoption × Low Performers	0.235	0.341*	-0.107	-0.009	0.147**	-0.015	0.095*	0.159***	0.044
	(0.166)	(0.184)	(0.082)	(0.024)	(0.071)	(0.063)	(0.051)	(0.056)	(0.061)
Adoption × New Agents	0.085	-0.018	0.103	-0.068	0.305*	-0.126	0.360	0.183	0.402***
	(0.060)	(0.060)	(0.084)	(0.097)	(0.158)	(0.085)	(0.228)	(0.259)	(0.087)
SalesStatus	0.914***	0.881***	0.034	0.002	0.005	0.005*	-0.002	0.007	-0.003
	(0.066)	(0.044)	(0.036)	(0.003)	(0.008)	(0.003)	(0.002)	(0.005)	(0.002)
Tenure	0.015***	0.012*	0.004	-0.013***	0.010	-0.011*	0.033***	0.026***	0.041***
	(0.006)	(0.007)	(0.005)	(0.003)	(0.006)	(0.006)	(0.009)	(0.003)	(0.011)
GradeLevel	0.013	-0.017	0.030	0.026	-0.029	0.033	0.015	-0.007	0.013
	(0.032)	(0.041)	(0.029)	(0.022)	(0.039)	(0.039)	(0.029)	(0.032)	(0.026)
SalesforumViews	-0.0005	-0.0003	-0.0002	0.0001	0.0004	0.00002	0.0001	-0.0001	0.0002
	(0.0005)	(0.0005)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.002	-0.004	0.005**	0.0006	0.009***	-0.002	-0.0004	-0.0005	0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	499	499	499	499	499	499	499	499	499
Departments (Cluster)	198	198	198	198	198	198	198	198	198
Observations	3,874	3,874	3,874	3,874	3,874	3,874	3,874	3,874	3,874
R-squared	0.733	0.697	0.505	0.666	0.608	0.493	0.534	0.499	0.508
Adjusted R-Squared	0.692	0.650	0.429	0.614	0.547	0.415	0.461	0.421	0.431
F Statistic	448.58***	203.66***	17.08***	7.60***	30.47***	42.34***	7.05***	6745.77***	5.19***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B.7: Adoption of Marketing Analytics and Sales Outcome Measures: Years 2016 to 2018

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (EA): Base	0.063***	-0.089**	0.153***	0.088***	-0.120***	0.163***	-0.028	-0.041	0.027
	(0.024)	(0.043)	(0.042)	(0.021)	(0.044)	(0.048)	(0.046)	(0.042)	(0.047)
Adoption × Low Performers	0.260	0.391*	-0.132	-0.021	0.162**	-0.011	0.093	0.144**	0.046
	(0.190)	(0.206)	(0.095)	(0.025)	(0.077)	(0.064)	(0.057)	(0.067)	(0.067)
Adoption × New Agents	0.074	0.007	0.067	-0.072	0.320**	-0.136	0.347	0.180	0.386***
	(0.061)	(0.061)	(0.086)	(0.098)	(0.159)	(0.089)	(0.229)	(0.260)	(0.090)
SalesStatus	0.911***	0.881***	0.030	0.001	0.002	0.004	-0.001	0.006	-0.002
	(0.066)	(0.044)	(0.034)	(0.002)	(0.006)	(0.003)	(0.002)	(0.005)	(0.002)
Tenure	-0.260	-0.084	-0.176***	0.046	-0.020	0.004	-0.474***	0.030	-0.482***
	(0.188)	(0.194)	(0.039)	(0.029)	(0.046)	(0.047)	(0.035)	(0.045)	(0.033)
GradeLevel	0.015	0.027	-0.013	0.026	-0.019	0.011	-0.009	-0.006	-0.007
	(0.041)	(0.052)	(0.031)	(0.027)	(0.048)	(0.042)	(0.033)	(0.045)	(0.028)
SalesforumViews	-0.0008	-0.0007	-0.0001	0.0002	0.0003	0.0002	0.0002	-0.0001	0.0005*
	(0.0005)	(0.0007)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.0007	-0.008**	0.009**	-0.001	0.009***	-0.001	-0.003	-0.003	0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	423	423	423	423	423	423	423	423	423
Departments (Cluster)	182	182	182	182	182	182	182	182	182
Observations	3,009	3,009	3,009	3,009	3,009	3,009	3,009	3,009	3,009
R-squared	0.730	0.698	0.526	0.636	0.588	0.510	0.542	0.515	0.522
Adjusted R-Squared	0.684	0.646	0.445	0.573	0.518	0.426	0.463	0.432	0.439
F Statistic	4.8e+07***	123.88***	96.26***a	2.88***	8.31***	6.07***a	1.1e+09***	6.08***a	2.2e+09***

Note: a. F Statistics are manually computed by using the number of parameters. Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B.8: Adoption of Marketing Analytics and Sales Outcome Measures: Years 2016 and 2018

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (EA): Base	0.116***	-0.071	0.187***	0.074**	-0.183***	0.165**	0.022	0.034	0.050
	(0.044)	(0.066)	(0.068)	(0.031)	(0.061)	(0.068)	(0.057)	(0.051)	(0.061)
Adoption × Low Performers	0.523	0.739*	-0.215*	0.007	0.248**	-0.021	0.102	0.177**	0.020
	(0.407)	(0.421)	(0.121)	(0.031)	(0.096)	(0.072)	(0.077)	(0.069)	(0.095)
SalesStatus	0.834***	0.813***	0.021	0.002	0.003	0.005**	-0.004**	0.006	-0.004*
	(0.169)	(0.157)	(0.023)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Tenure	-0.272	-0.140	-0.132***	0.062*	-0.071	0.067	-0.512***	0.015	-0.490***
	(0.172)	(0.176)	(0.044)	(0.032)	(0.054)	(0.054)	(0.042)	(0.061)	(0.037)
GradeLevel	-0.022	-0.046	0.024	0.042	-0.077	0.078	-0.047	-0.024	-0.015
	(0.046)	(0.060)	(0.038)	(0.033)	(0.056)	(0.052)	(0.043)	(0.063)	(0.034)
SalesforumViews	-0.002	-0.002	-0.0002	0.0002	0.0003	0.000004	0.0002	-0.0001	0.0007***
	(0.001)	(0.001)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.005	-0.014**	0.019***	-0.001	0.016***	-0.002	-0.007*	-0.003	-0.001
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	404	404	404	404	404	404	404	404	404
Departments (Cluster)	172	172	172	172	172	172	172	172	172
Observations	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997	1,997
R-squared	0.746	0.727	0.646	0.648	0.718	0.565	0.607	0.589	0.585
Adjusted R-Squared	0.678	0.655	0.552	0.555	0.643	0.451	0.503	0.481	0.475
F Statistic	5.4e+07***	64.85***	98.02***a	1.56*	10.32***	4.80***	27.33***a	8.19***a	27.60***a

Note: a. F Statistics are manually computed by using the number of parameters. Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.3 Alternative Sample Construction: Adoption Based on Tracked Records

We further explore robustness to an alternative measure of the adoption of marketing analytics by utilizing the tracked login records ($HasAdopted$, See HA in Figure 2). By employing this definition, we exclude the earlier post-analytics period (i.e., quarters in the implementation period) where only the cumulative records are available from our dataset. As a result, our new unbalanced panel dataset contains 546 sales agents with 3,638 quarterly sales observations. We have three quarters after marketing analytics, from the second quarter to the fourth quarter of the year 2018. Those who have ever used marketing analytics (i.e., those who have a nonzero cumulative number of logins) during the implementation period are defined as adopters from the beginning of the second quarter of the year 2018, together with those who started using marketing analytics at the quarter. While our earlier definition, $EventuallyAdopted$, treats the status of all adopters' pre-tracking periods (i.e., periods between the second quarter of the year 2017 and the quarter prior to the first login activity) as adopted, the definition $HasAdopted$ treats adopters as non-adopters unless the first login activity is observed. Given the positive adoption effect (see Table 6) under the previous definition ($EventuallyAdopted$), we expect the adoption effect to be greater with the alternative definition.

Table B.9 provides the results based on the alternative definition of adoption. For high performers, we find greater adoption effects on overall quota attainment rate (13.5%, column 1 in Table B.9) and among inactive accounts (16.4%, column 3 in Table B.9). In addition to the magnitude, the results remain statistically significant. For low performers, the magnitude of an adoption effect increases substantially yet is insignificant.

Furthermore, we find similar but stronger results on the effects of marketing analytics in sales funnel analysis: high performers achieved a greater sales winning rate from inactive accounts, while low performers achieved relatively greater sales winning rate and lead acceptance rate from active accounts.

Table B.9: Marketing Analytics Adoption and Sales Outcome Measures: Linear Fixed Effect Regression Results ($HasAdopted$ Dataset)

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (HA) : Base	0.135**	-0.048	0.164**	0.068**	-0.176***	0.169***	0.013	0.006	0.005
	(0.064)	(0.077)	(0.070)	(0.026)	(0.059)	(0.063)	(0.056)	(0.047)	(0.070)
Adoption × low performers	0.535	0.817	-0.204*	0.008	0.251**	-0.033	0.068	0.173***	0.024
	(0.493)	(0.573)	(0.112)	(0.026)	(0.100)	(0.066)	(0.078)	(0.066)	(0.103)
Adoption × new agents	-0.291*	-0.243	-0.019	-0.134***	0.075	-0.123	-0.183	-0.172	-0.037
	(0.160)	(0.269)	(0.141)	(0.035)	(0.088)	(0.094)	(0.120)	(0.151)	(0.085)
SalesStatus	0.814***	0.781***	0.023	0.002	0.007*	0.004*	-0.006**	0.008*	-0.006*
	(0.233)	(0.229)	(0.021)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Tenure	0.014	0.023*	0.007	-0.061**	0.020***	-0.009	0.019*	0.027***	0.047***
	(0.011)	(0.012)	(0.007)	(0.025)	(0.006)	(0.007)	(0.011)	(0.005)	(0.012)
GradeLevel	-0.007	-0.084	0.055*	0.030	-0.060	0.097**	-0.005	-0.022	0.004
	(0.028)	(0.051)	(0.033)	(0.019)	(0.042)	(0.039)	(0.025)	(0.040)	(0.038)
SalesforumViews	-0.0009	-0.0009	-0.0005*	0.0001	0.0005**	-0.00004	-0.0001	-0.00005	0.0002
	(0.0008)	(0.001)	(0.0003)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
VoluntaryTraining	0.002	-0.005	0.009***	0.0002	0.011***	-0.003	0.0008	0.0009	0.001
	(0.002)	(0.004)	(0.003)	(0.001)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	546	479	479	546	479	479	546	479	479
Departments (Cluster)	200	187	187	200	187	187	200	187	187
Observations	3,638	2,645	2,645	3,638	2,645	2,645	3,638	2,645	2,645
R-squared	0.760	0.737	0.641	0.752	0.724	0.558	0.568	0.561	0.553
Adjusted R-Squared	0.716	0.676	0.558	0.707	0.661	0.455	0.489	0.459	0.450
F Statistic	280.10***	62.06***	14.93***	4.54***	16.71***	8.68***	4.27***	1,349.66***	3.48***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.4 Alternative Sample Construction: Matching Adopter and Non-Adopter Samples

To better match the adopter and non-adopter samples, we create an alternative non-adopter sample using propensity score matching. Table B.10 shows the groupwise mean difference between the adopters and non-adopters. Although both the adopters and non-adopters follow a common trend from the coefficient plots for the quota attainment rate (see Figure 4), we found significant groupwise mean differences in conversion measures in the sales funnel (See Table B.10). The objective of propensity score matching is to find a corresponding sales agent from the non-adopter group that has the most similar characteristics to each sales agent in the adopter group so that the pair of sales agents are very similar to each other except in the adoption of marketing analytics.

To match adopters with non-adopters, we first limit our data to those who have at least one observation both before[15] and after the launch of marketing analytics. As a result, we have 228 sales agents: 60 adopters and 168 non-adopters. To ensure the sample size of non-adopters we use for matching is sufficiently large, for each adopter we allow up to the two most similar non-adopters to be selected. We use nearest neighbor matching using a linear propensity score, which is known to be particularly effective in reducing biases without the assumption of a normal distribution of covariates (Stuart, 2010; Rosenbaum and Rubin, 1983; Rubin, 2001). When calculating the distance between a pair, we use the average values of covariates (tenure, grade level, sales forum page views, voluntary training sessions, and pre-analytics sales performance[16]) during the pre-analytics period to avoid any potential bias (Chabé-Ferret, 2017). We trim nine adopters that do not have statistically close neighboring non-adopters by using a prespecified threshold (Austin, 2011; Rosenbaum and Rubin, 1985).[17]

After the matching, we have 145 sales agents with 2,035 observations. In Figure B.2,

[15] Since new agents, by definition, do not have data in the pre-analytics period, the entire group is excluded from this analysis.

[16] Rather than using the binary measure (i.e., High vs. low performer), we take each sales agent's average (annual, based on the annual audit report) quota attainment rate across the sales agent's annual records in the pre-analytics period.

[17] We identify the neighboring non-adopters whose propensity scores are within ±0.1 of each adopter's propensity score.

Table B.10: Groupwise Mean Difference: Adopters vs. Non-Adopters (*EventuallyAdopted* Dataset)

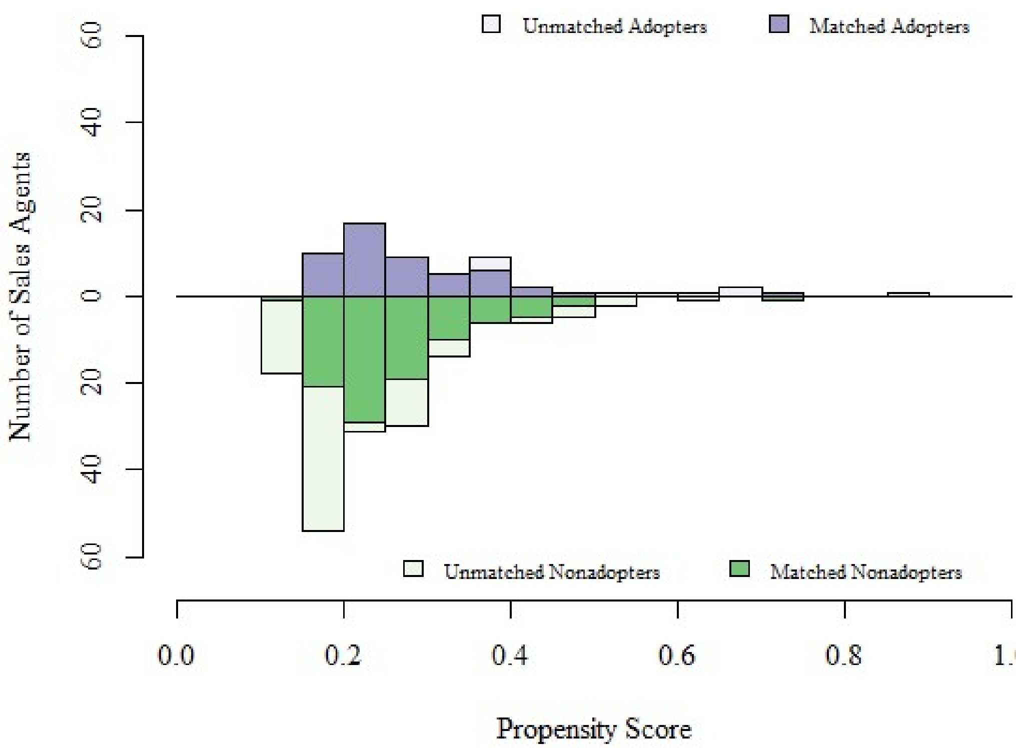
	Before Marketing Analytics (2014 Q1 to 2017 Q1)			After Marketing Analytics (2017 Q2 to 2018 Q4)		
	Adopters	Non-Adopters	t-test (p-value)	Adopters	Non-Adopters	t-test (p-value)
Number of sales agents	64	402		96	254	
Quota Attainment Rate	0.56 (0.29)	0.56 (0.44)	0.877	0.94 (1.82)	0.64 (0.51)	0.019
QAR from active[b] accounts	0.31 (0.28)	0.31 (0.35)	0.971	0.63 (1.80)	0.43 (0.46)	0.111
QAR from inactive[b] accounts	0.23 (0.29)	0.25 (0.39)	0.779	0.31 (0.43)	0.21 (0.31)	0.020
cf. Sales[a]	7.77 (16.61)	6.82 (11.61)	0.568	11.13 (21.73)	7.76 (11.12)	0.058
cf. Sales quota[a]	15.01 (32.27)	21.29 (42.76)	0.261	16.50 (33.62)	24.71 (47.86)	0.124
Sales Winning Rate	0.67 (0.14)	0.45 (0.36)	<0.001	0.67 (0.17)	0.60 (0.29)	0.021
SWR from active accounts	0.54 (0.33)	0.35 (0.38)	<0.001	0.63 (0.28)	0.53 (0.39)	0.022
SWR from inactive accounts	0.54 (0.19)	0.41 (0.32)	0.002	0.51 (0.23)	0.41 (0.29)	0.003
Lead Acceptance Rate	0.38 (0.30)	0.23 (0.29)	<0.001	0.50 (0.30)	0.29 (0.32)	<0.001
LAR from active accounts	0.29 (0.30)	0.15 (0.25)	<0.001	0.38 (0.32)	0.18 (0.27)	<0.001
LAR from inactive accounts	0.26 (0.27)	0.16 (0.25)	0.004	0.37 (0.31)	0.22 (0.31)	<0.001
Tenure	4.15 (3.26)	5.81 (3.67)	0.001	4.79 (3.68)	5.20 (4.01)	0.391
Grade Level	7.81 (0.51)	7.82 (0.66)	0.902	7.79 (0.56)	7.84 (0.71)	0.518
Sales forum pageviews	66.47 (54.96)	39.82 (41.47)	<0.001	61.53 (55.45)	43.15 (47.28)	0.002
Voluntary training sessions	2.37 (1.37)	1.98 (1.54)	0.057	0.64 (0.61)	0.66 (1.14)	0.883
Pre-analytics performance			0.804			0.731
High performers (N(%))	30 (46.9%)	186 (46.3%)		30 (31.2%)	90 (35.4%)	
Low performers (N(%))	30 (46.9%)	198 (49.3%)		30 (31.2%)	78 (30.7%)	
New agents (N%))	4 (6.2%)	18 (4.5%)		36 (37.5%)	86 (33.9%)	

[a] Annual Cumulative value, in millions.

[b] (In)Active accounts refer to the accounts with(out) sales records in the prior year. Statistics are based on four-year data (63 adopters and 334 non-adopters) as observations in 2014 have been dropped.

we observe that the matched adopters and non-adopters have a similar distribution of propensity scores. Table B.11 provides the groupwise mean difference of the matched dataset. Compared to the groupwise mean difference of the original dataset ($EventuallyAdopted$, in Table B.10), the result of the matched dataset implies no statistically significant groupwise difference in mean values of covariates and even of dependent variables, except for the lead acceptance rate and that of active accounts.

Figure B.2: Distribution of Propensity Scores: Adopters vs. Non-Adopters



To explore the impact of adoption on sales performance with the matched dataset, we first examine the quota attainment rate. The coefficient plots from Figure B.3, Figure B.4, and Figure B.5 look very similar to those from the main dataset. While the main adoption effect remains consistent (17.4%, column 3 in Table B.14), the adoption coefficient for high performers is less statistically robust (p = 0.055, column 1 in Table B.12) than that of in our main dataset. However,

Table B.11: Groupwise Mean Difference: Adopters vs. Non-Adopters (Matched Dataset)

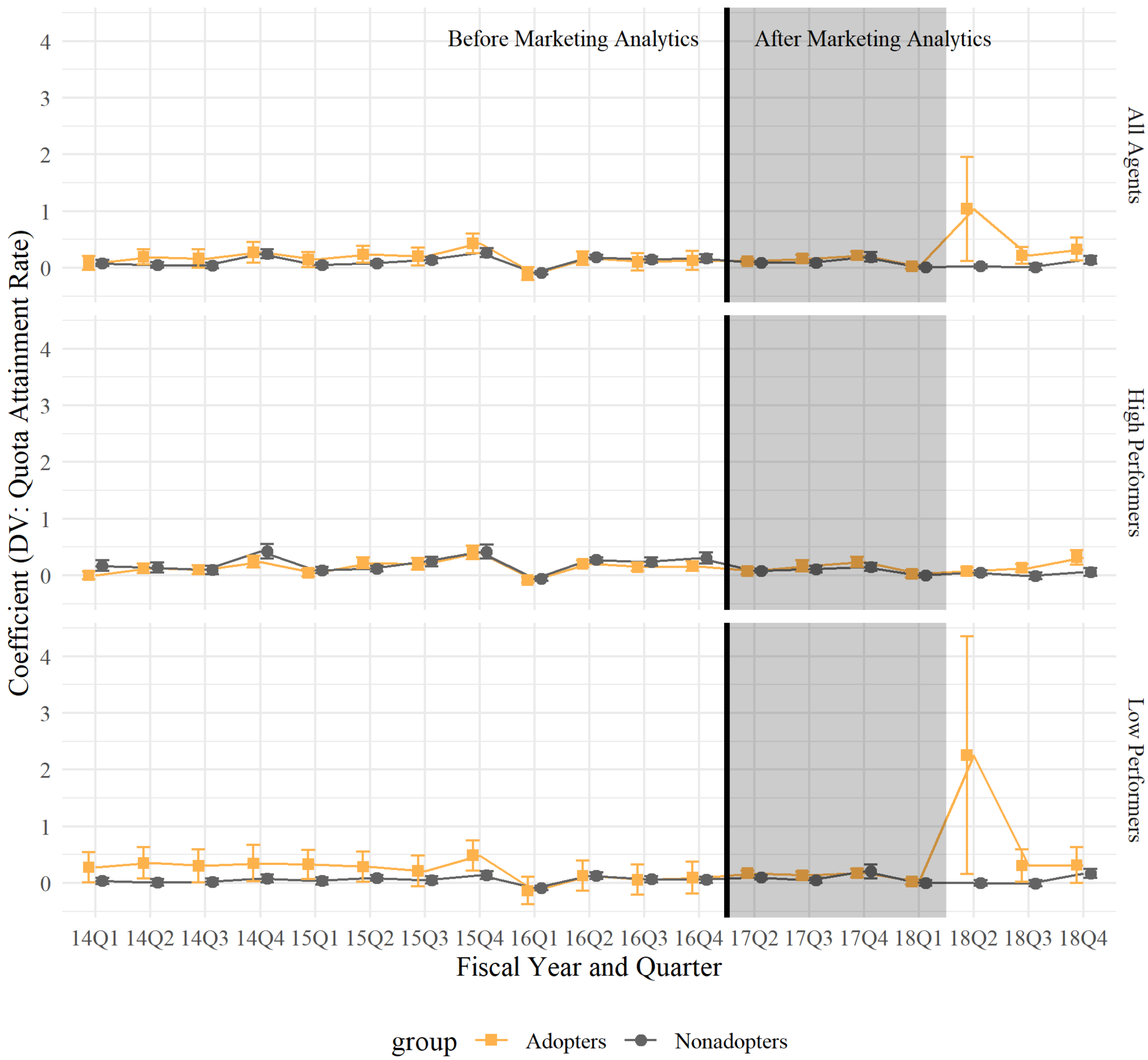
	Before Marketing Analytics (2014 Q1 to 2017 Q1)			After Marketing Analytics (2017 Q2 to 2018 Q4)		
	Adopters	Non-Adopters	t-test (p-value)	Adopters	Non-Adopters	t-test (p-value)
Number of sales agents	51	94		51	94	
Quota Attainment Rate	0.58 (0.27)	0.58 (0.33)	0.880	1.12 (2.44)	0.64 (0.38)	0.063
QAR from active accounts	0.35 (0.29)	0.29 (0.31)	0.237	0.96 (2.42)	0.53 (0.38)	0.098
QAR from inactive accounts	0.23 (0.27)	0.27 (0.33)	0.374	0.17 (0.18)	0.11 (0.16)	0.058
cf. Sales[a]	8.91 (18.39)	6.46 (8.67)	0.279	14.45 (27.53)	9.10 (11.96)	0.106
cf. Sales quota[a]	17.03 (35.92)	18.78 (34.42)	0.774	17.97 (33.17)	22.84 (37.69)	0.440
Sales Winning Rate	0.67 (0.14)	0.67 (0.23)	0.821	0.69 (0.17)	0.61 (0.30)	0.081
SWR from active accounts	0.56 (0.30)	0.49 (0.35)	0.228	0.76 (0.18)	0.66 (0.36)	0.066
SWR from inactive accounts	0.53 (0.19)	0.55 (0.24)	0.759	0.47 (0.26)	0.38 (0.30)	0.086
Lead Acceptance Rate	0.34 (0.28)	0.24 (0.29)	0.050	0.43 (0.27)	0.31 (0.31)	0.020
LAR from active accounts	0.27 (0.29)	0.17 (0.25)	0.033	0.38 (0.30)	0.26 (0.30)	0.027
LAR from inactive accounts	0.25 (0.27)	0.18 (0.27)	0.165	0.31 (0.29)	0.22 (0.30)	0.093
Tenure	4.37 (3.46)	4.21 (3.53)	0.796	6.51 (3.73)	5.90 (3.79)	0.360
Grade level	7.80 (0.51)	7.73 (0.59)	0.449	7.88 (0.53)	7.87 (0.60)	0.975
Sales forum pageviews	52.33 (37.42)	46.84 (38.95)	0.413	55.24 (46.03)	45.84 (40.84)	0.208
Voluntary training sessions	2.34 (1.29)	2.22 (1.30)	0.611	0.82 (0.64)	0.76 (1.21)	0.713
Pre-analytics performance			0.261			0.261
High performers (N(%))	28 (54.9%)	41 (43.6%)		28 (54.9%)	41 (43.6%)	
Low performers (N(%))	23 (45.1%)	53 (56.4%)		23 (45.1%)	53 (56.4%)	

[a] Annual Cumulative value, in millions.

[b] (In)Active accounts refer to the accounts with(out) sales records in the prior year. Statistics are based on four-year data (50 adopters and 93 non-adopters) as observations in 2014 have been dropped.

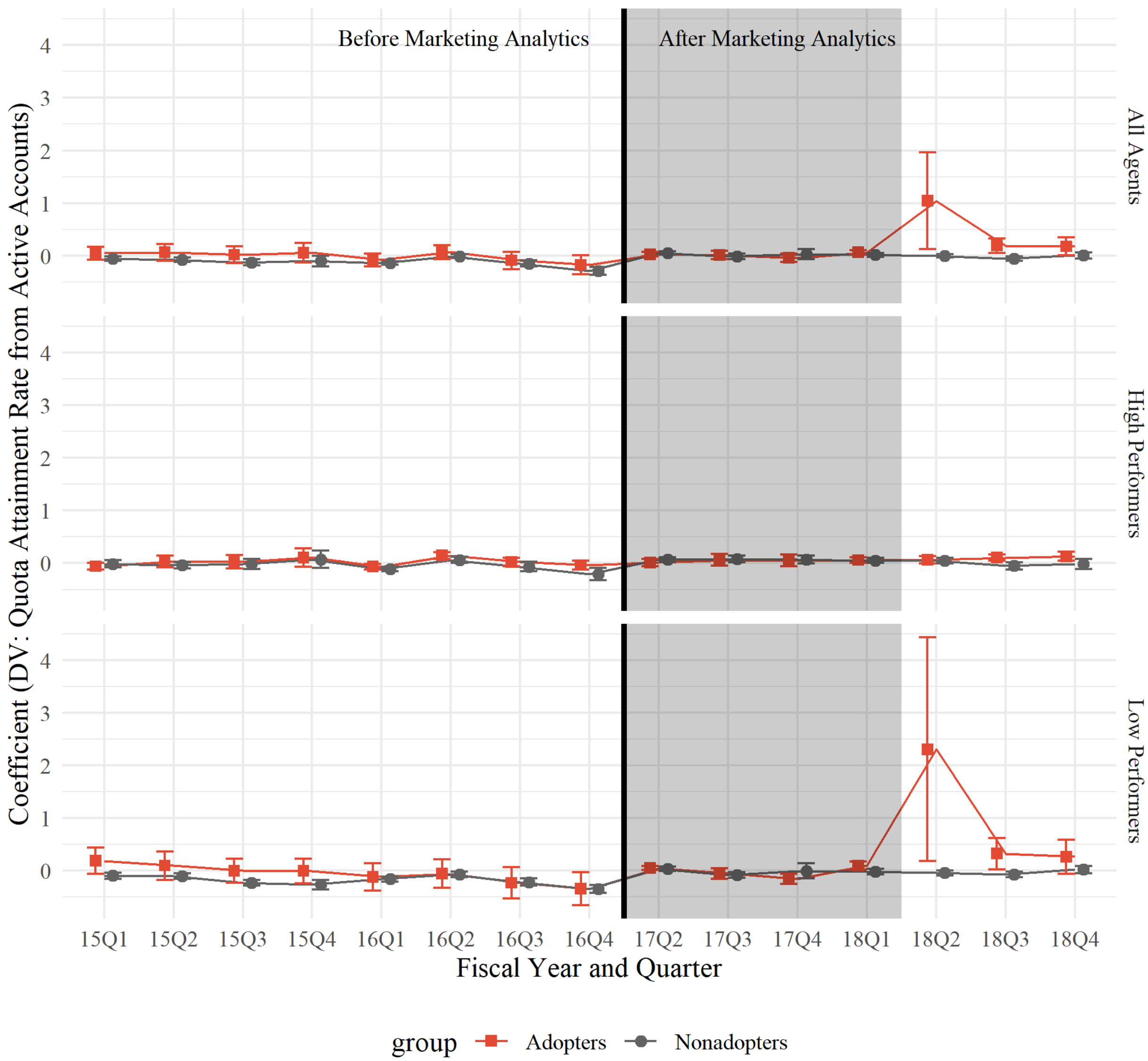
we find the two adoption effects are greater in magnitude. For other outcome measures such as the sales winning rate and lead acceptance rate (columns 5, 6, and 8 in Table B.12), we find consistent and significant results.

Figure B.3: Quota Attainment Rate Over Time: Overall Accounts from Matched Dataset)



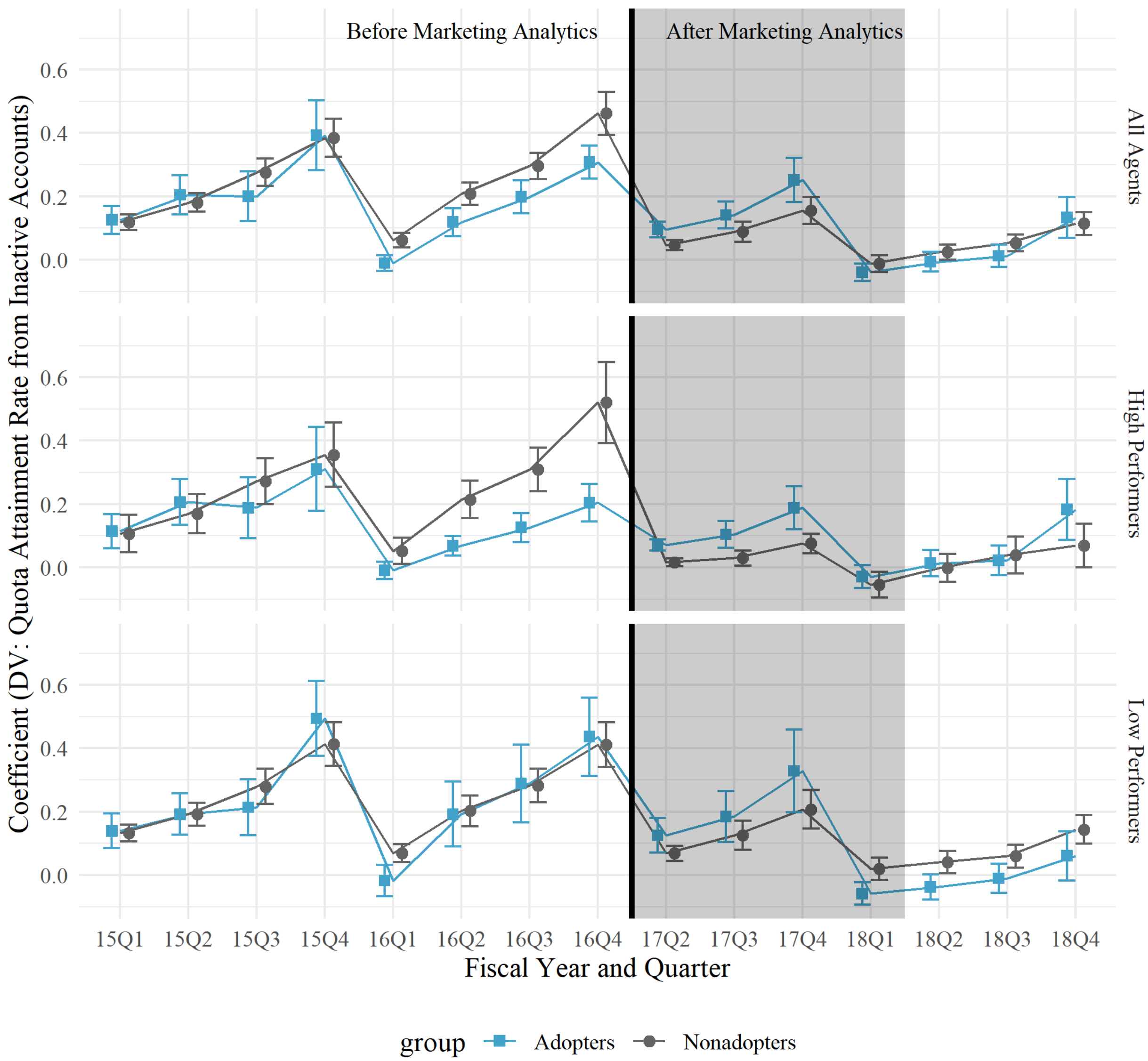
Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second and third graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure B.4: Quota Attainment Rate Over Time: Active Accounts from Matched Dataset)



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second and third graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure B.5: Quota Attainment Rate Over Time: Inactive Accounts from Matched Dataset)



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second and third graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Table B.12: Marketing Analytics Adoption and Sales Outcome Measures: Linear Fixed Effect Regression Results (Matched Dataset)

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (EA) : Base	0.058*	-0.078*	0.120***	0.070***	-0.081	0.131**	-0.031	-0.059	-0.004
	(0.030)	(0.046)	(0.042)	(0.022)	(0.049)	(0.054)	(0.048)	(0.053)	(0.050)
Adoption × low performers	0.280	0.414*	-0.087	-0.025	0.176**	-0.049	0.082	0.137**	0.044
	(0.204)	(0.236)	(0.078)	(0.026)	(0.077)	(0.059)	(0.057)	(0.061)	(0.070)
SalesStatus	0.905***	0.896***	0.007	0.002	0.003	0.003*	-0.001	0.005	-0.003
	(0.061)	(0.052)	(0.012)	(0.002)	(0.006)	(0.002)	(0.002)	(0.005)	(0.003)
Tenure	0.011	0.008	0.010	-0.073***	-0.001	-0.004	0.019**	0.025***	0.047***
	(0.007)	(0.007)	(0.006)	(0.026)	(0.007)	(0.006)	(0.008)	(0.005)	(0.006)
GradeLevel	0.018	-0.026	0.024	0.056**	0.011	-0.012	0.022	0.009	0.005
	(0.041)	(0.061)	(0.042)	(0.024)	(0.066)	(0.053)	(0.035)	(0.056)	(0.035)
SalesforumViews	-0.0008	-0.0006	-0.0003	0.000004	0.0005	-0.0005*	0.0003	0.0001	0.0003
	(0.0007)	(0.0009)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
VoluntaryTraining	0.002	-0.0003	0.002	0.0006	0.005	-0.002	-0.003	-0.004	0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	145	145	145	145	145	145	145	145	145
Departments (Cluster)	105	100[a]	100[a]	105	100[a]	100[a]	105	100[a]	100[a]
Observations	2,035	1,754	1,754	2,035	1,754	1,754	2,035	1,754	1,754
R-squared	0.716	0.697	0.360	0.484	0.448	0.414	0.489	0.464	0.472
Adjusted R-Squared	0.690	0.666	0.293	0.437	0.390	0.352	0.443	0.408	0.417
F Statistic	562.84***	374.70^{***b}	221.93^{***b}	4.56***	81.82^{***b}	134.58^{***b}	6.81***	3.1e+10***	1.9e+11***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. [a] Five clusters are dropped in the four-year dataset due to the insufficient observations. [b] F Statistics are manually computed by using the number of parameters. Standard errors in parentheses.

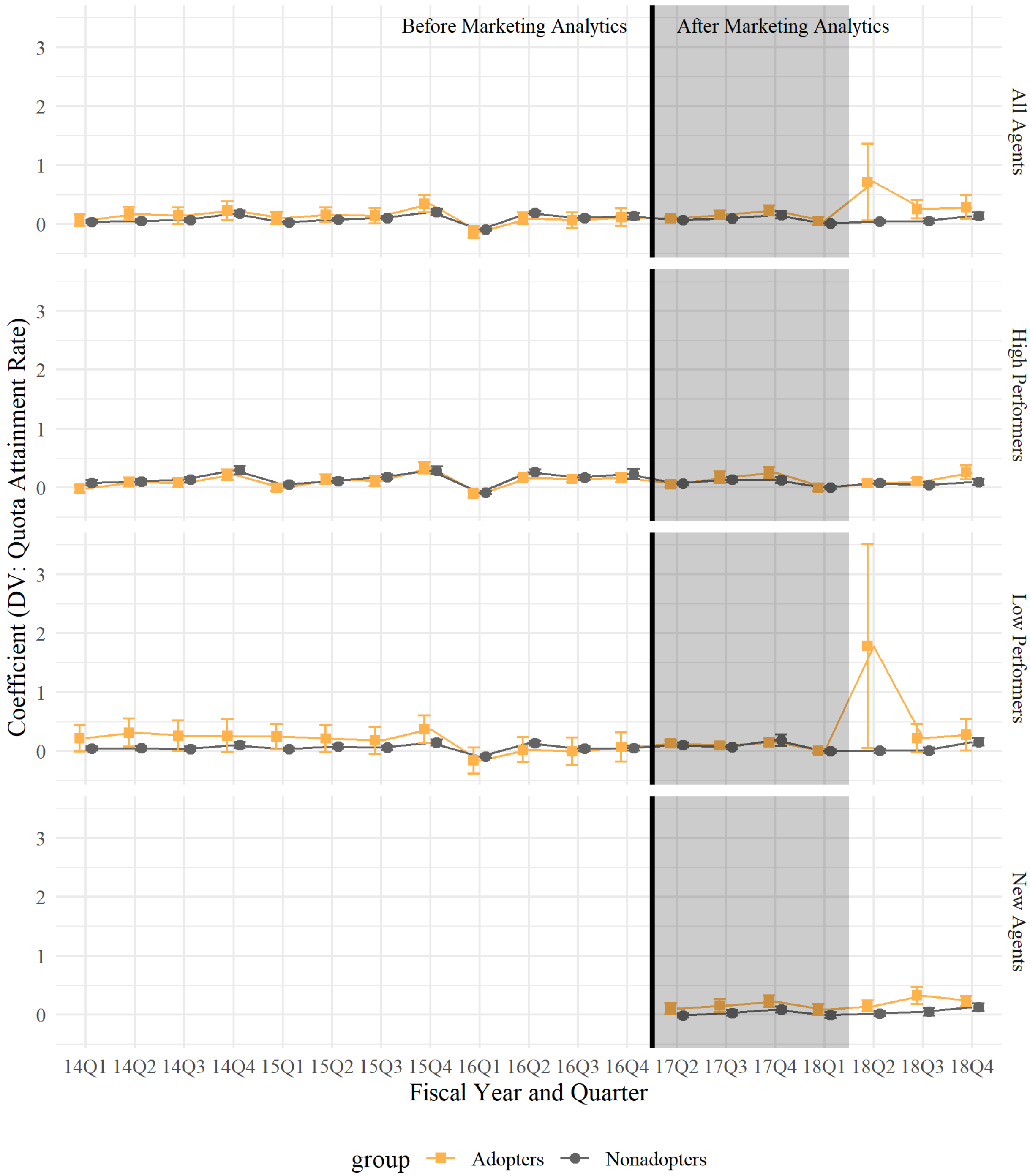
B.5 Alternative Sample Construction: Excluding Outliers

We rerun the models by excluding outliers in each quarter during the pre-analytics period. We define outliers as observations exceeding three standard deviations[18] from the mean value of the quota attainment rate. Dropping the outliers yields 532 sales agents with 4,412 quarterly sales observations.

In the coefficient plots (Figure B.6, Figure B.7, and Figure B.8), we can observe the trends are consistent with those based on our main dataset (Figure 4, Figure 5 and Figure 6). The estimated coefficients in Table B.13 support the robustness of our findings without outliers. We find consistent main adoption effect (15.2%, column 4 in Table B.14) and interaction adoption effect for the high performers (12.6%, column 3 in Table B.13) on the quota attainment rate. Yet, the adoption coefficients for low performers on the quota attainment rate and the sales winning rate are insignificant after we exclude outliers. The rest of the adoption effects on conversion rates in the sales funnel remain consistent.

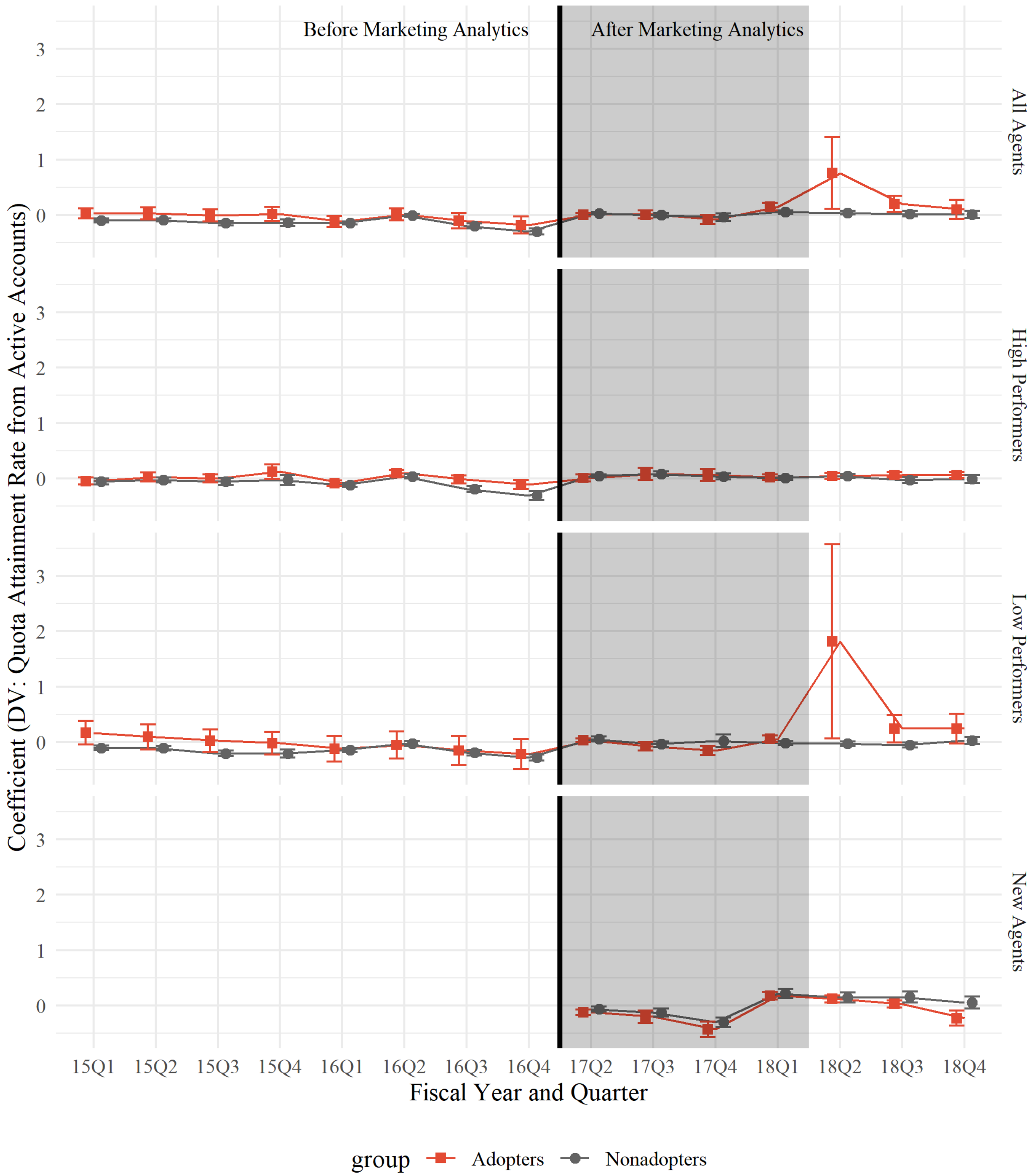
[18]Identifying outliers using three standard deviations from the mean is a common practice, where two standard deviations cut-off keeps 95% of the samples and four standard deviations cut-off keeps 99% of the samples in a normal distribution.

Figure B.6: Quota Attainment Rate Over Time: Overall Accounts from Outliers Dataset)



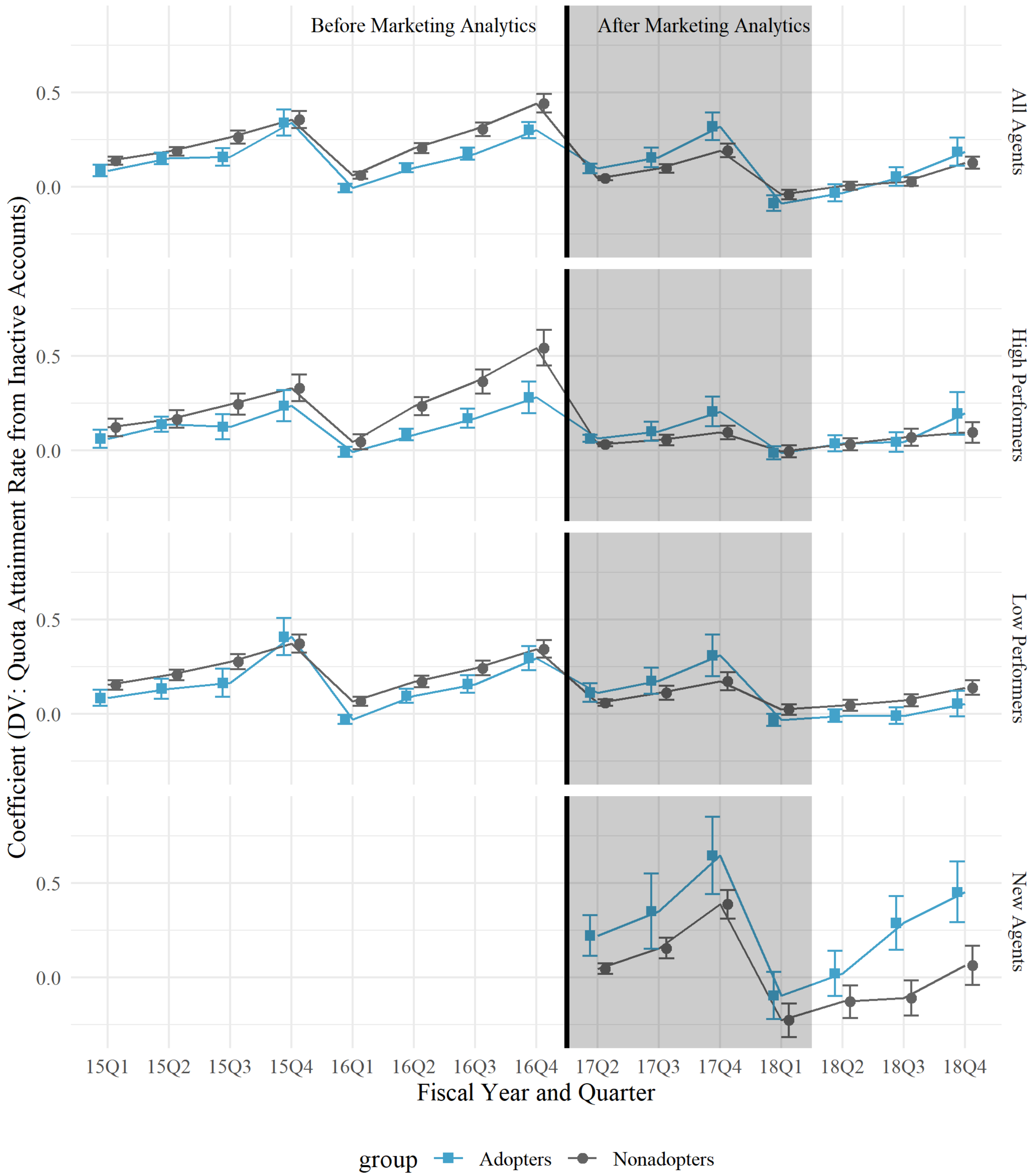
Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure B.7: Quota Attainment Rate Over Time: Active Accounts from Outlier Dataset



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Figure B.8: Quota Attainment Rate Over Time: Inactive Accounts from Outlier Dataset



Note: The first graph coefficients are from the main model ($EventualAdopters_i \times Time_t$) where the baseline group is non-adopter and baseline time is the first quarter of the year 2017 (i.e., 17Q1). Overall effect is presented (e.g., for adopters, we summate the coefficients of $Time_t$ and $EventualAdopters_i \times Time_t$). The second to fourth graphs' coefficients are from interaction model ($EventualAdopters_i \times Time_t \times Performance_{i,pre}$) with the high performers as the base performance group.

Table B.13: Marketing Analytics Adoption and Sales Outcome Measures: Linear Fixed Effect Regression Results (Outlier Dataset)

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (EA) : Base	0.043*	-0.089**	0.126***	0.080***	-0.113**	0.150***	-0.041	-0.073	0.004
	(0.022)	(0.041)	(0.040)	(0.021)	(0.048)	(0.053)	(0.042)	(0.045)	(0.042)
Adoption × low performers	0.229	0.292	-0.025	-0.011	0.107	0.015	0.096*	0.157**	0.086
	(0.157)	(0.196)	(0.053)	(0.025)	(0.071)	(0.062)	(0.052)	(0.063)	(0.055)
Adoption × new agents	0.067	-0.042	0.114	-0.078	0.305*	-0.109	0.351	0.208	0.409***
	(0.061)	(0.062)	(0.085)	(0.096)	(0.159)	(0.086)	(0.224)	(0.260)	(0.085)
SalesStatus	0.906***	0.885***	0.018	0.002	0.006	0.003*	-0.003	0.006	-0.003*
	(0.063)	(0.048)	(0.024)	(0.003)	(0.009)	(0.002)	(0.002)	(0.005)	(0.002)
Tenure	0.012*	0.012*	0.007	-0.073***	0.012**	-0.008	0.020**	0.030***	0.043***
	(0.006)	(0.006)	(0.005)	(0.027)	(0.006)	(0.006)	(0.009)	(0.004)	(0.010)
GradeLevel	0.008	-0.028	0.019	0.012	-0.034	0.021	0.011	-0.006	0.021
	(0.021)	(0.039)	(0.032)	(0.020)	(0.043)	(0.039)	(0.024)	(0.033)	(0.025)
SalesforumViews	-0.0005	-0.0003	-0.0003	0.0001	0.0005*	0.00004	-0.0002	-0.0001	0.0001
	(0.0004)	(0.0006)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	-0.0001	-0.002	0.003	-0.0001	0.010***	-0.005	0.0004	-0.001	0.002
	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	532	466	466	532	466	466	532	466	466
Departments (Cluster)	207	194	194	207	194	194	207	194	194
Observations	4,412	3,514	3,514	4,412	3,514	3,514	4,412	3,514	3,514
R-squared	0.728	0.696	0.513	0.716	0.611	0.493	0.536	0.502	0.519
Adjusted R-Squared	0.689	0.647	0.434	0.675	0.548	0.411	0.468	0.422	0.442
F Statistic	497.02***	194.59***	16.77***	4.53***	22.31***	88.60***	5.98***	4,324.30***	5.75***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.6 Alternative Sample Constructions: Main Adoption Effects

Table B.14 shows the main effect of adoption on quota attainment rate with different alternative sample constructions. Except for the different measure for adoption (i.e., $HasAdopted$), we can observe consistent and significant adoption coefficients for different samples.

Table B.14: Marketing Analytics Adoption and Sales Performance: Main Model Results for Different Datasets

	DV: Quota Attainment Rate			
Dataset	Eventually Adopted	Has Adopted	Matched	Outlier
Agent Characteristics	Main	Main	Main	Main
Account Characteristics	Overall	Overall	Overall	Overall
	(1)	(2)	(3)	(4)
Adoption (EA)	0.143**		0.174**	0.152**
	(0.063)		(0.075)	(0.073)
Adoption (HA)		0.371		
		(0.263)		
SalesStatus	0.921***	0.819***	0.907***	0.908***
	(0.069)	(0.231)	(0.062)	(0.063)
Tenure	0.008	0.015	0.010	0.011*
	(0.007)	(0.011)	(0.007)	(0.006)
GradeLevel	0.015	-0.009	0.014	0.005
	(0.026)	(0.029)	(0.040)	(0.022)
SalesforumViews	-0.0004	-0.0009	-0.0008	-0.0004
	(0.0003)	(0.0008)	(0.0007)	(0.0004)
VoluntaryTraining	0.001	0.002	0.003	-0.00003
	(0.001)	(0.002)	(0.002)	(0.002)
Individual Dummy Variables	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES
Sales Agents	566	546	145	532
Departments (Cluster)	211	200	105	207
Observations	4,867	3,638	2,035	4,412
R-squared	0.737	0.759	0.716	0.728
Adjusted R-Squared	0.701	0.715	0.690	0.689
F Statistic	496.20***	303.26***	538.79***	488.09***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

B.7 Dropping One-Time Users

We have defined the adoption of marketing analytics based on the login records. Under the definition, those who logged in at least once are treated as adopters. One may concern that there can be sales agents who used the tool only once and decide not to use the tool is labeled as adopters. Although adoption might have affected sales strategies of such single-time users, we can distinguish those who initially logged in once by looking at the cumulative logins and the last login time. Considering that the sales cycle takes around four months on average with a huge variance, we define the group who logged in initially once as those with a single time login during the year 2017 and not afterwards. We have 5 sales agents and this small number provides some assurance that our prior definition of adoption (i.e., irreversible) is sensible. Since five sales agents are not enough to be categorized as a separate group, we explore the robustness by excluding them from the adopter group (Table B.15) and treating them as non-adopters (Table B.16). We confirmed that the results are consistent: positive adoption coefficients on overall quota attainment rate and sales winning rate (column 1 and 4 in Table B.15 and B.16), positive adoption coefficients on all outcome measures in active accounts for low-performing sales agents (column 2, 5, and 8 in in Table B.15 and B.16), and positive adoption coefficients on quota attainment rate and sales winning rate in inactive accounts for high-performing sales agents (column 3 and 6 in Table B.15 and B.16).

Table B.15: Adoption of Marketing Analytics and Sales Outcome Measures: Exclude 5 One-Time Users

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (Base)	0.066***	-0.060	0.114**	0.084***	-0.081*	0.150***	-0.023	-0.046	0.014
	(0.024)	(0.048)	(0.045)	(0.021)	(0.048)	(0.056)	(0.042)	(0.048)	(0.042)
Adoption × low performers	0.183	0.316*	-0.095	-0.018	0.127*	-0.015	0.076	0.156**	0.043
	(0.155)	(0.189)	(0.086)	(0.024)	(0.074)	(0.073)	(0.050)	(0.061)	(0.059)
Adoption × new agents	0.052	-0.065	0.128	-0.177**	0.211	-0.197**	0.189	0.028	0.434***
	(0.074)	(0.063)	(0.107)	(0.071)	(0.191)	(0.081)	(0.255)	(0.306)	(0.104)
SalesStatus	0.919***	0.880***	0.034	0.002	0.005	0.004*	-0.002	0.006	-0.003
	(0.068)	(0.043)	(0.037)	(0.003)	(0.007)	(0.003)	(0.002)	(0.005)	(0.002)
Tenure	0.008	0.012*	0.004	-0.074***	0.010	-0.010*	0.016*	0.026***	0.041***
	(0.008)	(0.007)	(0.005)	(0.027)	(0.006)	(0.006)	(0.009)	(0.004)	(0.011)
GradeLevel	0.014	-0.019	0.029	0.027	-0.030	0.032	0.018	-0.006	0.011
	(0.026)	(0.041)	(0.029)	(0.019)	(0.039)	(0.039)	(0.021)	(0.032)	(0.026)
SalesforumViews	-0.0004	-0.0003	-0.0002	0.0001	0.0004	0.000004	-0.00002	-0.0001	0.0002
	(0.0003)	(0.0006)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.001	-0.004	0.005**	0.0001	0.008***	-0.003	0.0008	-0.0004	0.003
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	561	494	494	561	494	494	561	494	494
Departments (Cluster)	211	198	198	211	198	198	211	198	198
Observations	4,800	3,814	3,814	4,800	3,814	3,814	4,800	3,814	3,814
R-squared	0.737	0.697	0.507	0.712	0.608	0.492	0.527	0.500	0.512
Adjusted R-Squared	0.701	0.649	0.430	0.672	0.547	0.413	0.462	0.422	0.436
F Statistic	488.26***	194.80***	16.49***	4.65***	29.92***	41.71***	6.02***	6,109.46***	4.22***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table B.16: Adoption of Marketing Analytics and Sales Outcome Measures: Consider 5 One-Time Users as non-adopters

	DV: Quota Attainment Rate			*DV: Sales Winning Rate*			*DV: Lead Acceptance Rate*		
Agent Characteristics	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction	Interaction
Account Characteristics	Overall	Active	Inactive	Overall	Active	Inactive	Overall	Active	Inactive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Adoption (Base)	0.068***	-0.054	0.109**	0.081***	-0.075	0.146**	-0.021	-0.046	0.014
	(0.024)	(0.048)	(0.046)	(0.020)	(0.050)	(0.057)	(0.042)	(0.049)	(0.040)
Adoption × low performers	0.183	0.316*	-0.095	-0.018	0.126*	-0.015	0.076	0.156**	0.043
	(0.155)	(0.189)	(0.086)	(0.024)	(0.074)	(0.073)	(0.050)	(0.061)	(0.059)
Adoption × new agents	0.049	-0.072	0.132	-0.178**	0.205	-0.197**	0.187	0.026	0.434***
	(0.074)	(0.064)	(0.107)	(0.071)	(0.191)	(0.082)	(0.255)	(0.306)	(0.104)
SalesStatus	0.920***	0.881***	0.034	0.002	0.005	0.004*	-0.002	0.007	-0.003
	(0.068)	(0.044)	(0.036)	(0.003)	(0.008)	(0.003)	(0.002)	(0.005)	(0.002)
Tenure	0.008	0.011	0.004	-0.073***	0.009	-0.010*	0.016*	0.026***	0.041***
	(0.007)	(0.007)	(0.005)	(0.027)	(0.006)	(0.006)	(0.009)	(0.003)	(0.011)
GradeLevel	0.016	-0.015	0.027	0.025	-0.027	0.030	0.019	-0.007	0.012
	(0.026)	(0.041)	(0.029)	(0.019)	(0.039)	(0.039)	(0.021)	(0.032)	(0.026)
SalesforumViews	-0.0004	-0.0003	-0.0002	0.0001	0.0004	0.00003	-0.00003	-0.0001	0.0002
	(0.0003)	(0.0005)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
VoluntaryTraining	0.001	-0.004	0.005*	0.0003	0.009***	-0.002	0.0007	-0.0003	0.003
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Individual Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummy Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sales Agents	566	499	499	566	499	499	566	499	499
Departments (Cluster)	211	198	198	211	198	198	211	198	198
Observations	4,867	3,874	3,874	4,867	3,874	3,874	4,867	3,874	3,874
R-squared	0.738	0.697	0.505	0.712	0.607	0.493	0.526	0.499	0.508
Adjusted R-Squared	0.701	0.649	0.428	0.672	0.546	0.414	0.461	0.421	0.431
F Statistic	496.05***	205.51***	16.88***	4.69***	32.81***	49.65***	5.78***	5,097.13***	4.49***

Note: Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.