DOI: 10.1177/00222437221095097

JOURNAL of MARKETING RESEARCH

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Journal:	*Journal of Marketing Research*
Manuscript ID	JMR.18.0575.R4
Manuscript Type:	Revised Submission
Topics and Methods:	Sales force < Substantive area, Natural experiments < Method of discovery

Managing Positive and Negative Trends in Sales Call Outcomes:

The Role of Momentum

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Abstract

Existing research treats sales performance as a series of discrete, independent events rather than as a series of sales attempts with intertemporal spillover across these attempts. This research examines whether there are systematic short-term trends ("momentum") in sales performance. To do so, the authors use the clumpiness approach to examine the existence of sales momentum in a high-frequency call-level data set obtained from two call centers of a large European firm. They further investigate the effect of positive (negative) momentum, or the positive (negative) deviation from the long-term expected performance on subsequent sales performance. Exploiting the differences in the social environment of the call centers, the authors find that the social working environment mitigates the harmful effect of negative momentum and sustains positive momentum. Further, they demonstrate that calls made midday, early-week and late-week boost performance by mitigating the adverse effects of negative momentum. The findings suggest that monitoring sales performance can help managers detect momentum and use timely interventions to enhance sales productivity. Managers can also leverage momentum by creating a more social working environment to optimize overall salesperson performance.

Keywords: sales performance, sales force, personal selling, social influence, momentum

Research has long been interested in understanding salesperson performance (Albers, Mantrala, and Sridhar 2010; Franke and Park 2006). Much of this work focuses on identifying the drivers of sales success (e.g., Kishore et al. 2013); yet salespeople fail far more often than they succeed. A recent study of more than 1000 sales organizations finds that while an average salesperson has 11.9 sales conversations per day, only 4.8% of these result in meaningful sales opportunities (InsideSales 2017). Yet sales research typically does not explain how to overcome the influence of failure. Furthermore, most research on sales assumes that sales events are discrete and independent (e.g., Verbeke and Bagozzi 2000), though some work has questioned this assumption (e.g., Marinova, Singh, and Singh 2018; Misra and Nair 2011; Patil and Syam 2018). This article extends the stream of sales literature that examines the interdependence of sales events.

In this study, we systematically explore “sales momentum,” defined as the distinct short-term trends in salespeople’s performance outcomes above or below their long-term expected levels. We find that salespeople’s performance *does* exhibit momentum. In other words, salespeople experience periods of temporary elevation or decline in sales call outcomes compared with their overall expected performance. Such deviations are likely not just a statistical possibility of consecutive success or failure, but rather constitute a systematic clustering of outcomes over a short period (e.g., a run of successes with a small number of failures, or vice versa). Thus, given a period of sales calls, a salesperson with more successes (failures) than his or her long-term expected performance is said to be experiencing positive (negative) momentum.

To understand the perception of momentum and how it is managed in practice, we conducted a preliminary study with 160 salespeople (for details, see Web Appendix A), in which we gathered information on salespeople’s beliefs about momentum, their experiences, and whether their organizations actively managed momentum. We found that the majority of salespeople believed they had experienced both positive (86%) and negative (65%) momentum. The salespeople also presumed that their organization tried to both identify (67%) and actively manage (56%) their momentum. However, when we asked salespeople to report what their organization did to manage momentum, no consensus emerged, suggesting no clear understanding in the practice of how to do so, with most approaches based on intuition and guesswork. Some salespeople suggested actions such as trying to boost spirits, giving encouragement, or being positive, while others reported enforced breaks and meetings.

Thus, although sales practitioners have intuitive beliefs about sales momentum, there is neither a great deal of systematic investigation into this phenomenon nor strong managerial insights to estimate its impact and guide sale practice. To fill this research gap, we examine sales momentum and its impact on individual salesperson performance. Understanding whether specific working conditions can enhance momentum and its effects would further help manage momentum and augment salesperson performance. In particular, salespeople in dedicated sales environments make continuous calls throughout the day, and factors such as (1) the design of the sales environment, (2) individual worker characteristics, and (3) timing of the calls may augment the effect of momentum. To this end, we examine *where* the salesperson should work (i.e., a more or less social working environment), *who* should make the call (i.e., male or female salespeople), and *when* the call should be made (i.e., time of day and day of week), to strengthen or weaken the effect of momentum. Accordingly, we address three research questions:

1. Do short-term trends in salespeople's performance systematically deviate from their long-term expectations (i.e., does momentum exist)?
2. How does this *momentum* influence subsequent performance?
3. How do the social working environment, salesperson gender, and timing of the call moderate the effect of momentum on performance?

We examine our research questions in the context of inside sales, in which agents mostly reach customers remotely rather than face-to-face (Martin 2013), as we expect momentum to be more visible here than in a field sales context. Inside salespeople located in dedicated facilities engage in transactional selling activities that can be actively managed through continuous monitoring. That is, they make multiple sales pitches in a short period, which creates a fitting environment to detect momentum.

We use a novel disaggregate call-level data set from a large European firm operating two call centers. Salespeople in these call centers make outbound sales calls to sell an identical product. The high-frequency transactional data capture key details of each sales call and its outcome, enabling us to identify positive and negative salesperson momentum. With these data, we can also estimate the likelihood of success in the subsequent sales call and suggest ways that managers can augment (mitigate) the effect of positive (negative) momentum in their sales force.

We explore momentum using two related analyses. In Analysis 1, we formally test for the existence of momentum by examining short-term trends in salespeople's performance that deviate from their long-term expectations. To effectively capture sales momentum, a method should be able to capture moment-to-moment momentum, identify exactly when salespeople experience momentum, and take into account their inherent low absolute success rate. We follow Zhang, Bradlow, and Small's (2013) clumpiness approach, which tests for the existence of systematic clustering of a type of outcome over time, consistent with our definition of momentum. Intuitively, the method captures momentum behind sequences of outcomes that may appear completely random. By examining variation or disorderliness in a sequence of outcomes compared with the expected level of outcomes, the clumpiness approach captures salespeople's below-50% success rate and shows whether they were experiencing momentum as they made additional calls. The results provide robust evidence for the existence of momentum in sales performance.

In Analysis 2, we examine the relationship between momentum and sales performance using a fixed-effects logistic regression to test how momentum influences subsequent performance. We find a strong influence of momentum on the probability of success in a salesperson's next call. Specifically, we find that positive (negative) momentum enhances (decreases) the likelihood of selling in the next call. This finding can help managers estimate the likelihood of success in the next call, given the momentum state of the salesperson.

In addition, we explore the consequences of momentum in the sales context to provide implications of the type of work environment that can maximize salesperson performance. We focus on examining the moderating role of the social environment by exploiting a natural variation in the physical setup of our focal firm across two of its locations. The firm independently carried out a quasi-experiment to investigate the effect of social interaction on performance. In one location, referred to as the social call center (SCC), all salespeople were colocated in the same large space, with facilities such as a relaxation room and a communal kitchen. The SCC was specifically designed to enable greater social interaction than the firm's other location. The other location, referred to as the nonsocial call center (NSCC), was a repurposed office building in which salespeople were spread across different small rooms, with no communal relaxation facilities due to limited space. We find that being in the SCC weakens the harmful effect of negative momentum and enhances the favorable effect of positive momentum on sales performance. Considering the effect of SCC, we propose a logic for a decision support system (DSS). Using simulation, we test the effectiveness of the proposed DSS and find that salespeople in our data would have performed 18.4% better had the system been in place.

To provide further guidance on managing the effect of momentum, we explore the moderating effect of salesperson gender, time of day, and day of week to address for whom momentum is more (less) likely to influence performance in the next call when. Unlike previous research that found gender differences in behaviors (e.g., Cohen-Zada, Krumer, and Shtudiner

2017; He, Inman and Mittal 2008), we find that gender does not significantly influence the relationship between momentum and sales performance. However, making calls midday, early and late in the week mitigates the harmful effect of negative momentum.

The structure of this article is as follows: First, we describe the background literature on momentum and present details of our empirical context and data. Second, we conduct Analysis 1, which examines the existence of momentum using the test of clumpiness, and then Analysis 2, which assesses the influence of momentum on sales performance and its boundary conditions using the fixed-effects logit model. Third, we provide additional information about sales momentum, the financial implications of controlling for momentum, explain the logic for how a DSS can be implemented to detect and control momentum, and discuss the downstream consequences and long-term impact of momentum. Finally, we conclude with insights for theory and practice and directions for further research.

LITERATURE ON MOMENTUM

Introducing the concept of momentum to the social sciences, Adler (1981) defined momentum as a phenomenon in which the probability of success in the present event is influenced by the outcome of the preceding event. In a similar vein, Gilovich, Vallone, and Tversky (1985) explore the existence of the "hot hand" in sports. Momentum is related to a hot hand or "streakiness" but differs in important ways. Hot-hand literature examines the phenomenon as a statistical probability for the occurrence of consecutive events with the same outcome; by contrast, momentum (as used herein) examines the (short-term) trends in events (here, sales performance) that deviate significantly from long-term expectations. Momentum and similar phenomena have been explored in sports and gaming-related research for some time but only more recently in marketing and organizational contexts.

In the marketing context, research on shopping momentum shows that an initial purchase enhances the probability of a subsequent purchase (Dhar, Huber, and Khan 2007). Studies on "binge-watching" have found that viewers commonly consume several episodes of the same television series in a condensed period (Schweidel and Moe 2016; Zhang, Bradlow, and Small 2013). Rather than momentum, Zhang, Bradlow, and Small (2014, p. 196) call this phenomenon "clumpiness" or the "degree of nonconformity to equal spacing." Clumpiness examines the systematic clustering of an outcome over time, consistent with our definition of momentum. These studies on momentum and similar phenomena illustrate how an event in one period can lead to another event with a similar outcome (e.g., purchase, consumption, successful performance) in the following period; however, they have limited applicability to the sales context in which salespeople make multiple sales calls within a condensed period. For example, studies investigating momentum in consumption tend to examine a situation in which a customer makes multiple purchases, restricted by time and budget. By contrast, salespeople are involved in an incentivized work task, not a consumption context. Patil and Syam (2018) examine a sales context similar to ours and find that high-performing salespeople can experience consecutive months of well-performing periods. However, they study momentum at an aggregate level by comparing quota achievement information for each month. This finding raises the question of whether sales momentum exists only at an aggregate level or whether salespeople can also experience momentum moment-by-moment in their daily sales tasks. In addition, Patil and Syam (2018) assess heterogeneity in momentum effects by salespeople’s performance levels which calls for further research to examine other factors that moderate the effect of sales momentum.

Studies exploring the existence of momentum in sports and organizational theory also have limited implications to sales momentum, as they assume that two or more players compete against one another for victory in a single or sequential set of events (e.g., Cohen-Zada, Krumer, and Shtudiner 2017; Lehman and Hahn 2013). However, salespeople in our context do not compete among themselves for the same customer, as in a tennis match where players compete against each other to win a point, nor do they compete with customers other than in a very metaphorical sense. Furthermore, in many studies, momentum is a self-reported perception, observed with surveys or qualitative approaches (e.g., Kerick, Iso-Ahola, and Hatfield 2000; Markman and Guenther 2007), thus lacking information on how to detect sales momentum objectively and manage its effects.

To this end, we use a formal statistical test on sales call outcomes to show that momentum indeed exists in sales call tasks. Building on prior studies suggesting the existence of sales momentum, we examine the conditions of outgoing sales calls that may influence the effect of positive and negative momentum on performance. By leveraging our extensive data, we test a moderator (salesperson gender) of the effect of momentum previously explored in sports. Cohen-Zada, Krumer, and Shtudiner's (2017) study on professional sports players indicate that men's performance is significantly affected by momentum while women's is not. They speculate that this effect is caused by differences in testosterone, which can increase the following victory and enhance performance in sports and business contests (Verbeke and Masih 2020). We test to determine whether a similar effect would be observed in the sales context.

To assist managers' understanding of the effect of sales momentum, we examine two additional factors (sales call environment and timing of the call) that have not been explored in previous momentum studies. First, we explore whether the social working environment impacts the effect of momentum on performance. Salespeople in a more social working environment are, by definition, more likely to observe and/or interact with their coworkers. We suggest that the effects generated by these inherent features of a more social working environment moderate the momentum effect on sales performance through spillover of momentum perceptions (e.g., Moesch and Apitzsch 2012) and interruption of the workflow (e.g., Jett and George 2003). Second, we test how the timing of the calls impacts the effect of momentum on performance. Chronobiology research discusses biological rhythms that may explain differences in salespeople's behavior. For example, research often invokes circadian rhythm-based rationales for the influence of time of day on human cognitive and behavioral variables, such as working memory, alertness, and sustained attention (e.g., Kanuri, Chen, and Sridhar 2018). To account for the possible influence of biological rhythms on the effect of momentum, we explore the time of day and day of week the call is made.

Examining the moderating effects of the salesperson gender, sales call environment, and the timing of the calls allows us to provide a more complete picture of the effect of momentum on sales performance. Also, it helps to give recommendations on how firms can better manage momentum to maximize the potential for positive effects on sales performance and minimize the potential for negative effects. Table 1 presents an overview of selected literature on momentum from various fields.

RESEARCH DESIGN

Choice of Setting: Inside Sales Force

Momentum is most likely to occur in a context in which salespeople make multiple sales attempts in a short period. Thus, we test our hypotheses on an inside sales force, which is an increasingly dominant channel to connect with customers (Martin 2013). Approximately 47.2% of salespeople in the United States were considered inside sales representatives in 2017 (InsideSales 2017). Inside salespeople are agents who reach customers remotely rather than through face-to-face meetings (Martin 2013) and, in general, are located in dedicated facilities, augmented by technology and actively managed by continuous monitoring of performance. Inside sales forces often have more transactional roles focused on opening opportunities and/or selling less complex products. In such cases, sales forces located in dedicated call centers are more cost-efficient for firms because they can execute a large number of calls, without geographic restrictions.

Table 1. Selected Literature on Momentum.

Authors	Context/ Domain	Definition of Momentum	Operationalization of Momentum	Dependent Variable	Moderator	Gaps in Study
This study	Sales	Periods of increased or decreased rates of success and failure compared with an expected level of successful sales	Test of clumpiness on patterns of sales outcomes in a rolling window	Sales call outcome	Type of selling environment, gender, time of day, and day of week	
Cohen-Zada, Krumer, and Shtudiner 2017	Sports	Bidirectional concept affecting either the probability of success or failure as a function of the outcome of the preceding event (Adler 1981)	Momentum variable equals 1 if the favorite player won the last fight while the underdog player lost the last fight and zero otherwise	Probability of favorite player *i* to defeat underdog player *j*	Gender	1. Study assumes two players, both wanting to win, which cannot be applied to the salesperson selling context. 2. Having multiple wins greater than two is not incorporated into the study.
Dhar, Huber, and Kahn 2007	General purchase behavior	Initial purchase provides a psychological impulse that enhances the purchase of a second, unrelated product	Manipulated	Likelihood of purchasing a target item	Multiple sources of payment	Study examines the customer consumption context and cannot be applied to the salesperson selling context.
Kerick, Iso-Ahola, and Hatfield 2000	Sports	Integration of performance-related perceptions characterized by "added or gained psychological power."	Survey measure assessing momentum	Shooting performance	NA	Momentum is a self-reported survey (i.e., respondents indicate when they believe to be in momentum)
Lehman and Hahn 2013	Organizational theory	Sustained and systematic trajectory in performance over time	Positive momentum carries a value equal to the number of wins when the team is experiencing a winning streak and 0 otherwise. Negative momentum carries a value equal to the number of losses when the team is experiencing a losing streak and 0 otherwise.	Binary variable indicating risk-taking behavior	Comparison of performance and aspiration level	Definition and operationalization of momentum variable, a setting in which a percentage of win is 50%, are not realistic to sales setting, in which the percentage of a successful sale is far below 50%.
Markman and Guenther 2007	Sports & general	A psychological force that can powerfully influence performance	Survey measure assessing momentum	Expectations of performance outcomes	Interruption	Momentum is a self-reported survey (i.e., respondents indicate when they believe to be in momentum)

Patil and Syam 2018	Sales	Persistence in salesperson's performance in which success (failure) in exceeding the quota in the prior month is associated with success (failure) in the current month	Inferred through salesperson's quota achievement information across two months	Sales-to-quota ratio	Performance	Study examines sales momentum at an aggregated level (monthly) and leaves room to explore sales momentum at a disaggregated sales call level.
Schweidel and Moe 2016	Media consumption	Binge: consuming several episodes of the same series within a condensed period	Inferred from the result on customer viewing behavior over the course of the day and switching behavior across the genre of the current episode.	Probability to continue watching the same session or series	NA	Study examines customer consumption context and cannot be applied to salesperson selling context.
Zhang, Bradlow, and Small 2013	Media consumption	Clumpiness: degree of nonconformity to equal spacing	Measured through test of clumpiness	NA	NA	Study examines customer consumption context and cannot be applied to salesperson selling context.
Zhang, Bradlow, and Small 2014	General purchase behavior	Clumpiness: degree of nonconformity to equal spacing	Measured through test of clumpiness	NA	NA	Study examines customer consumption context and cannot be applied to salesperson selling context.

Inside sales forces have characteristics that distinguish them from traditional field sales forces and make them a good choice to observe momentum. First, inside salespeople have frequent face-to-face contact with their peers and managers. Thus, the potential for social effects within the inside sales force to influence performance is high. Frequent face-to-face contact also allows inside sales managers to measure real-time performance. Second, inside salespeople make sales calls at a far higher rate than field salespeople. For example, whereas a typical field salesperson in a specialty market in the pharmaceutical industry makes approximately 13 calls per day (Pharmaceutical Executive 2010), an inside salesperson makes approximately 121 calls per day (Richard 2015). These factors pose distinct challenges for inside sales managers. Therefore, principles applied in traditional field sales contexts tend to have limited applicability in the inside sales context. Even so, research has paid significantly less attention to inside sales force management than to traditional field sales force management. Our choice of setting (inside sales force) helps fill this research gap, while also providing first empirical evidence for momentum in sales performance.

Data

Inside sales forces tend to be located in dedicated call center facilities, which are not necessarily connected with the rest of the organization. Indeed, many firms now specialize in running inside sales campaigns on behalf of third parties. We use novel, high-frequency transactional data from one of these firms, specifically a large European sales specialist, to examine momentum. The empirical context of our analysis is based on an outbound sales campaign run over a three-month period, employing all sales agents in the firm. All agents were responsible for selling an identical product (a hard-copy reference work) with the same price (€4.86, equivalent to US$6.44 at the time of study), and customers could not purchase this product through any other channel. This product category is challenging for salespeople because it is not usually a sought-after product and lacks a large market share and demand, especially in the digital era. Thus, significant persuasion is required from the salesperson to make a sale. Our context is also significant, in that no other marketing interventions (e.g., sales promotion, advertising) were undertaken during the period, so no other factors influenced demand during the studied period. This makes the setting highly appropriate for the research questions under investigation, as the sales outcome is largely determined by the salesperson's effort and the demand for the product is minimized.

The individual call-level transactional data consist of 74,062 sales calls (after data cleaning) undertaken by 113 sales agents during the time of the campaign and the logs associated with the calls. The log of each call contains a time stamp and the outcome of the call ("successful" or "failed" sale). As is typical in many modern call centers, each sales agent is equipped with a computer terminal. The system automatically dials the customer by drawing a random number from a large database of potential customers (i.e., the calls are cold calls), and the call is then directed to a sales agent. Customer assignment is randomly generated, and salespeople have no control over whom they can call. After completing the call, the agent enters the details of the call outcome in a customer relationship management system. Then, the system automatically dials another random number. The system also allowed us to capture, as a control, the psychological state (confidence) of the sales agent before each call, by asking, "What is your level of confidence in having a successful sale in the next call?" Salespeople could choose 0%, 20%, 40%, 60%, 80%, and 100%. This entire process is automated through the computerized system protocol, and agents cannot avoid providing the measurement[1].

[1] The company independently added this feature into their CRM system to understand salespeople's confidence.

Differences Between the SCC and NSCC

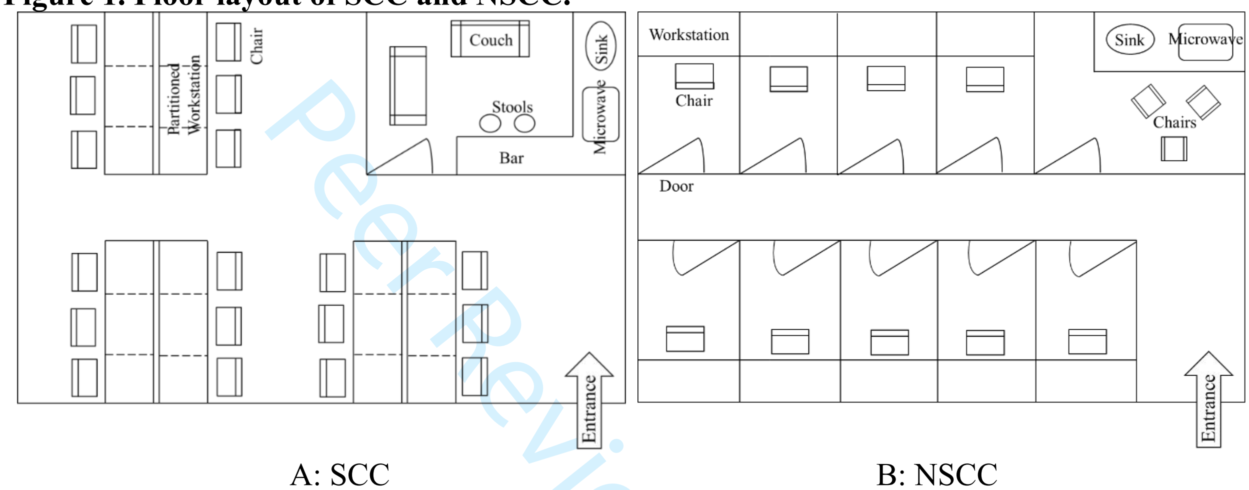
The focal firm operates two call centers, each located in a different city in the same country. Salespeople worked at the center in closest proximity to their homes. Both cities are highly entrepreneurial and are important business and industrial centers, containing multiple universities. Web Appendix B summarizes the similarities and differences of the call centers. All agents were recruited using the same process and were employed under the same terms, with identical incentive structures (unchanging over the course of the study) comprising a base hourly wage combined with a percentage commission. For each sale, salespeople were given a commission equivalent to US$.25. All agents were paid monthly, and there was no quota or target to gain a bonus. All agents received the same initial training course, which consisted of three days of theory and two days of practice, before being placed in one of the call centers. Both centers operated under the same hierarchical structure, with a manager and team leaders, who, in turn, supervised sales agents. All the agents worked from the same database of potential customers.

The natural variation we exploit to assess the influence of social factors is the difference in the physical arrangement and accommodation of the agents across the two call centers that give differing potential for social interactions.[2] In the SCC (Figure 1, Panel A), agents are located in a single large room. Each salesperson has a desk in an open space shared by all other salespeople in the SCC. The selling environment is modern but crowded, and agents are provided with comfortable facilities for relaxation and socialization. These facilities consist of couches, armchairs, and a fully equipped kitchen, designed to facilitate social interactions between salespeople. In the NSCC (Panel B), social interaction between salespeople is limited by the

[2] This was a quasi-experiment our focal firm carried out independently to determine whether a more social working environment helped or hurt salespeople's performance.

facilities due to limited space. Specifically, the agents are located in many individual small rooms on different floors. Owing to the lack of space and the physical structure of the site (multiple small rooms), the call center does not have dedicated socialization or relaxation facilities other than two small kitchens with few chairs.

Figure 1. Floor layout of SCC and NSCC.



Notes: Not drawn to scale. Layouts shown are simplified representations of the two call centers, designed to show the differences. The actual call centers contain many more workstations to fit more salespeople. The NSCC is spread over multiple floors of the same building, each with the same basic design. It also uses more space per salesperson and thus is larger than the SCC.

Table 2 provides descriptive statistics and compares the characteristics of the two call centers. The number of sales agents in our data is sufficiently large (n = 113), and on average, each salesperson made approximately 655 calls during the campaign period (21 calls per day). The total number of calls outgoing from each call center is 35,421 for NSCC and 34,641 for SCC. Observation dates for both call centers were the same except for two days when the NSCC was closed while the SCC was open. We removed these days from our data set, which left 31 observation days in both call centers. Excluding no-calls (e.g., missed calls, wrong numbers), the SCC had a higher success rate (28.12%) than the NSCC (15.06%), with an average of 20.49% across both. While we find that salespeople in the NSCC and SCC do not differ in the number of intercall time less than 1 minute, which suggests this time frame is likely to capture salespeople making back-to-back calls, they differ in most other aspects related to work efficiency. Our observation of the data reveals that salespeople in the SCC took a longer time in between calls (average of 47 seconds in NSCC vs. average of 54 seconds in SCC; $p < .01$), more frequent and longer (1 to 4 minutes) intercall times (average of 9.575 calls in NSCC vs. average of 12.662 calls in SCC; $p < .01$), and more frequent breaks each day (average of 3.8 breaks in NSCC vs. average of 4.1 breaks in SCC; $p < .01$). More time spent between calls also led people to make fewer calls per minute (average of 0.634 calls per minute in NSCC vs. average of 0.539 calls in SCC; $p < .01$). We also find that if one salesperson is taking a break in the SCC, at least one other salesperson is also likely to be taking a break (average of 77% in SCC vs. average of 70% in NSCC; $p < .05$). These observations suggest that salespeople in the SCC are both more likely to be interrupted in between calls and to interact with one another, thereby yielding a social effect. We exploit this natural variation in physical arrangement of the call center to examine the moderating effect of momentum on sales performance in the next period in Analysis 2.

Table 2. Descriptive Statistics and Comparison of NSCC and SCC.

	NSCC	SCC	Both	p-value	Insight
Total number of calls	35,421	34,641	74,062	NA	NA
Number of sales agents	49	64	113	NA	NA
Number of days in observation	31	33	34	NA	NA
Percentage of successful calls	15.06%	28.12%	20.49%	NA	NA
The average time between calls (seconds)	47	54	51	0.00	Salespeople in the SCC took a longer time in between calls.
Number of intercall time less than 1 minute (per day)	109.08	107.098	108.058	0.7218	Salespeople in the NSCC and SCC do not differ in making back-to-back calls.
Number of intercall time between 1 and 4 minutes (per day)	9.5747	12.662	11.167	0.0073	Salespeople in the SCC take more frequent and longer intercall times.
Number of intercall time above 4 minutes (per day)	3.8	4.1	4.0	0.00	Salespeople in the SCC take more frequent breaks each day.
Number of calls made per minute	0.634	0.539	0.581	0.00	Salespeople in the NSCC more efficiently make more calls.
Percentage of time at least one other salesperson in the same call center is also taking a break (given that there is at least one salesperson taking a break)	.70	.77	.74	.013	Salespeople in the SCC are more likely to take breaks with at least one other person.

* NA represents cells that are not applicable.

ANALYSIS AND RESULTS

As noted, we examine sales momentum in two related analyses. In Analysis 1, we assess the existence of sales momentum using individual sales call outcomes. In Analysis 2, we use the momentum calculation from Analysis 1 to assess the impact of momentum on the likelihood of a sale in the next period and explore boundary conditions of the momentum effect.

Analysis 1: Assessing the Existence of Momentum

We begin by providing visual evidence of momentum in the data and then presenting simple analyses to document the transition between calls. The heat map in Web Appendix C depicts the outcomes of a sample salesperson, in which we observe the clustering of sales (and no sales) at multiple times for this person (e.g., day 16 and day 31), which could represent positive and negative momentum, respectively. We observe similar patterns across our data set.

Table 3 represents sales momentum using a (first-order) Markov transition probability between the outcomes of consecutive calls. The Markov transition matrix provides the probability of a salesperson's transition from one outcome to another in successive calls. We find that the probability of having a successful sale after a successful sale (27%) is greater than the probability of having a successful sale after a failed sale (19%). Similarly, the probability of having a failed sale after a failed sale (81%) is greater than the probability of having a failed sale after a successful sale (73%). These findings suggest an inherent "stickiness" in the performance of a salesperson, but alone they do not provide systematic evidence for the existence of momentum. This is because Markov transition probability infers possible dependence of outcome in two periods only and does not account for salespeople's low success rate. Thus, we discuss the requirements for a suitable measure to systematically assess sales momentum in the next subsection.

Table 3. First-Order Markov Transition Probability in Sales Calls.

NSCC and SCC			NSCC			SCC		
	S_t	F_t		S_t	F_t		S_t	F_t
S_{t-1}	.27	.73	S_{t-1}	.17	.83	S_{t-1}	.31	.69
F_{t-1}	.19	.81	F_{t-1}	.14	.86	F_{t-1}	.25	.75

Methodological requirements for sales momentum. In our context, each salesperson makes outgoing calls, which are observed multiple times a day across various days. Most salespeople make hundreds of calls and achieve at least one successful sale in a day. We consider the regular and irregular clusters of failed and successful sales to examine momentum. Given this context, we highlight the preconditions for the method to assess sales momentum. First, the method should be able to identify when salespeople are experiencing momentum. Such an understanding can provide implications to managers on how to mitigate or enhance the momentum effect. However, most prior studies on momentum (e.g., Patil and Syam 2018; Schweidel and Moe 2016) infer that momentum exists but cannot distinguish when it is happening. For example, Schweidel and Moe (2016) examine Hulu viewers to infer momentum ("binge" behavior) from customer viewing behavior but are unable to tell precisely when the viewer is experiencing momentum. Not knowing when individuals are experiencing momentum makes it difficult to control for momentum effects and lacks managerial value in the sales context.

Second, in our context, the unit of analysis for sales momentum needs to be at the most disaggregated, individual call level to capture the exact nature of momentum in real time. Capturing momentum at the individual call level is necessary because salespeople make multiple calls within a short time frame, and thus experienced momentum may fluctuate from call to call. Confirming this point, prior studies examining random events have found that outcomes are viewed in "local" subsequences in a longer but finite "global" stream of events (Hahn and Warren 2009; Warren et al. 2018). Lehman and Hahn (2013) also examine moment-to-moment momentum but not directly applicable to sales. They use American football data to operationalize positive (negative) momentum by the number of wins (losses) when the team is in a winning (losing) streak. However, salespeople have a significantly lower chance of success (or winning) than professional football players, who have a relatively similar chance of winning and losing on average.[3]

Finally, the method needs to accommodate the chance of having a successful sale being lower than 50% because salespeople fail far more often than they succeed. Thus, capturing sales momentum as *consecutive runs* of outcomes is not ideal.[4] A suitable method to examine the existence of sales momentum thus needs to account for *clusters of outcomes* (e.g., success or failure of the sales call) in which one outcome is more likely to occur than the average level. To an observer, the salesperson outcomes from each sales call may seem independent of one another. Moreover, outcomes from a group of calls may also seem like a completely random sequence. Therefore, our objective is to find a system behind what may appear as disorderliness, and formal statistical assessment can help fully understand this system. Given the requirements for sales momentum analysis and assumptions, we adopt the test of clumpiness (Zhang, Bradlow, and Small 2013, 2014), which captures momentum consistent with our definition, has elegant statistical properties (see Web Appendix D), and provides a framework for statistical inference. In the next subsection, we provide a summary of the test of clumpiness and discuss our assumptions to accurately capture sales momentum in our context.

[3] As we operationalize positive and negative momentum in the "Analysis 2: Assessing the Impact of Momentum on Sales" section, we also need to incorporate salespeople's low chance of success while operationalizing momentum similar to Lehman and Hahn (2013). We achieve this objective by using the test of clumpiness and combining this method with Lehman and Hahn's method.
[4] Many statistical tests that examine the trend in outcomes consider sequences of consecutive runs of the same outcomes, especially in blocks of four or fewer (e.g., Sun and Wang 2010), and are criticized for their low power to detect an effect. Indeed, Gilovich, Vallone, and Tversky's (1985) seminal work on hot-hand effects was (eventually) similarly criticized (Iso-Ahola and Dotson 2014).

Test of clumpiness. Clumpiness is an entropy-based measure, where entropy refers to the variation (disorderliness) of outcomes in a sequence of events (i.e., sales calls). We use the outcome of the individual-level sales calls to represent whether salesperson *j* on day *d* was successful ($Outcome_{jtd}$ = 1) or not ($Outcome_{jtd}$ = 0) in each sales call *t*. We examine the clustering of individual sales outcomes by calculating the clumpiness score (H_p) for each salesperson across all the calls in the sampling period:

$$H_p = 1 + \frac{\sum_{i=1}^{n+1} \log(x_i) \cdot x_i}{\log(n+1)}, \tag{1}$$

where *n* is the number of successful sales and *N* is the total number of calls in the sequence interval (i.e., window) we examine. We denote the intersale occasion of the *i*th outcome (i.e., span between the successful sales) as x_i and compute it by

$$x_i = \begin{cases} t_1, & if\ i = 1, \\ t_i - t_{i-1}, & if\ i = 2, \cdots, n, \\ N + 1 - t_n, & if\ i = n+1, \end{cases} \tag{2}$$

where t_i is the occurrence occasion of the *i*th successful sale. We normalize the clumpiness score by dividing the intersale occasion by *N* + 1 to control for the length of the observation period[5].

We make two assumptions to accurately capture sales momentum using the test of clumpiness in our context. First, in line with prior research on random events, we assume that salespeople have a short-term memory of experiences (Farmer et al. 2017) and that the limited capacity of the window of experiences slides one event at a time through a finite number of experiences (Hahn and Warren 2009; Warren et al. 2018)[6]. Therefore, we test sales momentum

[5] For example, assume that Salesperson A makes nine calls on Day 1, two of which result in successful sales. The successful sales occur in the third and ninth calls, t_3 and t_9 (i.e., $Outcome_{A,1,1} = 0$, $Outcome_{A,1,2} = 0$, $Outcome_{A,1,3} = 1$, $Outcome_{A,1,4} = 0$, $Outcome_{A,1,5} = 0$, $Outcome_{A,1,6} = 0$,$Outcome_{A,1,7} = 0$, $Outcome_{A,1,8} = 0$, $Outcome_{A,1,9} = 1$). Then, $x_1 = 3$, $x_2 = 6$, and $x_3 = 1$; therefore, $H_p = 1 + \frac{\left(\log\left(\frac{3}{10}\right)\cdot\frac{3}{10}\right) + \left(\log\left(\frac{6}{10}\right)\cdot\frac{6}{10}\right) + \left(\log\left(\frac{1}{10}\right)\cdot\frac{1}{10}\right)}{\log(3)} = .1827$.

[6] Hahn and Warren (2009) and Warren et al. (2018) used a rolling window of 4-coin tosses to find that people experience short-term memory of experiences.

in a rolling window by using a fixed-window size[7] that moves sequentially from the beginning to the end of the sample by adding one next observation from the sample and dropping one from the end of the window. We illustrate clumpiness testing with a rolling window by way of an example. Consider Salesperson B who made eleven calls on Day 1 with successful sales occurring in the first, eighth, ninth, and tenth calls (i.e., $Outcome_{B,1,1} = 1$, $Outcome_{B,1,2} = 0$, $Outcome_{B,1,3} = 0$, $Outcome_{B,1,4} = 0$, $Outcome_{B,1,5} = 0$, $Outcome_{B,1,6} = 0$, $Outcome_{B,1,7} = 0$, $Outcome_{B,1,8} = 1$, $Outcome_{B,1,9} = 1$, $Outcome_{B,1,10} = 1$, $Outcome_{B,1,11} = 0$). For the first nine calls (the first to ninth calls), Salesperson A makes only three successful calls, at t_1, t_8, and t_9, with $x_1 = 1$, $x_2 = 7$, $x_3 = 1$ and $x_4 = 1$; therefore, the first H_p value is .3216. For the subsequent nine calls (the second to tenth calls), two sales occur at t_8 and t_9, with $x_1 = 8$, $x_2 = 1$, and $x_3 = 1$; therefore, the second H_p value is .4183.

Second, we assume that a salesperson has a fresh start every day. When salespeople finish their daily task of making back-to-back outgoing calls to customers, they have time off from work to rejuvenate. Sometimes, the time off from work can be as short as 15 hours (e.g., leave work after the last outgoing call at 6 P.M. on Monday and come back to make the first call at 9 A.M. on Tuesday) or as long as two and a half days (e.g., leave work after the last outgoing call at 6 P.M. on Friday and come back to make the first call at 9 A.M. on Monday). To capture salespeople's lengthy time off from making sales calls at night and on weekends, we examine the

[7] Prior research finds that a single event cannot generate momentum (e.g., Adler 1981; Lehman and Hahn 2013) and that several successful (unsuccessful) calls must occur to enter positive (negative) momentum. The window size for the rolling window should be small to avoid the risk of capturing multiple regime shifts in a window. We draw this number of calls from our data set by examining (1) the number of consecutive successes and failures made by the salespeople and (2) the number of calls (excluding no-calls) salespeople make without taking a break, which would be between nine and thirteen calls. Thus, we argue that the best window size in our study should be equivalent to the number of maximum consecutive sales excluding outliers, which is a window of 9 (Web Appendix E). On average, 9 calls span for about 27 minutes.

rolling window of sales momentum each day. Given these assumptions, we calculate H_p using a rolling window of nine calls within each day[8] for all salespeople.

Next, we compare H_p with a critical value ($C_{\alpha,g}$; where α is significance and $g = n/N$ is propensity) to determine whether salespeople experience momentum as they make each call, with a 5% significance level. As a critical value table is not readily available for clumpiness statistics, we adopt Monte Carlo simulation to compute the critical values (Zhang, Bradlow, and Small 2013, 2014; see Web Appendix F) for each g. Out of an abundance of caution, we classify an observation as "clumpy" or experiencing momentum when $H_p > C_{\alpha,g}$.[9]

Results. We run the test of clumpiness in a rolling window of nine calls to determine whether the next call is made while the salesperson is experiencing momentum. We find that 1.35% of calls are made while salespeople are experiencing momentum.[10] These momentum observations are spread out across multiple salespeople. We classify salespeople as having experienced momentum if they make at least one call while experiencing momentum. Of the 113 salespeople in our data set, we find that 81 (71.68%) experienced momentum at some point in time. When salespeople experience momentum, the momentum typically lasts for one to two more calls, then the patterns of outcomes become less clumpy.

As Table 4 shows, 58% of salespeople make 0.1% to 1.9% of calls while experiencing momentum during the entire campaign period. We also examined the distribution of momentum calls by day and hour (Table 5) to explore how momentum experience is distributed on and off across the days and hours worked. Salespeople who experience momentum do so at least once on

[8] In our empirical analysis, we tried rolling windows of 9, 11, and 13. We still find evidence for the existence of sales momentum (see Web Appendix G, Table W4).
[9] We use a more conservative statistical test by comparing the score as a one-way test (i.e., using only "greater than ($H_p > C_{\alpha,g}$)" and not "greater than or equal to ($H_p \geq C_{\alpha,g}$)") to test the existence of momentum. As such, we can only test with a window size of 9 or larger (see Web Appendix H).
[10] We examine the size of tests using simulation methods to show that Type I error is minimized (Web Appendix I).

an average of 31% of the days worked. Most salespeople make at least one call under momentum on 10% to 19.9% or 30% to 39% of the days worked (Table 5, Column 3). Given that salespeople experience momentum in a specific hour, salespeople make approximately 7.89% of calls in that hour while experiencing momentum.

Table 4. Frequency Distribution of Clumpiness Score at the Call Level.

Percentage Range (%)	Call Level	
	Frequency	Percentage (%)
0	32	27
0.1–1.9	65	58
2–2.9	11	10
3–3.9	3	3
4–4.9	1	1
5–5.9	1	1
Percentage of calls made under momentum	1.35%	

Table 5. Distribution of Clumpiness Score Across Days and Hours.

Percentage	Days		Hours	
Range (%)	Frequency	Percentage (%)	Frequency	Percentage (%)
0	32	28.3	32	28.3
0.1–9.9	7	6.2	56	49.6
10–19.9	18	15.9	22	19.5
20–29.9	16	14.2	2	1.8
30–39.9	17	15.0	1	0.9
40–49.9	9	8	0	0
50–59.9	9	8	0	0
60–69.9	3	2.7	0	0
70–79.9	1	0.9	0	0
>80	1	0.9	0	0

Robustness assessments. We run a nonhomogeneous hidden Markov model (HMM) to show that finding the existence of sales momentum is not bound to the particular method used. We also assess the robustness of the choice of the rolling window size by running our tests of clumpiness and the logit model with different sized windows.

Alternative method to capture sales momentum. The clumpiness metric has been thought of as an alternative method to HMM to capture bursts of activity separated by less active periods (Zhang et al., 2013). The HMM specify outcomes to be related to the states of the process and model the transition among the latent states (Netzer, Lattin, and Srinivasan 2008). Specifically, we use a first-order Markov model, in which we assume that future states, at t + 1, depend on the present state, t, but not on any other states preceding it. With HMM, we can glean insights into how the underlying states evolve as salespeople progress through successful or failed calls. We find evidence of momentum through the transition matrix (Web Appendix G, Table W2) by examining a strong latent-state persistence from the previous call to the next call.

Alternative rolling window for momentum measure. Throughout the analysis, we use a rolling window of nine calls. To enhance robustness of our findings, we also explore alternative rolling windows. We run the test of clumpiness using rolling windows of 11 and 13 to find that .89% and 2.51% of calls, respectively, were made while the salesperson was experiencing momentum. The distribution of percentages of calls experienced by the salesperson was also largely similar across multiple rolling window sizes (Web Appendix G, Tables W4 and W5). As an additional robustness check, we also assess across-day momentum by using outcome information from all calls made by salespeople in a day to determine whether they are experiencing momentum during a specific day (Table W6). We find that 37 of 113 (33%) salespeople experienced across-day momentum at least once.

Analysis 2: Assessing the Impact of Momentum on Sales

In Analysis 2, we assess the differential impact of positive and negative momentum on the outcome of the subsequent sales call using the previously calculated clumpiness scores from Analysis 1.

Measures. The dependent variable, $Outcome$, is a binary variable that captures whether the salesperson made a successful sale or not for the particular call. To explain our dependent variable, we include positive momentum and negative momentum. We operationalize positive and negative momentum following Lehman and Hahn (2013). Positive momentum takes a value equal to the clumpiness score when the success rate within nine consecutive calls is greater than or equal to the salesperson's overall success rate and takes a value of 0 otherwise. Similarly, negative momentum takes a value equal to the clumpiness score when the success rate within nine consecutive calls is less than the salesperson's overall success rate and takes a value of 0 otherwise. With this procedure, positive and negative momentum are mutually exclusive. We illustrate this with an example in Web Appendix J.

To see how the effect of positive and negative momentum differentially influence outcomes, we explore four types of factors: social, gender, time of day and day of week variables. *Social* is an indicator variable to differentiate salespeople in the SCC from those in the NSCC. *Female* is a binary variable indicating salespeople's gender. *MidDay*, *EarlyAfternoon*, and *LateAfternoon* are time of day indicator variables. *EarlyWeek* and *LateWeek* are the day of week indicator variables. We interact social working environment, gender, time and day variables with positive and negative momentum variables to delve into understanding factors that influence momentum.

We also add a set of control variables that may influence the outcome of each sales call. These include (1) salesperson self-reported precall confidence, because salespeople's own judgments about their likelihood of making a sale may be correlated with the effort they put into selling and therefore directly related to the outcome; (2) number of calls received by the customer, as customers who have already requested a callback may be more likely to make a purchase; (3) experience, to capture the impact of learning-by-doing over the tenure of the salesperson in the sales campaign; (4) number of prior breaks, to control for the salesperson's willingness to work for the entire day, as his or her motivation to work and expend effort can be related to outcome; (5) time since the last break, to control for salesperson's (reinvigorated) mindset from the prior break and its potential influence on outcome; and (6) time spent on prior break, to control for the impact of length of breaks on outcome. We define our notation of variables and measures in Table 6.

Table 6. Variable Descriptions.

Variables	Notation	Description
Outcome	$Outcome_{jdrt}$	A binary variable that captures whether the salesperson did or did not make a sale in the particular call. $Outcome_{jdt}$ = 1 if salesperson j made a sale on call t on day d, and $Outcome_{jdt}$= 0 otherwise.
Positive momentum	PM_{jdrt}	Equal to clumpiness score if success rate within nine consecutive calls is greater than or equal to the salesperson's overall success rate and 0 otherwise.
Negative momentum	NM_{jdrt}	Equal to clumpiness score if success rate within nine consecutive calls is less than the salesperson's overall success rate and 0 otherwise.
Social	$Social_j$	A binary variable that takes the value of 0 if NSCC and 1 if SCC.
Gender	$Female_j$	A binary variable that takes the value of 0 if male and 1 if female.
Time of day	$MidDay_{jdrt}$, $EarlyAfternoon_{jdrt}$, $LateAfternoon_{jdrt}$	Dummy variables indicating the time of the call made. Morning is 8:00 A.M. to 11:29 A.M., midday is 11:30 A.M. to 1:29 P.M., early afternoon is 1:30 P.M. to 5:29 P.M., and late afternoon is 5:30 P.M. to 7:00 P.M.
Day of week	$EarlyWeek_{jdrt}$, $LateWeek_{jdrt}$	Dummy variables indicating the day of the call made. Early week is Monday and Tuesday, midweek is Wednesday, and late week is Thursday and Friday.
Confidence	X_{jdrt}	Salesperson self-reported precall confidence for call *t*.
Number of calls received by a customer	X_{jdrt}	Number of calls received by a customer from the firm before call *t*.
Experience	X_{jdrt}	Total number of calls made by salesperson j before making call t across all days (i.e., throughout the campaign period).
Number of prior breaks	X_{jdrt}	Total number of breaks salesperson j took in a given day d.
Time since break	X_{jdrt}	Duration of time (in seconds) since the end of the previous break before making call t.
Time spent on prior break	X_{jdrt}	Time spent on the prior break (in seconds) before the salesperson makes call t.

Descriptive statistics of variables. The correlation table in Web Appendix K shows that none of the variables are highly correlated, which suggests no significant collinearity problems. Confidence has a low correlation with positive (r = .007) and negative (r = –.043) momentum, which suggests that salespeople are not always conscious of their momentum states, further emphasizing the importance of objective measurement of momentum rather than relying on perceived momentum, as in most prior work. The mean of positive momentum is .06, and the mean of negative momentum is .26. The comparatively low mean of positive momentum is consistent with the low sales rate (20.49%), which is typical of outbound inside sales. Salespeople fail more often than they succeed; therefore, in many cases, positive momentum is 0, while negative momentum carries a value. Web Appendix K provides correlations and descriptive statistics of the variables used in the study.

Identification Challenge and Strategy. The objective of Analysis 2 is to examine the differential effect of negative and positive momentum on the likelihood of a sale in a subsequent sales call. We assume the customer's decision is based solely on salesperson factors as customers in our context make purchase decisions based on their interaction with the salesperson, not by demand-side factors such as advertising and promotion. Therefore, we use logistic regression to examine the effect of positive and negative momentum on the outcome of each call as follows:

(3) $$Outcome_{jdrt} = \frac{A_{jdrt}}{1 + A_{jdrt}} + \epsilon_{jdrt}, \text{ and}$$

(4) $$A_{jdrt} = \exp\left(\beta_1 PM_{jdrt-1} + \beta_2 NM_{jdrt-1}\right),$$

where *j* is the salesperson index; *d* is the day index; *t* is the time index; *r* is the region index; $Outcome_{jdrt}$, PM_{jdrt}, and NM_{jdrt} are outcome, positive momentum, and negative momentum, respectively; and ϵ_{jdrt} is the error term. We include a salesperson's momentum from the preceding sales calls to explain the outcome in the next call, which minimizes reverse causality concerns as a future outcome cannot cause momentum in previous periods. However, there are other potential empirical challenges to assess the robust identification of momentum effects on performance with Equations 3 and 4.

Salespeople's strategic break-taking behavior can be the first empirical challenge. Our focal firm has a system for break allocation that allows some flexibility in salespeople's break-taking. Specifically, salespeople are allowed to take a five-minute break every hour. While breaks cannot be accumulated, salespeople can take their hourly break whenever they want during the hour. During this break time, salespeople typically go to the bathroom or get some air. Given that salespeople have some control[11] over their breaks, they may strategically take a break depending on their performance. While it is unlikely that salespeople will strategically take a break when they feel they are performing better than usual (i.e., when in positive momentum),[12] a frustrated salesperson may strategically take a break when not performing well (i.e., when in negative momentum). Therefore, it is possible that negative momentum is biased while positive momentum is not.

In addition to salespeople's strategic break-taking behavior that may bias negative momentum, other unobservable factors may impact momentum and influence performance. Even with an extensive set of control variables employed to account for the heterogeneity in salespeople's performance, capturing all factors that may influence momentum is not possible. For example, prior research indicates that salespeople strategically manage their performance depending on prior outcomes and sales quotas and ceilings (e.g., Misra and Nair 2011), which are unobserved. Although salespeople in the studied firm were not assigned quotas or ceilings, they were verbally reminded by managers to try to make at least one sale per hour. Such pressure may therefore influence negative momentum to be biased and have a weaker effect.

Given the above discussion, regressing positive and negative momentum on the salesperson's outcome in the next call with logistic regression may yield biased estimators. To control for endogeneity between momentum variables and the outcome, conducting a field

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[11] Inside salespeople have *some*, not full, control over their break because they often have restrictions on the number of breaks they can take. For example, our focal firm advised salespeople to take one five-minute break every hour.
[12] Our survey results lend support to this assumption. Most salespeople continue trying to sell when they are in a positive momentum (Web Appendix A).

experiment in which both observed and unobserved strategic behaviors of salespeople are controlled would be ideal. For example, managers can control any incentive or pressure that would spark a temporary rise in performance. Managers can also randomly assign breaks to salespeople to help reduce their inclination to walk away from the task when they are experiencing negative momentum. However, such a randomized experiment was not feasible for two reasons. First, it is not realistic to take away the control from the salespeople to take a bathroom break when needed. Second, the focal firm was involved in its own natural experiment to examine the role of social effects in performance and did not want to interfere with salespeople's natural behavior. Therefore, we alleviate endogeneity concerns empirically.

We correct for our negative momentum variable by including a copula term in our model to directly capture the correlation between the endogenous variable and the error of the regression (Park and Gupta 2012). While classical endogeneity correction methods rely on instrumental variables to partition the endogenous variable into exogenous and endogenous components, the copula method does not require instrumental variables. Instead, the copula method assumes a nonnormal endogenous variable. We confirm the nonnormal distribution of negative momentum by running the Shapiro–Wilk normality test (Datta et al. 2017). We find that the distribution of negative momentum is significantly different from the normal distribution (W=.1844, $p < .01$).

Our identification strategy captures the joint distribution of negative momentum and the error term using a copula, which is generated using the nonparametric density estimation method, and then finds the marginal distribution function of negative momentum. We include the copula term in the regression to obtain consistent estimates that do not suffer from endogeneity problems. In line with previous studies in marketing literature using the copula approach, we outline specific steps.

To generate the copula term, P^*, we construct an empirical distribution nonparametrically with

$$\hat{F}(s_k) = \frac{1}{M}\sum_{m=1}^{M} I(s_m \leq s_k), \tag{5}$$

where s_k denote negative momentum of k^th observation from our data, k is 1 to M and M is the number of observations. Then, the copula term is

$$P_k^* = \Phi^{-1}\left(\hat{F}(s_k)\right), \tag{6}$$

where Φ^{-1} is the inverse distribution function of the standard normal. We include the copula term P^* in the fixed-effects logit model, which serves as an effective way to address endogeneity. Therefore, our full model with all variables and interaction terms is,

$$\begin{aligned} A_{jdrt} = \exp\,(&\beta_0 P^*_{jdrt} + \beta_1 PM_{jdrt-1} + \beta_2 NM_{jdrt-1} \\ &+ \beta_3 PM_{jdrt-1} \times Social_j + \beta_4 NM_{jdrt-1} \times Social_j \\ &+ \beta_5 PM_{jdrt-1} \times Female_j + \beta_6 NM_{jdrt-1} \times Female_j \\ &+ \beta_7 PM_{jdrt-1} \times MidDay_{jdrt} + \beta_8 NM_{jdrt-1} \times MidDay_{jdrt} \\ &+ \beta_9 PM_{jdrt-1} \times EarlyAfternoon_{jdrt} + \beta_{10} NM_{jdrt-1} \times EarlyAfternoon_{jdrt} \\ &+ \beta_{11} PM_{jdrt-1} \times LateAfternoon_{jdrt} + \beta_{12} NM_{jdrt-1} \times LateAfternoon_{jdrt} \\ &+ \beta_{13} PM_{jdrt-1} \times EarlyWeek_{jdrt} + \beta_{14} NM_{jdrt-1} \times EarlyWeek_{jdrt} \\ &+ \beta_{15} PM_{jdrt-1} \times LateWeek_{jdrt} + \beta_{16} NM_{jdrt-1} \times LateWeek_{jdrt} \\ &+ \textstyle\sum_{i=17}^{23} \beta_i X_{ijdrt} + \alpha_{\mathrm{j}} + \gamma_r)\,, \end{aligned} \tag{7}$$

where i is the control variable index; $Social_j$ and $Female_j$ are indicators of the type of call center and salesperson gender, respectively; $MidDay_{jdrt}$, $EarlyAfternoon_{jdrt}$, $LateAfternoon_{jdrt}$, $EarlyWeek_{jdrt}$, $LateWeek_{jdrt}$ are time-variant indicator variables that indicate time of day and day of week; and X_{ijdrt} is the set of time-variant control variables.

We include α_{j} and γ_r which captures salesperson and customer region-level fixed effects, respectively. The salesperson fixed effect controls unobserved heterogeneity in salesperson characteristics that may influence their sales ability in the workplace. For example, some salespeople are more skilled than others and are better at dynamically adapting their effort levels. Similarly, some salespeople may interact more with their coworkers and therefore experience stronger peer influence. In addition, we include customer region fixed effects to control unobserved heterogeneity in customer characteristics that may influence customers' purchase likelihood. While customers' phone numbers are randomly drawn from a list of potential customers and every customer in the database had an equal chance of being contacted, their purchase likelihood may not be random and vary by their disposable income. We assume that customers in more affluent regions have more disposable income and, therefore, a higher likelihood of purchasing the good. Hence, our use of a fixed-effects logit model accounts for various unobserved heterogeneity (e.g., salesperson's motivation, customer's mood due to weather) that may come from omitted variable bias. Because the copula term is not directly observed but generated, standard errors do not account for extra variation coming from the copula term. Therefore, we bootstrap the standard errors of the model to obtain valid standard errors (Park and Gupta 2012).

Results. Table 7 shows the results of the estimation of the salesperson's outcome in the next call. Model 1 (Table 7, Column 2) is the baseline model without copula correction term. Model 2 (Column 3) shows the role of positive and negative momentum in explaining for salesperson's outcome in the next call. As can be inferred from the table, positive momentum ($\beta = 7.9415$, $p < .01$) has a positive effect on the outcome. This suggests that when in a positive momentum state, a salesperson is more likely to make a sale on the subsequent call. To explore the impact of the social working environment, our main moderator of interest, on the effect of positive and negative momentum, we run Model 3 (Column 4). The main effect of positive momentum ($\beta = 7.4721, p < .01$) is similar to that in the previous model. The interactions between positive momentum and the type of call center are significant ($\beta = 1.2680, p < .01$), showing that the effect of positive momentum on performance is dependent on the social level of the working environment.

Model 4 (Table 7, Column 5) is our main model, which explores additional factors that may influence the effect of momentum on performance. Specifically, we examine the impact of three potential factors: (1) gender, (2) time of day (morning, midday, and early and late afternoon), and (3) day of week (early, midweek, and late week). We find that positive momentum ($\beta = 7.2844, p < .01$) has a positive effect on the outcome, while negative momentum ($\beta = -.6269, p < .05$) has a negative effect. This suggests that when in a positive (negative) momentum state, a salesperson is more (less) likely to make a sale on the subsequent call. Our results imply that momentum influences the outcome of immediate future calls. Thus, identifying salespeople who are in momentum enables firms to better manage the dynamics of individual salesperson performance and, collectively, that of the sales force.

The interactions between both forms of momentum and the type of call center are significant (positive momentum: $\beta = 1.3169, p < .01$; negative momentum: $\beta = .1956, p < .01$). The effect of positive or negative momentum on performance is thus dependent on whether the salesperson is in the SCC or NSCC. While negative momentum decreases the likelihood of a sale, being in the SCC weakens this effect. Similarly, being in the SCC strengthens the positive effect of positive momentum.[13]

We find that day and time of the call influence the effect of positive and negative

[13] To explore the value of the SCC further, we leverage the observable nature of the interruption aspect of the SCC and run an additional model, *intercall interruption interaction model* (see Web Appendix L). We find the same significant direction of effects as in our *social interaction momentum model*, which suggests that social effect plays an important role in reversing a losing trend by interrupting salespeople's momentum.

momentum on performance. Compared with midweek (Wednesday), the effect of negative momentum is significantly different in the early week (Monday, Tuesday; $\beta = .1552, p < .1$) and late week (Thursday, Friday; $\beta = .2316, p < .05$). Specifically, compared with calls made midweek, calls made early and late week mitigate the harmful effect of negative momentum. We find that calls made midday ($\beta = .1824, p < .01$) significantly influence negative momentum while late afternoon ($\beta = -0.5453, p < .01$) influence positive momentum. Specifically, compared with calls in the morning, midday calls mitigate the harmful effect of negative momentum while late-afternoon calls weaken the beneficial effect of the positive momentum. Our findings show that sales momentum yields different effects depending on the day of week, time of day, and the level of the social working environment of the salesperson making the call.

Finally, we find that gender does not significantly impact the effect of momentum on performance in the sales context. The insignificant effect of gender is different from prior studies on professional sports players that find the varying effect of momentum by gender, theorized to be due to differences in testosterone (e.g., Cohen-Zada, Krumer, and Shtudiner 2017). The nonsignificant effect of gender in driving sales momentum may be due to a more sedentary repetitive activity being performed, thereby not activating testosterone or risk-seeking differences in gender.

Table 7. Regression Analysis for Likelihood of a Sale.

	Model 1	Model 2	Model 3	Model 4
Copula		-0.0974***	-0.0552	-0.0541
		(0.0234)	(0.0623)	(0.0421)
Confidence	0.0012**	0.0011**	0.0012	0.0012*
	(0.0006)	(0.0005)	(0.0009)	(0.0009)
Number of calls received by a customer	-0.2143***	-0.2151***	-0.2154***	-0.2142**
	(0.0613)	(0.0499)	(0.0713)	(0.0392)
Experience	0.0001**	0.0001	0.0001	0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Number of prior breaks	-0.0081	-0.0128	-0.0076	-0.0079
	(0.0092)	(0.0091)	(0.0118)	(0.0066)
Time since break (in minutes)	-0.0002	-0.0003*	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Time spent on prior break (in minutes)	-0.0002	-0.0003	-0.0002	-0.0002
	(0.0008)	(0.0011)	(0.0011)	(0.0006)
Positive momentum	7.3290***	7.9415***	7.4721***	7.2844***
	(0.4124)	(0.1991)	(0.3764)	(0.3363)
Negative momentum	-0.9055***	-0.0569	-0.3467	-0.6269**
	(0.1707)	(0.1011)	(0.3068)	(0.2643)
Positive momentum × Social	1.3925***		1.2680***	1.3169***
	(0.2367)		(0.4856)	(0.6678)
Negative momentum × Social	0.1939***		0.1684	0.1956***
	(0.0852)		(0.1374)	(0.0636)
Positive momentum × Female	0.0622			0.0640
	(0.3335)			(0.2818)
Negative momentum × Female	0.1021			0.0973
	(0.1219)			(0.1510)
Early week	-0.1810***		-0.1319***	-0.1792***
	(0.0420)		(0.0322)	(0.0287)
Positive momentum × Early week	0.3307			0.32783
	(0.2623)			(0.2315)
Negative momentum × Early week	0.1615			0.1552*
	(0.1160)			(0.0892)
Late week	-0.1383***		-0.0985***	-0.1369***
	(0.0414)		(0.0360)	(0.0466)
Positive momentum × Late week	0.1368			0.1334
	(0.2627)			(0.3139)
Negative momentum × Late week	0.2354**			0.2316**
	(0.1157)			(0.1116)
Midday (baseline morning)	-0.0738***		-0.0523***	-0.0732***
	(0.0425)		(0.0325)	(0.0242)
Positive momentum ×	-0.0018			-0.0058

Midday	(0.2505)			(0.1591)
Negative momentum × Midday	0.1822*			0.1824***
	(0.1066)			(0.0522)
Early afternoon	-0.0477		-0.0625	-0.0482
	(0.0435)		(0.0451)	(0.0447)
Positive momentum × Early afternoon	-0.0971			-0.0965
	(0.2407)			(0.1951)
Negative momentum × Early afternoon	-0.0294			-0.0282
	(0.1014)			(0.0700)
Late afternoon	-0.0166		-0.1045	-0.0186
	(0.0700)		(0.0922)	(0.0596)
Positive momentum × Late afternoon	-0.54589			-0.5453***
	(0.4130)			(0.1843)
Negative momentum × Late afternoon	-0.3047*			-0.3016
	(0.1760)			(0.2077)
Customer region fixed effects	Yes	Yes	Yes	Yes
Salesperson fixed effects	Yes	Yes	Yes	Yes
Number of observations (N)	74060	74060	74060	74060
Log-likelihood	-31241.469	-31277.78	-31249.053	-31240.277

Notes: Numbers reported represent coefficients; numbers in parentheses represent bootstrapped standard errors. The *no-momentum model* has regular standard errors in parentheses.
$^*p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Robustness assessments. We assess the robustness of our results using another method as an identification strategy. In addition, we evaluate the robustness of our key moderating factors: social working environment variable and time-of-day variables.

Alternative identification strategy. To assess the robustness of our findings with the copula method, we introduce an instrumental variable and use a control function approach (e.g., Petrin and Train 2010). As an instrumental variable for negative momentum, we use the number of calls made since the last involuntary break, which is a period off from putting effort into selling due to no-calls (e.g., missed calls, wrong numbers). The control function approach includes predicted first-stage residuals as additional regressors in second-stage estimation (Rutz and Watson 2019). Specifically, we derive a proxy variable (i.e., predicted residuals) that conditions on the part of negative momentum that depends on ϵ_{jdt}, the error term from Equation

W14.2. Conditioning on the predicted residual allows us to parse out exogenous variation in the negative momentum variable to obtain a consistent estimator. We find that the results with instrument (i.e., control function approach) and without instrument (i.e., including copula term) are substantially similar (Web Appendix M, Table W11). Therefore, we are sufficiently confident and can safely conclude that our method and results capture the phenomena of momentum correctly.

Alternative assessment of social working environment. In our previous analysis, we found that the social effect (i.e., being in the SCC) augments the effect of positive momentum, and ameliorates the effect of negative momentum. In other words, salespeople in the SCC were able to break negative momentum faster than those in the NSCC. This difference is due to the different magnitudes of negative (positive) momentum generated across the two call centers. Our challenge is to examine the social effect associated with (1) weaker negative momentum, which makes it easier for salespeople to "snap out" of negative momentum, and (2) stronger positive momentum, which makes salespeople "stickier" in positive momentum. Thus, we apply matching methods that balance treatment and control groups according to observables (Avery et al. 2012). Matching methods enable us to isolate any individual salesperson characteristics that influence the magnitude of momentum. Therefore, we can test the moderation of the social effect of negative (positive) momentum more robustly. We find that the social effect is associated with weaker (stronger) negative (positive) momentum in the SCC than the NSCC, independent of any other confounder (Web Appendix M).

Alternative definition of time-of-day variables. To ensure that our results are robust across a different definition of time-of-day variables, we change the operationalization of these variables (Kanuri, Chen, and Sridhar 2018). We redefine morning as 8:00 A.M. to 10:59 A.M., midday as 11:00 A.M. to 1:29 P.M., early afternoon as 1:30 P.M. to 4:59 P.M., and late afternoon as 5:00 P.M. to 7:00 P.M. Our results are robust to this alternative definition of time-of-day variables (Web Appendix M, Table W13).

ADDITIONAL ANALYSES

To provide supplementary information about sales momentum as observed in our context, we run additional related analyses. Specifically, we (1) examine financial implications of controlling the sales momentum, (2) propose logic for a DSS and test its performance using simulation, (3) explore possible downstream consequences of sales momentum, and (4) assess the potential long-term effect of momentum.

Financial Implications

As we find that sales momentum effects can be managed through the social effect, time of day, and day of week of making sales calls, we assess the economic value to our focal firm had it controlled for the impact of momentum through these factors. In estimating the financial consequences of controlling momentum, we use Equation 7.

(7) Financial impact = odds ratio × product price × total number of products sold.

In our context, *total number of products sold* is 5217 units of the product sold in the NSCC. *Product price* is US$6.44 per each unit of product. The odds ratio would be calculated using the coefficient from the *gender, time-day, and social interaction model* (Table 7). In assessing the impact of momentum on sales, we find that for a one-unit increase in negative momentum, there is a 46.6% decrease in the odds of making a successful sale in the next call for a salesperson in the NSCC making calls morning of mid-week. We compare the impact of social, time of day and day of week effects to this number.

Financial consequences of accounting for negative momentum with social effect. If the salesperson had been in the SCC, the expected decrease in odds would be only 35.0%. Therefore, by weakening the effect of negative momentum, salespeople would have been able to sell 11.5% more (equivalent to 600 more units) had the NSCC been operated as the SCC. We evaluate the financial consequences for our focal firm of effectively managing negative momentum by designing a social working environment with Equation 7 and find that the benefit of operating an SCC is roughly US$3,863.71, over the course of three months of the campaign period. In other words, had the focal firm operated the NSCC as an SCC, it would have generated US$1,287.90 per month *more* than what it generated in revenue.[14]

Financial consequences of accounting for negative momentum with time of day and day of week. Negative momentum midweek leads to a 9.0% (13.9%) decrease in revenue compared to early (late) in the week. Consequently, compared to midweek, the financial benefit of salespeople in the NSCC making a call earlier in the week is US$3,013.54 (US$1,004.51 per month), and making a call later in the week is US$4,677.86 (US$1,559.29 per month). Negative momentum in the morning leads to a 10.7% decrease in the chances of selling compared to midday. Therefore, the benefit of salespeople in the NSCC making calls midday as opposed to morning is roughly US$3,591.55 (US$1,197.18 per month) within three months of the campaign period.[15]

Decision Support System (DSS) Simulation

To provide practitioners with specific directions on how to spot and manage momentum effects, we propose DSS decision-making steps (Figure 2) and simulate the extent to which salespeople's performance would have improved had our focal firm used such a DSS to manage momentum. The lay out of the DSS is as follows:

[14] Had the focal firm operated the NSCC as an SCC, it would have faced a 1% increase in the entire profit each month.
[15] Had the focal firm operated only during midday as opposed to mornings, it would have generated a roughly .9% increase in the entire profit each month. Had the focal firm operated only during early (late) week as opposed to midweek, it would have generated a roughly .8% (1.2%) increase in the entire profit each month.

Step 1. Salesperson j on day d makes call t and enters the outcome ($Outcome_{jdt}$) of the call into the system.

Step 2. Determine whether salesperson j on day d is in momentum from Equations 1 and 2 using $Outcome_{jdt}$, where t is 1 to T.

Step 2.1. If the salesperson is in negative momentum, go to Step 3.

Step 2.2. If the salesperson is in positive momentum, go to Step 4.

Step 2.3. If the salesperson is not in momentum, go back to Step 1 (t becomes t + 1).

Step 3. The salesperson is in *negative momentum*. The salesperson is given a break.

Step 4. The salesperson is in *positive momentum*.

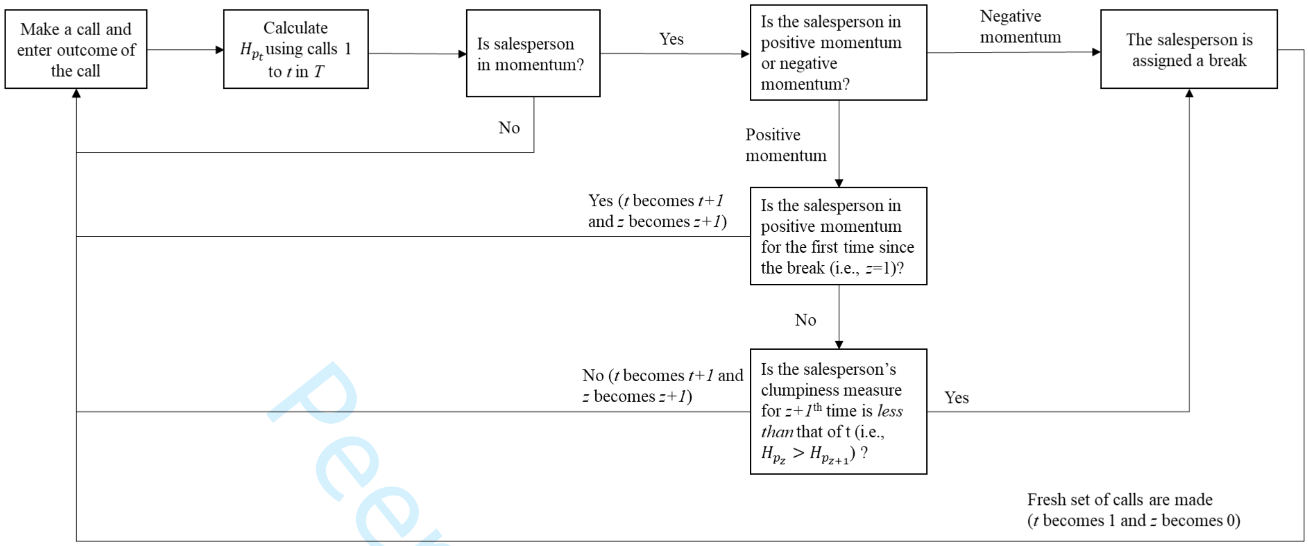
Step 4.1. If the salesperson is in positive momentum for the first time (i.e., z = 1), go back to Step 1 and build on previous outcomes to calculate the momentum calculation (i.e., t becomes t + 1).

Step 4.2. If the salesperson's clumpiness measure for $z + 1^{\text{th}}$ time is *less than* that of z (i.e., $H_{p_z} > H_{p_{z+1}}$), the salesperson is given a break.

Step 4.3. If the salesperson's clumpiness measure for $z + 1^{\text{th}}$ time is *greater than or equal to* that of t (i.e., $H_{p_z} \leq H_{p_{z+1}}$), go back to Step 1 and build on previous outcomes to calculate the momentum calculation (i.e., t becomes t + 1).

We test the performance of this proposed logic by comparing the actual outcome from our data with the simulated outcome using the proposed DSS logic. Doing so gives an idea of how much better (or worse) the salesperson would have performed if there was a DSS. We find that salespeople in our data would have performed 18.4% better after each momentum experience had the system been in place. Web Appendix N lays out the specific steps in simulating the outcomes.

Figure 2. DSS Decision-Making Steps.



Downstream Consequences of Momentum

While the objective of this study is to examine the impact of sales momentum and its moderating factors, there may be unknown downstream consequences of salespeople's momentum experience. We explore potential downstream consequences of momentum on salesperson efficiency and confidence in making sales calls. First, we assess whether salespeople are becoming more efficient in call durations by examining the correlation of positive and negative momentum from the previous call with call duration in the next call. We take the average time spent on successful calls and unsuccessful calls and assess the difference in time for each outcome type.[16] We find that stronger positive (r = –.0385) and negative (r = –.0957) momentum in the previous call leads to shorter subsequent calls. However, these correlations are weak (Anderson and Sclove 1986), and we do not have sufficient evidence to conclude that momentum leads salespeople to make calls more efficiently. Second, we assess the downstream consequences of positive (negative) momentum leading to overconfidence (underconfidence) by examining the correlation of positive (negative) momentum in the previous call and confidence

[16] The duration of successful calls includes not only the time to sell a product but also the time spent on obtaining payment information. Therefore, by nature, call duration of successful calls is longer than that of failed calls.

in the next call. We find that confidence has a weak correlation with positive (r = .007) and negative (r = –.043) momentum. While positive (negative) momentum may lead to increased (decreased) confidence, again, the correlation is weak, and we do not have sufficient evidence to conclude that positive (negative) momentum may lead to overconfidence (underconfidence).

Weak correlations in downstream consequences analysis can be due to salesperson consciousness of momentum being mostly *ex post*. We expect that salespeople typically realize that they were in momentum only in hindsight. Given these weak correlations, we conclude that salespeople in momentum are unaware of their state of momentum and do not behave accordingly.

Long-Term Effect of Sales Momentum

While sales momentum examined in the current context is, by nature, a short-lived phenomenon, we check the potential long-term effect of momentum. The momentum effect should be treated as having a long-term impact if a short-term impact is carried forward and sets a new trend in performance (Dekimpe and Hanssens 1995). Therefore, we examine whether momentum affects performance in calls made not immediately after but two or three calls later, for example. To do so, we create *n* lags in momentum variables and determine whether they significantly influence performance made *n + 1* calls later. We create lags up to n = 3. Similar to our original model, we run a logit model with lagged momentum variables and a set of control variables, as follows:

$$\begin{aligned} Outcome_{jdrt} = {} & \beta_1 PM_{jdrt-1} + \beta_2 NM_{jdrt-1} + \beta_3 PM_{jdrt-2} + \beta_4 NM_{jdrt-2} + \beta_5 PM_{jdrt-3} \\ & + \beta_6 NM_{jdrt-3} + \beta_7 PM_{jdrt-4} + \beta_8 NM_{jdrt-4} + \sum_{i=9}^{15} \beta_i X_{ijdrt} + \alpha_{\mathrm{j}} + \epsilon_{jdrt}, \end{aligned} \tag{8}$$

where *j* is the salesperson index, *d* is the day index, *r* is the region index, *t* is the time index, *i* is the control variable index, $Outcome$ is outcome, PM_{jdrt-4} and NM_{jdrt-4} variables are positive and negative momentum from four calls ago, $PM_{jdrt-3}$and NM_{jdrt-3}variables are positive and negative momentum from three calls ago, $PM_{jdrt-2}$and NM_{jdrt-2}variables are positive and negative momentum from two calls ago, and $PM_{jdrt-1}$and NM_{jdrt-1}variables are positive and negative momentum from the previous call, which we examine in other models (i.e., *positive momentum* and *negative momentum* variables in Table 7) to check the impact of momentum in the subsequent call.

As the results in Web Appendix O show, virtually none of the lagged momentum variables used to capture the long-term impact are significant. By contrast, the short-term effect variables, $PM_{jdrt-1}$and NM_{jdrt-1}, are significant, consistent with our findings in Table 7. This result shows that positive and negative momentum effects are not persistent in the long run and are likely to only have a short-term effect.

DISCUSSION

This study provides evidence that momentum is relevant to and can be directly observed (vs. inferred) in individual sales performance. In doing so, it is, to the best of our knowledge, the first work to show direct (vs. perceived) effects of both positive and negative momentum using sales call outcomes. Specifically, we (1) detect the existence of momentum in individual disaggregated sales performance outcomes, (2) demonstrate the role of momentum in driving improvements and decrements in future sales performance, (3) show that the social environment in the workplace is an important factor that impacts the effect of momentum on performance, and (4) show that timing of the call (i.e., time of day and day of week) also influences the relationship between momentum and performance.

Theoretical Contributions

First, we contribute to the literature on sales effectiveness by providing evidence on temporal spillovers of sales call outcomes. Most studies examining drivers of salesperson performance either use cross-sectional or aggregate data, thus ignoring momentum in actual outcomes across consecutive (individual) sales calls. The limited research on the influence of historical call performance might explain why existing models of individual sales performance rarely exhibit high explanatory power (for meta-analyses, see Albers, Mantrala, and Sridhar 2010; Franke and Park 2006). Also, aggregate data cannot capture salespeople's moment-to-moment momentum experience, which can be an important factor explaining sales call outcomes in a context where salespeople make back-to-back sales calls throughout the day. To examine momentum at the individual call level, we treat performance as a series of related sales attempts and offer a systematic way to determine the temporal spillover for each call.

Second, we contribute to sales literature by demonstrating the importance of positive and negative momentum as drivers of sales performance. A few studies have explored issues similar to the momentum we study herein but do not explicitly distinguish the effect of positive and negative momentum. Discerning the positive and negative effects allows us to examine potential asymmetric effect sizes and moderating effects on the two types of momentum. By leveraging our rich set of disaggregate call-level data, we show how clusters of outcomes from preceding calls (i.e., momentum) influence the outcomes of subsequent calls and categorize the clusters of outcomes as positive and negative momentum. This categorization allows us to explore the distinct influence of both salesperson failure and success. We indeed find a varying effect of momentum, such that positive momentum increases while negative momentum decreases the likelihood of sales in the next call. The timing of the calls has an asymmetric impact on the effect of positive and negative momentum, such that the timing significantly moderates the effect of negative momentum but does not impact the effect of positive momentum. This asymmetric impact of moderators shows that distinguishing the bidirectional characteristics of momentum gives a holistic view of factors influencing salespeople's performance.

Third, we contribute to the momentum literature in general by exploring additional factors that influence the effect of momentum. While Patil and Syam (2018) explore the moderating role of salespeople's performance, most momentum research examines (1) interruption (Adler 1981; Markman and Guenther 2007), (2) gender (Cohen-Zada, Krumer, and Shtudiner 2017), (3) source of payment (Dhar, Huber, and Kahn 2007), and (4) comparison of own performance and competitor's performance (Lehman and Hahn 2013). While the latter two are not applicable in a sales context, we include interruption as part of our social effect and also gender in our model. Adding to this relatively limited list, we find that midday, early and late-week activities mitigate the harmful effect of negative momentum. These findings augment the nascent body of research exploring factors that moderate the effect of momentum. In addition, we overturn a moderator from prior studies (i.e., gender), which we find is not significant in the sales context.

Finally, we extend workspace management literature related to salespeople by identifying the social environment as an important factor influencing the relationship between momentum and performance. We add to previous sales research that has identified the possible influence of social effects (e.g., Chan, Li, and Pierce 2014) by showing that social effects help support positive momentum and hinder negative momentum. We also add to general workspace design and management work by showing that the interruptions inherent in social workplaces have similar substantive effects to those of the broader social environment.

Managerial Implications

For many years, scientists were confident that belief in momentum was a pervasive human bias. Nevertheless, this belief remained quite popular in many contexts. Indeed, our salesperson survey shows that, while most organizations try to identify salespeople who are in momentum (Web Appendix A), managers do not have a systematic method to detect momentum, nor do they know how to effectively manage momentum. Our study not only shows that momentum exists and has a substantive effect on performance but is the first to provide a usable method by which sales organizations can objectively detect their salespeople's momentum state in real time and thus react to it. Our results, therefore, have substantial managerial implications and are likely to be generalizable to sales settings in which salespeople make multiple sales calls within a short period.

We find that the social environment has a moderating effect on both positive and negative momentum, enhancing the odds of making a successful sale. To harness these effects, managers might consider designing workspaces to increase social interaction. In addition to avoiding the physical separation of salespeople when designing new workspaces, managers could implement simple changes to their existing workplace practices. Interaction could be encouraged through gatherings such as team lunches or by creating a game room to encourage salespeople to interact with one another on breaks. Such initiatives could help increase interaction among coworkers, enhance the effect of positive momentum, and decrease the effect of negative momentum.

Alternatively, firms could replicate the interruption mechanism of the SCC by building a predefined logic into the system that distinguishes when salespeople are in momentum and when to assign a break. This can be done by incorporating a computerized DSS, such as the one we design in this study, that can instantly control sales momentum with the latest data on outcomes, eliminating lags in the decision process. As the system randomly selects customers' phone numbers, it could simultaneously calculate salespeople's clumpiness based on their outcomes in previous calls. If the system finds that salespeople are experiencing negative momentum, it could interrupt this momentum inconspicuously by not assigning the next phone number but perhaps giving some other task instead temporarily. Then, the system could start calculating the momentum measure from a new call sequence. Conversely, if the system finds that salespeople are experiencing positive momentum, it could compare the change in momentum across calls. When the strength of salespeople's positive momentum is weakening, the system could again interrupt, which our results show helps sustain positive momentum. In this case, the system calculates momentum for the next call and so on in continuation of the previous momentum calculation. We simulate this logic for DSS and find that salespeople in our data would have performed 18.4% better than how they actually performed if DSS had been implemented. In practice, managers can use real-time performance data to assess salespeople's momentum experience before each sales call.

Finally, we show that while momentum management can enhance salespeople's short-term performance, it does not affect their performance in the long run or significantly influence their selling behavior. That is, momentum does not have any significant downstream consequences for salespeople's behavior, as salespeople's consciousness of momentum is mostly *ex post*, rather than during the experience. In addition, momentum is short-lived and does not have long-lasting effects. Taken together, our results show that managers need not worry about any possible change in salespeople's selling behavior after the momentum experience, but instead should focus on timely detection of momentum, most likely through a DSS of the type we design here. Such a system will help enhance the likelihood of selling in the short run, therefore augmenting overall performance.

Limitations and Further Research

Our results should be considered with several caveats and limitations in mind. First, although we establish the existence of momentum, our model was not intended to address how and why salespeople enter momentum, which was limited by our ability to observe this process directly (e.g., Miller and Sanjurjo 2018). Because we find that momentum exerts an influence on performance, future studies should investigate the factors that cause momentum. For example, some environmental conditions may make salespeople prone to entering momentum. Such conditions could be individual-based but also situation-specific, either within or outside the workplace.

Second, with the observational data collected through a natural experiment, we infer the interruption and interaction aspects of the social effect from different break-taking behavior and by showing that intercall interruptions yield similar results to the general social effect. We leave it to future studies to test the causal mechanisms behind the social effect and its influence on the relationship between momentum and performance. To directly capture interruption and interruption aspects of the social working environment, studies could conduct a field experiment to collect information on which salespeople are interacting when and preferably with whom (e.g., location maps), in addition to information on salespeople's performance by time. We strongly recommend that future studies run experiments to examine the role of emotional or other state spillovers in social working environments, to further advance our line of study. In addition, studies could exploit an exogeneous event (e.g., fire alarm drills) to determine whether the unexpected event can disrupt a salesperson's momentum similar to social settings.

Third, throughout the analysis, we used a constant rolling window to capture momentum. Specifically, in assessing the impact of momentum on sales, we used a rolling window of nine calls and captured individual differences using salesperson fixed effects. This allowed us to compare momentum in a panel setting consistent with the scope of our research. Future studies could explore other effective ways to capture momentum using individual-specific rolling windows to account for any personal differences in momentum experience.

Fourth, we assume that salespeople have short-term memory of experiences during the 9 call window. This assumption is based on prior literature that found short-term memory of experiences in a rolling window of 4 coin tosses (Hahn and Warren 2009; Warren et al. 2018). Future studies can examine the maximum number of call experiences that is salient, across multiple contexts.

Lastly, we use simulation to evaluate the performance of the proposed DSS. Specifically, we identify the first momentum experience by each salesperson each day and compare the expected outcome with the observed to find that salespeople in our data would have performed 18.4% better after experiencing a momentum with DSS in place. However, it may be suboptimal in practice to assign a break after experiencing momentum every time, especially if a salesperson experiences momentum frequently. Future studies can run a field experiment to find the ideal number of assigned breaks that maximize a salesperson's performance while managing momentum effects.

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WEB APPENDIX

Managing Positive and Negative Trends in Sales Call Outcomes: The Role of Momentum

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Disclosure: These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

WEB APPENDIX A: EVIDENCE OF SALESPEOPLE'S BELIEFS IN MOMENTUM

Description and Additional Findings from the Survey

To determine the importance of momentum in sales calls, we surveyed 160 salespeople and managers. Respondents were a mix of salespeople (47%), midlevel (41%) and upper-level managers in the sales function (12%), with multiple years of experience in sales, making them suitable informants for this study. Table W1 details the sample's characteristics.

Our survey results show strong evidence that salespeople believe in sales momentum. That is, 86% and 74% of salespeople believe in positive and negative momentum, respectively, and 87% of 65% of salespeople believe that they have experienced positive and negative momentum, respectively, at some point in time. Salespeople also indicated that momentum influences their performance in the next call. Survey results also show that 77% (57%) of salespeople believe that being in positive (negative) momentum is likely to increase (decrease) their chances of making a sale in the next call.

The results also highlight salespeople's beliefs that sales momentum can be managed. That is, 68% (56%) of salespeople indicated that their organizations try to identify salespeople who are in a negative (positive) momentum. When asked about things they would do when they are in positive momentum, 34% of the salespeople indicated that they would keep trying to sell to sustain it. Others mentioned that they would talk to a coworker who is doing well (17%), take a break from selling (13%), or take a walk (12%). To break out of negative momentum, they would take a break from selling (20%), take a walk (19%), talk to a coworker who is performing well (18%), or visit the bathroom (8%), although we noted that a number of salespeople reported that they would keep trying to sell (19%). The latter is particularly interesting compared with our empirical results, which suggest that salespeople in negative momentum are best served to take a break.

When asked about potential drivers of positive and negative momentum, the majority of salespeople (26%) believed that being in a good mood can help develop positive momentum. Other drivers of positive momentum included being able to concentrate on their work (22%), being more experienced (20%), not getting distracted (16%), and having good luck (15%). When asked about drivers of negative momentum, 32% of the salespeople believed that being in a bad mood can lead to negative momentum. Other drivers of negative momentum included being less experienced (24%), being able to concentrate on one's own work (17%), and having bad luck (16%).

Table W1. Sample Characteristics from the Survey

Number of potential customers talked to per day	% of Respondents
More than 50	20.71%
30-49	37.87%
10-29	30.77%
Fewer than 10	10.06%

Description of the job	% of Respondents
My main role is to sell	46.60%
My main role is partly selling and partly managing other salespeople	41.36%
My main role is managing salespeople	11.52%

Number of years in working in sales	% of Respondents
Under 2 years	7.33%
Between 2 and 5 years	29.84%
Between 6 and 10 years	26.70%
Between 11 and 15 years	15.18%
Between 16 and 20 years	6.28%
Over 20 years	14.66%

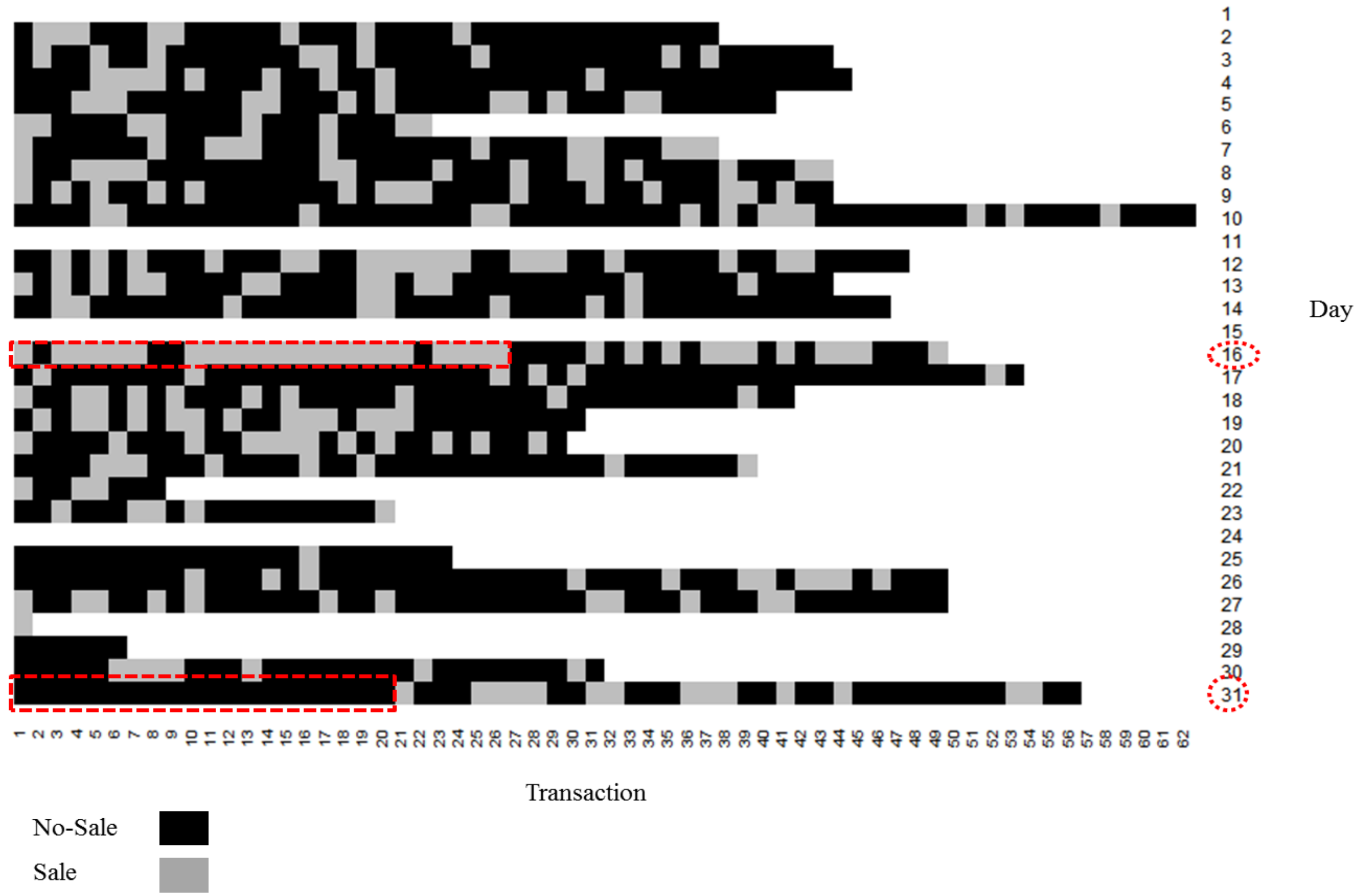
Gender	% of Respondents
Male	50.79%
Female	48.17%

Highest level of education completed	% of Respondents
Did not complete high school	1.05%
High school	6.28%
Some college or vocational courses	19.37%
Vocational qualification	2.09%
College degree	44.50%
Master's degree	21.47%
Advanced graduate work or doctorate	4.19%
Prefer not to answer	1.05%

WEB APPENDIX B: CALL CENTER CHARACTERISTICS

	SCC	NSCC
Type of employment	Temporary contracts, full time, and part time	
Products	The same product in both call centers	
Potential customers	The same database	
Management structure	One manager, two team leaders, coach	
Recruitment process	Appointment, recruitment interview with tasks	
Training structure	Five-day training, three days theoretical and two days practical	
Payment structure	Basic, guaranteed salary (per hour) plus commission	
Social facilities	Comfortable, spatial, fully equipped kitchen with relaxation space with sofas and armchairs	Two small, poorly equipped kitchens with chairs
Physical arrangement	One big open space; located on second floor, with no lift	Many small individual rooms, located on third floor, with a lift
Additional rewards	Social events – very often; Small prizes - very often	Social events – rarely; Small prizes – very often
Interaction during the day	Good relationship between agents and leaders	Some relationship between agents and leaders

WEB APPENDIX C: SAMPLE HEAT MAP OF THE SALES OUTCOME OF A SALESPERSON



Notes: Successful sales appear in gray, failed sales in black, and no-calls in white. During our sampling period, this focal salesperson made 2391 calls, 433 of which resulted in successful sales (success rate = 18.1%). The maximum number of calls the salesperson made in a workday is 62.

WEB APPENDIX D: PROPERTIES OF THE CLUMPINESS MEASURE

By *minimum property*, we mean that the clumpiness measure is at its minimum when a type of outcomes (e.g., sale) are equally spaced apart from one another (i.e., when a salesperson is not experiencing momentum). By *maximum property*, we mean that the measure is at its maximum when types of outcomes are gathered together (i.e., when a salesperson is experiencing momentum). By *continuity property*, we mean that shifting outcome times slightly should only change the measure by a small amount. By *convergence property*, we mean that the measure increases (decreases) as a type of outcomes move closer together (farther away). Although not every outcome is consecutive, a type of outcomes close to each other should be taken as being in momentum. By using the continuity and convergence properties, we can also compare the magnitude of momentum between calls or salespeople, in which a higher value means stronger momentum. For example, suppose a salesperson makes call A and call B while in momentum. If call A has a higher value than call B, call A has stronger momentum than call B. Therefore, it is easier for the salesperson as he or she makes subsequent calls to lose momentum for call B than for call A. As another example, suppose a salesperson makes calls C and D while not in momentum. If call C has a higher value than call D, call C is more likely to further the salesperson’s momentum than call D as he or she makes subsequent calls.

WEB APPENDIX E: ASSESSING CONSECUTIVE NUMBER OF SALES

Number of Consecutive Successful Sales	Frequency
2	654
3	331
4	145
5	51
6	16
7	10
8	4
9	3
10	1
11	1
12	1
13	1
14	0
15	0
16	1
17	1

WEB APPENDIX F: CALCULATING THE CRITICAL VALUE FOR THE TEST OF CLUMPINESS

To determine the existence of momentum given a set of outcomes (i.e., successful or failing sales), we compare the calculated clumpiness metric with a critical value. We calculate the critical value using a Monte Carlo simulation. We follow Zhang, Bradlow, and Small's (2014) algorithm to calculate the appropriate critical value (*Z*-table). We lay out the specific steps we took to generate the *Z*-table as follows:

1. Generate 100,000 sequences with binomial random numbers given the number of observations (*N*) and the probability of having a sale (*p*), where $p = \frac{number\ of\ successful\ outcomes\ (n)}{number\ of\ observations\ (N)}$.
2. For all *n* in 1 to *n*,
   A. Take only patterns with *n* successful outcome from 100,000 sequences.
   B. Calculate the clumpiness measure of the random sample.
   C. Find the 95% percentile of the computed clumpiness measures in the random sample as the critical value.

The test of clumpiness can be implemented by comparing the calculated clumpiness measure with the critical value, $C_{\alpha,g}$, from the final *Z*-table. The null hypothesis stating the nonexistence of momentum is rejected, as a sequence is deemed as having momentum when the clumpiness measure is higher than the corresponding critical value.

WEB APPENDIX G: ROBUSTNESS ASSESSMENTS FOR ANALYSIS 1

Alternative Method to Capture Sales Momentum

We run an HMM to show that finding momentum is not bound to a particular method used. We use a nonhomogeneous HMM approach to understand the factors affecting the dynamics of the individual salesperson performance and uncover the latent states while allowing for transition between latent states to evolve by time-varying factors. For the development of the model, we make three assumptions in our model: (1) discrete latent states, (2) time-varying transition states of the salesperson, and (3) individual observed and unobserved heterogeneity between agents.

First, we assume discrete underlying psychological (latent) states.[1] Theory and practice of sales suggest that latent states tend to experience discrete shifts over time. Theoretical models suggest that buyer-seller exchanges are discrete events (e.g., Dwyer, Schurr, and Oh 1987). Moreover, the statistical tests for stationary of the outcome suggest a regime shift that is discrete. In practice though, it is likely that salespeople believe that their confidence evolves in a stochastic manner as influenced by external and internal factors, such as the previous sales outcome, and mood change. Past research using HMMs have treated latent states such as customer relationship (e.g., Ascarza and Hardie 2013; Luo and Kumar 2013; Netzer, Lattin, and Srinivasan 2008) as discrete. We follow previous literature and also assume a discrete latent state space where each sale situation is not continuous in period of time, but rather there is a regime shift between latent states (i.e., salesperson confidence).

Second, we account for the second assumption, time-varying transition states of the salesperson, with the nonhomogeneous setup of the model. We develop a nonhomogeneous

[1] Though assuming that discrete underlying states are not ideal in our context, HMM assumes discrete latent state transition.

HMM specified with a multinomial logit transition matrix and conditional distribution for the sales outcomes. In a nonhomogeneous HMM, transition probabilities are formulated as functions of time-varying covariates (Hughes and Guttorp 1994; Netzer, Lattin, and Srinivasan 2008; Shi and Zhang 2014; Zhang, Netzer, and Ansari 2014). We specifically use the time of day that the call is made to set up the nonhomogeneous model. Following prior literature (e.g., Altman 2007), we use a logit transition to account for the dynamics of transition between states using covariates and random effects to capture differences among processes. We also specify the logistic emission equation with control variables used in our main model to find factors influencing the sales outcome.

Third, we assume individual observed and unobserved heterogeneity between agents. We capture both the observed and unobserved heterogeneity between and within agents with the latent class specification. Latent classes identify the smallest number of groups that describe the associations among a set of observed indicators.

We specify these three assumptions in the nonhomogeneous HMM model and estimate the model with expectation–maximization (EM) estimation. We present our results in the next section.

Results. For the model with the best fit based on Bayesian information criterion values, we find a two class-four state model. The multiple class and state model is the best fit for our data which confirms the importance of modeling the underlying relationship states, classes, and the transition dynamics. It also shows that salespeople are heterogeneous in their behaviors and underlying states. We find that two groups of salespeople (core performers who make up 88% of the sample, and stars who make up 12%) have different behaviors and different degrees of latent state persistence across four latent states.

Salespeople belong in one state with each selling occasion and transition to another (or stay at the same) state the next selling occasion. The states are arranged in increasing order of salesperson performance with state 1 being the lowest confidence state (i.e., pessimistic) and state 4 being the highest confidence state (i.e., optimistic). We find evidence of momentum through the transition matrix (Table W2) by examining the probability of staying in the same latent state from the past call to the next call.

Of the two groups, we find that core performers, as compared to stars, have a higher latent state persistence. Specifically, the probability of core performers staying in the same state from the previous call to the next call is 81.6%, 70%, 94.4%, and 79.9% in states 1, 2, 3, and 4, respectively. The probability of stars staying in the same state from the previous call to the next call is 58.9%, 75.5%, 78.9%, and 59.5% in states 1, 2, 3, and 4, respectively. Therefore, core performers, as compared to stars, are more likely to experience momentum. Stars are more likely to transition from one state to another from the past call to the next call. For example, while only 4.7% of core performers in state 1 are likely to transition to state 4, 30.2% of stars in state 1 are likely to transition to state 4. Table W3 shows parameter estimates of the nonhomogeneous HMM model. All variables are significant at .01 level except the number of calls received by a customer.

Table W2. Transition Matrix for Stars and Core Performers

	Core Performers						Stars				
		t						t			
	State	1	2	3	4		State	1	2	3	4
t – 1	1	0.816	0.009	0.128	0.047	t-1	1	0.589	0.051	0.058	0.302
	2	0.189	0.700	0.012	0.098		2	0.061	0.775	0.113	0.052
	3	0.015	0.033	0.944	0.009		3	0.052	0.094	0.789	0.064
	4	0.031	0.051	0.139	0.779		4	0.053	0.251	0.101	0.595

Table W3. Estimated Result for Nonhomogenous HMM

	Coefficient
State-dependent intercept (State 1)	-0.134
State-dependent intercept (State 2)	0.007
State-dependent intercept (State 3)	0.111
State-dependent intercept (State 4)	0.016
Number of calls received by a customer	0.069
Confidence (State 1)	-1.868
Confidence (State 2)	3.716
Confidence (State 3)	-1.236
Confidence (State 4)	-0.613
Experience (State 1)	-35.682
Experience (State 2)	122.000
Experience (State 3)	-60.245
Experience (State 4)	-26.072
Number of prior breaks (State 1)	-2.374
Number of prior breaks (State 2)	2.658
Number of prior breaks (State 3)	0.740
Number of prior breaks (State 4)	-1.024
Time since break (State 1)	-2189.543
Time since break (State 2)	1182.261
Time since break (State 3)	-251.398
Time since break (State 4)	1258.681
Time spent on prior break (State 1)	-1386.856
Time spent on prior break (State 2)	1879.251
Time spent on prior break (State 3)	322.801
Time spent on prior break (State 4)	-815.196

*All parameters are significant ($p < .01$) except the number of calls received by a customer, which is not significant.

Alternative Rolling Window for Momentum Measure

We run the test of clumpiness using windows of 11 and 13 to show that the existence of momentum is not bound to a specific window size. We find that 0.89% and 2.51% of calls are made while the salesperson is experiencing momentum in the rolling window of 11 and 13, respectively. 70% and 88% of salespeople experience momentum at some point in time in the rolling windows of 11 and 13, respectively. Similar to results using the rolling window of 9 (Table 4), most salespeople experience momentum for 0.1% to 1.9% of calls (Table W4). Again, we looked at the distribution of momentum within the day to examine whether salespeople experience momentum on and off throughout the day and hour (Table W5). Using the window of 11, most salespeople make at least one call under momentum on 20% to 29% of the days worked and on 0.1% to 9% of hours worked. Using the window of 13, most salespeople make at least one call under momentum on 30% to 39% of the days worked and on 10% to 19% of hours worked. Due to the continuity property of the clumpiness metric, a small change in the event only changes the measure by a small amount. Therefore, clumpiness measures for each call should only change by a small amount, thus the result from one window is roughly similar to results from a slightly larger rolling window.

As an additional robustness check, we also assess across-day momentum by using outcome information from all calls made by a salesperson in a day to determine whether salespeople are experiencing momentum during a specific day (Table W6). Therefore, the window size varies for each salesperson for each day. For example, if salesperson A made 50 calls on the first day, outcomes from all 50 calls have been used to determine whether salesperson A was experiencing momentum day 1. If salesperson A made 63 calls on the second day, outcomes from all 63 calls have been used to run the test of clumpiness to determine whether salesperson A was experiencing momentum on day 2. We find that 37 out of 113 (33%) salespeople experienced across-day momentum at least once. We observe some salespeople experiencing across-day momentum on multiple days. For example, 7 salespeople (6.2%) experienced momentum during the entire day on 10% to 19% of days worked. Showing existence of momentum during the entire day using various window sizes demonstrates that the existence of momentum is not bound to the specific window size, but is a phenomenon salespersons' experience.

Table W4. Test of Clumpiness Robustness Check using Various Window Sizes

	Window 11		Window 13	
Percentage Range (%)	Frequency	Percentage (%)	Frequency	Percentage (%)
0	34	30	14	12
0.1–1.9	75	66	66	58
2–2.9	2	2	21	19
3–3.9	1	1	10	9
4–4.9	0	0	1	1
5–5.9	1	1	0	0
Percentages of calls made under momentum	0.89%		2.51%	

Table W5. Distribution of Percentages of Calls Made under Momentum per Hour and Day for Various Window Sizes

	Window 11-Day		Window 11-Hour		Window 13-Day		Window 13-Hour	
Percentage Range (%)	Freq.	Percentage (%)	Freq.	Percentage (%)	Freq.	Percentage (%)	Freq.	Percentage (%)
0	34	30.1	34	30.1	14	12.4	14	12.4
0.1–9.9	15	13.3	72	63.7	1	0.9	35	31.0
10–19.9	21	18.6	5	4.4	6	5.3	54	47.8
20–29.9	30	26.5	1	0.9	17	15.0	7	6.2
30–39.9	10	8.8	1	0.9	28	24.8	0	0
40–49.9	2	1.8	0	0	19	16.8	1	0.9
50–59.9	0	0	0	0	10	8.8	1	0.9
60–69.9	0	0	0	0	11	9.7	0	0
70–79.9	1	0.9	0	0	5	4.4	0	0
80-89.9	0	0	0	0	1	0.9	1	0.9
>90	0	0	0	0	1	0.9	0	0

Table W6. Frequency Distribution of Day-Level Clumpiness Score

Percentage Range (%)	Frequency	Percentage (%)
0	76	67
0.1–9.9	25	22
10–19.9	7	6
20–29.9	2	2
30–39.9	0	0
40–49.9	0	0
50–59.9	2	2
60–69.9	0	0
70–79.9	0	0
80-89.9	0	0
>90	1	1
Total	113	100%

WEB APPENDIX H: ASSESSING THE SMALLEST ROLLING WINDOW SIZE WITH CONSERVATIVE STATISTICAL TEST

Out of an abundance of caution, we classify an observation as clumpy when H_p is greater than (not greater than or equal to) the critical value. With this way of testing, the smallest window testable is one of 9 calls. Monte Carlo simulation draws sequences of window *N* from the random binomial distribution. There can be 2^N possible sequences. When *N* is below 9, the number of possible sequences is limited, and therefore only a few H_p values are possible for $C_{\alpha,g}$. For example, if *N* = 4 and *n* = 3, only six possible sequences are possible (Table W7). All randomly generated sequences are one of these six sequences, which will carry 0.039. Therefore, at the 95th percentile, H_p is 0.039, and no possible sequence with H_p greater than 0.039 can be identified as clumpy (i.e., momentum). When *N* is greater or equal to 9, there are many more possible sequences given *N* and *n*. For example, if *N* = 9 and *n* = 3, there are 84 sequences possible, with H_p values varying from 0.015 to 0.322. Therefore, when we find the 95th percentile H_p value from simulated random sequences, the critical value does not equal the maximum possible H_p, and some sequences are considered clumpy.

Table W7. List of All Possible Sequences when N=4

n	$Outcome_1$	$Outcome_2$	$Outcome_3$	$Outcome_4$	H_p	Critical Value ($C_{\alpha,g}$)
0	0	0	0	0	INF	INF
1	0	0	0	1	0.278	0.278
1	0	0	1	0	0.029	0.278
1	0	1	0	0	0.029	0.278
1	1	0	0	0	0.278	0.278
2	0	0	1	1	0.135	0.135
2	0	1	0	1	0.040	0.135
2	0	1	1	0	0.040	0.135
2	1	0	0	1	0.135	0.135
2	1	0	1	0	0.040	0.135
2	1	1	0	0	0.135	0.135
3	0	1	1	1	0.039	0.039
3	1	0	1	1	0.039	0.039
3	1	1	0	1	0.039	0.039
3	1	1	1	0	0.039	0.039
4	1	1	1	1	0	0

WEB APPENDIX I: SIMULATED PROBABILITY OF TYPE I ERROR

Criticism of statistical classical hypothesis testing is the prespecified significance level, α, which is also the maximum probability of committing a Type I error (Heiberger and Holland 2004). Type I error will manifest in any classical statistical testing in which the true parameter is unknown. While a Type I error cannot be completely ruled out, we did two things to minimize it. First, we used more conservative statistical criteria to test for clumpiness. We classify an observation with a $H_p > C_{\alpha,g}$ rather than $H_p \geq C_{\alpha,g}$ as "clumpy," or experiencing momentum. Second, we increased the iteration size for the Monte Carlo simulation to find the critical value. We use 100,000 iterations in the simulation to reduce the Type I error.

To show that the Type I error is minimized by taking the aforementioned measures, we compare the percent of tests rejected (observed) under each propensity to the true Type I error rate (expected). For each cell of expected Type I error rate, we set N equal to 9 to correspond to our window size of 9 calls and simulated 100,000 iterations under the binomial distribution. We report the percentages of iterations that are rejected at a 5% significance level. As Table W8 shows, the % of tests rejected for propensity 0.11, 0.22, and 0.89 is 0. This is because no observation had $H_p > C_{\alpha,g}$, suggesting that the possibility of Type I error for these propensities is zero since there cannot be any false positives if there are no positives. The percentage of tests rejected as observed within our data is higher than the expected Type I error rate for all other propensities. Therefore, we believe that the Type I error is minimized and findings are robust.

Table W8. Comparison of Observed and Expected Type I Error for each Propensity

Propensity	% clumpy test reject within propensity (observed)	Type 1 error rate (expected)
0.11	0.0000	0.0053
0.22	0.0000	0.0167
0.33	0.0524	0.0272
0.44	0.0435	0.0310
0.56	0.0430	0.0256
0.67	0.0154	0.0151
0.78	0.0069	0.0054
0.89	0.0000	0.0007

WEB APPENDIX J: EXAMPLE OF CALCULATING POSITIVE AND NEGATIVE MOMENTUM VARIABLES

Suppose Salesperson C, who has an overall success rate of 35%, made a successful sale in the first call, followed by no sale, sale, sale, sale, no sale, sale, no sale, and no sale, in that order (i.e., $Outcome_{C,1} = 1$, $Outcome_{C,2} = 0, Outcome_{C,3} = 1, Outcome_{C,4} = 1, Outcome_{C,5} = 0, Outcome_{C,6} = 0, Outcome_{C,7} = 1$, $Outcome_{C,8} = 0$, $Outcome_{C,9} = 0, Outcome_{C,9} = 0, Outcome_{C,10} = 0, Outcome_{C,11} = 0$). In the first nine calls, this salesperson had four successful calls and five failed calls; thus, the success rate for these calls is 44.4%. As the salesperson has a greater success rate, 44.4%, in the current window than his overall success rate of 35%, he or she would have positive momentum when making a sales call at t = 10. The positive momentum equals .0650, which is the value of the clumpiness score, and the negative momentum equals zero. In the following nine calls (second call to the tenth call), the salesperson made three successful calls and had six failed calls; thus, the success rate for this window would be 33.3%. As his or her success rate for the current window is less than his or her overall success rate, the salesperson would have negative momentum, which equals .0768, and the positive momentum equals zero at t = 11. In the subsequent nine calls (third to the eleventh call), the salesperson made three successful calls and had six failed calls. At t = 12, the salesperson would have negative momentum, which equals .1572, and the positive momentum equals zero.

WEB APPENDIX K: CORRELATIONS AND DESCRIPTIVE STATISTICS

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	Confidence	1																
(2)	Number of calls received by a customer	0.052	1															
(3)	Experience	0.129	0.079	1														
(4)	Number of prior breaks	0.054	0.067	0.068	1													
(5)	Time since break (in minutes)	0.022	0.015	0.039	0.07	1												
(6)	Time spent on prior break (in minutes)	0.064	0.071	0.053	0.419	0.036	1											
(7)	Positive momentum	0.007	0.026	-0.092	-0.043	-0.028	-0.02	1										
(8)	Negative momentum	-0.034	0.022	0.055	-0.043	-0.016	-0.027	-0.378	1									
(9)	Gender	-0.159	0.026	0.164	0.05	-0.094	-0.079	0.009	0.044	1								
(10)	Social	0.003	0.013	-0.127	0.021	0.097	0.049	-0.097	-0.196	-0.129	1							
(11)	Morning	-0.079	-0.033	-0.005	-0.205	-0.329	-0.298	0.018	0.048	0.061	-0.113	1						
(12)	Midday	-0.054	-0.029	0.023	-0.01	-0.119	-0.113	-0.005	-0.022	-0.006	0.013	-0.351	1					
(13)	Early afternoon	0.08	0.045	0.039	0.121	0.205	0.206	-0.007	-0.007	-0.039	0.018	-0.287	-0.549	1				
(14)	Late afternoon	0.052	0.016	-0.082	0.068	0.244	0.201	-0.003	-0.009	-0.004	0.077	-0.168	-0.321	-0.262	1			
(15)	Early week	-0.011	-0.028	-0.103	0.009	0.015	0.038	0.003	0.026	-0.025	-0.03	-0.037	-0.019	0.019	0.04	1		
(16)	Mid week	-0.019	-0.017	-0.012	-0.003	0.007	0.026	0.004	-0.025	-0.004	0.017	-0.013	-0.017	0.007	0.028	-0.392	1	
(17)	Late week	0.026	0.042	0.112	-0.007	-0.021	-0.058	-0.007	-0.006	0.028	0.016	0.047	0.032	-0.025	-0.063	-0.68	-0.408	1
	Summary Statistics																	
	M	58.941	1.033	665.446	2.374	39.198	22.806	0.064	0.257	0.760	0.522	0.155	0.402	0.310	0.133	0.394	0.191	0.415
	SD	28.502	0.183	531.633	2.118	49.569	24.681	0.101	0.385	0.430	0.500	0.362	0.490	0.462	0.34	0.489	0.393	0.493
	Min.	0	1	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Max.	100	3	2563	15	420	266	1	1	1	1	1	1	1	1	1	1	1

WEB APPENDIX L: RESULTS FOR THE INTERCALL INTERRUPTION INTERACTION MODEL

Our findings thus suggest that being in the SCC can influence the effect of negative (positive) momentum. To explore the value of the SCC further, we leverage the observable nature of the interruption aspect of the SCC and run an additional model. Model 5 (Table W9) introduces the interaction of intercall interruption ($interruption_{jdt}$) with the momentum variables, in replacement of $Social_{jdt}$, in the Model 3 from Table 7. The term $interruption_{jdt}$ takes the value of 1 if the intercall time between call *t* and *t* – 1 is greater than 60 seconds.

The main effects of positive momentum ($\beta = 7.921, p < .01$) is similar to those in the Model3. The interaction terms between both forms of momentum and intercall interruption ($\beta = 0.2536, p < .1$ for positive momentum; $\beta = 0.1978, p < .1$ for negative momentum). Again, we find the same significant direction of effects as in the Model 3. Interruptions moderate the effect of positive and negative momentum on the likelihood of a sale, just as social effects moderate positive and negative momentum in explaining the likelihood of a sale. Specifically, having an intercall interruption enhances the favorable effect of positive momentum and weakens the harmful effect of negative momentum. As such, we find that the social effect plays an important role in reversing a losing trend through the interruption of salespeople’s momentum.

Table W9. Break Interaction Regression Analysis for Likelihood of a Sale

	Model 5
Copula	-0.0949**
	(0.0425)
Confidence	0.0012
	(0.0008)
Number of calls received by a customer	-0.2141***
	(0.0788)
Experience	0.0001
	(0.0000)
Number of prior breaks	-0.0076
	(0.0088)
Time since break (in minutes)	-0.0001
	(0.0002)
Time spent on prior break (in minutes)	-0.0002
	(0.0009)
Inter-call interruption	-0.0347
	(0.0463)
Positive momentum	7.9210***
	(0.2685)
Negative momentum	-0.813
	(0.1906)
Positive momentum × Inter-call interruption	0.2536*
	(0.1391)
Negative momentum × Inter-call interruption	0.1973*
	(0.1065)
Early Week (baseline Wednesday)	-0.1333***
	(0.0325)
Late Week	-0.0989***
	(0.0358)
Mid-Day (baseline Morning)	-0.0537**
	(0.0267)
Early Afternoon	-0.0643*
	(0.0374)
Late Afternoon	-0.1089*
	(0.0619)
Customer region fixed effects	Yes
Salesperson fixed effects	Yes
Number of observations (N)	74060
Log-likelihood	-31262.07

WEB APPENDIX M: ROBUSTNESS ASSESSMENTS FOR ANALYSIS 2

Alternative Identification Strategy

We assess the robustness of the results for "Assessing the Impact of Momentum on Sales" with another method as an identification strategy. To this end, we introduce an instrumental variable and use a control function approach (e.g., Petrin and Train 2010; Wooldridge 2015). As an instrumental variable for negative momentum, we use the number of calls since the involuntary break, which is a period off from putting effort into selling due to no-calls (e.g., missed calls, wrong numbers). Salespeople run into these types of calls at random and have no control over when they occur. Such no-calls can take up to several minutes when they accumulate, and if this accumulation exceeds four minutes (to maintain consistency with voluntary break times), we mark the salesperson as taking an involuntary break and operationalize the instrumental variable as the number of calls from an involuntary break to the current call. The time off from making selling efforts are likely to mitigate negative momentum (i.e., relevance criterion). Conversely, due to their random occurrence, no-calls are unlikely to influence unobserved factors related to salespeople's future performance (i.e., exclusion criterion). To ensure that the number of calls since an involuntary break is a suitable instrument, we discuss the relevance and exclusion criteria below.

First, to meet the relevance criterion, the number of calls since an involuntary break should influence negative momentum. Salespeople who take a break from selling may lose momentum, thus decreasing the intensity of the negative momentum.[2] As salespeople in negative momentum attend to more calls without any external interruption, the intensity of this negative

[2] We use the number of calls since the involuntary break rather than an indicator for the break because negative momentum contains information about the outcome from previous calls. Therefore, having an involuntary break per se cannot drastically influence the negative momentum value, though it can slowly influence negative momentum over the next few calls after an involuntary break.

momentum becomes stronger (Markman and Guenther 2007), thus increasing its value. Conversely, if salespeople in negative momentum take a random involuntary break due to no-calls, the intensity of the negative momentum is likely to decrease. We find that this assumption is empirically supported in our data, and we discuss the details in the "Results" subsection.

Second, the exclusion criterion requires that the instrument not directly influence any unobserved factors related to the salesperson's performance. The involuntary break from no-calls happens from customers not answering the phone or by calling the wrong number. As mentioned, these no-calls occur randomly, and salespeople have no control over them or when they can take an involuntary break. We argue that the number of calls since the involuntary break is unlikely to directly influence performance, which can depend on unobserved factors, such as salespeople's ability or fatigue. An involuntary break is unlikely to strengthen or weaken salespeople's ability to sell, as ability should not vary over the day throughout the random occurrence of no-calls. Furthermore, an involuntary break is also unlikely to impact fatigue, as evidenced by empirical exploration of salespeople's confidence in selling. We assume that if salespeople are fatigued, their confidence in selling is likely to drop.[3] Therefore, we use confidence as a proxy for fatigue to see how confidence change with involuntary breaks and find that confidence is not related to involuntary breaks. Consequently, the number of calls since the involuntary break is unlikely to influence unobserved factors related to the salesperson's future performance.[4]

[3] A possible criticism could be that a lengthy involuntary break is associated with fatigue, which can affect subsequent performance. First, we compare the distribution of confidence in making a sale in the next call for three call types: (1) all calls, (2) calls immediately after an involuntary break, and (3) regular calls (without any prior break). We find that the confidence distributions for these three call types are relatively similar, which shows that salespeople do not feel any less or more confident after an involuntary break. Second, we find the correlation of time since involuntary break and confidence is r=0.0062 which suggests no linear relationship.

[4] We perform a weak instrument variable test to ensure that "the number of calls since the involuntary break" is a suitable instrument variable. We find an F-value of 7431.1, which is larger than 10, suggesting that the instrument is not weak. We also show the validity of exclusion restriction by examining the correlation between the excluded variable and the residuals in the second stage. We find a ρ-value of −0.0526, which suggests no linear relationship (Anderson and Sclove 1986).

As our interest is in running a nonlinear second-stage regression with our dichotomous dependent variable, $Outcome_{jdt}$, implementing a standard two-stage least squares method will yield an inefficient and inconsistent result (Wooldridge 2015). Therefore, we use the control function approach, which includes predicted first-stage residuals as additional regressors in second-stage estimation (Rutz and Watson 2019). Using the control function method gives a consistent estimator in the presence of an endogenous variable (i.e., negative momentum) that may be correlated with ϵ_{jdt} (Wooldridge 2015). Specifically, we derive a proxy variable (i.e., predicted residuals) that conditions on the part of negative momentum that depends on ϵ_{jdt}, the error term from Equation W14.2. Conditioning on the predicted residual allows us to parse out exogenous variation in the negative momentum variable to obtain a consistent estimator. We outline specific steps in line with previous studies in marketing literature using the control function approach (e.g., Albuquerque and Bronnenberg 2012; Gordon, Goldfarb, and Li 2013).

First, we estimate a linear model, regressing the negative momentum on the instrument, number of calls since the involuntary break, and a set of control variables that enter the second-stage regression as follows:

$$\begin{aligned} NM_{jdrt} = {} & \gamma_0 + \gamma_1 involbreak\ calls_{jdrt} + \gamma_2 MidDay_{jdrt} + \gamma_3 EarlyAfternoon_{jdrt} \\ & + \gamma_4 LateAfternoon_{jdrt} + \gamma_5 EarlyWeek_{jdrt} + \gamma_6 LateWeek_{jdrt} \\ & + \sum_{i=7}^{13} \gamma_r X_{ijdrt} + \delta_{\mathrm{j}} + \theta_r + \tau_{jdrt}, \end{aligned} \tag{W14.1}$$

where *j* is the salesperson index; *d* is the day index; *t* is the time index; *r* is the region index; *i* is the control variable index; NM_{jdrt} is the negative momentum; $involbreak\_calls_{jdrt}$ is our instrument of number of calls since involuntary break; $MidDay_{jdrt}$, $EarlyAfternoon_{jdrt}$, $LateAfternoon_{jdrt}$, $EarlyWeek_{jdrt}$, $LateWeek_{jdrt}$ are time-variant indicator variables that indicate time of day and day of week; X_{ijdrt} is the set of time-variant control variables[5] included in the study; δ_j captures salesperson and θ_r captures customer region-level fixed effects; and τ_{jdrt} is the normally distributed error term.

Second, we include the predicted residual, $\hat{\tau}_{jdrt}$, from Equation W14.1 to the second-stage fixed-effects logit model, which serves as an effective way to address endogeneity. Intuitively, the predicted residual captures the variation in negative momentum that depends on unobservable factors (e.g., strategic break-taking) and is devoid of the component that is predictable with the observed factors in the first-stage regression. Conditioning on the predicted residual enables us to obtain a consistent estimate of the parameters while partitioning negative momentum into two parts: (1) an endogenous component (that is correlated with ϵ_{jdrt}) and (2) an exogenous component (that is not correlated with ϵ_{jdrt}). The second-stage logistic regression is represented as follows:

(W14.2) $Outcome_{jdrt} = \frac{A_{jdrt}}{1+A_{jdrt}} + \epsilon_{jdrt}$, and

(W14.3)
$$\begin{aligned} A_{jdrt} = \exp(&\beta_0\hat{\tau}_{jdrt} + \beta_1 PM_{jdrt-1} + \beta_2 NM_{jdrt-1} \\ &+\beta_3 PM_{jdrt-1} \times Social_j + \beta_4 NM_{jdrt-1} \times Social_j \\ &+\beta_5 PM_{jdrt-1} \times Female_j + \beta_6 NM_{jdrt-1} \times Female_j \\ &+\beta_7 PM_{jdrt-1} \times MidDay_{jdrt} + \beta_8 NM_{jdrt-1} \times MidDay_{jdrt} \\ &+\beta_9 PM_{jdrt-1} \times EarlyAfternoon_{jdrt} + \beta_{10} NM_{jdrt-1} \times EarlyAfternoon_{jdrt} \\ &+\beta_{11} PM_{jdrt-1} \times LateAfternoon_{jdrt} + \beta_{12} NM_{jdrt-1} \times LateAfternoon_{jdrt} \\ &+\beta_{13} PM_{jdrt-1} \times EarlyWeek_{jdrt} + \beta_{14} NM_{jdrt-1} \times EarlyWeek_{jdrt} \\ &+\beta_{15} PM_{jdrt-1} \times LateWeek_{jdrt} + \beta_{16} NM_{jdrt-1} \times LateWeek_{jdrt} \end{aligned}$$

[5] Typically, all variables that enter the second-stage regression should also enter the first-stage regression. We included all the control variables in the second-stage regression, but we did not include the positive momentum variable in the first-stage regression because this variable has a strong correlation with the negative momentum by design, due to the dichotomous nature of its operationalization.

$$+\sum_{i=17}^{23} \beta_r X_{ijdrt} + \alpha_\mathrm{j} + \gamma_r),$$

where $Outcome_{jdrt}$, PM_{jdrt}, and NM_{jdrt} are outcome, positive momentum, and negative momentum, respectively; $Social_j$ and $Female_j$ are indicators of the type of call center and salesperson gender, respectively; α_j captures salesperson and γ_r captures customer region-level fixed effects; and ϵ_{jdrt} is the error term. Our use of a fixed-effects logit model accounts for unobserved heterogeneity that may come from omitted variable bias and relaxes restrictions on the correlation between independent variables. We include a salesperson's momentum from the preceding sales calls to explain the outcome. Therefore, reverse-causality issues are minimized, as a future outcome cannot cause momentum in previous periods. Because the introduction of the predicted residual, $\hat{\tau}_{jdrt}$, is an estimate of the true value of the exogenous explanatory variable, standard errors obtained in the second stage do not account for the extra variation coming from the predicted residual. Therefore, we bootstrap the standard errors of the model to obtain valid standard errors (Petrin and Train 2010; Rutz and Watson 2019; Wooldridge 2015).

Results. We present the first-stage linear regression in Table W10 and the estimation results in Table W11. First-stage linear regression results show that the number of calls since the involuntary break is positive and significant ($\gamma_1 = .0005, p < .01$), confirming the relevance of our instrumental variable. The direction of this variable is also consistent with our assumption that as more calls are made after a break, the negative momentum strengthens.

We find similar results using the copula method to those using the control function method. We find that for the Model 2 (Table W11, Column 3), positive momentum ($\beta = 8.0778, p < .01$) has a positive effect on the outcome, while negative momentum ($\beta = -1.7052, p < .1$) has a negative effect. The Model 3 (Table W11, Column 4) shows a similar main effect of positive momentum ($\beta = 7.5190, p < .01$), while the effect of negative momentum is nonsignificant. The interactions between both forms of momentum and the type of call center are significant (positive momentum: $\beta = 1.3449, p < .01$; negative momentum: $\beta = .1660, p < .01$). Lastly, our results from Model 4 (Table 7, Column 5) show that all interactions between positive momentum and time-day indicators are not significant, but the effect of negative momentum on performance depends on the time and day of the call. Compared with midweek (Wednesday), the effect of negative momentum is significantly different in the early week (Monday, Tuesday; $\beta = .1626, p < .1$). We find that calls made midday ($\beta = .1837, p < .05$) and late afternoon ($\beta = -0.3015, p < .1$) significantly influence negative momentum. As the results of our four different models show, the results with (i.e., control function approach) and without (i.e., including copula term) instruments are substantially similar, confirming the robustness of the results.

Table W10. First-Stage Linear Regression Result (DV: Negative Momentum)

	Coefficient
Number of calls since involuntary break	.0005*** (.0001)
Confidence	-.0011*** (.0001)
Number of calls received by a customer	-.0193** (.0081)
Experience	.0001*** (.0000)
Number of prior breaks	-.0022 (.0012)
Time since break (in minutes)	-.0002*** (.0001)
Time spent on prior break (in minutes)	.0001 (.0001)
Midday (baseline morning)	-.0150*** (.0039)
Early afternoon	.0088* (.0043)
Late afternoon	.0247*** (.0070)
Early week (baseline Wednesday)	.0269*** (.0038)
Late week	.0174*** (.0038)

p* < .10, ** *p* < .05, * *p* < .01.

Table W11. Regression Analysis for Likelihood of a Sale.

	Model 1	Model 2	Model 3	Model 4
Predicted residual (from first-stage regression)		1.1582	0.6351	0.6421
		(1.0058)	(1.1200)	(0.6996)
Confidence	0.0027***	-0.0001	0.0006	0.0005
	(0.0005)	(0.0012)	(0.0013)	(0.0006)
Number of calls received by a customer	-0.1959***	-0.2408***	-0.2291***	-0.2282***
	(0.0571)	(0.0609)	(0.0539)	(0.0645)
Experience	0.0000	0.0001***	0.0001**	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of prior breaks	-0.0177*	-0.0149*	-0.0097	-0.0100
	(0.0082)	(0.0100)	(0.0116)	(0.0166)
Time since break (in minutes)	-0.0001*	-0.0004	-0.0003	-0.0003
	(0.0002)	(0.0003)	(0.0004)	(0.0002)
Time spent on prior break (in minutes)	0.0006	-0.0002	-0.0002	-0.0002
	(0.0007)	(0.0009)	(0.0009)	(0.0012)
Positive momentum		8.0778***	7.5190***	7.3234***
		(0.1442)	(0.1728)	(0.5429)
Negative momentum		-1.7052*	-1.2577	-1.5490**
		(1.0083)	(1.1201)	(0.6424)
Social				
Positive momentum × Social			1.3449***	1.3914***
			(0.1900)	(0.1843)
Negative momentum × Social			0.1660***	0.1936***
			(0.0626)	(0.0538)
Female				
Positive momentum × Female				0.0611
				(0.4625)
Negative momentum × Female				0.1018
				(0.0891)
Early week			-0.1147**	-0.1630***
			(0.0512)	(0.0382)
Positive momentum × Early week				0.3333
				(0.3630)
Negative momentum × Early week				0.1626*
				(0.1041)
Late week			-0.0894***	-0.1288*
			(0.0365)	(0.0511)
				0.1392

Positive momentum × Late week				(0.5140)
Negative momentum × Late week				0.2370
				(0.1669)
Midday (baseline morning)			-0.0562***	-0.0782**
			(0.0224)	(0.0376)
Positive momentum × Midday				0.0038
				(0.2803)
Negative momentum × Midday				0.1837**
				0.0794
Early afternoon			-0.0509*	-0.0370
			(0.0316)	(0.0329)
Positive momentum × Early afternoon				-0.0908
				(0.2519)
Negative momentum × Early afternoon				-0.0279
				(0.0726)
Late afternoon			-0.0840*	0.0014
			(0.0488)	(0.0512)
Positive momentum × Late afternoon				-0.5399
				(0.5664)
Negative momentum × Late afternoon				-0.3015*
				(0.1881)
Customer region fixed effects	No	Yes	Yes	Yes
Salesperson fixed effects	No	Yes	Yes	Yes
Number of observations (N)	74060	74060	74060	74060
Log-likelihood	-36261.478	-31318.468	-31077.299	-31262.429

Notes: Numbers reported represent coefficients; numbers in parentheses represent bootstrapped standard errors. The *no-momentum model* has regular standard errors in parentheses.

* $p < .10$, ** $p < .05$, *** $p < .01$.

Alternative Assessment of Social Working Environment Impact by Examining the Resilience of Positive and Negative Momentum

In our previous analysis, we found that the social effect (i.e., being in the SCC) augments the effect of positive momentum, and ameliorates the effect of negative momentum. In other words, salespeople in the SCC were able to break negative momentum faster than those in the NSCC. This difference is due to the different magnitudes of negative (positive) momentum generated across the two call centers. Our challenge is to examine the social effect associated with (1) weaker negative momentum, which makes it easier for salespeople to "snap out" of negative momentum, and (2) stronger positive momentum, which makes salespeople "stickier" in positive momentum. Thus, we apply matching methods that balance treatment and control groups according to observables (Avery et al. 2012). Matching methods enable us to isolate any individual salesperson characteristics that influence the magnitude of momentum. Therefore, we can more robustly test the social effects moderation of negative (positive) momentum. Specifically, we use a matching method (Rosenbaum and Rubin 1983) to examine the effect of negative (positive) momentum had a salesperson in the SCC been placed in the NSCC.

First, we examine the association between the social effect and negative (positive) momentum by adopting propensity score matching to estimate probability weights. Second, we use inverse probability weighting (IPW) to estimate the average social effect of SCC salespeople (ASES).[6] We have 55 salespeople in the SCC and 48 salespeople in the NSCC. IPW accounts for the imbalance in the number of salespeople between centers by weighting each observation by the propensity score.

[6] ASES is analogous to what the propensity score matching literature calls average treatment effect of treated, which calculates the average effect on treatment had treatment not been treated. However, we are interested in examining the association, not the causal effect, between social effect and the negative (positive) momentum and therefore examine ASES.

We estimate the propensity score of each salesperson in the SCC and NSCC using manager assessments of each salesperson's characteristics across six domains. Using seven-point Likert scales, managers rated the degree to which each salesperson is self-confident, cheerful, optimistic, outgoing, shy, and liked by the rest of the team. We computed standardized mean differences between salespeople in the SCC and NSCC for each variable. Observed salesperson characteristics in the SCC and NSCC are considered balanced if the standardized mean difference is lower than .25 (Avery et al. 2012). Table W12 shows that most of the standardized mean differences are far below this value. Therefore, call center assignment is reasonably unconfounded with the characteristics used to calculate the propensity score. For our study, the propensity score is the probability that a salesperson is placed in the SCC, given values of observed characteristic variables. We derive propensity scores using a logistic regression in which the dependent variable indicates whether or not the *j*th salesperson belongs in the SCC (Rosenbaum and Rubin 1983). We have

$$\text{(W14.4)} \qquad \ln\left(\frac{p_j}{1-p_\mathrm{j}}\right) = \delta_0 + \delta_1 C_{1j} + \delta_2 C_{2j} + \cdots + \delta_6 C_{6j} + \epsilon_j,$$

where p_j is the propensity score given a set of observed salesperson characteristics, $C_{1j}$to C_{6j}.

Then, we use the estimated propensity score to compute weighted averages of negative momentum and ASES. We define the ASES as

$$\text{(W14.5)} \qquad ASES = \mathrm{E}[(NM_{1j}\text{-}NM_{0j})|Social_j = 1] = \mathrm{E}[NM_{1j}|Social_j = 1] - \mathrm{E}[NM_{0j}|Social_j = 1],$$

where $NM_{1j}$is the negative momentum for a salesperson in the SCC and NM_{0j} is the negative momentum for a salesperson in the NSCC.

To find the ASES, we need to know the average negative momentum of salespeople from the SCC when they were working in the SCC ($NM_{1i}|Social_j = 1$) and the NSCC ($NM_{0j}|Social_j = 1$). We assume two potential outcomes for negative momentum for each salesperson: one for SCC (NM_{1j}) and one for NSCC (NM_{0j}). However, we observe only one of the two outcomes because the salesperson cannot be in both SCC and NSCC. Specifically, we do not observe NM_{0j} for salespeople in the SCC, because they will never be in the NSCC. Therefore, we estimate the effect of negative momentum for salespeople in the SCC if they were placed in the NSCC by weighting the outcome for NSCC with the inverse of the propensity scores from the first step. We use the propensity score estimated in the first step to calculate the weight, defined as

$$w_j = \frac{Social_j}{p_j} + \frac{(1 - Social_j)}{1 - p_j}. \quad \text{(W14.6)}$$

We multiply the weight by p_j, so salespeople in the SCC receive a weight of 1 and a weight for ASES, $w_{j,ASES} = Social_j + \frac{p_j(1-Social_j)}{1-p_j}$. Therefore, salespeople in the SCC serve as the reference population with which we compare the salespeople in both centers. When we substitute the weight into ASES, we can estimate ASES by

$$\frac{1}{n_1}\sum_{j=1}^{n_1} NM_{1j} - \frac{1}{n_0}\sum_{j=1}^{n_0} NM_{0j}\left(\frac{p_j(1-Social_j)}{1-p_j}\right). \quad \text{(W14.7)}$$

We run the same procedure for positive momentum.

Results. We find that the social effect affects the magnitude of the momentum. Consistent with our expectations, the average negative momentum magnitude of salespeople in the SCC is only 84.2%[7] of the negative momentum if they were in the NSCC. Similarly, we find that the average positive momentum magnitude of salespeople in the SCC is 130.80%[8] of what would have been had they been in the NSCC. These results suggest that the social effect is associated with weaker (stronger) negative (positive) momentum in the SCC than the NSCC, independent of any other confounder.

[7] ASES for negative momentum is statistically different from zero (SE = .005426, p = .042).
[8] ASES for positive momentum is statistically different from zero (SE = .006231, p = .006).

Table W12. Summary of Matched Variables and Standardized Mean Differences

Matched Variable	SCC		NSCC		Standardized Mean Differences
	M	SD	M	SD	
Self-confident	4.82	1.71	4.77	1.29	0.03
Cheerful	5.30	1.23	5.10	0.75	0.20
Optimistic	4.48	1.09	4.52	0.90	-0.04
Outgoing	4.64	1.57	4.25	0.98	0.30
Shy	3.25	1.83	3.35	1.56	-0.06
Liked by team	4.89	1.58	4.40	1.05	0.37

Table W13. Robustness Checks for Fixed-Effects Logistic Regression Analysis for Likelihood of a Sale

	Alternative Time-of-Day Definition
Copula	-0.0552*
	(0.0311)
Confidence	0.0012*
	(0.0007)
Number of calls received by a customer	-0.2155***
	(0.0266)
Experience	0.0001*
	(0.0000)
Number of prior breaks	-0.0064
	(0.0107)
Time since break (in minutes)	-0.0002
	(0.0002)
Time spent on prior break (in minutes)	-0.0003
	(0.0012)
Positive momentum	7.1333***
	(0.3524)
Negative momentum	-0.6487***
	(0.1722)
Positive momentum × Social	1.2999***
	(0.3598)
Negative momentum × Social	0.1999**
	(0.0892)
Positive momentum × Female	0.0457
	(0.4336)
Negative momentum × Female	0.0861
	(0.1348)
Early Week	-0.1804***
	(0.0147)
Positive momentum × Early Week	0.3272
	(0.2265)
Negative momentum × Early Week	0.1616***
	(0.0472)
Late Week	-0.1804*
	(0.0147)
Positive momentum × Late Week	0.3272
	(0.2265)
Negative momentum × Late Week	0.1616***
	(0.0472)
Mid-Day (baseline Morning)	-0.1078**
	(0.0455)
Positive momentum × Mid-Day	0.2312
	(0.1553)
Negative momentum × Mid-Day	0.1699**

	(0.0861)
Early Afternoon	-0.0843*
	(0.0518)
Positive momentum × Early Afternoon	0.0547
	(0.3233)
Negative momentum × Early Afternoon	0.0444
	(0.0502)
Late Afternoon	-0.1153***
	(0.0411)
Positive momentum × Late Afternoon	-0.0983
	(0.1841)
Negative momentum × Late Afternoon	-0.2381***
	(0.0721)
Customer region fixed effects	Yes
Salesperson fixed effects	Yes
Number of observations (N)	74060
Log-likelihood	-31238.1

Notes: Numbers reported represent coefficients; numbers in parentheses represent bootstrapped standard errors.
*p < .10, ** p < .05, *** p < .01.

WEB APPENDIX N: DSS SIMULATION STEPS

The lay out of the specific steps we took to simulate potential outcome from a DSS is as follows:

Step 1. Take the outcome of first 9 calls ($Outcome_{jdt}$ for *t* 1 to 9) from our data to identify the first occasion the salesperson experiences momentum in a given day *d* for all salespeople *j* in J.

Step 2. Determine whether the salesperson *j* in day *d* is in momentum using equations 1 and 2 to calculate H_{p_t} with the outcome from calls 1 to *t* in *T*.

Step 2.1. If the salesperson is in negative momentum, go to Step 3.

Step 2.2. If the salesperson is in positive momentum, go to Step 4.

Step 2.3. If the salesperson is not in momentum, go to Step 1. *t* becomes *t +1*.

Step 3. The salesperson is in *negative momentum*. The salesperson is given a break. Go to Step 5 to simulate what the salesperson's performance could be with a break ($\widetilde{Outcome}_{t+1}$).

Step 4. The salesperson is in *positive momentum*.

Step 4.1. If the salesperson is in positive momentum for the **first time** (i.e., *z*=1), go to step 4 and build on previous outcomes to calculate the momentum calculation (i.e., *t* becomes *t+1*).

Step 4.2. If the salesperson's clumpiness measure for $z+1^{\text{th}}$ time is *less than* that of *z* (i.e., $H_{p_z} > H_{p_{z+1}}$), the salesperson is given a break. Go to Step 5 to simulate what the salesperson's performance could be with a break.

Step 4.3. If the salesperson's clumpiness measure for $z+1^{\text{th}}$ time is *greater than or equal* to that of t (i.e., $H_{p_z} \leq H_{p_{z+1}}$), go to Step 4 and build on previous outcomes to calculate the momentum calculation (i.e., *t* becomes *t+1*).

Step 5. Simulate 100 sequences with binomial random numbers given salesperson's propensity to sell, g.

Step 6. Randomly select one outcome from 100 sequences. This outcome is $\widetilde{Outcome}_{t+1}$. Compare $\widetilde{Outcome}_{t+1}$ with $Outcome_{t+1}$.

Step 7. Repeat steps 5 and 6 for 10,000 times.

WEB APPENDIX O: LONG-TERM IMPACT OF MOMENTUM RESULTS

	Lag Model
Confidence	.0012**
	(.0006)
Number of calls received by a customer	-.0967*
	(.0582)
Experience	.0000
	(.0000)
Time since break (in minutes)	.0000
	(.0002)
Number of prior breaks	-.0023
	(.0085)
Time spent on prior break (in minutes)	.0004
	(.0007)
Positive momentum-4	-.0272
	(.1022)
Negative momentum-4	-.0070
	(.0317)
Positive momentum-3	-.1063
	(.1012)
Negative momentum-3	-.0594*
	(.0318)
Positive momentum-2	.0604
	(.1005)
Negative momentum-2	.0143
	(.0317)
Positive momentum-1	4.3079***
	(.0914)
Negative momentum-1	-1.0272***
	(.0415)
Salesperson fixed effects	Yes
Number of observations (N)	73,628
Log-likelihood	-32852.556

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