ESSAYS ON THE IMPACT OF SOCIAL MEDIA IN THE AUTOMOBILE INDUSTRY

By

Yen-Yao Wang

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ABSTRACT

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The U.S. automobile industry is increasing reliance on social media marketing and is ranked the highest one in traditional and digital advertising spending. Despite a significant body of research in social media, the effectiveness of social media in this competitive marketplace has not received the detailed examination. My dissertation seeks to fill in this gap by conducting two studies to examine the impact of social media on customers' engagement behaviors as well as firms' sale performance.

My first essay examines the dynamic interactions between firm-generated content (FGC), user-generated content (UGC), and offline sales (light vehicles) in the setting of the firm's Facebook fan page in the U.S. automobile industry. The findings suggest that (1) FGC is more effective in influencing offline car sales than UGC, (2) offline car sales would trigger more FGC and UGC activities, and (3) there is a positive feedback effect between FGC and UGC. These findings vary across different forms of format presentation and content of post, suggesting that firms need to fully customize their social media strategy to reach their goals more efficiently. Furthermore, customers in different groups (luxury versus non-luxury) demonstrate dramatically different patterns.

My second essay explores the dynamics of online word-of-mouth (WOM) and its spillover effects by considering the relative effects at the stages of customer awareness and consideration. The findings indicate that (1) online WOM at the stage of consideration has the stronger effect on offline car sales than online WOM at the stage of awareness, (2) spillover effects exist across both stages of awareness and consideration, though effects are heterogeneous in direction: positive spillover effects at the stage of awareness while negative spillover effects at the stage of consideration, and (3) at the stage of awareness, online WOM initiated by firms is more effective in influencing offline car sales than online WOM initiated by users. Furthermore, not every mechanism at Facebook (i.e., post, like, comment, and share) has the equal impact on offline car sales and these different mechanisms also influence how customers appreciate online WOM at the stage of consideration. Finally, the results vary significantly across origin of brand, market structure, and price factor.

In summary, my dissertation offers valuable insights for firms on how to better develop their social media strategy to engage with their customers and boost offline car sales in this economically important industry. Furthermore, these two studies would also advance the literature by understanding further the dynamics of social media on offline sales of the durable or high-involvement products. Finally, the unique and rich data also allows me to test the underlying mechanism at work that will shed light on our theoretical understanding of the impact of social media from different perspectives.

The dissertation is dedicated to my family.

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CHAPTER 1. OVERVIEW OF DISSERTATION

The automobile is one typical example of durable goods. When purchasing durable goods, customers are more likely to experience high-involvement decisions, meaning that customers may engage in an extensive search for information or a comprehensive evaluation of the choice alternatives because the wrong decision would force customers to deal with the poor product for long periods of time. Currently, the power of digitization is challenging the business model of the automobile industry. In particular, social media has dramatically changed the way of how firms maintain the relationships with their customers and how customers engage an extensive search for their vehicle purchase behaviors.

The U.S. automobile industry is increasing reliance on social media marketing and is ranked the highest one in traditional and digital advertising spending. Despite the significant amount of spending in digital advertising and anecdotal evidence of social media in driving up automobile sales, the effectiveness of social media in this competitive marketplace has not received the detailed examination.

Furthermore, in the setting of customer purchase decision-making, customers may experience a multi-stage decision process, which typically includes the stage of awareness, interest, and final decision. However, our understanding about the role of social media across these different stages of decision process and its corresponding impact is still very limited.

The goal of this dissertation is to integrate the IS and marketing literature and to study the mechanisms by which social media impacts customer demands in the U.S. automobile industry. Specifically, essay one examines the dynamic relationships between firm-generated content (FGC), user-generated content (UGC), and offline car sale in the setting of the firm-initiated Facebook fan page and studies how different forms of format presentation, content of post, and firm characteristics would vary these dynamic relationships. Essay two explores the dynamics of online word-of-mouth (WOM) and its spillover effects by considering the relative effects at the stages of customer awareness and consideration and also explores how different mechanisms at the stage of customer awareness would change customers' appreciation about the role of social media at the stage of consideration and how firm characteristics would vary this dynamics.

In summary, my dissertation offers valuable insights for firms on how to better develop their social media strategy to engage with their customers and boost offline car sales in this economically important industry. Furthermore, these two studies would also advance the literature by understanding further the dynamics of social media on offline sales of the durable goods. Finally, the unique and rich data also allows me to test the underlying mechanisms at work that will shed light on our theoretical understanding of the impact of social media from different perspectives.

CHAPTER 2.

ESSAY 1: ONLINE TO OFFLINE: THE IMPACT OF SOCIAL MEDIA ON OFFLINE SALES IN THE AUTOMOBILE INDUSTRY

2.1 INTRODUCTION

With the explosion of social media, firms have been exploring how to harness social media and promote consumer-firm relationships, learn about customers and the marketplace, and improve their market performance (Chen, De, & Hu, 2015; Dewan & Ramaprasad, 2014). Among the different forms of social media, Facebook strongly leads the social networking space, with 87% of social networkers accessing the platform regularly, followed by 43% of Instagram users (eMarketer, 2015c). In particular, Deloitte's recent report indicates that Facebook added $100 billion to the U.S. economy and helped support 1 million jobs in the U.S. in 2014 (Deloitte, 2015). Due to its significant impact, Facebook has become a leading avenue for more than 54 million businesses to set up their online brand communities (i.e., fan page) for marketing purposes (Facebook, 2015a). At a firm's Facebook page, both firms and users can generate contents to interact with firms or other users (hereafter termed as firm-generated content (FGC) and user-generated content (UGC)). To influence customers' purchase decisions, firms deliberately engage in advertising, products/services, deals, and customer relationship (Goh, Heng, & Lin, 2013). Simultaneously, customers are also allowed and encouraged to voice their opinions, express their personal experiences about the firm, and form relationships with other customers as well as the focal firm, thereby creating social interactions (Agarwal, Animesh, & Prasad, 2009). Because of the simultaneous engagement of consumers and marketers on social media, consumers' purchase decisions are often influenced by both FGC and UGC (Goh et al., 2013).

Despite the prevalent use of social media and extensive research in this domain, the relationship between FGC, UGC, and firm performance has not received systematic scrutiny. Anecdotal evidence suggests that such a relationship exists, but to the best of our knowledge, no study directly tests for this relationship or explains the direction and magnitude of its effect. First, previous research has documented that firm' efforts on social media can affect marketing outcomes (e.g., Luo, Zhang, & Duan, 2013) and that UGC can affect sales (e.g., Ghose & Ipeirotis, 2011; Tirunillai & Tellis, 2012). However, this same literature typically examines the isolated impact of either FGC or UGC on sales or does not distinguish between these two social media contents. This approach neglects any effects that FGC and UGC might have on one another, and indirectly, through one another on sales. More importantly, this isolated approach fails to explain how firm's media channels should operate as a system and thus scholars call for more systematic research on the firm's integrated media channels (e.g., Dewan & Ramaprasad, 2014; Luo et al., 2013; Smith, Gopalakrishna, & Chatterjee, 2006; Stephen & Galak, 2012). Second, most studies in this stream focus on the impact of FGC or UGC on online sales of non-durable and media goods such as movie, DVD, music, book, or clothing (e.g., Chen et al., 2015;

Goh et al., 2013). Yet, as of the 4th quarter 2015, online sales only account for 7.5% of all retail purchases (U.S. Department of Commerce, 2016). Third, previous studies focus considerably on UGC in the form of online consumer review (e.g., Chevalier & Mayzlin, 2006; Gu, Park, & Konana, 2012), forum (e.g., Stephen & Galak, 2012), or blog (e.g., Dewan & Ramaprasad, 2014; Luo et al., 2013). However, FGC or UGC in the setting of the firm's Facebook fan page represents different aspects of goals (e.g., advertising, customer engagement, or social networking) and could reach a variety of audiences. It, therefore, demonstrates a very different context. Finally, the extant literature examines the impact of social media exclusively either over a short duration of time (e.g., Chen et al., 2015; Dewan & Ramaprasad, 2014) or in a single firm (e.g., Goh et al., 2013; Rishika, Kumar, Janakiraman, & Bezawada, 2013; Stephen & Galak, 2012). As a result, to properly understand the total impact of both FGC and UGC on offline sales of the durable goods and vice versa, it is necessary to have an integrated perspective.

The objective of this essay is to assess the dynamic interactions between FGC, UGC, and offline sales of light vehicles (durable goods) in the setting of the firm-initiated Facebook fan page. The study context involves the U.S. automobile industry. The U.S. automobile industry is ranked as the second highest in digital advertising spending (eMarketer, 2015b) and the highest one in both traditional and digital advertising spending (Nielsen, 2015). Despite the large amount of spending in digital advertising and the abundant anecdotal evidence indicating that social media could drive up automobile sales (e.g., eMarketer, 2014a; MacArthur, 2015), no empirical research examines the relative effectiveness of FGC and UGC on offline car sales in the setting of the firm-initiated Facebook page. Therefore, this study aims to answer the following research questions:

(1) Do FGC and UGC have an effect on offline car sales, after controlling for other influential factors such as traditional media spending?

(2) What are the dynamic relationships between FGC, UGC, and offline car sales?

(3) How do these dynamic relationships vary across different forms of format presentation (link, photo, status, and video) and content of post (informative post and sentiment of post)?

(4) How do these dynamic relationships vary for luxury versus non-luxury car brands?

To answer the above questions, I collected detailed FGC and UGC data from the official Facebook pages of 30 car companies in the U.S. and matched these data with their offline car sales from 2009 to 2014 in the monthly level. I also supplemented the data from these firms' traditional media spending, Google Trends, gasoline index, consumer confidence index, and S&P 500. This approach allows me to avoid potential bias in the estimation of the effect of FGC and UGC on offline car sales or inferring a spurious relationship. My empirical analysis is conducted using the panel vector autoregression (PVAR) model at three different dimensions: overall post (volume), format presentation (link, photo, status, and video), and content of posts (informative posts and sentiment of posts). The PVAR is suitable in our setting for several reasons. First, UGC or FGC is generated continuously over time and it is not a discrete event

(Srinivasan & Hanssens, 2009). The PVAR model allows me to examine the immediate and lagged-term effects of FGC and UGC on offline product sales (Love & Zicchino, 2006). Second, it allows me to treat all of the major variables (i.e., FGC, UGC, and offline car sales) as jointly endogenous, and assess the nature of bidirectional causality between all pairs of variables, in addition to controlling for a variety of factors that can affect offline car sale. Finally, I supplement the PVAR results with impulse response functions (IRFs) to investigate the evolutionary pattern of the PVAR model.

My results suggest that (1) FGC is more effective in influencing offline car sales than UGC, (2) offline car sales would attract more customers' and firms' attentions by disseminating information or voicing opinions more actively to strengthen customer/customer or customer/firm relationships and, (3) there is a positive feedback effect between FGC and UGC. These findings vary across different forms of format presentation and content of post. Furthermore, customers in two different groups (luxury versus non-luxury car brands) demonstrate dramatically different patterns.

This paper makes a number of contributions to the IS and marketing literature. First, to the best of our knowledge, this is the first academic study that rigorously examines the intricate and distinct roles of FGC and UGC and quantifies their economic impact on consumers' offline commerce activities on the durable product (vehicle) at the industry level. I uncover that customers hold different perspectives on two different forms of social media content and show

how customers' offline commerce activities would influence their engagement behaviors online and firms' social media strategy. Thus, this work echoes and promotes the importance of taking a systematic view of the firm's media channels and its firm performance (e.g., Dewan & Ramaprasad, 2014; Luo et al., 2013; Smith et al., 2006; Stephen & Galak, 2012). Second, I add to the literature by showing that different forms of social media channels have their own characteristics and firms should pay special attention to their resource allocations if they have a significant presence at other social media channels. Prior research has focused exclusively on online reviews (e.g., Gu et al., 2012), online forum (e.g., Gopinath, Chintagunta, & Venkataraman, 2013), or blog (e.g., Dewan & Ramaprasad, 2014). I provide evidence that UGC in our setting is not very effective in driving offline car sales. My study, in fact, also reinforces the importance of context-specific theorizing in IS research (Hong, Chan, Thong, Chasalow, & Dhillon, 2013).

Third, my work sheds light on customers' evaluations of content in different formats and shows how firms can utilize the combinations of different formats and contents to reach their goals more efficiently. Currently, retailers are increasingly focusing on driving consumers into their physical store locations while maintaining their online presence (i.e., online to offline setting) (eMarketer, 2014b). Particularly in the automobile industry, companies often feature their online automobile models online, trying to attract potential buyers into the showroom where a test drive is often followed by a purchase (Maloney, 2000). Thus, the design of an effective online format presentation becomes an extremely important issue to maintain companies' competitive advantage. In light of my findings, companies need to reconsider the format and content of their marketing communications in social media and strive to develop the most appropriate conversations to engage customers and boost offline sales. My study, therefore, responds to the recent call on online content formats in customer preferences (Berger, Matt, Steininger, & Hess, 2015; Yi, Jiang, & Benbasat, 2015), the importance of social media contents (e.g., Chen et al., 2015; Gopinath, Thomas, & Krishnamurthi, 2014), and customers' social media participation (e.g., Rishika et al., 2013). Finally, this essay serves as the first attempt to measure how customers in two different markets (luxury versus non-luxury car brands) would hold different views on firms' social media strategy and opinions of other customers. This approach provides insights for managers in two different markets to fully customize their social media strategy. Together, my study yields interesting managerial implications for companies interested in leveraging social media to boost their offline sales and customer engagements online and in understating the true needs of their targeted audiences.

In the remainder of this paper, I first provide an overview of the relevant prior literature and develop hypotheses. After elaborating on my data and their sources, I detail our PVAR empirical specification and the estimation procedure. Then I present my results before concluding with a discussion of the implications of my findings.

2.2 LITERATURE REVIEW

The current study is related to the literature that examines the effect of online contents on marketing outcomes. The advent of social media has burgeoned understanding how the effect of online FGC and UGC can influence sales and other marketing performance. In this section, I briefly review the current streams of research and discuss how my study contributes to the extant literature.

2.2.1 Effect of UGC on Sales

User generated content (UGC) on social media refers to content created by users to share information and/or opinions with others (Tang, Fang, & Wang, 2014). Prior research focuses considerably on the impact of online reviews, online ratings, blogs, and forums on online sales of media and non-durable goods such as movie, book, DVD, or music. For example, Chevalier and Mayzlin (2006) examined the effects of online reviews on the relative sales of books at Amazon.com and Barnesandnoble.com and found a positive relationship between online book reviews and online book sales. Focusing on movie ratings from professional and amateur communities, Moon et al. (2010) suggest that high early movie revenues enhance subsequent movie ratings and high advertising spending on movies supported by high ratings maximizes the movie's revenues. Furthermore, online video game reviews have a greater influence on the sales of less popular games (Zhu & Zhang, 2010).

Some scholars have taken more nuanced approaches to examine the relationship between online reviews and online sales. For instance, Forman et al. (2008) examine attributes of reviewers and posit that reputable reviews have greater impact on online book sales. Ghose and Ipeirotis (2011) find that the extent of subjectivity, informativeness, readability, and linguistic correctness in reviews matters in Amazon's sales. Scholars also examined other forms of UGC to investigate their economic impacts on sales. For example, consumer blogs are considered to be a prominent source for future Amazon album sales (Dhar & Chang, 2009). Rui et al. (2013) suggest that the valence of the tweet, influence level of the tweeter, and the intentions expressed by the tweeter influence movie sales. More recently, Dewan and Ramaprasad (2014) examined the relationship between consumer blogs, traditional media, and music sales. They found that radio play is positively related to future music sales at both the song and album levels.

2.2.2 Effect of FGC on Sales

On social media, firm generated content (FGC) refers to messages or posts made by company representatives on an official company blog, forum, Twitter, Facebook, or other forms of social media channels (Goh et al., 2013). Compared to UGC, firms own more control of FGC because they can decide when, how, and what they want to distribute and communicate with their customers (Miller & Tucker, 2013). Consistent with the findings on the impact of UGC on sales, the extant literature generally suggests that FGC on social media positively influence their marketing outcomes. For example, Goh et al. (2013) find that FGC in a firm's Facebook page influences consumers' apparel purchase expenditures. Furthermore, Chen et al. (2015) study the effect of artists' broadcasting activities on MySpace and suggest that broadcasting in social media has a significant effect on music sales and the effect mainly comes from personal messages (one form of FGC on social media) rather than automated messages. In essence, current research concludes that FGC and UGC mostly in the form of online review, blog, or forum positively influence online sales of experience, information, and non-durable goods. However, this literature either does not distinguish FGC from UGC (e.g., Dewan & Ramaprasad, 2014), or it tends to examine these effects independently (e.g., H. Chen et al., 2015; Gu et al., 2012), thereby making it difficult to compare the relative effects of FGC and UGC on marketing outcomes such as sales.

2.2.3 Relative Effects of UGC and FGC on Sales

As of yet, there is little academic research directly studying the relative effectiveness of FGC and UGC on offline sales of the durable goods (vehicle in our case). FGC and UGC on the firm's Facebook pages represent a different form of online content. First, compared to online reviews, FGC and UGC on Facebook pages may embed a variety of topics range from new product/service announcements, deal information, after-sales services, customer loyalty, customer complaints to customer reviews (Goh et al., 2013). Second, FGC and UGC on Facebook may reach more audiences than online reviews (eMarketer, 2015a; Goh et al., 2013). For example, online reviews tend to reach people who are interested in buying a certain product or service, whereas FGC and UGC on Facebook may go beyond this audience by including the firm itself, other consumers with common interests, and one's Facebook friends and acquaintances. Third, FGC and UGC on Facebook represent richer content than online reviews in terms of format presentation. In the context of online reviews, reviewers usually use the text to evaluate a certain product or service. However, in the setting of the firm's Facebook pages, both firms and customers usually use a mixture of photo, video, link, and status to distribute information or express opinions. Previous research indicates that different forms of format presentation (e.g., text, graphic, or video) do matter in influencing people's decision-makings (Berger et al., 2015; Lim & Benbasat, 2000; Yi et al., 2015). However, the assessment regarding consumers' appreciation of different formats is still under-explored in the setting of the firm's Facebook page (Berger et al., 2015). Finally, FGC and UGC tend to have a higher degree of social interactivity than blogs or forums (Stephen & Galak, 2012). To conclude, due to the uniqueness of each form of FGC and UGC, the current findings from the existing literature need extension (see Table 1 for a summary of selected research). In line with a recent call for more comprehensive and multifaceted research on social media (Chen et al., 2015; Stephen & Galak, 2012), I examine the joint effects of FGC and UGC on offline car sales in the setting of the firm's Facebook fan page.

There are some notable studies of the relative effects of FGC versus UGC. For example, Chen and Xie (2008) used analytic models to argue that online reviews can serve as a newer element in the marketing communication mix. They used these models to answer when and how the sellers should adjust their own marketing communication in response to consumer reviews. However, their study does not provide the relative comparison on the profit impact of consumer reviews and traditional marketing communications. Stephen and Galak (2012) examined how traditional media (publicity and press mentions) and social media (blog and online forum posts) affect sales and activity in each other. However, their research setting is a nonprofit organizational and focuses on blog and forum. Accordingly, they call for more research to examine how firms' media channels should operate as a system. Finally, Goh et al.'s study (2013) is highly relevant to my research context. They studied the relative impacts of FGC and UGC on sales in the setting of a causal wear apparel retailer's Facebook page. However, our study (1) explains how firms can leverage social media to affect offline sales of the durable product, (2) focuses on the impact at the industry level, (3) captures the lagged effects when the effects of marketing activities on sales are studied, and (4) takes the role of format presentation and firm characteristics into account. By contract, I explicitly look at all of these different aspects and aim to provide a comprehensive view on the impact of social media as a marketing channel.

Table 1. Summary of Selected Literature

Research	FGC	UGC	Sale Metric	Key Findings
Godes and Mayzlin (2004)	X	Online forum activities	TV show ratings	UGC positively influences TV show ratings.
Chevalier and Mayzlin (2006)	X	Online reviews	Online book sales	UGC positively influences sales.
Duan et al. (2008)	X	Online reviews	Movie sales	UGC positively influences sales.
Forman et al. (2008)	X	Online reviews	Online book sales	Reviewer disclosure of identity-descriptive information matters in sales.
Trusov et al. (2009)	X	Online referrals	Sign-ups for the online social networking site	UGC has longer carryover effects than traditional marketing actions.
Dhar and Chang (2009)	X	Blog posts	Online music sales	UGC positively influences sales.
Zhu and Zhang (2010)	X	Online reviews	Console and video game sales	UGC is more influential for sales of less popular games and games whose players have greater Internet experience.
Feng and Papatla (2011)	X	Online reviews	Car sales	UGC positively influences sales.
Ghose and Ipeirotis (2011)	X	Online reviews	Online audio player, video player, digital camera, and DVD sales	The extent of subjectivity, informativeness, readability, and linguistic correctness in reviews matters in sales and perceived usefulness.
Moe and Trusov (2011)	X	Online ratings	Bath, fragrance, and beauty products	UGC is influenced by previously posted ratings and has the direct impact on sales.
Gu et al. (2012)	X	Online reviews	Online digital camera sales	Internal UGC (Amazon) has a limited impact on sales, while external UGC (CNET, Gpreview, and Epinions) has a significant impact on sales.
Stephen and Galak (2012)	Firm's blog post	Blog posts from Google blog search	Financial services (microloans)	Both UGC and FGC influence sales.

Table 1 (cont'd)

Goh et al. (2013)	Firm's posts and comments	Customers' posts and comments	Appeal sales	UGC exhibits a stronger impact than FGC on sales.
Gopinath et al. (2013)	X	Blog posts	Movie sales	UGC metrics matter in sales and the effects Vary across pre-and post-release movie days.
Lu et al. (2013)	Firms' Online coupons	Online reviews	Restaurant revenue	Both UGC and FGC influence sales.
No-Dac et al. (2013)	X	Online reviews	Online blue-ray and DVD player sales	UGC positively influences sales of models of weak brands, while it does not have the impact on sales of the model of strong brands.
Rui et al. (2013)	X	Twitter	Movie sales	UGC positively influences sales and the celebrity effect does matter.
Dewan and Ramaprasad (2014)	X	Blog posts from Google blog search	Music sales	UGC is not related to album sales but negatively related to song sales.
Gopinath et al. (2014)	X	Online forum activities	Cell phone sales	UGC positively influences sales.
Chen et al. (2015)	Artists' personal messages	Online reviews	Online music sales	Both UGC and FGC positively influence sales but there is a much weaker or no association between UGC and FGC.

2.3 RESEARCH MODEL AND HYPOTHESES

In contrast to the existing literature, my study is unique in the following ways. First, I distinguish two different social media contents, FGC and UGC, and examine the dynamics of a system of interdependent variables. This approach allows me to understand how firm's media channels could operate as a system (e.g., Dewan & Ramaprasad, 2014; Stephen & Galak, 2012). Furthermore, I examine the dynamics of FGC, UGC, and offline car sales in the setting of the firm's initiated Facebook page. Compared to online reviews, online forums, or blog, the nature of Facebook is dramatically different because the content represents more aspects of goals from advertising, customer engagement, to social networking and could reach a variety of audiences (eMarketer, 2015a; Goh et al., 2013). Thus, focusing on UGC and FGC at Facebook could shed light on the effectiveness of social media in this stream of the literature. Finally, I focus on what firms and consumers do online versus consumers' commerce activities that occur in offline settings. Particularly, the difference between non-durable products (e.g., music, movie) and durable products (i.e., vehicle in our setting) allows me to explore the impacts of social media from the different perspectives.

My conceptual model is shown in Figure 1. I examine these relationships at three different dimensions: overall post (volume), format presentation, and content of post. Figure 2 shows one example of FGC and UGC. Previous research indicates that the content format (e.g., text, graphic, or video) does matter in influencing people's decision-makings (Berger et al., 2015; Nah, Eschenbrenner, & DeWester, 2011; Yi et al., 2015). In the online setting, the content format is critical for firms that want to leverage online content to generate more revenues (Berger et al., 2015; Yi et al., 2015). Therefore, I emphasize four common types of content formats at Facebook: *link, photo, status, and video* (see Figure 3 for the example of FGC in these four different forms). For the content of the post, I focus on two aspects: *informative posts* and *sentiment of posts*. Informative posts should include details about products, promotions, availability, price, comparisons with alternatives, and product related aspects that could be used in optimizing the purchase decision (Abernethy & Franke, 1996; Resnik & Stern, 1977). Thus, the relevance of this consideration reflects the common advertising practice of rational appeals that tends to highlight product attributes (Gopinath et al., 2014). With respect to sentiment of posts, I focus on *positive* and *negative* posts. Delineating between informative posts and sentiment of posts is indeed grounded in the information processing domain of the existing literature (e.g., Gopinath et al., 2014; Shiv & Fedorikhin, 1999). Finally, I am also interested in how the interactions shown in Figure 1 vary by firm characteristics, that is, luxury versus non-luxury car brands.

Figure 1. Conceptual Framework

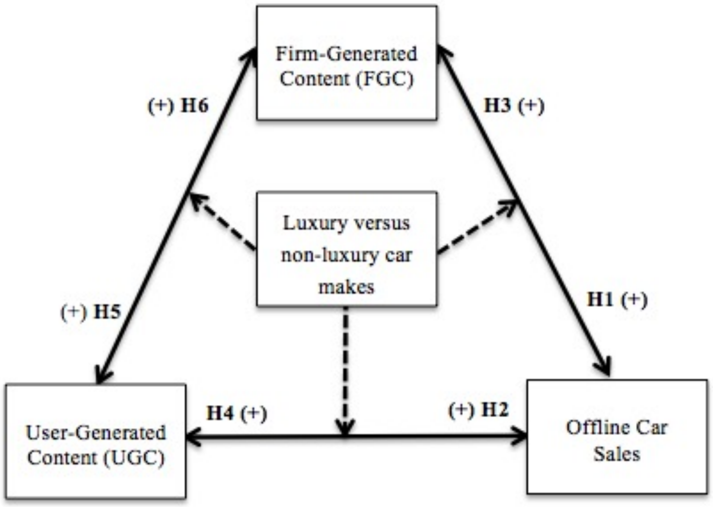
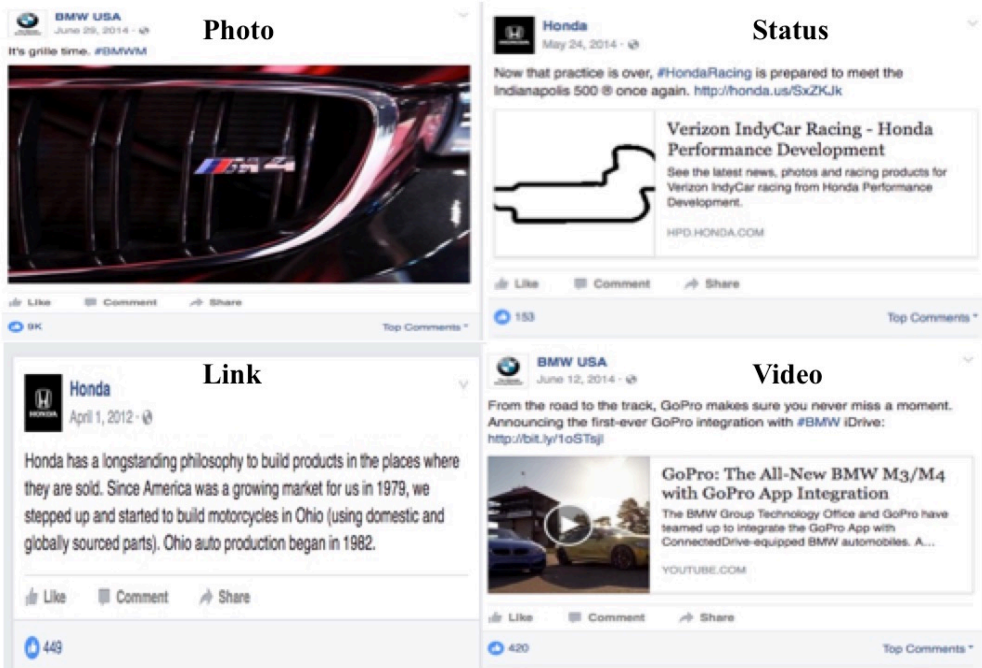


Figure 2. Example of FGC (left) and UGC (right)

Figure 3. Example of FGC in the form of Link, Photo, Status, and Video



The effect of FGC on sales has been well documented in prior research. For instance, to explicitly look at online content created by artists as a means of marketing communication, Chen et al. (2015) compared personal messages created by artists with automated messages created by MySpace and find that personal messages are predictive of music sales. I posit a positive relationship between FGC created on the firm-initiated Facebook page and offline car sales. In the journey of purchasing a product, as consumers are typically averse to losses (Narayanan, Chintagunta, & Miravete, 2007; Nelson, 1970), they may seek more product-related information to reduce their uncertainties (Goh et al., 2013). In turn, when uncertainties regarding a product are reduced during this purchasing journey, consumers bear more confidence in making purchase decisions and therefore are more likely to purchase that specific product (Goh et al., 2013; Schubert & Ginsburg, 2000). In the setting of the firm-initiated Facebook page, firms explicitly and actively promote products/services and engage customer relationship to attract more visitors and influence customers' purchase decisions (Goh et al., 2013; Miller & Tucker, 2013). Thus, I hypothesize:

Hypothesis 1: *FGC is positively associated with offline car sales.*

Ample evidence has indicated a significant impact of UGC on various marketing outcomes. For example, the earlier studies show that activities on the online discussion forum affect TV show ratings (Godes & Mayzlin, 2004), online reviews influence sales such as book, music, digital camera, and DVD (Chevalier & Mayzlin, 2006; Forman et al., 2008; Gu et al., 2012), blog posts influence music sales (Dhar & Chang, 2009). More recently, UGC is also considered as a leading indicator of firm equity value (Lu et al., 2013; Luo & Zhang, 2013). I expect that there is a positive association between UGC on the firm-initiated Facebook page and offline car sales. Consumers often love to share and relate their product experiences with members of a brand community and their participations in the brand community are critical to brand-related purchase behavior (Algesheimer, Dholakia, & Herrmann, 2005; Rishika et al., 2013). The firm-initiated Facebook page as one form of the online brand community provides a platform for consumers to share their product experiences or voice personal opinions (e.g., customer satisfaction with a product) with other consumers and the focal firm. Therefore, the positive effect of UGC on offline car sales is due to the WOM (word of mouth) effect, whereby social interactions and influence between consumers affect their purchasing decision making

(Dewan & Ramaprasad, 2014). Accordingly, I hypothesize:

Hypothesis 2: *UGC is positively associated with offline car sales.*

Previous research has demonstrated that sales may trigger more FGC and UGC activities. For example, Stephen and Galak (2012) indicate that repeat loan sales are positively associated with the number of blog posts. Dewan and Ramaprasad (2014) suggest that album sales positively influence album blog buzz, whereas song sales negatively influence song blog buzz. I posit that there is a positive relationship from offline car sales to both UGC and FGC in the setting of the firm-initiated Facebook page. The underlying principle is intuitive: for firms that extensively leverage the Facebook pages as one of their marketing channels, an increase in firms' sales can raise their brand recognition and appreciation on the Facebook pages so that both firms and customers are more likely to disseminate their products related information and brand experiences through this channel. An increase in firms' sales implies that firms need to maintain or enhance their current customer-firm relationships to sustain their competitive advantage. Therefore, it is reasonable to expect that an increase in sales will trigger firms to have a more active and vibrant Facebook community by posting a variety of topics regularly and actively. Such an active approach also allows customers to infer the level of a firm's relationship commitment and therefore strengthens customers' bond with the firm (Rishika et al., 2013). From the customers' perspectives, given that they often love to relate their product experiences with members of a brand community (Algesheimer et al., 2005), an increase in firms' sales expand the firms' existing customer pools and therefore trigger more new and old customers to share their experiences with other customers in a brand community. In addition, because individuals also wish to validate their choices in an environment that further strengthens their own affinity with the firm (Zhu, Benbasat, & Jiang, 2010), the firm-initiated Facebook page provides a great environment to form this relationship. Thus, it is intuitively logical that an increase in offline sales will drive more UGC. As a result, I hypothesize:

Hypothesis 3: *Offline car sales are positively associated with FGC.*

Hypothesis 4: *Offline car sales are positively associated with UGC.*

The firm-initiated Facebook page creates a channel for communicating with the firm's customers and building relationships with them (Miller & Tucker, 2013). An active social media page with regular new messages/postings can help customers form more positive attitudes toward the firm and increase the interactions between firms and customers (Rishika et al., 2013). These increased interactions are essential to form customer identification with the firm and can create greater trust to the firm and customer loyalty (Algesheimer et al., 2005). Prior research in relationship marketing claims that commitment and trust are two critical components for a party's intentions to continue the relationship with the other part (Morgan & Hunt, 1994). Therefore, in the setting of the firm-initiated Facebook page, if firms can interact their customers actively by providing more products/services information, customer are more likely to get involve in the interaction with firms as well as other customers. In addition, Miller and Tucker's study (2013) on social media management provides empirical evidence that actively managing a Facebook page (i.e., updating status more frequently) increases UGC activities. Therefore, I hypothesize:

Hypothesis 5: *FGC is positively associated with UGC.*

Previous research suggests that UGC changes sellers' communication strategy to best respond to those user-based reviews (Chen & Xie, 2008). I posit that UGC positively influences FGC in the setting of the firm-initiated Facebook page. UGC is a direct expression of consumers' personal experiences toward firms' products or services (Goh et al., 2013) and allows firms to better realize their customers' preferences. In the context of the firm-initiated Facebook page, if a large number of consumers exhibit favorable attitudes and sentiments toward a product or service, firms are more likely to disseminate more information related to that product or service to enhance customer relationships, advertise that product or service, and therefore boost sales. The extant literature has recognized the importance of active social media management and suggested that firm's posts need to be specifically targeted to clients' interests (Miller & Tucker, 2013). In this regard, one of the key approaches for firms to generate targeted content is through the learning of UGC at the firm-initiated Facebook page. Thus, I hypothesize

Hypothesis 6: *UGC is positively associated with FGC.*

2.4 DATA AND EMPIRICAL METHODOLOGY

2.4.1 Research Context

My major research context is Facebook because it is the most visited social media site in the US (eMarketer, 2015c). As a result, more than 54 million businesses have set up their online brand communities (i.e., fan page) for marketing purposes (Facebook, 2015a). Thus, the firm-initiated Facebook pages are representative sources of FGC and UGC. I selected the U.S. automobile industry because of its economic importance and increasing reliance on social media marketing (eMarketer, 2015b; Tang et al., 2014). The U.S. automobile industry generates sales representing 3%-3.5% of U.S. gross domestic sales and remains one of the most important segments in the U.S. economy (Hill, Menk, & Cooper, 2010). In response to the global economic recession, automobile companies have turned their attention to social media marketing to enhance customer relationships, disseminate a variety of information, engage customers, and boost sales (Tang et al., 2014). Accordingly, the U.S. automobile industry represents a great setting to examine the dynamics of relationships between FGC, UGC, and offline car sales.

2.4.2 Data

My samples consist of 30 major car brands in the U.S. automobile industry[1]. Each one of these brands has its official Facebook fan page. I used three main data sources for our panel,

[1] These car brands include Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, Honda, Hyundai, Infiniti, Jaguar, KIA, Lexus, Mazda, Mercedes-Benz, Mitsubishi, Nissan, Porsche, Toyota, Volkswagen, Volvo, Lincoln, Subaru, Saab, FIAT, Jeep, Land Rover, and Scion.

namely, the Facebook graph API (Application Programming Interface)[2] for FGC and UGC, monthly offline car sales from the WardsAuto Premium database, and traditional media advertising expenditure[3] from Kantar Media. I also collected the consumer search volume index in the U.S. from Google Trends to control for the popularity effects of each car make (Luo et al., 2013). Finally, I collected some macroeconomic indicators to control for their potential impacts on offline car sales. These indicators include the monthly gasoline price index from U.S. Bureau of Labor Statistics, the conference board's consumer confidence index, and S&P 500 monthly return.

To collect FGC and UGC, I built a software tool in PHP to connect with the Facebook graph API. I started our data collection on FGC and UGC on November 2014. It took around three months to collect detailed information on all activities from these 30 car manufacturers' official Facebook pages over a period of 66 months (2009.5 to 2014.10)[4]. Specifically, my data on FGC and UGC included post id, post time, post type, post source (user or firm), post content, and post link. I aggregated my data at the monthly level for two reasons: (1) the variation of firm' social media activities at both levels was relatively small, and more importantly (2) offline car sale data from the WardsAuto Premium database is only available at the monthly level.

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[2] Facebook Graph API: https://developers.facebook.com/docs/graph-api

[3] Traditional media categories included network TV, Spanish-language network TV, cable TV, syndication, sport TV, magazines, Sunday magazines, local magazines, Hispanic magazines, B-to-B magazines, national newspapers, newspapers, Hispanic newspapers, network radio, national sport radio, local radio summary, local radio historical, and outdoor displays.

[4] My goal was to provide a historical trend of FGC and UGC. Thus, I collected data from the beginning of each Facebook page. Most car brands initiated their Facebook pages on May 2009. Among these 30 car brands, 23 firms started their pages in 2009, 5 firms started their pages in 2010, and 2 firms started their pages in 2011.

My raw dataset included 58,158 firm-generated posts and 806,705 user-generated posts. I cleaned user-generated posts to reflect the following criteria[5]: keeping only messages written in English and removing spam[6]. At some firms' pages, users started to post at pages few months after firms had initiated their pages. Given my research objective, we also removed the months that had zero activity on user-generated posts. For example, in my dataset, one car brand initiated its Facebook page on May 2009. However, users started to post on that page on August 2009. Thus, the starting point for this car brand was August 2009. After clearing, my final dataset included 58,158 firm-generated posts and 706,527 user-generated posts with a total of 1,764 firm-month observations. To conduct content analysis, I relied on the Harvard General Inquirer[7], which classifies words into 182 categories such as positive, negative, weak, etc. It has been widely used in the literature to extract the tone and sentiment of many textual contents such as financial reports (e.g., Loughran & McDonald, 2011), news stories (e.g., Tetlock, Saa-Tsechansky, & Macskassy, 2008), and review text (e.g., Shen, Hu, & Rees, 2015). Tables 2 and 3 present the definition of variables and summary statistics, respectively.

Table 2. Variable Definition

Variable	Definition
Sales	Total number of offline car sales made by one car make in month t
FGC-Post	Total number of posts by one car make in month t
FGC-Link	Total number of link posts by one car make in month t
FGC-Photo	Total number of photo posts by one car make in month t
FGC-Status	Total number of status posts by one car make in month t
FGC-Video	Total number of video posts by one car make in month t
Informative-FGC	Total number of informative posts by one car make in month t

[5] I only applied the criteria to user-generated posts because firm-generated posts were always written in English and relevant to the individual car make.

[6] Users may use the firm-initiated Facebook pages to advertise products, services, or Web sites that are not relevant to car brands.

[7] Harvard General Inquirer: http://www.wjh.harvard.edu/~inquirer/

Table 2 (cont'd)

Pos-FGC	Total number of positive posts by one car make in month t
Neg-FGC	Total number of negative posts by one car make in month t
UGC-Post	Total number of posts by users at one car make's Facebook page in month t
UGC-Link	Total number of link posts by users at one car make's Facebook page in month t
UGC-Photo	Total number of photo posts by users at one car make's Facebook page in month t
UGC-Status	Total number of status posts by users at one car make's Facebook page in month t
UGC-Video	Total number of video posts by users at one car make's Facebook page in month t
Informative-UGC	Total number of informative posts by users at one car make's Facebook page in month t
Pos-UGC	Total number of positive posts by users at one car make's Facebook page in month t
Neg-UGC	Total number of negative posts by users at one car make's Facebook page in month t
Traditional Media Spending (TMS)	Total amount of money spent by one car make on traditional media in month t
Google Trends (GT)	The Google Trends search interest index for one car make in month t in the U.S.
Gasoline Price Index (Cao, Gedajlovic, & Zhang)	The U.S. gasoline price index in month t
Consumer Confidence Index	The conference board consumer confidence index in month t
S&P 500 Monthly Return (S&P500)	The S&P 500 return index in month t

Table 3. Descriptive Statistics

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	1764	38643.63	48343.08	97	245,239
FGC-Post	1764	33.53	34.74	0	1,042
FGC-Link	1764	6.61	8.64	0	62
FGC-Photo	1764	20.76	33.05	0	973
FGC-Status	1764	2.54	5.99	0	74
FGC-Video	1764	3.19	3.35	0	20
Informative-FGC	1764	25.61	15.42	0	218
Pos-FGC	1764	20.31	12.68	0	170
Neg-FGC	1764	0.92	1.08	0	6
UGC-Post	1764	400.53	426.34	4	3,543
UGC-Link	1764	40.36	54.19	0	487
UGC-Photo	1764	137.92	208.51	0	1,910
UGC-Status	1764	207.12	248.37	0	2,512
UGC-Video	1764	15.21	20.87	0	380
Informative-UGC	1764	257.66	273.12	0	2,439
Pos-UGC	1764	165.52	191.91	0	3,212
Neg-UGC	1764	59.65	70.79	0	1,023
TMS	1764	34357912	34516073.9	14,800	197,000,000
GT	1764	61.33	18.72	16	100
GPI	1764	3.41	.39	2.31	3.98
CCI	1764	66.34	12.84	40.9	94.1
S&P 500	1764	1440.06	288.94	919.14	2018.05

2.4.3 PVAR Model Specification

I used a PVAR model to examine the dynamic interactions between FGC, UGC, and offline car sales. The PVAR model or the VAR (Vector Autoregression) model is suitable for studying the relationships between a system of interdependent variables without imposing ad hoc model restrictions (Adomavicius, Bockstedt, & Gupta, 2012). It has been proven to be especially useful for examining the dynamic behavior of firms' efforts on social media and marketing outcomes (e.g., Chen et al., 2015; Dewan & Ramaprasad, 2014; Luo et al., 2013). Particularly in our setting, because UGC or FGC is generated continuously over time and is not a discrete event (Srinivasan & Hanssens, 2009), the PVAR model allows us to examine the immediate and lagged-term effects of FGC and UGC on sales and the system of interdependent relationships. The strengths of the PVAR model come from the benefits of the VAR model and the structure of panel data. In a PVAR model, main variables are assumed to be endogenous, so no prior information is required (Chen et al., 2015). It also allows the inference of bidirectional relationships between endogenous variables and ensures robustness of the model to issues of non-stationarity, spurious causality, endogeneity, serial correlation, and reverse causality (Granger & Newbold, 1986). Furthermore, the long-term dynamics between endogenous variables can be assessed through impulse response functions (H. Chen et al., 2015). The availability of panel data allows to control for unobserved individual heterogeneity and utilizes instruments within the model such as lagged dependent variables in the GMM (generalized method of moments) estimation to obtain consistent estimates (Chen et al., 2015; Love & Zicchino, 2006). It is also worth noting the limitation of PVAR. One of key limitations is the number of endogenous variables or the number of lags. Given the structure of PVAR, as the number of endogenous variables or the number of lags increase, the number of parameters increase rapidly, leading to inefficiencies in the estimation approach (Chen et al., 2015). Therefore, studies should proceed with caution when applying PVAR to examine the dynamic relationships.

My PVAR model is specified (for all different dimensions) as follows:

$$y_{i,t} = \begin{pmatrix} Sale_{i,t} \\ FGC_{i,t} \\ UGC_{i,t} \end{pmatrix} = \sum_{s=1}^{p} \Phi_s \cdot \begin{pmatrix} Sale_{i,t-s} \\ FGC_{i,t-s} \\ UGC_{i,t-s} \end{pmatrix} + \beta_1 \cdot Trad_{i,t-1} + \beta_2 \cdot GoogleTrends_{\ i,t-1} + \beta_3 \cdot Gasoline_{t-1} + \beta_4 \cdot Consumer_{t-1} + \beta_5 \cdot S\&P500_{t-1} + \xi_t + f_i + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ = $(Sale_{i,t}, FGC_{i,t}, UGC_{i,t})''$ is a three-element column vector for each car brand i iat time tt, containing the log and Helmert transformation of the dependent variable (see 3.4 for the rationale of log and Helmert transformation); Φ'_s are 3x3 matrices of slope coefficients for endogenous variables; p is the number of lags; $Trad_{i,t-1}$ is the log and Helmert transformation of the monthly expenditure on traditional channel promotions by car make i at time $t-1$; $GoogleTrends_{\ i,t-1}$GoogleTrends$_{\text{i,t-s}}$ is the log and Helmert transformation of the monthly Google search index in the U.S. for car brand i at time $t-1$; $Gasoline_{t-1}$ is the log and Helmert transformation of the monthly gasoline price index at time $t-1$; $Consumer_{t-1}$ is the log and Helmert transformation of the monthly consumer confidence index at time $t-1$; $S\&P500_{t-1}$ is the log and Helmert transformation of the monthly S&P 500 return index at time $t-1$; $\xi_t = (\xi_{1,t}, \xi_{2,t}, \xi_{3,t})'$ is a column vector of monthly time dummies that control for any time effect such as seasonality; $f_i = (f_{1,i}, f_{2,i}, f_{3,i})'$is a column vector of unobserved individual effects, characterizing car brands' time-invariant attributes; and $\varepsilon_{i,t}$ = $(\varepsilon_{1,i,t}, \varepsilon_{2,i,t}, \varepsilon_{3,i,t})'$

$(\varepsilon_{1,i,t}, \varepsilon_{2,i,t}, \varepsilon_{3,i,t})'$is a three-element vector of errors, satisfying the assumption that $E(\varepsilon_{m,i,t}) = E(\varepsilon_{m,i,t}\varepsilon_{m,i,s}) = 0$ for $m = 1, 2, 3$ and $t \neq s$. To conclude, the endogenous variables include offline sales, FGC, and UGC. I also control for exogenous variables such as traditional media expenditure, Google Trends, gasoline price index, consumer confidence index, S&P 500 monthly return index, and time effects.

2.4.4 PVAR Model Estimation Procedure

I followed the standard approaches to conduct our PVAR analysis: helmert transformation, unit root tests, lag length selection, PVAR model analysis, impulse response functions, and sample split PVAR analysis. Figure 4 shows my analysis procedure. First, to conduct PVAR related analysis, the variables must be stationary. Given the unbalanced panel, I conducted Fisher-Type (Choi, 2001) and Im-Pesaran-Shin (Im, Pesaran, & Shin, 2003) root unit tests to verify the absence of unit roots. The results for Fisher-Type and Im-Pesaran-Shin tests are shown in Tables 4 and 5, respectively. All p-values are smaller than 0.01, except for S&P 500; so, I conclude that there is no unit root in our panel except for S&P 500. I thus used the first differences for S&P 500 as suggested by the current literature (e.g., Luo et al., 2013; Tirunillai & Tellis, 2012) and no unit root remained in ΔS&P 500.

Table 4. Fisher-type Unit-Root Tests

Variable	Inverse chi-squared	Inverse normal	Inverse logit t	Modified inverse chi-squared
Sale	483.62 (0.000)	-18.24 (0.000)	-24.41 (0.000)	38.67 (0.000)
FGC-Post	380.85 (0.000)	-15.56 (0.000)	-19.19 (0.000)	29.29 (0.000)
FGC-Link	304.06 (0.000)	-13.16 (0.000)	-15.27 (0.000)	22.28 (0.000)
FGC-Photo	123.47 (0.000)	-5.08 (0.000)	-5.09 (0.000)	5.52 (0.000)
FGC-Status	417.54 (0.000)	-16.24 (0.000)	-21.03 (0.000)	32.63 (0.000)
FGC-Video	509.65 (0.000)	-18.94 (0.000)	-25.73 (0.000)	41.04 (0.000)
Informative-	237.45 (0.000)	-10.1 (0.000)	-11.55 (0.000)	16.19 (0.000)

Table 4 (cont'd)

FGC				
Pos-FGC	263.62 (0.000)	-10.95 (0.000)	-12.89 (0.000)	18.59 (0.000)
Neg-FGC	725.75 (0.000)	-23.56 (0.000)	-36.63 (0.000)	60.77 (0.000)
UGC-Post	306.82 (0.000)	-12.65 (0.000)	-15.31 (0.000)	22.53 (0.000)
UGC-Link	149.47 (0.000)	-6.59 (0.000)	-6.88 (0.000)	8.17 (0.000)
UGC-Photo	342.01 (0.000)	-12.37 (0.000)	-16.89 (0.000)	25.74 (0.000)
UGC-Status	349.46 (0.000)	-13.83 (0.000)	-17.48 (0.000)	26.42 (0.000)
UGC-Video	148.92 (0.000)	-6.68 (0.000)	-6.89 (0.000)	8.12 (0.000)
Informative-UGC	324.34 (0.000)	-12.88 (0.000)	-16.16 (0.000)	24.13 (0.000)
Post-UGC	389.34 (0.000)	-14.09 (0.000)	-19.48 (0.000)	30.06 (0.000)
Neg-UGC	341.64 (0.000)	-13.45 (0.000)	-17.08 (0.000)	25.71 (0.000)
TMS	597.52 (0.000)	-20.97 (0.000)	-30.16 (0.000)	49.06 (0.000)
GT	430.44 (0.000)	-16.93 (0.000)	-21.72 (0.000)	33.82 (0.000)
GPI	337.55 (0.000)	-14.21 (0.000)	-17.02 (0.000)	25.33 (0.000)
CCI	384.56 (0.000)	-16.05 (0.0000)	-19.42 (0.000)	29.62 (0.000)
ΔS&P 500	916.76 (0.000)	-27.5 (0.000)	-46.29 (0.000)	78.21(0.000)

Notes: The tests here are conducted on logged, Helmert transformed variables as suggested by Dewan and Ramaprasad (2014). Numbers in parentheses are p-value. The null hypothesis that all panels contain unit roots is rejected for all variables. These criteria also apply for the Table 5.

Table 5. Im-Pesaran-Shin Unit-Root Tests

Variable	Z-t-tilde-bar
Sale	-16.49 (0.000)
Sale	-16.49 (0.000)
FGC-Post	-13.23 (0.000)
FGC-Link	-10.78 (0.000)
FGC-Photo	-10.76 (0.000)
FGC-Status	-14.61 (0.000)
FGC-Video	-18.09 (0.000)
Informative-FGC	-13.81 (0.000)
Pos-FGC	-14.6 (0.000)
Neg-FGC	-24.2 (0.000)
UGC-Post	-13.43 (0.000)
UGC-Link	-7.72 (0.000)
UGC-Photo	-12.31 (0.000)
UGC-Status	-14.69 (0.000)
UGC-Video	-9.57 (0.000)
Informative-UGC	-13.79 (0.000)
Post-UGC	-14.78 (0.000)
Neg-UGC	-14.35 (0.000)
TMS	-17.2 (0.000)
GT	-9.22 (0.000)
GPI	-6.3 (0.001)
CCI	-10.22 (0.000)
ΔS&P 500	-27.98 (0.000)

Second, I determined the appropriate lag length using a set of criteria: Akaike's information criterion (Zaichkowsky) (Akaike, 1969) and moment and model selection criteria (MMSC) (Andrews & Lu, 2001). As the first step, I followed the standard approach in the VAR literature using AIC (see Holtz-Eakin, Newey, & Rosen, 1988; Love & Zicchino, 2006). Specifically, following Dewan and Ramaprasad (2014), I calculated AIC for each cross section and took the modal value of the optimal lag length among all cross sections. The results indicate that first-order panel VAR (lag 1) is the preferred model. Subsequently, to double check the validity of my selection, I followed Abrigo and Love (2015) to apply the consistent MMSC for GMM models. Andrews and Lu (2001) proposed consistent MMSC for GMM models based on Hansen's (1982) statistic of over-identifying restrictions. Their proposed MMSC are analogous to various commonly used maximum likelihood-based model selection such as AIC. Tables 6 to 12 report the results of MMSC for overall posts, format presentation (link, photo, status, and video), and content of posts (informative and sentiment), respectively. The criterion is to select the test with the smallest MMSC-Bayesian information criterion (MBIC), MMSC-Akaike's information criterion, and MMSC-Hannan and Quinn information criterion (MQIC). The results indicate that the length of lag 1 is the preferred number for each corresponding model, providing further evidence on the legitimacy of the selection of 1 in my research setting.

Table 6. Lag Selection of Overall Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999	50.05	0.059	-213.08	-21.95	-93.17
2	0.999	36.04	0.114	-161.3	-17.95	-71.37
3	0.998	22.79	0.198	-108.7	-13.21	-48.82
4	0.984	5.59	0.779	-60.18	-12.4	-30.20

Notes: CD stands for the overall coefficient of determination; J stands for Hansen's J chi-squared statistic.

Table 7. Lag Selection of Link Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999	70.31	0.0005	-192.76	-1.62	-72.84
2	0.997	35.75	0.12	-161.6	-18.25	-71.66
3	0.994	21.52	0.253	-110.03	-14.47	-50.07
4	-0.001	7.97	0.537	-57.81	-10.02	-27.83

Table 8. Lag Selection of Photo Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999	50.73	0.053	-212.4	-21.26	-92.48
2	0.998	25.28	0.558	-172.07	-28.71	-82.12
3	0.998	15.67	0.615	-115.89	-20.32	-55.93
4	0.991	4.99	0.834	-60.78	-13.00	-30.80

Table 9. Lag Selection of Status Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.997	45.33	0.13	-217.79	-26.66	-97.88
2	0.998	25.39	0.55	-171.95	-28.6	-82.02
3	0.995	16.11	0.58	-115.44	-19.88	-55.48
4	0.983	4.19	0.99	-61.67	-13.89	-31.69

Table 10. Lag Selection of Video Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.995	71.98	0.0003	-191.14	-0.015	-71.23
2	0.981	29.04	0.359	-168.31	-24.96	-78.37
3	0.970	13.05	0.788	-118.51	-22.94	-58.55
4	0.895	5.43	0.795	-60.35	-12.56	-30.37

Table 11. Lag Selection of Informative Post Model

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999	42.37	0.215	-220.75	-29.62	-100.84
2	0.999	26.17	0.509	-171.18	-27.83	-81.24
3	0.998	14.2	0.72	-117.36	-21.79	-57.40
4	0.996	8.94	0.442	-56.83	-9.05	-26.86

Table 12. Lag Selection of Sentiment Post Model

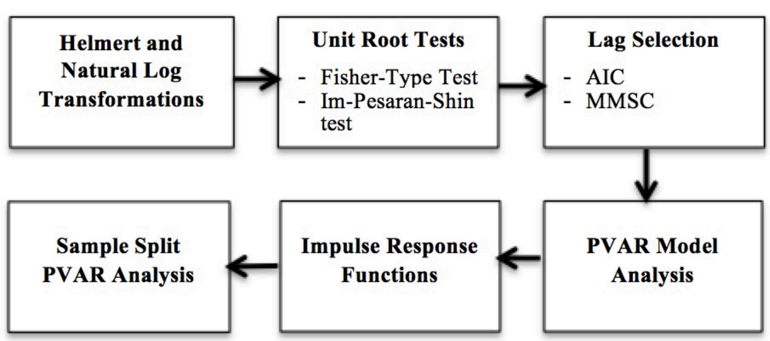
Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999	119.76	0.08	-611.16	-80.23	-278.06
2	0.998	60.42	0.89	-487.76	-89.75	-237.94
3	0.996	37.28	0.91	-328.17	-62.71	-161.63
4	0.976	14.92	0.94	-167.8	-35.07	-84.53

To conduct PVAR analysis, I performed two transformations on all variables: natural log[8] and Helmert transformation. I took the natural log to remove the scaling effects to improve the model fit. Second, although introducing the fixed effects allows us to ensure the underlying structure the same by allowing for individual heterogeneity, these fixed effects are correlated with the regressors due to the lags of the dependent variables (Arellano & Bover, 1995; Dewan

[8] Since some FGC and UGC have zero observations, I added 1 to them before the log transformation.

& Ramaprasad, 2014; Love & Zicchino, 2006). To avoid this problem, I used forward-mean differencing, also referred to as the Helmert transformation (see Arellano & Bover, 1995). This transformation removes the mean of all the future observations available for each and thus ensures orthogonality between the forward-differenced variables and their lagged values (Love & Zicchino, 2006). Accordingly, to address the issue of simultaneity, I can use the lagged regressors as instruments and estimate the coefficient by the system GMM estimator (Arellano & Bover, 1995; Love & Zicchino, 2006). Also, the use of forward orthogonal deviations does not induce autocorrelation in the error terms and frees me from serial correlation (Drakos & Konstantinou, 2014). Finally, I supplemented our PVAR analysis with the impulse response functions (IRFs) to obtain the evolutionary patterns of our interested relationships. Together PVAR and IRFs allow me to gain a comprehensive understanding of the relationships between FGC, UGC, and offline car sales. I then applied the same PVAR analysis for my sample split analysis.

Figure 4. Analysis Procedure



2.5 RESULTS

2.5.1 Main PVAR Analysis Results

2.5.1.1 Effect of Overall Posts

Table 13 shows the estimation results for overall posts (volume). In the *Sales* equation, the coefficient estimate on F-Post at lag 1 is positive (0.032) and statistically significant at the 0.1% level, indicating that FGC at month t-1 positively influences offline car sales at month t and therefore H1 is supported. On the contrary, the coefficient estimate on U-Post is negative (-0.018) and insignificant at the 5% level, thereby rejecting H2. The results from FGC and UGC at the overall post level are the important findings of this study and can be explained by the nature of the durable product and Facebook.

Compared to media and non-durable products (e.g., book, DVD, or music), the vehicle is a durable product. As a result, exposure to UGC may not have a direct impact on offline sales of the durable product because customers may need to invest additional effort before making their purchase decisions. In addition, the nature of Facebook may also matter. Although online review sites and Facebook are all considered social media channels, the purpose of these two platforms is dramatically different. The review site such as Amazon's online review provides an environment for current and potential customers to share their usage experience and help other consumers to make better purchase decisions (Forman et al., 2008). On the other hand, the firm's Facebook fan page provide an environment for customers to express their loyalty, receive the latest information from the firm, and interact with other customers, namely, social networking. Therefore, the various topics on UGC may result in the insignificant effect of UGC on offline car sales. The results from FGC and UGC also imply that firm-initiated Facebook pages play different roles in terms of predicting offline car sales from firms' and customers' perspectives. In addition, the results also appear that offline car sales are positively related to FGC, whereas offline car sales do not have any discernible association with UGC, thereby supporting H3 and rejecting H4. Finally, in the *U-Post* equation, the coefficient estimate on F-Post is positive (0.01) and insignificant at the 5% level, rejecting H5. Furthermore, I also cannot find the positive effect of UGC on FGC, thus rejecting H6.

Table 13. Overall Post PVAR Regression Results

	Dependent variable		
IV	$Sales_{i,t}$	$F\text{-}Post_{i,t}$	$U\text{-}Post_{i,t}$
$Sales_{i,t-1}$	0.574*** (0.059)	0.727*** (0.188)	-0.62 (0.177)
$F\text{-}Post_{i,t-1}$	0.032*** (0.008)	0.701*** (0.032)	0.01 (0.022)
$U\text{-}Post_{i,t-1}$	-0.018^{+} (0.01)	0.049^{+} (0.028)	0.787*** (0.032)
$TMS_{i,t-1}$	0.053*** (0.015)	0.091** (0.034)	0.108** (0.036)
$GT_{i,t-1}$	-0.11^{+} (0.065)	0.059 (0.177)	0.048 (0.193)
GPS_{t-1}	0.145** (0.049)	0.038 (0.155)	0.21 (0.154)
CCI_{t-1}	0.149** (0.038)	-0.247* (0.102)	-0.181^{+} (0.106)
$\Delta S\&P500_{t-1}$	0.248* (0.1)	-0.576^{+} (0.3)	-0.245 (0.289)

Notes: IV stands for the independent variable. Numbers in parentheses are standard errors. Time fixed effects are included in the estimation, but the coefficient estimates are not shown to conserve space. This applies to Tables 7 to 19. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

2.5.1.2 Effect of Format Presentation

To further explore consumers' appreciation on content in different formats and the individual assessment of each format, I differentiated total numbers of posts into four major categories of format presentation at Facebook (link, photo, status, and video), reported in Tables 14 to 17. Table 14 shows the results for posts in the form of link. The results suggest that both

FGC and UGC in the form of link are not effective in driving offline car sales, rejecting both H1 and H2. Furthermore, results support H3 while H4 has to be rejected, suggesting that offline car sales positively influence FGC in the form of link. Finally, I find the support for both H5 and H6, suggesting that there is a positive feedback effect between FGC and UGC in the form of link.

Table 14. Format Presentation: Link PVAR Regression Results

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Link_{i,\,t}$	$U\text{-}Link_{i,\,t}$
$Sales_{i,\,t\text{-}1}$	0.558*** (0.122)	1.61* (0.82)	1.127 (0.89)
$F\text{-}Link_{i,\,t\text{-}1}$	0.008 (0.006)	0.712*** (0.038)	0.09** (0.035)
$U\text{-}Link_{i,\,t\text{-}1}$	-0.004 (0.007)	0.124** (0.042)	0.82*** (0.042)
$TMS_{i,\,t\text{-}1}$	0.084*** (0.02)	-0.178^{+} (0.104)	0.234* (0.117)
$GT_{i,\,t\text{-}1}$	-0.107 (0.128)	1.497 (0.916)	1.65^{+} (0.969)
$GPS_{t\text{-}1}$	0.171* (0.088)	-1.161* (0.627)	-0.234 (0.573)
$CCI_{t\text{-}1}$	0.249*** (0.07)	-1.677** (0.482)	0.064 (0.456)
$\Delta S\&P500_{t\text{-}1}$	0.449*** (0.126)	-2.29** (0.823)	-0.951 (0.805)

Tables 15 and 16 show the results for posts in the form of photo and status, respectively. These results indicate similar patterns even though they show different trends compared to the results in Table 14, suggesting that different forms of format presentation have different impacts in influencing offline car sales and customer engagements. For example, FGC in the form of photo and status is effective in predicting offline car sales with the stronger effect via FGC in the form of status, in support of H1, while H2 is rejected. I also find evidence that offline car sales are positively associated with FGC, confirming H3, while offline car sales do not positively influence UGC. Finally, there is no positive feedback effect between FGC and UGC in the form of photo and status, rejecting H5 and H6.

Table 15. Format Presentation: Photo PVAR Regression Results

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Photo_{i,\,t}$	$U\text{-}Photo_{i,\,t}$
$Sales_{i,\,t\text{-}1}$	0.523*** (0.081)	1.48** (0.49)	0.381 (0.327)
$F\text{-}Photo_{i,\,t\text{-}1}$	0.01** (0.005)	0.77*** (0.03)	-0.002 (0.018)
$U\text{-}Photo_{i,\,t\text{-}1}$	-0.003 (0.006)	-0.06^{+} (0.038)	0.79*** (0.029)
$TMS_{i,\,t\text{-}1}$	0.051** (0.015)	0.084 (0.071)	0.164** (0.049)

Table 15 (cont'd)

$GT_{i, t-1}$	-0.13^{+} (0.076)	1.2* (0.543)	0.482 (0.297)
GPS_{t-1}	0.18*** (0.053)	0.807* (0.37)	0.396^{+} (0.228)
CCI_{t-1}	0.166*** (0.048)	-0.207 (0.265)	-0.182 (0.18)
$\Delta S\&P500_{t-1}$	0.301** (0.104)	-0.601 (0.651)	0.647 (0.438)

Table 16. Format Presentation: Status PVAR Regression Results

	Dependent variable		
IV	$Sales_{i, t}$	$F\text{-}Status_{i, t}$	$U\text{-}Status_{i, t}$
$Sales_{i, t-1}$	0.448** (0.113)	1.26* (0.51)	0.48 (0.454)
$F\text{-}Status_{i, t-1}$	0.022** (0.007)	0.66*** (0.033)	-0.01 (0.031)
$U\text{-}Status_{i, t-1}$	-0.014 (0.011)	-0.009 (0.041)	0.7*** (0.052)
$TMS_{i, t-1}$	0.09*** (0.019)	0.007 (0.06)	0.064 (0.06)
$GT_{i, t-1}$	-0.198^{+} (0.118)	0.103 (0.43)	1.19* (0.467)
GPS_{t-1}	0.222** (0.075)	-0.74* (0.33)	0.34 (0.31)
CCI_{t-1}	0.317*** (0.074)	-1.48*** (0.336)	-0.67* (0.291)
$\Delta S\&P500_{t-1}$	0.427** (0.131)	-2.38*** (0.59)	-0.63 (0.479)

Table 17 shows the results for posts in the form of video. In this relationship, I only observe that that user-generated videos positively influence the number of firm-generated videos, supporting my H6. Together, we see that the dynamic relationships shown in Figure 1 vary across different forms of format presentation, implying that firms need to leverage different combinations of formats to maximize the utility of each post. Specifically, FGC in the form of photo and status drives consumptions. However, UGC in any form of format presentation does not influences offline car sales, contrary to the general belief that UGC is effective in influencing sales. In addition, the positive feedback between UGC and FGC only exits in the form of link. I also observe that UGC in the form of video positively influences FGC in the form of video. Finally, offline car sales positively influence FGC in the form of link, photo, and status.

Table 17. Format Presentation: Video PVAR Regression Results

	Dependent variable		
IV	$Sales_{i, t}$	$F\text{-}Video_{i, t}$	$U\text{-}Video_{i, t}$
$Sales_{i, t-1}$	0.6*** (0.07)	0.303 (0.34)	0.46 (0.37)
$F\text{-}Video_{i, t-1}$	0.008 (0.006)	0.466*** (0.02)	0.013 (0.027)
$U\text{-}Video_{i, t-1}$	-0.002 (0.006)	0.09** (0.03)	0.832*** (0.038)
$TMS_{i, t-1}$	0.06** (0.022)	0.065 (0.06)	0.098 (0.072)
$GT_{i, t-1}$	-0.186^{+} (0.101)	-0.637 (0.46)	-0.53 (0.48)
GPS_{t-1}	0.159* (0.062)	-0.032 (0.35)	0.22 (0.42)
CCI_{t-1}	0.161*** (0.043)	-0.46* (0.213)	-0.02 (0.218)
$\Delta S\&P500_{t-1}$	0.442** (0.11)	-0.175 (0.53)	-0.725 (0.598)

2.5.1.3 Effect of Content

To investigate what kinds of content matters in influencing offline car sales and customer engagements, I followed prior research to use the keyword approach to conduct our content analysis (e.g., Chen et al., 2015; Shen et al., 2015). Specifically, I used the frequency of keywords to measure if a post belongs to our interested categories. The underlying rationale is that when a certain keyword appears, I can use that keyword to classify the topics discussed in posts. I relied on nine categories of the Harvard General Inquirer to identify informative posts: "*exch", "place", "goal", "know", "quality", "quan", "numb", "space", and "compare"*[9]. For sentiment analysis, I leveraged "*positive"* and *"negative"* categories from the Harvard General Inquirer. Table 18 shows the examples of these posts. Tables 19 and 20 show the results of these two aspects respectively. The results from informative posts (see Table 19) only support our H1 and H3, suggesting that firm's attribute-based posts positively influence customers' offline commerce activities and vice versa. I now turn my attention to the sentiment of posts. Given that I have more than one variable in each category (e.g., positive FGC and negative FGC), I only present our findings here instead of examining each hypothesis described above.

Table 18. Examples of Content

Category	Sample Messages
Informative FGC	*Our Project Driveway program featuring Equinox fuel cell EVs powered by hydrogen passed 1 million miles this week. No other automaker comes close to the number of miles we've driven in real world conditions with real people driving these vehicles. Check out this Good Morning America segment from today's show. (Chevrolet, 2009.9)*
Informative UGC	*Would be nice if Ford offered this to other C-max as a retrofit. Shouldn't be to hard fasten on top and Run a wire to the batteries. Charge a few hundred bucks*

[9] Categories of Harvard General Inquirer: http://www.wjh.harvard.edu/~inquirer/homecat.htm

Table 18 (cont'd)

	to do it (Ford's user, 2014.1).
Positive FGC	*The Mustang can inspire powerful moments and create memories that are as unique as you are. Capture your moment in a photo and post it to Instagram using the #MustangInspires hashtag bit.ly/1eokGYK. (Ford, 2013.10)*
Negative FGC	*We want to let you know that we are conducting a voluntary safety recall on the 2010 model year Lexus HS 250h vehicles to update software in the anti-lock brake system. For more information, please visit Our Newsroom at http://bit.ly/ds2BRy. (Lexus, 2010.2)s*
Positive UGC	*Got this yesterday. I LOVE YOU HONDA. (Honda's user, 2013.5)*
Negative UGC	*I have a 2010 White Toyota Sienna. The Van has dulled out spots all over it. The problem was noticed about 6 months after we bought the van brand in 2010. What can I do to get these dull spots out. It looks awful. Never had this problem with other vehicles. (Toyota's user, 2014.6)*

In the *Sales* equation, the results appear that positive FGC positively affects offline car sales and negative UGC negatively affects offline car sales. In the *Pos-F* equation, I find that both offline car sales and negative FGC positively influence positive FGC. Furthermore, in the *Neg-F* equation, offline car sales, positive FGC, and negative UGC positively influence negative FGC, while positive UGC negatively affects the number of negative FGC. Finally, I observe that the more positive UGC at time t-1, the more negative UGC at time t. This is a very interesting finding and suggests the importance of the firm's effective control and management on social media (Miller & Tucker, 2013). Particularly, given my finding, firms could benefit of more positive UGC, on one hand, and these positive UGC could backfire by triggering more negative UGC, on the other hand. Although firms' Facebook pages provide a good channel for customers to voice opinions, firms should pay special attention to what customers really talk about or address customers' complaints in a timely manner. For example, firms should contact users with negative experience to figure out the issues of their products/services more effectively or provide some incentives for users who show concerns on firms' products/services. By these approaches, firms could fully leverage social media to trigger more positive UGC and reduce negative UGC simultaneously.

Table 19. Informative Post PVAR Regression Results

	Dependent variable		
IV	$Sales_{i,\,t}$	$Info\text{-}F_{i,\,t}$	$Info\text{-}U_{i,\,t}$
$Sales_{i,\,t-1}$	0.42*** (0.084)	1.0*** (0.25)	-0.03 (0.241)
$Info\text{-}F_{i,\,t-1}$	0.027* (0.01)	0.68*** (0.03)	0.005 (0.028)
$Info\text{-}U_{i,\,t-1}$	-0.014 (0.013)	0.02 (0.03)	0.69*** (0.042)
$TMS_{i,\,t-1}$	0.079*** (0.017)	0.085* (0.038)	0.087* (0.04)
$GT_{i,\,t-1}$	-0.17 (0.112)	0.28 (0.263)	0.35 (0.29)
GPS_{t-1}	0.179* (0.073)	0.005 (0.193)	0.63** (0.192)
CCI_{t-1}	0.267*** (0.051)	-0.4* (0.11)	-0.15 (0.13)
$\Delta S\&P500_{t-1}$	0.51*** (0.126)	-0.31 (0.32)	-0.03 (0.321)

Table 20. Sentiment PVAR Regression Results

			Dependent variable		
IV	$Sales_{i,\,t}$	$Pos\text{-}F_{i,\,t}$	$Neg\text{-}F_{i,\,t}$	$Pos\text{-}U_{i,\,t}$	$Neg\text{-}U_{i,\,t}$
$Sales_{i,\,t-1}$	0.527*** (0.052)	0.416** (0.142)	0.371* (0.418)	0.31^{+} (0.166)	-0.008 (0.169)
Table 20 (cont'd)					
$Pos\text{-}F_{i,\,t-1}$	0.022** (0.008)	0.689*** (0.025)	0.081** (0.026)	-0.028 (0.024)	-0.001 (0.025)
$Neg\text{-}F_{i,\,t-1}$	-0.01^{+} (0.006)	0.036* (0.017)	0.117*** (0.02)	0.032^{+} (0.019)	0.014 (0.019)
$Pos\text{-}U_{i,\,t-1}$	0.012^{+} (0.012)	0.012 (0.03)	-0.082* (0.036)	0.777*** (0.037)	0.183*** (0.037)
$Neg\text{-}U_{i,\,t-1}$	-0.02* (0.011)	-0.007 (0.028)	0.121*** (0.036)	0.005 (0.032)	0.603*** (0.63
$TMS_{i,\,t-1}$	0.078*** (0.013)	0.18*** (0.031)	-0.067^{+} (0.043)	0.17*** (0.042)	0.115** (0.039
$GT_{i,\,t-1}$	-0.17* (0.07)	0.088 (0.183)	0.247 (0.248)	0.371 (0.238)	0.08 (0.227)
GPS_{t-1}	0.11* (0.048)	0.171 (0.135)	-0.5** (0.178)	0.091 (0.157)	0.26^{+} (0.15)
CCI_{t-1}	0.234*** (0.034)	-0.156^{+} (0.091)	-0.171 (0.133)	-0.304** (0.107)	0.024 (0.105)
$\Delta S\&P500_{t-1}$	0.525*** (0.096)	0.09 (0.269)	-0.384 (0.342)	-0.038 (0.293)	-0.25 (0.293)

2.5.2 Sample Split PVAR Analysis Results

I next explore how the relationships in Figure 1 vary for firm characteristics (luxury brands versus non-luxury brands)[10]. Descriptive statistics for luxury and non-luxury are shown in Tables 21 and 22, respectively. The PVAR results for luxury versus non-luxury are reported in Tables 23 to 36.

Table 21. Descriptive Statistics for Luxury Car Makes

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	787	11429.27	8620.54	97	43981
FGC-Post	787	30.78	24.78	0	436
FGC-Link	787	5.48	7.33	0	51
FGC-Photo	787	19.36	24.69	0	422

[10] Luxury: Acura, Audi, BMW, Buick, Cadillac, Infiniti, Jaguar, Lexus, Mercedes-Benz, Porsche, Volvo, Lincoln, Saab, and Land Rover. Non-Luxury: Chevrolet, Chrysler, Dodge, Ford, Honda, Hyundai, KIA, Mazda, Mitsubishi, Nissan, Toyota, Volkswagen, Subaru, FIAT, Jeep, and Scion.

Table 21 (cont'd)

FGC-Status	787	2.14	3.58	0	37
FGC-Video	787	3.35	3.30	0	17
Informative-FGC	787	23.86	13.14	0	81
Pos-FGC	787	19.1	10.53	0	74
Neg-FGC	787	0.93	1.06	0	5
UGC-Post	787	246.52	212.78	4	1557
UGC-Link	787	31.91	46.23	0	353
UGC-Photo	787	80.64	105.41	0	1422
UGC-Status	787	122.79	113.77	0	977
UGC-Video	787	11.32	19.51	0	380
Informative-UGC	787	141.93	108.30	6	879
Pos-UGC	787	97.39	135.36	3	3212
Neg-UGC	787	33.77	51.17	0	879
TMS	787	17803196.95	12804924.54	14800	75289900
GT	787	65.47	17.28	23	100
GPI	787	3.43	0.38	2.59	3.98
CCI	787	66.47	12.82	40.9	94.1
S&P 500	787	1444.49	286.04	919.32	2018.05

Table 22. Descriptive Statistics for non-Luxury Car Makes

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	977	60565.53	55528.65	500	245239
FGC-Post	977	35.75	40.92	0	1042
FGC-Link	977	7.53	9.48	0	62
FGC-Photo	977	21.89	38.47	0	973
FGC-Status	977	2.85	7.38	0	74
FGC-Video	977	3.05	3.38	0	20
Informative-FGC	977	27.02	16.9	0	218
Pos-FGC	977	21.28	14.11	0	170
Neg-FGC	977	0.91	1.09	0	6
UGC-Post	977	524.58	507.28	4	3543
UGC-Link	977	47.16	58.99	0	487
UGC-Photo	977	184.06	24558	0	1910
UGC-Status	977	275.04	301.08	0	2512
UGC-Video	977	18.35	21.41	0	182
Informative-UGC	977	350.87	325.28	0	2439
Pos-UGC	977	220.39	212.17	0	1512
Neg-UGC	977	80.49	77.27	0	654
TMS	977	47693184.08	40253712.69	238700	197000000
GT	977	57.98	19.18	16	100
GPI	977	3.40	0.4	2.31	3.98
CCI	977	66.25	12.87	40.9	94.1
S&P 500	977	1436.49	291.35	919.14	2018.05

2.5.2.1 Effect of Overall Posts

Tables 23 and 24 shows results for overall posts for the luxury and non-luxury groups, respectively. Consistent with my main results (see Table 4), FGC shows a positive impact on offline cars sales for both luxury and non-luxury groups, although the magnitude of the coefficient for the luxury group is larger than the corresponding coefficient for the non-luxury group. I also observe that offline car sales also positively influence FGC for both groups and that the magnitude of the coefficient for the non-luxury group is larger than the corresponding coefficient for the luxury group. Finally, FGC positively influence the volume of UGC for the luxury group, whereas it does not have any impact on UGC for the non-luxury group.

Table 23. Overall PVAR Regression Results (Luxury)

IV	Dependent variable $Sales_{i,\,t}$	$F\text{-}Post_{i,\,t}$	$U\text{-}Post_{i,\,t}$
$Sales_{i,\,t-1}$	0.444*** (0.073)	0.453*** (0.183)	-0.054 (0.214)
$F\text{-}Post_{i,\,t-1}$	0.04** (0.013)	0.67*** (0.045)	0.109** (0.032)
$U\text{-}Post_{i,\,t-1}$	-0.008 (0.0014)	0.012 (0.037)	0.689*** (0.044)
$TMS_{i,\,t-1}$	0.096*** (0.018)	0.089* (0.039)	0.035 (0.041)
$GT_{i,\,t-1}$	-0.304 (0.209)	1.152* (0.516)	-0.636 (0.531)
GPS_{t-1}	0.008 (0.073)	0.371^{+} (0.203)	0.143 (0.197)
CCI_{t-1}	0.285*** (0.05)	-0.24^{+} (0.132)	-0.24^{+} (0.138)
$\Delta S\&P500_{t-1}$	0.653*** (0.155)	0.078 (0.423)	-0.527 (0.402)

Table 24. Overall PVAR Regression Results (Non-Luxury)

IV	Dependent variable $Sales_{i,\,t}$	$F\text{-}Post_{i,\,t}$	$U\text{-}Post_{i,\,t}$
$Sales_{i,\,t-1}$	0.583*** (0.07)	0.801** (0.238)	-0.359 (0.22)
$F\text{-}Post_{i,\,t-1}$	0.024* (0.009)	0.75*** (0.044)	-0.007 (0.029)
$U\text{-}Post_{i,\,t-1}$	-0.017 (0.0012)	0.059 (0.04)	0.791*** (0.04)
$TMS_{i,\,t-1}$	0.047** (0.021)	0.09 (0.081)	0.205* (0.085)
$GT_{i,\,t-1}$	-0.08 (0.068)	0.35 (0.216)	0.201 (0.193)
GPS_{t-1}	0.187* (0.077)	-0.148 (0.279)	0.329 (0.215)
CCI_{t-1}	0.186*** (0.041)	-0.33* (0.14)	0.124 (0.126)
$\Delta S\&P500_{t-1}$	0.413** (0.139)	-1.17* (0.442)	0.036 (0.366)

2.5.2.2 Effect of Format Presentation

Tables 25 and 26 shows the results of the sample split for posts in the form of link for two groups, respectively. The findings for the non-luxury group are consistent with our main results shown in Table 14 while there are some differences for the luxury group.

Table 25. Link PVAR Regression Results (Luxury)

IV	Dependent variable $Sales_{i,\,t}$	$F\text{-}Link_{i,\,t}$	$U\text{-}Link_{i,\,t}$
$Sales_{i,\,t-1}$	0.596*** (0.062)	0.285 (0.246)	0.714** (0.252)
$F\text{-}Link_{i,\,t-1}$	-0.002 (0.007)	0.815*** (0.026)	0.064* (0.029)
$U\text{-}Link_{i,\,t-1}$	0.001 (0.007)	0.053* (0.025)	0.908*** (0.03)
$TMS_{i,\,t-1}$	0.093*** (0.015)	0.041 (0.051)	-0.086 (0.053)
$GT_{i,\,t-1}$	-0.022 (0.142)	0.057 (0.515)	-0.635 (0.598)
GPS_{t-1}	0.11 (0.071)	-0.791** (0.286)	0.729* (0.348)
CCI_{t-1}	0.16** (0.051)	-0.708** (0.215)	-0.039 (0.218)
$\Delta S\&P500_{t-1}$	0.612*** (0.139)	-2.779*** (0.536)	-0.811 (0.586)

Table 26. Link PVAR Regression Results (Non-Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Link_{i,\,t}$	$U\text{-}Link_{i,\,t}$
$Sales_{i,\,t\text{-}1}$	0.602*** (0.086)	1.14* (0.469)	0.277 (0.417)
$F\text{-}Link_{i,\,t\text{-}1}$	0.008 (0.006)	0.71*** (0.038)	0.059* (0.028)
$U\text{-}Link_{i,\,t\text{-}1}$	-0.004 (0.006)	0.166*** (0.042)	0.933*** (0.03)
$TMS_{i,\,t\text{-}1}$	0.04 (0.026)	-0.296^{+} (0.155)	0.263* (0.141)
$GT_{i,\,t\text{-}1}$	0.013 (0.066)	-0.372 (0.42)	0.024 (0.341)
$GPS_{t\text{-}1}$	0.217* (0.096)	-1.67** (0.55)	-0.879^{+} (0.493)
$CCI_{t\text{-}1}$	0.212*** (0.06)	-1.55*** (0.379)	0.32 (0.296)
$\Delta S\&P500_{t\text{-}1}$	0.524*** (0.138)	-2.217* (0.96)	0.482 (0.711)

Tables 27 and 28 present the results of the sample split for posts in the form of photo for two groups. The results for the non-luxury group are consistent with major results (Table 15). Interestingly, for the luxury group, the findings indicate that both FGC and UGC positively influence offline car sales and the impact of UGC on sales is stronger than the impact of FGC on sales, suggesting that for customers in the luxury group, they rely more on other customers' opinions in the form of photo to make purchase decisions than firms' activities. However, for the non-luxury group, we cannot observe this relationship, implying that customers in different groups focus on different aspects when making their purchase decisions. Furthermore, I find that although offline car sales are positively associated with FGC for both groups, the magnitude of the coefficient for the non-luxury group is larger than the corresponding coefficient for the luxury group.

Table 27. Photo PVAR Regression Results (Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Photo_{i,\,t}$	$U\text{-}Photo_{i,\,t}$
$Sales_{i,\,t\text{-}1}$	0.549*** (0.052)	0.398*** (0.17)	0.198 (0.185)
$F\text{-}Photo_{i,\,t\text{-}1}$	0.01* (0.005)	0.818*** (0.029)	-0.007 (0.023)
$U\text{-}Photo_{i,\,t\text{-}1}$	0.017** (0.006)	-0.015 (0.027)	0.823*** (0.03)
$TMS_{i,\,t\text{-}1}$	0.102*** (0.013)	-0.004 (0.037)	0.211*** (0.034)
$GT_{i,\,t\text{-}1}$	-0.152^{+} (0.092)	0.527 (0.349)	-0.116 (0.292)
$GPS_{t\text{-}1}$	-0.065 (0.047)	0.658** (0.235)	0.589** (0.212)
$CCI_{t\text{-}1}$	0.169*** (0.033)	0.134 (0.14)	-0.201 (0.14)
$\Delta S\&P500_{t\text{-}1}$	0.231* (0.114)	0.319 (0.511)	1.937*** (0.465)

Table 28. Photo PVAR Regression Results (Non-Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Photo_{i,\,t}$	$U\text{-}Photo_{i,\,t}$
$Sales_{i,\,t-1}$	0.624*** (0.078)	1.00* (0.365)	0.2 (0.343)
$F\text{-}Photo_{i,\,t-1}$	0.013* (0.005)	0.835*** (0.037)	0.028 (0.023)
$U\text{-}Photo_{i,\,t-1}$	-0.003 (0.009)	-0.001 (0.043)	0.78*** (0.05)
$TMS_{i,\,t-1}$	0.001 (0.019)	0.049 (0.109)	0.011 (0.114)
$GT_{i,\,t-1}$	-0.163* (0.078)	1.05** (0.393)	0.674* (0.343)
GPS_{t-1}	0.178* (0.073)	0.657 (0.416)	0.474 (0.331)
CCI_{t-1}	0.093* (0.044)	-0.275 (0.232)	-0.225 (0.189)
$\Delta S\&P500_{t-1}$	0.21 (0.141)	-0.177 (0.722)	0.36 (0.559)

The results for posts in the form of status for two groups, shown in Tables 29 and 30, also indicate interesting patterns. For example, I find that FGC positively influence offline sales of the non-luxury group, whereas FGC is not effective in driving offline car sales of the luxury group. I also observe that offline car sales positively influence FGC for both groups, although the magnitude of the coefficient for the non-luxury group is stronger than the corresponding coefficient for the luxury group. Finally, FGC positively influence UGC for the luxury group, whereas FGC does not have any impact on UGC for the non-luxury group.

Table 29. Status PVAR Regression Results (Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Status_{i,\,t}$	$U\text{-}Status_{i,\,t}$
$Sales_{i,\,t-1}$	0.591*** (0.073)	1.001*** (0.278)	-0.014 (0.195)
$F\text{-}Status_{i,\,t-1}$	0.003 (0.007)	0.74*** (0.032)	0.051* (0.025)
$U\text{-}Status_{i,\,t-1}$	-0.007 (0.001)	0.034 (0.039)	0.741*** (0.043)
$TMS_{i,\,t-1}$	0.097*** (0.018)	-0.059 (0.05)	0.029 (0.042)
$GT_{i,\,t-1}$	-0.241 (0.179)	-0.771 (0.68)	1.253** (0.496)
GPS_{t-1}	0.084 (0.061)	-0.806** (0.253)	0.342^{+} (0.176)
CCI_{t-1}	0.243** (0.055)	-1.101*** (0.212)	-0.359* (0.157)
$\Delta S\&P500_{t-1}$	0.52*** (0.152)	0.743 (0.551)	-0.231 (0.442)

Table 30. Status PVAR Regression Results (Non-Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Status_{i,\,t}$	$U\text{-}Status_{i,\,t}$
$Sales_{i,\,t-1}$	0.55*** (0.101)	1.76* (0.85)	0.337 (0.47)
$F\text{-}Status_{i,\,t-1}$	0.016* (0.007)	0.58*** (0.066)	0.007 (0.035)
$U\text{-}Status_{i,\,t-1}$	-0.02^{+} (0.011)	0.1 (0.096)	0.73*** (0.06)
$TMS_{i,\,t-1}$	0.06* (0.03)	0.145 (0.256)	0.116 (0.137)
$GT_{i,\,t-1}$	0.011 (0.069)	0.202 (0.574)	0.491 (0.426)
GPS_{t-1}	0.269** (0.088)	-1.31 (0.851)	0.422 (0.426)
CCI_{t-1}	0.2*** (0.065)	-1.87*** (0.66)	-0.568^{+} (0.31)
$\Delta S\&P500_{t-1}$	0.45*** (0.144)	-4.44** (1.64)	-1.11^{+} (0.65)

I find another interesting patterns for posts in the form of video, as shown in Tables 31 and 32. For example, the results from the non-luxury group are consistent with the main results, supporting H6. However, for the luxury group, I observe that there is a positive feedback effect between UGC and FGC, supporting both H5 and H6. In addition, offline car sales also positively influence UGC, supporting H4.

Table 31. Video PVAR Regression Results (Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Video_{i,\,t}$	$U\text{-}Video_{i,\,t}$
$Sales_{i,\,t-1}$	0.529*** (0.068)	0.269 (0.324)	0.766* (0.341)
$F\text{-}Video_{i,\,t-1}$	0.004 (0.007)	0.452*** (0.037)	0.081* (0.037)
$U\text{-}Video_{i,\,t-1}$	-0.014 (0.009)	0.103* (0.041)	0.798*** (0.043)
$TMS_{i,\,t-1}$	0.095*** (0.017)	0.076 (0.059)	-0.062 (0.061)
$GT_{i,\,t-1}$	-0.008 (0.125)	0.049 (0.604)	-0.773 (0.625)
GPS_{t-1}	0.191* (0.008)	-0.252 (0.407)	0.562 (0.422)
CCI_{t-1}	0.247*** (0.049)	-0.618** (0.227)	-0.118 (0.235)
$\Delta S\&P500_{t-1}$	0.532*** (0.154)	-0.948 (0.644)	-1.268^{+} (0.656)

Table 32. Video PVAR Regression Results (Non-Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$F\text{-}Video_{i,\,t}$	$U\text{-}Video_{i,\,t}$
$Sales_{i,\,t-1}$	0.714*** (0.069)	0.26 (0.369)	0.27 (0.355)
$F\text{-}Video_{i,\,t-1}$	0.008 (0.005)	0.535*** (0.033)	0.042 (0.034)
$U\text{-}Video_{i,\,t-1}$	-0.002 (0.007)	0.085* (0.042)	0.84*** (0.047)
$TMS_{i,\,t-1}$	0.017 (0.02)	0.151 (0.098)	0.315* (0.129)
$GT_{i,\,t-1}$	-0.008 (0.06)	-0.345 (0.338)	-0.088 (0.373)
GPS_{t-1}	0.08 (0.008)	-0.033 (0.491)	0.074 (0.55)
CCI_{t-1}	0.106* (0.042)	-0.281 (0.255)	0.093 (0.247)
$\Delta S\&P500_{t-1}$	0.349** (0.121)	0.372 (0.652)	1.46^{+} (0.79)

2.5.2.3 Effect of Content

Tables 33 and 34 shows the results of the sample split for informative posts. Consistent with major results (Table 19), there is a positive feedback effect between informative FGC and offline car sales (H1 and H3). In particular, in the *Sales* equation, the magnitude of the coefficient from *Info-F* for the luxury group is larger than the corresponding coefficient for the non-luxury group. On the other hand, in the *Info-F* equation, the magnitude of the coefficient from *Sales* for the non-luxury group is larger than the corresponding coefficient for the luxury group.

Table 33. Informative Post PVAR Regression Results (Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$Info\text{-}F_{i,\,t}$	$Info\text{-}U_{i,\,t}$
$Sales_{i,\,t-1}$	0.41*** (0.072)	0.45* (0.211)	-0.21 (0.18)
$Info\text{-}F_{i,\,t}$	0.043* (0.016)	0.71*** (0.039)	0.035 (0.035)
$Info\text{-}U_{i,\,t}$	-0.021 (0.017)	-0.043 (0.045)	0.68*** (0.053)
$TMS_{i,\,t-1}$	0.121*** (0.018)	0.092* (0.039)	0.069^{+} (0.037)
$GT_{i,\,t-1}$	0.012 (0.266)	0.097 (0.75)	-0.5 (0.65)
GPS_{t-1}	0.097 (0.085)	0.6* (0.24)	0.756*** (0.21)
CCI_{t-1}	0.285*** (0.053)	-0.33* (0.149)	-0.19 (0.136)
$\Delta S\&P500_{t-1}$	0.6*** (0.164)	0.171 (0.42)	-0.592 (0.4)

Table 34. Informative Post PVAR Regression Results (Non-Luxury)

	Dependent variable		
IV	$Sales_{i,\,t}$	$Info\text{-}F_{i,\,t}$	$Info\text{-}U_{i,\,t}$
$Sales_{i,\,t-1}$	0.51*** (0.07)	0.72** (0.21)	-0.12 (0.23)
$Info\text{-}F_{i,\,t}$	0.027** (0.009)	0.72** (0.035)	-0.02(0.03)
$Info\text{-}U_{i,\,t}$	-0.019 (0.012)	0.037 (0.035)	0.78*** (0.047)
$TMS_{i,\,t-1}$	0.042* (0.02)	0.08 (0.06)	0.172^{+} (0.091)
$GT_{i,\,t-1}$	-0.1 (0.72)	0.33* (0.159)	0.231 (0.2)
GPS_{t-1}	0.2** (0.078)	-0.077 (0.239)	0.31 (0.237)
CCI_{t-1}	0.19*** (0.042)	-0.21^{+} (0.11)	0.08 (0.12)
$\Delta S\&P500_{t-1}$	0.45** (0.138)	-0.67* (0.34)	0.13 (0.38)

Tables 35 and 36 shows the results of the sample split for sentiment of posts. First, for the luxury group, the results appear that negative FGC and positive UGC positively influence car sales. Surprisingly, I cannot find the positive impact of positive FGC on offline car sales. This seems to suggest that for customers who purchase luxury cars, they already have their strong mindsets regarding their purchase decisions. That is, they may not pay special attentions to positive contents that firms try to deliver to them to influence their purchase decisions. On the other hand, for the same group of customers, they may pay attention to negative FGC and these negative FGC may influence their purchase decisions. The fact that negative FGC positively influences offline car sales is also a very interesting finding because it contradicts the general belief that negative posts may have the negative impact on sales. However, my detailed examination on those negative FGC shows that these negative posts are exclusively the company's voluntary announcements on vehicle recalls[11]. The current literature suggests that negative posts can still increase sales by increasing product awareness (Berger, Sorensen, & Rasmussen, 2010).

In addition, prior research also indicates that automobile companies can leverage social media to discover vehicle defect efficiently and manage their reputation before it becomes crisis (Abrahams, Jiao, Wang, & Fan, 2012; Yan Liu & Shankar, 2015). In fact, practitioners start to utilize social media to mitigate the impact of the negative events such as vehicle recalls[12]. Therefore, the results for the luxury group represent one example of how firms can leverage social media to increase customers' awareness and mitigate the impact of the negative events. In contrast to the luxury group, positive FGC positively influences offline car sales of the non-luxury group, while negative UGC negatively influences offline car sales of the non-luxury. The rest of comparisons between these groups provide further evidence that customers' evaluations of sentiment in two groups demonstrate different patterns.

Table 35. Sentiment PVAR Regression Results (Luxury)

	Dependent variable				
IV	$Sales_{i,t}$	$Pos\text{-}F_{i,t}$	$Neg\text{-}F_{i,t}$	$Pos\text{-}U_{i,t}$	$Neg\text{-}U_{i,t}$
$Sales_{i,t-1}$	0.535*** (0.037)	0.178^{+} (0.095)	0.176 (0.136)	0.204* (0.098)	-0.15 (0.11)
$Pos\text{-}F_{i,t-1}$	0.005 (0.008)	0.71*** (0.025)	0.121*** (0.026)	0.12*** (0.023)	0.163*** (0.027)
$Neg\text{-}F_{i,t-1}$	0.026** (0.007)	0.095*** (0.018)	0.198*** (0.026)	0.01 (0.01)	0.005 (0.02)
$Pos\text{-}U_{i,t-1}$	0.022* (0.011)	0.055* (0.027)	-0.139*** (0.032)	0.846*** (0.025)	0.1** (0.036)
$Neg\text{-}U_{i,t-1}$	-0.015 (0.01)	0.014 (0.027)	0.09** (0.033)	-0.094*** (0.02)	0.62*** (0.03)
$TMS_{i,t-1}$	0.11*** (0.011)	0.1*** (0.022)	-0.039 (0.032)	0.059* (0.024)	-0.02 (0.03)
$GT_{i,t-1}$	-0.455* (0.12)	-0.43 (0.28)	-1.72*** (0.41)	-0.78* (0.3)	-1.3*** (0.37)
GPS_{t-1}	0.049 (0.045)	0.13 (0.12)	-0.029 (0.14)	0.09 (0.11)	0.19 (0.13)

[11] One example of negative FGC from Lexus: https://www.facebook.com/90671958533/posts/296236784524

[12] http://www.nytimes.com/2014/03/24/business/after-huge-recall-gm-speaks-to-customers-through-social-media.html?_r=0

Table 35 (cont'd)

CCI_{t-1}	0.227*** (0.029)	-0.189 (0.075)	-0.038 (0.109)	-0.35*** (0.292)	-0.08 (0.098)
$\Delta S\&P500_{t-1}$	1.04*** (0.1)	1.09*** (0.252)	-0.178 (0.352)	0.15 (0.272)	-0.11 (0.303)

Table 36. Sentiment PVAR Regression Results (Non-Luxury)

	Dependent variable				
IV	$Sales_{i, t}$	$Pos\text{-}F_{i, t}$	$Neg\text{-}F_{i, t}$	$Pos\text{-}U_{i, t}$	$Neg\text{-}U_{i, t}$
$Sales_{i, t-1}$	0.517*** (0.068)	0.91*** (0.193)	0.621* (0.3)	-0.142 (0.235)	-0.4 (0.3)
$Pos\text{-}F_{i, t-1}$	0.03*** (0.009)	0.681*** (0.035)	0.019 (0.037)	-0.004 (0.029)	-0.042 (0.037)
$Neg\text{-}F_{i, t-1}$	-0.013^{+} (0.007)	0.032 (0.023)	0.08* (0.033)	0.03 (0.027)	0.017 (0.028)
$Pos\text{-}U_{i, t-1}$	0.009 (0.016)	0.013 (0.049)	0.122* (0.06)	0.6*** (0.06)	0.296*** (0.063)
$Neg\text{-}U_{i, t-1}$	-0.03* (0.015)	0.045 (0.046)	-0.023 (0.056)	0.117** (0.043)	0.45*** (0.06)
$TMS_{i, t-1}$	0.06** (0.02)	0.017 (0.063)	-0.0001 (0.11)	0.193* (0.08)	0.359** (0.1)
$GT_{i, t-1}$	-0.09 (0.06)	0.416** (0.16)	0.489^{+} (0.251)	0.266 (0.175)	0297 (0.241)
GPS_{t-1}	0.267*** (0.075)	-0.169 (0.243)	-1.16*** (0.178)	0.391 (0.243)	0.609* (0.3)
CCI_{t-1}	0.211*** (0.043)	-0.337** (0.129)	0.075 (0.192)	-0.111 (0.135)	0.442** (0.168)
$\Delta S\&P500_{t-1}$	0.429** (0.124)	-1.95*** (0.373)	-0.29 (0.519)	-0.714* (0.363)	0.2 (0.464)

Taken together, the luxury/non-luxury sample split suggests again that different forms of format presentation and contents of post show different patterns on customers' online engagements and offline commerce activities. In addition, each car brand, depending on its belonging group, would take the dramatically different approaches to boost offline sales and encourage customer engagements. The summary of PVAR analysis results is shown in Table 37.

Table 37. Summary of Results

Analysis level	Results
Whole sample	
Overall Post	H1 and H3
Link	H3, H5, and H6
Photo	H1 and H3
Status	H1 and H3
Video	H6
Informative Post	H1 and H3
Sentiment	PF->S, NU (-)-> S, S ->PF, NF->PF, S-> NF, PF->NF, PU (-)-> NF, NU->NF, PU-> NU
Sample split	
Overall Post	**Luxury:** H1, H3, and H5; **Non-Luxury**: H1 and H3
Link	**Luxury:** H4, H5, and H6; **Non-Luxury:** H3, H5, and H6
Photo	**Luxury:** H1, H2, and H3; **Non-Luxury:** H1 and H3
Status	**Luxury:** H3 and H5; **Non-Luxury:** H1 and H3
Video	**Luxury:** H4, H5, and H6; **Non-Luxury:** H6
Informative Post	**Luxury:** H1 and H3; **Non-Luxury:** H1 and H3
Sentiment	**Luxury:** NF->S, PU->S, NF->PF, PU->PF, PF->NF, PU (-)->NF, NU->NF, S->PU, PF->PU, NU (-)-> PU, PF->NU, PU->NU **Non-Luxury:** PF->S, NU (-)->S, S->PF, S->NF, PU->NF, NU->PU, PU->NU

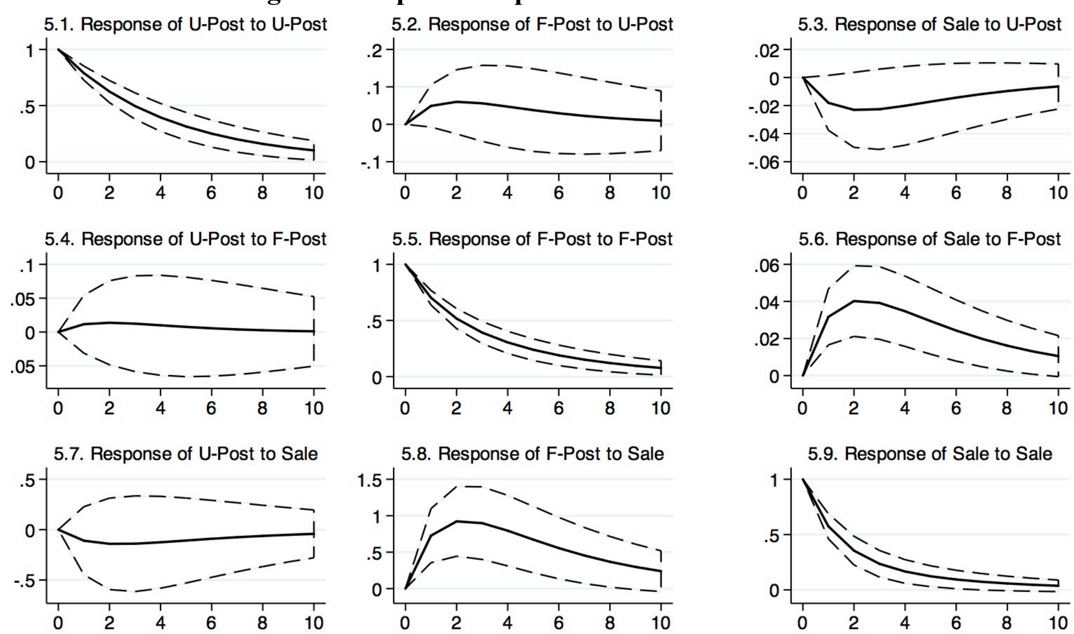
Notes: PF refers to positive FGC; NF refers to negative FGC; PU refers to positive UGC; NU refers to negative UGC; S refers to offline car sales. The sign of "-" stands for a negative relationship for the corresponding relationship; otherwise, it is a positive relationship.

2.5.3 Impulse Response Functions (IRFs) Results

I supplement the PVAR regression estimates with the analysis of the corresponding IRFs. IRFs allow us to learn whether a shock to one variable (e.g., FGC -> Sales) will have a permanent or transitory effect on any of the dependent variables, and if the effect is transitory, how long it will take to dissipate, namely, the dynamics of interested variables over time. Thus, IRFs provide an alternative means of measuring the trajectory of the effectiveness of one variable in the PVAR system on another variable. Specifically, IRFs plot the response of current and future values of the variables in the PVAR model to one-unit increase in the current value of one of the PVAR error terms (Enders, 2008; Stock & Watson, 2001). The assumption here is that the error return to zero in subsequent periods and all of the other errors are zero. I conducted IRFs along with 95% confidence intervals generated from Monte Carlo simulations with 1,000 repetitions. Figures 5 to 11 shows IRFs results for the whole sample.

Figure 5 illustrates the results of IRFs for the complete sample for overall posts. Particularly, Figures 5.3 and 5.6 allow me to observe how offline car sales respond to a shock to UGC and FGC over time, respectively. For example, the results show that an unexpected one-unit increase in the variable FGC (or UGC) is associated with 3.2% increase (or 1.8% decrease) in the logarithm of offline car sales at t=1. The effect of FGC to sales is significantly different from zero; however, the effect of UGC is not significantly different from zero. I also observe that the effect of FGC to offline car sales reaches a peak at t=2 with around a 4% increase in the logarithm of offline car sales and this effect attenuates gradually over time. Figures 5.7 and 5.8 show how UGC and FGC respond to a shock to offline car sales, respectively. Finally, I observe that the effect of sales to UGC is not significantly different from zero (see Figure 5.7). However, offline car sales have the strong immediate and significant impact on FGC in the subsequent month and this impact starts to attenuate at around month 3 (see Figure 5.8).

Figure 5. Impulse Response Functions for Overall Post



Notes: X-axis is the forecast horizon (in months), and y-axis is the forecasted response of the dependent variable to a unit shock in the corresponding error term. F stands for "firm-generated" and U stands for "user-generated". This applies to Figures 6 to 25.

Figure 6 presents the results of IRFs for posts in the form of link for the complete sample. In contrast to Figure 5, there is a positive feedback effect between FGC and UGC in the form of link. Figures 6.2 and 6.4 demonstrate how firm-generated links respond to a shock to user-generated links and how user-generated links respond to a shock to firm-generated links, respectively. Specifically, in Figure 6.2, a one- unit increase in user-generated links at time zero results in around 12.5% increase in the logarithm of firm-generated links at month 1 and this effect reaches the equilibrium levels at month 4. Similarly, the magnitude of the effect of FGC on UGC (both in the form of link) in the first time period is around 0.1 (see Figure 6.4), implying that a one-unit increase in firm-generated links at time zero results in 10% increase in the logarithm of user-generated links at month 1. Furthermore, this effect also reaches the equilibrium level at month 4.

Figure 6. Impulse Response Functions for Link

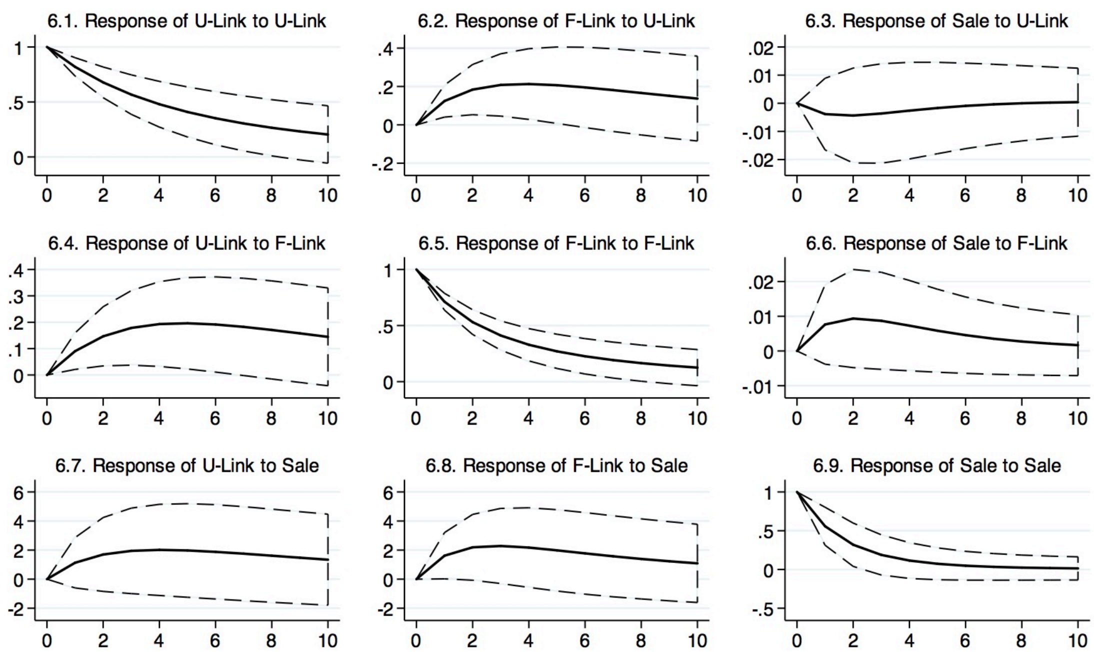


Figure 7 illustrates the results of IRFs for posts in the form of photo for the complete sample. Figure 7.6 allows me to observe how offline car sales respond to a shock to firm-generated photos over time. Specifically, the result shows that a one-unit increase in firm-generated photos is associated with 1 % increase in the logarithm of offline car sales at t=1 and this effect reaches a peak at t=2 with around 1.7% increase in the logarithm of offline car sales.

Additionally, Figure 7.8 also shows that offline car sales have the strong immediate and significant impact on firm-generated photos in the subsequent month and this impact starts to attenuate at around month 3 (see Figure 7.8).

Figure 7. Impulse Response Functions for Photo

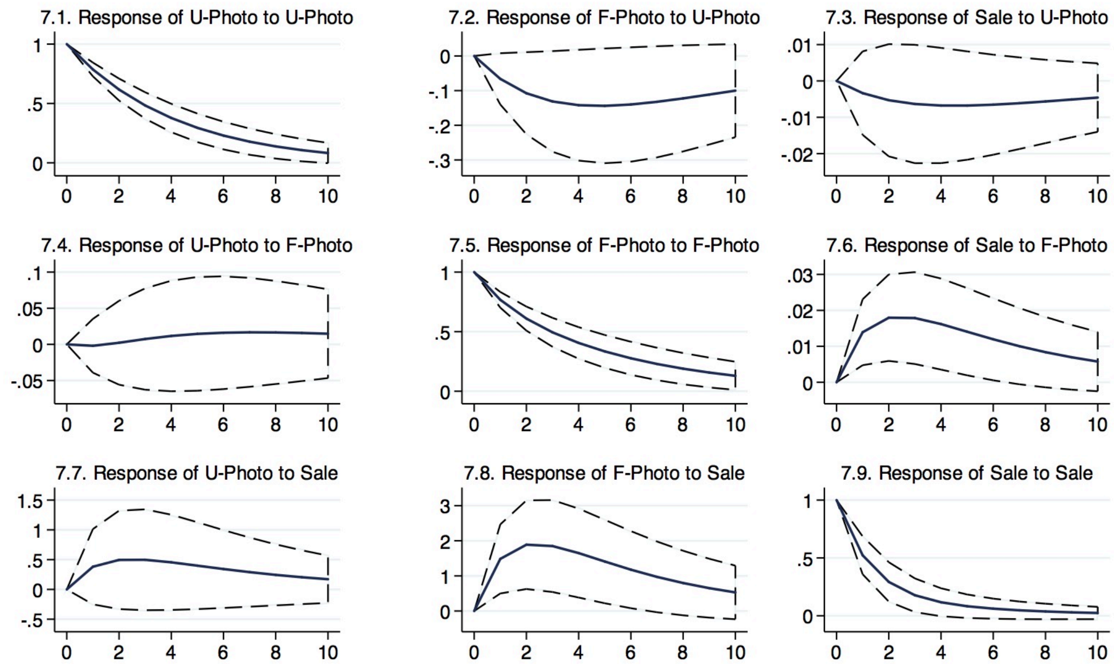


Figure 8 illustrates the results of IRFs for posts in the form of status for the complete sample and shows the similar patterns with Figure 7. For example, similar to Figure 7.6, Figure 8.6 shows that a one-unit increase in firm-generated statuses is associated with 2.2 % increase in the logarithm of offline car sales at t=1, suggesting that firm-generated statuses are more effective in influencing offline car sales than firm-generated photos. Figure 8.8 also shows that offline car sales have the strong immediate and significant impact on firm-generated photos in the subsequent month and this impact starts to diminish at around month 3 (see Figure 8.8).

Figure 8. Impulse Response Functions for Status

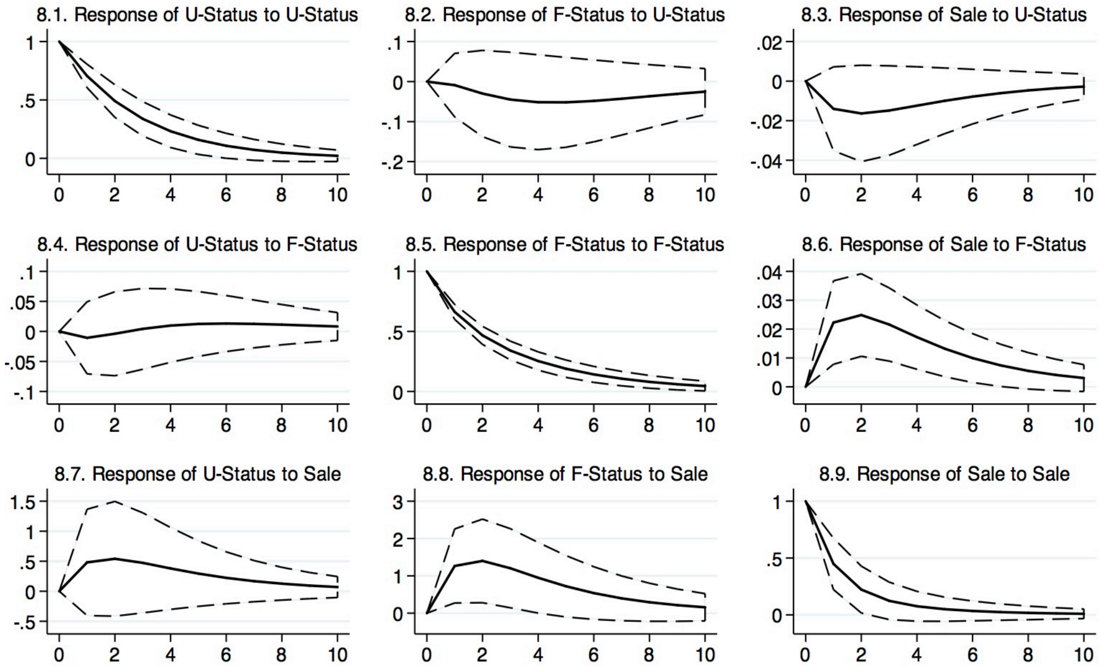


Figure 9 illustrates the results of IRFs for posts in the form of video for the complete sample. Figure 9.2 shows that a one-unit increase in user-generated videos is associated with around 9% increase in the logarithm of firm-generated videos.

Figure 9. Impulse Response Functions for Video

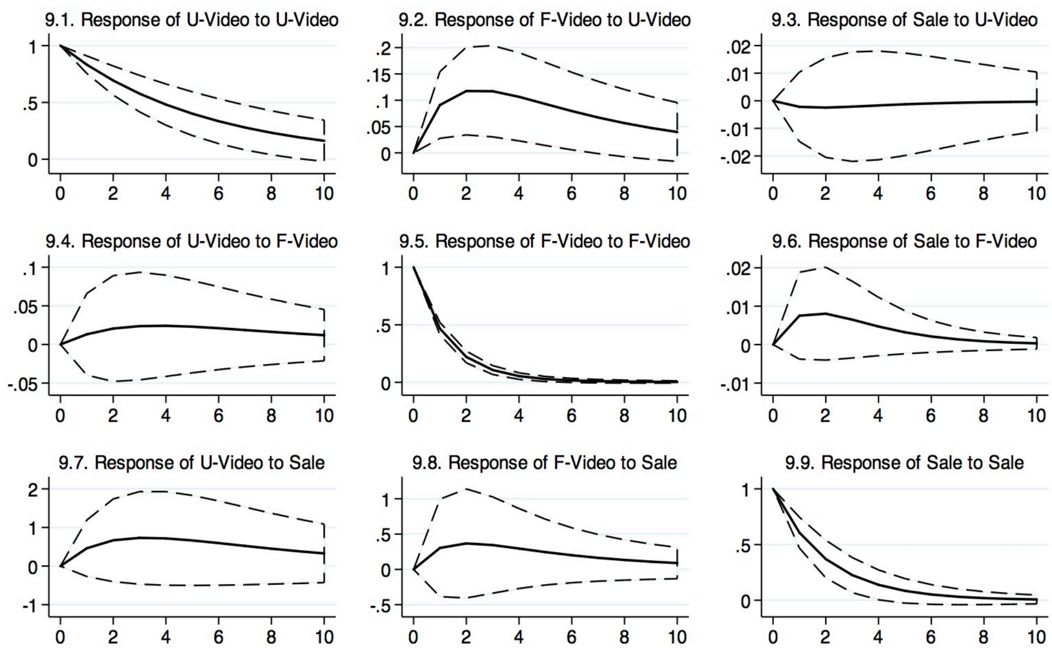
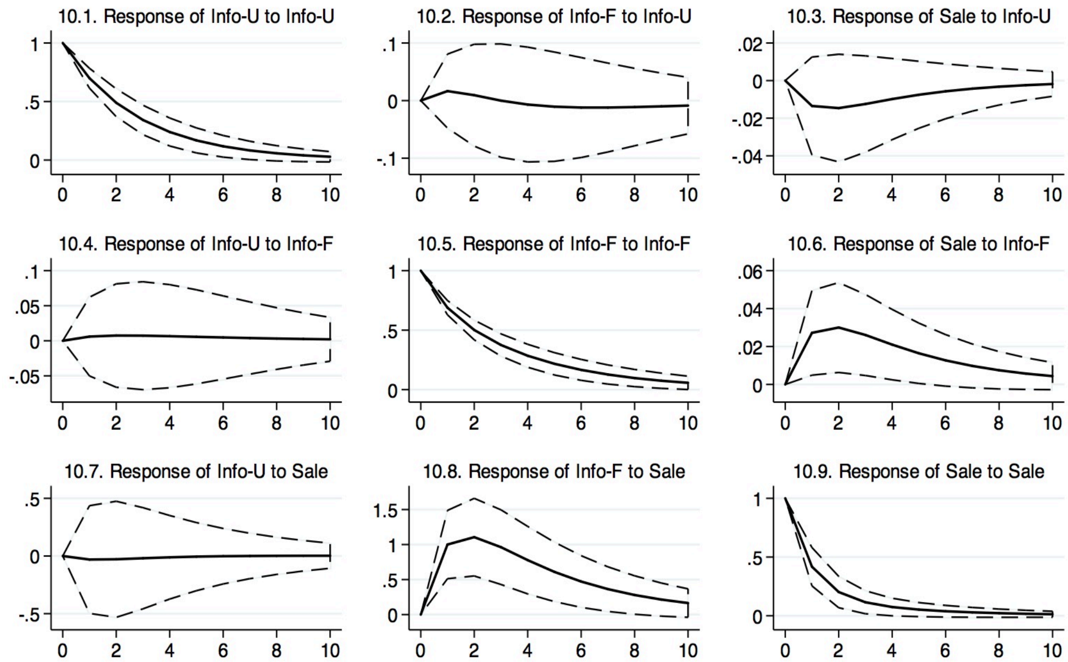


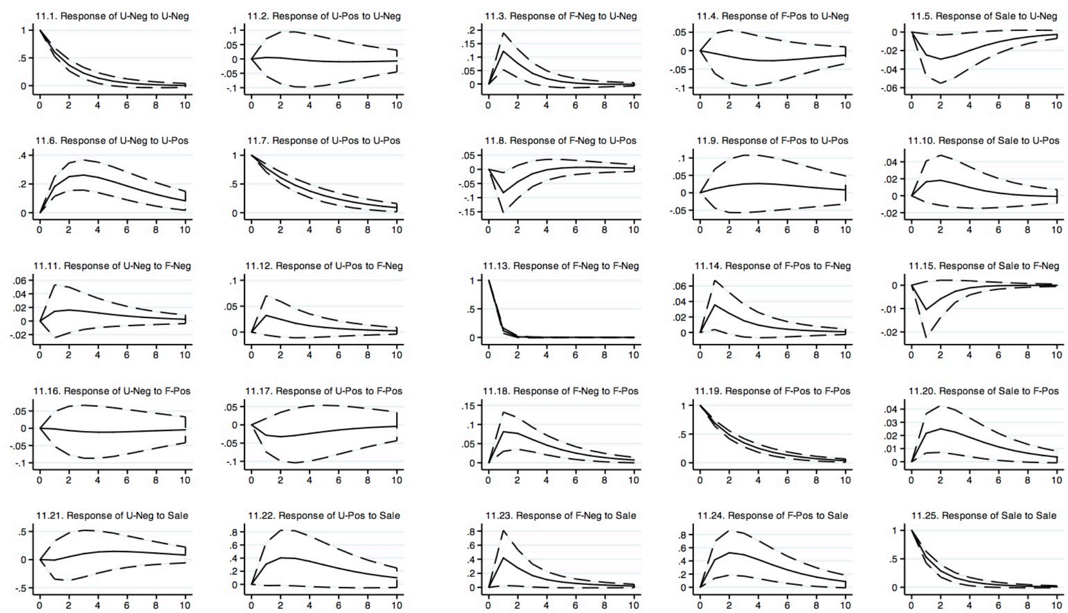
Figure 10 shows the results of IRFs for informative posts for the complete sample. In particular, Figure 10.6 illustrates that a one-unit shock of informative FGC has an increasing impact on the logarithm of offline car sales, reaching a peak at month 2. The results also suggest that offline car sales also have an immediately positive impact on informative FGC (see Figures 10.8), suggesting a positive feedback effect between informative FGC and offline car sales.

Figure 10. Impulse Response Functions for Informative Posts



Finally, Figure 11 illustrates the results of IRFs for sentiment for the complete sample. Figure 11.20 shows that a one-unit increase in positive FGC is associated with 2% increase in the logarithm of offline car sales at t=1 and this effect reaches a peak at t=2 with around 2.2% increase in the logarithm of offline car sales. I also observe that in Figure 4.5 a one-unit increase in negative UGC is associated with 2% decrease in the logarithm of offline car sales at t=1 and this effect reaches the lowest point at t=2. Figures 11.14 and 11.24 illustrate how positive FGC responds to a shock to negative FGC and sales over time, respectively. I observe that a one-unit increase in negative FGC is associated with 3.6% increase in the logarithm of positive FGC and this effect reaches a peak at month 1. Furthermore, a one-unit increase in offline sales is associated with around 42% increase in the logarithm of positive FGC and this effect reaches a peak at month 2 (see Figure 11.24). Figures 11.3, 11.8, 11.18, and 11.23 show how negative FGC responds to a shock to negative UGC, positive UGC, positive FGC, and offline car sales over time, respectively. Finally, Figure 11.6 shows how negative UGC responds to a shock to positive UGC over time. The result indicates that a one-unit increase in positive UGC is associated with around 18% increase in the logarithm of negative UGC and this effect reaches a peak at t=2.

Figure 11. Impulse Response Functions for Sentiment



2.5.3.1 Sample Split Impulse Response Functions (IRFs) Results

I now turn my attention to the IRFs for my sample split analysis. Figures 12 and 13 show the results of IRFs for overall posts for the luxury and non-luxury groups, respectively. Figures 12.6 and 13.6 show how offline car sales respond to FGC over time, suggesting that for the luxury group an unexpected one-unit increase in the variable FGC is associated with 4% increase in the logarithm of offline car sales at t=1 while for the non-luxury group it has around 2.5% increase at t=1. For both groups, these effects reach the peak at around month 2. Particularly for the luxury group, I also observe that an unexpected one-unit increase in the variable FGC is associated with 10% increase in the logarithm of UGC at t=1 and this effect continuous to reach the peak at around month 3 (see Figure 12.4), suggesting again that customers in two different groups demonstrate different patterns in their engagements.

Figure 12. Impulse Response Functions for Overall Post (Luxury)

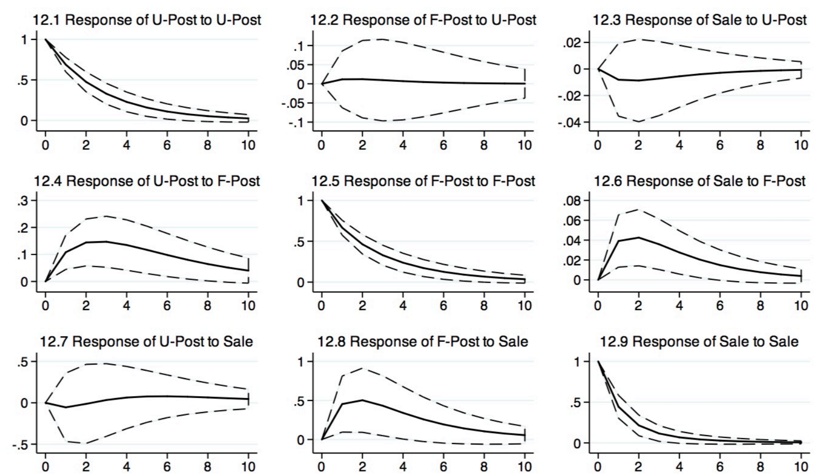
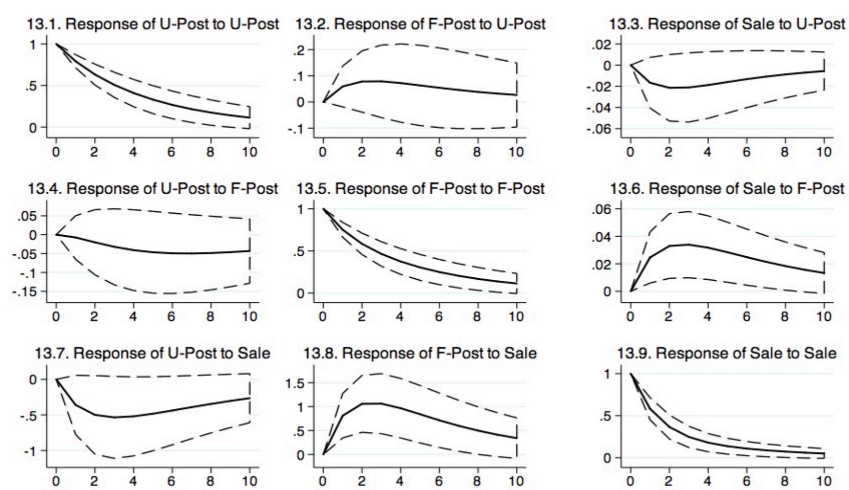


Figure 13. Impulse Response Functions for Overall Post (Non-Luxury)



Figures 14 and 15 show the results of IRFs for posts in the form of link for the luxury and non-luxury groups, respectively. Consistent with the main results, there is a positive feedback relationship between user-generated links and firm-generated links for both groups (see Figures 14.2, 14.4, 15.2, and 15.4) and there effects last for around three months. For the luxury group, I also observe that an unexpected one-unit increase in the variable offline car sale is associated with 70% increase in the logarithm of UGC at t=1 and this effect continuous to reach the peak at around month 4 (see Figure 14.7). On the other hand, for the non-luxury group, I find that an unexpected one-unit increase in the variable offline car sale is associated with 120% increase in the logarithm of FGC at t=1 and this effect starts to attenuate at month 4 (see Figure 15.8).

Figure 14. Impulse Response Functions for Link (Luxury)

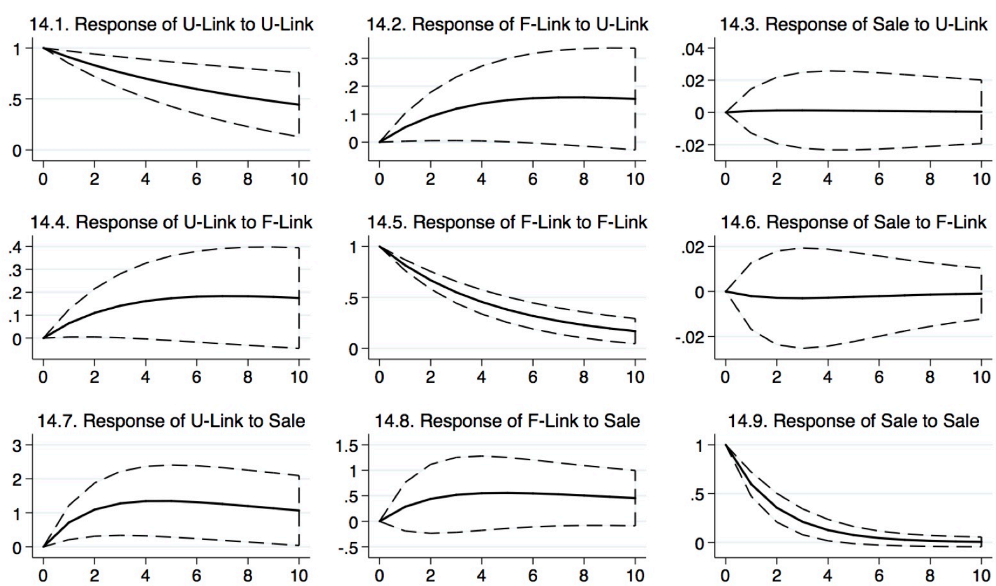
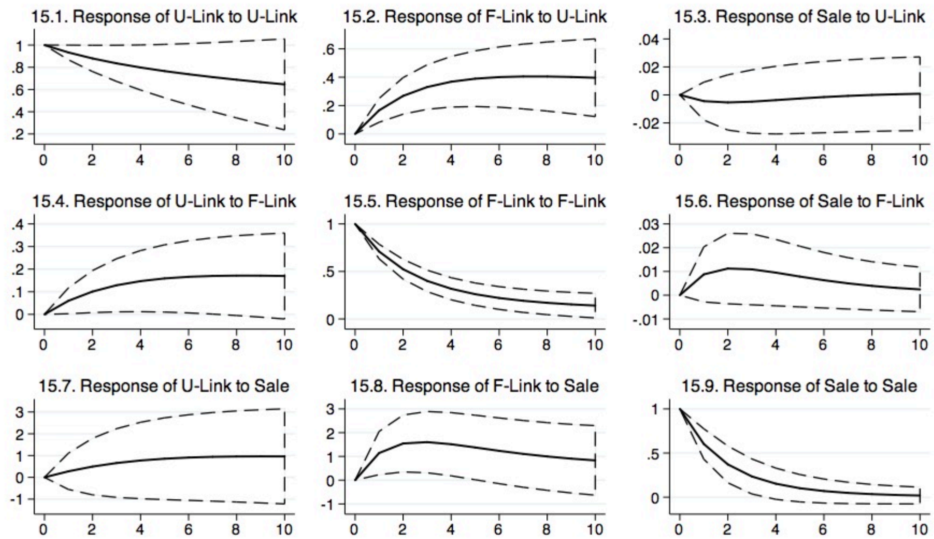


Figure 15. Impulse Response Functions for Link (Non-Luxury)



Figures 16 and 17 show the results of IRFs for posts in the form of photo for the luxury and non-luxury groups, respectively. Consistent with the main results, I find that there is a positive feedback relationship between offline car sales and firm-generated photo for two groups and these effects all reach the peak at around month 4 (see Figures 16.6, 16.8, 17.6, and 17.8). Interestingly, for the luxury group, I find that an unexpected one-unit increase in user-generated photo is associated with 2% increase in the logarithm of offline car sales at t=1 (see Figure 16.3) and this effect lasts for around three months.

Figure 16. Impulse Response Functions for Photo (Luxury)

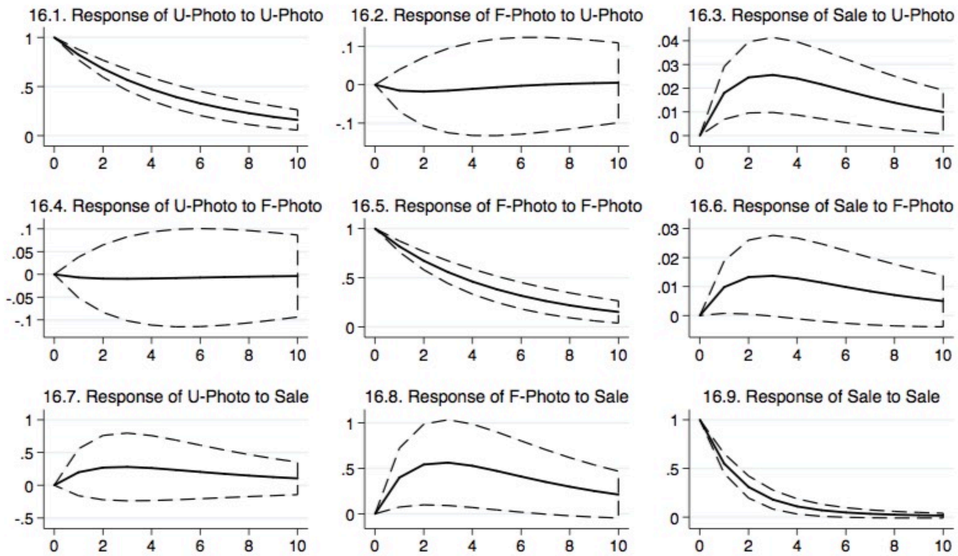
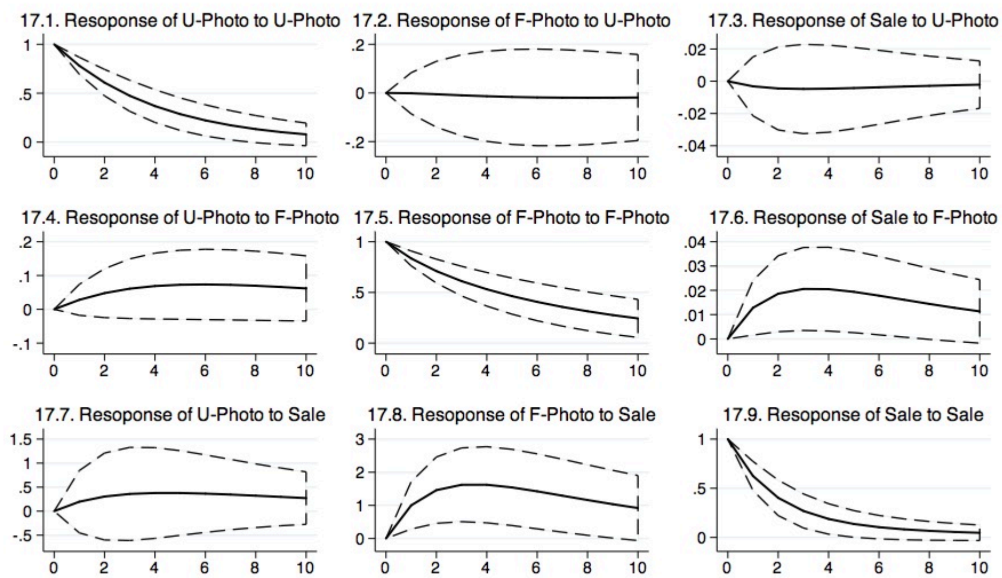


Figure 17. Impulse Response Functions for Photo (Non-Luxury)



Figures 18 and 19 show the results of IRFs for posts in the form of status for the luxury and non-luxury groups, respectively. These two groups demonstrate different patterns in terms of the dynamics between user-generated status, firm-generated status, and offline car sales. For example, Figure 18.8 shows how firm-generated status responds to offline car sales over time, suggesting that an unexpected one-unit increase in offline car sales has the immediately positively impact on firm-generated status and this effect reaches the peak at month 4, while this relationship cannot find in the non-luxury group (see Figure 19.8).

Figure 18. Impulse Response Functions for Status (Luxury)

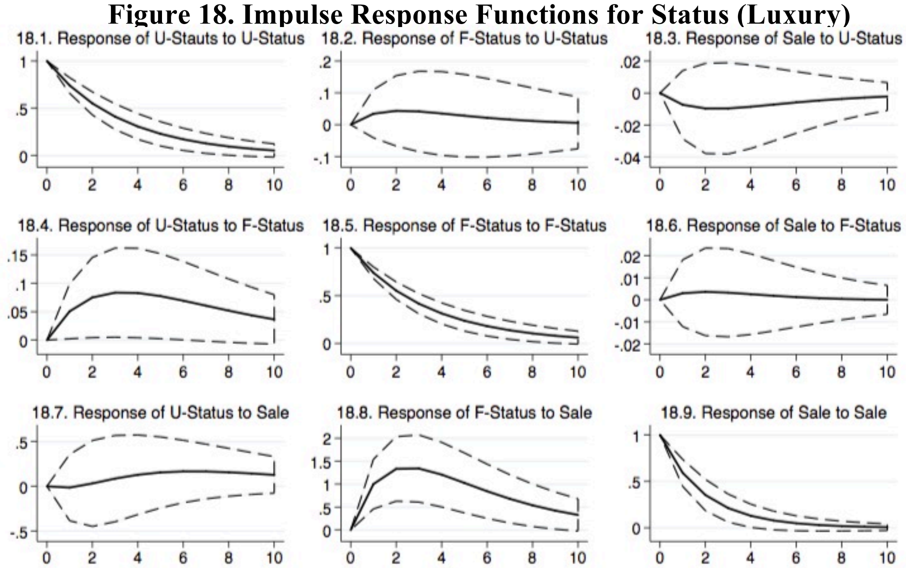
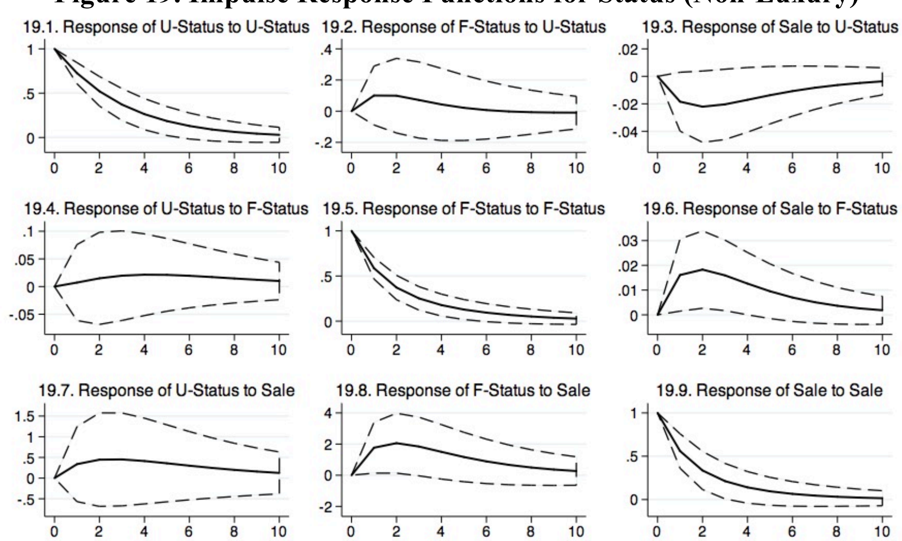


Figure 19. Impulse Response Functions for Status (Non-Luxury)



Figures 20 and 21 show the results of IRFs for posts in the form of video for the luxury and non-luxury groups, respectively. The results demonstrate again that customers in two different groups show dramatically different patterns in terms of the interactions between firm-generated video, user-generated video, and offline car sales. For example, fort the luxury group, there is a positive feedback between firm-generated video and user-generated video (see Figures 20.2 and 20.4) and the effects reach the peak at month two. On the other hand, for the non-luxury group I only find that an unexpected one-unit increase in user-generated video is associated with 8% increase in the logarithm of firm-generated video at t=1 (see Figure 21.2) and this effect starts to attenuate at month four.

Figure 20. Impulse Response Functions for Video (Luxury)

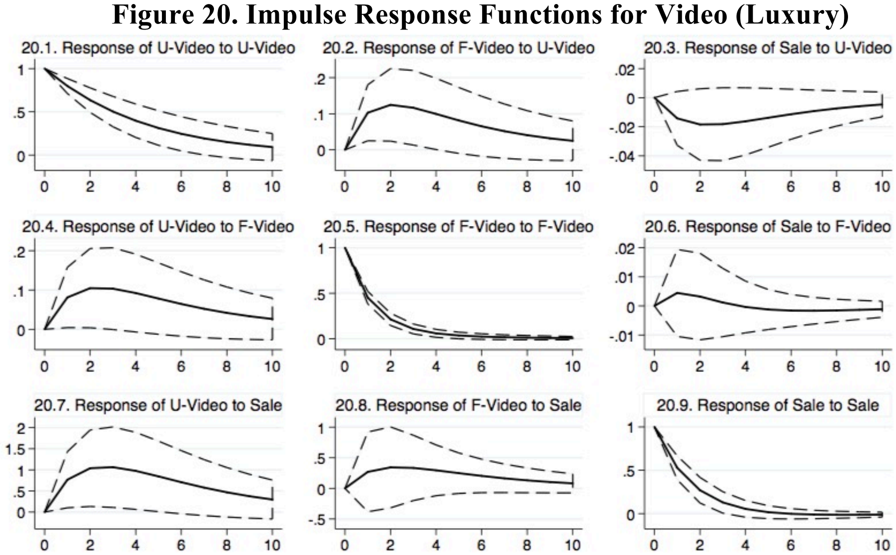
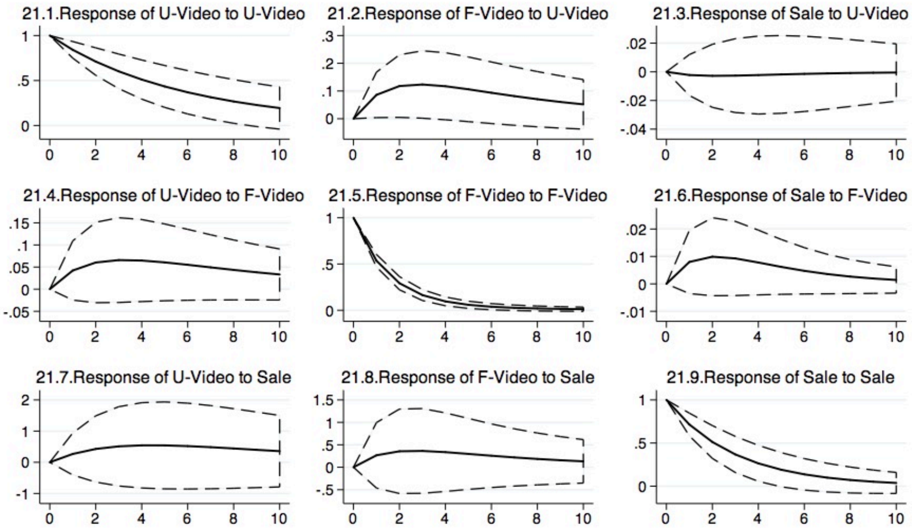


Figure 21. Impulse Response Functions for Video (Non-Luxury)



Finally, Figures 22 to 25 show the results of IRFs for informative posts and sentiment for two different groups. For informative posts, these two groups share similar patterns with the positive feedback relationship between firm-generated informative posts and offline car sales (see Figures 22.6, 22.8, 23.6, and 23.8). Finally, the results of IRFs for sentiment appear again that how customers appreciate sentiment from these two different groups are dramatically different.

Figure 22. Impulse Response Functions for Informative Posts (Luxury)

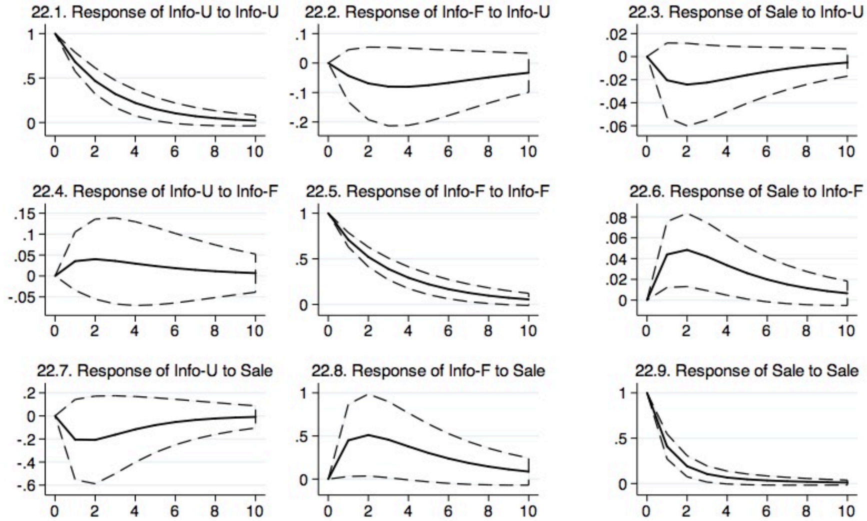


Figure 23. Impulse Response Functions for Informative Posts (Non-Luxury)

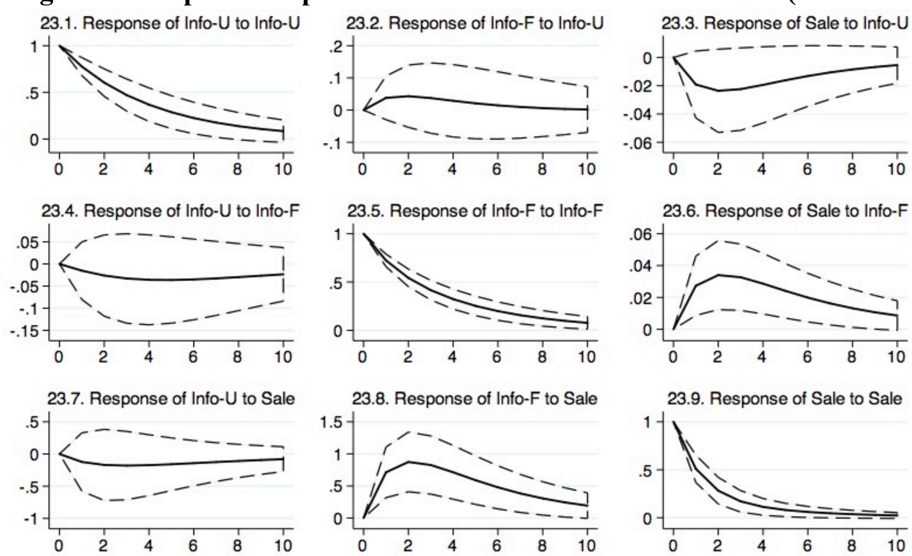


Figure 24. Impulse Response Functions for Sentiment (Luxury)

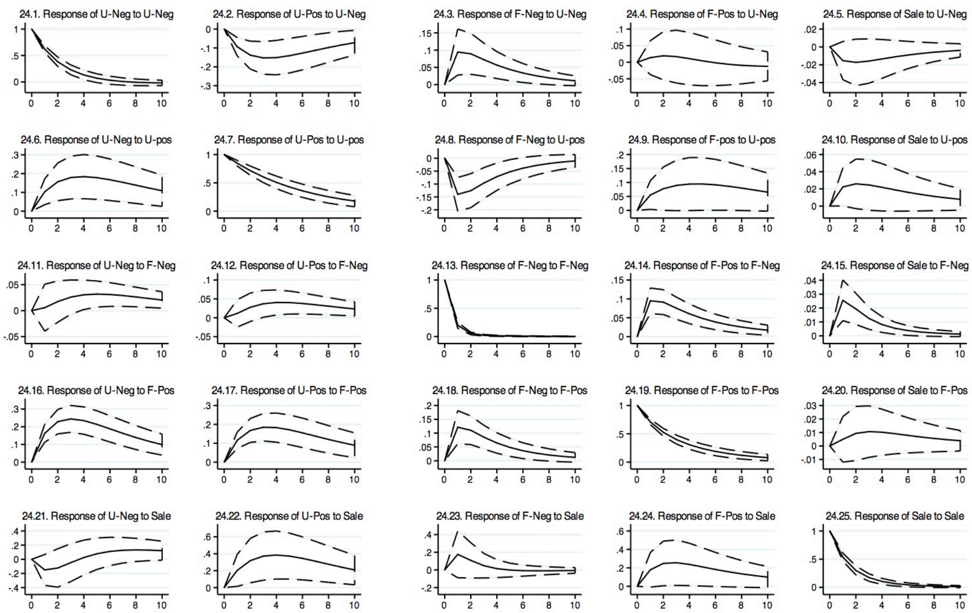
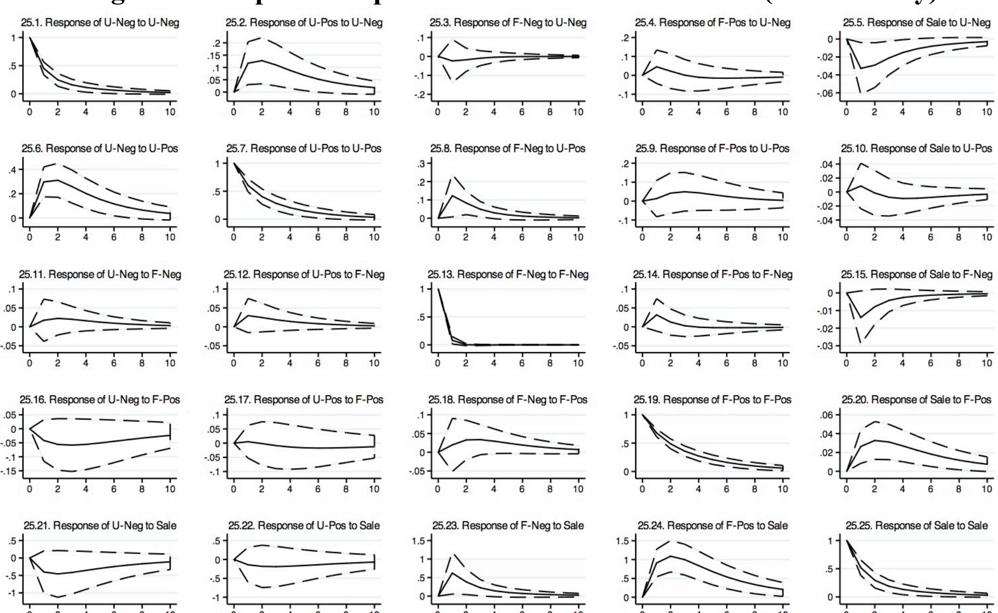


Figure 25. Impulse Response Functions for Sentiment (Non-Luxury)



Together, IRFs provide a graphical representation of the evolutionary patterns of our interested relationships, and their short-term results at t=1 are consistent with the interpretation of the coefficient estimates shown above in PVAR analysis results.

2.6 DISCUSSION

Motivated by the fact that most of the current literature focus exclusively on the isolated impact of either FGC or UGC on online sales of non-durable or media products, the current study explores the dynamic relationships among FGC, UGC, and offline car sales in the U.S. automobile industry in the setting of the firm’s Facebook fan page. Overall, the results suggest that (1) FGC is more effective in triggering offline car sales than UGC, (2) offline car sales would attract more customers’ and firms’ attentions by disseminating information or voicing opinions more actively to strengthen customer/customer or customer/firm relationships, and (3) there is a positive feedback effect between FGC and UGC. Furthermore, different forms of format presentation and contents of posts do play important roles in these dynamic relationships. Finally, the results vary significantly across luxury versus non-luxury car brands. These varied results also provide further evidence that depending upon their belonging groups firms would leverage different mechanisms to strategically drive sales and encourage customer engagements.

2.6.1 Theoretical Implications

There are several key contributions from this research. First and foremost, the predominant emphasis of prior social media research focuses on the isolated impact of either FGC or UGC on online sales of media and non-durable goods such as movie, DVD, or music, thereby overlooking any effects that FGC and UGC might have on one another, and indirectly, through on another on offline sales of other types of products. The current study is the first academic study that rigorously examines and quantifies the relative effectiveness of FGC and UGC on offline sales of the durable product (i.e., vehicle) and their feedback effects on each other over a long period of time at the industry level. Therefore, my work echoes the call for more research on how firms' media channels should operate as a system (e.g., Dewan & Ramaprasad, 2014; Luo et al., 2013; Smith et al., 2006; Trusov et al., 2009) and the impact of social media on different types of products (e.g., Goh et al., 2013; Stephen & Galak, 2012). Interestingly, I find that FGC consistently has a positive impact on offline car sales throughout a set of analysis, whereas UGC is not very effective in driving offline car sales in the setting of the firm-initiated Facebook page. The results of UGC on sales contradict the general belief that UGC is effective in driving sales (e.g., Ghose & Ipeirotis, 2011) and could be explained by the nature of the durable product and Facebook. Compared to media and non-durable products, customers may need to involve more efforts before making purchase decisions on durable products. Thus, UGC may not have a direct impact on offline car sales. In fact, buying a car is a high involvement activity. Therefore, customers may need to take a series of test-drives before purchasing a car. The differences between the durable product and non-durable products may constitute a possible alternative explanation for the ineffectiveness of UGC in my setting. The nature of Facebook may also contribute to why UGC is less effective in driving sales. The major purpose of voicing opinions at Facebook is to build social intractability (Stephen & Galak, 2012). In particular, the firm's Facebook fan page provides an environment for customers to express their loyalty, receive the latest information from the firm, and interact with other customers, namely, social networking. On the other hand, UGC in the form of online review tends to help potential customers to make better purchase decisions (Forman et al., 2008). Indeed, in a majority of UGC in our setting, I find that customers tend to use firm's Facebook page to build the relationships with the focal firm and other customers. Therefore, the difference between online review sites and firm's Facebook pages may explain why most of UGC in our setting do not have a direct impact on sales.

Second, not all format presentations are similar. My research suggests that some format presentations are more effective in influencing offline car sales, whereas other aspects of format presentations are more effective in triggering customer engagements. My study, therefore, responds to Berger et al.'s (2015) call for further examination on consumers' appreciation of different content formats and the individual assessment of each content format. Depending on the purpose of each post, firms or customers use different combinations to maximize the utility of each post. Interestingly, we find that to effectively boost sales, firms could rely more on contents in the form of *photo* and *status*. On the other hand, if firms want to trigger more customer engagements, they should rely more on contents in the form of *link*. Thus, my study sheds light on customers' evaluations of content in different formats and contributes to both decision-making and marketing literature by demonstrating how firms can utilize the combinations of format presentation to achieve their goals effectively.

Third, my content analysis on informative posts and sentiment also contributes to the current literature by showing how firms can develop and control of their posts to trigger consumptions and customer engagements. My study shows that if firms can provide enough product information for their customers, the likelihood of customers' consumptions would increase accordingly. Further, prior research has suggested that firms can leverage social media to mitigate the impact of the negative events by increasing customer awareness (Abrahams et al., 2012; Berger & Milkman, 2012; Yan Liu & Shankar, 2015). I agree and extend this stream of research by showing that luxury groups' voluntary announcements on the negative events (i.e., vehicle recalls) can increase customer awareness and, in fact, have the positive impact on sales. Thus, given the popularity of social media, firms can equip with more potent tools to avoid a negative event before it becomes a crisis.

Finally, my split sample analysis offers very interesting insights regarding customers' behaviors in two different groups. For example, for customers who belong to the luxury group, their exposure to overall FGC, FGC in the form of photo, negative FGC, positive UGC, and informative FGC would influence their purchase behaviors. On the other hand, customers who belong to the non-luxury group demonstrate dramatically different patterns. Given the limited resources, firms do need to customize their social media strategy based on their targeted audiences. Therefore, my study contributes to the current literature by showing the patterns of how firms with different focus and market can develop their social media strategy more effectively.

2.6.2 Managerial Implications

The study also provides important managerial implications. Due to the popularity of Facebook, a number of firms have set up their fan page for marketing purposes. My results demonstrate that maintaining online communities in the form of Facebook fan page has marketing implications for companies to reach their customers and then boost sales. This is important for firms with the limited resources to reach large amounts of customers. However, it should leverage social media with caution that not every form of format presentation has the equal impact on sales and customer engagements. Therefore, firms should pay special attention to the content of their marketing communications and develop the most effective conversations to engage their customers. Second, although UGC is not effective in influencing offline car sales in our setting, it does not mean that firms can get rid of this part in their fan page. Instead, firms need to look at these contents seriously. For example, firms may try to identify if there are any opinion leaders in their online communities. Identifying these opinion leaders would be very important for firms if they want to initiate some seed marketing campaign. Third, my split sample analysis also implies that firms need to be aware of their own identity. That is, depending on the targeted market, firms need to carefully choose their contents to match their customers' preferences. Finally, the insight from the positive impact of negative FGC on sales also provide the lesson to managers that they can leverage social media to mitigate the negative events to maintain their reputation.

2.6.3 Limitations and Future Research

This study does have some limitations. First, I only focus on Facebook. However, it is likely that firms have a significant presence at other social media sites, such as Twitter and Instagram, as well. Activities on these sites could affect offline car sales. Due to data limitations, I am not able to study the interactions between offline car sales and the overall marketing intensity across different social media sites. Second, I only examine the dynamic interactions between FGC, UGC, and offline car sales in one industry. Finally, the current study only explores the volume of FGC and UGC and some aspects of content. It may be interesting for future research to develop systematics categories on contents by applying some techniques such as topic modeling, so the abstract topics can be distinguished from one another. For example, latent dirichlet allocation (LDA) could be utilized to take a step further to examine the impact of social media.

2.7 CONCLUDING REMARKS

While prior studies examine the impacts of social media from different perspectives, they focus exclusively on the isolated impacts of either FGC or UGC on online sales of nondurable and media products. In addition, how FGC and UGC may influence offline sales of the durable product and the relationships between FGC and UGC is under explored. Therefore, this study provides an initial step on exploring the dynamic relationships between FGC, UGC, and offline car sales in the setting of the firm-initiated Facebook fan page and how these relationships vary across format presentation, content of post, and firm characteristics.

CHAPTER 3.

ESSAY 2: DYNAMICS OF ONLINE WORD OF MOUTH (WOM) SPILLOVER EFFECTS

3.1 INTRODUCTION

A significant body of research has established that online word-of-mouth (WOM) play an important aspect in consumers' purchasing decisions (e.g., Chen et al., 2015; Dewan & Ramaprasad, 2014) and provide a means for firms to learn about customers and the marketplace (Borah & Tellis, 2016). However, online WOM regarding a specific product or brand may also remind the consumers of options that would not have been salient otherwise. For example, a customer's experience of Samsung Galaxy note 7 shared on social media channels may influence other potential or existing customers' perception or confidence of Samsung's smartphones in general, and thereby influence the latter's decision to buy a non-Samsung smartphone[13]. This is one way by which online WOM about the focal brand's competitors may influence performance of the focal product through the spillover effects. Spillover effects occur when information and existing perceptions influence beliefs that are not directly addressed by or related to the original information source or perception object (Ahluwalia, Unnava, & Burnkrant, 2001). The presence and strength of spillover effects in consumer decision-making is extremely important (Chae, Stephen, Bart, & Yao, 2017; Dong & Chintagunta, 2015; Sabnis & Grewal, 2015). Particularly

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[13] Some Samsung Galaxy Note 7 Buyers Are Defecting to the iPhone: http://fortune.com/2016/09/27/note-7-defecting-iphone/

in the setting of online WOM, because firms use online WOM to compete, studying online WOM spillover effects is extremely important to inform a focal firm's own performance (Sabnis & Grewal, 2015).

Despite the richness of research on online WOM, prior research on the dynamics of online WOM spillover effects is very scarce with few exceptions (e.g., Borah & Tellis, 2016; Chae et al., 2017; Sabnis & Grewal, 2015). Anecdotal evidence suggests such relationships exist, but our current knowledge is still very limited on how online WOM about the focal brand or product would influence the performance of the focal brand (i.e., static view of online WOM). First of all, the current literature focuses considerably on the impact of online WOM on online sales of non-durable, media goods such as movie, DVD, music, book, or clothing (e.g., Chen et al., 2015; Goh et al., 2013). For this type of product, customers are more likely to experience low-involvement decisions, meaning that a consumer rarely engage in an "extensive search for information or a comprehensive evaluation of the choice alternatives" (Zaichkowsky, 1985, p.341). On the other hand, customers who purchase durable products such as cars are more likely to engage in extensive search because the wrong decision force the consumer to deal with the poor product for long periods of time (Laurent & Kapferer, 1985). Due to these two extremely different search processes, the findings from the existing literature may or may not apply to non-durable products. Besides, while online WOM is increasing in importance, as of the 4th quarter 2015, online sales only account for 7.5% of all retail purchases (Commerce, 2016). Therefore, there is a significant knowledge gap on the phenomenon of online WOM to offline sales of durable products.

Second, the same stream of the literature focuses considerably on the immediate effects of online WOM about the focal brand on the performance of the focal brand without considering the competition nature in the marketplace (e.g., Goh et al., 2013). However, it is very likely that in the competitive marketplace, customers will be influenced not only by online WOM of interest to them but also by online WOM of other competing or related products before making purchases. Unfortunately, the broader consequences of the effects of online WOM (i.e., the competition nature of online WOM) have received scant attention in the current literature.

Third, prior research on consumer choice suggests that purchase decisions are considered to be the result of a multi-stage decision process (Bettman, 1979; Hauser & Wernerfelt, 1990; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991), which typically includes the stages of awareness, interest, and final decision (De Bruyn & Lilien, 2008). Depending on certain circumstances, this multi-stage decision process does not necessarily imply sequencing and it may occur simultaneously (De Bruyn & Lilien, 2008; Shocker et al., 1991). However, most of the current literature in online WOM does not distinguish the stage of awareness from the stage of interest or just examines exclusively the mixed effect from these two stages on firm performance (e.g., Borah & Tellis, 2016; Chevalier & Mayzlin, 2006; Duan et al., 2008; Goh et al., 2013; Sabnis & Grewal, 2015). For example, although Sabnis and Grewal (2015) provide one of initial evidence about online WOM spillover effects in the cable industry, they still do not explain the relative effects from the stages of awareness and interest. Similarly, although Borah and Tellis (2016) and Chae et al. (2017) provide further evidence of online WOM spillover effects, their studies tend to examine the mixed effects from the stages of awareness and interest in essence. Separate analyses on each stage of the purchase decision process would provide deeper insight into the questions of how firms could allocate their resources and efforts in each stage and convert potential customers into actual sales. However, our knowledge on the relative degree to which online WOM effects and their spillover effects from these two stages jointly influence firm performance is still not clear.

The objective of this paper is to examine the dynamics of online WOM and its spillover effects by considering the relative effects at the stages of customer awareness and consideration in the U.S. automobile industry. I define online WOM spillover effect as the positive or negative influence of online WOM about competitors on offline car sales of the focal brand. I select the U.S. automobile industry because of its considerable economic significant and its increasing reliance social media marketing (eMarketer, 2015b; Tang et al., 2014). Specifically, I am interested in the following research questions:

(1) *What are the relative effects of online WOM at the stage of awareness and online WOM at the stage of consideration on offline car sales?*

(2) *Do the spillover effects exist in online WOM at the stages of awareness and consideration?*

That is, does online WOM about competitors at the stages of awareness and consideration spill over into offline car sales of the focal brand?

(3) *What are the patterns of spillover effects across two stages and how do these patterns vary if different mechanisms at the stage of awareness are considered?*

(4) How do dynamics of online WOM vary across firm characteristics (i.e., origin of brand, market structure, and price factor)?

To measure online WOM and its spillover effects across two stages of customer purchase processes, I suggest combining data from firms' Facebook fan pages and customers' test drive experience shared on different social media channels. Among different forms of social media, Facebook strongly leads the social networking space (eMarketer, 2015c). Due to its popularity, Facebook has become a leading avenue for more than 54 million businesses to set up their online brand communities (i.e., fan page) to enable direct communication with prospective customers, increase their awareness, and make profits (Facebook, 2015b; Goh et al., 2013). Particularly, it is noteworthy the newsfeed function at Facebook. The newsfeed function at Facebook allows users to be exposed to customized content posted on the network based on each their own using behaviors (e.g., the frequency to interact with the friends, pages, or public figures) (Backstrom, 2013). Due to this unique feature, firms' Facebook fan pages is particularly effective to raise awareness for their products (Debatin, Lovejoy, Horn, & Hughes, 2009; Yong Liu, 2006) by appearing in the newsfeeds of all fans (Goh et al., 2013) and by increasing fan page engagement and usage intensity (Verma, Jahn, & Kunz, 2012). Therefore, activities at firms' Facebook fan pages provide a good proxy to measure online WOM at the stage of awareness. I leverage data specifically about customers' test drive experience shared on different social media channels as a proxy for online WOM at the stage of interest (i.e., consideration). Because automobile purchase is a high-involvement decision for most consumers, the test drive is one of the critical aspects of the pre-purchase production evaluation. Therefore, by focusing on the test-drive as a measure for online WOM at the stage of interest where more specific aspects of the product, such as part particular product attributes or functionalities, are provided, I can understand deeply about the effects of online WOM and its spillover effects occurred at the stage of interest.

The results indicate that (1) online WOM at the stage of consideration has the stronger effect on offline car sales than online WOM at the stage of awareness, (2) spillover effects exist across both stages of awareness and consideration, though effects are heterogeneous in direction: positive spillover effects at the stage of awareness while negative spillover effects at the stage of consideration, and (3) at the stage of awareness, online WOM initiated by firms is more effective in influencing offline car sales than online WOM initiated by users. Furthermore, not every mechanism at Facebook (i.e., post, like, comment, and share) has the equal impact on offline car sales and these different mechanisms also influence how customers appreciate online WOM at the stage of consideration. Finally, the results vary significantly across origin of brand, market structure, and price factor.

The rest of this paper is organized as follows. The second section presents the current stream of the literature and the gaps, the third section introduces research model and hypotheses, the fourth section describes the method, and the last two sections present the results and discussion.

3.2 LITERATURE REVIEW

The current study is related to the literature that examines the effect of online WOM on marketing outcomes. In this section, I briefly review the current streams of research and discuss how my study contributes to the extant literature.

3.2.1 Effect of Online WOM on Sales

A number of studies have examined the impact of online WOM on online sales of media or non-durable products (i.e., products that customers usually experience low-involvement decisions). For example, Chevalier and Mayzlin (2006) examine the effect of online reviews on relative sales of books at Amazon.com and Barnesandnoble.com and find the positive relationship between online book reviews and online book sales. Forman et al. (2008) posit that reviews posted by reputable reviewers have greater impact on product sales than those by less reputable reviewers. Ghose and Ipeirotis (2011) find that reviews that have a mixture of objective, and highly subjective sentences are negatively associated with product sales, compared to reviews that tend to include only subjective or only objective information.

Furthermore, Goh et al. (2013) study the relative impacts of firm-generated content and UGC on sales in the setting of a casual wear apparel retailer's Facebook page and find that FGC in a firm's Facebook page influences consumers' apparel purchase expenditures. More recently, Chen et al. (2015) study the effect of artists' broadcasting activities on MySpace and suggest that broadcasting in social media has a significant effect on music sales and the effect mainly comes from personal messages (one form of FGC on social media) rather than automated messages.

Although the current literature helps us understand the impact of online WOM on firm performance, our understanding regarding the impact of online WOM on offline sales of the high-involvement products is still very limited. Prior research indicates that information-search behaviors have been shown to vary for different levels of product involvement (Geva, Oestreicher-Singer, Efron, & Shimshoni, 2017). Product involvement refers to consumers' interest in a product and their perceptions regarding its importance (Richins & Bloch, 1986; Traylor, 1981). One major difference between high-involvement products and low-involvement products is the effort for searching for product information to make the right decision (Gu et al., 2012). For high-involvement products, customers often spend a significant amount of time conducting information searches before purchasing these products (Kuruzovich, Viswanathan, Agarwal, Gosain, & Weitzman, 2008). On the other hand, for low-involvement products such as music, because the consequences of making the wrong purchase decisions are limited (Gu et al., 2012), consumers are less likely to conduct extensive information searches before making the purchase (Mathwick & Rigdon, 2004). Therefore, it can be simply stated that the more important the product is to a consumer, the more motivated the consumer is to search and be involved in the decision (Geva et al., 2017). Gu et al.'s study (2012) is one of remarkable examples on the impact of online WOM on products that would trigger high-involvement decisions. They find that a retailer's internal WOM has a limited influence on its sales of high-involvement products, while external WOM sources have a significant impact on the retailer' sales. However, they still only focus on online sales in the setting of Amazon. Particularly, in the setting of automobile industry, Tang et al. (2014) and Geva et al. (2017) are two remarkable examples to examine the effect of online WOM on offline sales of durable products (vehicles). Given that online sales only account for 7.5% of all retail purchases (U.S. Department of Commerce, 2016) and customers experience two dramatically different decision processes for two types of products, our knowledge on the impact of online WOM on the offline sales of durable product is still very limited.

Another noteworthy gap in this stream of literature is that we still know very little about the role of online WOM played in different stages of customer decision process. Prior research suggests that in the setting of purchase decision process, customers may experience the stages of awareness, interest (consideration), and final decision (Bettman, 1979; De Bruyn & Lilien, 2008; Hauser & Wernerfelt, 1990; Shocker et al., 1991). Depending on certain circumstances, this multi-stage decision process does not necessarily imply sequencing and it may occur simultaneously (De Bruyn & Lilien, 2008; Shocker et al., 1991). At the stage of awareness, consumers know the alternative exists, but may not have either interest in it or sufficient information to understand its possible benefits, while at the stage of interest, customers are aware of available alternatives, and hence decide to learn more about the product (De Bruyn & Lilien, 2008). It is generally believed that at the stage of awareness, customers tend to expose more general and abstract information given that their product selection set is relatively large (Shocker et al., 1991). On the other hand, at the stage of interest stage, customers tend to expose to more concrete or detailed information given that they have decided to pay more attention on the subset of their selection set (Shocker et al., 1991). However, a considerable literature does not examine the relative role played by online WOM across these two stages or tend to examine the mixed effect from these two stages on firm performance (e.g., Borah & Tellis, 2016; Chevalier & Mayzlin, 2006; Duan et al., 2008; Geva et al., 2017; Sabnis & Grewal, 2015). Therefore, our knowledge on the role played by online WOM in different stages of decision process is still very limited.

3.2.2 Spillover Effects of Online WOM

Spillover effects occur when information and existing perceptions influence beliefs that are not directly addressed by or related to the original information source or perception object (Ahluwalia et al., 2001). Prior research has provided evidence of spillover effects in various setting such as IT investment (Tambe & Hitt, 2013), advertising (Sabnis & Grewal, 2015), brand scandal (Roehm & Tybout, 2006), brand portfolio (Lei, Dawar, & Lemmink, 2008), or customer satisfactory (Dong & Chintagunta, 2015). The accessibility-diagnosticity theory proposed by Feldman and Lynch (1988) provides an appropriate framework to study and explain spillover effects. They suggest that if a consumer thinks that information for brand A is accessible and diagnostic of brand B (i.e., informative about), the consumer will use perceptions of brand A's quality to infer quality of brand B (e.g., Ahluwalia & Gürhan-Canli, 2000; Roehm & Tybout, 2006). Accessibility is such that concepts, such as brand, firm characteristics, and product attributes, reside in a network and can activate one another when having strong links (Anderson, 2013; Collins & Loftus, 1975). On the other hand, diagnosticity is a function of consumers' implicit theories about how things relate in the world (Broniarczyk & Alba, 1994a, 1994b). Therefore, it is intuitive that in the competitive marketplace, firm's performance depends not only on its own marketing strategy and effort but also of its competitors (Dubé & Manchanda, 2005; Naik, Raman, & Winer, 2005).

In the context of online WOM, some scholars have started to examine spillover effects of online WOM in different settings. For example, Sabnis and Grewal (2015) study the dyanimcs of online WOM in the cable industry and find evidecne of a statistically significant relationship between competitors' user-generated content and focal firm's viewership. Particually in the automobile industry, Borah and Tellis (2016) stduy spillover effects of online WOM in the setting of automobile recalls and find that negative online chatter about one nameplate increase negative chatter for another nameplate. More recently, Chae et al. (2017) investigate the effects of Seeded marketing campaigns (SMCs) that extend beyond the generation of WOM for a campaign's focal product by considering how seeding can affect WOM spillover effects at the brand and category levels. Their study provides further evidence of online WOM spillover effects and suggests that marketers can use SMCs to focus online WOM on a particular product by drawing consumers away from talking about other related, but off-topic, products.

Althoguh the extant literature has provided the initial understanding about online WOM spillover effects, these studis, again, ingore the relative role of online WOM played during different stages of consumer decision process (i.e., the stage of awareness and interest (consideration). Distinct from these stuides of online WOM and spillover effects, I examine whetehr online WOM spillover effects occur across the stage of awareness and interst (consideration) and how firm characteristics may vary these spillover effects.

3.3 RESEARCH MODEL AND HYPOTHESES

In contrast to the existing literature, the current study is unique in the following ways. First, I consider the role played by online WOM across the stage of awareness and consideration in the consumer decision process and examine their relative effect on offline car sales. This approach allows me to better understand the impact of online WOM and expects to provide a more insightful lesson to practitioners in terms of their resource allocation to leverage online

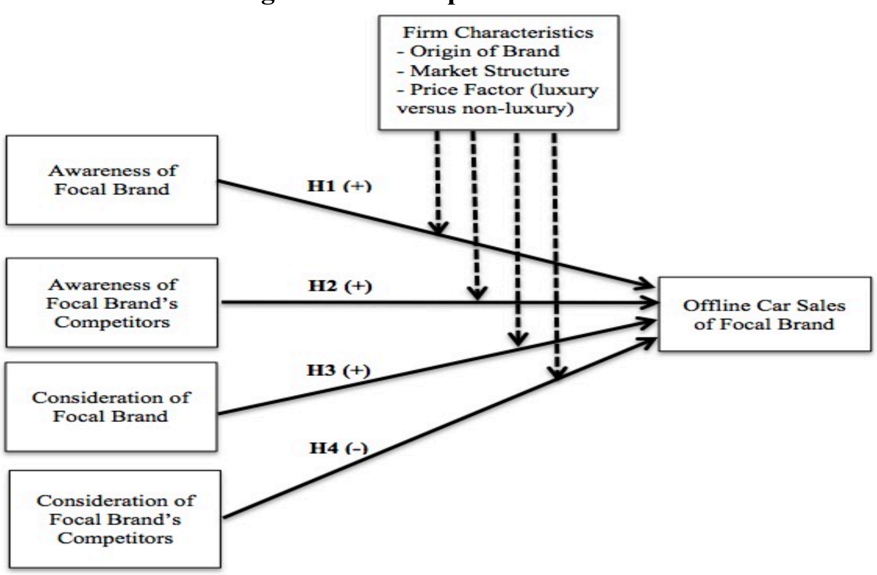
WOM. Second, by considering online WOM spillover effects across two stages, the current study could shed light on the effectiveness of online WOM and better realize the competition nature in the competitive marketplace. Finally, I focus on what firms and consumers do online versus consumers' commerce activities that occur in offline settings. Particularly, the difference between non-durable products (e.g., music, movie) and durable products (i.e., vehicle in our setting) allows me to explore the impacts of online WOM from the different perspective.

My conceptual model is shown in Figure 26. Regarding online WOM at the stage of awareness, I leverage data from firm's official Facebook page. Currently, due to the popularity of Facebook, most of firms set up their Facebook fan pages to disseminate information to their customers more effectively. In general, firms tend to leverage their Facebook pages to catch their customers' attention first and then refer their customers to some specific sites or representatives for further details. In other words, at Facebook pages, information tends to be more abstract and more general, which coincides with the nature of the stage of awareness (Shocker et al., 1991). Therefore, leveraging data from firm's Facebook pages provides a good proxy for online WOM at the stage of awareness. I emphasize four major mechanisms at the firm's Facebook page and examine how these four mechanisms may vary the relationships shown in Figure 26. These mechanisms include post, "Like" associated posts (i.e., how many likes a single post received), "Comment" associated with posts (i.e., how many comments a single post received), and "Share" associated with posts (i.e., how many shares a single post received). Since at the firm's

Facebook, both firms and users can initiate contents to interact with firms or other users, I also consider these two sources of online WOM at the stage of awareness together to shed light on how firm's media channels could operate as a system (Dewan & Ramaprasad, 2014; Stephen & Galak, 2012). For online WOM at the stage of consideration, I focus specifically on test drive experience shared from different social media channels. Compared to posts at firm's Facebook, test drive experience posts shared on social media channels tend to be very detailed and concern information, which provides sufficient information for customers to narrow down their selection set. The nature of detailed and concern information also coincides with the characteristics of the stage of consideration (Shocker et al., 1991).

I am also interested in how the interactions shown in Figure 26 vary by firm characteristics. Specifically, I focus on three different aspects of firm characteristics: origin of brand, market structure, and price factor. Prior research suggests that country of origin would moderate the spillover effects (Borah & Tellis, 2016) because consumers might use the origin as an attribute and make similar inferences for brands that belong to the same origin (Hong & Wyer, 1990). Thus, in the category of origin of brand, I focus on Asian-based, European-based, and US-based brands to investigate how origin of brand may vary dynamics of online WOM in the current setting. Furthermore, I also focus on market structure. Netzer, Feldman, Goldenberg, and Fresko (2012) applied the text-mining approach on user-generated content in the U.S automobile industry to identify market structure of the US automobile industry. I, therefore, leverage their three sub market structures to examine how market structure may vary the relationships shown in Figure 26. Finally, prior research on WOM has indicated that consumers' motivation to engage in online WOM differs across brands and that consumers may be particularly inclined to converse about highly regarded or high-quality brands (Lovett, Peres, & Shachar, 2013). Therefore, I consider the price factor by examining how the category of luxury versus non-luxury may vary dynamics of online WOM examined in the current study.

Figure 26. Conceptual Model



It has been widely acknowledged that customer awareness on firms have a positive impact on firm performance (e.g., Goh et al., 2013; Homburg, Klarmann, & Schmitt, 2010; Hoyer & Brown, 1990). Customer awareness is defined as the capacity of decision-makers to distinguish or recall a brand (Homburg et al., 2010; Hoyer & Brown, 1990). Typically, in the journey of consumer choice, customers are uncertain about product quality and therefore perceive their decisions as risky because the consequences of a purchase cannot be entirely anticipated (Homburg et al., 2010). Prior research suggests that customer awareness is effective in reducing customer uncertainty by reducing buyer information costs and buyer-perceived risk (Erdem & Swait, 1998; Erdem, Swait, & Valenzuela, 2006; Homburg et al., 2010).

In the setting of firms' Facebook pages, to increase customer awareness with the hope of converting customers into profits, firms deliberately engage in advertising, products/services, deals, and customer relationship (Goh et al., 2013; Miller & Tucker, 2013). The intensity of these marketing efforts has been shown to have a positive impact on firm performance (Goh et al., 2013). Particularly, the newsfeed function at Facebook allows firm's efforts (e.g., new postings) to automatically appear in the personal newsfeed of all Facebook users directly connected to the fan page in addition to appearing on the fan page itself (Debatin et al., 2009). This mechanism is very effective for awareness creation (Debatin et al., 2009) because it increases the likelihood for and the speed of viral information distribution through network effects (Trusov et al., 2009). Thus, I hypothesize:

H1*: Online WOM about the focal brand at the stage of awareness is positively associated with offline car sales of the focal brand.*

I posit that online WOM about the focal brand's competitors at the stage of awareness will have a positive impact on offline car sales of the focal brand (i.e., positive online WOM spillover effects). Prior research on marketing spillover effects find positive spillover effects such that a marketing-related action has an effect in the same direction on a focal product and associated products (Chae et al., 2017). For example, in the context of online advertising, Lewis and Nguyen (2015) find positive spillover effects where display ads for Samsung tablets increase search volume for that product and Apple iPads. Similarly, Borah and Tellis (2016) also identify a positive spillover effect (they refer it as the "perverse halo effect). They find that in the setting of U.S. automobile recalls negative consumer sentiment an automotive brand increases negative sentiment toward other automotive brands in the same category.

The positive spillover effects could be explained by the fact that firm's marketing efforts for the focal brand can cue consumers to think about associated but broader concepts related to non-focal brands (Chae et al., 2017). Namely, thinking about a focal brand or product could trigger thoughts about higher-level concepts, which in turn open up the possibility of thinking about other brands or products (Berger & Schwartz, 2011). Construal level theory also further supports this positive nature (Trope & Liberman, 2010; Trope, Liberman, & Wakslak, 2007). This perspective also implies that in the context of customer purchase decisions if consumers, in response to exposure to a stimulus, adopt an abstract and broad perspective (i.e., higher-level construal), a positive spillover effect could occur (Chae et al., 2017).

In the stage of awareness, customers know the alternative exists, but may not have either interest in it or sufficient information to understand its possible benefits (De Bruyn & Lilien, 2008). Particularly, compared to test drive experience shared on different social media channels, firms' Facebook fan pages tends to provide more general information to catch customers' attention and let them aware information in a timely manner. For more specific information, firms tend to ask their customers refer to some specialists for further information. Thus, it is plausible that relative to online WOM at the stage of interest, measured by test drive experience, customers tend to receive abstract and broad information in the stage of awareness, which is measured by activities at firm's Facebook page. Thus, I hypothesize:

H2: *Online WOM about the focal brand's competitors at the stage of awareness is positively associated with offline car sales of the focal brand.*

Extant research has well recognized the positive impact of online WOM on various marketing outcomes (Chevalier & Mayzlin, 2006; Forman et al., 2008; Sabnis & Grewal, 2015). I posit that online WOM about the focal brand at the consideration stage, measured by customers' test drive experience, has the positive impact on offline car sales of the focal brand. Compared to low-involvement products such as music, customers who experience high-involvement decisions (i.e., purchasing a car in my setting) would engage in a comprehensive evaluation of the choice alternatives before purchasing (Zaichkowsky, 1985). Online WOM, measured by test drive experience, provides a good outlet for potential customers to comprehensively and seriously evaluate the vehicles and their alternatives. Usually, customers would provide very detailed information about their test drive experience range from exterior looks, interior designs, price information, car features (e.g., horsepower), to control conditions in the road, namely, a very narrow and concrete aspects of the vehicle and test drive experience. This detailed information allows customers to deeply understand the features of each evaluated vehicle and therefore make a better purchase decision. Thus, I hypothesize:

H3: *Online WOM about the focal brand at the stage of consideration is positively associated with offline car sales of the focal brand.*

I posit the opposite direction for online WOM spillover effects at the stage of interest (i.e., negative online WOM spillover effects). At the stage of consideration, customers already know the alternatives existed, start to develop some interest, and hence decide to learn more about the brand or product (De Bruyn & Lilien, 2008). In other words, at this stage customers would seek for narrower, detailed, and concrete information to help them refine their selection set (Shocker et al., 1991). As described above, online WOM, measured by test drive experience, provides a very concrete and narrow description about the functionality of each evaluated vehicles. Therefore, compared to online WOM from firms' Facebook fan page that usually provides more abstract and broader information, test drive experience provides more information about functionality and feasibility rather than only desirability. These types of information have been shown to represent lower-level construal (R. Dhar & Kim, 2007; Liberman & Trope, 1998), which will show the opposite effect as higher-level construal would have. Thus, I hypothesize:

H4: *Online WOM about the focal brand's competitors at the stage of consideration is negatively associated with offline car sales of the focal brand.*

3.4 DATA AND EMPIRICAL METHODOLOGY

3.4.1 Research Context

I select the U.S. automobile industry to analyze the relative effects of online WOM of the stages of awareness and interest and their spillover effects for several reasons. First, the U.S. automobile industry is of considerable economic significance. It generates sales representing 3%-3.5% of U.S. gross domestic sales and accounts for 1 in 7 jobs in the U.S. economy (Hill et al., 2010; Kalaignanam, Kushwaha, & Eilert, 2013; Pauwels & Srinivasan, 2004). In response to the global economic recession, automobile companies have turned their attention to social media marketing to enhance customer relationships, disseminate a variety of information, engage customers, and boost sales (Pauwels & Srinivasan, 2004). This suggests that the U.S. automobile industry provides an appropriate setting to study online WOM related issues. Second, the high-involvement nature of the automobile industry leads consumers to discuss and gather information more frequently than other industries (Borah & Tellis, 2016). Given this unique nature, the automobile industry provides a considerable amount of online WOM as consumers actively and frequently participate in numerous social media sites (Borah & Tellis, 2016).

I focus on firm's Facebook fan page as a proxy for online WOM at the stage of awareness because Facebook is the most visited social media site in the US (eMarketer, 2015c). Due to this popularity, more than 54 million businesses have set up their online brand communities (i.e., fan page) for marketing purposes (Facebook, 2015b). More importantly, in the setting of firm's Facebook page, firms usually use general information to catch their customer attention first. Once customers are aware of this information, firms would ask those customers to refer to some specialists or some web sites for more detailed information. The nature of general information at firm's Facebook fan page matches the characteristics of the stage of awareness. Namely, customers know the alternative exists, but may note have either interest in it or sufficient information to understand its possible benefits. Thus, firm's Facebook fan page provides a representative sources to measure online WOM at the stage of awareness.

For online WOM at the stage of consideration, I focus on customers' test drive experience shared on different social media channels. As discussed, the automobile industry is a high-involvement industry. Thus, customers actively and frequently share their information such as test drive experience in different social media sites. Because test drive experience is one of the critical factors before the final purchase decision, I, therefore, believe that customer test drive experience shared on different social media sites represent an appropriate source as a proxy for online WOM at the stage of consideration.

3.4.2 Data

My samples consist of 30 major car brands in the U.S. automobile industry[14]. My dataset on online WOM covers two parts from May 2009 to October 2014: (1) firm's Facebook data for

[14] These car brands are: Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, FIAT, Ford, Honda, Hyundai, Infiniti, Jaguar, Jeep, KIA, Land Rover, Lexus, Lincoln, Mazda, Mercedes-Benz, Mitsubishi, Nissan, Porsche, Saab, Scion, Subaru, Toyota, Volkswagen, and Volvo.

the stage of awareness and (2) customers' test drive experience shared on different social media channels for the stage of consideration (interest). To collect online WOM at the stage of awareness from firm's Facebook fan pages, I relied on the Facebook graph API (Application Programming Interface)[15]. Each of these thirty brands has its official Facebook fan page. Thus, I built a software tool in PHP to connect with the Facebook graph API to collect data at the stage of awareness. My data starting point was May 2009 because most car brands initiated their Facebook pages on May 2009[16].

I considered four major mechanisms at firm's Facebook page as the metrics for online WOM at the stage of awareness, trying to understand how these mechanisms may vary the relationships shown in my research model. These four metrics include: (1) total number of posts, (2) total number of likes associated with posts, (3) total number of comments associated with posts, and (4) total number of shares associated with posts. For each single post, my data covered detailed information, including post id, post time, post type, post source, post content, and post link. In addition, each single comment associated with each single was also collected. Figure 27 shows one example of the firm's post at its Facebook fan page and its associated metrics. In this example, there are 271 "Likes", 16 "Comments", and 30 "Shares" associated with this post. Besides, as discussed above, firms tend to use their Facebook fan page to let their customers

[15] Facebook Graph API: https://developers.facebook.com/docs/graph-api

[16] Among these 30 car brands, 23 firms started their pages in 2009, 5 firms started their pages in 2010, and 2 firms started their pages in 2011.

aware some information available. Namely, at firm's Facebook page, relative to customers' test-drive experience, firms use more abstract and general information to catch their attention without providing too many details. For those customers who have paid attention to some particular information, firms would ask them to refer to some specialists for detailed information. Therefore, this approach provides further evidence of why firm's Facebook fan page could be a good proxy for online WOM at the stage of awareness. In other words, through firm's Facebook page, customers only know the alternative exists, but they do not have sufficient information to understand its possible benefits. To conclude, my data on online WOM at the stage of awareness from firm's Facebook fan page included 59,405 firm-generated posts, 146,556,793 likes associated with those firm-generated posts, 4,209,129 comments associated with those firm-generated posts, 11,257,103 shares associated with those firm-generated posts, 811,387 user-generated posts, 19,395,881 likes associated with those user-generated posts, 1,634,363 comments associated with those user-generated posts, and 155,343 shares associated with those user-generated posts.

To collect customers' test drive experience for online WOM at the stage of consideration (interest), I used a combination of web crawler and artificial intelligence based text reducer provided by a commercial third party analyst. This type of the approach has been used recently to collect more comprehensive online WOM to better understand its impact in various settings (e.g., Borah & Tellis, 2016). There were three major steps to collect customers test-drive experience data shared from different social media channels. First, I collected the completed list of nameplates for each single brand (e.g., Toyota Corolla, Toyota Camry, Honda Civic) from the WardsAuto Premium database. Then, for each single nameplate, I used the combination of each nameplate and test drive keyword as a search query to collect test drive data by using the server provided by this third party analyst at the monthly level[17]. Third, for each single brand (e.g., Toyota), I summed up all test drive data in the nameplate level. The approach of collecting test drive data in the nameplate level and then summing them up for the brand level allows me have the most comprehensive set of online WOM data for the stage of consideration (interest). The dataset included customers' test drive experience on different platforms of social media (e.g., Facebook), various forums such as Automotiveforum.com*,* and review sites such as Edmunds.com. Overall, approximately 1,000 different social media sites were included in my dataset. Specifically, this third-party data provider scraped these sites to obtain any online WOM related to customers' test drive experience that mentioned nameplate across the time frame of the current study. For each single post, this third-party data provider also reported published time, the source of the post, the link of the post, and the author of the post. Figure 28 shows the screen shot of one test drive experience post and Table 38 shows the full content examples of test-drive experience from my dataset. As these sample examples show, relative to posts at firm's

[17] Example of the search query for collecting test drive posts used in the current study: (Chevrolet OR #Chevrolet OR #ChevroletMalibu OR #Malibu OR @Chevrolet OR @ChevyCustCare OR @ChevyLife) NEAR/3 ("Malibu") AND (test drive)

Facebook pages, these posts represent very detailed and narrow descriptions for the functionality of each evaluated vehicle rather than just desirability, which provide more sufficient and concrete information at the stage of consideration (interest). To conclude, there were 444,035 test drive related posts in my final dataset.

I collected monthly offline car sales and list prices from the WardsAuto Premium database, and traditional media advertising expenditure from Kantar Media. I also collected the consumer search volume index in the U.S. from Google Trends to control for the popularity effect of each car brand. Finally, I collected the monthly gasoline price index from the U.S. Bureau of Labor Statistics and the conference board's consumer confidence index. I focused on monthly data because offline car sale data is only available at the monthly level. My final panel contains total 1,789 firm-month observations. Tables 39 and 40 present the definition of variables and summary statistics, respectively.

Figure 27. Example of Post at the Stage of Awareness

Figure 28. Example of Post at the Stage of Consideration

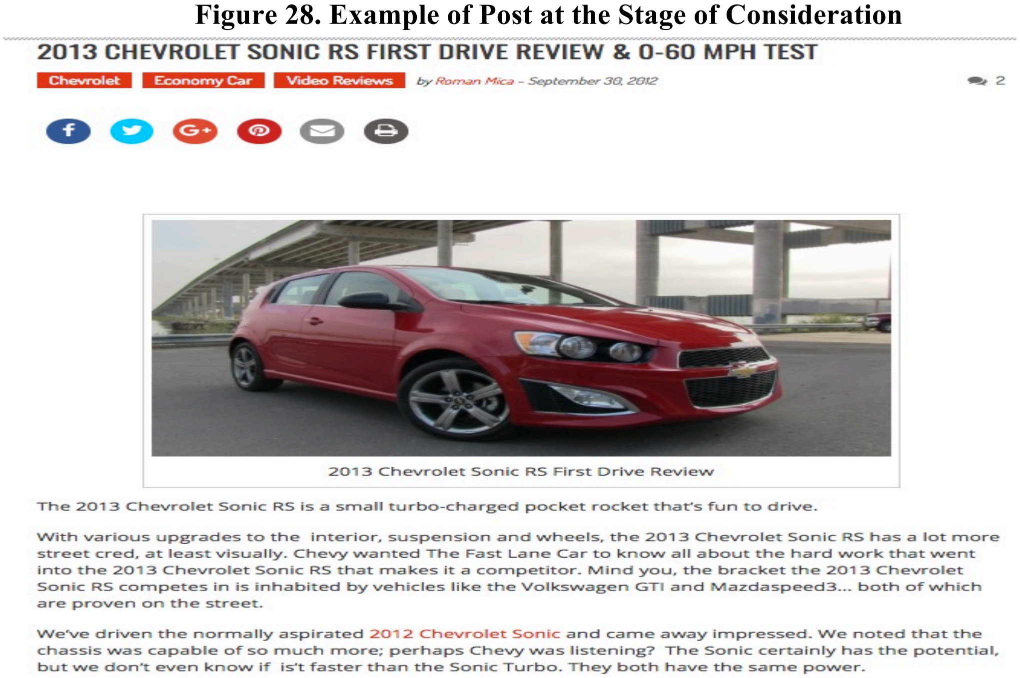


Table 38. Full Content Example of Test Drive Experience

Link	Note
https://goo.gl/C25cxg	Test drive for BMW
http://goo.gl/10iH7S	Test drive for Chevrolet
http://goo.gl/tYX91M	Test drive for Nissan

Table 39. Variable Definition

Variable	Definition
Sales	Total number of offline car sales made by one car make in month t
F-Post (a)	Total number of posts by one car make at its Facebook page in month t
C-F-Post (a)	Total number of posts by competitors at their Facebook pages in month t
F-Like (a)	Total number of likes associated with one car make's posts at its Facebook page in month t
C-F-Like (a)	Total number of likes associated with competitors' posts at their Facebook pages in month t
F-Comment (a)	Total number of comments associated with one car make's posts at its Facebook page in month t
C-F-Comment (a)	Total number of comments associated with competitors' posts at their Facebook pages in month t
F-Share (a)	Total number of shares associated with one car make's posts at its Facebook page in month t
C-F-Share (a)	Total number of comments associated with competitors' posts at their Facebook pages in month t
U-Post (a)	Total number of posts by one car make's users at its Facebook page in month t
C-U-Post (a)	Total number of posts by competitors' users at their Facebook pages in month t
U-Like (a)	Total number of likes associated with one car make's users posts at its Facebook page in month t
C-U-Like (a)	Total number of likes associated with competitors' users posts at their Facebook pages in month t
U-Comment (a)	Total number of comments associated with one car make's users posts at its Facebook page in month t
C-U-Comment (a)	Total number of comments associated with competitors' users posts at their Facebook pages in month t
U-Share (a)	Total number of shares associated with one car make's users posts at its Facebook page in month t
C-U-Share (a)	Total number of shares associated with competitors' users posts at their Facebook pages in month t
TD-Post (c)	Total number of test drive posts associated with one car make from different Social media channels in month t
C-TD-Post (c)	Total number of test drive posts associated with competitors from different Social media channels in month t
Traditional Media Spending (TMS)	Total amount of money spent by one car make on traditional media in month t
Price	Average price of one car make in month t
Google Trends (GT)	The Google Trends search interest index for one car make in month t in the U.S.
Gasoline Price Index	The U.S. gasoline price index in month t
Consumer Confidence Index	The conference board consumer confidence index in month t

Notes: (a) refers to the metrics at the stage of awareness (i.e., activities from firm's Facebook page); (c) refers to the metrics at the stage of consideration (i.e., test drive experience).

Table 40. Descriptive Statistics

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	1789	38331.55	48224.67	97	244,501
F-Post (a)	1789	33.21	34.62	0	1,042
C-F-Post (a)	1789	916.79	407.61	48	2,605
F-Like (a)	1789	81914.72	149010.7	0	1,128,101
C-F-Like (a)	1789	2,291,620	2,133,963	3,093	5,997,541
F-Comment (a)	1789	2352.78	2849.67	0	26,648
C-F-Comment (a)	1789	65377.8	38698.07	420	153,749
F-Share (a)	1789	6292.4	12465.24	0	115,372
C-F-Share (a)	1789	176240.8	174943.3	27	580,559
U-Post (a)	1789	453.54	537.73	0	9,624
C-U-Post (a)	1789	12439.43	4422.59	0	22,539
U-Like (a)	1789	10841.74	30856.97	0	560,219
C-U-Like (a)	1789	303,613	386555.5	254	2,498,196
U-Comment (a)	1789	913.56	1840.7	0	36,118
C-U-Comment (a)	1789	25309.42	16117.62	480	109,163
U-Share (a)	1789	86.83	515.17	0	16,400
C-U-Share (a)	1789	2434.79	3915.27	0	21,905
TD-Post (c)	1789	248.2	334.9	5	3,771
C-TD-Post (c)	1789	6972.81	4910.05	1,862	35,106
TMS	1789	34332752.43	34561846.7	65,200	200,000,000
Price	1789	35357.37	15608.98	14192.5	90,775
GT	1789	54.86	19.59	7	100
GPI	1789	3.39	0.4	2.31	3.98
CCI	1789	66.11	12.89	40.9	94.1

3.4.3 Bayesian Model Specification and Estimation Procedure

I employ a Bayesian framework to examine dynamics of online WOM and estimate it using Markov Chain Monte Carlo (MCMC) method for several reasons. First, there have always been some arguments among frequentists regarding the appropriate sample size for utilizing the asymptotic inference (Rossi & Allenby, 2003). The Bayesian framework is compelling in the sense that it provides a unified approach to modeling, incorporation of prior information, and inference (Rossi & Allenby, 2003). Inference in the setting of the Bayesian framework refers to making a posterior statement about all unobservable variables, including both parameters and, as yet unrealized, data (prediction) (Rossi & Allenby, 2003). Thus, Bayesian inference adheres to the likelihood principle and is conducted using formal rules of probability theory, meaning that under mind condition, Bayes estimators are consistent, asymptotically efficient, and admissible (Rossi & Allenby, 2003). The nature of Bayesian inference also allows this framework to naturally get rid of the asymptotic assumption and deliver exact and finite sample inference (Rossi & Allenby, 2003). Second, MCMC method is flexible and robust to estimate any functions of parameters without the "plug-in" method due to its nature of simulation process (Rossi & Allenby, 2003). Given the unique nature of the Bayesian framework, a considerable literature in online WOM has utilized the Bayesian framework to study the effect of online WOM (e.g., Ghose, Goldfarb, & Han, 2012; Sabnis & Grewal, 2015; Zhou & Duan, 2016).

My Bayesian model is specified as follows:

$$Sale_{A,t} = \beta_0 + \beta_1 Awareness_{A,t-1} + \beta_2 \sum_{J \neq A} Awareness_{J,t-1} + \beta_3 Consideration_{A,t-1} + \beta_4 \sum_{J \neq A} Consideration_{J,t-1} + \beta_5 TraditionalMedia_{A,t-1} + \beta_6 Price_{A,t-1} + \beta_7 GoogleTrends_{A,t-1} + \beta_8 GasolinePirceIndex_{t-1} + \beta_9 ConsumerConfidenceIndex_{t-1} + \tau_A + \xi_t + \varepsilon_{A,t} \; (1)$$

$$\varepsilon_{A,t} \sim \text{i.i.d. } N(0, \sigma_0^2), \tau_A \sim \text{i.i.d. } N\left(0, \sigma_{firm}^2\right), \beta_0 \sim N(0, 100), \beta_1 \sim N(0, 100), \beta_2 \sim N(0, 100),$$
$$\beta_3 \sim N(0, 100), \beta_4 \sim N(0, 100), \beta_5 \sim N(0, 100), \beta_6 \sim N(0, 100), \beta_7 \sim N(0, 100), \beta_8 \sim N(0, 100),$$
$$\beta_9 \sim N(0, 100), \xi_t \sim 1 \text{ (flat)}, \; \sigma_0^2 \sim \text{InvGamma}(0.001, 0.001), \sigma_{firm}^2 \sim \text{InvGamma}(0.001, 0.001)$$

, where $Sale_{A,t}$ are offline car sales for the focal brand at time t; $Awareness_{A,t-1}$ are online WOM at the stage of awareness, measured by activities at the focal brand's official Facebook page (i.e., post , like, comment, or share), for the focal brand at time t-1; $Awareness_{J,t-1}$ are online WOM at the stage of awareness for the focal brand's competitors at time t-1 (i.e., online WOM spillover effects at the stage of awareness); $Consideration_{A,t-1}$ are online WOM at the stage of consideration, measured by test drive experience, for the focal brand at time t-1; $Consideration_{J,t-1}$ are online WOM at the stage of consideration for the focal brand's competitors at time t-1 (i.e., online WOM spillover effects at the stage of consideration); $TraditionalMedia_{A,t-1}$ is the traditional media spending for the focal brand at time t-1; $Price_{A,t-1}$ is the average price for the focal brand at time t-1; $GoogleTrends_{A,t-1}$ is the Google search index in the U.S. for the focal brand at time t-1 $GasolinePriceIndex_{t-1}$is the U.S. gasoline price index at time t-1; $ConsumerConfidenceIndex_{t-1}$is the conference board consumer confidence index at time t-1; τ_A are random effects to control for individual heterogeneity; ξ_t are monthly time dummies ; $\varepsilon_{A,t}$ is the error term.

To estimate my model, I used MCMC methods (e.g., Rossi & Allenby, 2003). Specifically, I used Metropolis-Hastings (MH) algorithm and implemented the estimation procedures in Stata. The estimation gives the parameters for the effects of own online WOM, competitive effects of competitors' online WOM (i.e., spillover effects), and unobserved heterogeneity. I took the natural log on all variables to remove the scaling effect. I used conjugate and noninformative priors for all parameters. Specifically, β_0 to β_9 follow the normal distribution with mean 0 and variance 100. σ_0^2 and σ_{firm}^2 follow the inverse gamma distribution with parameters 0.001 and 0.001. τ_A follows the normal distribution. Finally, ξ_t follows the uniform distribution. To assess model convergence, I checked trace plots, autocorrelation plots, histogram plots, and kernel density plots, which showed that the model specification converged. To test the significance of parameter values, I checked whether the 95% posterior intervals contained 0 (the norm in Bayesian estimation; e.g., Rossi & Allenby, 2003) to verify if the estimated parameter is different from 0.

3.5 RESULTS

3.5.1 Main Bayesian Analysis Results

Table 41 shows my Bayesian estimation results at the post level (i.e., Facebook post and test drive post). In this model, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence (i.e., the burn-in time period). Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations.

First of all, at the stage of awareness, I find that firm-generated posts by the focal firm (F-Post (a)) have the positive impact on offline car sales of the focal firm, supporting my H1. On the other hand, firm-generated posts by competitors (C-F-Post (a)) also have the positive impact on offline car sales of the focal firm (i.e., positive spillover effect), thereby supporting my H2. However, regarding user-generated posts by the focal firm (U-Post (a)) and competitors (C-U-Post (a)) at the stage of awareness, I cannot find any evidence to support my H1 and H2.

The results also suggest that online WOM for the focal brand at the stage of consideration (TD-Post (c)) positively influences offline car sales of the focal brand, supporting my H3. In addition, the negative spillover effect is observed at the stage of consideration. Namely, test drive posts about the competitors (C-TD-Post (c)) have the negative impact on offline car sales of the focal firm (i.e., negative spillover effect), supporting my H4. The assessment of model convergence (see Figures 29 to 39) showed that the model specification converged.

Table 41. Bayesian Estimation Results for Posts

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	**0.02 (0.009)**	**(0.003, 0.037)**
C-F-Post (a) $_{J, t-1}$	**0.163 (0.019)**	**(0.126, 0.19)**
U-Post (a) $_{A, t-1}$	-0.007 (0.006)	(-0.019, 0.006)
C-U-Post (a) $_{J, t-1}$	**-0.044 (0.016)**	**(-0.075, -0.013)**
TD-Post (c) $_{A, t-1}$	**0.029 (0.012)**	**(0.006, 0.052)**
C-TD-Post (c) $_{J, t-1}$	**-0.06 (0.015)**	**(-0.09, -0.029)**
TMS $_{A, t-1}$	**0.12 (0.01)**	**(0.1, 0.14)**
Price $_{A, t-1}$	0.031 (0.062)	(-0.089, 0.153)
GT $_{A, t-1}$	**0.11 (0.034)**	**(0.041, 0.174)**
GPI $_{A, t-1}$	**0.15 (0.069)**	**(0.018, 0.286)**
CCI $_{A, t-1}$	**0.237 (0.039)**	**(0.158, 0.313)**

Notes: Posterior means and posterior standard deviations (in parentheses) are reported, and estimates that are significant at 95%. C- refers to competitors (i.e., spillover effects), (a) refers to the metrics at the stage of awareness, (c) refers to the metrics at the stage of consideration (i.e., test drive experience), TMS refers traditional media spending, GPI refers to the gas price index, and CCI refers to the consumer confidence index. Please also note that I took the natural log transformations on all of these variables to remove the scaling effect. These criteria apply for the rest of results.

Figure 29. Assessment of Model Convergence for F-Post (a)

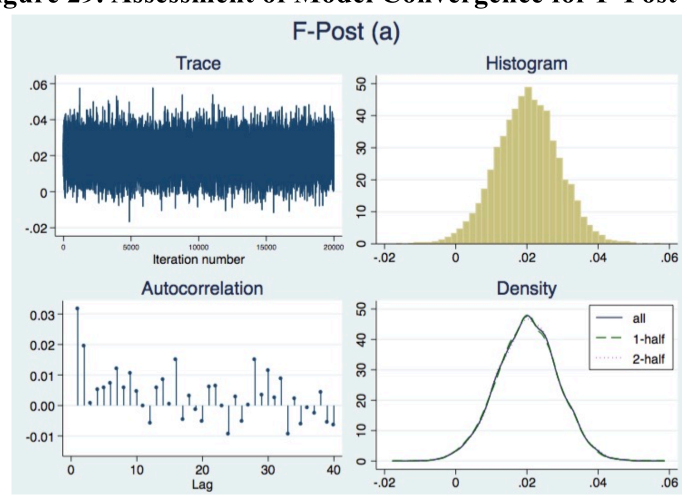


Figure 30. Assessment of Model Convergence for C-F-Post (a)

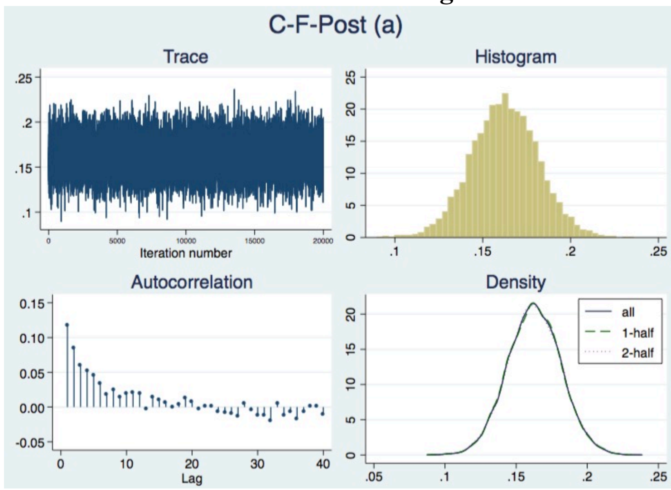


Figure 31. Assessment of Model Convergence for U-Post (a)

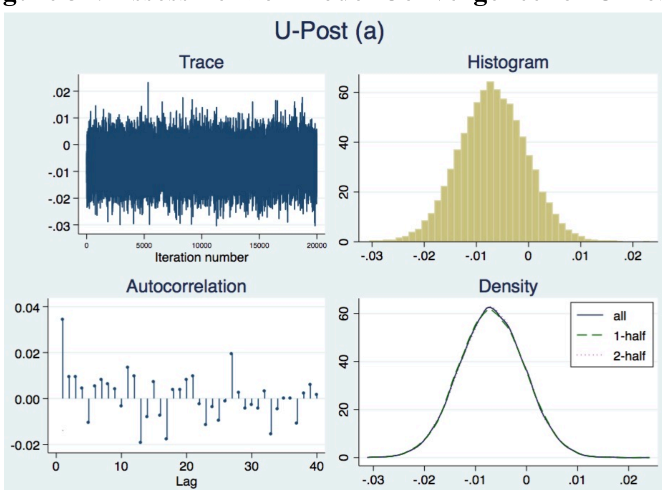


Figure 32. Assessment of Model Convergence for C-U-Post (a)

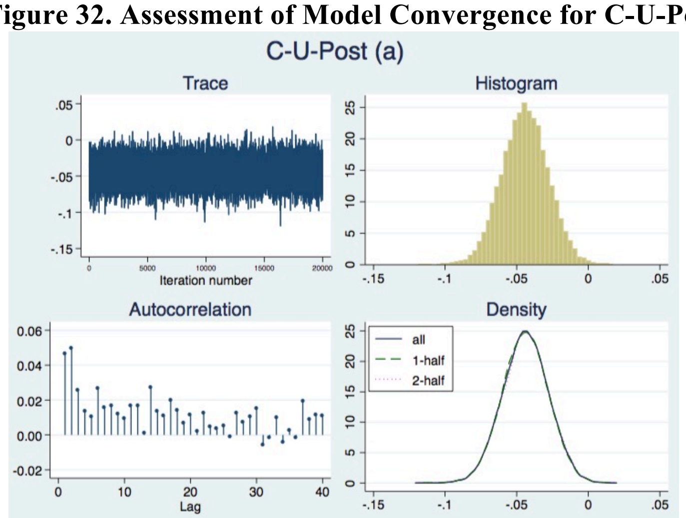


Figure 33. Assessment of Model Convergence for TD-Post (c)

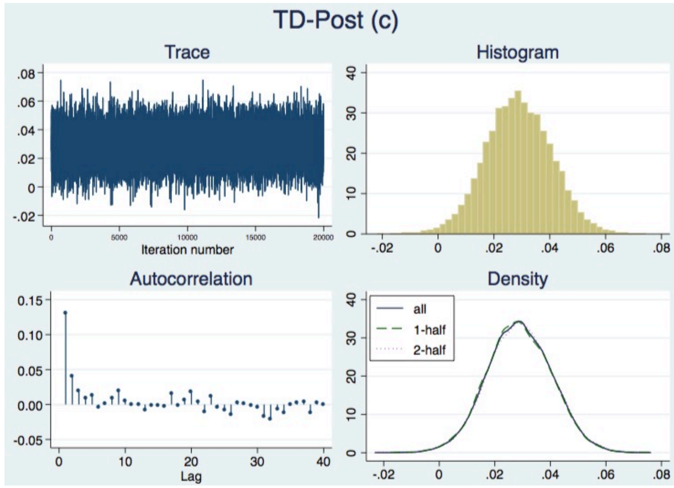


Figure 34. Assessment of Model Convergence for C-TD-Post (c)

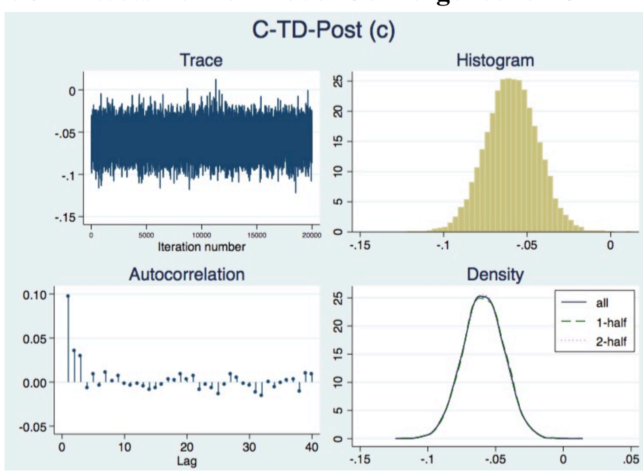


Figure 35. Assessment of Model Convergence for TMS

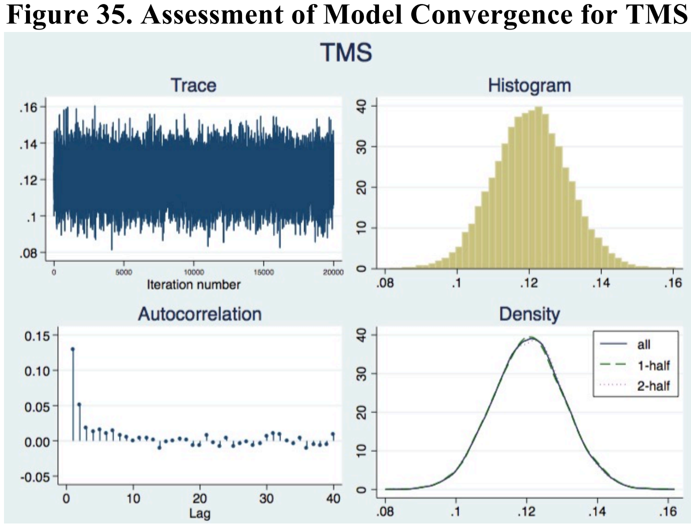


Figure 36. Assessment of Model Convergence for Price

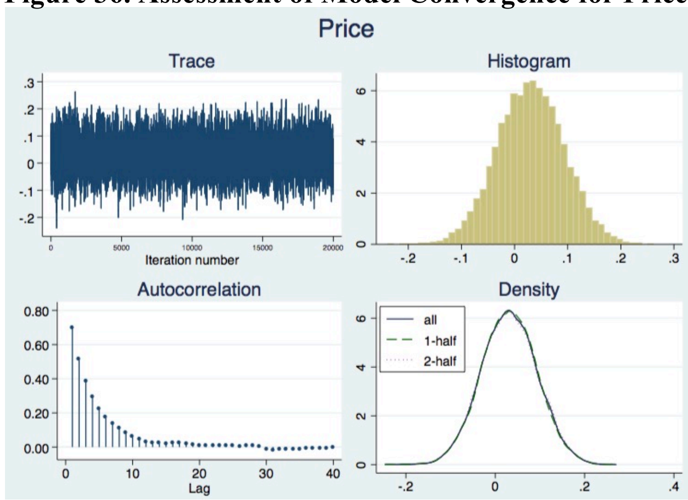


Figure 37. Assessment of Model Convergence for GT

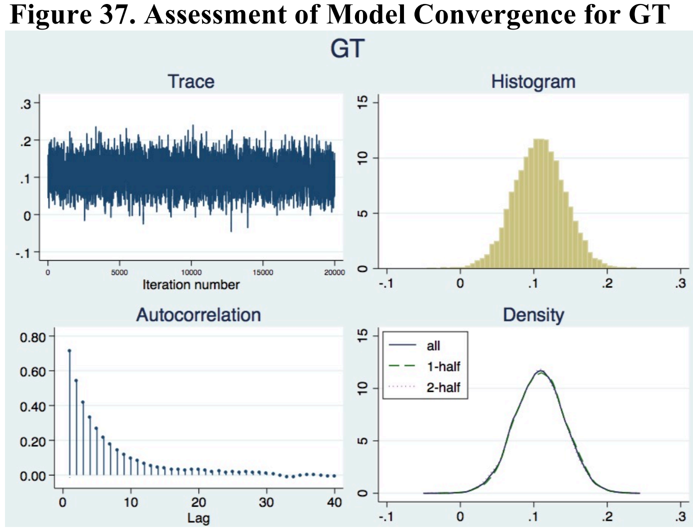


Figure 38. Assessment of Model Convergence for GPI

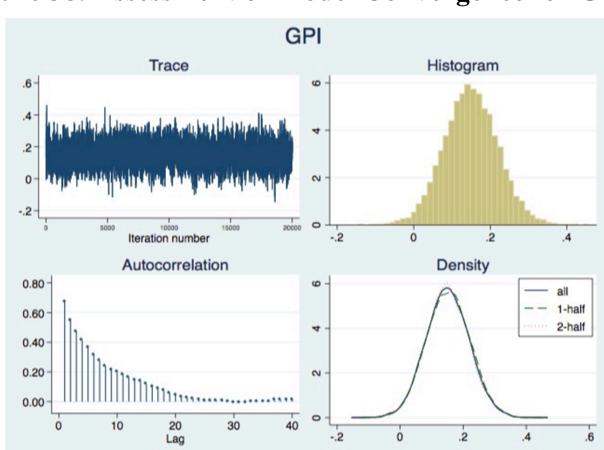
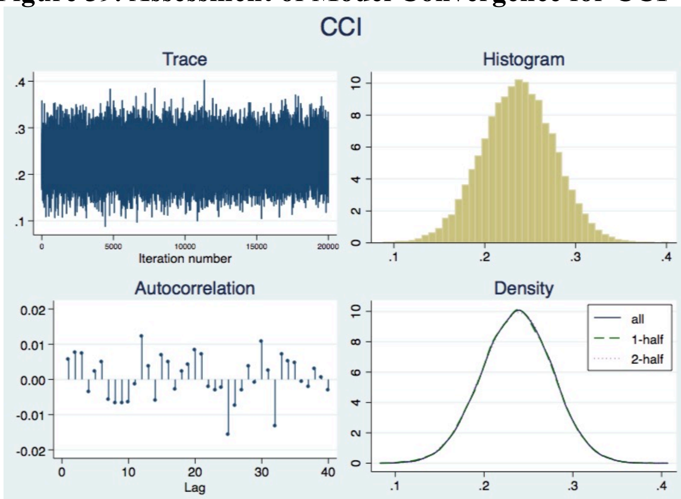


Figure 39. Assessment of Model Convergence for CCI



I then turn my attention to three different mechanisms associated with posts at the stage of awareness: Like, Comment, and Share. Table 42 shows my Bayesian estimation results at the like level (i.e., "Like" associated with posts at Facebook and test drive post). In this model, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence (i.e., the burn-in time period). I also thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations in this relationship. The assessment of model convergence (Figures 40 to 50) also suggested the model specification converged.

In this relationship, at the stage of awareness, I find that the volume of like associated with the focal firm's posts (F-Like (a)) does not have the impact on offline car sales of the focal firm, suggesting that "Like" may not be an effective mechanism for the focal firm to enhance their profit. On the other hand, the volume of like associated with competitors' posts (C-U-Like (a)) have the positive impact on offline car sales of the focal firm (i.e., positive spillover effects), in support of H2. For likes associated with the focal firm's user posts (U-Like (a)) and competitors' user posts (C-U-Like (a)), I cannot find evidence of supporting my H1 and H2, implying that customers pay different attentions on information generated by firms and customers at the stage of awareness. At the stage of consideration, both H3 and H4 are supported.

Table 42. Bayesian Estimation Results for Likes

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	-0.009 (0.005)	(-0.018, 0.0009)
C-F-Like (a) $_{J, t-1}$	**0.075 (0.01)**	**(0.055, 0.095)**
U-Like (a) $_{A, t-1}$	0.0007 (0.003)	(-0.006, 0.008)
C-U-Like (a) $_{J, t-1}$	0.017 (0.009)	(-0.001, 0.036)
TD-Post (c) $_{A, t-1}$	**0.025 (0.011)**	**(0.003, 0.047)**
C-TD-Post (c) $_{J, t-1}$	**-0.039 (0.014)**	**(-0.07, -0.011)**
TMS $_{A, t-1}$	**0.114 (0.009)**	**(0.095, 0.133)**
Price $_{A, t-1}$	-0.011 (0.06)	(-0.129, 0.108)
GT $_{A, t-1}$	**0.151 (0.034)**	**(0.084, 0.218)**
GPI $_{A, t-1}$	-0.056 (0.062)	(-0.179, 0.067)
CCI $_{A, t-1}$	**0.083 (0.04)**	**(0.005, 0.161)**

Figure 40. Assessment of Model Convergence for F-Like

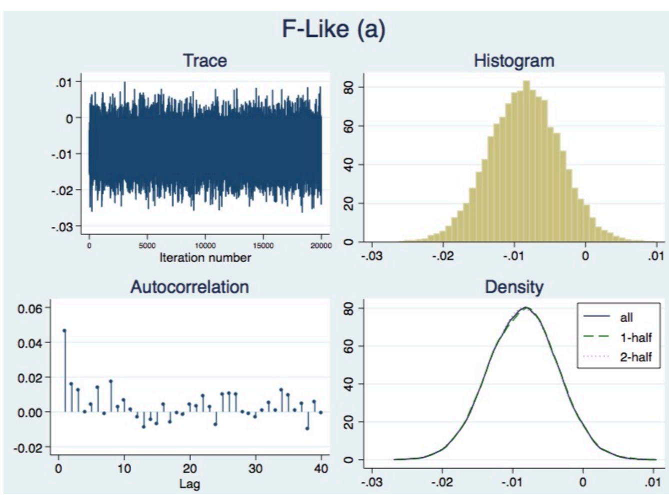


Figure 41. Assessment of Model Convergence for C-F-Like

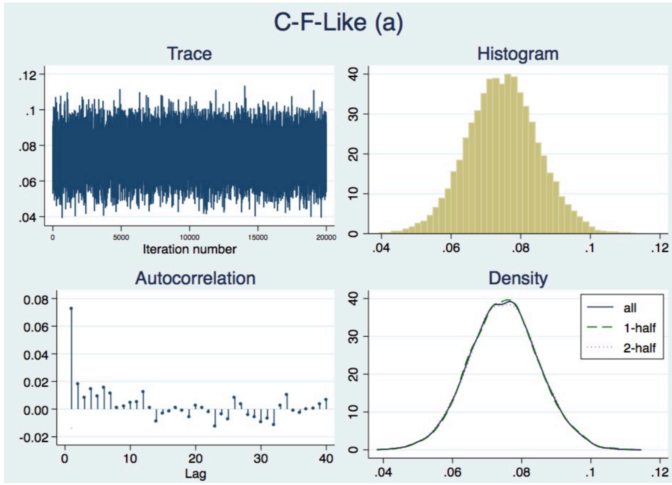


Figure 42. Assessment of Model Convergence for U-Like

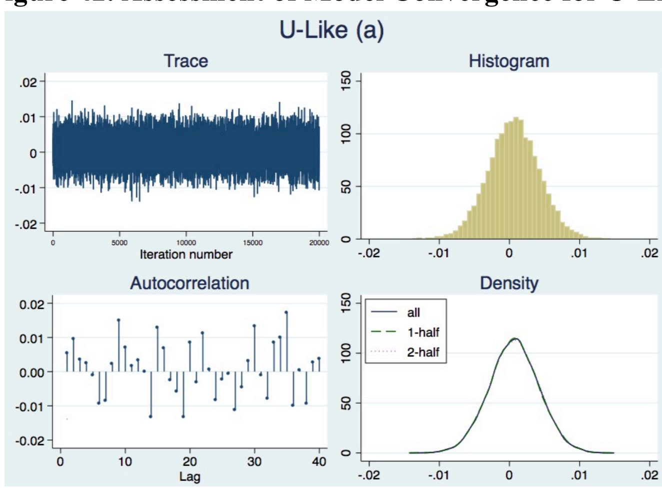


Figure 43. Assessment of Model Convergence for C-U-Like (a)

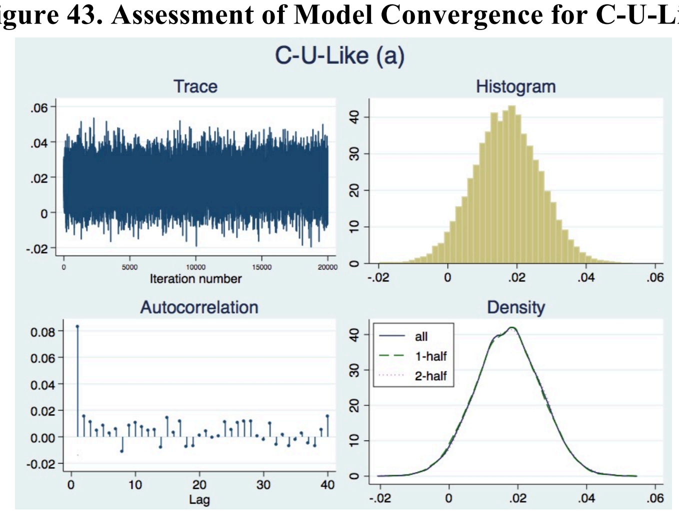


Figure 44. Assessment of Model Convergence for TD-Post (c)

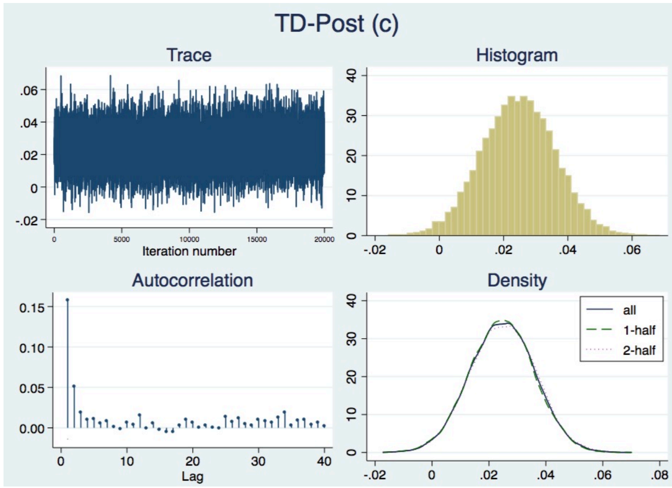


Figure 45. Assessment of Model Convergence for C-TD-Post (c)

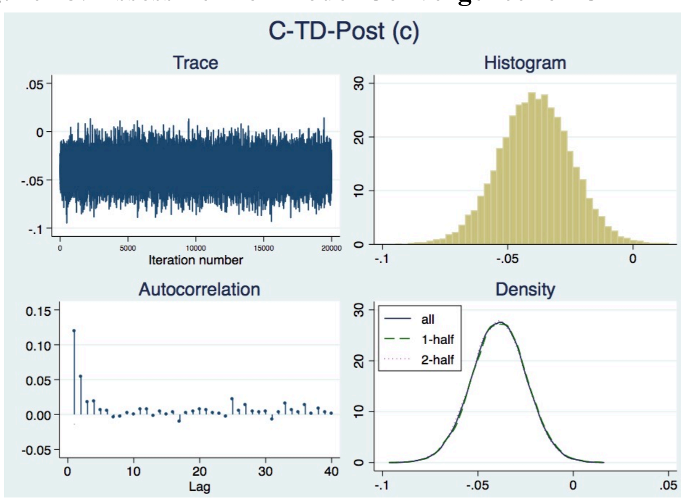


Figure 46. Assessment of Model Convergence for TMS

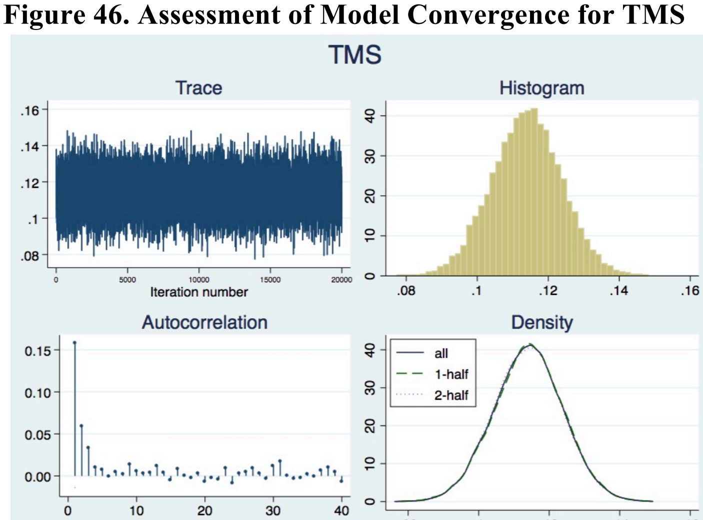


Figure 47. Assessment of Model Convergence for Price

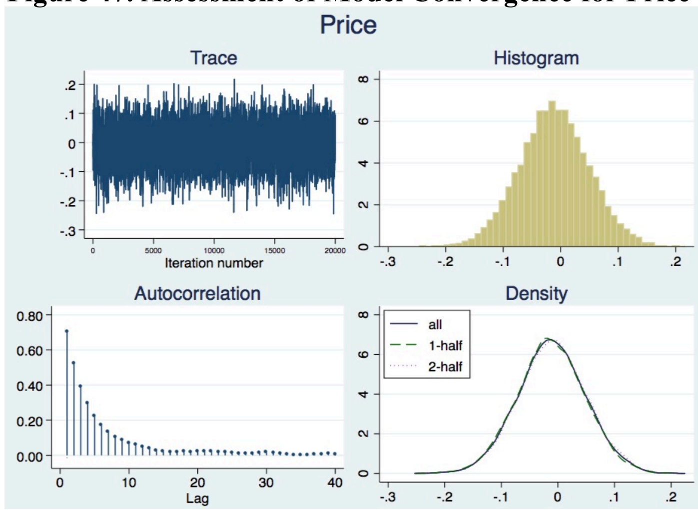


Figure 48. Assessment of Model Convergence for GT

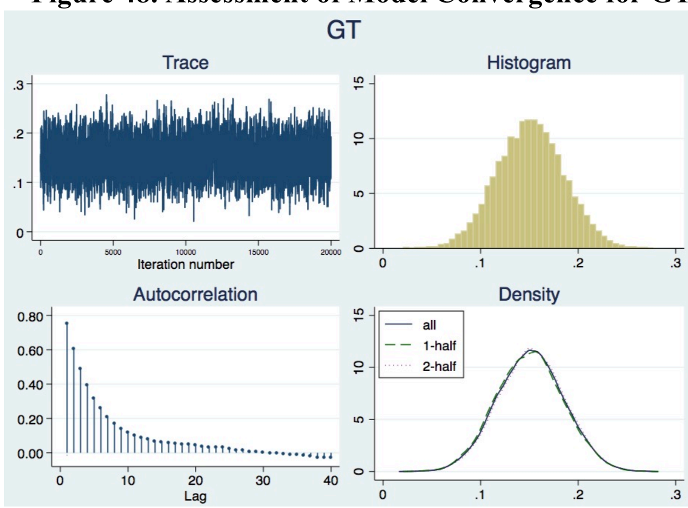


Figure 49. Assessment of Model Convergence for GPI

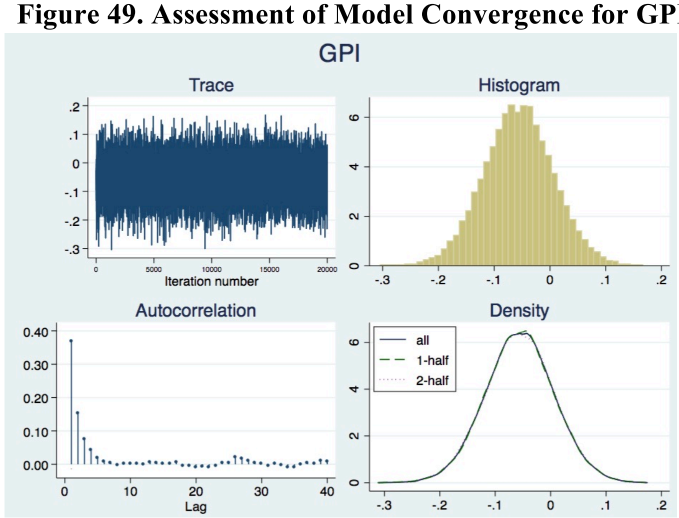


Figure 50. Assessment of Model Convergence for CCI

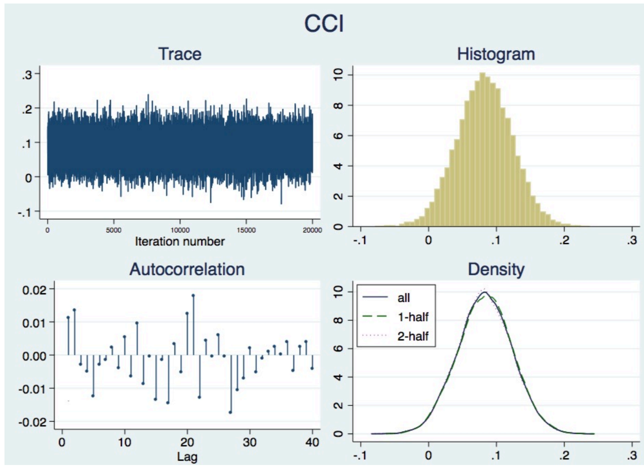


Table 43 shows my Bayesian estimation results at the comment level (i.e., “Comment” associated with posts at Facebook and test drive post). In this model, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence (i.e., the burn-in time period). I also thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations in this relationship. The assessment of model convergence (Figures 51 to 61) also suggested the model specification converged.

In this relationship, a very interesting pattern is observed. First, similar to results at the like level, at the stage of awareness, I only find that the volume of comment associated with competitors’ posts (C-F-Comment (a)) has the positive impact on offline car sales of the focal firm (i.e., positive spillover effects), in support of H2. The volume of comment associated with the focal firm’s posts again does not have the impact on offline car sales of the focal firm, rejecting H1. The mechanism of comment also changed how customers appreciate online WOM at the stage of consideration. For example, in this relationship, test drive posts related to the focal brand (TD-Post (c)) do not have any impact on offline car sales of the focal brand, rejecting my H3. On the other hand, I find that negative spillover effects still exist in this relationship, in support of H4.

Table 43. Bayesian Estimation Results for Comments

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	-0.002 (0.005)	(-0.012, 0.008)
C-F-Comment (a) $_{J, t-1}$	**0.107 (0.012)**	**(0.084, 0.13)**
U-Comment (a) $_{A, t-1}$	-0.003 (0.004)	(-0.011, 0.006)
C-U-Comment (a) $_{J, t-1}$	0.009 (0.011)	(-0.012, 0.031)
TD-Post (c) $_{A, t-1}$	0.02 (0.011)	(-0.001, 0.043)
C-TD-Post (c) $_{J, t-1}$	**-0.057 (0.014)**	**(-0.085, -0.029)**
TMS $_{A, t-1}$	**0.113 (0.009)**	**(0.093, 0.132)**
Price $_{A, t-1}$	0.007 (0.059)	(-0.109, 0.126)
GT $_{A, t-1}$	**0.163 (0.02)**	**(0.125, 0.204)**
GPI $_{A, t-1}$	**0.138 (0.052)**	**(0.037, 0.239)**
CCI $_{A, t-1}$	**0.206 (0.038)**	**(0.132, 0.282)**

Figure 51. Assessment of Model Convergence for F-Comment (a)

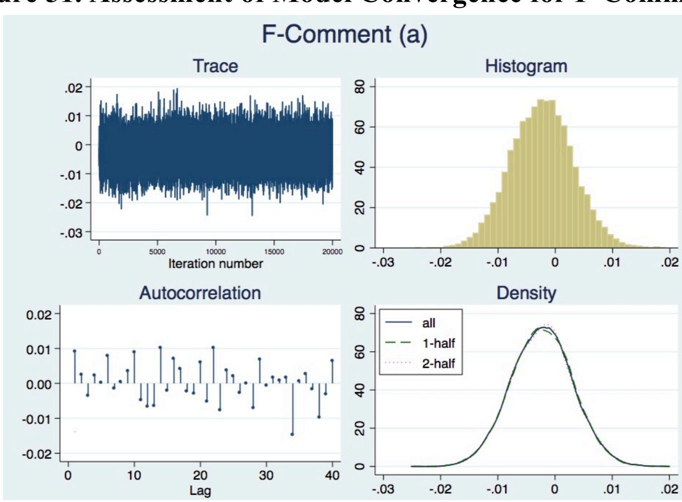


Figure 52. Assessment of Model Convergence for C-F-Comment

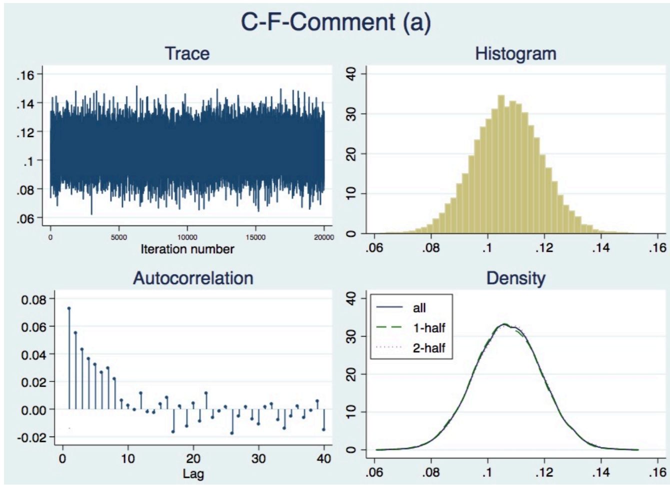


Figure 53. Assessment of Model Convergence for U-Comment (a)

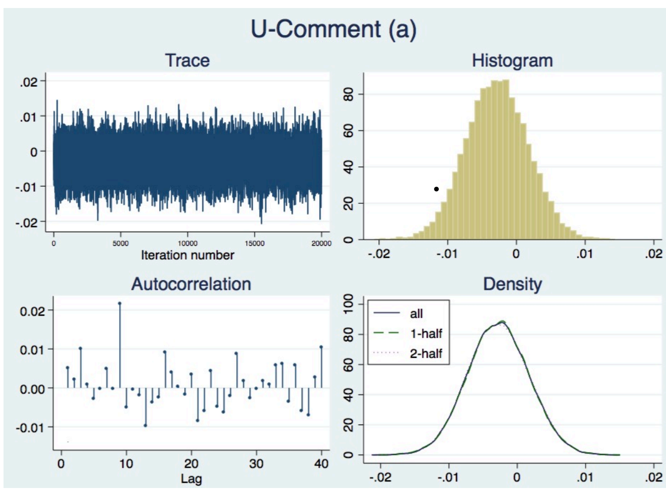


Figure 54. Assessment of Model Convergence for C-U-Comment (a)

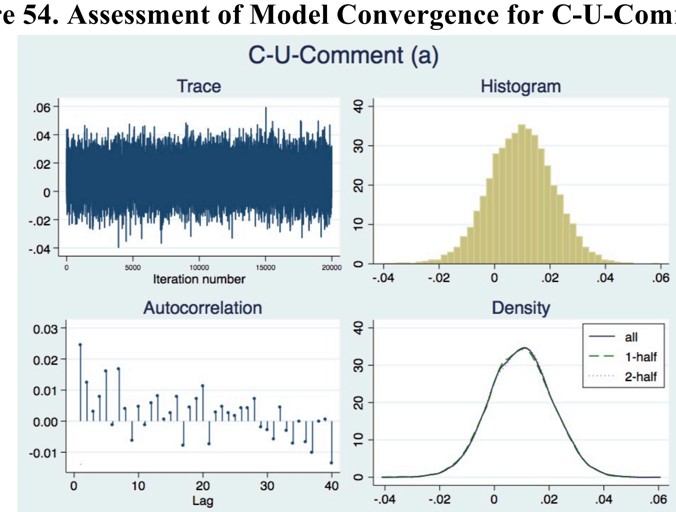


Figure 55. Assessment of Model Convergence for TD-Post (c)

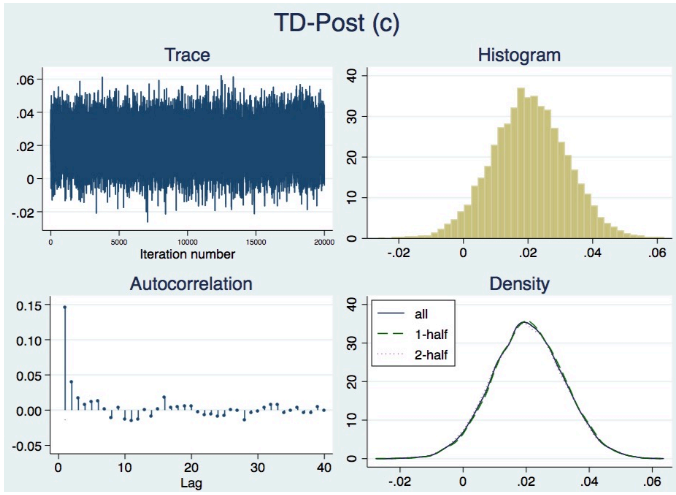


Figure 56. Assessment of Model Convergence for C-TD-Post (c)

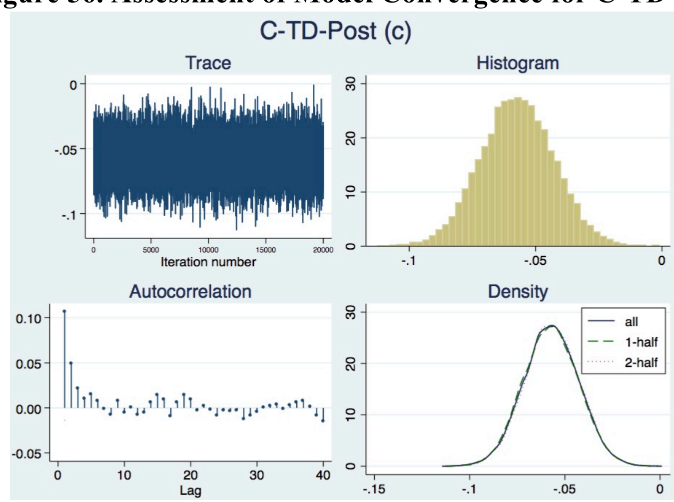


Figure 57. Assessment of Model Convergence for TMS

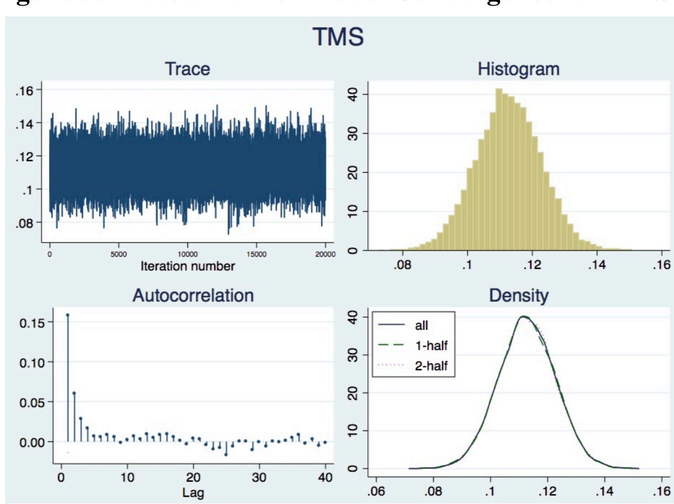


Figure 58. Assessment of Model Convergence for Price

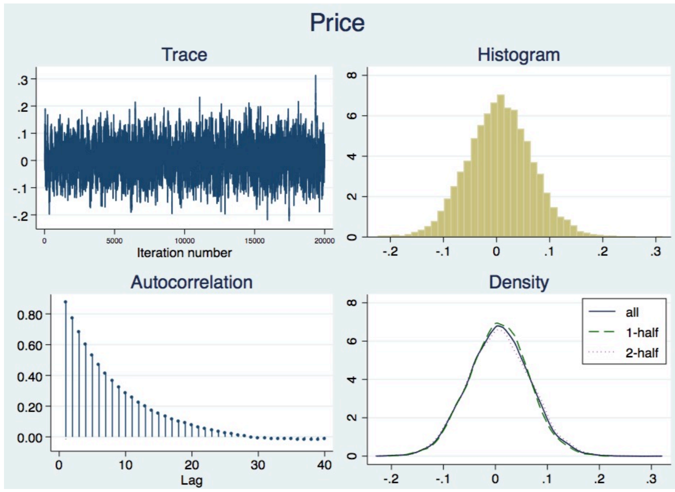


Figure 59. Assessment of Model Convergence for GT

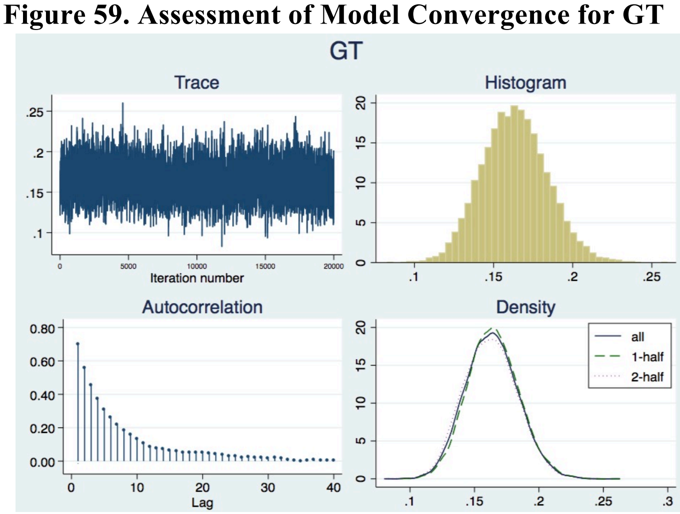


Figure 60. Assessment of Model Convergence for GPI

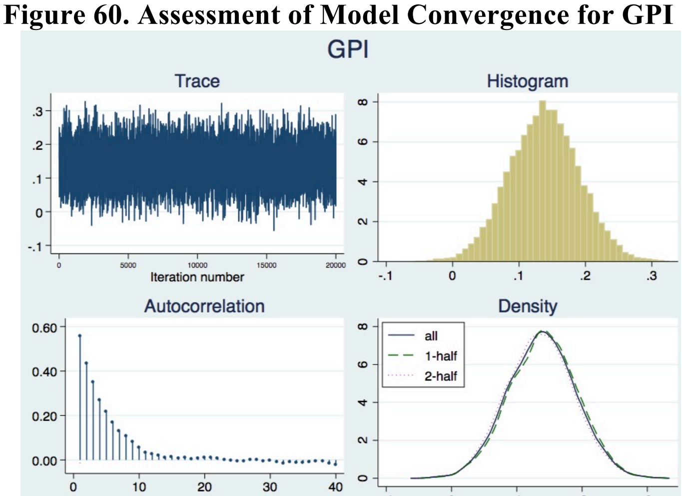


Figure 61. Assessment of Model Convergence for CCI

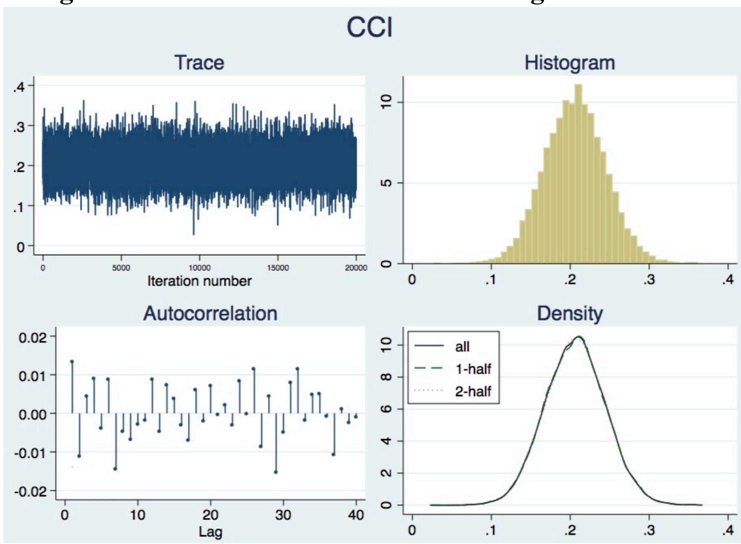


Table 44 shows my Bayesian estimation results at the share level (i.e., "Share" associated with posts at Facebook and test drive post). In this model, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence (i.e., the burn-in time period). I also thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations in this relationship. The assessment of model convergence (Figures 62 to 72) also suggested the model specification converged.

The results at the share level show another interesting patterns, suggesting that not very mechanism at the firm's Facebook page has the equal impact on firm performance and different mechanism also changes the effect of online WOM across the stages of awareness and consideration. For example, I observe that at the stage of awareness, the more shares associated with competitors' posts (C-F-Share (a)), the most offline sales of the focal brand (i.e., positive spillover effects), in support of H2. Regarding the volume of share associated with the focal brand's user posts (U-Share (a)) and competitors' user posts (C-U-Share (a)), I, again, cannot find any evidence to support my H1 and H2. Finally, in this relationship, at the stage of consideration, I find that test drive posts associated with the focal brand have the positive impact on offline car sales of the focal brand, supporting my H3. On the other hand, the mechanism of share does change the way of how competitors' customers appreciate the effect of online WOM at the stage of consideration. I cannot find evidence to support spillover effects in this relationship, rejecting my H4.

The results from the whole sample analysis could be summarized as the following. First, at the stage of awareness, online WOM regarding the focal brand and competitors has the *positive* impact on offline car sales of the focal firm. This implies that in the U.S. automobile industry customers think that abstract and general information (i.e., characteristics of information for the stage of awareness) for brand A is accessible and diagnostic of brand B and customers will use perception of brand A's quality to infer quality of brand B. This linking mechanism therefore has the positive impact on offline car sales of the focal brand. Second, once customers decide to receive more concrete or detailed information (i.e., characteristics of information for the stage of consideration), online WOM regarding the focal brand and competitors demonstrates the opposite effect on offline car sales of the focal firm with the positive effect from the focal brand and the negative effect from the competitors (i.e., negative spillover effect). Third, at the stage of awareness, information initiated by firms (e.g., F-Post (a), F-Share (a)) and users (e.g., U-Post (a), U-Share (a)) shows dramatically different impacts on firm performance, suggesting that customers place different weight on these two different sources of online WOM when making their purchase decisions. Finally, the results suggest that different mechanisms showed at the stage of awareness (i.e., post, like, comment, and share) do not have the equal impact on firm performance and these varied mechanisms also change how customers appreciate the effect of online WOM at the stage of consideration. For example, the results suggest that the volume of posts by firms is the most effective mechanism to influence customer purchase decisions and the "secondary" mechanisms (like, comment, share) are not very effective.

Table 44. Bayesian Estimation Results for Shares

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	-0.001 (0.003)	(-0.007, 0.005)
C-F-Share (a) $_{J, t-1}$	**0.049 (0.007)**	**(0.035, 0.062)**
U-Share (a) $_{A, t-1}$	0.006 (0.003)	(-0.0007, 0.013)
C-U-Share (a) $_{J, t-1}$	**-0.017 (0.007)**	**(-0.031, -0.004)**
TD-Post (c) $_{A, t-1}$	**0.034 (0.011)**	**(0.011, 0.056)**
C-TD-Post (c) $_{J, t-1}$	-0.024 (0.016)	(-0.054, 0.007)
TMS $_{A, t-1}$	**0.118 (0.009)**	**(0.098, 0.138)**
Price $_{A, t-1}$	0.011 (0.061)	(-0.108, 0.13)
GT $_{A, t-1}$	**0.108 (0.033)**	**(0.042, 0.172)**
GPI $_{A, t-1}$	**0.268 (0.072)**	**(0.128, 0.408)**
CCI $_{A, t-1}$	**0.224 (0.038)**	**(0.149, 0.297)**

Figure 62. Assessment of Model Convergence for F-Share

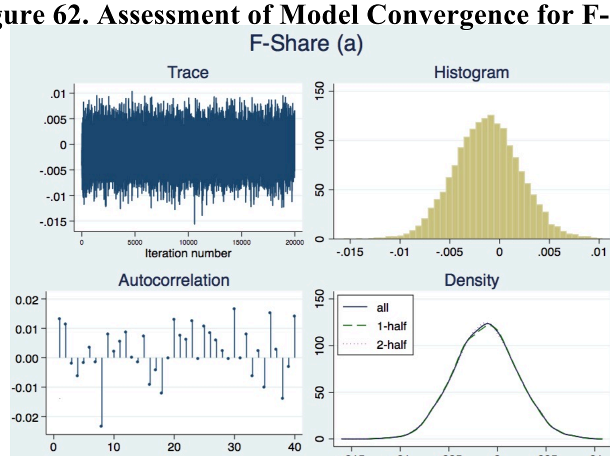


Figure 63. Assessment of Model Convergence for C-F-Share (a)

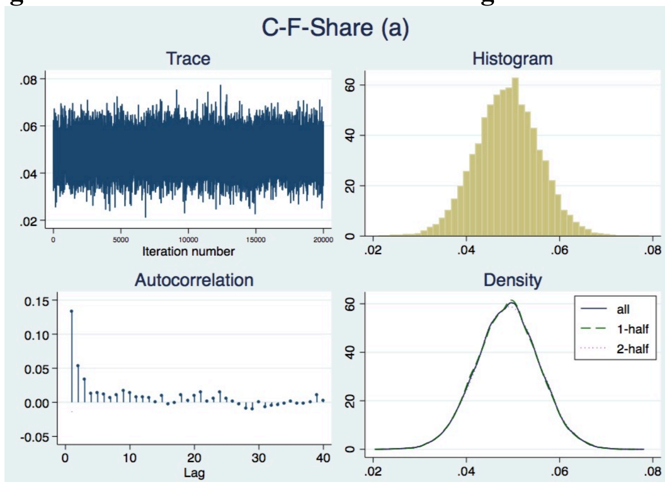


Figure 64. Assessment of Model Convergence for U-Share

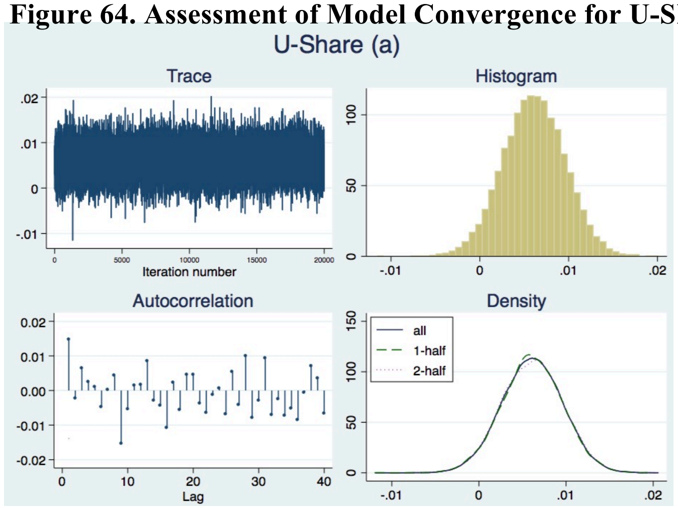


Figure 65. Assessment of Model Convergence for C-U-Share (a)

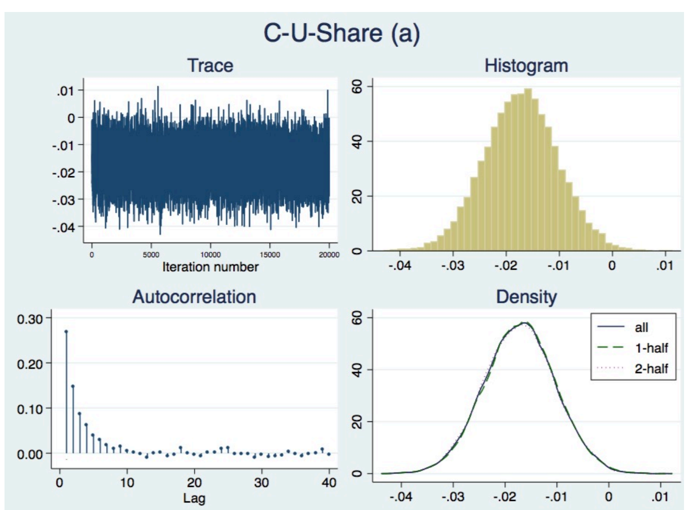


Figure 66. Assessment of Model Convergence for TD-Post (c)

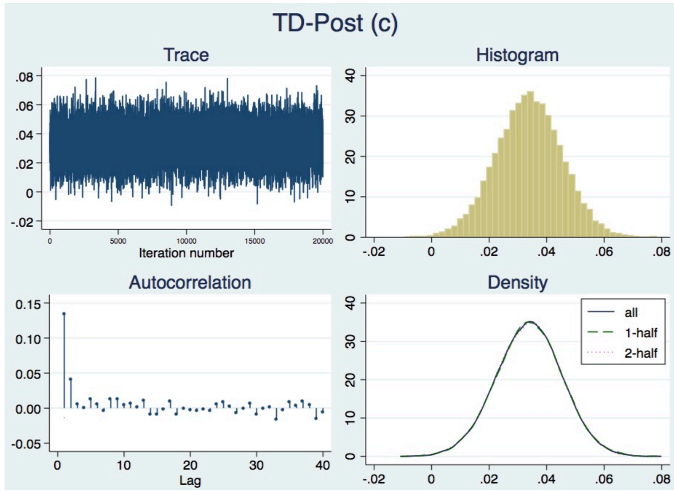


Figure 67. Assessment of Model Convergence for C-TD-Post (c)

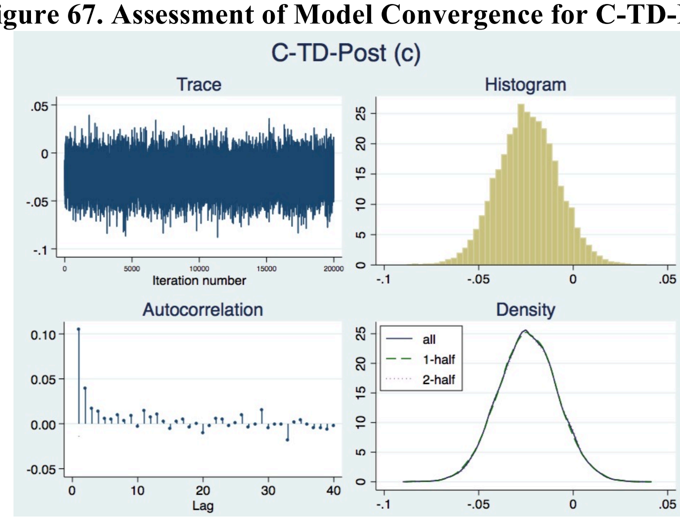


Figure 68. Assessment of Model Convergence for TMS

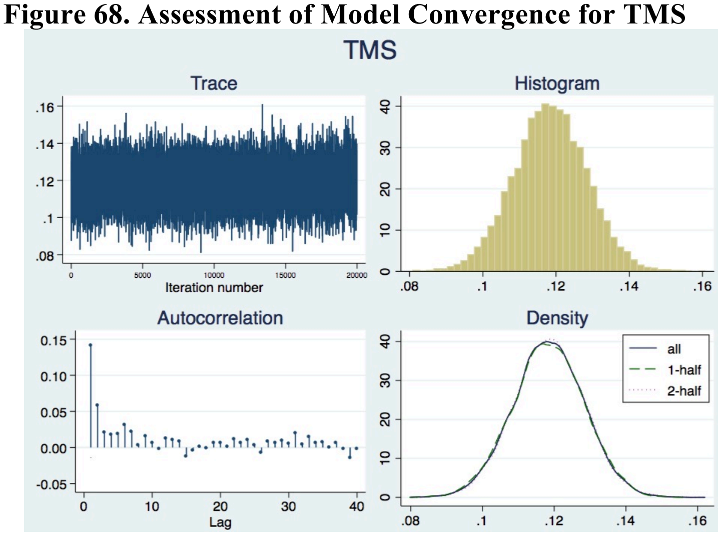


Figure 69. Assessment of Model Convergence for Price

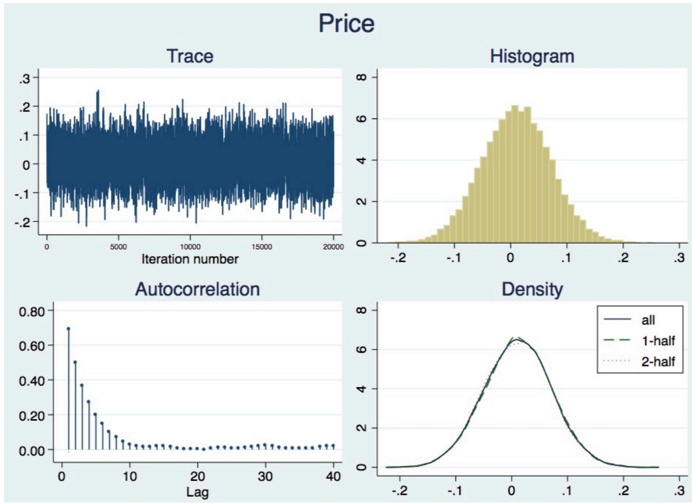


Figure 70. Assessment of Model Convergence for GT

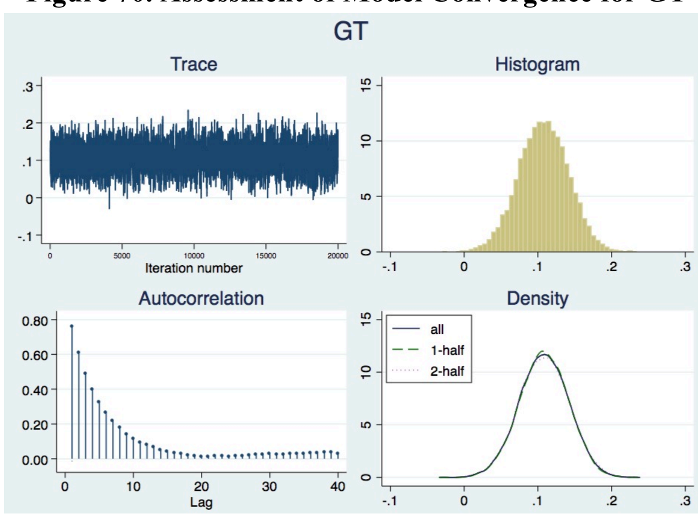


Figure 71. Assessment of Model Convergence for GPI

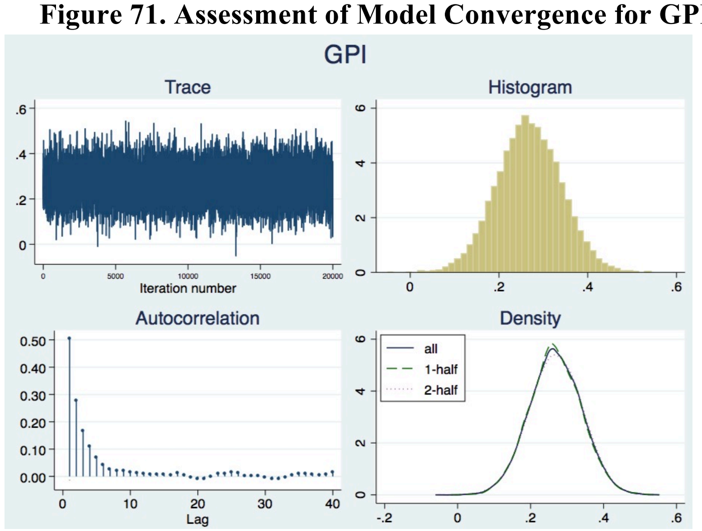
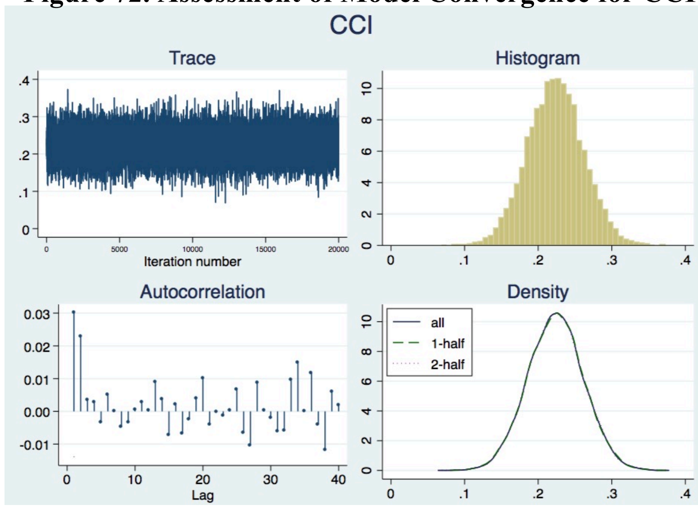


Figure 72. Assessment of Model Convergence for CCI



3.5.2 Sample Split Bayesian Analysis Results on the Origin of Brands

Prior research suggests that country of origin effects would moderate the spillover effects (Borah & Tellis, 2016; Maheswaran & Chen, 2006) because consumers might use the origin as an attribute and make similar inferences for brands that belong to the same origin (Hong & Wyer, 1990). Therefore, in this sample split analysis, I examine how the origin of brand may moderate dynamics of online WOM by considering three origins of brand: Asian-based, European-based, and US-based brands[18]. Tables 45 to 47 show descriptive statistics for Asian-based, European-based, and US-based brands, respectively.

Table 45. Descriptive Statistics for Asian-Based Brands

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	745	43368.12	43,517	2,923	210,134
F-Post (a)	745	32.8	23.69	0	344
C-F-Post (a)	745	913.54	404.5	53	2,605
F-Like (a)	745	55067.66	96237.15	0	722,146
C-F-Like (a)	745	2,302,998	2,153,474	4,583	6,000,000
F-Comment (a)	745	1884.11	2533.42	0	26,648
C-F-Comment (a)	745	65603.57	38718.41	863	153,749
F-Share (a)	745	3418.65	543,1	0	41,089
C-F-Share (a)	745	177862.8	177686.9	84	580,559
U-Post (a)	745	364.48	387.56	0	4,625

[18] **Asian-based:** Acura, Honda, Hyundai, Infiniti, KIA, Lexus, Mazda, Mitsubishi, Nissan, Scion, Subaru, and Toyota; **European-based:** Audi, BMW, Jaguar, Land Rover, Mercedes-Benz, Porsche, Saab, Volkswagen, and Volvo; **US-based:** Buick, Cadillac, Chevrolet, Chrysler, Dodge, FIAT, Ford, Jeep, and Lincoln.

Table 45 (cont'd)

C-U-Post (a)	745	12523.47	4339.73	971	22,539
U-Like (a)	745	6866.44	22293.83	0	463,332
C-U-Like (a)	745	305631.8	391109.5	808	2,500,000
U-Comment (a)	745	666.67	1593.09	0	36,118
C-U-Comment (a)	745	25504.07	16093.13	923	109,059
U-Share (a)	745	69.16	616.79	0	16,400
C-U-Share (a)	745	2432.74	3904.39	0	21,905
TD-Post (c)	745	270.98	369.72	11	3,771
C-TD-Post (c)	745	7023.92	4989.19	1,862	35,106
TMS	745	38013691.28	32083898.34	1,500,000	200,000,000
Price	745	28531.08	9927.16	14192.5	50928.1
GT	745	52.74	20.2	10	100
GPI	745	3.39	0.4	2.31	3.98
CCI	745	66.06	12.87	40.9	94.1

Table 46. Descriptive Statistics for European-Based Brands

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	489	12255.04	11221.09	97	44,005
F-Post (a)	489	32.17	28.73	0	436
C-F-Post (a)	489	934.83	405.91	48	2,579
F-Like (a)	489	150018.5	231163.8	0	1,100,000
C-F-Like (a)	489	2,252,274	2,074,290	4,226	5,900,000
F-Comment (a)	489	2752.16	3217.59	0	20,577
C-F-Comment (a)	489	65926.9	37798.81	826	151,722
F-Share (a)	489	11349.78	19854.05	0	115,372
C-F-Share (a)	489	173222.3	170249.1	84	572,859
U-Post (a)	489	376.35	524.82	0	9,624
C-U-Post (a)	489	12735.96	4423.51	647	22,520
U-Like (a)	489	11050.07	36830.84	0	560,219
C-U-Like (a)	489	307736.4	384425.1	254	2,500,000
U-Comment (a)	489	499.99	887.49	0	10,539
C-U-Comment (a)	489	26123.09	16149.87	480	109,163
U-Share (a)	489	89.04	472.43	0	5,283
C-U-Share (a)	489	2469.14	3940.1	0	21,904
TD-Post (c)	489	188.09	194.82	5	1,595
C-TD-Post (c)	489	7050.71	4932.11	1,983	35,072
TMS	489	14894591.82	13042812.82	65,200	75,000,000
Price	489	51335.55	16294.94	23798.6	90,775
GT	489	57.08	14.42	26	91
GPI	489	3.42	0.4	2.31	3.98
CCI	489	66.27	12.89	40.9	94.1

Table 47. Descriptive Statistics for US-Based Brands

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	555	54546.26	62880.57	500	244,501
F-Post (a)	555	34.66	48.83	0	1,042
C-F-Post (a)	555	905.28	413.41	50	2,584
F-Like (a)	555	57968.14	81127.72	0	490,822
C-F-Like (a)	555	2,311,868	2,163,995	3,093	6,000,000
F-Comment (a)	555	2630.02	2820.77	0	25,734
C-F-Comment (a)	555	64590.92	39502.81	420	152,256
F-Share (a)	555	5693.99	8978.39	0	62,457
C-F-Share (a)	555	176722.9	175590.4	27	578,089
U-Post (a)	555	641.12	661.59	0	4,918
C-U-Post (a)	555	12065.34	4513.38	857	22,459
U-Like (a)	555	15994.46	34099.1	0	252,535
C-U-Like (a)	555	297731.1	385749.9	613	2,500,000
U-Comment (a)	555	1609.36	2473.05	0	28,081
C-U-Comment (a)	555	24331.22	16101.68	690	108,643
U-Share (a)	555	108.61	384.94	0	6,362
C-U-Share (a)	555	2407.29	3914.77	0	21,905
TD-Post (c)	555	270.59	374.96	10	3,348
C-TD-Post (c)	555	6835.58	4787.97	1,885	34,817
TMS	555	46518267.92	42715942.85	238,700	190,000,000
Price	555	30442.51	10386.73	16,000	55828.8

Table 47 (cont'd)

GT	555	55.75	22.29	7	100
GPI	555	3.39	0.4	2.31	3.98
CCI	555	66.04	12.93	40.9	94.1

Tables 48 to 50 show my sample split Bayesian estimation results at the post level (i.e., Facebook post and test drive post) for Asian-based, European-based, and US-based brands, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (Figures 73 to 105) also suggested the model specification converged for each relationship.

The results in the post level indicate heterogeneity across three origins of brands regarding the effects of online WOM on offline car sales of the focal brand at the stages of awareness and consideration. First, at the stage of awareness, I observe that online WOM initiated by the focal firm (F-Post (a)) has the positive impact on offline car sales for the European-based group only, supporting H1. Regarding spillover effects at the stage of awareness, all three groups share similar patterns, namely, the more posts by competitors within the given group (C-F-Post (a)), the more offline car sales of the focal brand in the given group, with the strongest magnitude of the coefficient from the Asian-based group. Thus, H2 is supported for three different groups. Regarding posts generated by users at the stage of awareness (U-Post (a) or C-U-Post (a)), I find that the significant effect of U-Post (a) on offline car sales of the US-based group, although the direction of this effect is opposite as hypothesized, thereby rejecting my H1. Interestingly, for the Asian-based and European-based group, I also observe negative spillover effects from posts by competitors' user posts (C-U-Post (a)), which show the opposite direction as hypothesized. Therefore, these results provide further evidence that when considering online WOM to make better purchase decisions, customers place different weights on those WOM by firms and WOM by other customers.

Finally, with respect to online WOM at the stage of consideration, H3 and H4 are supported for the Asian-based group only. For European-based and US-based group, customers seek detailed or other sufficient information from other sources rather than test drive posts to help them make better purchase decisions at the stage of consideration.

Table 48. Bayesian Estimation Results for Posts (Asian-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	0.008 (0.012)	(-0.014, 0.03)
C-F-Post (a) $_{J, t-1}$	**0.172 (0.027)**	**(0.12, 0.23)**
U-Post (a) $_{A, t-1}$	0.003 (0.012)	(-0.019, 0.026)
C-U-Post (a) $_{J, t-1}$	**-0.083 (0.024)**	**(-0.13, -0.035)**
TD-Post (c) $_{A, t-1}$	**0.038 (0.017)**	**(0.004, 0.072)**
C-TD-Post (c) $_{J, t-1}$	**-0.053 (0.022)**	**(-0.095, -0.011)**
TMS $_{A, t-1}$	**0.072 (0.018)**	**(0.035, 0.11)**
Price $_{A, t-1}$	**0.214 (0.092)**	**(0.034, 0.397)**
GT $_{A, t-1}$	**0.118 (0.044)**	**(0.03, 0.203)**
GPI $_{A, t-1}$	0.069 (0.099)	(-0.126, 0.263)
CCI $_{A, t-1}$	**0.218 (0.055)**	**(0.108, 0.328)**

Table 49. Bayesian Estimation Results for Posts (European-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	**0.055 (0.02)**	**(0.013, 0.096)**
C-F-Post (a) $_{J, t-1}$	**0.132 (0.043)**	**(0.048, 0.216)**
U-Post (a) $_{A, t-1}$	-0.006 (0.01)	(-0.027, 0.016)
C-U-Post (a) $_{J, t-1}$	**-0.067 (0.034)**	**(-0.133, -0.0006)**
TD-Post (c) $_{A, t-1}$	0.035 (0.023)	(-0.01, 0.08)
C-TD-Post (c) $_{J, t-1}$	-0.059 (0.03)	(-0.12, 0.008)
TMS $_{A, t-1}$	**0.12 (0.016)**	**(0.09, 0.15)**
Price $_{A, t-1}$	-0.02 (0.124)	(-0.266, 0.227)
GT $_{A, t-1}$	**0.33 (0.1)**	**(0.133, 0.526)**

Table 49 (cont'd)

GPI $_{A, t-1}$	**0.44 (0.16)**	**(0.135, 0.749)**
CCI $_{A, t-1}$	**0.27 (0.084)**	**(0.107, 0.438)**

Table 50. Bayesian Estimation Results for Posts (US-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	0.011 (0.015)	(-0.02, 0.04)
C-F-Post (a) $_{J, t-1}$	**0.164 (0.029)**	**(0.106, 0.221)**
U-Post (a) $_{A, t-1}$	**-0.041 (0.013)**	**(-0.067, -0.015)**
C-U-Post (a) $_{J, t-1}$	0.029 (0.027)	(-0.025, 0.083)
TD-Post (c) $_{A, t-1}$	0.013 (0.02)	(-0.027, 0.054)
C-TD-Post (c) $_{J, t-1}$	-0.046 (0.028)	(-0.101, 0.01)
TMS $_{A, t-1}$	**0.167 (0.02)**	**(0.1, 0.14)**
Price $_{A, t-1}$	0.15 (0.113)	(-0.089, 0.153)
GT $_{A, t-1}$	-0.054 (0.061)	(0.041, 0.174)
GPI $_{A, t-1}$	0.17 (0.115)	(0.018, 0.286)
CCI $_{A, t-1}$	**0.279 (0.065)**	**(0.158, 0.313)**

Figure 73. Assessment of Model Convergence for F-Post (a) (Asian-based)

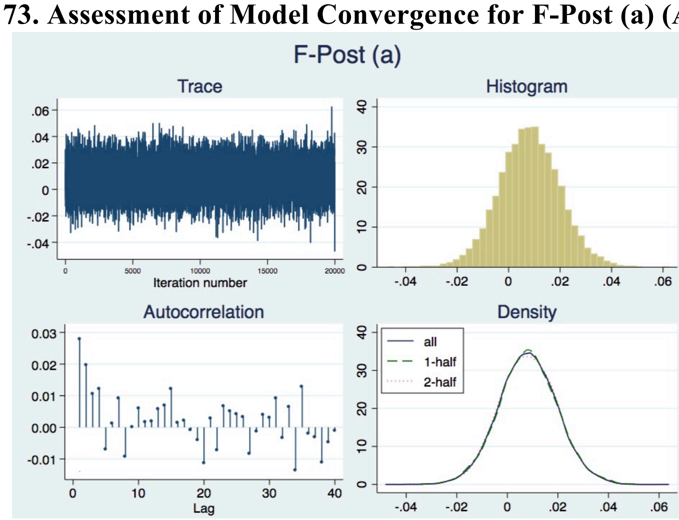


Figure 74. Assessment of Model Convergence for C-F-Post (a) (Asian-based)

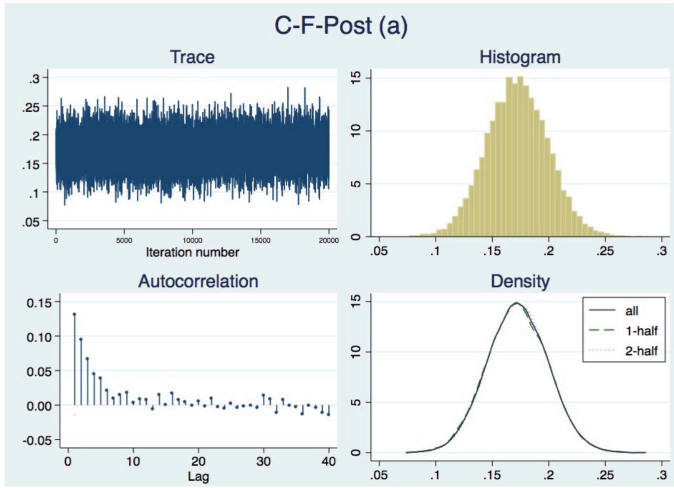


Figure 75. Assessment of Model Convergence for U-Post (a) (Asian-based)

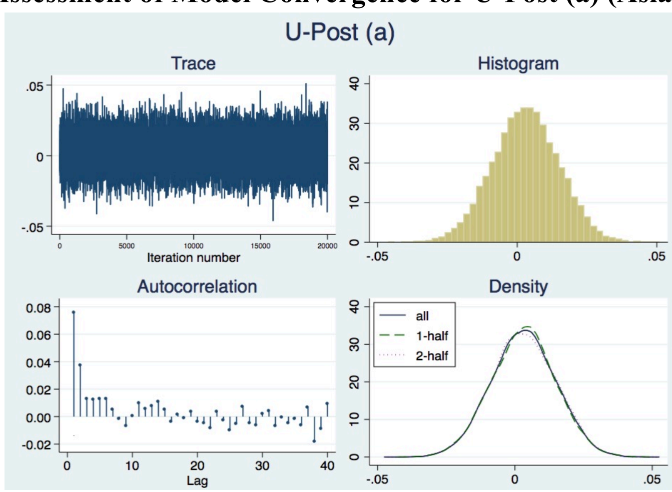


Figure 76. Assessment of Model Convergence for C-U-Post (a) (Asian-based)

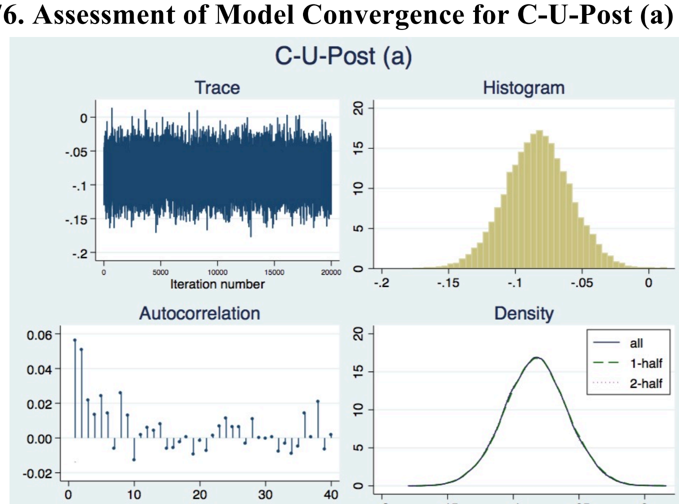


Figure 77. Assessment of Model Convergence for TD-Post (c) (Asian-based)

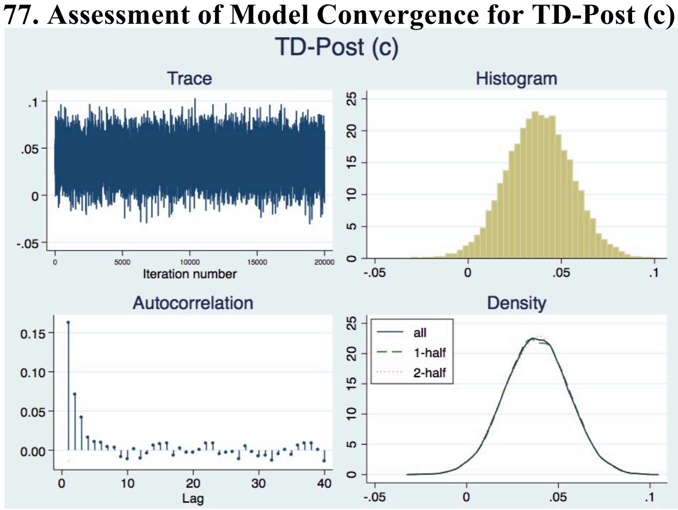


Figure 78. Assessment of Model Convergence for C-TD-Post (c) (Asian-based)

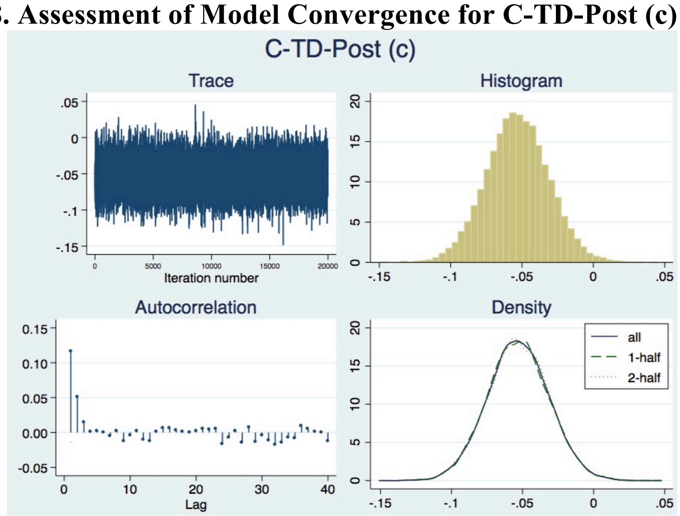


Figure 79. Assessment of Model Convergence for TMS (Asian-based)

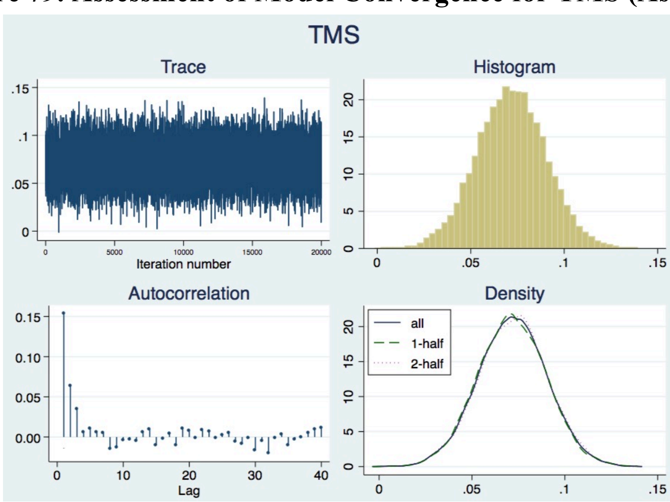


Figure 80. Assessment of Model Convergence for Price (Asian-based)

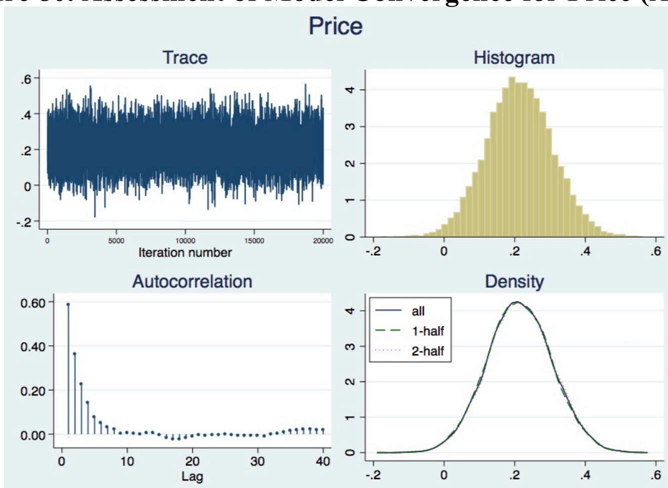


Figure 81. Assessment of Model Convergence for GT (Asian-based)

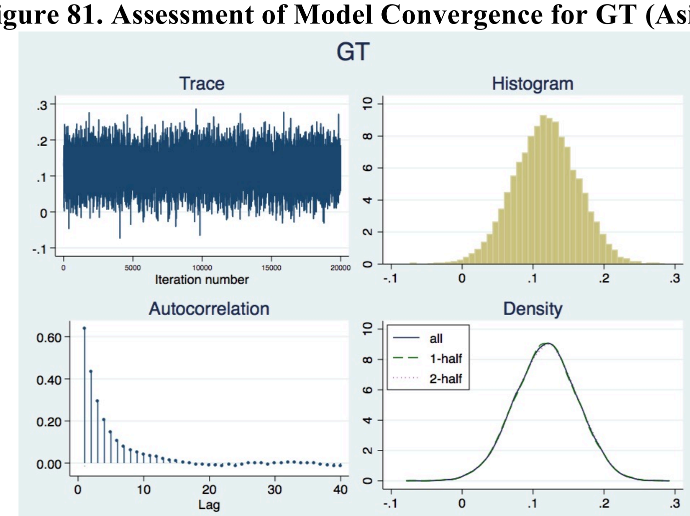


Figure 82. Assessment of Model Convergence for GPI (Asian-based)

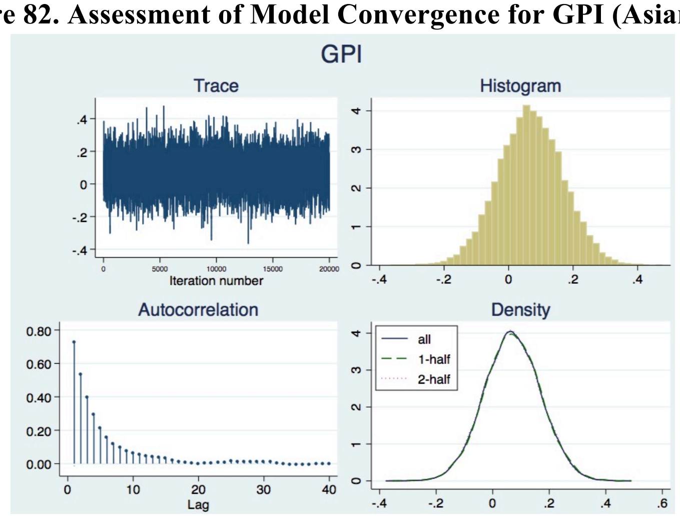


Figure 83. Assessment of Model Convergence for CCI (Asian-based)

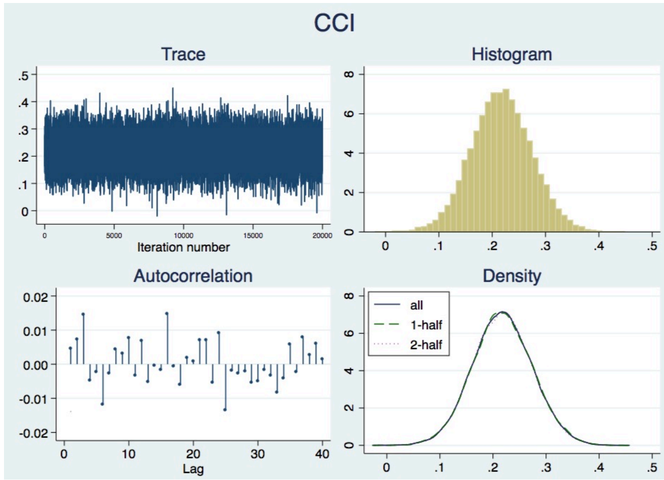


Figure 84. Assessment of Model Convergence for F-Post (a) (European-based)

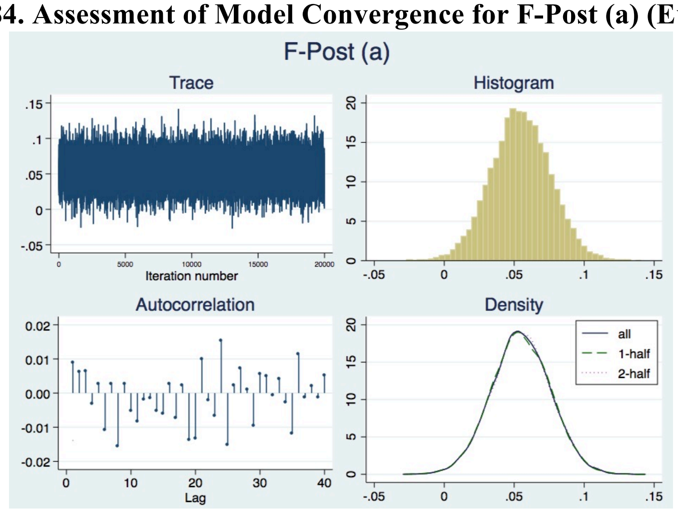


Figure 85. Assessment of Model Convergence for C-F-Post (a) (European-based)

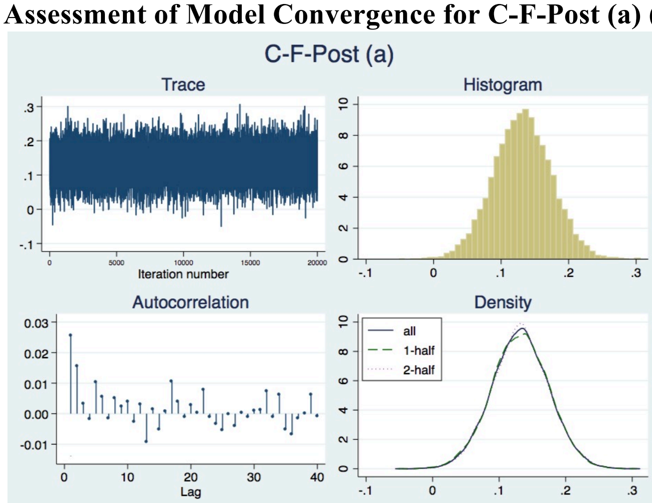


Figure 86. Assessment of Model Convergence for U-Post (a) (European-based)

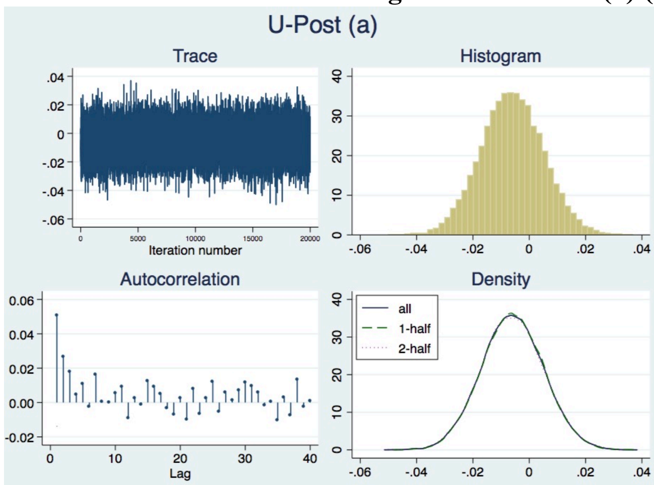


Figure 87. Assessment of Model Convergence for C-U-Post (a) (European-based)

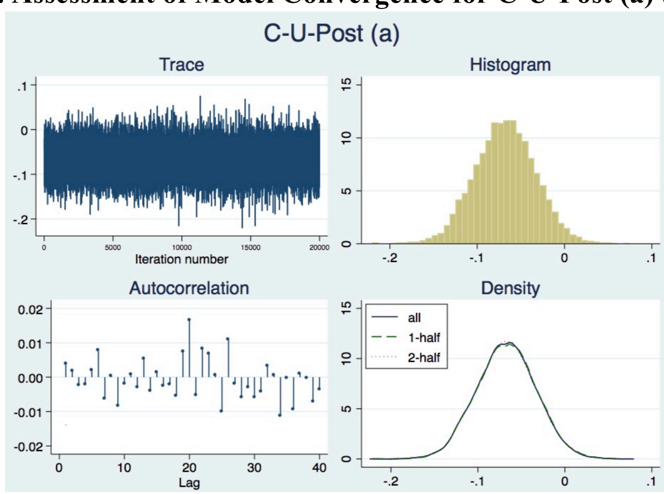


Figure 88. Assessment of Model Convergence for TD-Post (c) (European-based)

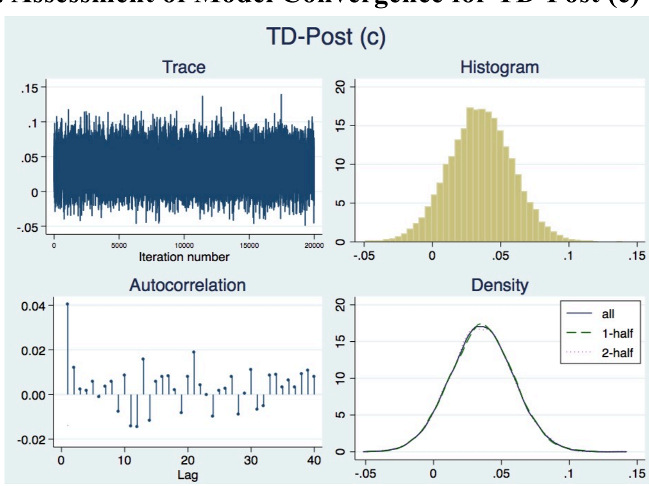


Figure 89. Assessment of Model Convergence for C-TD-Post (c) (European-based)

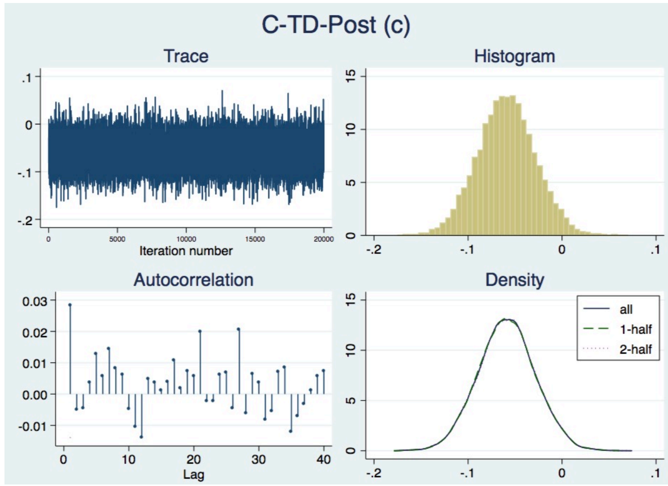


Figure 90. Assessment of Model Convergence for TMS (European-based)

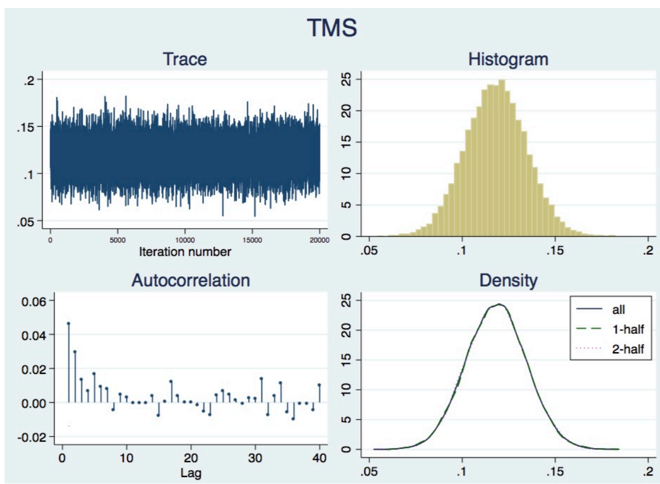


Figure 91. Assessment of Model Convergence for Price (European-based)

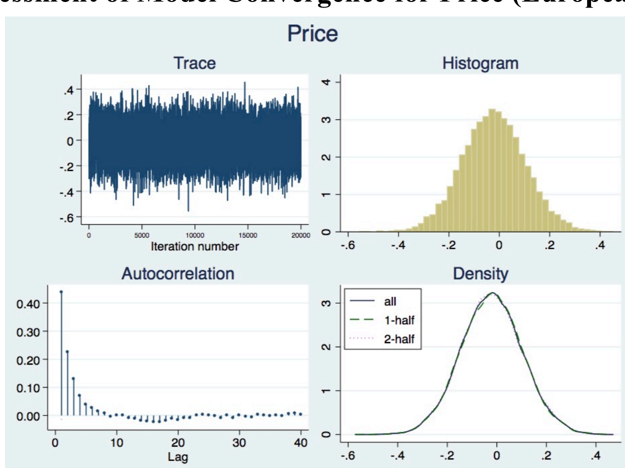


Figure 92. Assessment of Model Convergence for GT (European-based)

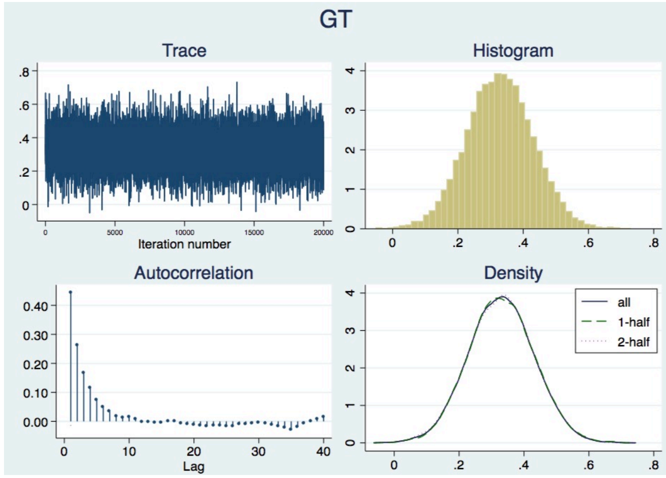


Figure 93. Assessment of Model Convergence for GPI (European-based)

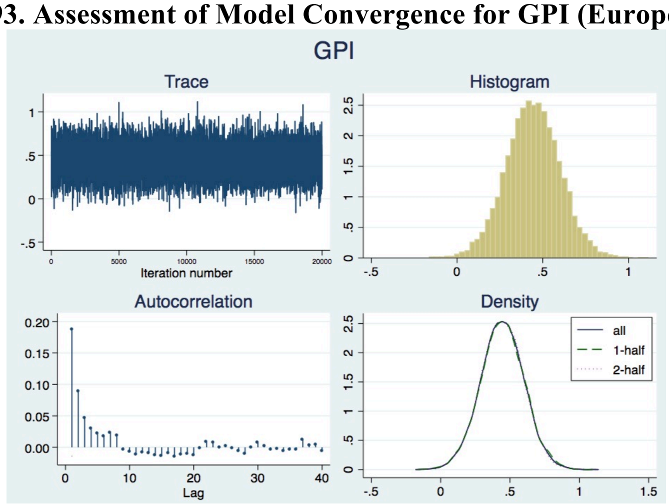


Figure 94. Assessment of Model Convergence for CCI (European-based)

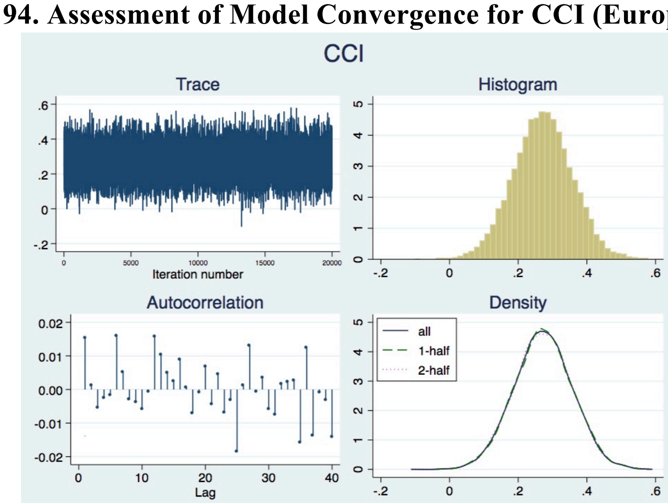


Figure 95. Assessment of Model Convergence for F-Post (a) (US-based)

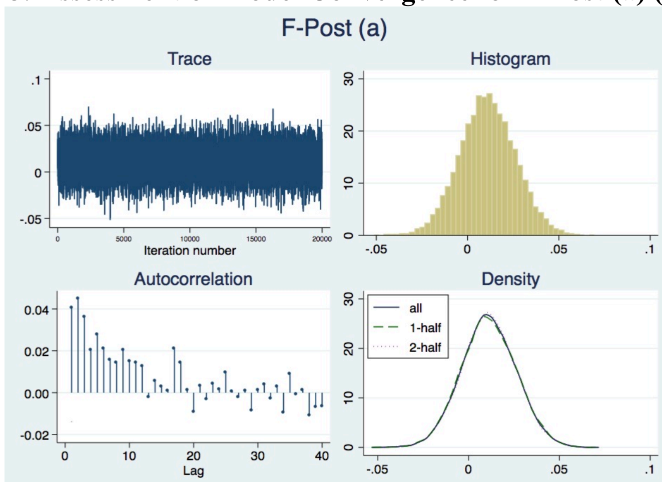


Figure 96. Assessment of Model Convergence for C-F-Post (a) (US-based)

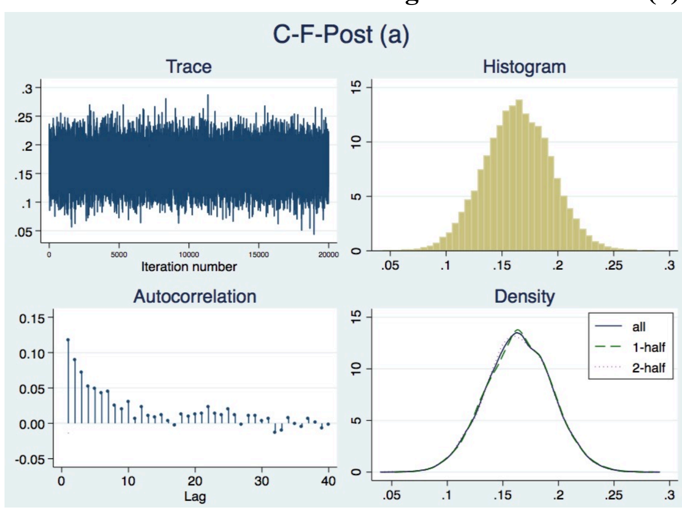


Figure 97. Assessment of Model Convergence for U-Post (a) (US-based)

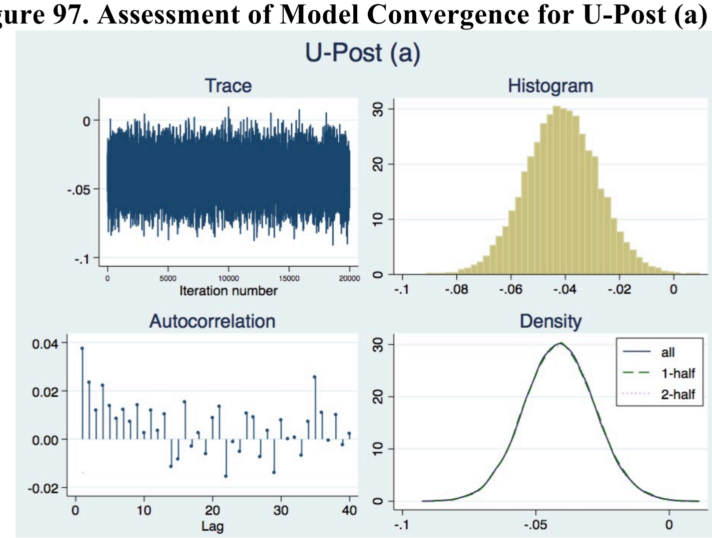


Figure 98. Assessment of Model Convergence for C-U-Post (a) (US-based)

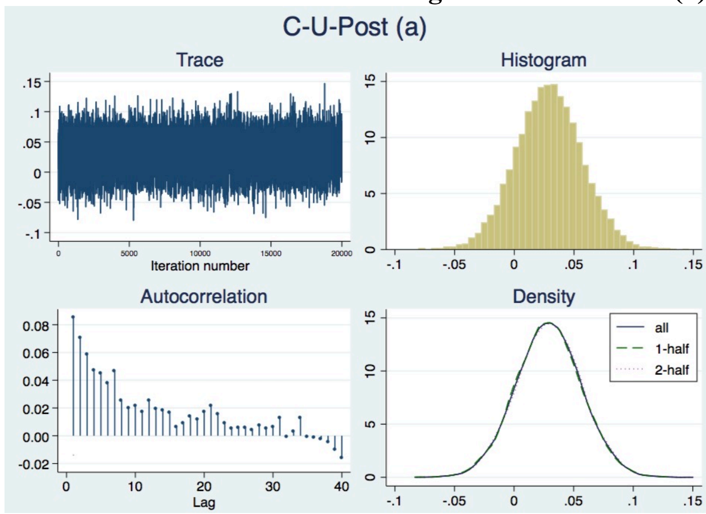


Figure 99. Assessment of Model Convergence for TD-Post (c) (US-based)

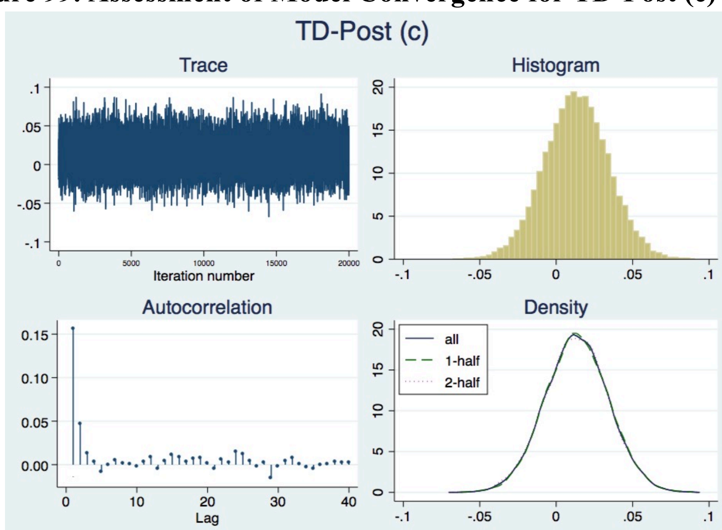


Figure 100. Assessment of Model Convergence for C-TD-Post (c) (US-based)

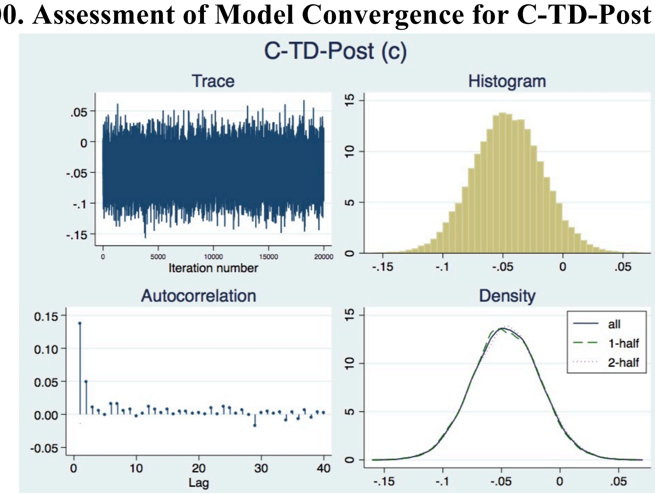


Figure 101. Assessment of Model Convergence for TMS (US-based)

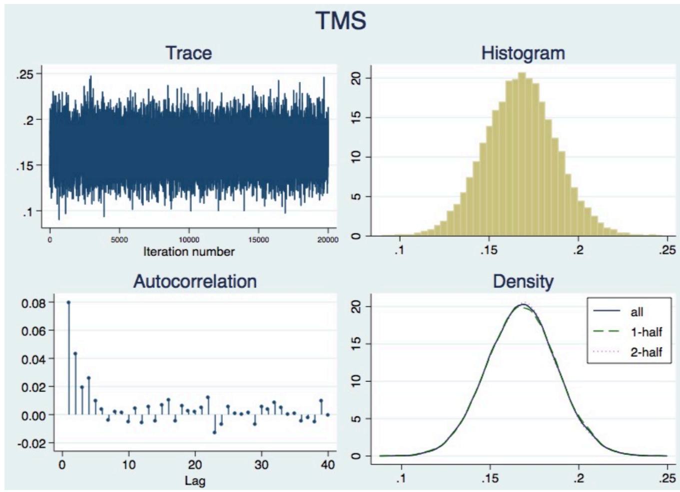


Figure 102. Assessment of Model Convergence for Price (US-based)

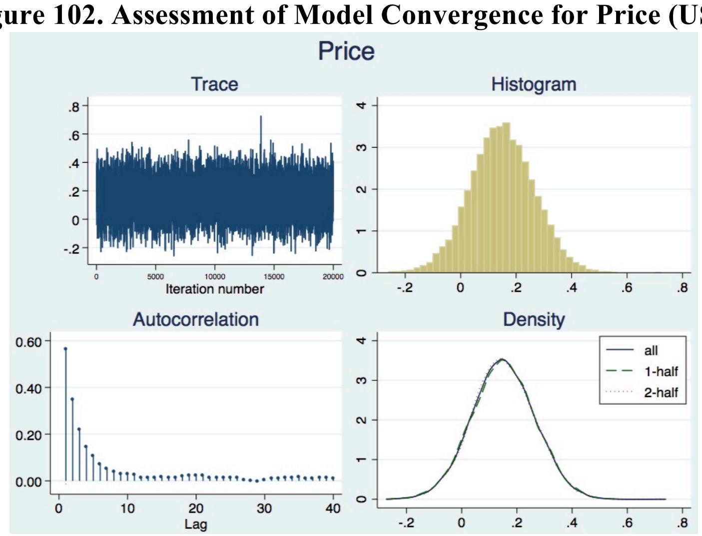


Figure 103. Assessment of Model Convergence for GT (US-based)

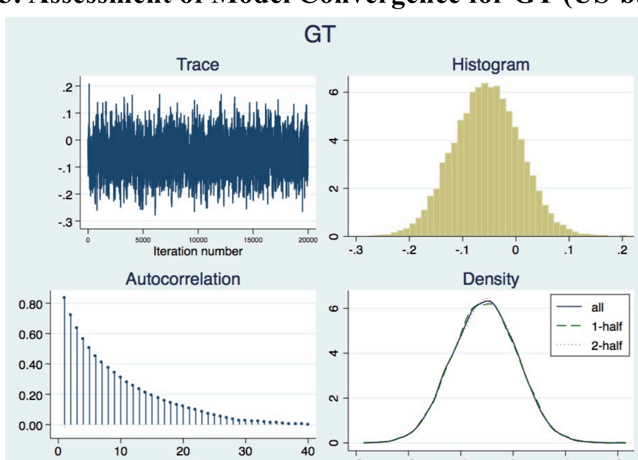


Figure 104. Assessment of Model Convergence for GPI (US-based)

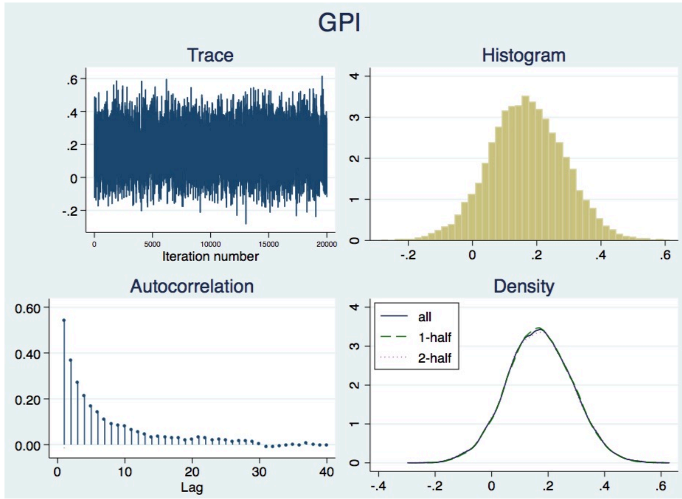
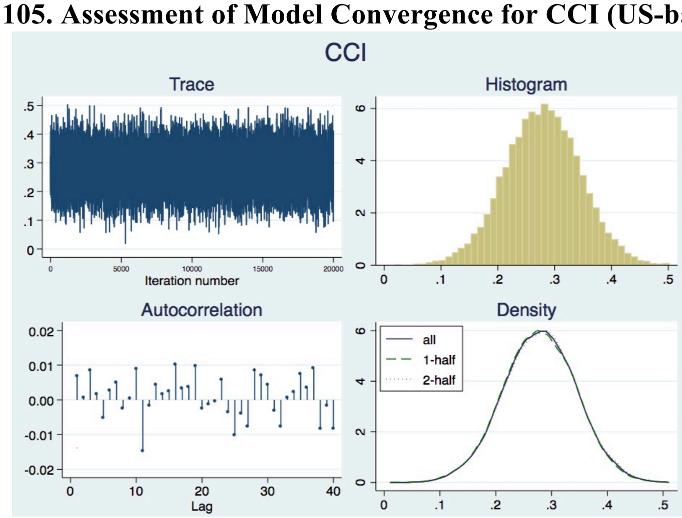


Figure 105. Assessment of Model Convergence for CCI (US-based)



I then turn my attention to examine how these three sub categories may vary the relationships for three different mechanisms at firms' Facebook pages: Like, Comment, and Share. Tables 51 to 53 show my sample split Bayesian estimation results at the like level (i.e., "Like" associated with posts at Facebook and test drive post) for Asian-based, European-based, and US-based brands, respectively. In these models, I also ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 106 to 138) suggested that the model specification converged for each relationship.

In this set of analysis, the results provide further evidence on heterogeneity across origins of brands regarding the effects of online WOM in the form of like at the stage of awareness and test drive posts at the stage of consideration. Consistent with the main results (see Table 42), the volume of like associated with competitors' posts (C-F-Like (a)) show positive spillover effects on offline car sales of the focal firm in each given group, supporting H2. However, the volume of like associated with the focal brand's posts (F-Like (a)) is still not very effective mechanism to influence focal firm performance, thereby rejecting H1. I also find that for the US-based group, the volume of like associated with competitors' user posts (C-U-Like (a)) has positive spillover effects on offline car sales of the US-based focal brand, supporting H2. Finally, regarding online at the stage of consideration, none of relationships (H3 and H4) are supported in this particular relationship.

Table 51. Bayesian Estimation Results for Likes (Asian-based)

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	0.003 (0.008)	(-0.012, 0.0181)
C-F-Like (a) $_{J, t-1}$	**0.063 (0.015)**	**(0.034, 0.093)**
U-Like (a) $_{A, t-1}$	-0.002 (0.005)	(-0.013, 0.008)
C-U-Like (a) $_{J, t-1}$	0.01 (0.014)	(-0.018, 0.038)
TD-Post (c) $_{A, t-1}$	0.032 (0.017)	(-0.001, 0.066)
C-TD-Post (c) $_{J, t-1}$	-0.039 (0.02)	(-0.079, 0.001)
TMS $_{A, t-1}$	**0.062 (0.018)**	**(0.027, 0.098)**
Price $_{A, t-1}$	0.159 (0.089)	(-0.017, 0.335)
GT $_{A, t-1}$	**0.142 (0.044)**	**(0.054, 0.229)**
GPI $_{A, t-1}$	-0.149 (0.089)	(-0.322, 0.025)
CCI $_{A, t-1}$	0.103 (0.057)	(-0.009, 0.215)

Table 52. Bayesian Estimation Results for Likes (European-based)

Parameters	Sales $_{A,\,t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A,\,t-1}$	-0.011 (0.009)	(-0.031, 0.008)
C-F-Like (a) $_{J,\,t-1}$	**0.116 (0.022)**	**(0.073, 0.159)**
U-Like (a) $_{A,\,t-1}$	0.009 (0.006)	(-0.002, 0.021)
C-U-Like (a) $_{J,\,t-1}$	-0.025 (0.019)	(-0.063, 0.013)
TD-Post (c) $_{A,\,t-1}$	0.041 (0.022)	(-0.003, 0.085)
C-TD-Post (c) $_{J,\,t-1}$	-0.005 (0.028)	(-0.104, 0.004)
TMS $_{A,\,t-1}$	**0.114 (0.016)**	**(0.082, 0.145)**
Price $_{A,\,t-1}$	-0.014 (0.119)	(-0.248, 0.218)
GT $_{A,\,t-1}$	**0.418 (0.098)**	**(0.224, 0.611)**
GPI $_{A,\,t-1}$	0.201 (0.134)	(-0.065, 0.46)
CCI $_{A,\,t-1}$	0.085 (0.086)	(-0.083, 0.253)

Table 53. Bayesian Estimation Results for Likes (US-based)

Parameters	Sales $_{A,\,t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A,\,t-1}$	-0.009 (0.008)	(-0.026, 0.007)
C-F-Like (a) $_{J,\,t-1}$	**0.052 (0.015)**	**(0.022, 0.082)**
U-Like (a) $_{A,\,t-1}$	**-0.023 (0.007)**	**(-0.036, -0.009)**
C-U-Like (a) $_{J,\,t-1}$	**0.068 (0.016)**	**(0.038, 0.099)**
TD-Post (c) $_{A,\,t-1}$	0.017 (0.019)	(-0.021, 0.055)
C-TD-Post (c) $_{J,\,t-1}$	-0.025 (0.026)	(-0.076, 0.027)
TMS $_{A,\,t-1}$	**0.166 (0.018)**	**(0.13, 0.202)**
Price $_{A,\,t-1}$	0.087 (0.107)	(-0.122, 0.296)
GT $_{A,\,t-1}$	-0.052 (0.058)	(-0.167, 0.061)
GPI $_{A,\,t-1}$	-0.016 (0.11)	(-0.218, 0.181)
CCI $_{A,\,t-1}$	0.087 (0.066)	(-0.042, 0.217)

Figure 106. Assessment of Model Convergence for F-Like (a) (Asian-based)

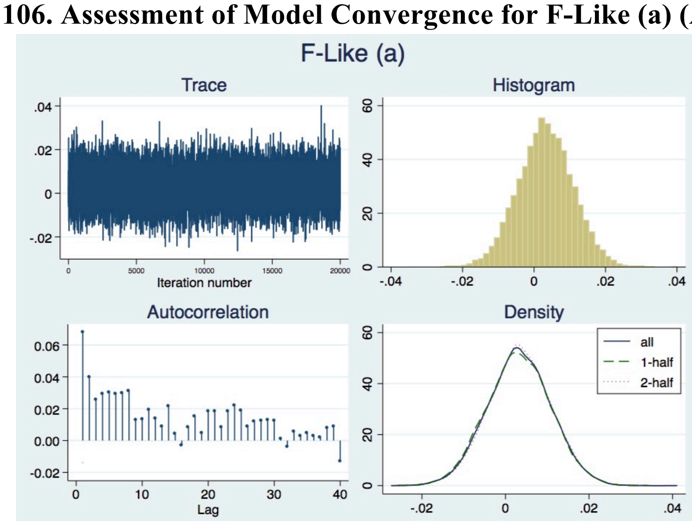


Figure 107. Assessment of Model Convergence for C-F-Like (a) (Asian-based)

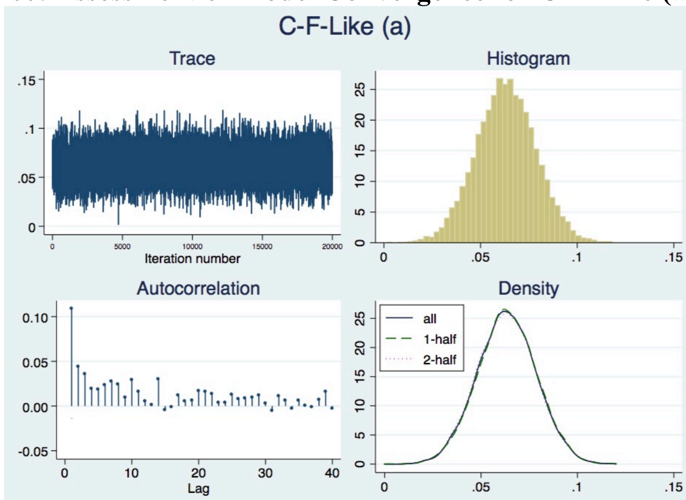


Figure 108. Assessment of Model Convergence for U-Like (a) (Asian-based)

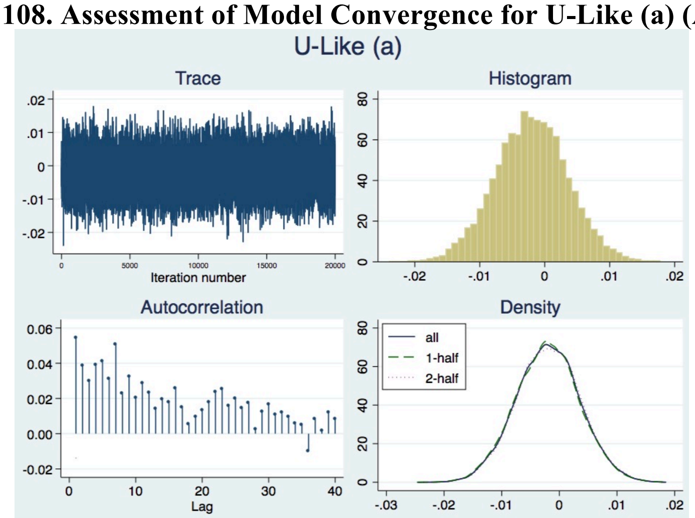


Figure 109. Assessment of Model Convergence for C-U-Like (a) (Asian-based)

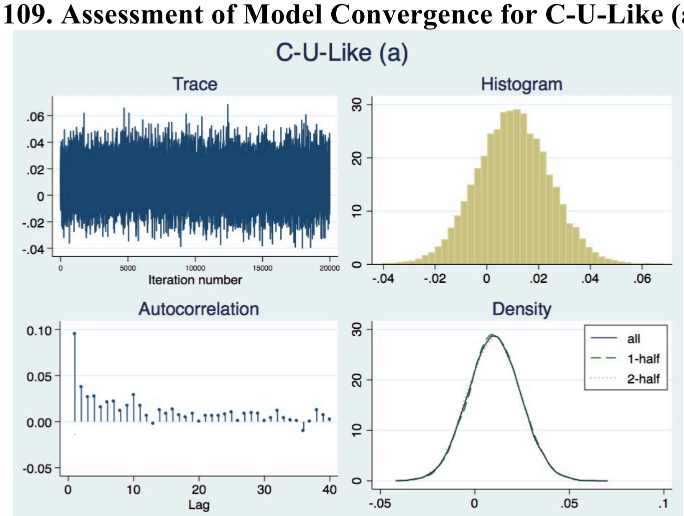


Figure 110. Assessment of Model Convergence for TD-Post (c) (Asian-based)

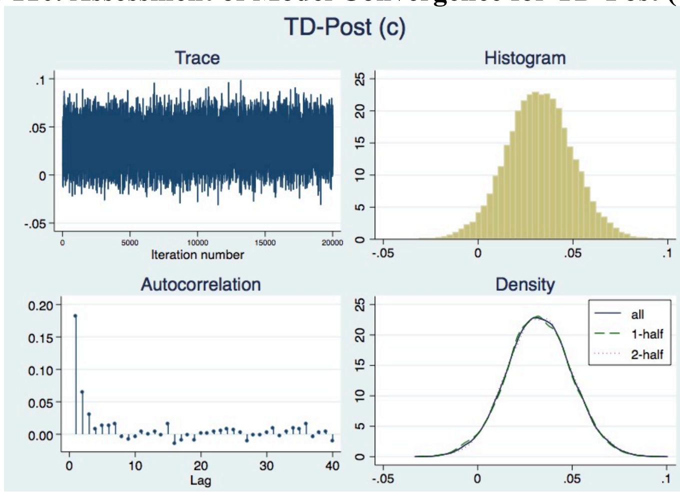


Figure 111. Assessment of Model Convergence for C-TD-Post (c) (Asian-based)

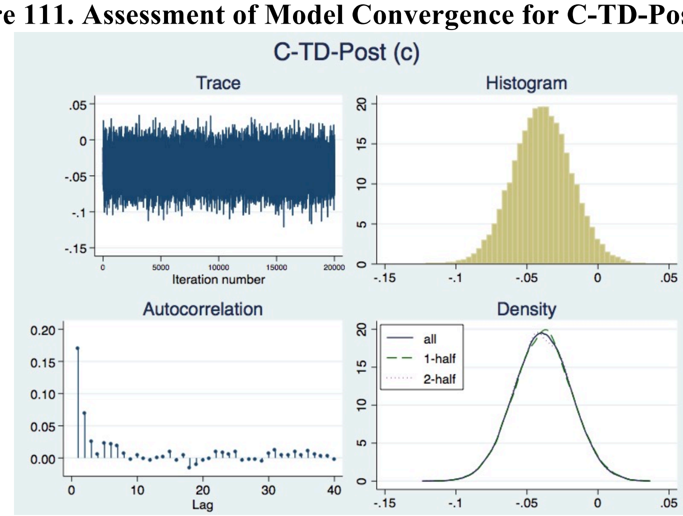


Figure 112. Assessment of Model Convergence for TMS (Asian-based)

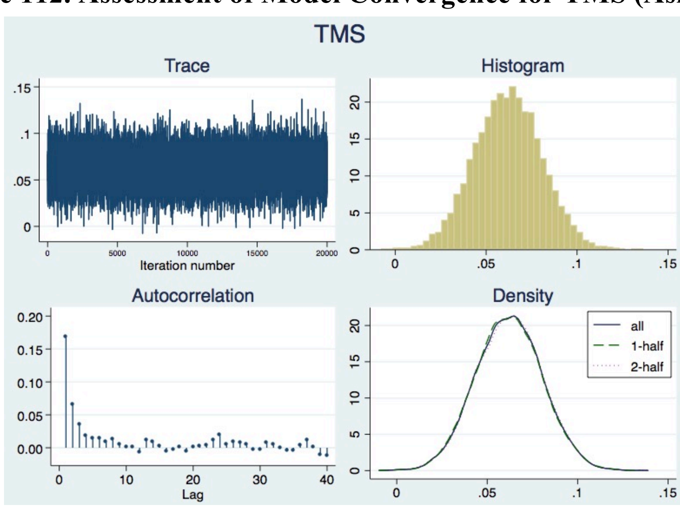


Figure 113. Assessment of Model Convergence for Price (Asian-based)

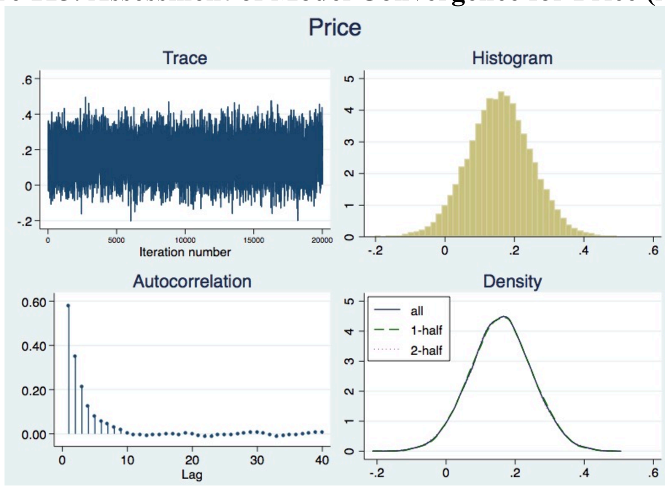


Figure 114. Assessment of Model Convergence for GT (Asian-based)

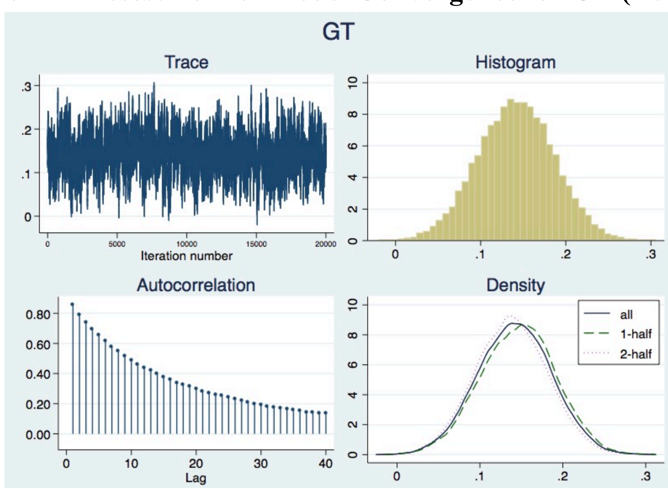


Figure 115. Assessment of Model Convergence for GPI (Asian-based)

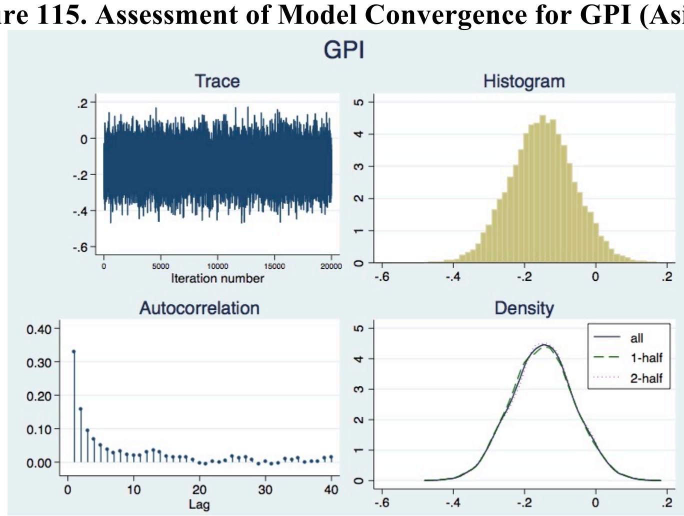


Figure 116. Assessment of Model Convergence for CCI (Asian-based)

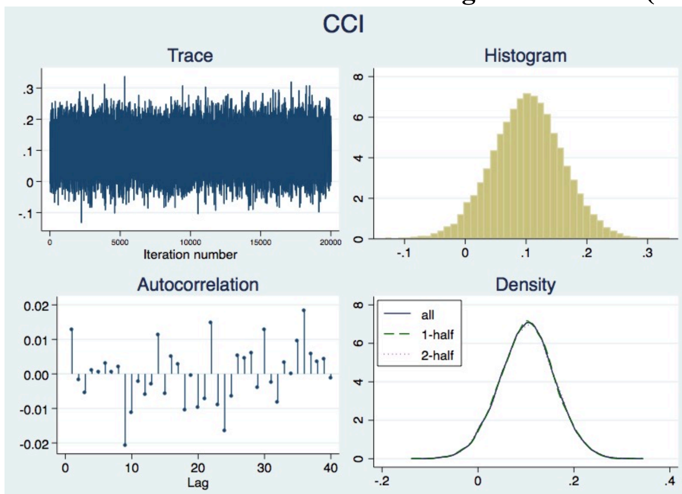


Figure 117. Assessment of Model Convergence for F-Like (a) (European-based)

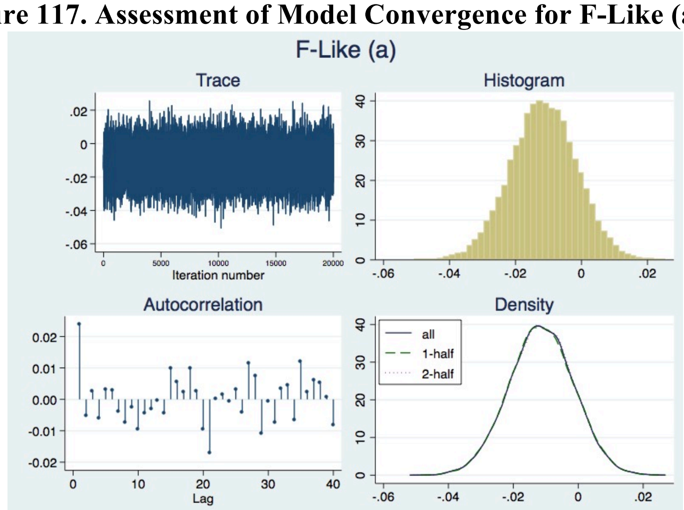


Figure 118. Assessment of Model Convergence for C-F-Like (a) (European-based)

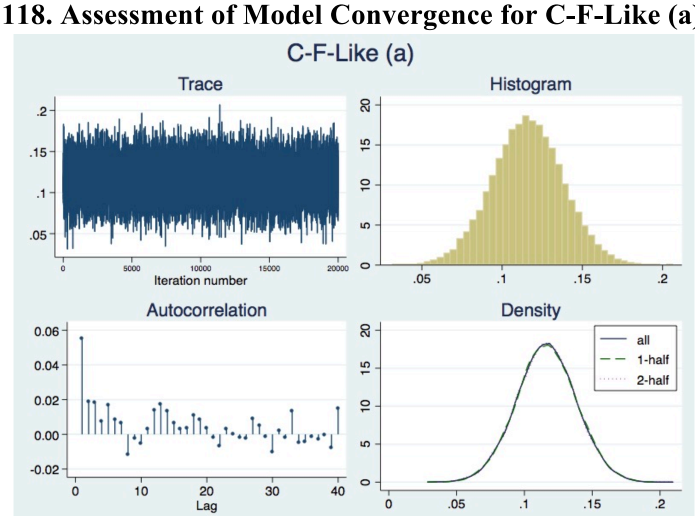


Figure 119. Assessment of Model Convergence for U-Like (a) (European-based)

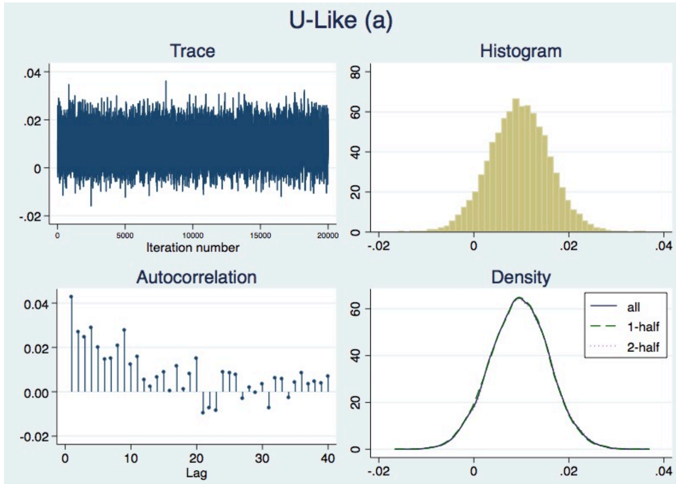


Figure 120. Assessment of Model Convergence for C-U-Like (a) (European-based)

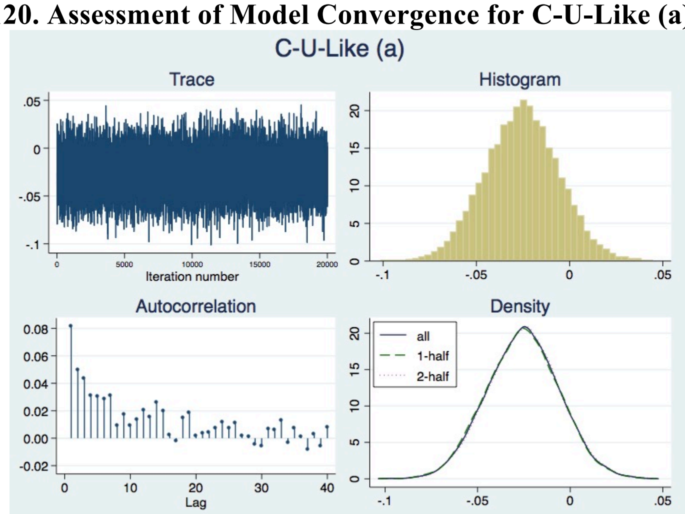


Figure 121. Assessment of Model Convergence for TD-Post (c) (European-based)

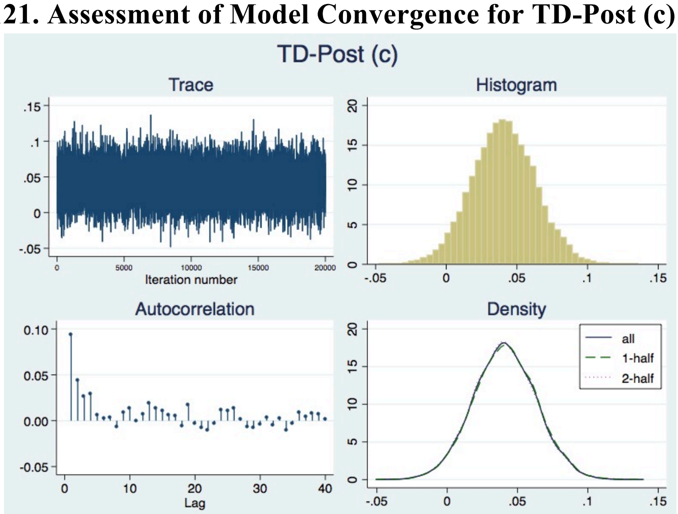


Figure 122. Assessment of Model Convergence for C-TD-Post (c) (European-based)

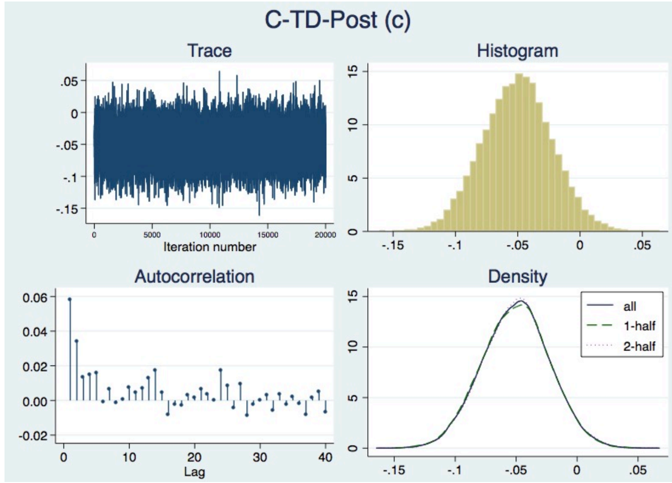


Figure 123. Assessment of Model Convergence for TMS (European-based)

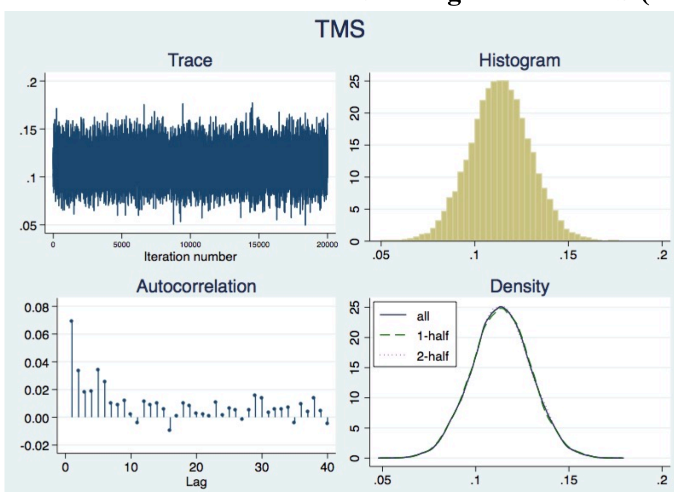


Figure 124. Assessment of Model Convergence for Price (European-based)

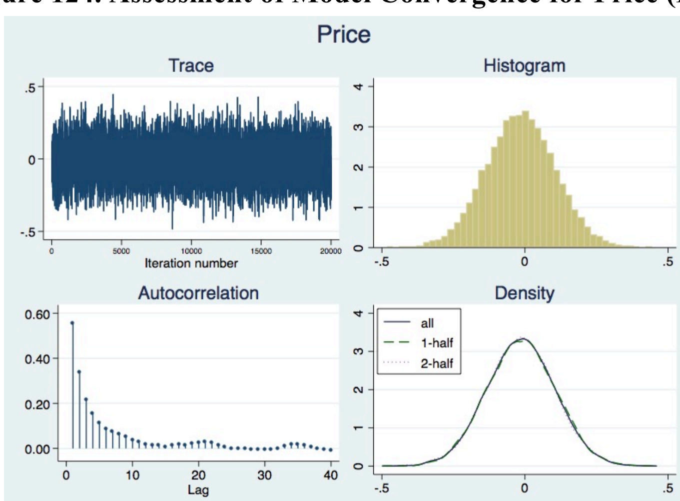


Figure 125. Assessment of Model Convergence for GT (European-based)

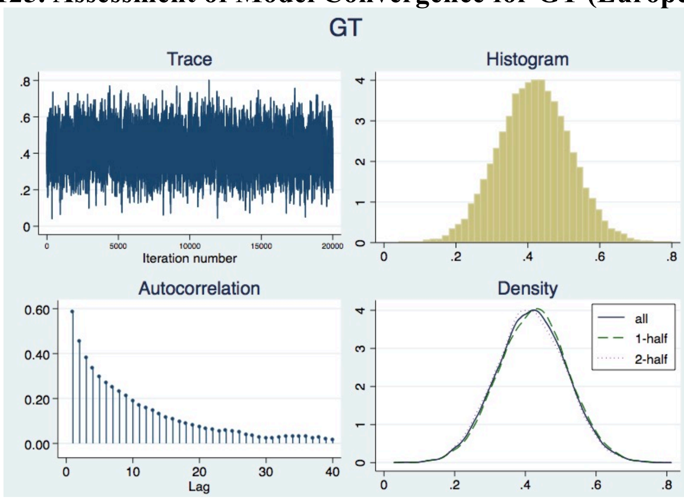


Figure 126. Assessment of Model Convergence for GPI (European-based)

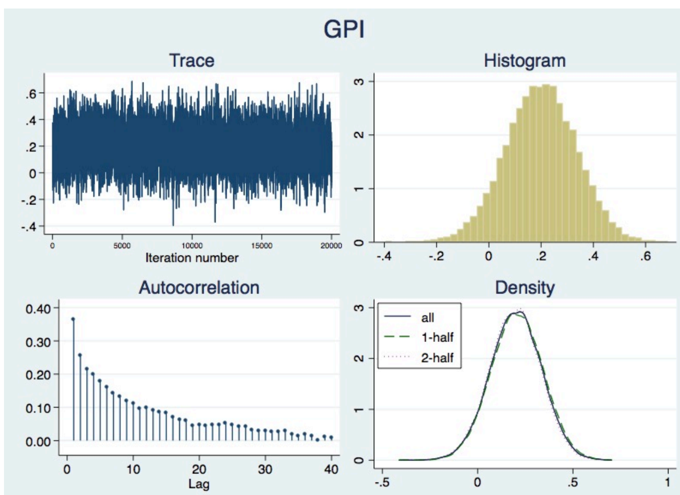


Figure 127. Assessment of Model Convergence for CCI (European-based)

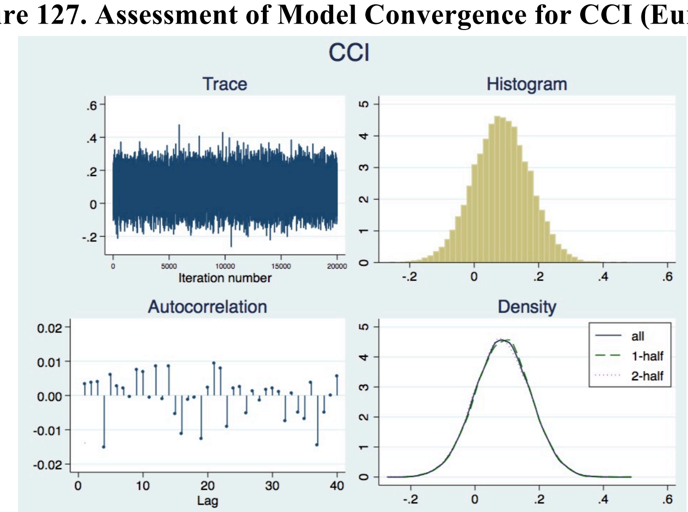


Figure 128. Assessment of Model Convergence for F-Like (a) (US-based)

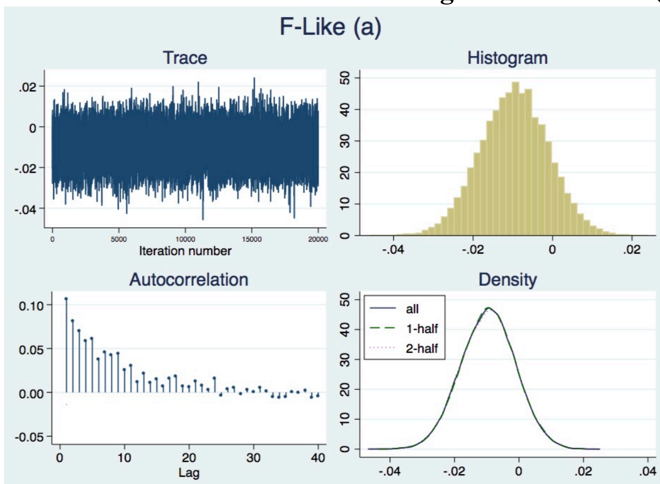


Figure 129. Assessment of Model Convergence for C-F-Like (a) (US-based)

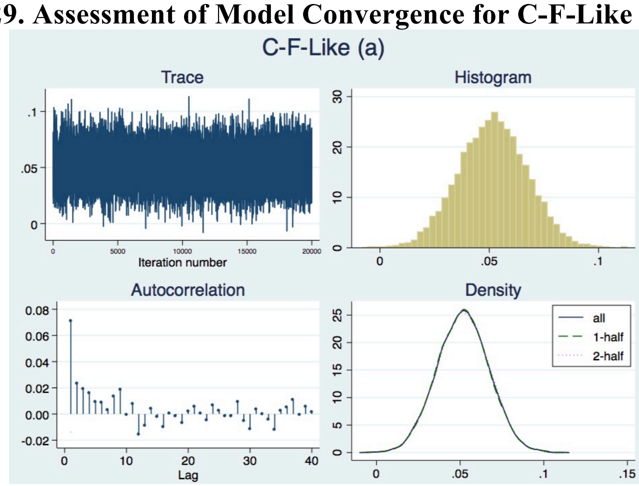


Figure 130. Assessment of Model Convergence for U-Like (a) (US-based)

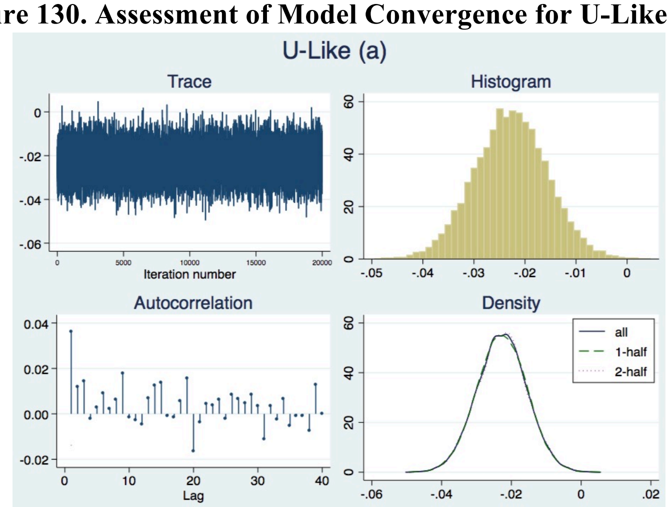


Figure 131. Assessment of Model Convergence for C-U-Like (a) (US-based)

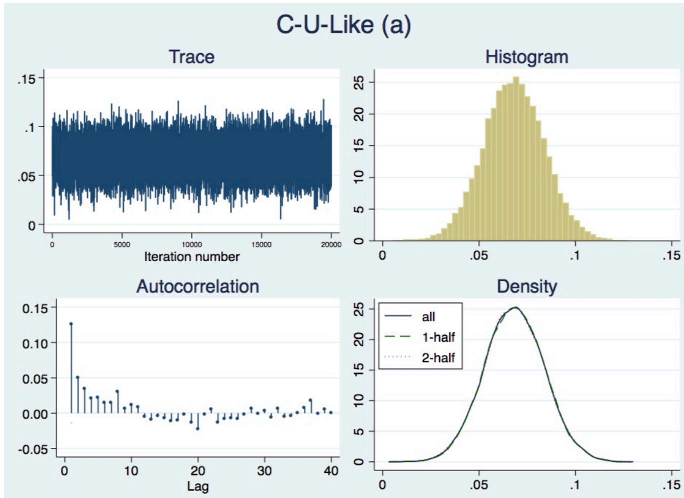


Figure 132. Assessment of Model Convergence for TD-Post (c) (US-based)

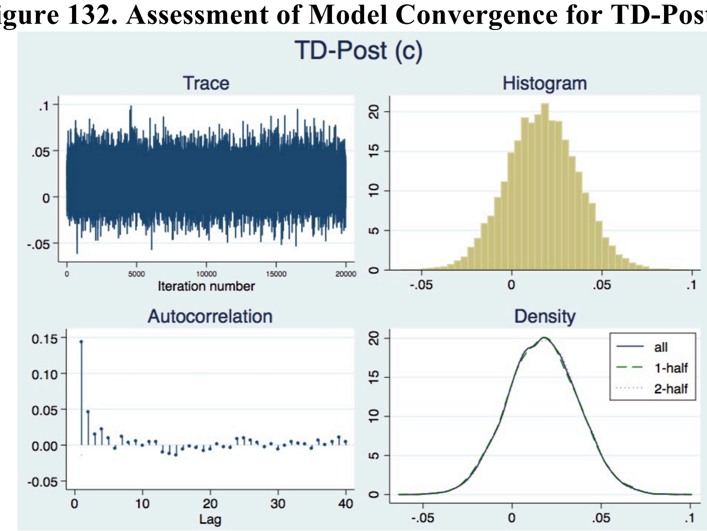


Figure 133. Assessment of Model Convergence for C-TD-Post (c) (US-based)

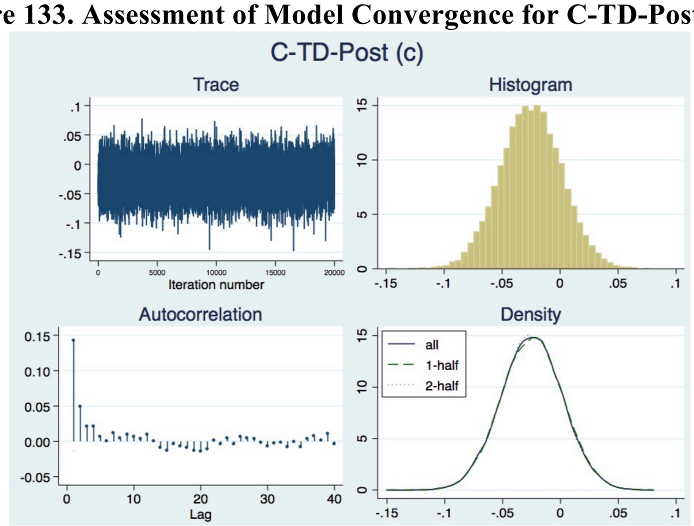


Figure 134. Assessment of Model Convergence for TMS (US-based)

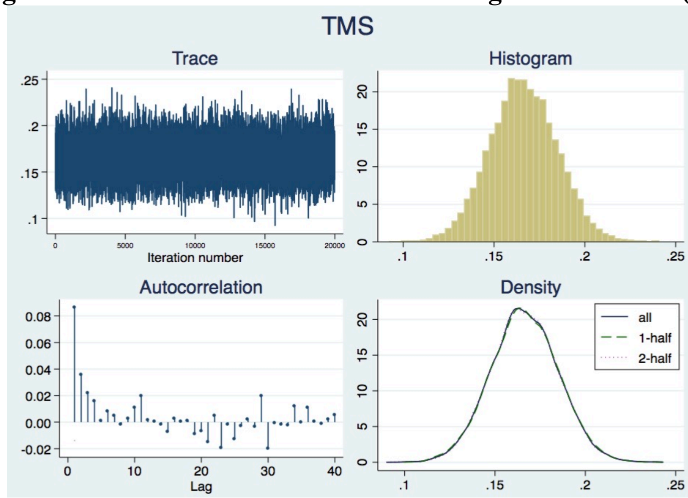


Figure 135. Assessment of Model Convergence for Price (US-based)

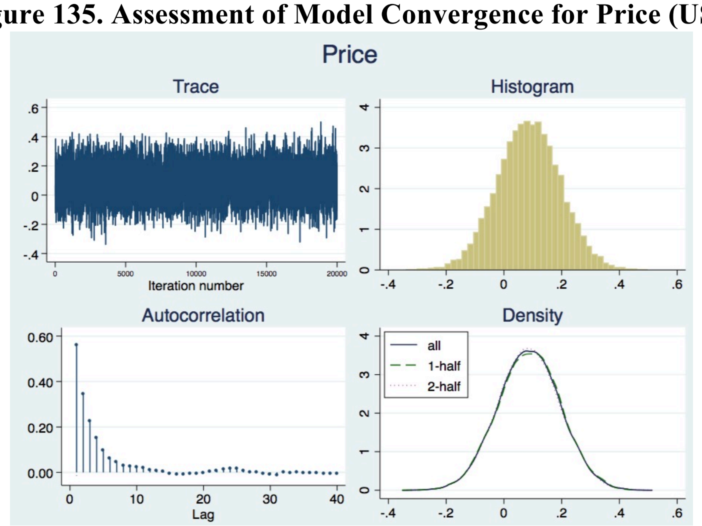


Figure 136. Assessment of Model Convergence for GT (US-based)

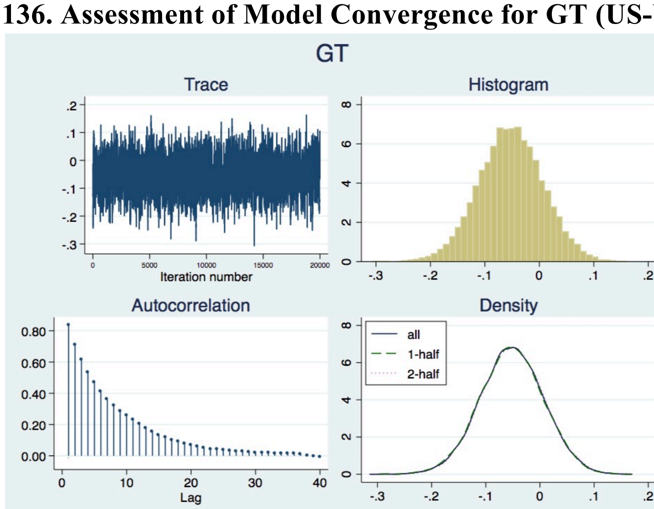


Figure 137. Assessment of Model Convergence for GPI (US-based)

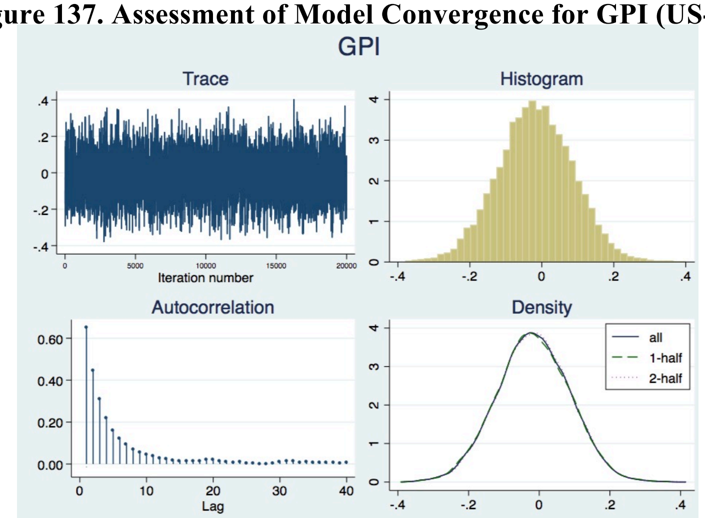
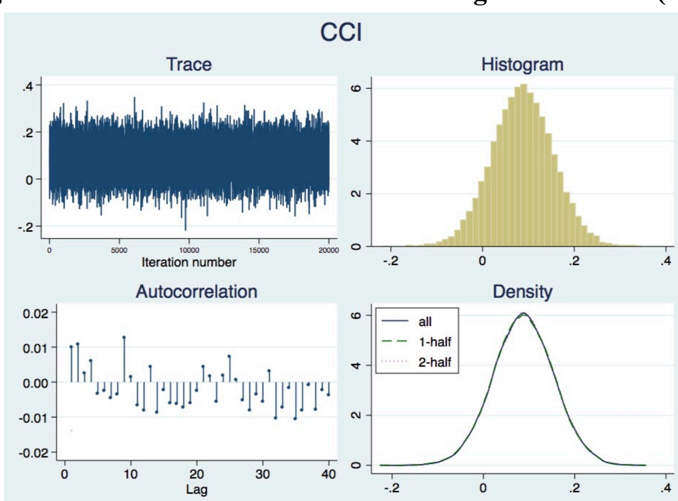


Figure 138. Assessment of Model Convergence for CCI (US-based)



Tables 54 to 56 show my sample split Bayesian estimation results at the comment level (i.e., "Comment" associated with posts at Facebook and test drive post) for Asian-based, European-based, and US-based brands, respectively. In these models, I ran the MCMC chain for 1,849,921 iterations and, I discarded the first 250,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every eightieth iterations for the remaining iterations. The assessment of model convergence (see Figures 139 to 171) suggested that the model specification converged for each relationship.

First, I find that consistent with main results (see Table 43), the volume of comments related to competitors' posts (C-F-Comment (a)) has the positive spillover effects across three different groups, supporting H2. On the other hand, the volume of comment associated with the focal brand's posts (F-Comment (a)) does not have any impact on offline car sales of the focal brand, rejecting H1. The mechanism of comment related to the focal brand's user posts (U-Comment (a)) and competitors' user posts (C-U-Comment (a)) shows another interesting patterns. For example, I find that for the European-based group, the volume of comment associated with the focal brand's user posts has the positive impact on offline car sales of the focal brand, supporting H1. For the US-based group, I observe that the effect of comment associated with the focal brand's user posts has the negative impact on offline car sales of the focal firm, which contradicts with my H1 and positive spillover effects (C-U-Comment (a)) are observed, thereby supporting H2. Finally, consistent with main results, at the stage of consideration, test drive posts regarding competitors have negative spillover effects for the Asian-based and European-based group, supporting H4. However, for the US-based group, at the stage of consideration, online WOM for the focal brand and online WOM for competitors do not have any impact on offline car sales of the focal brand.

Table 54. Bayesian Estimation Results for Comments (Asian-based)

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	0.011 (0.008)	(-0.003, 0.026)
C-F-Comment (a) $_{J, t-1}$	**0.089 (0.017)**	**(0.055, 0.124)**
U-Comment (a) $_{A, t-1}$	0.0001 (0.007)	(-0.014, 0.014)
C-U-Comment (a) $_{J, t-1}$	-0.011 (0.017)	(-0.044, 0.022)
TD-Post (c) $_{A, t-1}$	0.032 (0.017)	(-0.002, 0.066)
C-TD-Post (c) $_{J, t-1}$	**-0.057 (0.021)**	**(-0.098, -0.012)**
TMS $_{A, t-1}$	**0.067 (0.019)**	**(0.031, 0.104)**
Price $_{A, t-1}$	**0.189 (0.093)**	**(0.007, 0.369)**
GT $_{A, t-1}$	**0.126 (0.046)**	**(0.037, 0.215)**
GPI $_{A, t-1}$	0.043 (0.082)	(-0.119, 0.206)
CCI $_{A, t-1}$	**0.212 (0.055)**	**(0.105, 0.318)**

Table 55. Bayesian Estimation Results for Comments (European-based)

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	-0.021 (0.012)	(-0.046, 0.003)
C-F-Comment (a) $_{J, t-1}$	**0.155 (0.027)**	**(0.102, 0.208)**
U-Comment (a) $_{A, t-1}$	**0.02 (0.009)**	**(0.003, 0.037)**
C-U-Comment (a) $_{J, t-1}$	-0.035 (0.024)	(-0.081, 0.012)
TD-Post (c) $_{A, t-1}$	0.03 (0.022)	(-0.014, 0.075)
C-TD-Post (c) $_{J, t-1}$	**-0.077 (0.028)**	**(-0.123, -0.012)**
TMS $_{A, t-1}$	**0.118 (0.016)**	**(0.086, 0.14)**
Price $_{A, t-1}$	-0.048 (0.119)	(-0.28, 0.191)
GT $_{A, t-1}$	**0.33 (0.098)**	**(0.141, 0.526)**
GPI $_{A, t-1}$	**0.303 (0.125)**	**(0.058, 0.545)**
CCI $_{A, t-1}$	**0.207 (0.08)**	**(0.052, 0.366)**

Table 56. Bayesian Estimation Results for Comments (US-based)

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	-0.003 (0.008)	(-0.021, 0.014)
C-F-Comment (a) $_{J, t-1}$	**0.083 (0.018)**	**(0.049, 0.12)**
U-Comment (a) $_{A, t-1}$	**-0.043 (0.008)**	**(-0.059, -0.027)**
C-U-Comment (a) $_{J, t-1}$	**0.089 (0.019)**	**(0.053, 0.127)**
TD-Post (c) $_{A, t-1}$	0.016 (0.019)	(-0.023, 0.055)
C-TD-Post (c) $_{J, t-1}$	-0.038 (0.027)	(-0.09, 0.014)
TMS $_{A, t-1}$	**0.162 (0.019)**	**(0.125, 0.199)**
Price $_{A, t-1}$	0.142 (0.106)	(-0.066, 0.349)
GT $_{A, t-1}$	-0.049 (0.05)	(-0.147, 0.053)
GPI $_{A, t-1}$	**0.237 (0.092)**	**(0.055, 0.418)**
CCI $_{A, t-1}$	**0.233 (0.062)**	**(0.11, 0.35)**

Figure 139. Assessment of Model Convergence for F-Comment (a) (Asian-based)

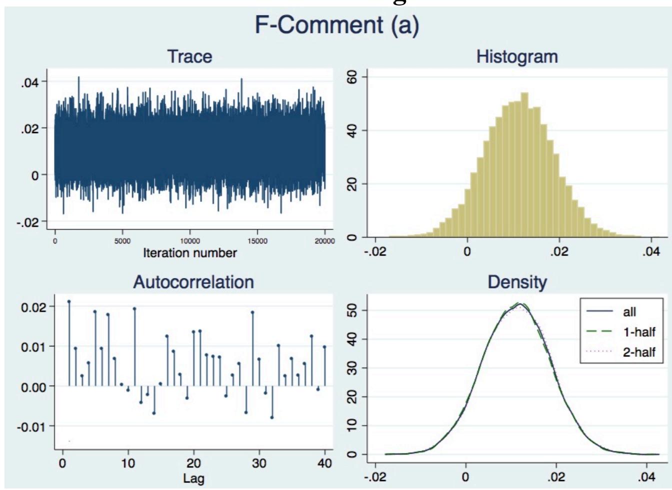


Figure 140. Assessment of Model Convergence for C-F-Comment (a) (Asian-based)

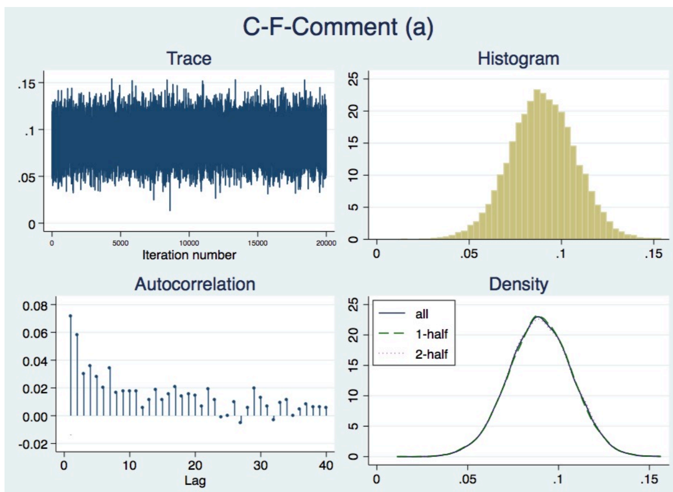


Figure 141. Assessment of Model Convergence for U-Comment (a) (Asian-based)

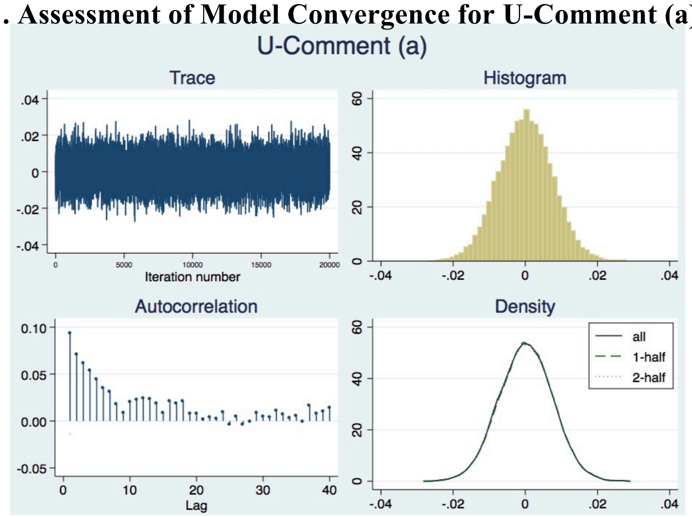


Figure 142. Assessment of Model Convergence for C-U-Comment (a) (Asian-based)

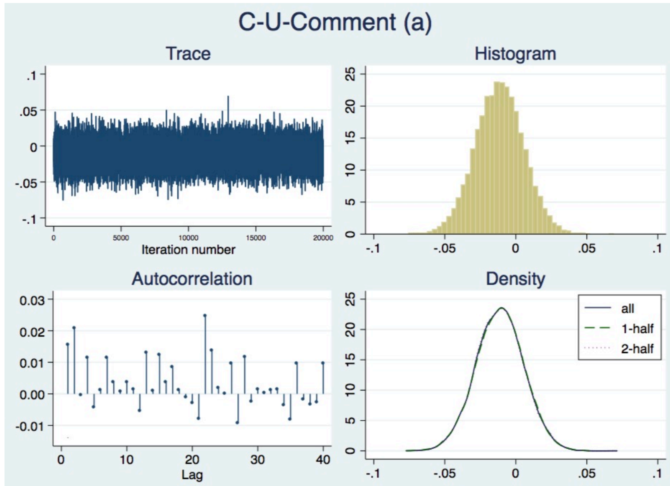


Figure 143. Assessment of Model Convergence for TD-Post (c) (Asian-based)

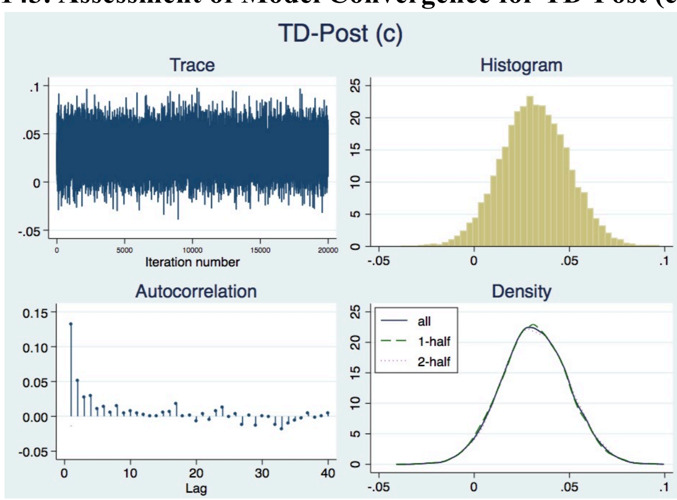


Figure 144. Assessment of Model Convergence for C-TD-Post (c) (Asian-based)

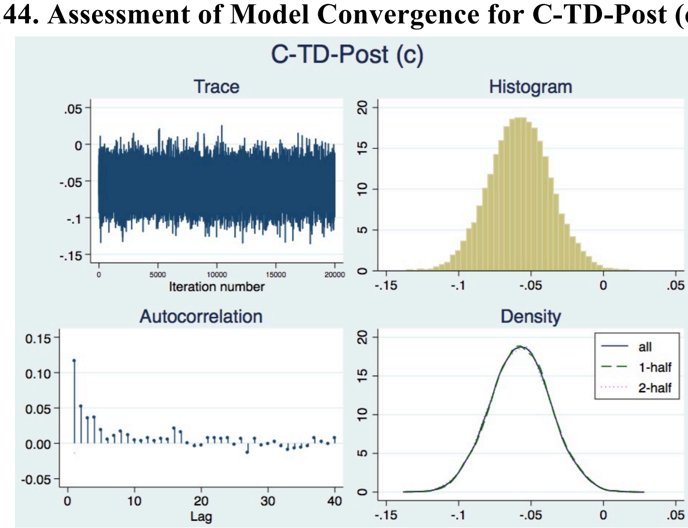


Figure 145. Assessment of Model Convergence for TMS (Asian-based)

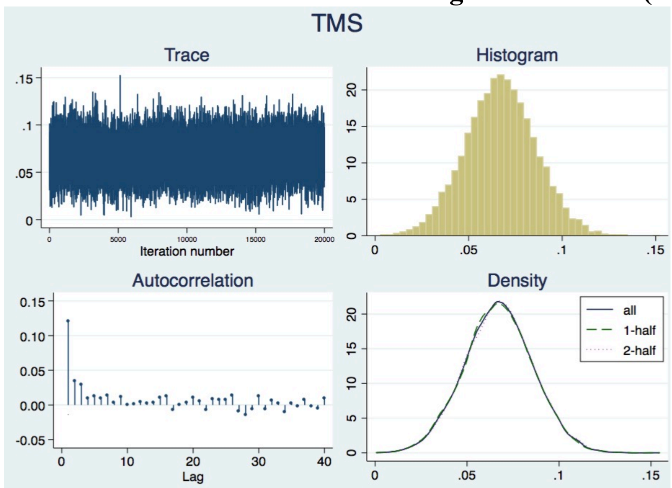


Figure 146. Assessment of Model Convergence for Price (Asian-based)

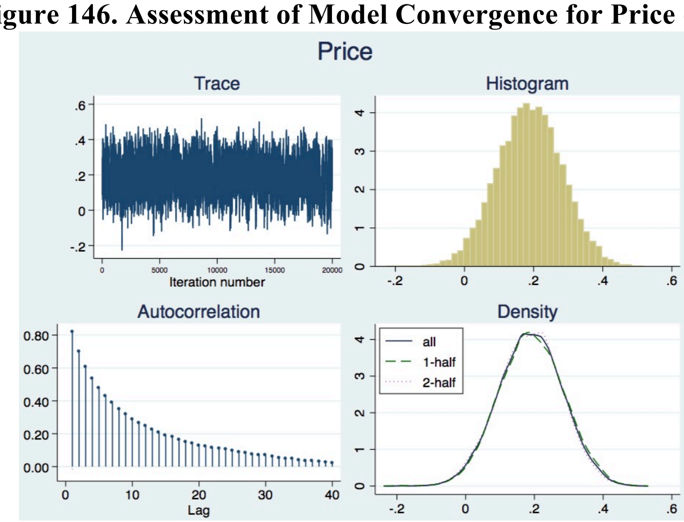


Figure 147. Assessment of Model Convergence for GT (Asian-based)

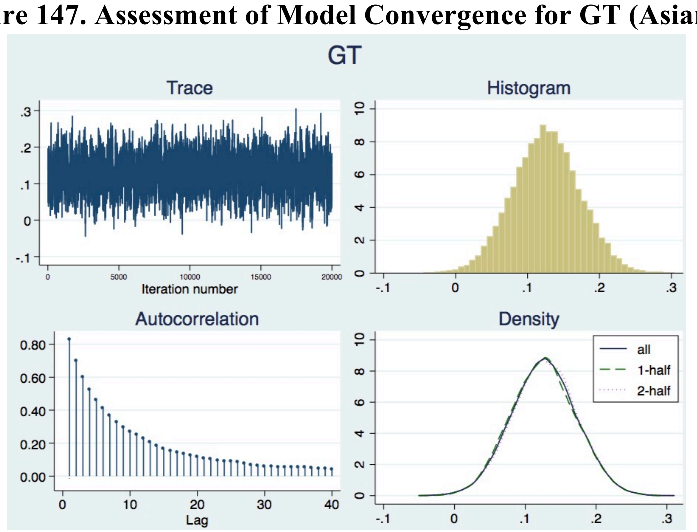


Figure 148. Assessment of Model Convergence for GPI (Asian-based)

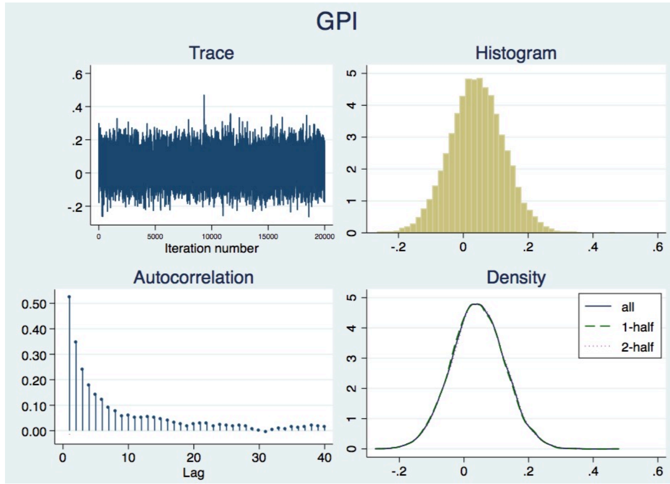


Figure 149. Assessment of Model Convergence for CCI (Asian-based)

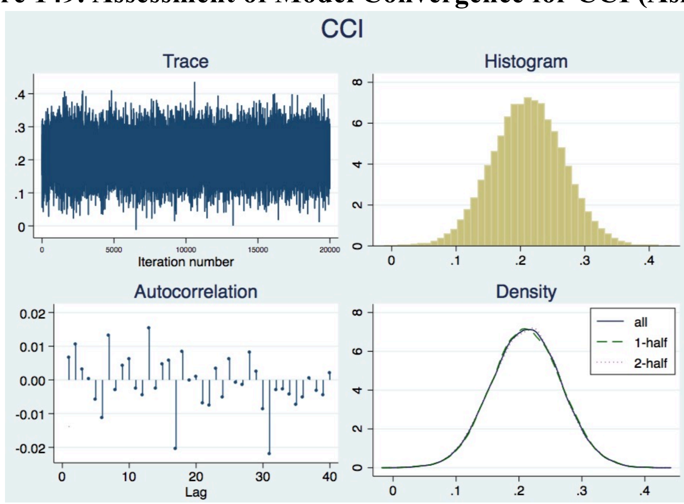


Figure 150. Assessment of Model Convergence for F-Comment (a) (European-based)

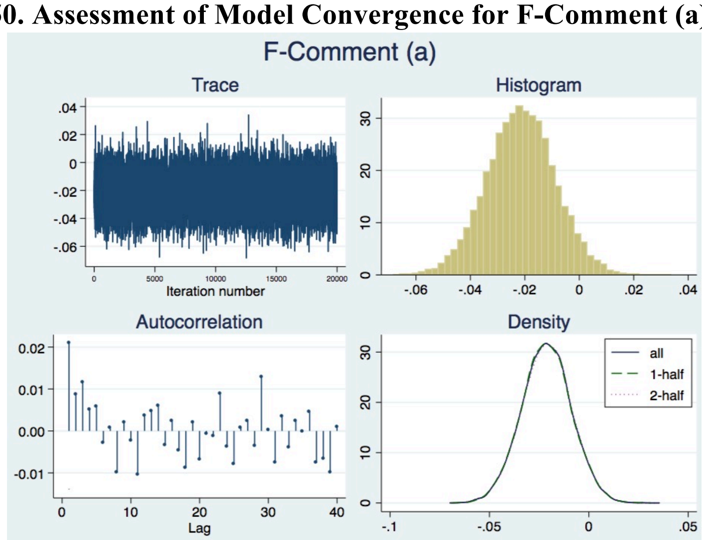


Figure 151. Assessment of Model Convergence for C-F-Comment (a) (European-based)

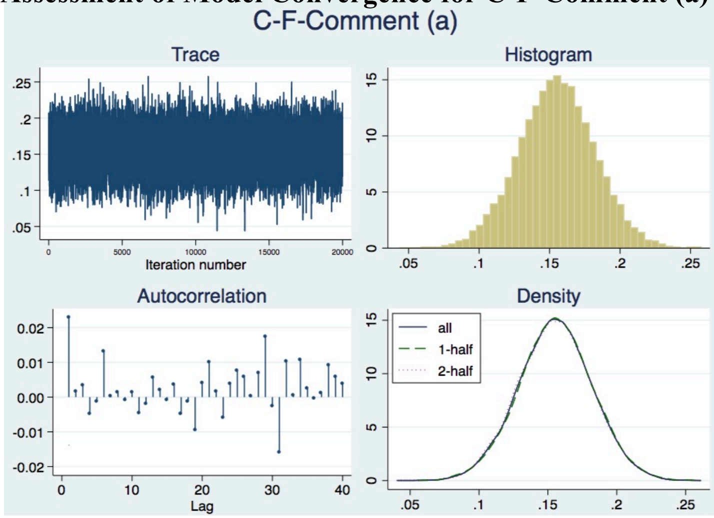


Figure 152. Assessment of Model Convergence for U-Comment (a) (European-based)

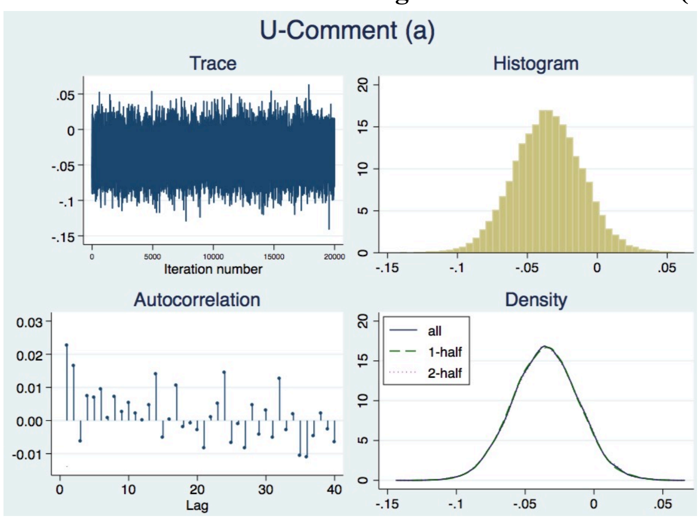


Figure 153. Assessment of Model Convergence for C-U-Comment (a) (European-based)

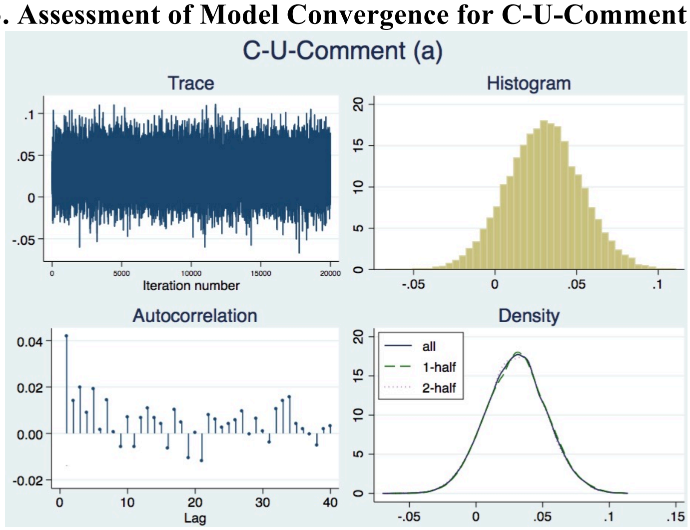


Figure 154. Assessment of Model Convergence for TD-Post (c) (European-based)

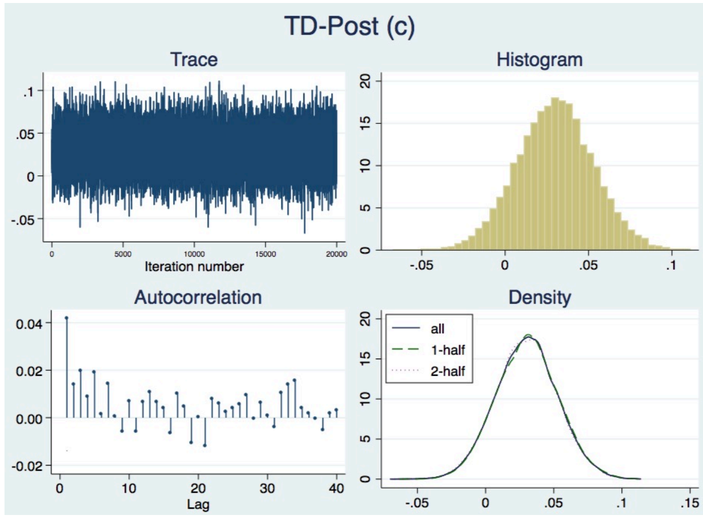


Figure 155. Assessment of Model Convergence for C-TD-Post (c) (European-based)

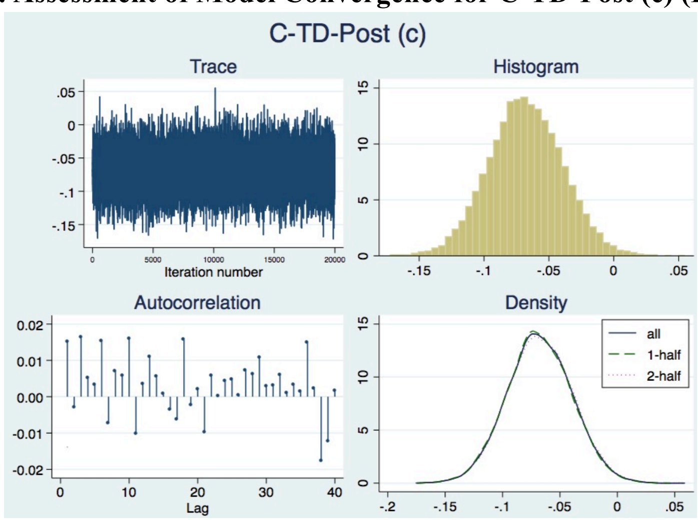


Figure 156. Assessment of Model Convergence for TMS (European-based)

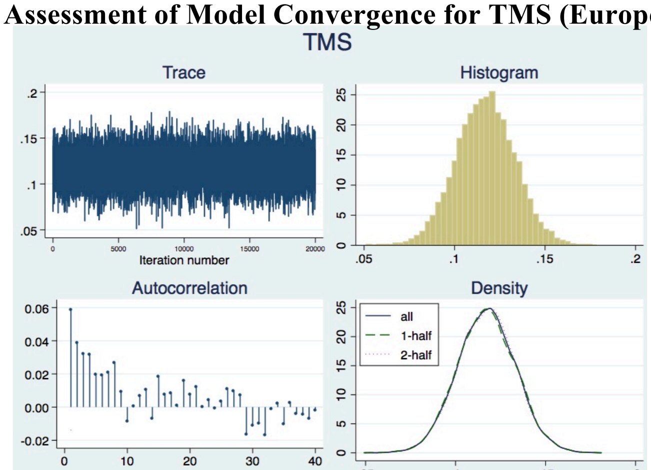


Figure 157. Assessment of Model Convergence for Price (European-based)

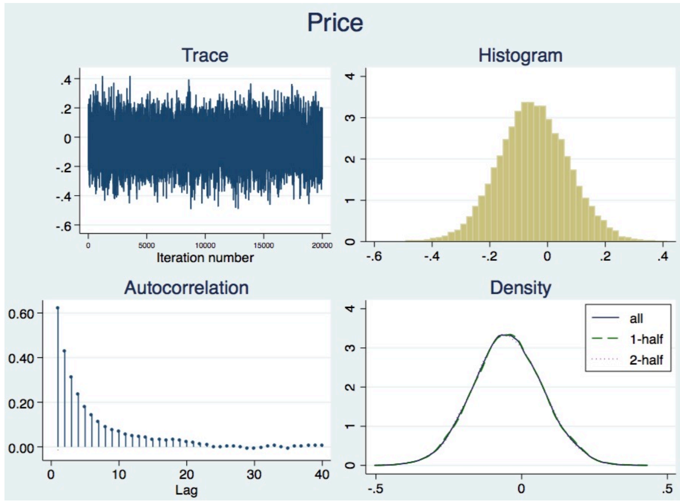


Figure 158. Assessment of Model Convergence for GT (European-based)

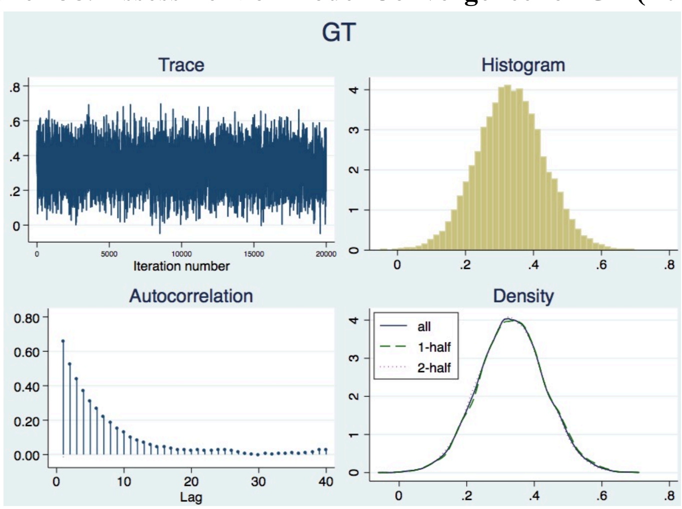


Figure 159. Assessment of Model Convergence for GPI (European-based)

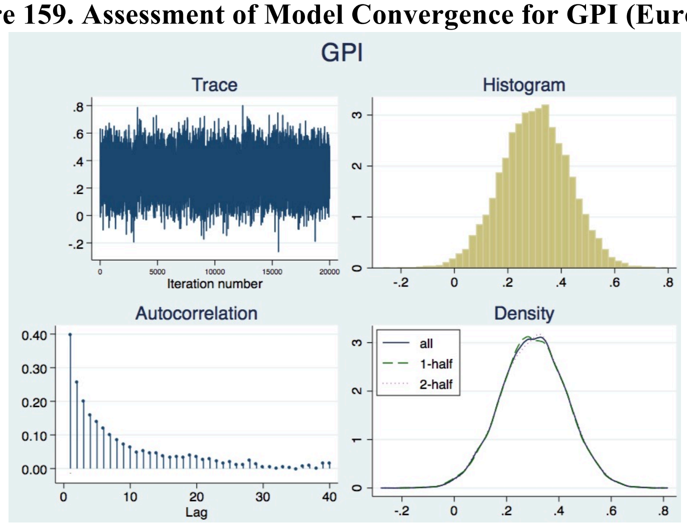


Figure 160. Assessment of Model Convergence for CCI (European-based)

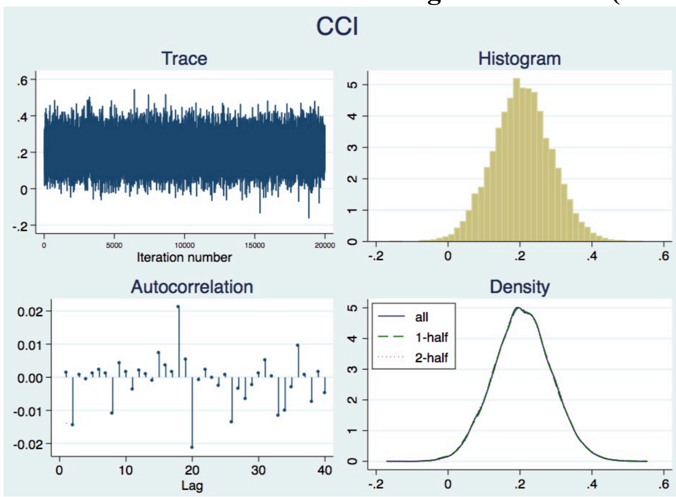


Figure 161. Assessment of Model Convergence for F-Comment (a) (US-based)

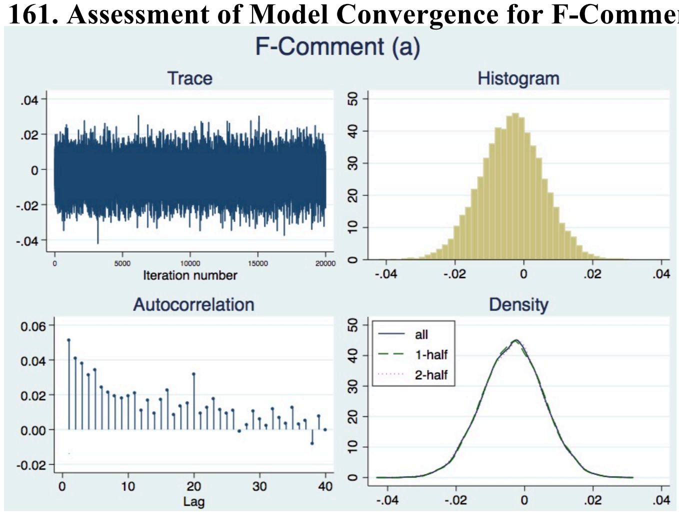


Figure 162. Assessment of Model Convergence for C-F-Comment (a) (US-based)

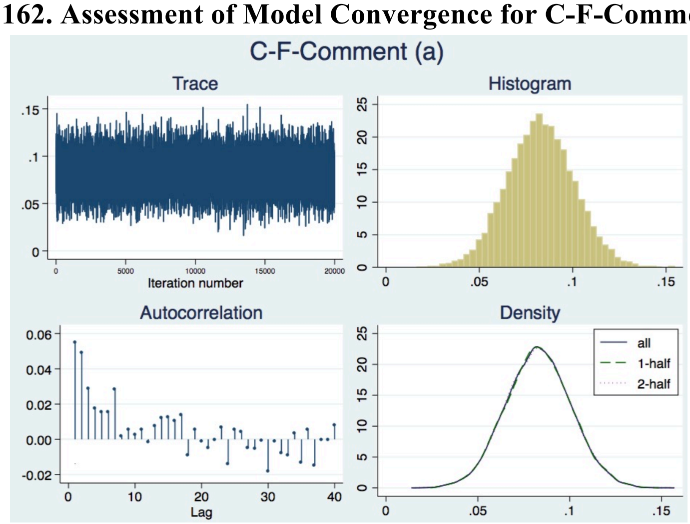


Figure 163. Assessment of Model Convergence for U-Comment (a) (US-based)

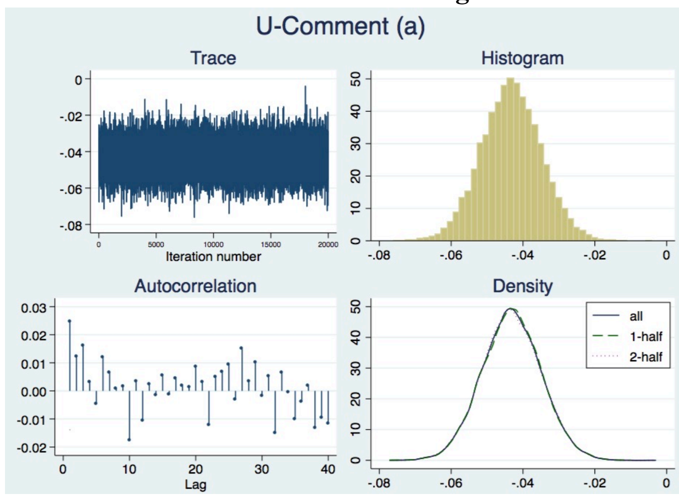


Figure 164. Assessment of Model Convergence for C-U-Comment (a) (US-based)

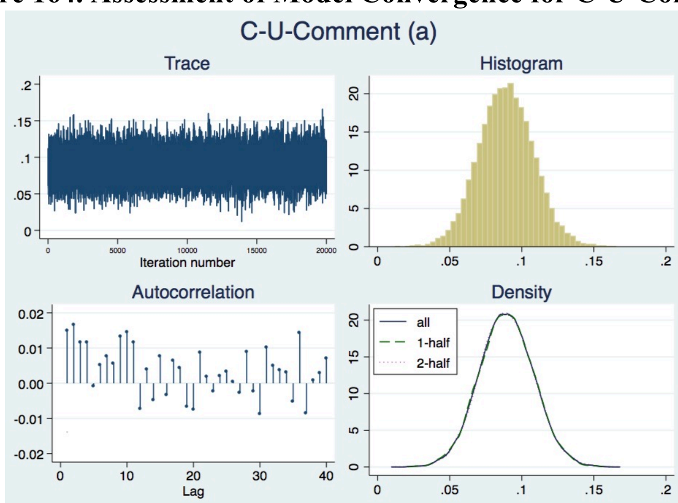


Figure 165. Assessment of Model Convergence for TD-Post (c) (US-based)

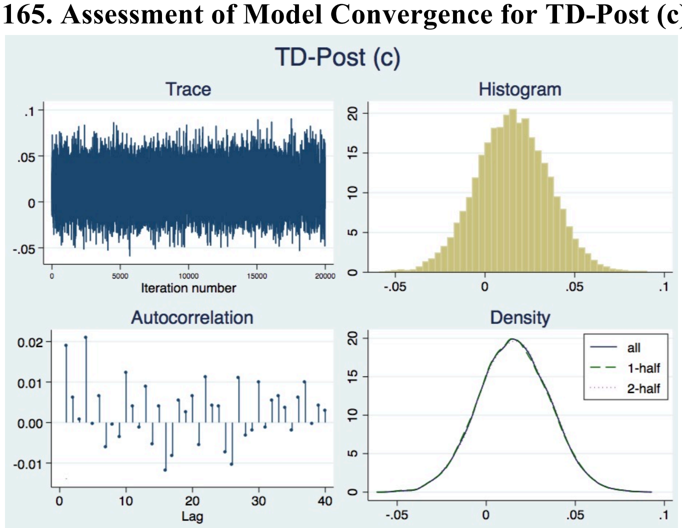


Figure 166. Assessment of Model Convergence for C-TD-Post (c) (US-based)

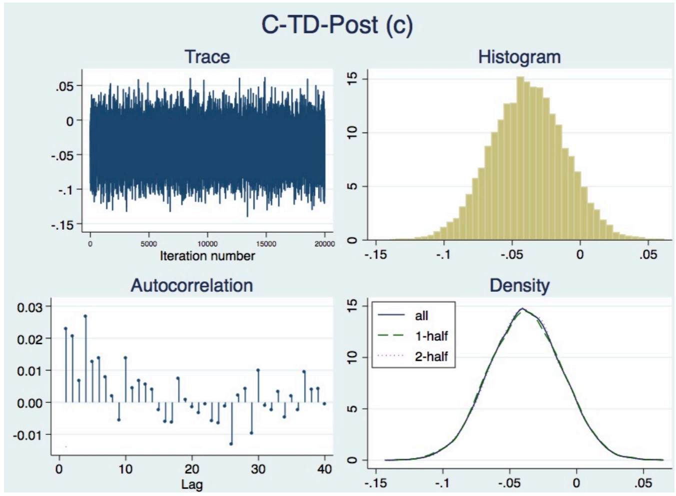


Figure 167. Assessment of Model Convergence for TMS (US-based)

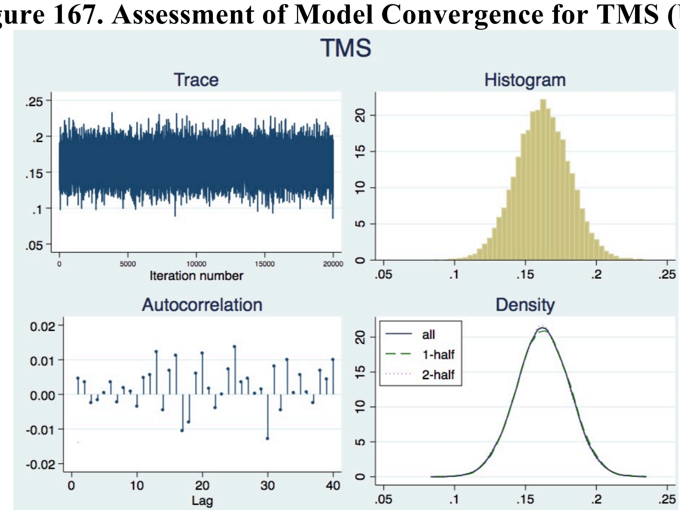


Figure 168. Assessment of Model Convergence for Price (US-based)

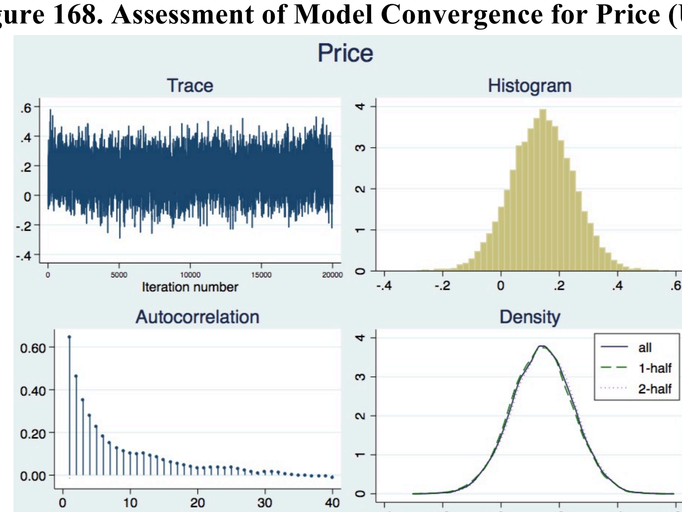


Figure 169. Assessment of Model Convergence for GT (US-based)

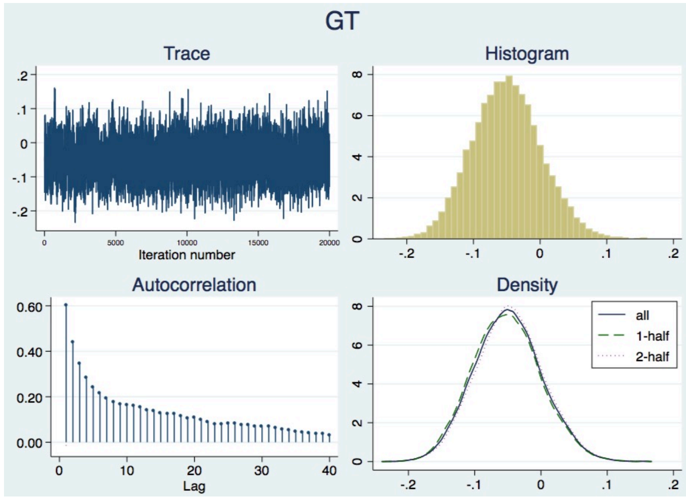


Figure 170. Assessment of Model Convergence for GPI (US-based)

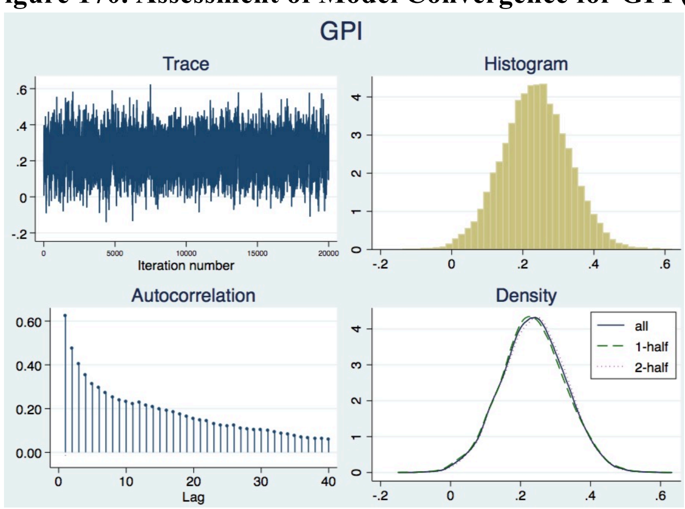
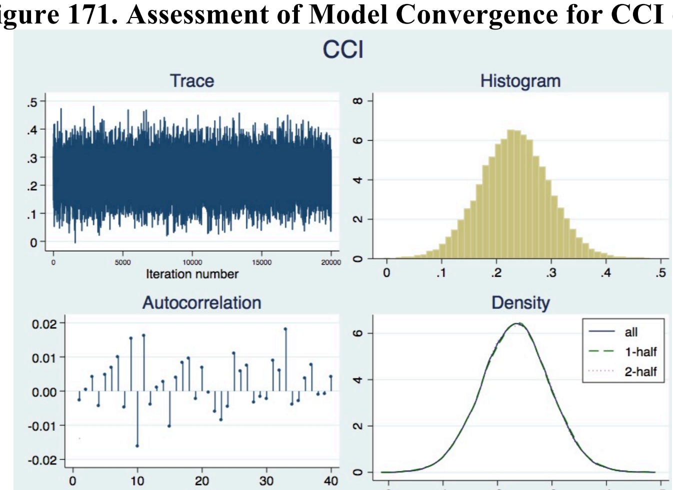


Figure 171. Assessment of Model Convergence for CCI (US-based)



Tables 57 to 59 show my sample split Bayesian estimation results at the share level (i.e., "Share" associated with posts at Facebook and test drive post) for Asian-based, European-based, and US-based brands, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 172 to 204) suggested that the model specification converged for each relationship.

First, I find that consistent with main results (see Table 41), the mechanism of share associated with the focal brand's posts (F-Share (a)) is not effective in influencing offline car sales of the focal brand across three groups, rejecting H1. However, the volume of share associated with competitors' posts has positive spillover effects on offline car sales of the focal brand, thereby supporting H2. Regarding the effect related to user posts (U-Share (a) and C-U-Shared (a)), I cannot find any support for my H1 and H2. The results also suggest that share associated with the focal brand's user posts (U-Share (a)) and competitors' user posts (C-U-Share (a)) is also not very effective in influencing offline car sales of the focal brand, thereby rejecting both H1 and H2. Finally, I find that at the stage of consideration, test drive posts about the focal brand have the positive impact on offline car sales of the focal brand for the Asian-based and European-based group only, supporting H3.

To summarize, this series of analysis suggests that in the U.S. automobile industry, customers do use the origin of brands as an attribute and make similar inferences for brands that belong to the same origin. Besides, customers from different groups do appreciate different mechanism significantly about how these mechanisms may influence their purchase decisions.

Table 57. Bayesian Estimation Results for Shares (Asian-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	-0.000003 (0.004)	(-0.008, 0.009)
C-F-Share (a) $_{J, t-1}$	**0.043 (0.009)**	**(0.024, 0.062)**
U-Share (a) $_{A, t-1}$	0.001 (0.005)	(-0.008, 0.011)
C-U-Share (a) $_{J, t-1}$	-0.007 (0.009)	(-0.025, 0.012)
TD-Post (c) $_{A, t-1}$	**0.039 (0.017)**	**(0.006, 0.073)**
C-TD-Post (c) $_{J, t-1}$	-0.029 (0.022)	(-0.073, 0.015)
TMS $_{A, t-1}$	**0.053 (0.018)**	**(0.017, 0.089)**
Price $_{A, t-1}$	**0.187 (0.088)**	**(0.013, 0.36)**
GT $_{A, t-1}$	**0.125 (0.042)**	**(0.042, 0.207)**
GPI $_{A, t-1}$	0.031 (0.1)	(-0.17, 0.231)
CCI $_{A, t-1}$	**0.217 (0.052)**	**(0.114, 0.318)**

Table 58. Bayesian Estimation Results for Shares (European-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	0.009 (0.008)	(-0.006, 0.025)
C-F-Share (a) $_{J, t-1}$	**0.035 (0.015)**	**(0.004, 0.065)**
U-Share (a) $_{A, t-1}$	0.007 (0.007)	(-0.008, 0.021)
C-U-Share (a) $_{J, t-1}$	-0.11 (0.016)	(-0.04, 0.02)
TD-Post (c) $_{A, t-1}$	**0.049 (0.023)**	**(0.003, 0.095)**
C-TD-Post (c) $_{J, t-1}$	-0.041 (0.032)	(-0.105, 0.022)
TMS $_{A, t-1}$	**0.118 (0.016)**	**(0.087, 0.149)**
Price $_{A, t-1}$	-0.027 (0.12)	(-0.27, 0.21)
GT $_{A, t-1}$	**0.37 (0.097)**	**(0.179, 0.563)**
GPI $_{A, t-1}$	**0.42 (0.158)**	**(0.107, 0.73)**
CCI $_{A, t-1}$	**0.27 (0.082)**	**(0.11, 0.43)**

Table 59. Bayesian Estimation Results for Shares (US-based)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	-0.008 (0.005)	(-0.018, 0.003)
C-F-Share (a) $_{J, t-1}$	**0.06 (0.011)**	**(0.04, 0.082)**
U-Share (a) $_{A, t-1}$	0.011 (0.006)	(-0.0005, 0.023)
C-U-Share (a) $_{J, t-1}$	**-0.028 (0.011)**	**(-0.05, -0.007)**
TD-Post (c) $_{A, t-1}$	0.022 (0.02)	(-0.018, 0.062)
C-TD-Post (c) $_{J, t-1}$	-0.009 (0.028)	(-0.065, 0.046)
TMS $_{A, t-1}$	**0.172 (0.019)**	**(0.136, 0.208)**
Price $_{A, t-1}$	0.13 (0.11)	(-0.087, 0.35)
GT $_{A, t-1}$	**-0.129 (0.055)**	**(-0.233, -0.019)**

Table 59 (cont'd)		
GPI $_{A, t-1}$	**0.4 (0.12)**	**(0.171, 0.635)**
CCI $_{A, t-1}$	**0.22 (0.062)**	**(0.098, 0.34)**

Figure 172. Assessment of Model Convergence for F-Share (a) (Asian-based)

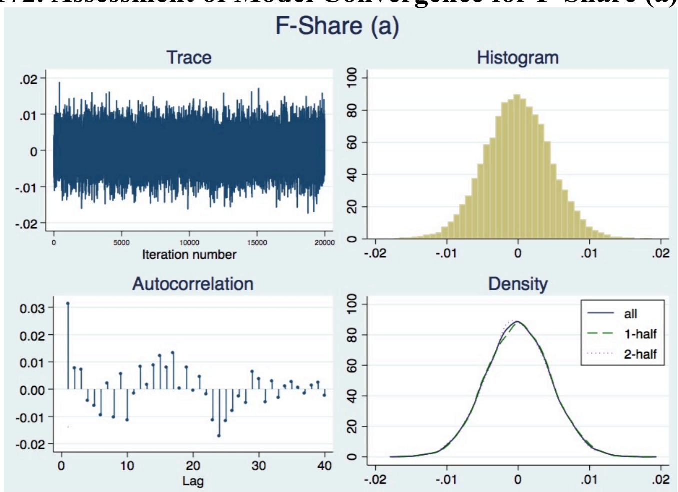


Figure 173. Assessment of Model Convergence for C-F-Share (a) (Asian-based)

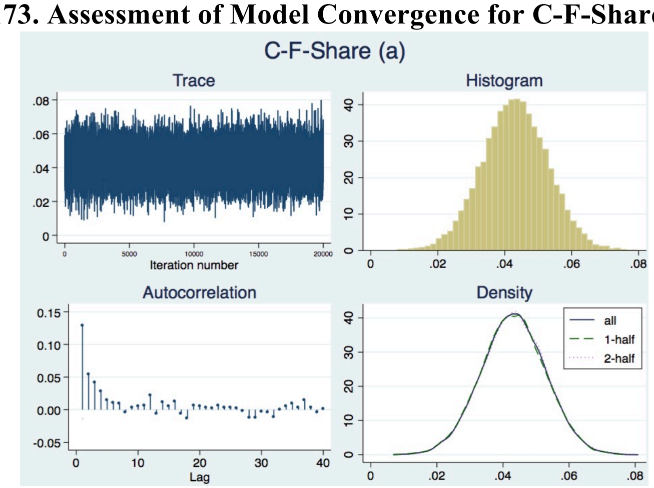


Figure 174. Assessment of Model Convergence for U-Share (a) (Asian-based)

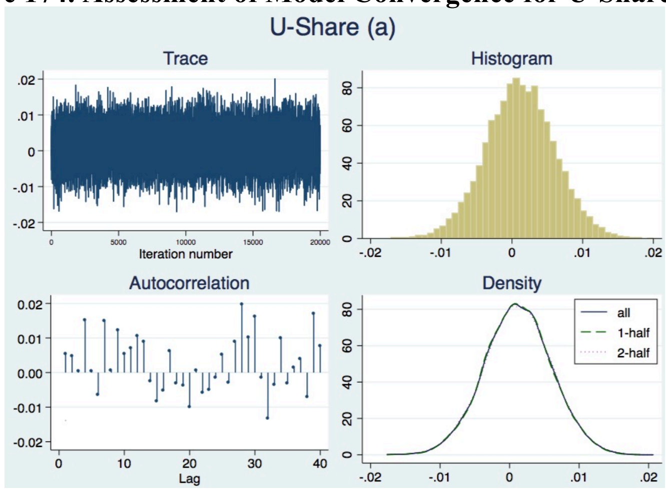


Figure 175. Assessment of Model Convergence for C-U-Share (a) (Asian-based)

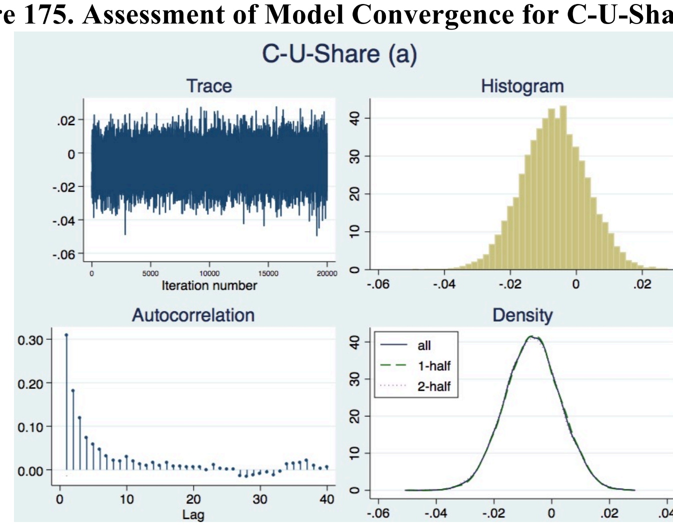


Figure 176. Assessment of Model Convergence for TD-Post (c) (Asian-based)

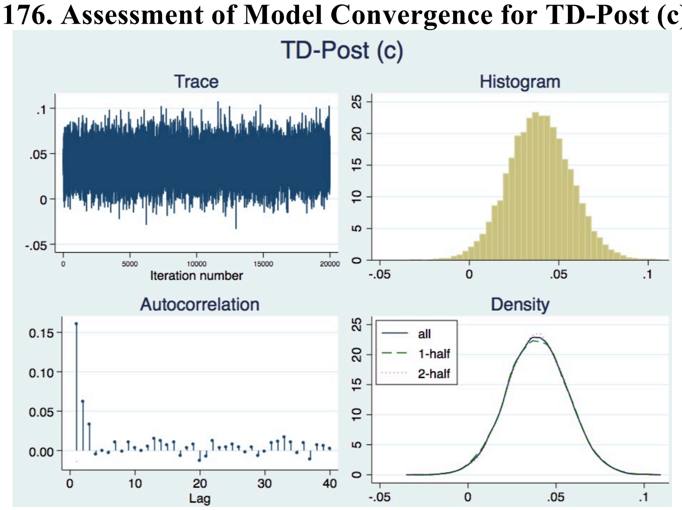


Figure 177. Assessment of Model Convergence for C-TD-Post (c) (Asian-based)

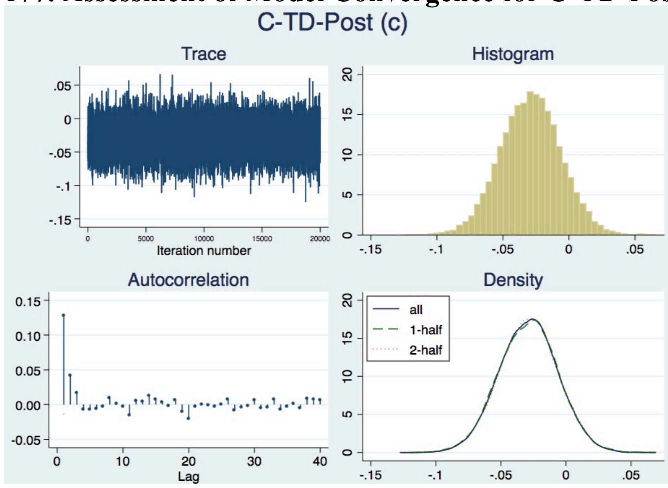


Figure 178. Assessment of Model Convergence for TMS (Asian-based)

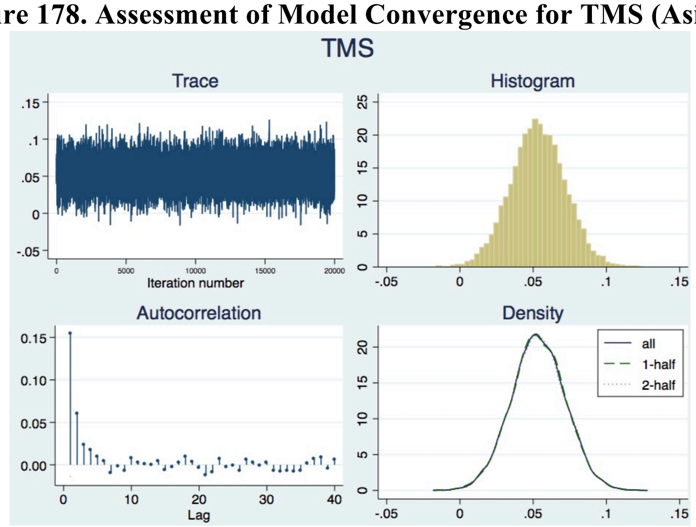


Figure 179. Assessment of Model Convergence for Price (Asian-based)

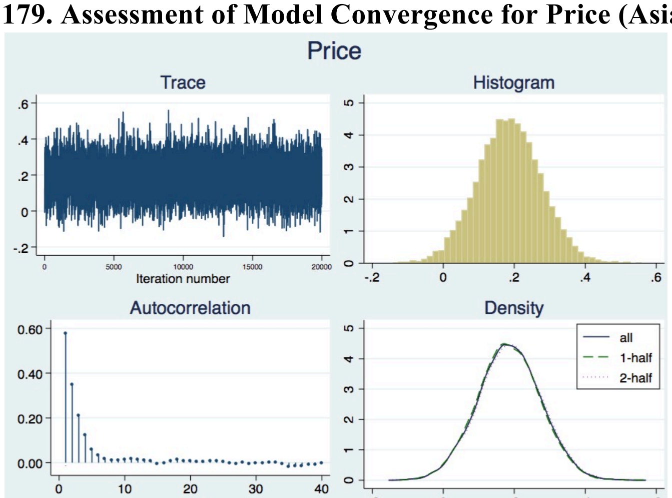


Figure 180. Assessment of Model Convergence for GT (Asian-based)

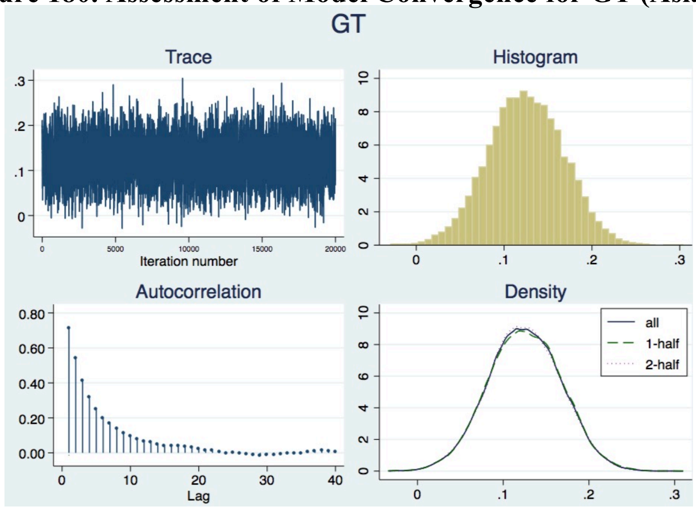


Figure 181. Assessment of Model Convergence for GPI (Asian-based)

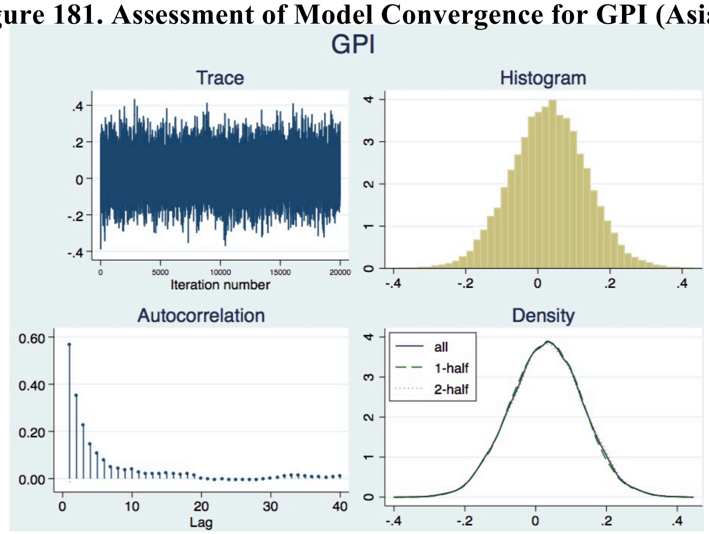


Figure 182. Assessment of Model Convergence for CCI (Asian-based)

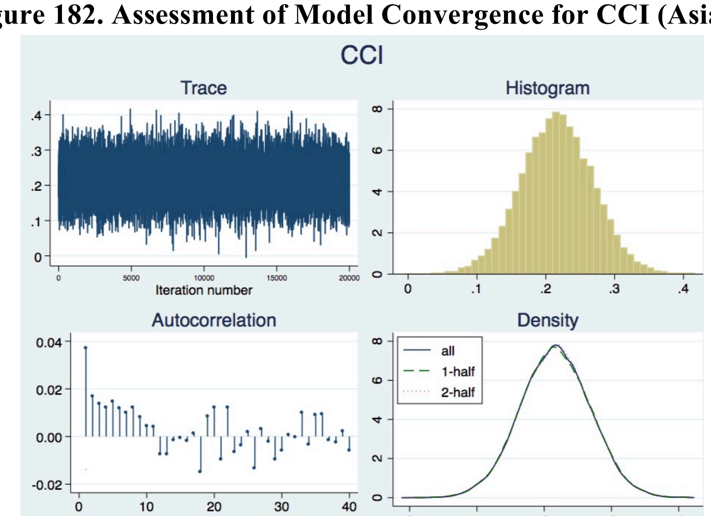


Figure 183. Assessment of Model Convergence for F-Share (a) (European-based)

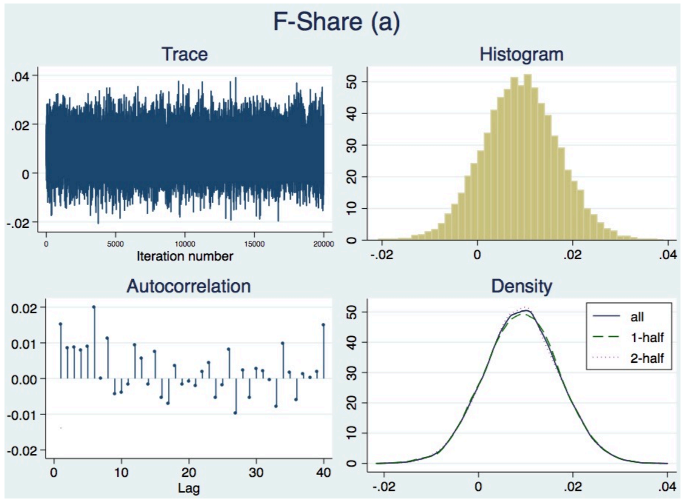


Figure 184. Assessment of Model Convergence for C-F-Share (a) (European-based)

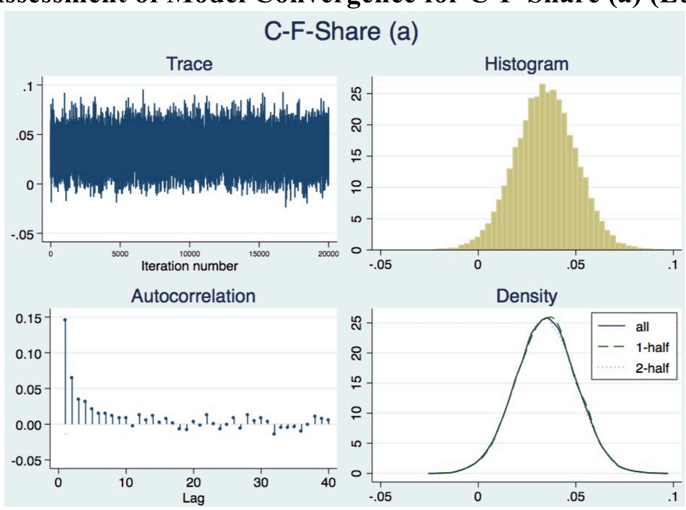


Figure 185. Assessment of Model Convergence for U-Share (a) (European-based)

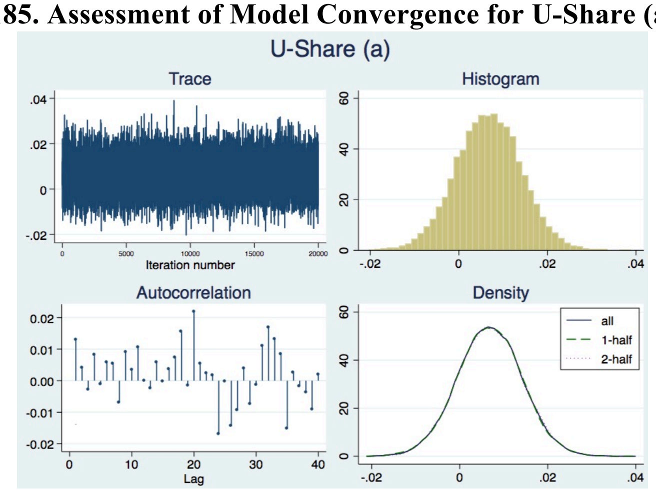


Figure 186. Assessment of Model Convergence for C-U-Share (a) (European-based)

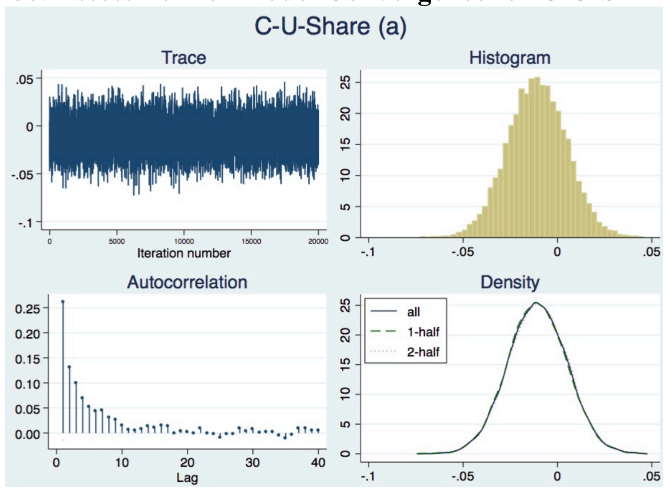


Figure 187. Assessment of Model Convergence for TD-Post (c) (European-based)

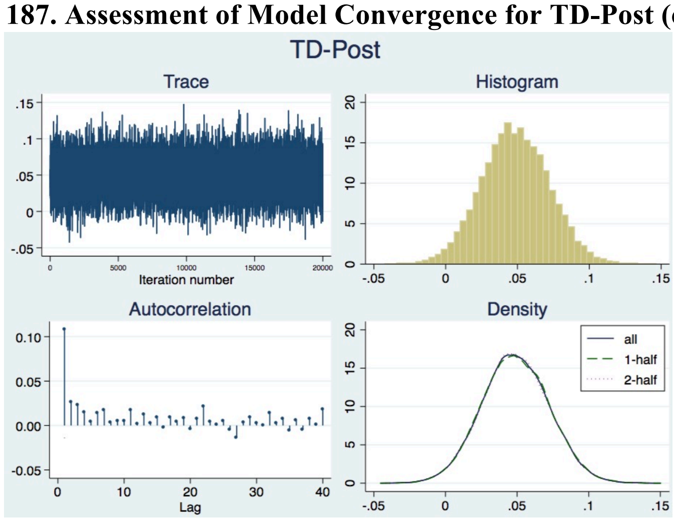


Figure 188. Assessment of Model Convergence for C-TD-Post (c) (European-based)

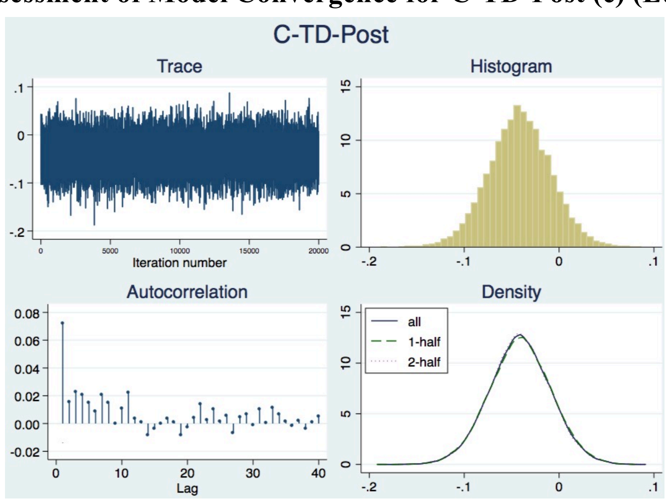


Figure 189. Assessment of Model Convergence for TMS (European-based)

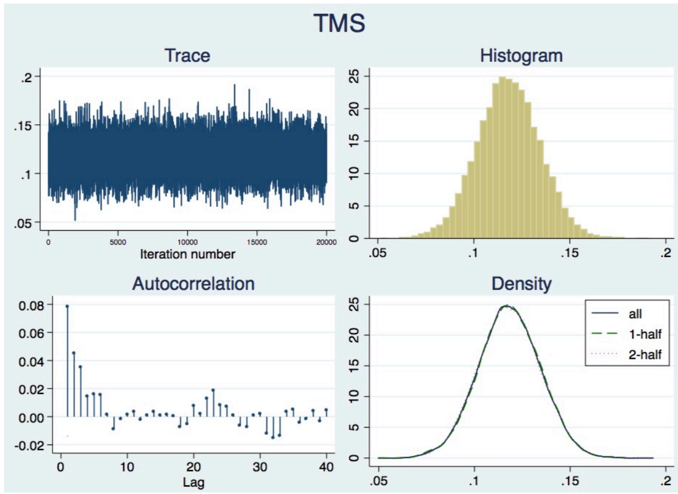


Figure 190. Assessment of Model Convergence for Price (European-based)

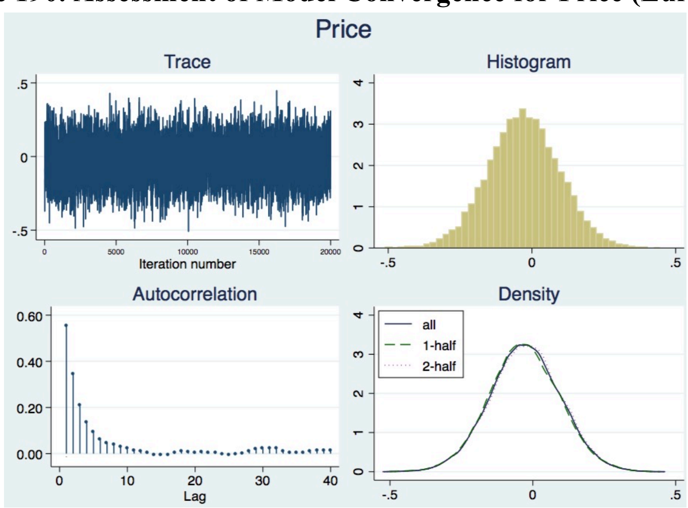


Figure 191. Assessment of Model Convergence for GT (European-based)

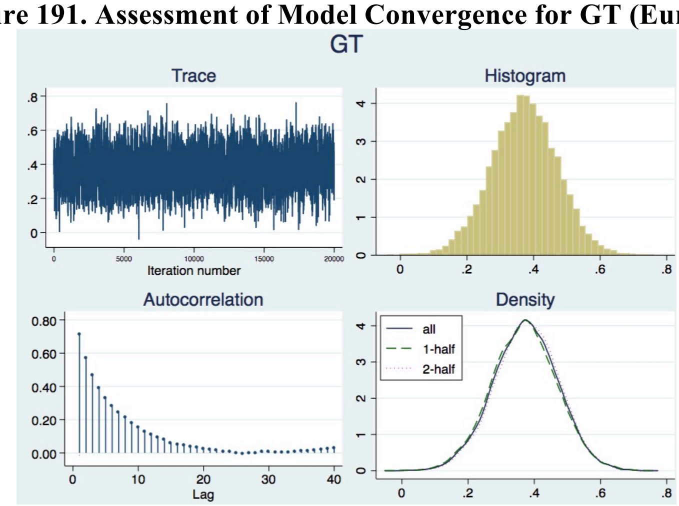


Figure 192. Assessment of Model Convergence for GPI (European-based)

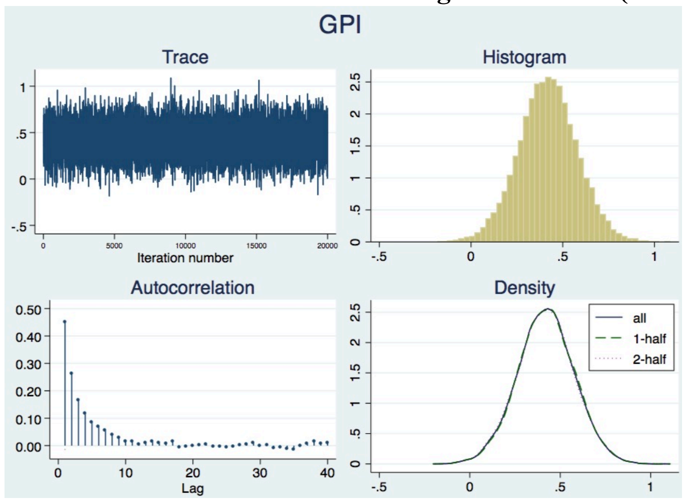


Figure 193. Assessment of Model Convergence for CCI (European-based)

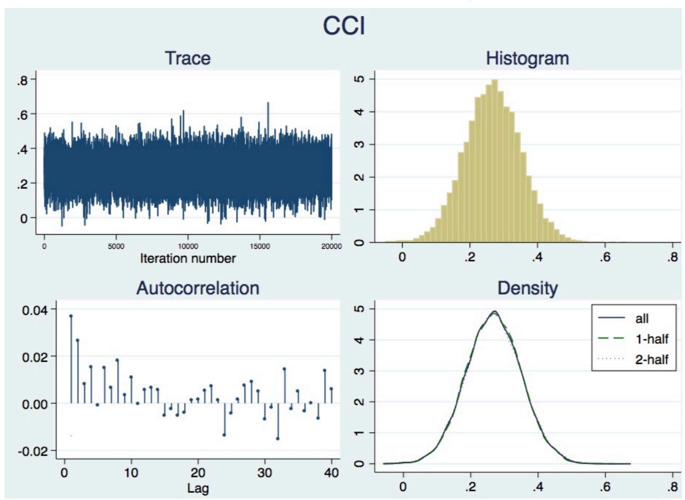


Figure 194. Assessment of Model Convergence for F-Share (a) (US-based)

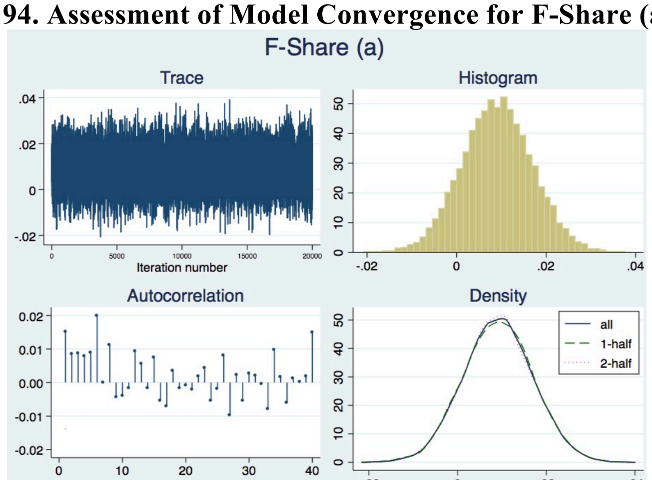


Figure 195. Assessment of Model Convergence for C-F-Share (a) (US-based)

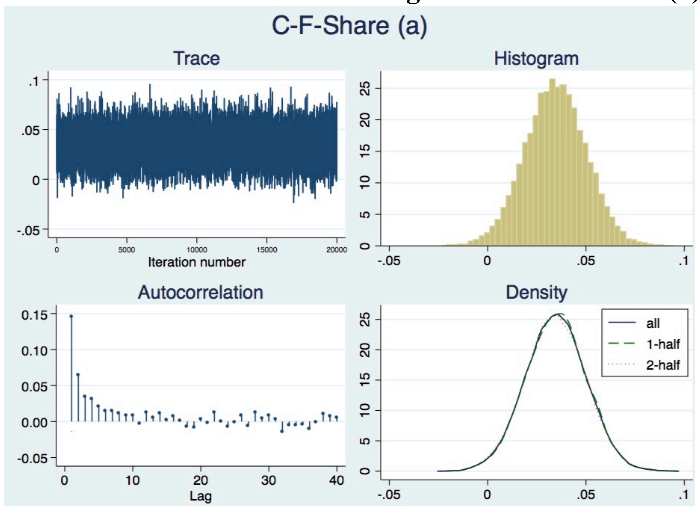


Figure 196. Assessment of Model Convergence for U-Share (a) (US-based)

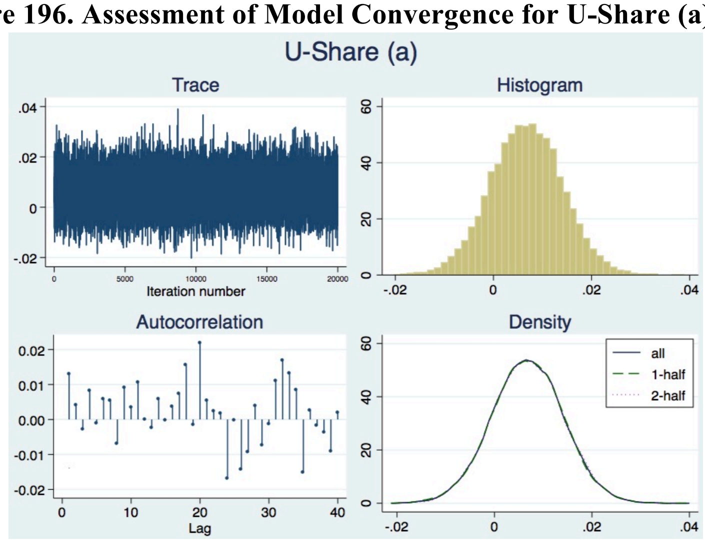


Figure 197. Assessment of Model Convergence for C-U-Share (a) (US-based)

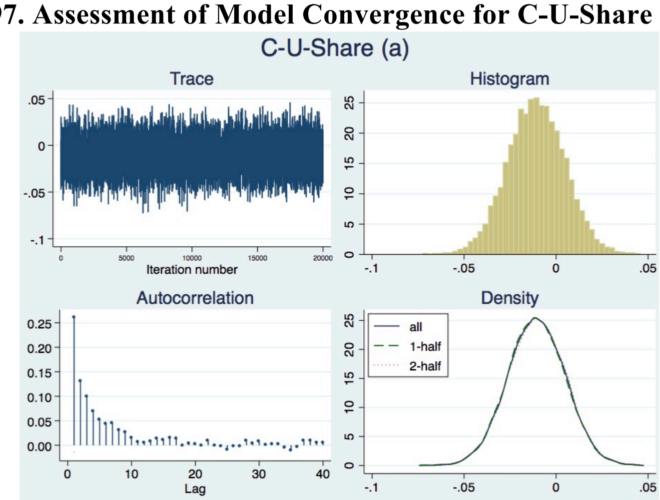


Figure 198. Assessment of Model Convergence for TD-Post (c) (US-based)

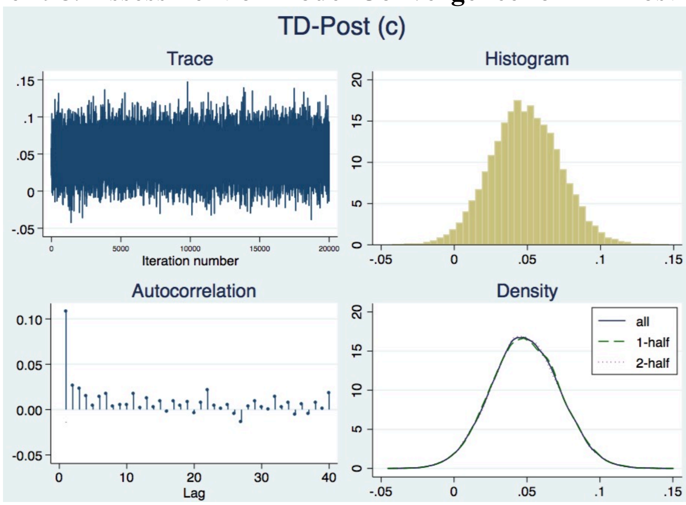


Figure 199. Assessment of Model Convergence for C-TD-Post (c) (US-based)

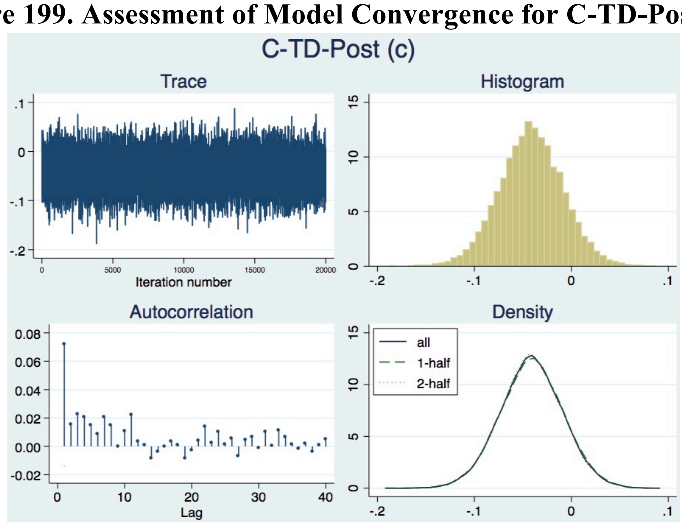


Figure 200. Assessment of Model Convergence for TMS (US-based)

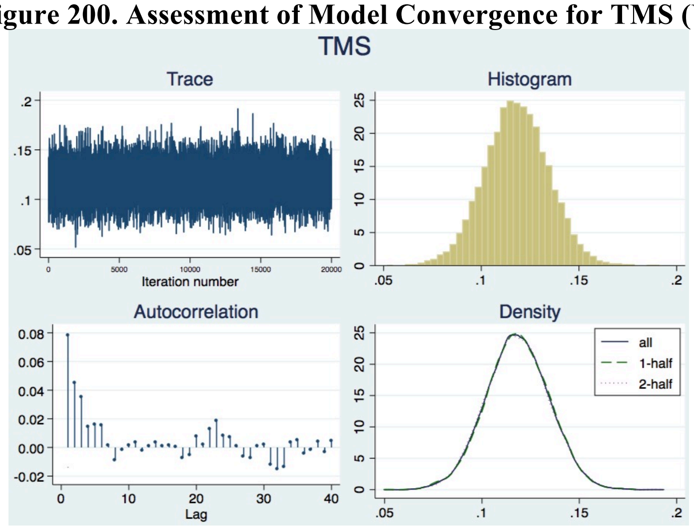


Figure 201. Assessment of Model Convergence for Price (US-based)

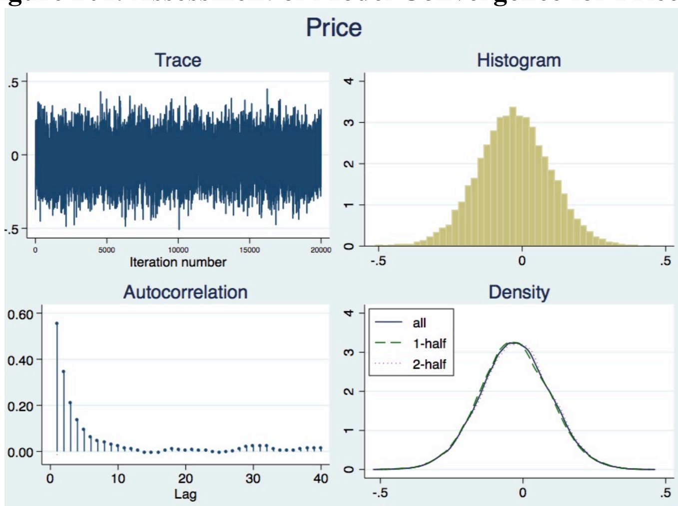


Figure 202. Assessment of Model Convergence for GT (US-based)

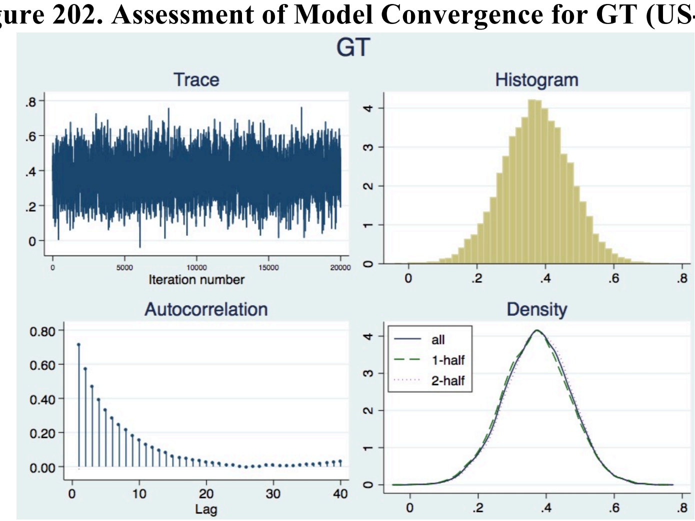


Figure 203. Assessment of Model Convergence for GPI (US-based)

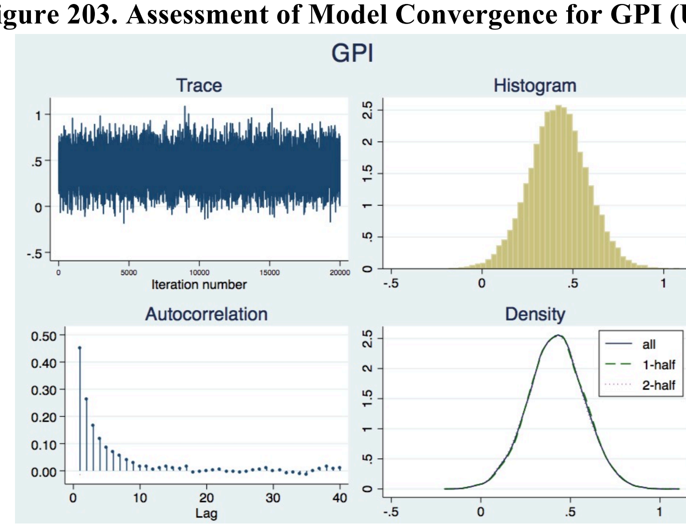
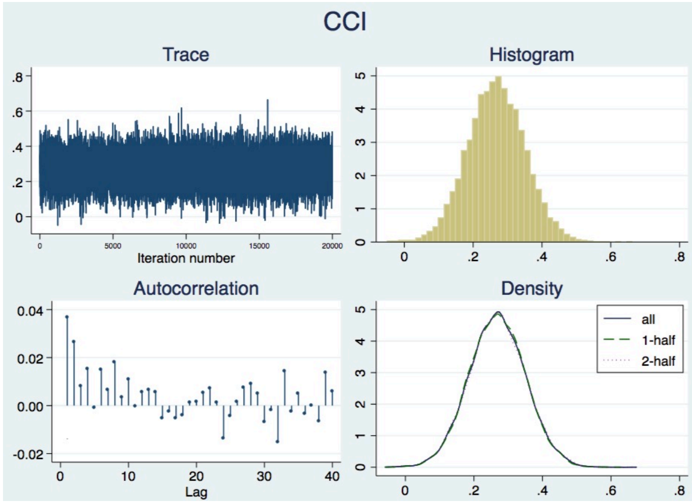


Figure 204. Assessment of Model Convergence for CCI (US-based)



3.5.3 Sample Split Bayesian Analysis Results on Market Structure

I then turn my attention to market structure. Netzer et al. (2012) applied the text-mining approach on user-generated content in the U.S automobile industry to better understand market structure and they identified three different sub market structures (see Figure 205 for their identified market structure). I therefore, categorize my whole sample into these three sub market structures[19] to examine how these market structures may vary dynamics of online WOM in the current study. Tables 60 to 62 show descriptive statistics for these three groups, respectively.

[19] **Group 1:** Acura, Audi, BMW, Cadillac, Infiniti, Jaguar, Land Rover, Lexus, Mercedes-Benz, Porsche, Saab, and Volvo; **Group 2:** Buick, Chevrolet, Chrysler, Dodge, FIAT, Ford, Jeep, and Lincoln; **Group 3:** Honda, Hyundai, KIA, Mazda, Mitsubishi, Nissan, Scion, Subaru, Toyota, and Volkswagen. Please note that some brands (e.g., Land Rover) covered in the current did not include in Netzer et al.'s study (2012). I assigned those brands into the corresponding groups based on their existing characteristics. For example, Land Rover could be considered into the group 1 based on the price factor. Scion could be considered into the group 3 based on the origin of the brand.

Figure 205. Netzer et al.'s (2012) Market Structures

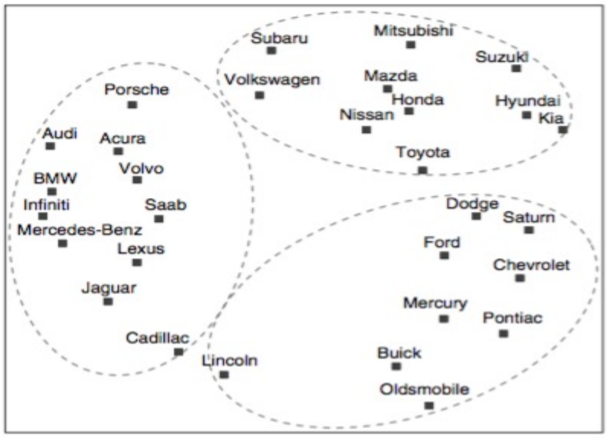


Table 60. Descriptive Statistics for Group 1

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	679	11208.15	8387.419	97	37,399
F-Post (a)	679	30.67	23.19	0	436
C-F-Post (a)	679	926.96	408.36	64	2,579
F-Like (a)	679	133154.7	211997.3	0	1,100,000
C-F-Like (a)	679	2,243,497	2,086,161	4,230	5,900,000
F-Comment (a)	679	2347.04	2573.44	0	15,943
C-F-Comment (a)	679	65674.85	38301.75	861	152,429
F-Share (a)	679	9337.56	17383.42	0	115,372
C-F-Share (a)	679	173316.9	172271.3	83	577,231
U-Post (a)	679	303.73	436.88	0	9,624
C-U-Post (a)	679	12698.2	4436.63	853	22,520
U-Like (a)	679	9959.97	32970.16	0	560,219
C-U-Like (a)	679	305400.4	384998.7	561	2,500,000
U-Comment (a)	679	474.42	961.21	0	11,461
C-U-Comment (a)	679	25904.62	16147.87	670	109,163
U-Share (a)	679	65.58	388.85	0	5,283
C-U-Share (a)	679	2463.07	3958.59	0	21,904
TD-Post (c)	679	148.87	157.30	5	1,595
C-TD-Post (c)	679	7093.65	4971.08	1,983	35,072
TMS	679	16830862.15	12915655.9	65,200	75,000,000
Price	679	51759.78	12193.72	33,175	90,775
GT	679	63.44	16.04	26	100
GPI	679	3.40	0.4	2.31	3.98
CCI	679	66.13	12.89	40.9	94.1

Table 61. Descriptive Statistics for Group 2

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	489	60169.34	64971.91	500	244,501
F-Post (a)	489	35.28	51.74	0	1,042
C-F-Post (a)	489	910.04	410.38	50	2,584
F-Like (a)	489	53748.09	75189.46	0	490,822
C-F-Like (a)	489	2,336,259	2,169,217	3,093	6,000,000
F-Comment (a)	489	2648.58	2817.23	0	25,734
C-F-Comment (a)	489	65037.49	39476.79	420	152,256
F-Share (a)	489	5613.42	9153.28	0	62,457
C-F-Share (a)	489	178403.5	175696.5	27	578,089
U-Post (a)	489	685.83	691.16	0	4,918
C-U-Post (a)	489	12076.33	4470.32	857	22,459
U-Like (a)	489	16323.49	34578.98	0	252,535
C-U-Like (a)	489	299962.7	387392.4	613	2,500,000
U-Comment (a)	489	1703.87	2539.45	0	28,081
C-U-Comment (a)	489	24395.63	16118.24	690	108,643
U-Share (a)	489	114.95	408.40	0	6,362
C-U-Share (a)	489	2422.84	3915.44	0	21,905

Table 61 (cont'd)

TD-Post (c)	489	290.91	393.26	10	3,348
C-TD-Post (c)	489	6811.77	4761.93	1,885	34,817
TMS	489	48687195.71	44841280.14	238,700	190,000,000
Price	489	27558.14	7208.62	16,000	45,142
GT	489	52.12	21.13	7	100
GPI	489	3.39	0.4	2.31	3.98
CCI	489	66.14	12.93	40.9	94.1

Table 62. Descriptive Statistics for Group 3

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	621	50792.28	44383.67	2,923	210,134
F-Post (a)	621	34.33	27.37	1	344
C-F-Post (a)	621	911	405	48	2,605
F-Like (a)	621	48086.88	76472.79	1	722,146
C-F-Like (a)	621	2,309,850	2,161,101	4,226	6,000,000
F-Comment (a)	621	2126.13	3131.96	7	26,648
C-F-Comment (a)	621	65320.97	38569.89	826	153,749
F-Share (a)	621	3497.47	5775.98	0	41,089
C-F-Share (a)	621	177734.7	177469.3	84	580,559
U-Post (a)	621	434.42	426.21	0	4,625
C-U-Post (a)	621	12442.41	4356.02	647	22,539
U-Like (a)	621	7489.32	24087.75	0	463,332
C-U-Like (a)	621	304945.3	390721.6	254	2,500,000
U-Comment (a)	621	771.39	1720.94	0	36,118
C-U-Comment (a)	621	25378.18	16077.35	480	108,721
U-Share (a)	621	87.91	683.83	0	16,400
C-U-Share (a)	621	2413.28	3873.41	0	21,905
TD-Post (c)	621	323.17	395.96	13	3,771
C-TD-Post (c)	621	6967.49	4961.65	1,862	35,106
TMS	621	42166022.54	33500246.34	1,500,000	200,000,000
Price	621	23564.44	4149.23	14192.5	33783.9
GT	621	47.62	18.31	10	100
GPI	621	3.39	0.4	2.31	3.98
CCI	621	66.06	12.87	40.9	94.1

Tables 63 to 65 show my sample split Bayesian estimation results at the post level (i.e., Facebook post and test drive post) for group 1 of market structure, group 2 of market structure, and group 3 of market structure, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (Figures 206 to 238) also suggested the model specification converged for each relationship.

The results in the post level demonstrate that customers from these three different groups show dramatically different patterns in terms of how online WOM across two different stages would influence their purchase decision. First, the results from group 1 (Table 63) are consistent with main results (see Table 41) except for the effect of the focal brand's posts on offline car sales of the focal firm. The comparison of group 2 and group 3 also indicates interesting patterns. For example, for group 3, at the stage of awareness, both posts from focal brand and its competitors positively influence offline car sales of the focal brand, supporting both H1 and H2. However, for group 3, I only observe positive spillover effects (C-F-Post (a)) at the stage of awareness, supporting H2 only. Group 2 also shows the opposite effect of posts by the focal brand's users (U-Post (a)), rejecting H1. Regarding the effect of online WOM at the stage of consideration, H3 and H4 are supported for group 1 only. I cannot find any effect of online WOM at the stage of consideration for group 2 and group 3.

Table 63. Bayesian Estimation Results for Posts (Group 1)

Parameters	Sales $_{A,t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A,t-1}$	0.025 (0.017)	(-0.008, 0.06)
C-F-Post (a) $_{J,t-1}$	**0.157 (0.035)**	**(0.07, 0.226)**
U-Post (a) $_{A,t-1}$	0.002 (0.009)	(-0.017, 0.02)
C-U-Post (a) $_{J,t-1}$	**-0.065 (0.028)**	**(-0.12, -0.009)**
TD-Post (c) $_{A,t-1}$	**0.047 (0.019)**	**(0.008, 0.086)**
C-TD-Post (c) $_{J,t-1}$	**-0.06 (0.026)**	**(-0.118, -0.016)**
TMS $_{A,t-1}$	**0.113 (0.014)**	**(0.084, 0.14)**
Price $_{A,t-1}$	-0.056 (0.11)	(-0.271, 0.155)
GT $_{A,t-1}$	0.124 (0.083)	(-0.038, 0.288)
GPI $_{A,t-1}$	0.045 (0.124)	(-0.201, 0.286)
CCI $_{A,t-1}$	**0.287 (0.069)**	**(0.149, 0.424)**

Table 64. Bayesian Estimation Results for Posts (Group 2)

Parameters	Sales $_{A,t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A,t-1}$	0.003 (0.015)	(-0.026, 0.033)
C-F-Post (a) $_{J,t-1}$	**0.168 (0.031)**	**(0.109, 0.229)**
U-Post (a) $_{A,t-1}$	**-0.052 (0.013)**	**(-0.079, -0.025)**
C-U-Post (a) $_{J,t-1}$	0.041 (0.028)	(-0.015, 0.097)
TD-Post (c) $_{A,t-1}$	0.003 (0.021)	(-0.038, 0.045)
C-TD-Post (c) $_{J,t-1}$	-0.047 (0.03)	(-0.107, 0.012)
TMS $_{A,t-1}$	**0.166 (0.02)**	**(0.125, 0.205)**

Table 64 (cont'd)

Price $_{A, t-1}$	0.132 (0.114)	(-0.09, 0.361)
GT $_{A, t-1}$	-0.021 (0.06)	(-0.143, 0.098)
GPI $_{A, t-1}$	**0.25 (0.121)**	**(0.02, 0.497)**
CCI $_{A, t-1}$	**0.26 (0.068)**	**(0.125, 0.391)**

Table 65. Bayesian Estimation Results for Posts (Group 3)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	**0.032 (0.011)**	**(0.009, 0.054)**
C-F-Post (a) $_{J, t-1}$	**0.162 (0.027)**	**(0.108, 0.216)**
U-Post (a) $_{A, t-1}$	-0.002 (0.01)	(-0.022, 0.019)
C-U-Post (a) $_{J, t-1}$	**-0.068 (0.023)**	**(-0.114, -0.023)**
TD-Post (c) $_{A, t-1}$	0.011 (0.019)	(-0.027, 0.048)
C-TD-Post (c) $_{J, t-1}$	-0.031 (0.022)	(-0.075, 0.013)
TMS $_{A, t-1}$	**0.093 (0.021)**	**(0.051, 0.135)**
Price $_{A, t-1}$	0.006 (0.097)	(-0.184, 0.198)
GT $_{A, t-1}$	**0.179 (0.043)**	**(0.095, 0.266)**
GPI $_{A, t-1}$	**0.28 (0.11)**	**(0.081, 0.479)**
CCI $_{A, t-1}$	**0.188 (0.057)**	**(0.073, 0.301)**

Figure 206. Assessment of Model Convergence for F-Post (a) (Group 1)

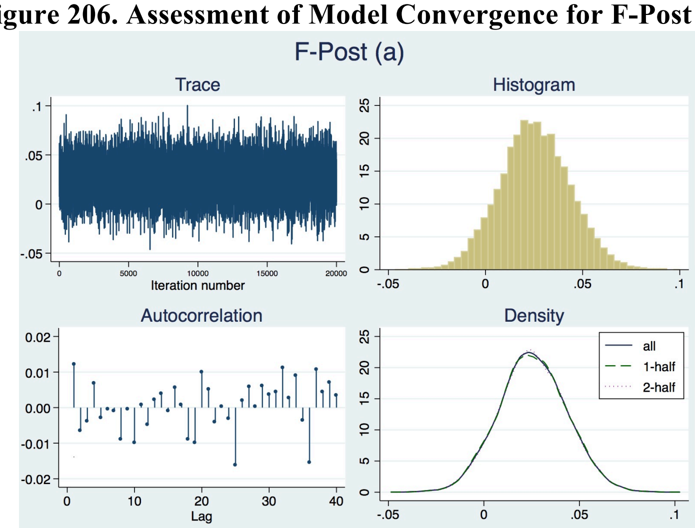


Figure 207. Assessment of Model Convergence for C-F-Post (a)

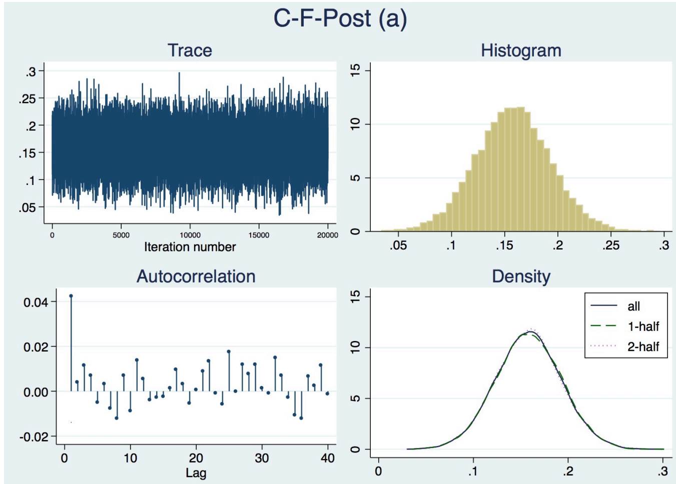


Figure 208. Assessment of Model Convergence for U-Post (a) (Group 1)

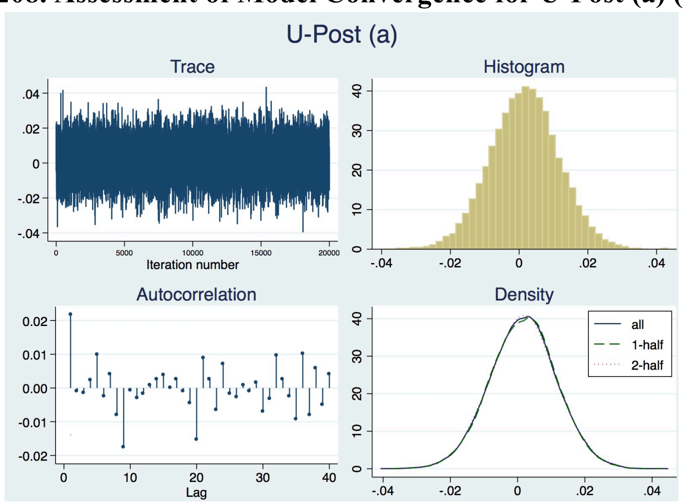


Figure 209. Assessment of Model Convergence for C-U-Post (a)

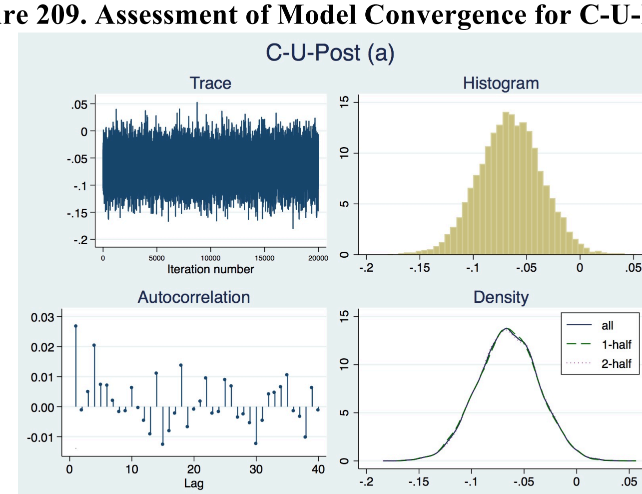


Figure 210. Assessment of Model Convergence for TD-Post (c) (Group 1)

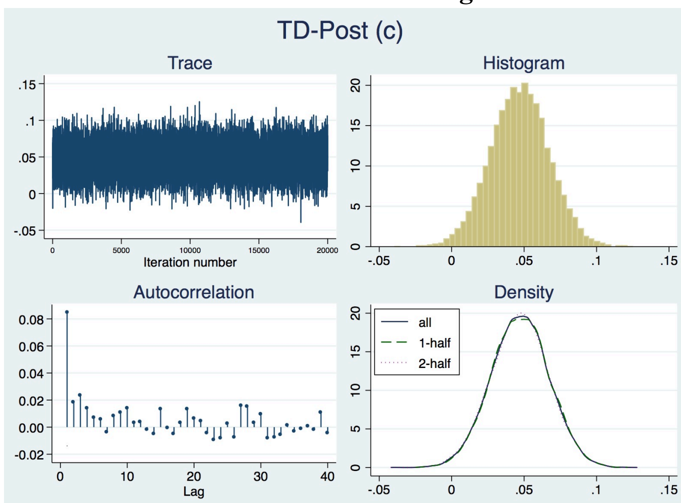


Figure 211. Assessment of Model Convergence for C-TD-Post (c) (Group 1)

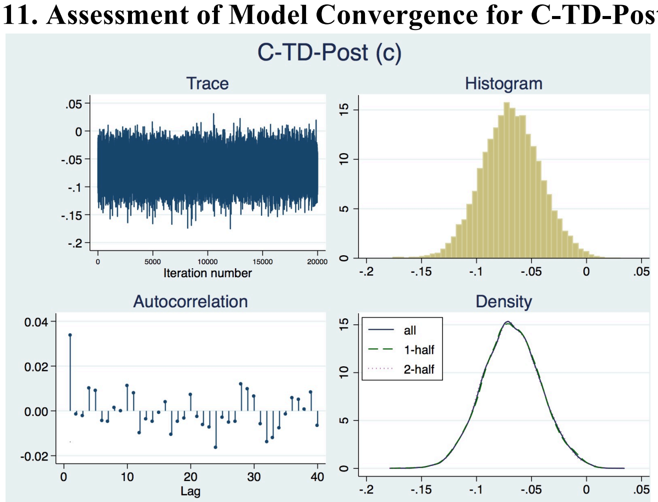


Figure 212. Assessment of Model Convergence for TMS (Group 1)

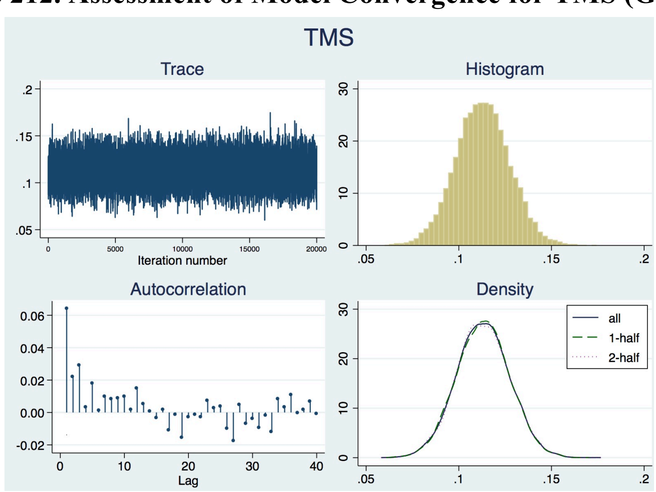


Figure 213. Assessment of Model Convergence for Price (Group 1)

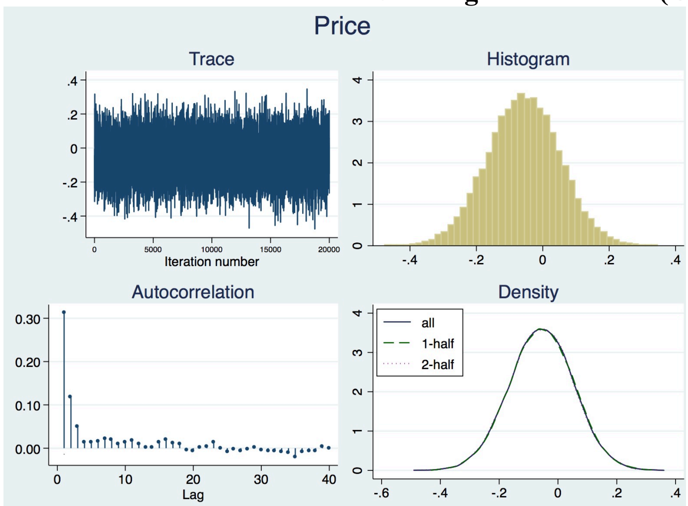


Figure 214. Assessment of Model Convergence for GT (Group 1)

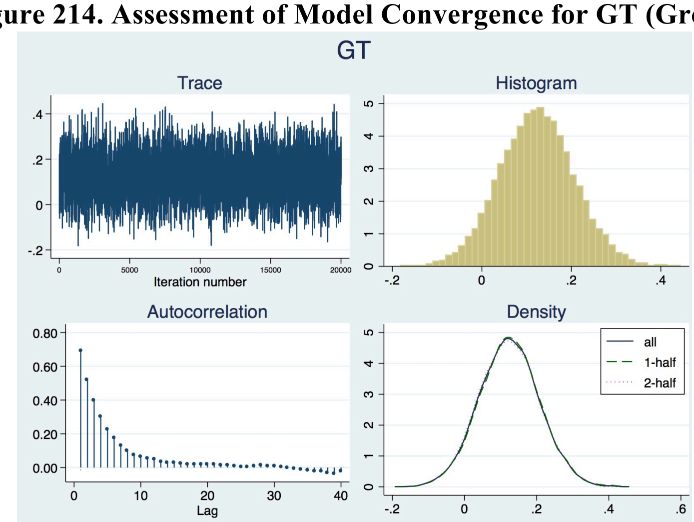


Figure 215. Assessment of Model Convergence for GPI (Group 1)

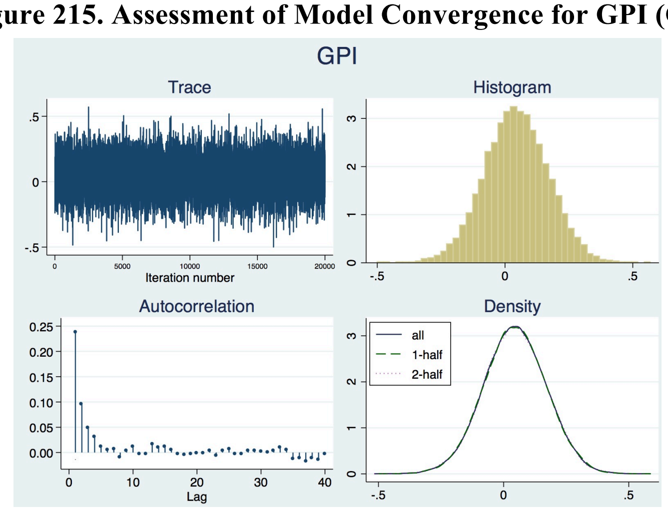


Figure 216. Assessment of Model Convergence for CCI (Group 1)

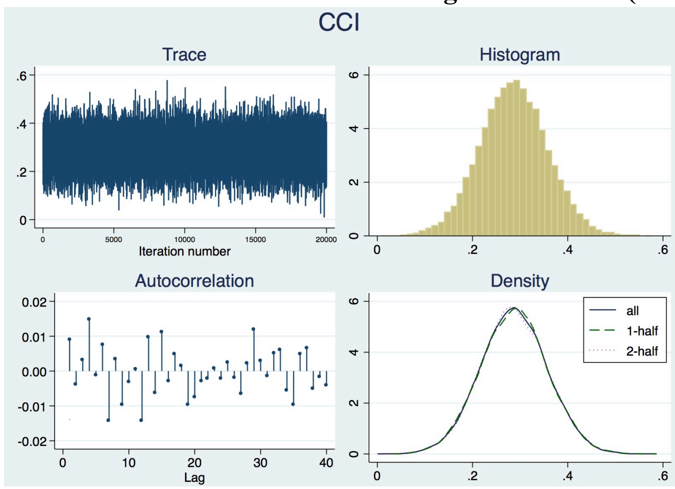


Figure 217. Assessment of Model Convergence for F-Post (a) (Group 2)

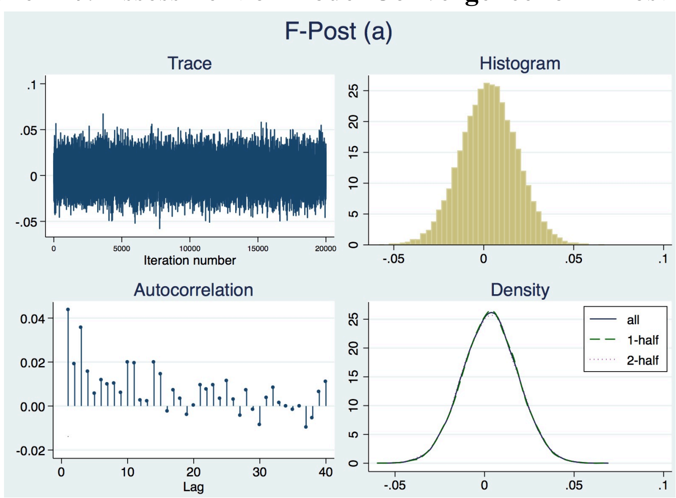


Figure 218. Assessment of Model Convergence for C-F-Post (a) (Group 2)

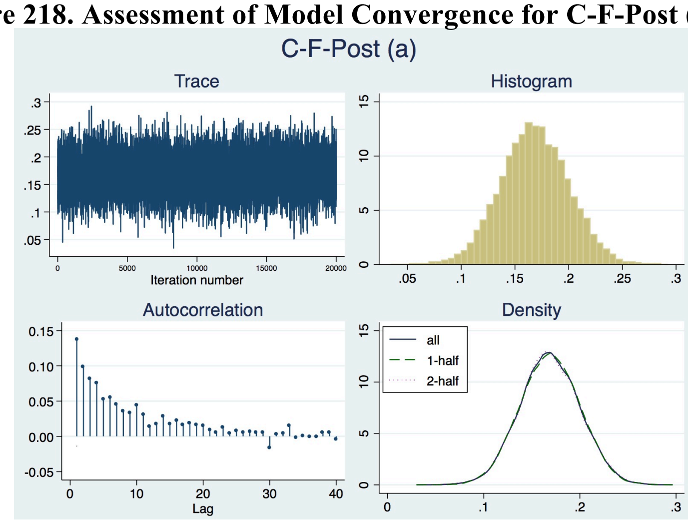


Figure 219. Assessment of Model Convergence for U-Post (a) (Group 2)

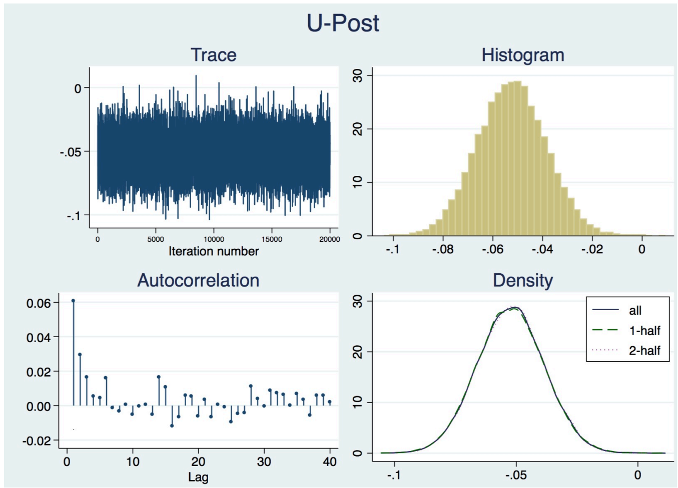


Figure 220. Assessment of Model Convergence for C-U-Post (a) (Group 2)

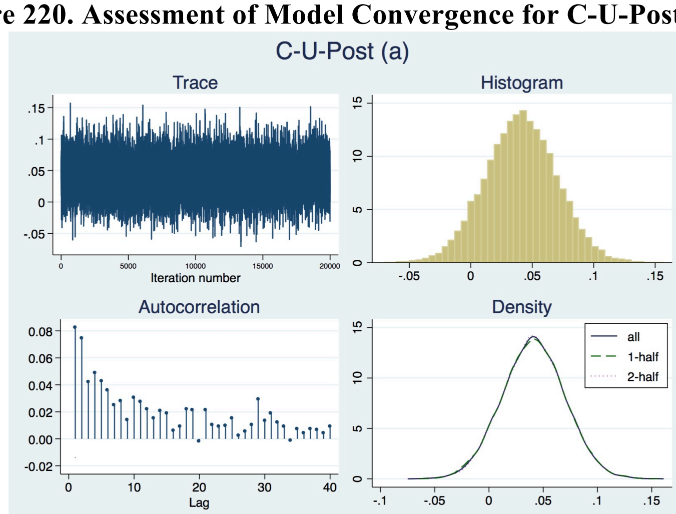


Figure 221. Assessment of Model Convergence for TD-Post (c) (Group 2)

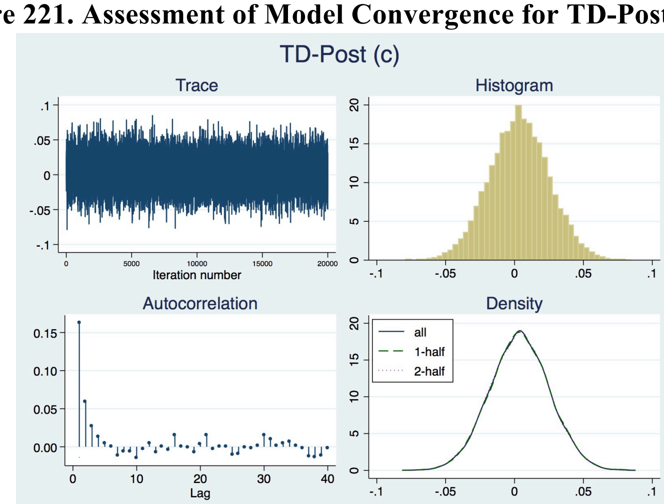


Figure 222. Assessment of Model Convergence for C-TD-Post (c) (Group 2)

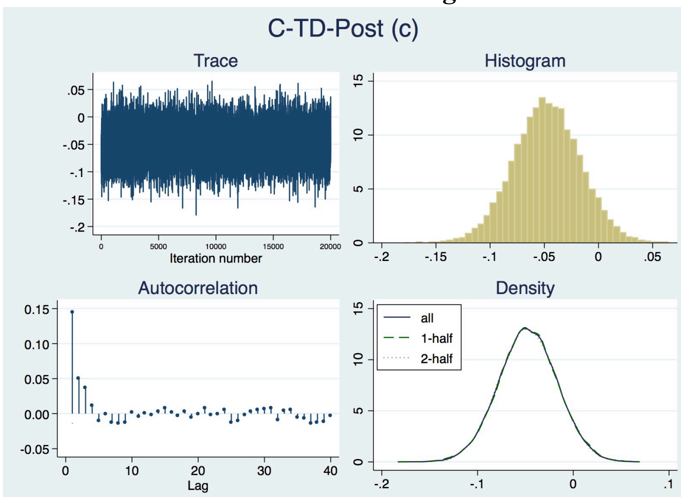


Figure 223. Assessment of Model Convergence for TMS (Group 2)

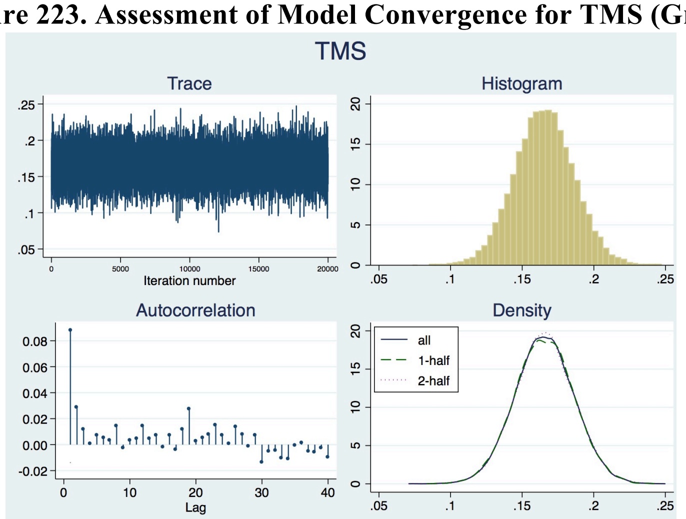


Figure 224. Assessment of Model Convergence for Price (Group 2)

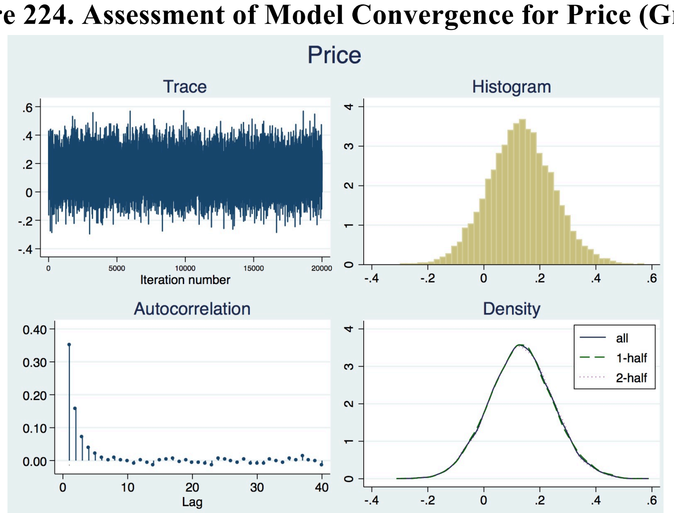


Figure 225. Assessment of Model Convergence for GT (Group 2)

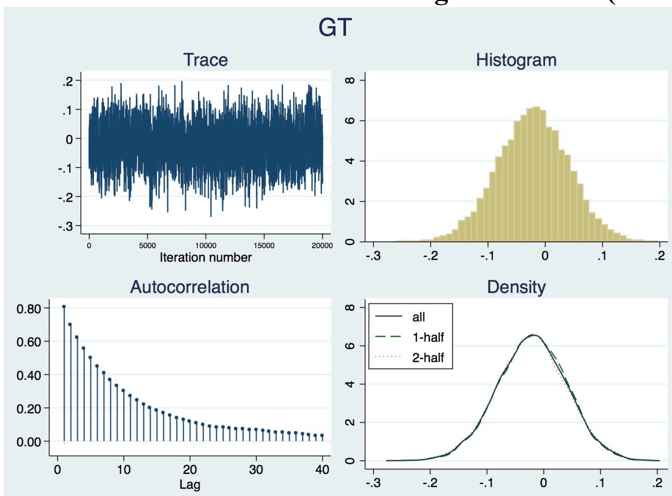


Figure 226. Assessment of Model Convergence for GPI (Group 2)

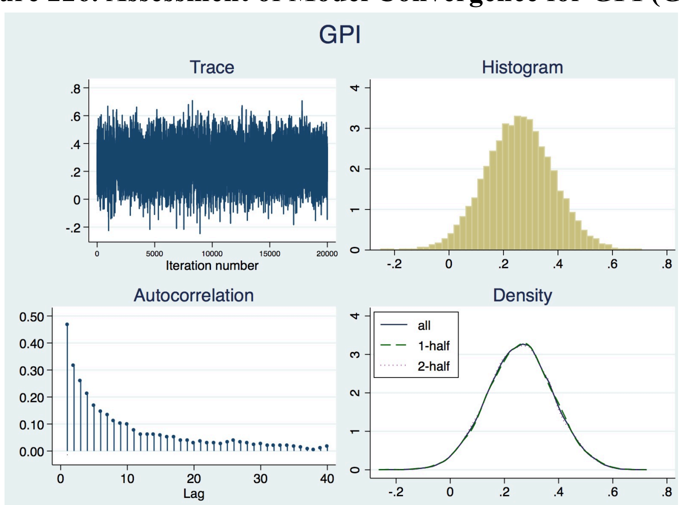


Figure 227. Assessment of Model Convergence for CCI (Group 2)

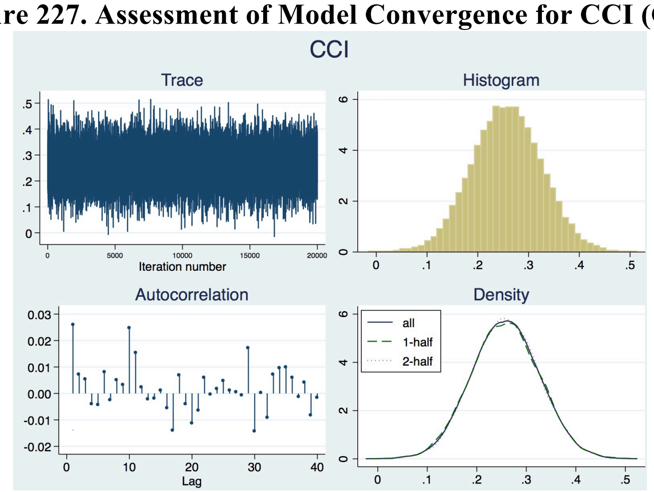


Figure 228. Assessment of Model Convergence for F-Post (a) (Group 3)

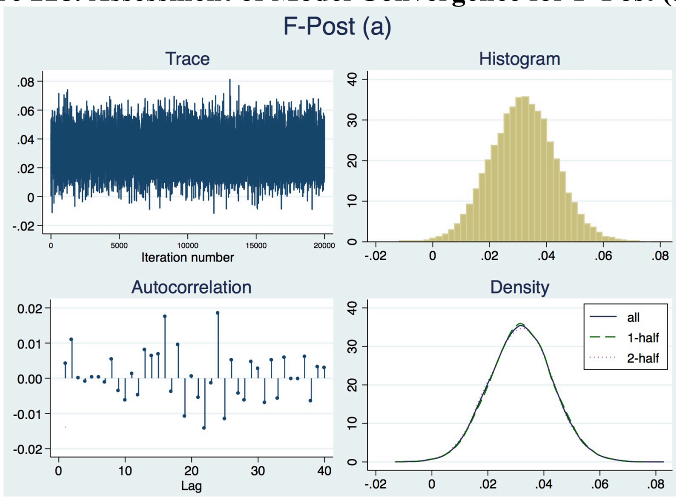


Figure 229. Assessment of Model Convergence for C-F-Post (a) (Group 3)

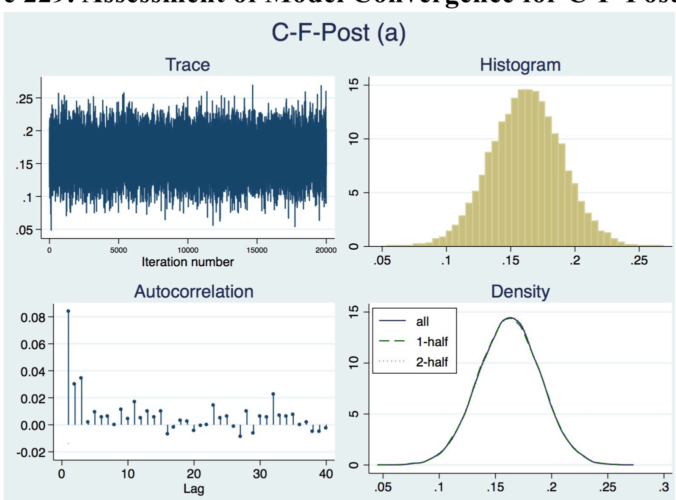


Figure 230. Assessment of Model Convergence for U-Post (a) (Group 3)

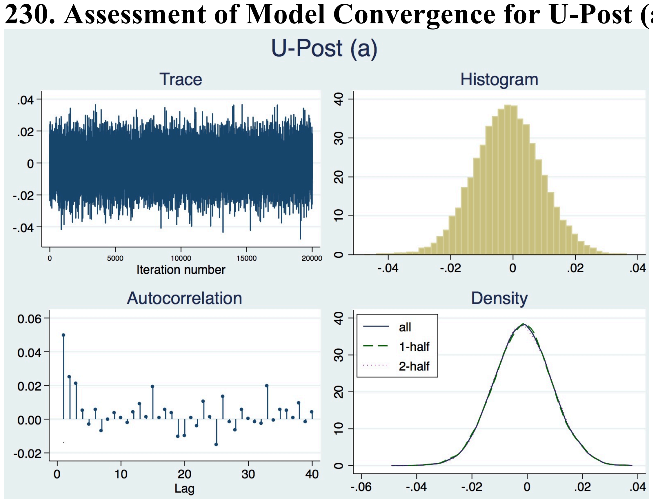


Figure 231. Assessment of Model Convergence for C-U-Post (a) (Group

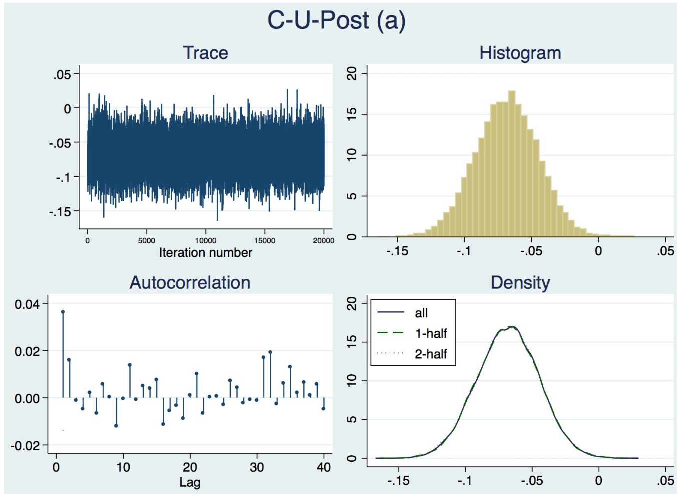


Figure 232. Assessment of Model Convergence for TD-Post (c) (Group 3)

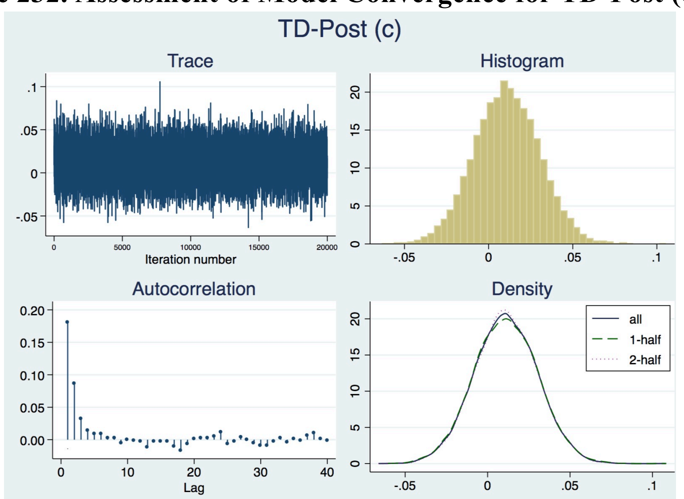


Figure 233. Assessment of Model Convergence for C-TD-Post (c)

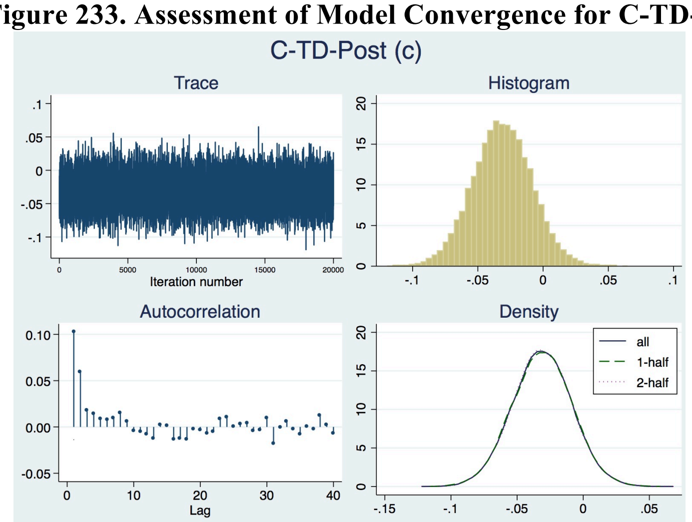


Figure 234. Assessment of Model Convergence for TMS (Group 3)

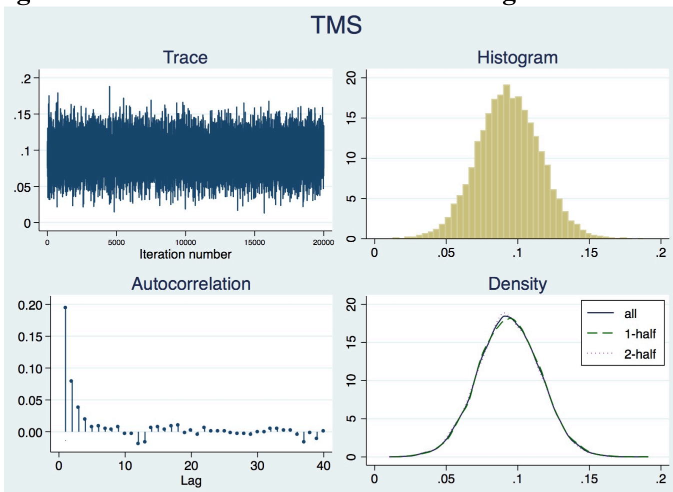


Figure 235. Assessment of Model Convergence for Price (Group 3)

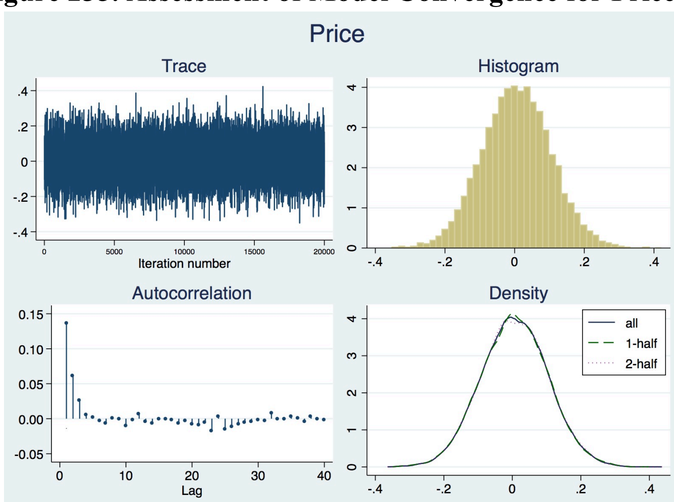


Figure 236. Assessment of Model Convergence for GT (Group 3)

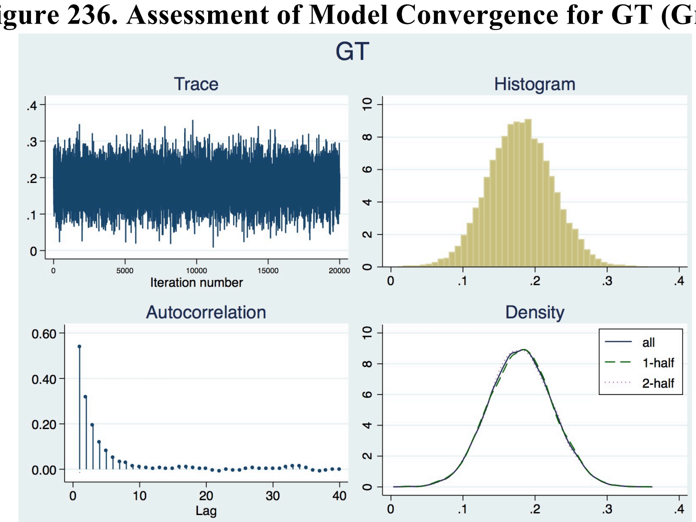


Figure 237. Assessment of Model Convergence for GPI (Group 3)

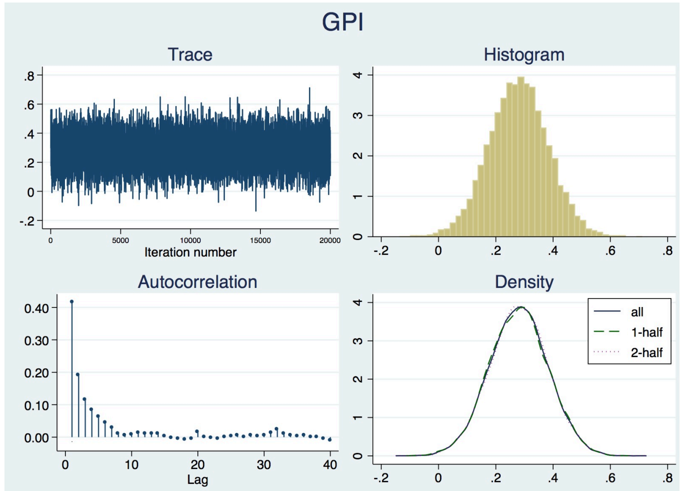
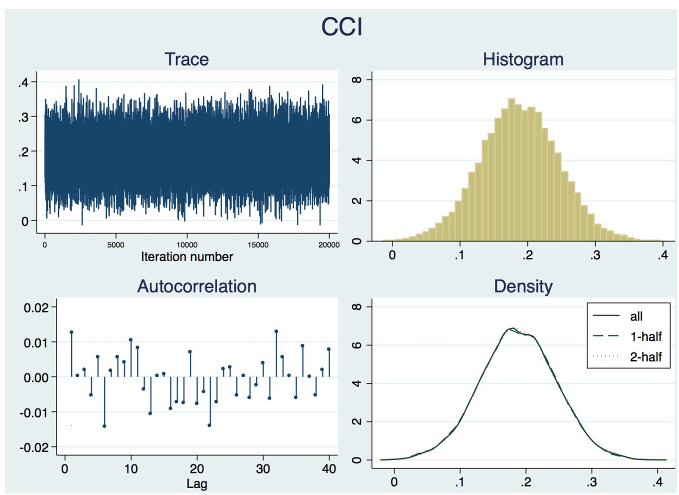


Figure 238. Assessment of Model Convergence for CCI (Group 3)



Tables 66 to 68 show my sample split Bayesian estimation results at the like level (i.e., "Like" associated with posts at Facebook and test drive post) for group 1 of market structure, group 2 of market structure, and group 3 of market structure, respectively. In these models, I also ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 239 to 271) suggested that the model specification converged for each relationship.

First, this sub group analysis in the like level, consistent with main results (see Table 42), suggests that the volume of like associated with the focal brand's posts (F-Like (a)) is not effective in influencing offline car sales of the focal brand across three different groups, rejecting H1. On the other hand, the volume of like associated with competitors' user posts (C-F-Like (a)) has positive spillover effects on offline car sales of the focal brand across there different groups with the strongest the magnitude of the coefficient for group 1, supporting H2. Interestingly, I also find that for group 1 the volume of like related to the focal brand's user posts (U-Like (a)) positively influences offline car sales of the focal brand, which is the relationship that I cannot find in previous analysis, supporting H1. Furthermore, for online WOM at the stage of consideration, I only find H3 supported for group 1, implying again that market structure does influence how customers leverage online WOM to make their purchase decisions.

Table 66. Bayesian Estimation Results for Likes (Group 1)

Parameters	$Sales_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	-0.008 (0.008)	(-0.02, 0.008)
C-F-Like (a) $_{J, t-1}$	**0.099 (0.018)**	**(0.064, 0.134)**
U-Like (a) $_{A, t-1}$	**0.002 (0.005)**	**(0.01, 0.024)**
C-U-Like (a) $_{J, t-1}$	-0.023 (0.016)	(-0.055, 0.008)
TD-Post (c) $_{A, t-1}$	**0.038 (0.018)**	**(0.002, 0.075)**
C-TD-Post (c) $_{J, t-1}$	-0.044 (0.023)	(-0.089, 0.001)
TMS $_{A, t-1}$	**0.107 (0.013)**	**(0.08, 0.133)**
Price $_{A, t-1}$	-0.028 (0.105)	(-0.233, 0.177)
GT $_{A, t-1}$	**0.215 (0.082)**	**(0.056, 0.377)**
GPI $_{A, t-1}$	-0.165 (0.11)	(-0.38, 0.053)
CCI $_{A, t-1}$	0.113 (0.07)	(-0.023, 0.252)

Table 67. Bayesian Estimation Results for Likes (Group 2)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	-0.014 (0.009)	(-0.031, 0.004)
C-F-Like (a) $_{J, t-1}$	**0.05 (0.017)**	**(0.017, 0.083)**
U-Like (a) $_{A, t-1}$	**-0.028 (0.007)**	**(-0.042, -0.014)**
C-U-Like (a) $_{J, t-1}$	**0.078 (0.017)**	**(0.046, 0.11)**
TD-Post (c) $_{A, t-1}$	0.012 (0.02)	(-0.03, 0.052)
C-TD-Post (c) $_{J, t-1}$	-0.029 (0.027)	(-0.083, 0.024)
TMS $_{A, t-1}$	**0.16 (0.019)**	**(0.12, 0.19)**
Price $_{A, t-1}$	0.062 (0.11)	(-0.148, 0.271)
GT $_{A, t-1}$	-0.018 (0.059)	(-0.135, 0.096)
GPI $_{A, t-1}$	0.065 (0.11)	(-0.145, 0.273)
CCI $_{A, t-1}$	0.06 (0.067)	(-0.075, 0.196)

Table 68. Bayesian Estimation Results for Likes (Group 3)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	0.012 (0.009)	(-0.005, 0.028)
C-F-Like (a) $_{J, t-1}$	**0.045 (0.016)**	**(0.015, 0.077)**
U-Like (a) $_{A, t-1}$	-0.003 (0.005)	(-0.013, 0.008)
C-U-Like (a) $_{J, t-1}$	0.02 (0.014)	(-0.004, 0.05)
TD-Post (c) $_{A, t-1}$	0.011 (0.018)	(-0.025, 0.048)
C-TD-Post (c) $_{J, t-1}$	-0.021 (0.021)	(-0.063, 0.02)
TMS $_{A, t-1}$	**0.085 (0.021)**	**(0.044, 0.127)**
Price $_{A, t-1}$	-0.061 (0.094)	(-0.25, 0.124)
GT $_{A, t-1}$	**0.21 (0.043)**	**(0.123, 0.296)**
GPI $_{A, t-1}$	0.086 (0.09)	(-0.092, 0.263)
CCI $_{A, t-1}$	0.082 (0.058)	(-0.034, 0.196)

Figure 239. Assessment of Model Convergence for F-Like (a) (Group 1)

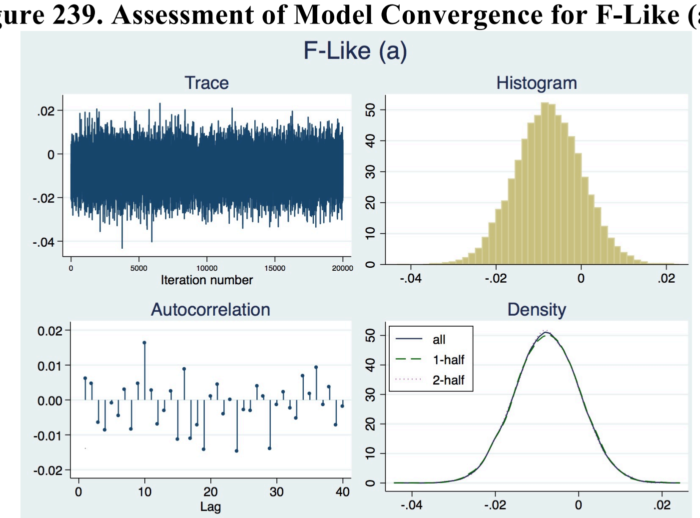


Figure 240. Assessment of Model Convergence for C-F-Like (a) (Group 1)

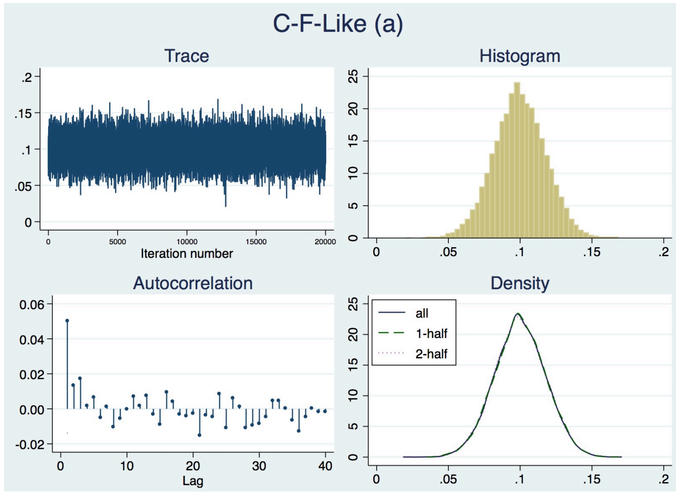


Figure 241. Assessment of Model Convergence for U-Like (a) (Group 1)

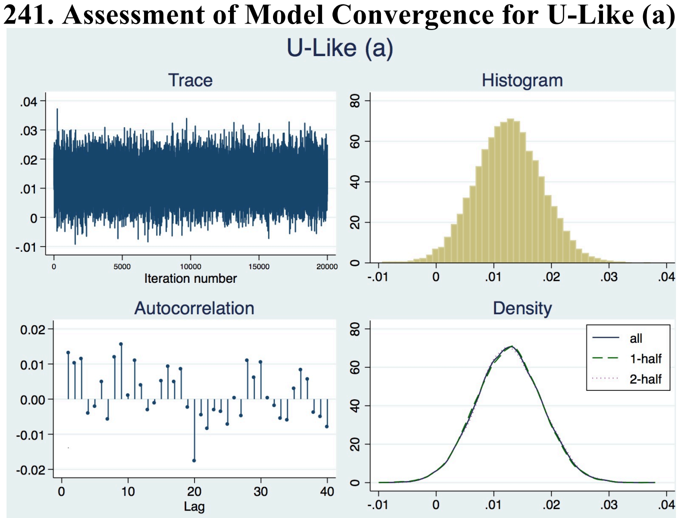


Figure 242. Assessment of Model Convergence for C-U-Like (a) (Group 1)

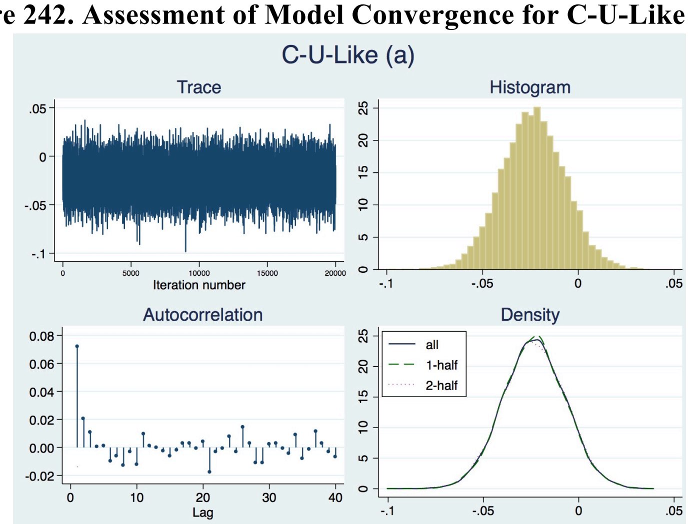


Figure 243. Assessment of Model Convergence for TD-Post (c) (Group 1)

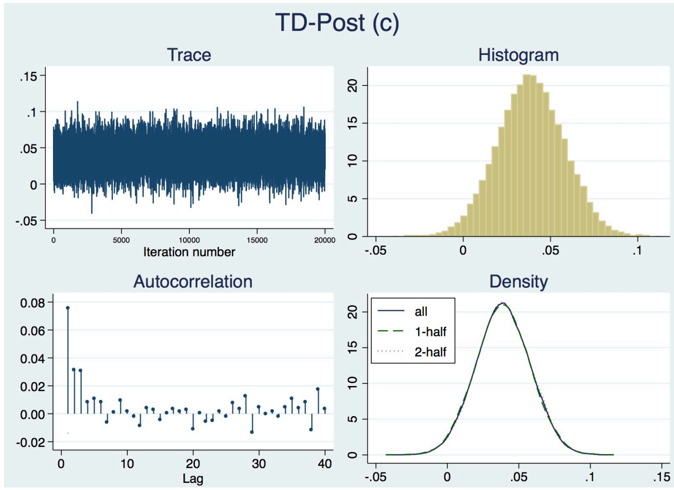


Figure 244. Assessment of Model Convergence for C-TD-Post (c) (Group 1)

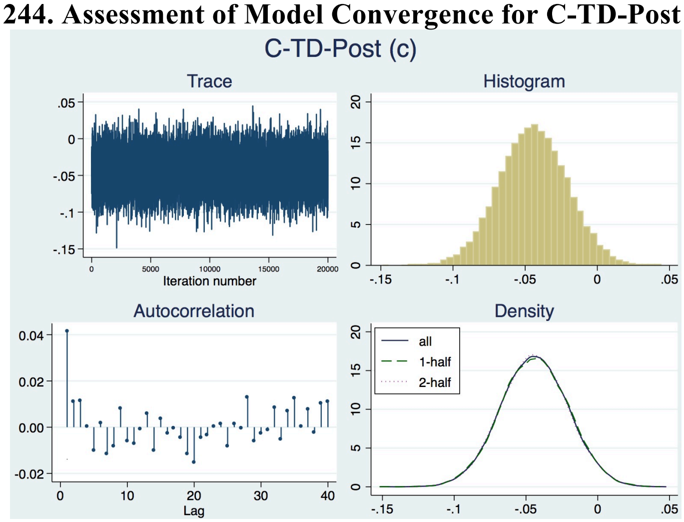


Figure 245. Assessment of Model Convergence for TMS (Group 1)

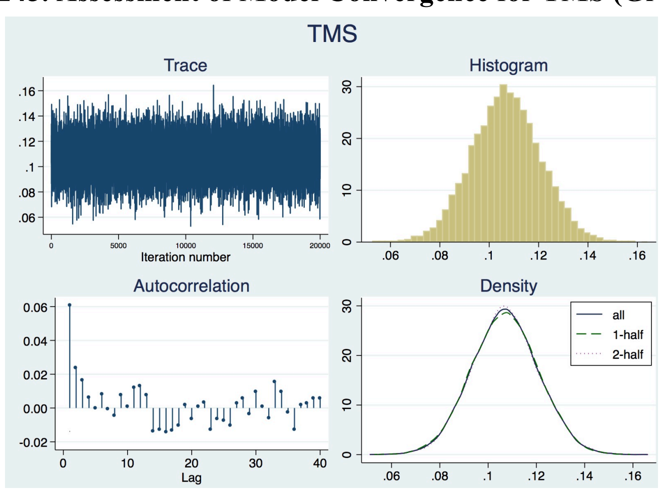


Figure 246. Assessment of Model Convergence for Price (Group 1)

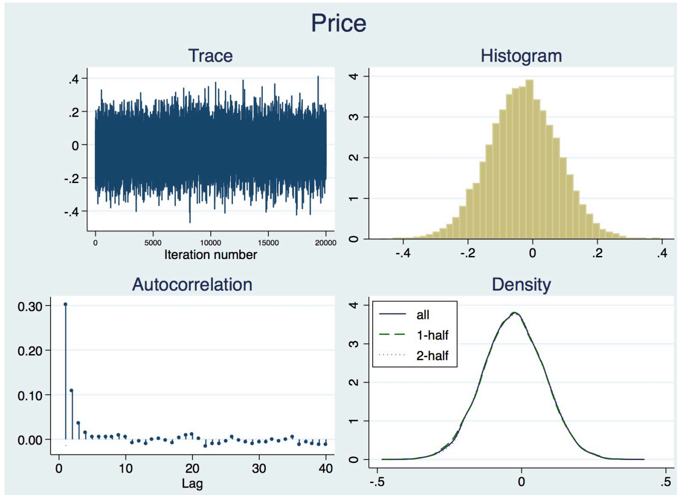


Figure 247. Assessment of Model Convergence for GT (Group 1)

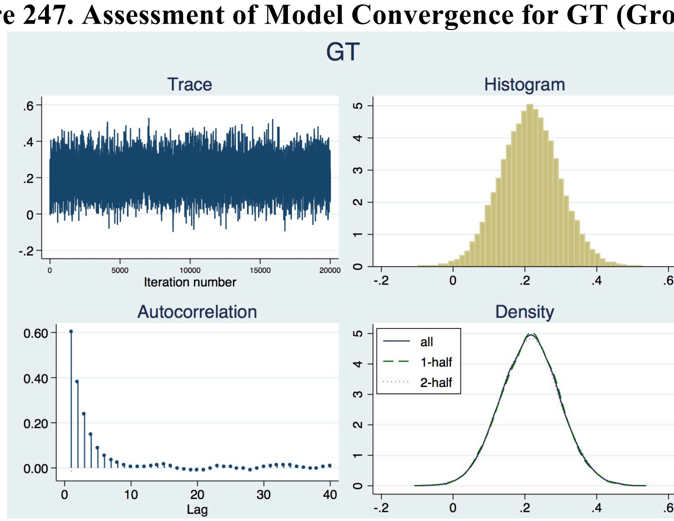


Figure 248. Assessment of Model Convergence for GPI (Group 1)

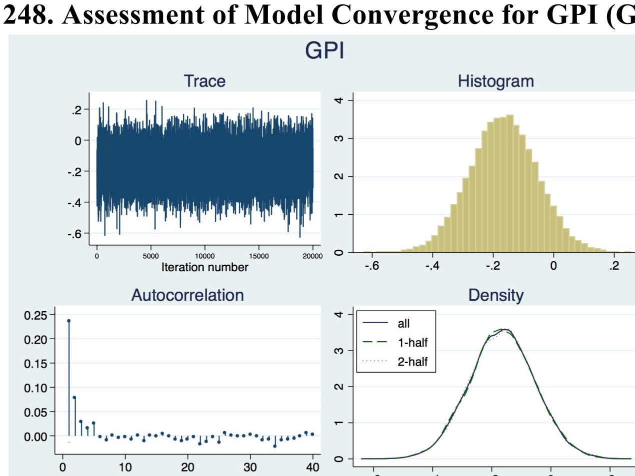


Figure 249. Assessment of Model Convergence for CCI (Group 1)

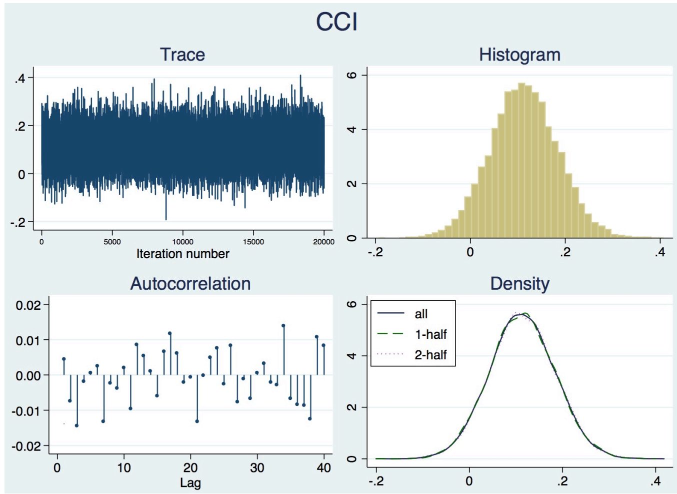


Figure 250. Assessment of Model Convergence for F-Like (a) (Group 2)

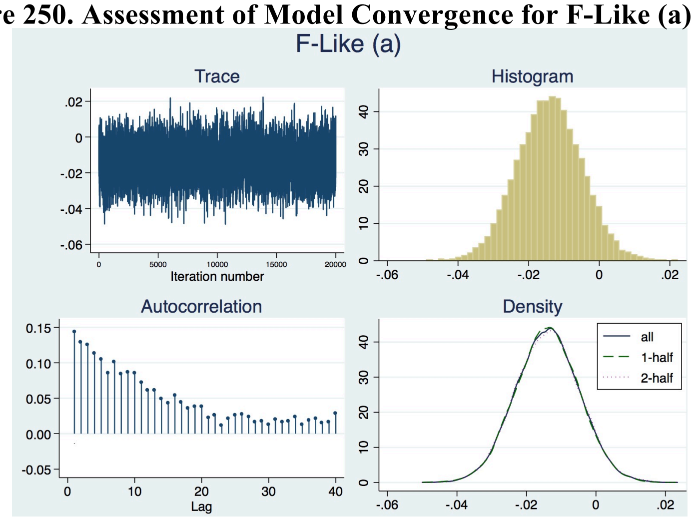


Figure 251. Assessment of Model Convergence for C-F-Like (a) (Group 2)

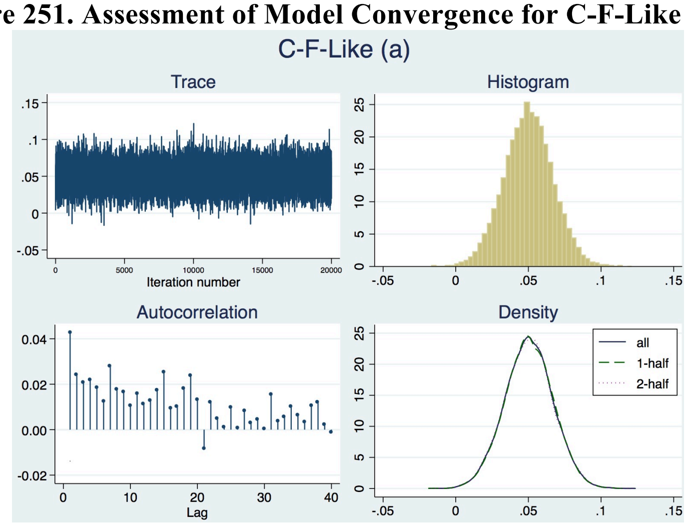


Figure 252. Assessment of Model Convergence for U-Like (a) (Group 2)

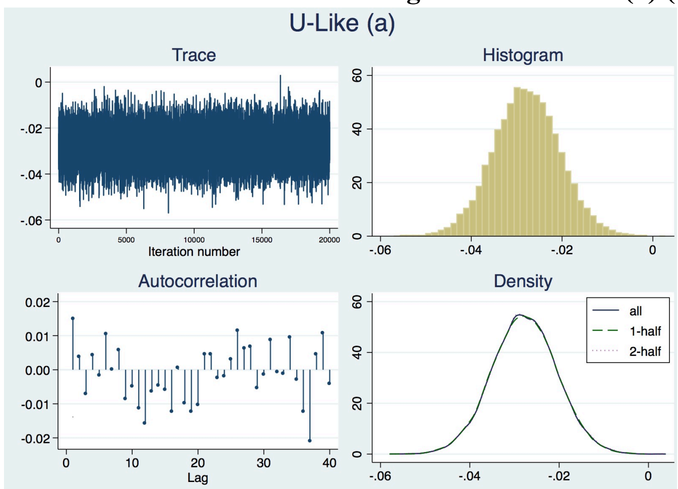


Figure 253. Assessment of Model Convergence for C-U-Like (a) (Group 2)

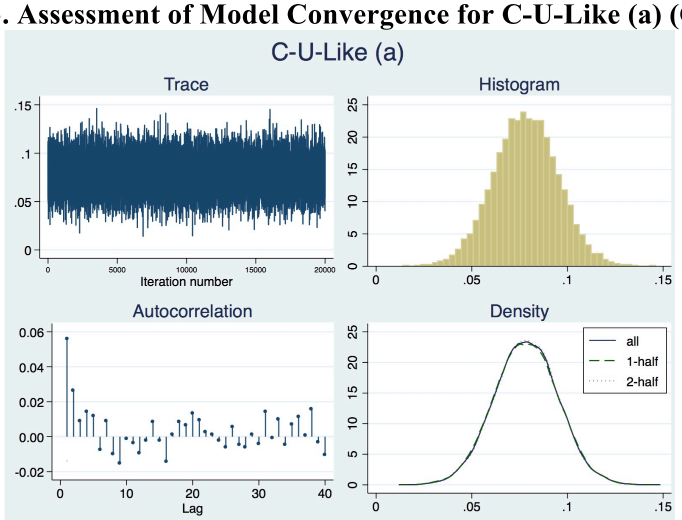


Figure 254. Assessment of Model Convergence for TD-Post (c) (Group 2)

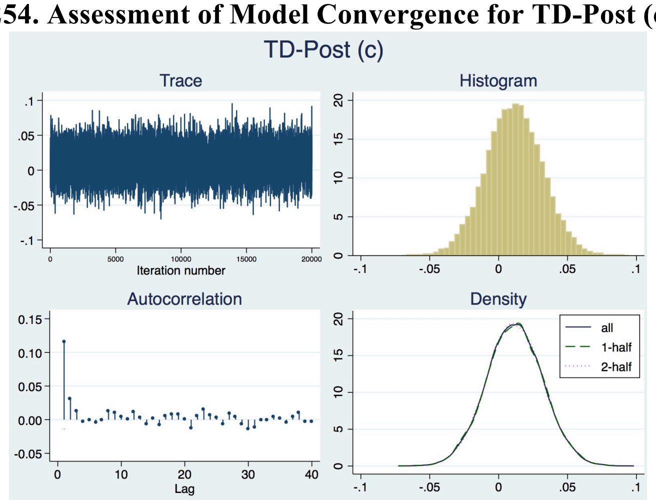


Figure 255. Assessment of Model Convergence for C-TD-Post (c) (Group 2)

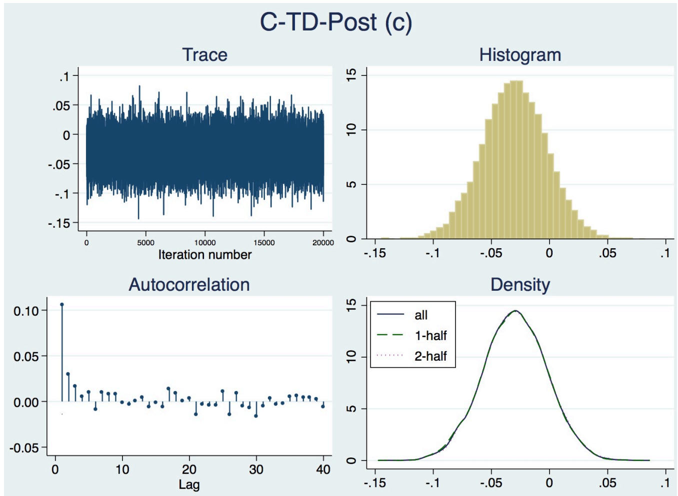


Figure 256. Assessment of Model Convergence for TMS (Group 2)

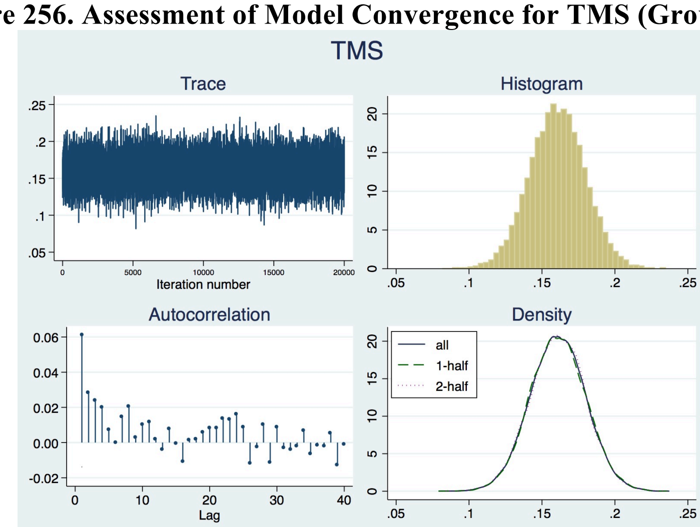


Figure 257. Assessment of Model Convergence for Price (Group 2)

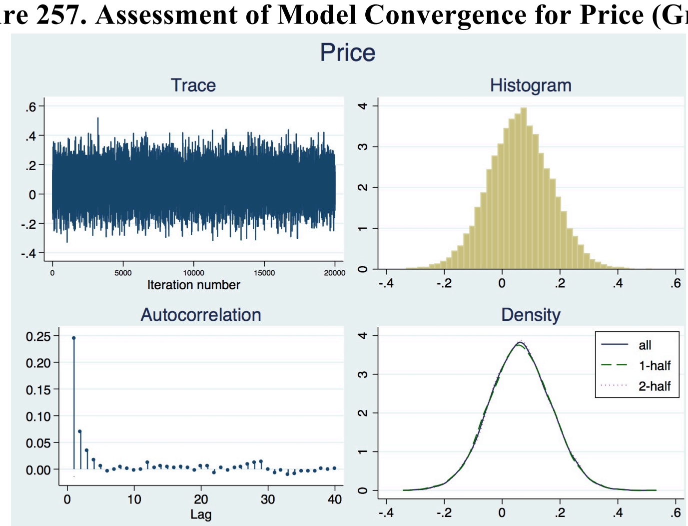


Figure 258. Assessment of Model Convergence for GT (Group 2)

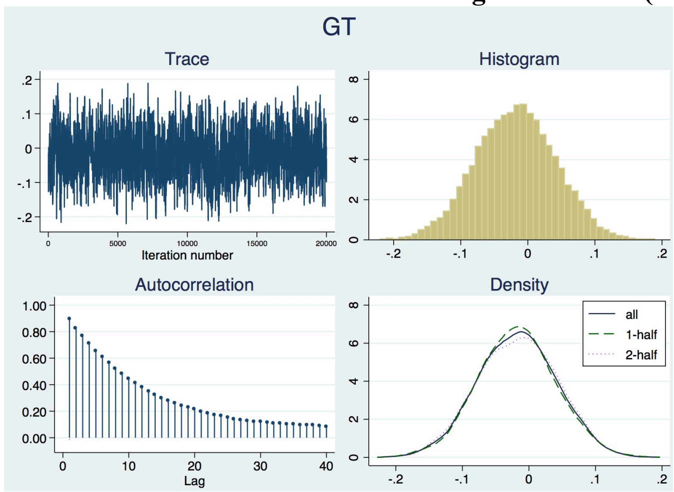


Figure 259. Assessment of Model Convergence for GPI (Group 2)

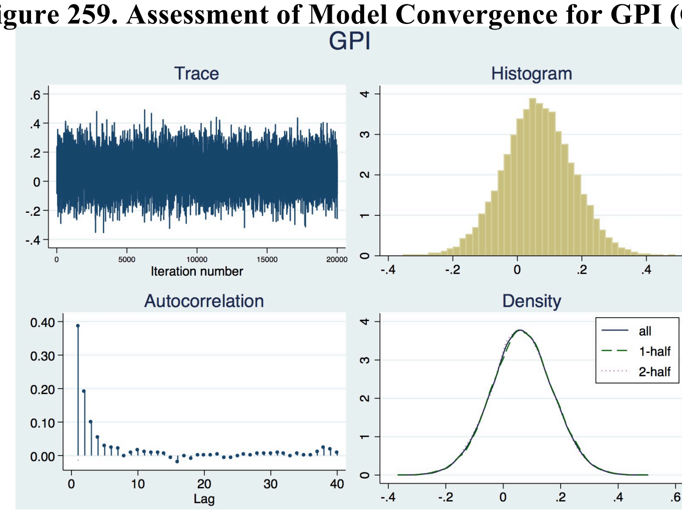


Figure 260. Assessment of Model Convergence for CCI (Group 2)

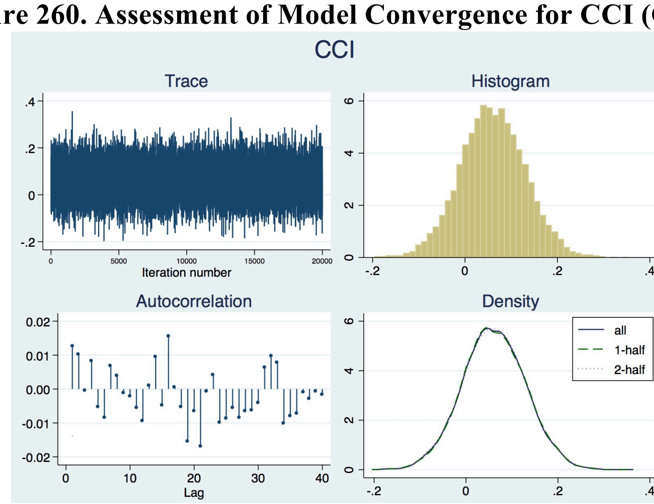


Figure 261. Assessment of Model Convergence for F-Like (a) (Group 3)

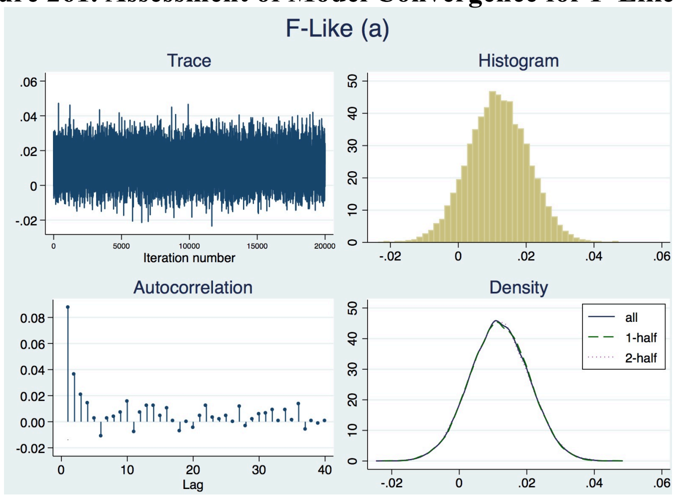


Figure 262. Assessment of Model Convergence for C-F-Like (a) (Group 3)

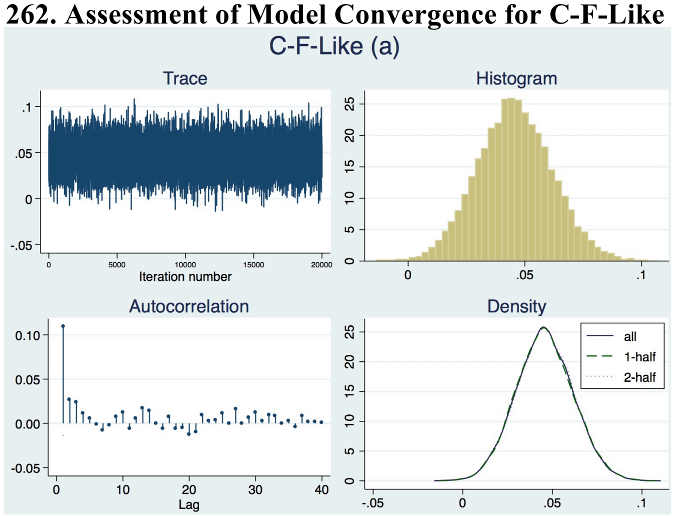


Figure 263. Assessment of Model Convergence for U-Like (a) (Group 3)

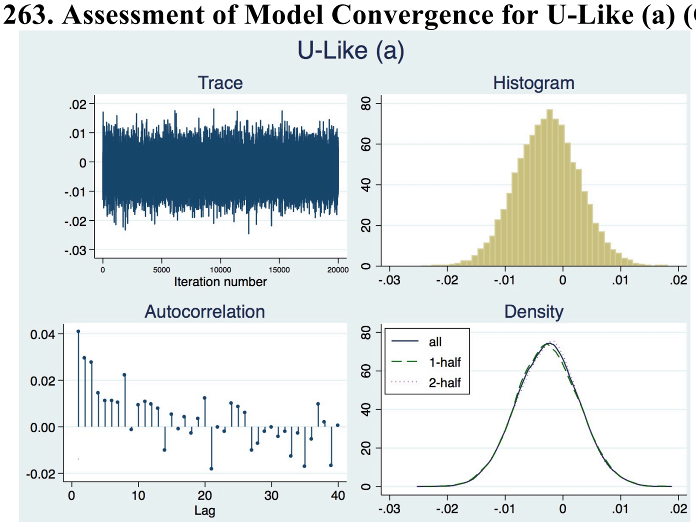


Figure 264. Assessment of Model Convergence for C-U-Like (a) (Group

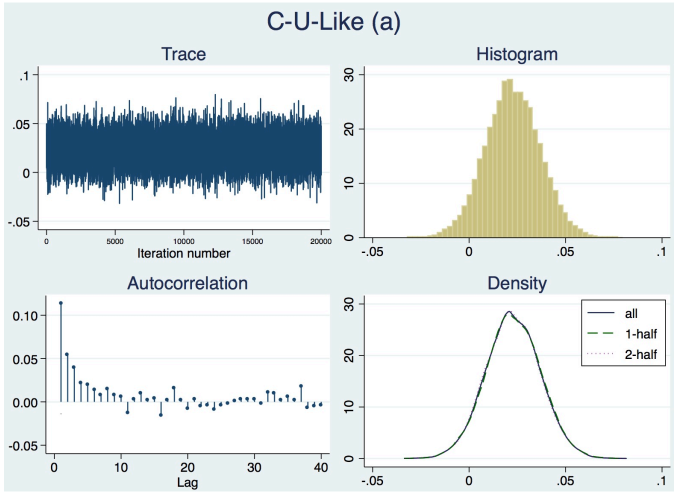


Figure 265. Assessment of Model Convergence for TD-Post (c) (Group

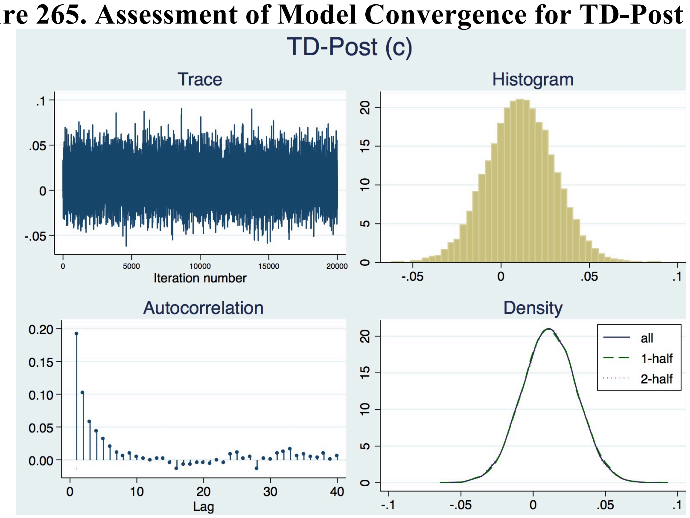


Figure 266. Assessment of Model Convergence for C-TD-Post (c) (Group 3)

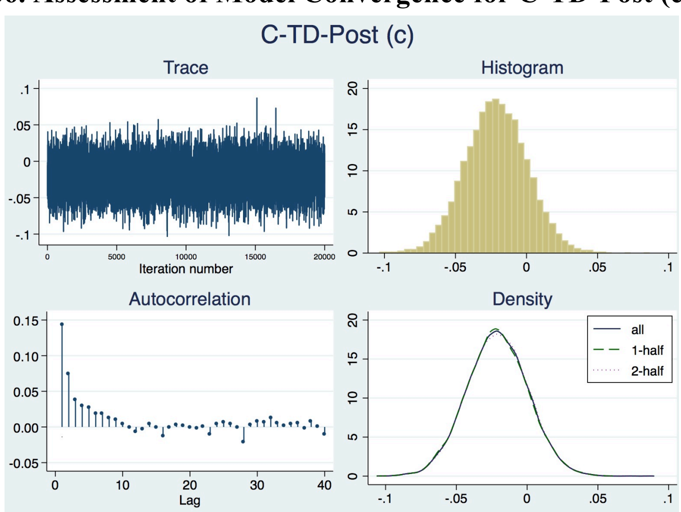


Figure 267. Assessment of Model Convergence for TMS (Group 3)

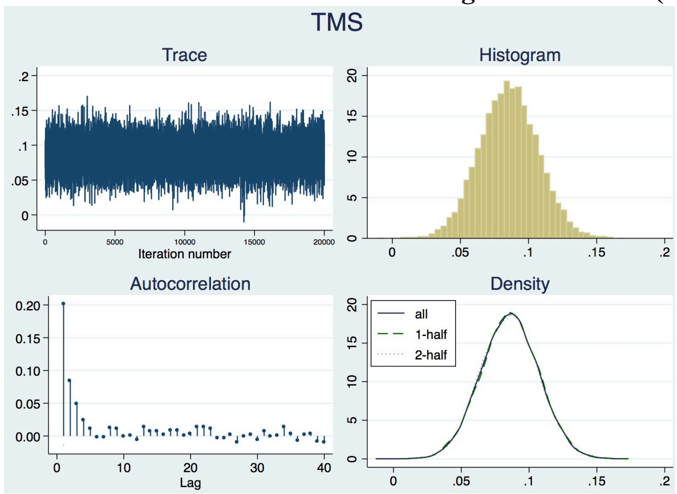


Figure 268. Assessment of Model Convergence for Price (Group 3)

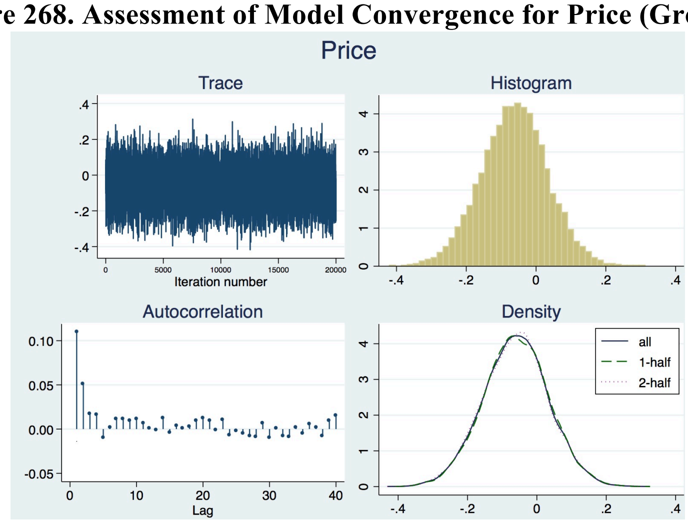


Figure 269. Assessment of Model Convergence for GT (Group 3)

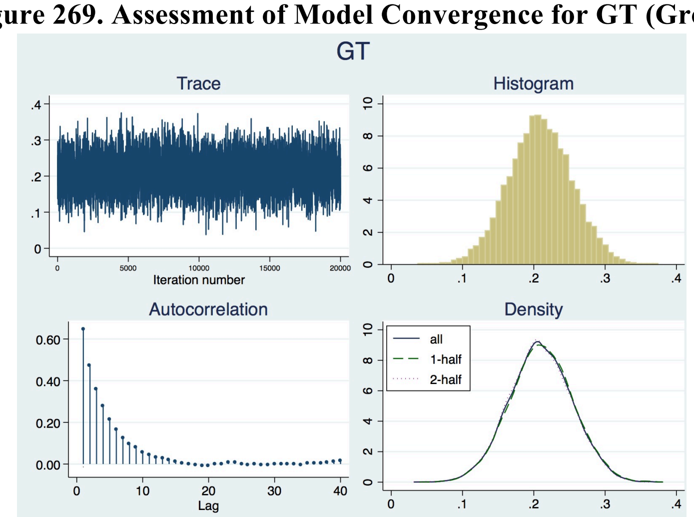


Figure 270. Assessment of Model Convergence for GPI (Group 3)

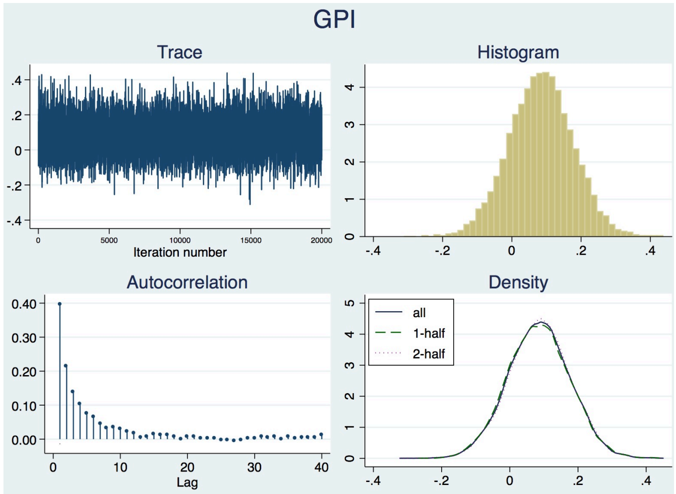
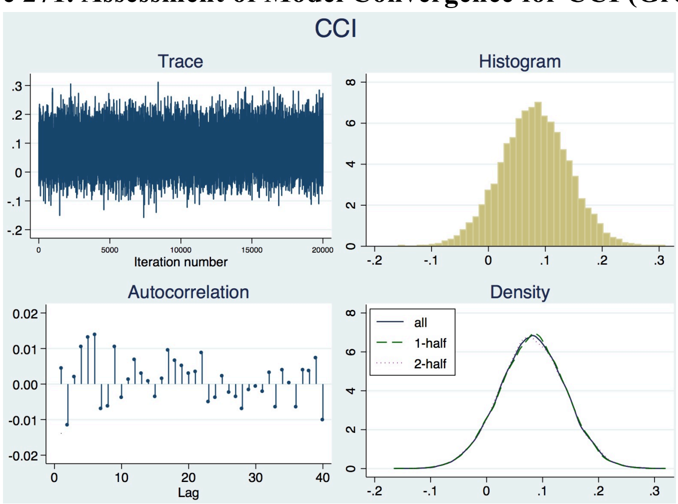


Figure 271. Assessment of Model Convergence for CCI (Group 3)



Tables 69 to 71 show my sample split Bayesian estimation results at the comment level (i.e., "Comment" associated with posts at Facebook and test drive post) for group 1 of market structure, group 2 of market structure, and group 3 of market structure, respectively. I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 272 to 304) suggested that the model specification converged for each relationship.

This split sample analysis in the comment level shows many interesting patterns that I cannot obverse in my earlier analysis. For example, for group 3, I find that the volume of comment associated with the focal brand's posts (F-Comment (a)) and its competitors' posts (C-F-Comment (a)) have the positive impact on offline car sales of the focal brand, supporting both H1 and H2. For group 2, I only find that C-F-Comment (a) has positive spillover effects on offline car sales of the focal brand, supporting H2. However, for group 1, I only observe negative spillover effects from the volume of comments received from competitors' posts (C-F-Comment (a)), thereby rejecting H2. Regarding the effects associated with user posts at the stage of awareness (U-Comment (a) and C-U-Comment (a)), I only find H2 supported for group 2. Namely, C-U-Comment (a) has positive spillover effects on offline car sales of the focal brand. Finally, for online WOM at the stage of consideration, I find that C-TD-Post (c) negatively influences offline car sales of the focal brand for group 1 only, supporting my H4.

Table 69. Bayesian Estimation Results for Comments (Group 1)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	0.028 (0.019)	(-0.003, 0.026)
C-F-Comment (a) $_{J, t-1}$	**-0.063 (0.023)**	**(0.055, 0.124)**
U-Comment (a) $_{A, t-1}$	0.014 (0.008)	(-0.014, 0.014)
C-U-Comment (a) $_{J, t-1}$	-0.03 (0.02)	(-0.044, 0.022)
TD-Post (c) $_{A, t-1}$	0.028 (0.019)	(-0.009, 0.065)
C-TD-Post (c) $_{J, t-1}$	**-0.062 (0.024)**	**(-0.109, -0.016)**
TMS $_{A, t-1}$	**0.11 (0.014)**	**(0.008, 0.135)**
Price $_{A, t-1}$	-0.052 (0.11)	(-0.265, 0.16)
GT $_{A, t-1}$	**0.177 (0.081)**	**(0.015, 0.33)**
GPI $_{A, t-1}$	-0.061 (0.11)	(-0.25, 0.137)
CCI $_{A, t-1}$	**0.22 (0.161)**	**(0.084, 0.35)**

Table 70. Bayesian Estimation Results for Comments (Group 2)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	-0.011 (0.009)	(-0.029, 0.007)
C-F-Comment (a) $_{J, t-1}$	**0.081 (0.018)**	**(0.045, 0.12)**
U-Comment (a) $_{A, t-1}$	**-0.047 (0.008)**	**(-0.063, -0.031)**
C-U-Comment (a) $_{J, t-1}$	**0.097 (0.019)**	**(0.059, 0.135)**
TD-Post (c) $_{A, t-1}$	0.008 (0.02)	(-0.031, 0.048)
C-TD-Post (c) $_{J, t-1}$	-0.037 (0.027)	(-0.092, 0.017)
TMS $_{A, t-1}$	**0.157 (0.019)**	**(0.119, 0.195)**
Price $_{A, t-1}$	0.096 (0.11)	(-0.11, 0.31)
GT $_{A, t-1}$	-0.003 (0.058)	(-0.12, 0.11)
GPI $_{A, t-1}$	**0.35 (0.097)**	**(0.157, 0.538)**
CCI $_{A, t-1}$	**0.217 (0.063)**	**(0.092, 0.342)**

Table 71. Bayesian Estimation Results for Comments (Group 3)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	**0.028 (0.009)**	**(0.01, 0.045)**
C-F-Comment (a) $_{J, t-1}$	**0.066 (0.018)**	**(0.031, 0.1)**
U-Comment (a) $_{A, t-1}$	0.004 (0.007)	(-0.01, 0.018)
C-U-Comment (a) $_{J, t-1}$	-0.003 (0.016)	(-0.035, 0.03)
TD-Post (c) $_{A, t-1}$	0.014 (0.019)	(-0.022, 0.051)
C-TD-Post (c) $_{J, t-1}$	-0.04 (0.022)	(-0.084, 0.002)
TMS $_{A, t-1}$	**0.092 (0.022)**	**(0.05, 0.135)**
Price $_{A, t-1}$	-0.038 (0.096)	(-0.23, 0.149)
GT $_{A, t-1}$	**0.176 (0.045)**	**(0.085, 0.267)**
GPI $_{A, t-1}$	**0.286 (0.083)**	**(0.124, 0.45)**
CCI $_{A, t-1}$	**0.19 (0.056)**	**(0.085, 0.3)**

Figure 272. Assessment of Model Convergence for F-Comment (a) (Group 1)

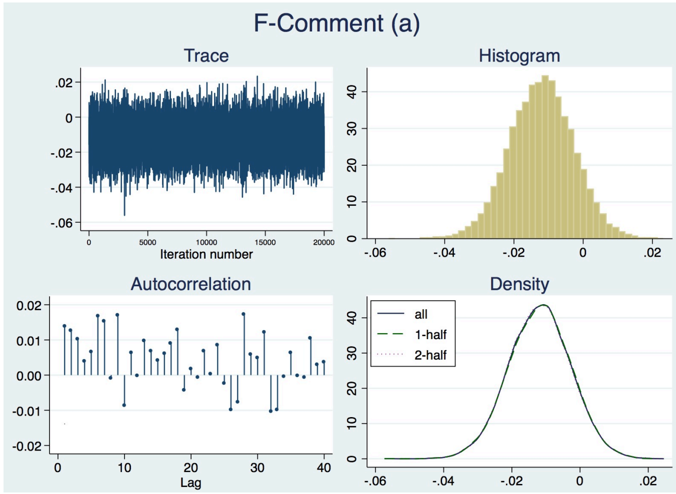


Figure 273. Assessment of Model Convergence for C-F-Comment (a) (Group 1)

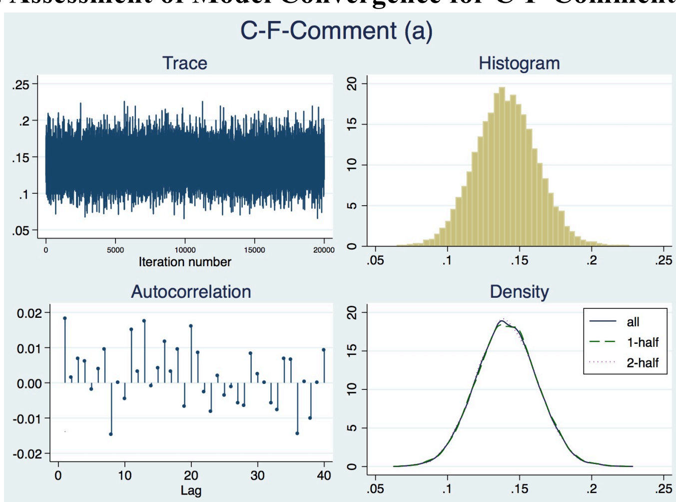


Figure 274. Assessment of Model Convergence for U-Comment (a) (Group 1)

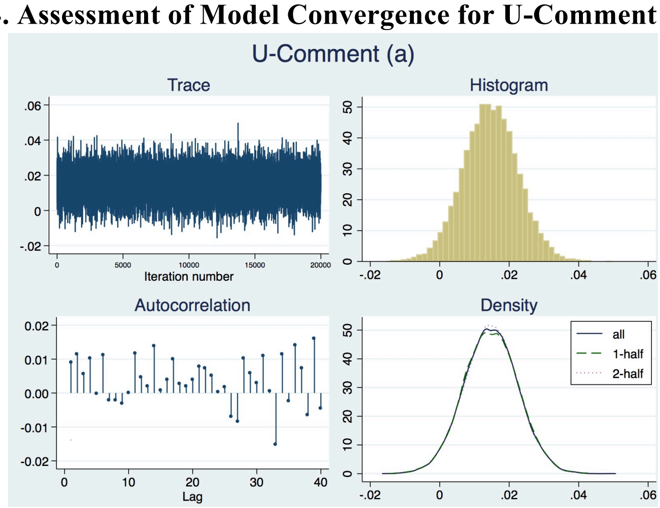


Figure 275. Assessment of Model Convergence for C-U-Comment (a) (Group 1)

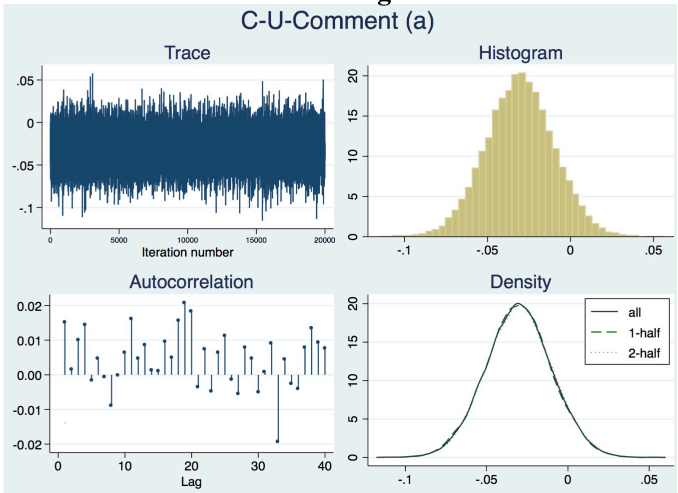


Figure 276. Assessment of Model Convergence for TD-Post (c) (Group 1)

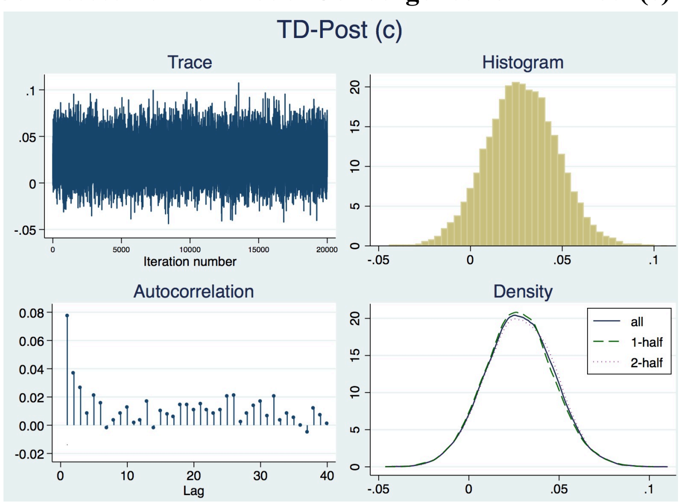


Figure 277. Assessment of Model Convergence for C-TD-Post (c) (Group 1)

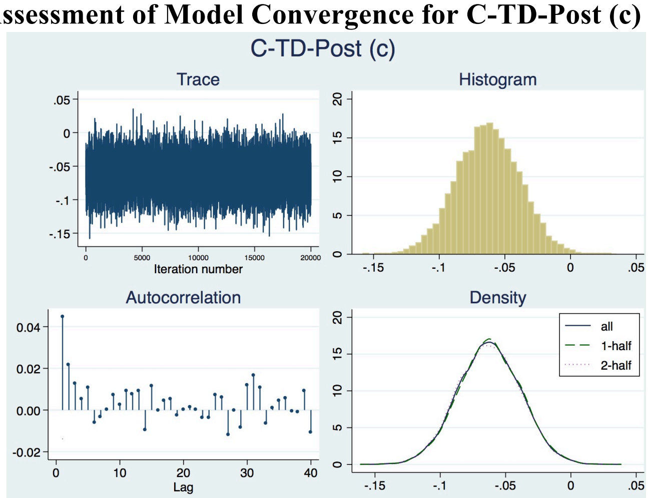


Figure 278. Assessment of Model Convergence for TMS (Group 1)

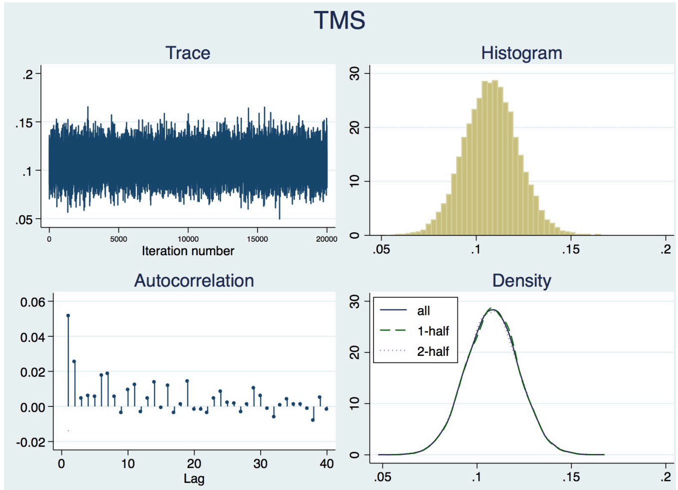


Figure 279. Assessment of Model Convergence for Price (Group 1)

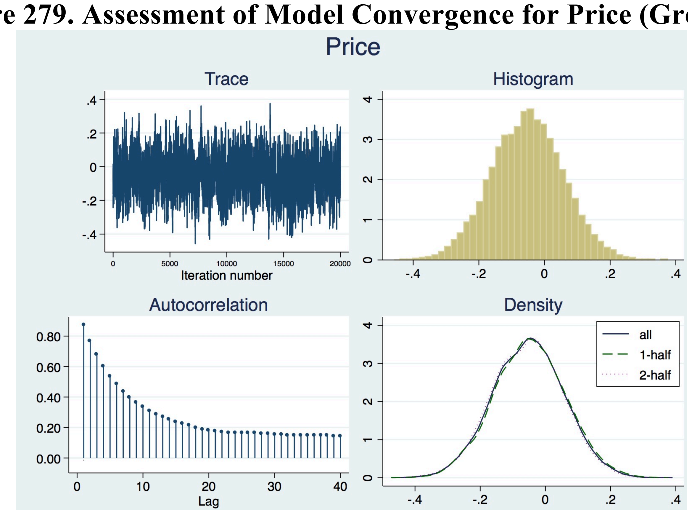


Figure 280. Assessment of Model Convergence for GT (Group 1)

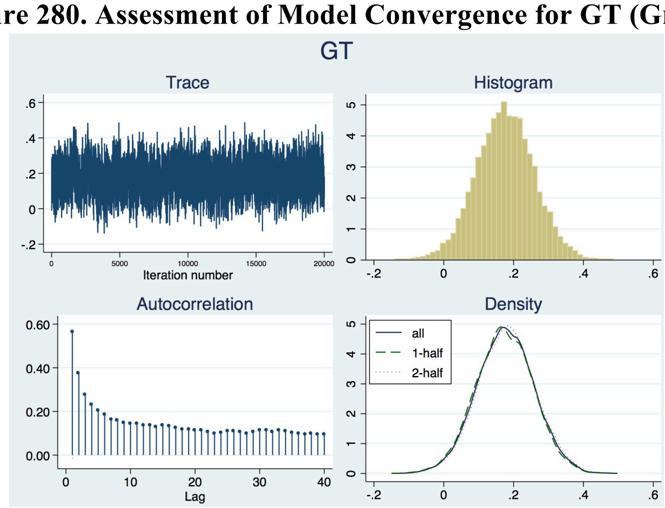


Figure 281. Assessment of Model Convergence for GPI (Group 1)

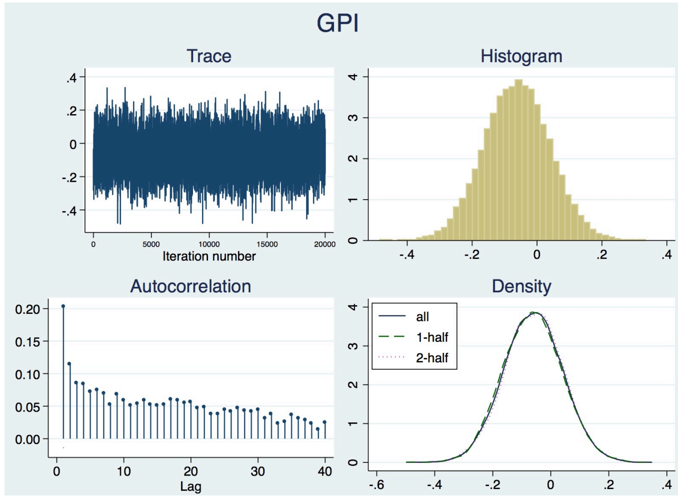


Figure 282. Assessment of Model Convergence for CCI (Group 1)

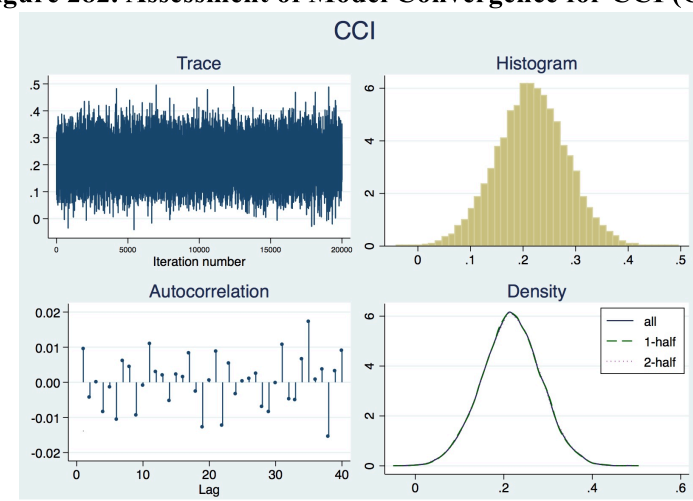


Figure 283. Assessment of Model Convergence for F-Comment (a) (Group 2)

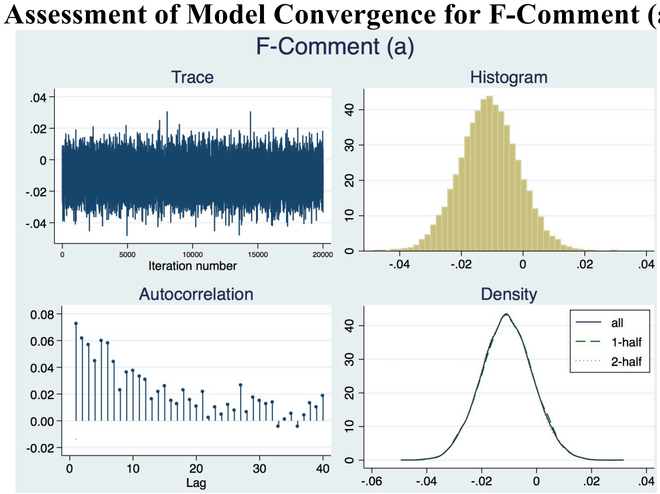


Figure 284. Assessment of Model Convergence for C-F-Comment (a) (Group 2)

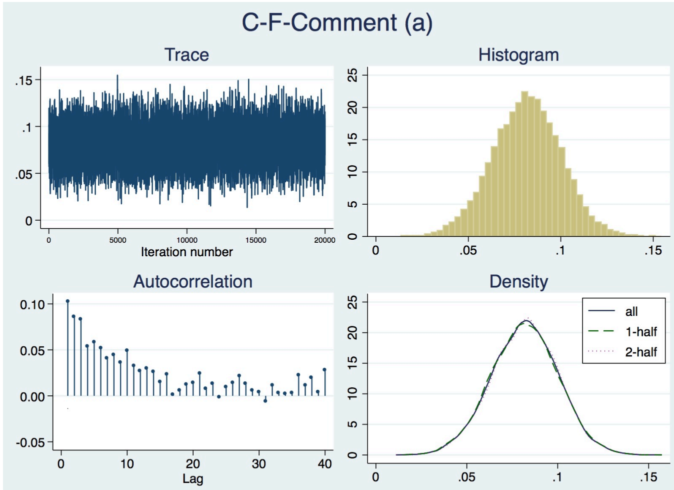


Figure 285. Assessment of Model Convergence for U-Comment (a) (Group 2)

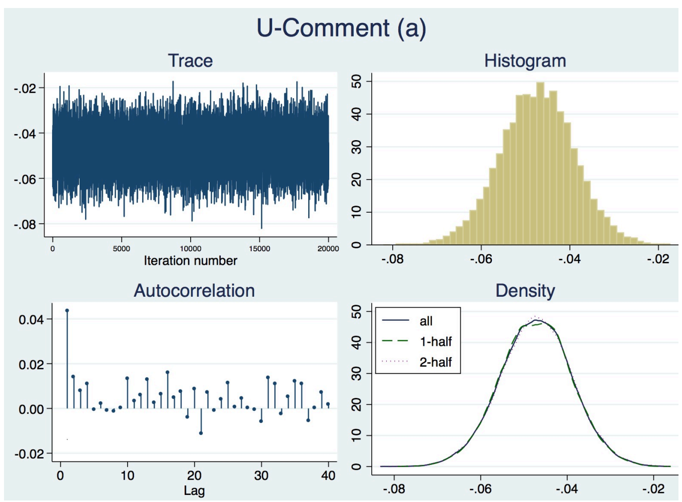


Figure 286. Assessment of Model Convergence for C-U-Comment (a) (Group 2)

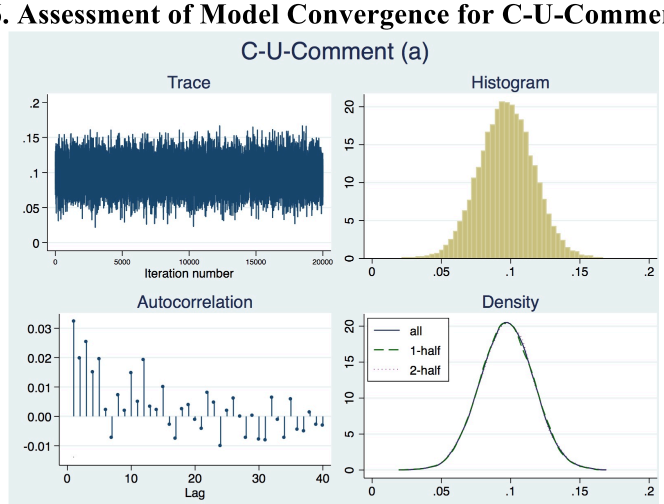


Figure 287. Assessment of Model Convergence for TD-Post (c) (Group 2)

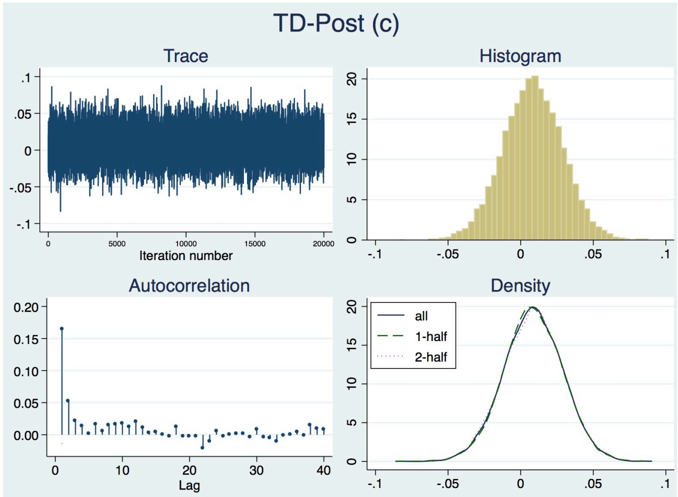


Figure 288. Assessment of Model Convergence for C-TD-Post (c) (Group 2)

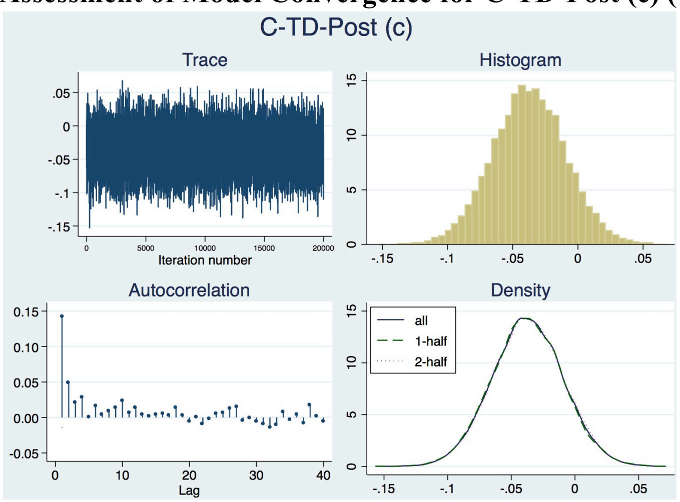


Figure 289. Assessment of Model Convergence for TMS (Group 2)

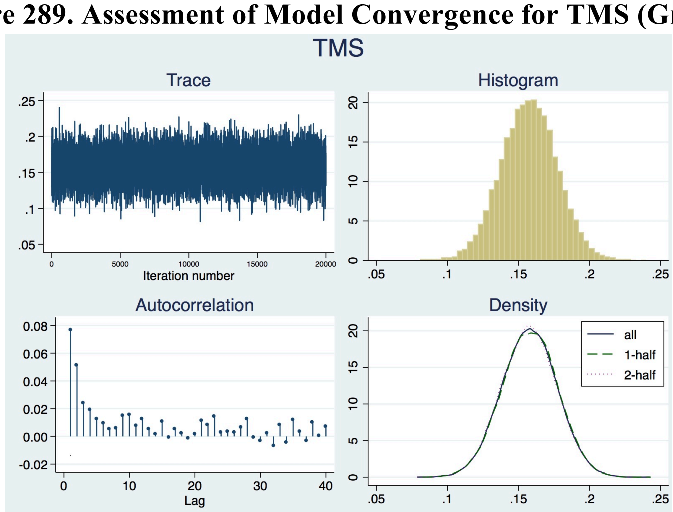


Figure 290. Assessment of Model Convergence for Price (Group 2)

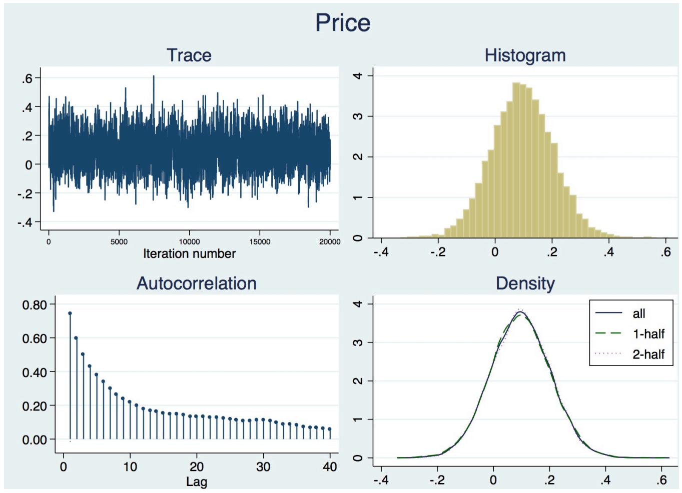


Figure 291. Assessment of Model Convergence for GT (Group 2)

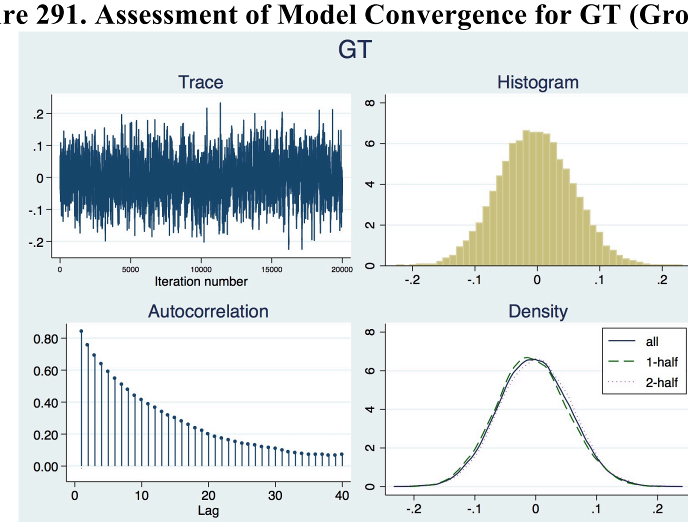


Figure 292. Assessment of Model Convergence for GPI (Group 2)

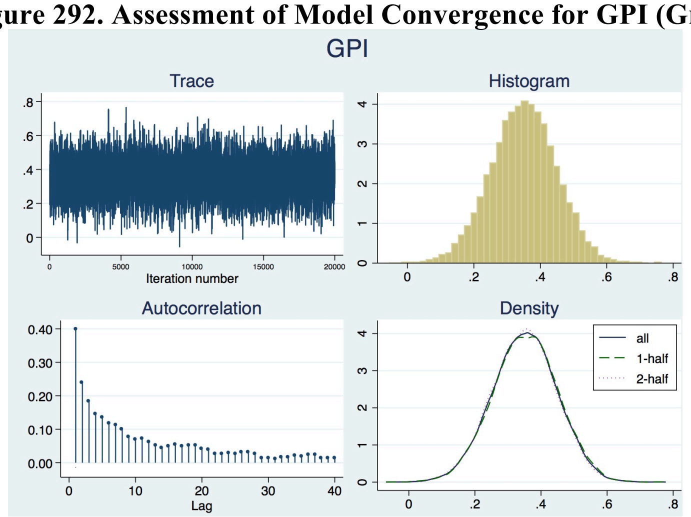


Figure 293. Assessment of Model Convergence for CCI (Group 2)

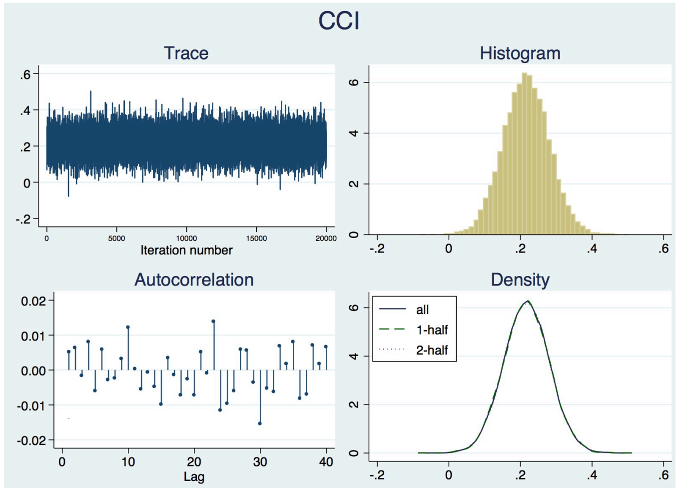


Figure 294. Assessment of Model Convergence for F-Comment (a) (Group 3)

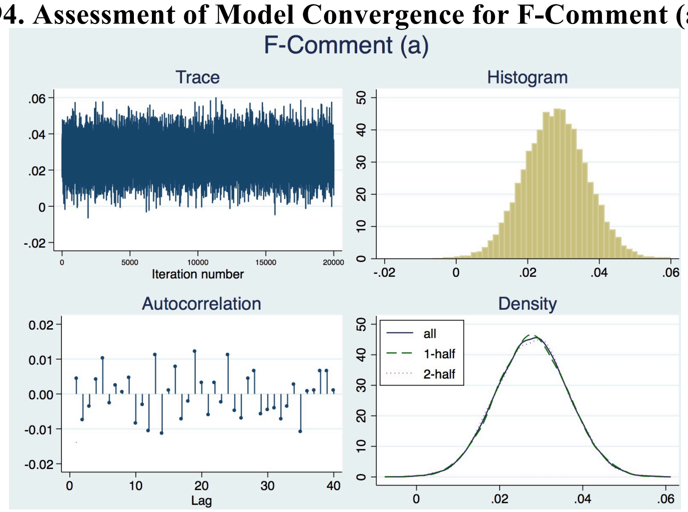


Figure 295. Assessment of Model Convergence for C-F-Comment (a) (Group 3)

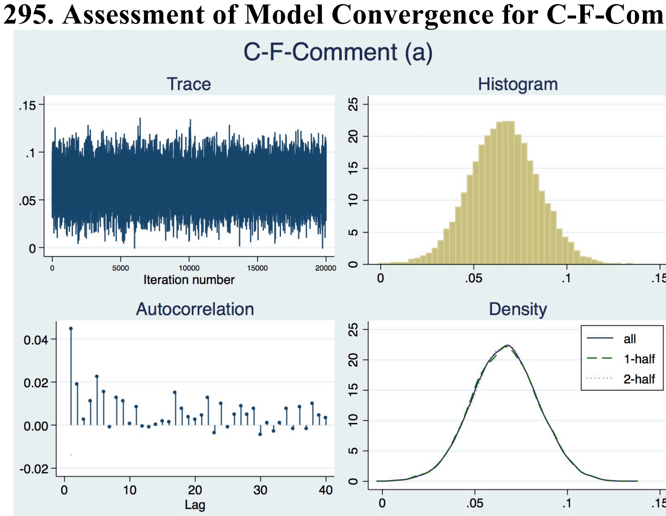


Figure 296. Assessment of Model Convergence for U-Comment (a) (Group 3)

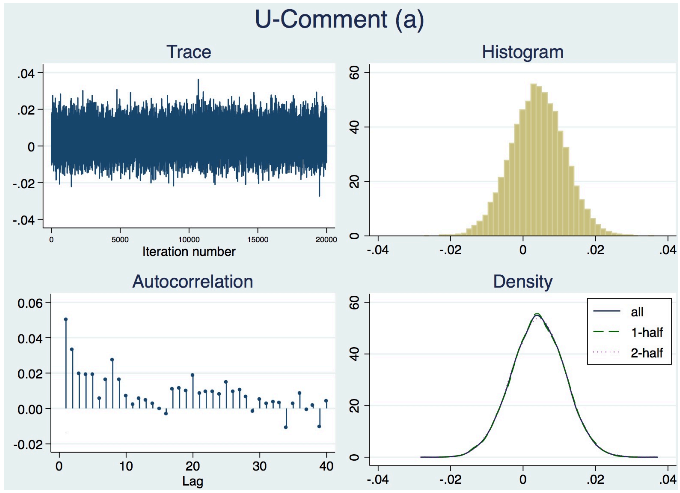


Figure 297. Assessment of Model Convergence for C-U-Comment (a) (Group 3)

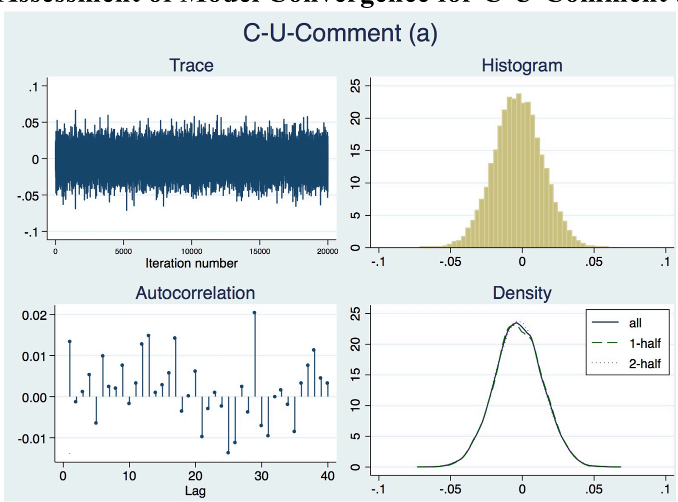


Figure 298. Assessment of Model Convergence for TD-Post (c) (Group 3)

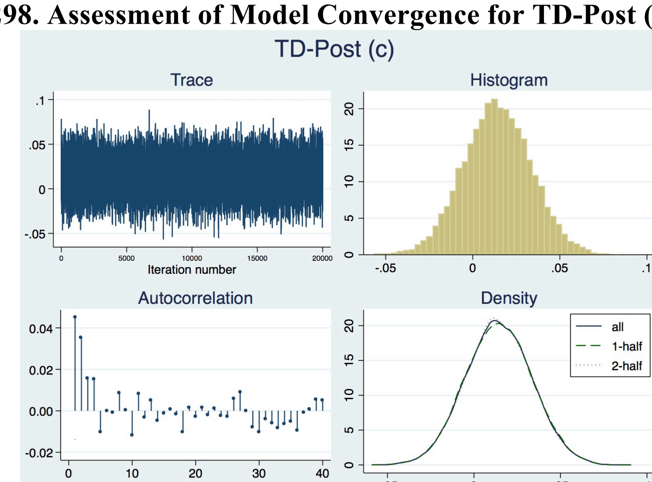


Figure 299. Assessment of Model Convergence for C-TD-Post (c) (Group 3)

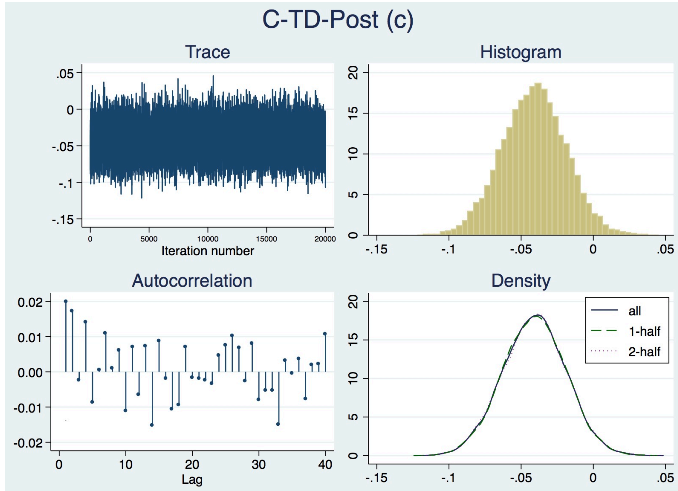


Figure 300. Assessment of Model Convergence for TMS (Group 3)

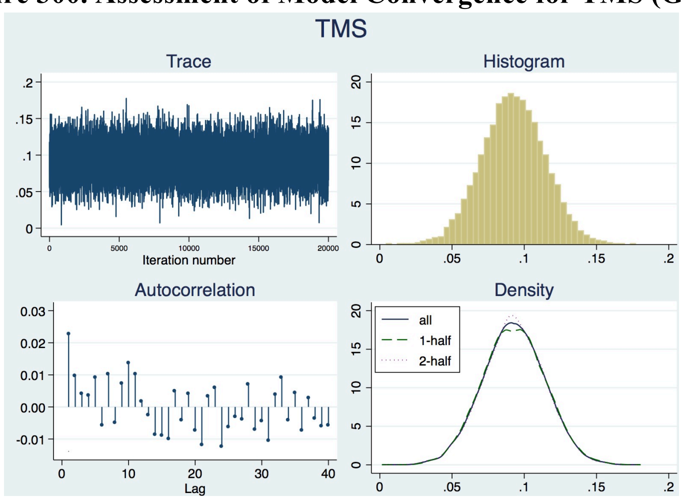


Figure 301. Assessment of Model Convergence for Price (Group 3)

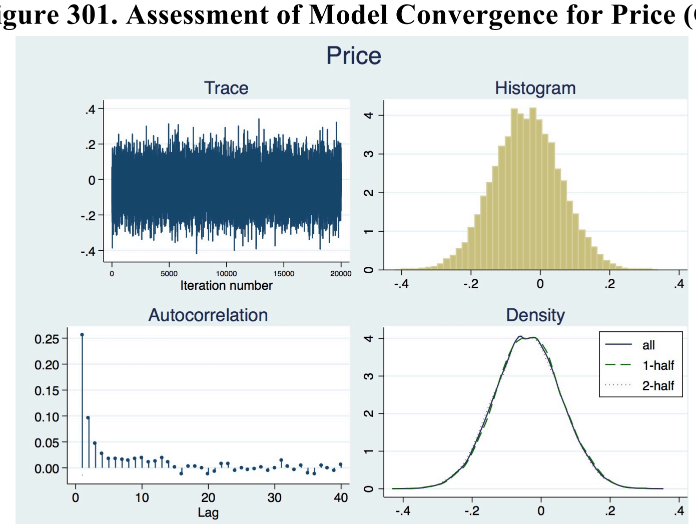


Figure 302. Assessment of Model Convergence for GT (Group 3)

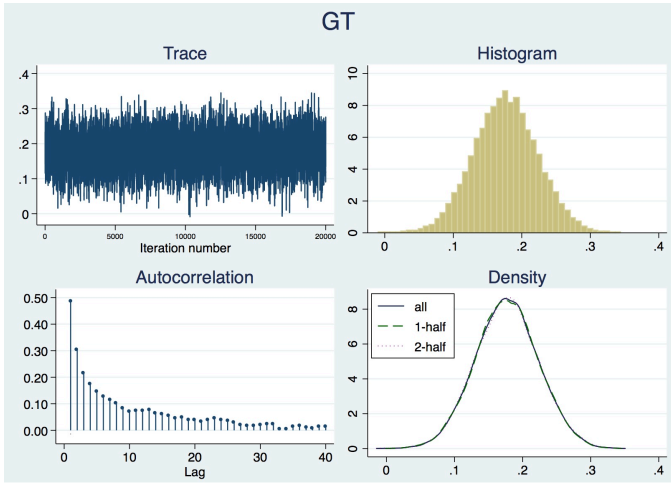


Figure 303. Assessment of Model Convergence for GPI (Group 3)

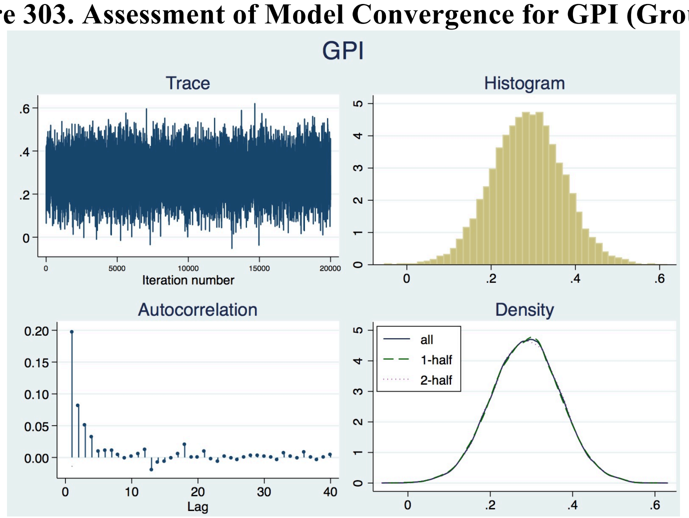
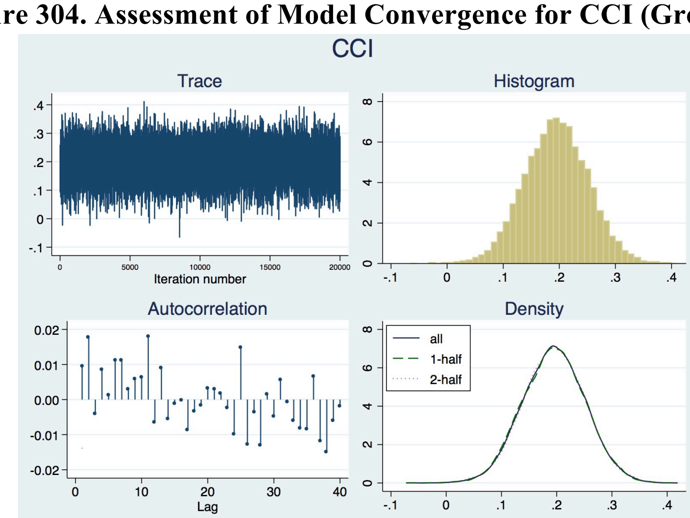


Figure 304. Assessment of Model Convergence for CCI (Group 3)



Tables 72 to 74 show my sample split Bayesian estimation results at the share level (i.e., “Share” associated with posts at Facebook and test drive post) for group 1 of market structure, group 2 of market structure, and group 3 of market structure, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 305 to 337) suggested that the model specification converged for each relationship.

Consistent with main results (see Table 44), the results suggest that at the stage of awareness F-Share (a) is not very effective in influencing offline car sales of the focal brand across three groups, rejecting H1. On the other hand, C-F-Share (a) shows positive spillover effects on offline car sales of the focal brand across three different groups, supporting H2. Regarding effects associated with user posts at the stage of awareness, I only find that U-Share (a) has the positive impact on offline car sales, supporting my H1. Finally, for online WOM at the stage of consideration, I find that TD-Post (c) has the positive impact on offline car sales of the focal brand for group 1 only, in support of H3. However, no online WOM spillover effects observed at the stage of consideration in this set of analysis.

Table 72. Bayesian Estimation Results for Shares (Group 1)

Parameters	$Sales_{A,t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A,t-1}$	-0.004 (0.006)	(-0.016, 0.007)
C-F-Share (a) $_{J,t-1}$	**0.053 (0.012)**	**(0.029, 0.076)**
U-Share (a) $_{A,t-1}$	-0.0001 (0.006)	(-0.012, 0.012)
C-U-Share (a) $_{J,t-1}$	-0.016 (0.013)	(-0.04, 0.008)
TD-Post (c) $_{A,t-1}$	**0.056 (0.019)**	**(0.018, 0.094)**
C-TD-Post (c) $_{J,t-1}$	-0.042 (0.027)	(-0.095, 0.011)
TMS $_{A,t-1}$	**0.11 (0.014)**	**(0.083, 0.138)**
Price $_{A,t-1}$	-0.029 (0.106)	(-0.238, 0.179)
GT $_{A,t-1}$	**0.2 (0.082)**	**(0.037, 0.363)**
GPI $_{A,t-1}$	0.169 (0.129)	(-0.086, 0.424)
CCI $_{A,t-1}$	**0.274 (0.067)**	**(0.144, 0.404)**

Table 73. Bayesian Estimation Results for Shares (Group 2)

Parameters	$Sales_{A,t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A,t-1}$	-0.006 (0.006)	(-0.017, 0.005)
C-F-Share (a) $_{J,t-1}$	**0.057 (0.011)**	**(0.035, 0.078)**
U-Share (a) $_{A,t-1}$	**0.016 (0.006)**	**(0.004, 0.029)**
C-U-Share (a) $_{J,t-1}$	**-0.025 (0.012)**	**(-0.048, -0.002)**
TD-Post (c) $_{A,t-1}$	0.008 (0.02)	(-0.033, 0.048)
C-TD-Post (c) $_{J,t-1}$	-0.014 (0.029)	(-0.07, 0.043)
TMS $_{A,t-1}$	**0.17 (0.019)**	**(0.132, 0.209)**
Price $_{A,t-1}$	-0.12 (0.11)	(-0.1, 0.342)
GT $_{A,t-1}$	**-0.119 (0.056)**	**(-0.228, -0.008)**
GPI $_{A,t-1}$	**0.381 (0.123)**	**(0.138, 0.621)**
CCI $_{A,t-1}$	**0.19 (0.064)**	**(0.063, 0.316)**

Table 74. Bayesian Estimation Results for Shares (Group 3)

Parameters	$Sales_{A,t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A,t-1}$	0.008 (0.005)	(-0.0007, 0.018)
C-F-Share (a) $_{J,t-1}$	**0.032 (0.01)**	**(0.012, 0.052)**
U-Share (a) $_{A,t-1}$	0.006 (0.005)	(-0.004, 0.015)
C-U-Share (a) $_{J,t-1}$	**-0.009 (0.009)**	**(-0.029, 0.009)**
TD-Post (c) $_{A,t-1}$	0.014 (0.018)	(-0.022, 0.05)
C-TD-Post (c) $_{J,t-1}$	0.002 (0.023)	(-0.044, 0.048)
TMS $_{A,t-1}$	**0.079 (0.021)**	**(0.037, 0.12)**
Price $_{A,t-1}$	-0.026 (0.093)	(-0.208, 0.158)
GT $_{A,t-1}$	**0.18 (0.042)**	**(0.097, 0.262)**
GPI $_{A,t-1}$	**0.303 (0.106)**	**(0.097, 0.51)**
CCI $_{A,t-1}$	**0.211 (0.054)**	**(0.104, 0.32)**

Figure 305. Assessment of Model Convergence for F-Share (a) (Group 1)

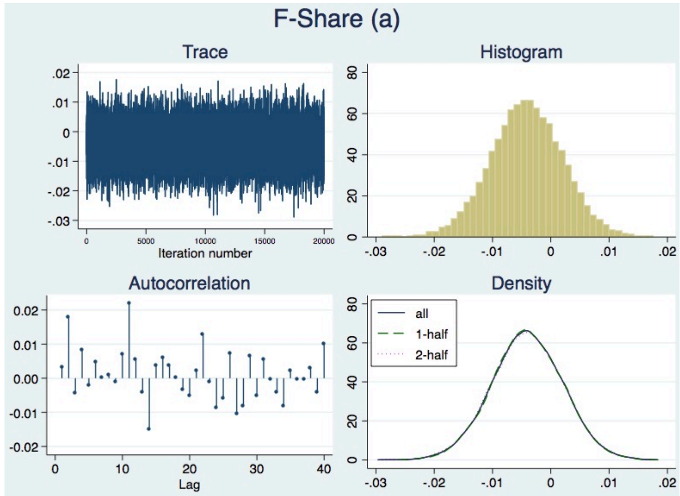


Figure 306. Assessment of Model Convergence for C-F-Share (a) (Group 1)

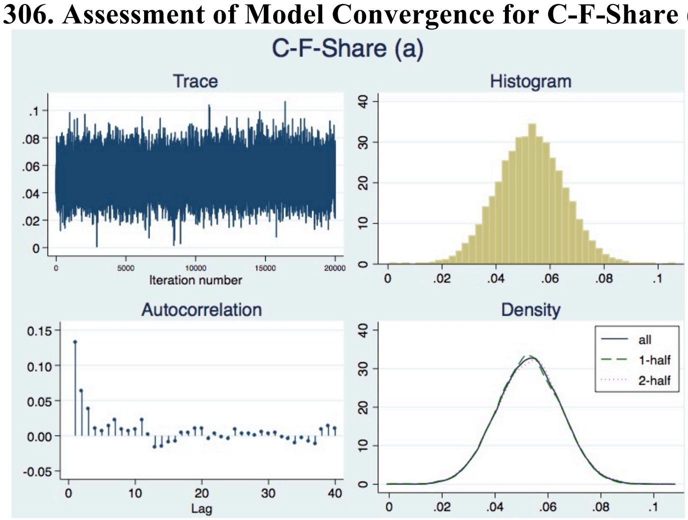


Figure 307. Assessment of Model Convergence for U-Share (a) (Group 1)

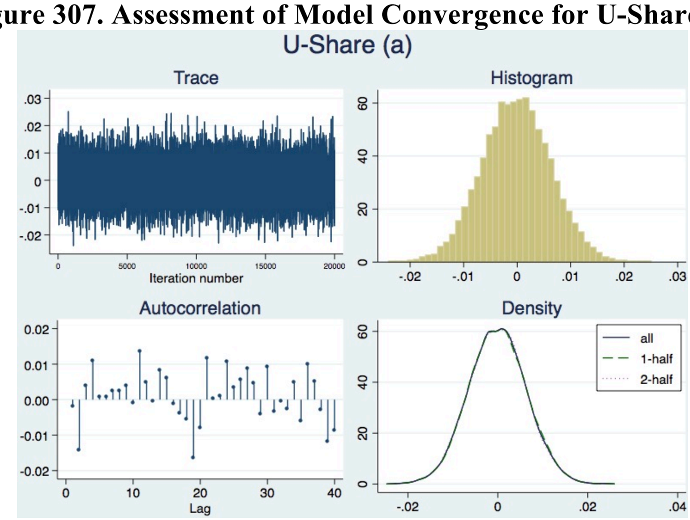


Figure 308. Assessment of Model Convergence for C-U-Share (a) (Group 1)

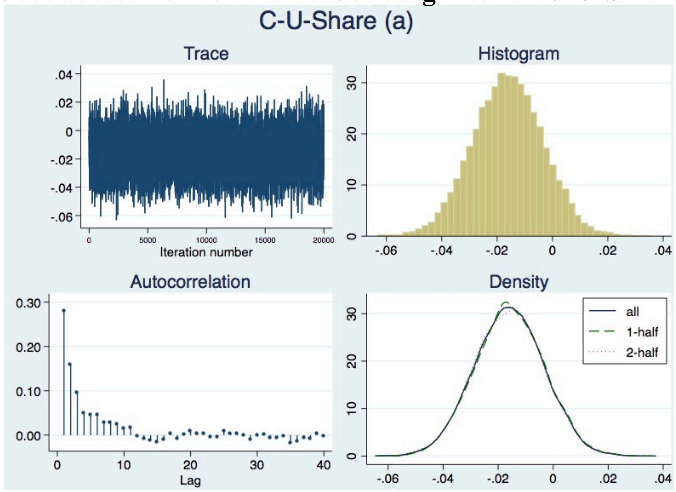


Figure 309. Assessment of Model Convergence for TD-Post (c) (Group 1)

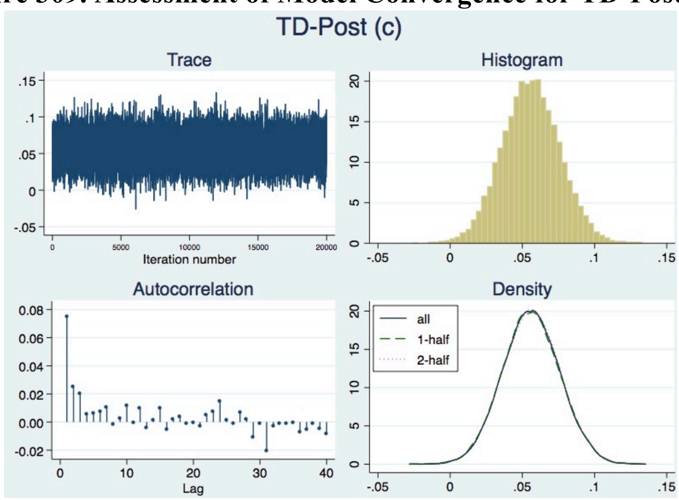


Figure 310. Assessment of Model Convergence for C-TD-Post (c) (Group 1)

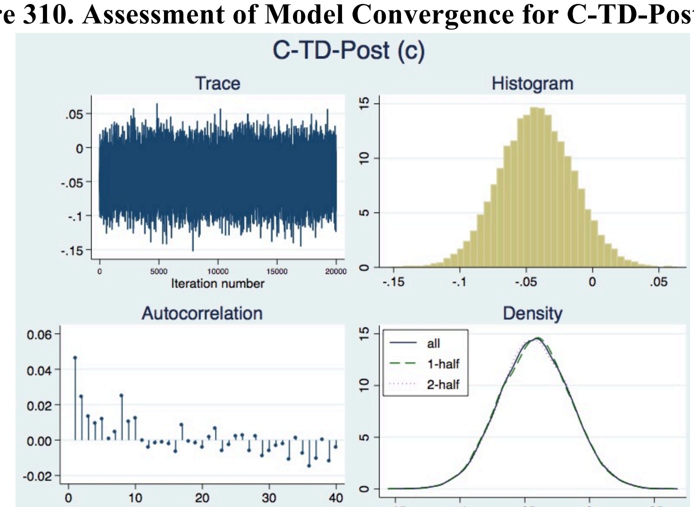


Figure 311. Assessment of Model Convergence for TMS (Group 1)

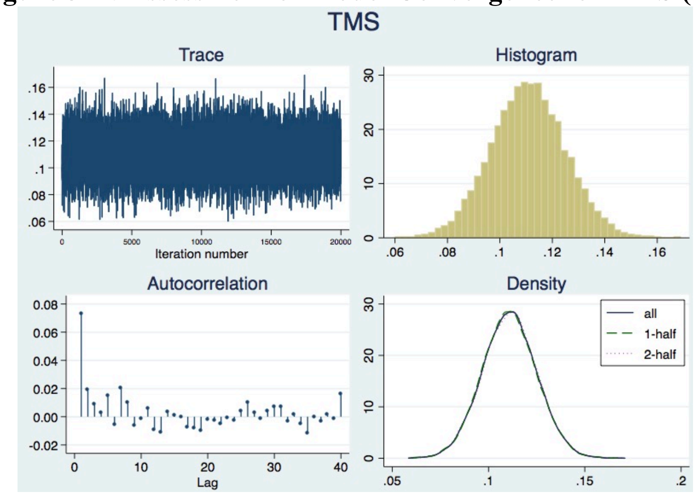


Figure 312. Assessment of Model Convergence for Price (Group 1)

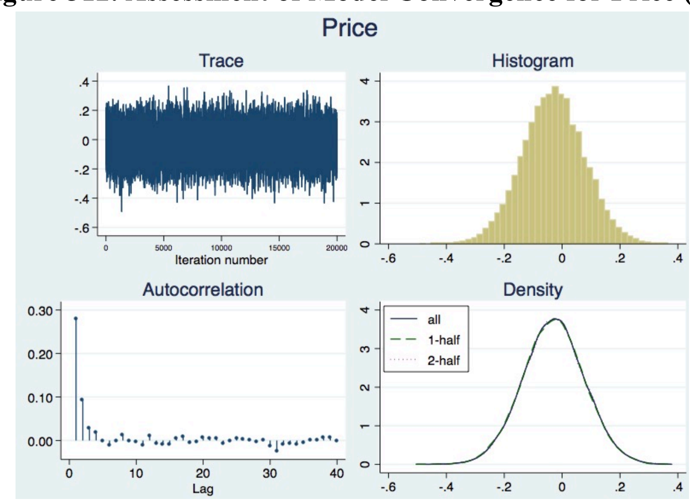


Figure 313. Assessment of Model Convergence for GT (Group 1)

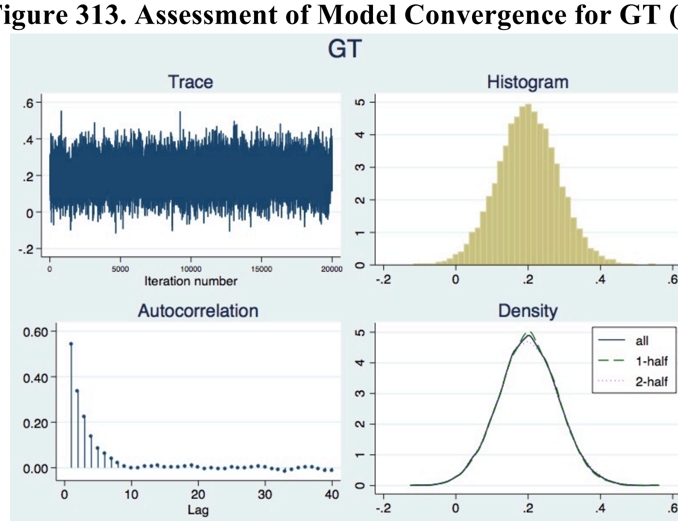


Figure 314. Assessment of Model Convergence for GPI (Group 1)

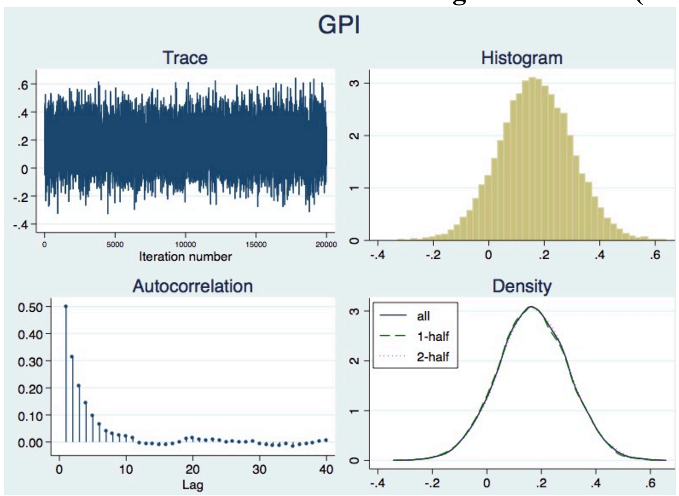


Figure 315. Assessment of Model Convergence for CCI (Group 1)

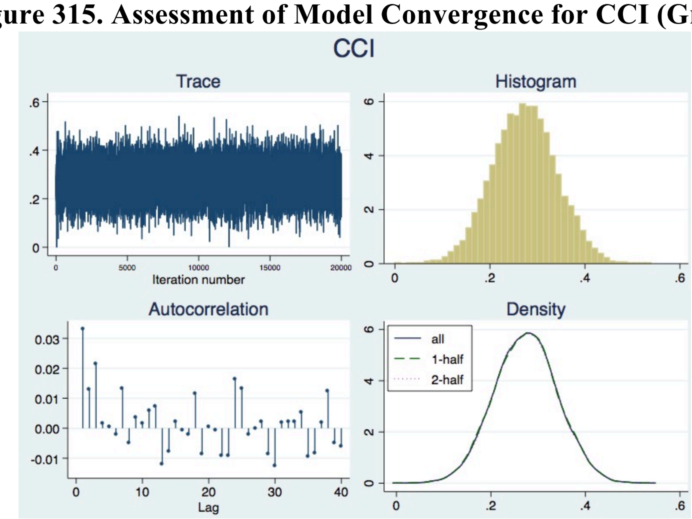


Figure 316. Assessment of Model Convergence for F-Share (a) (Group 2)

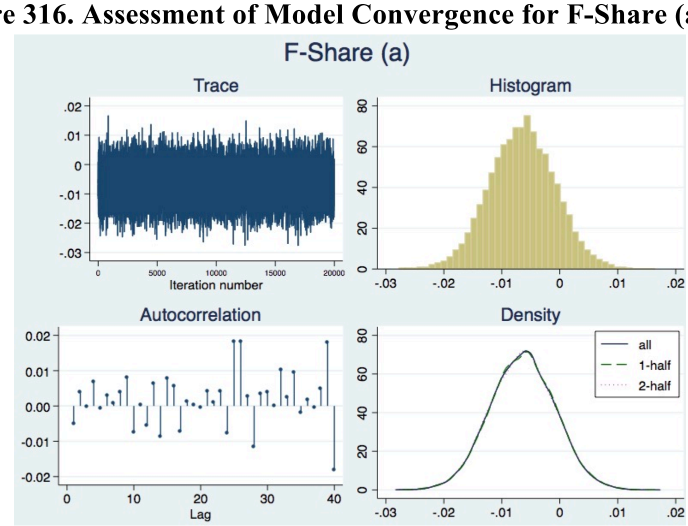


Figure 317. Assessment of Model Convergence for C-F-Share (a)

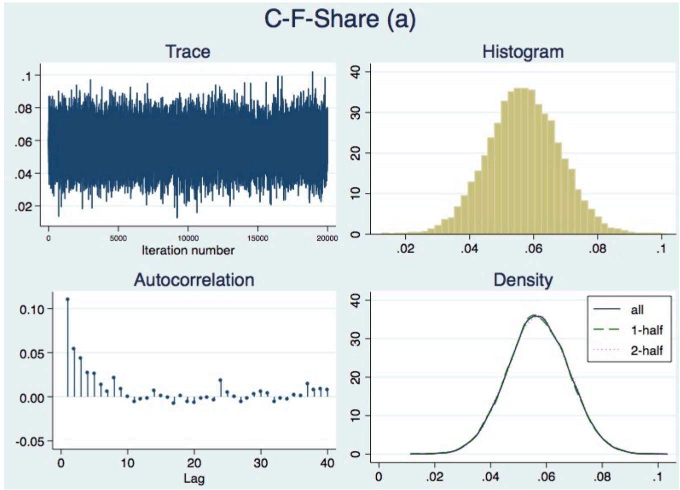


Figure 318. Assessment of Model Convergence for U-Share (a) (Group 2)

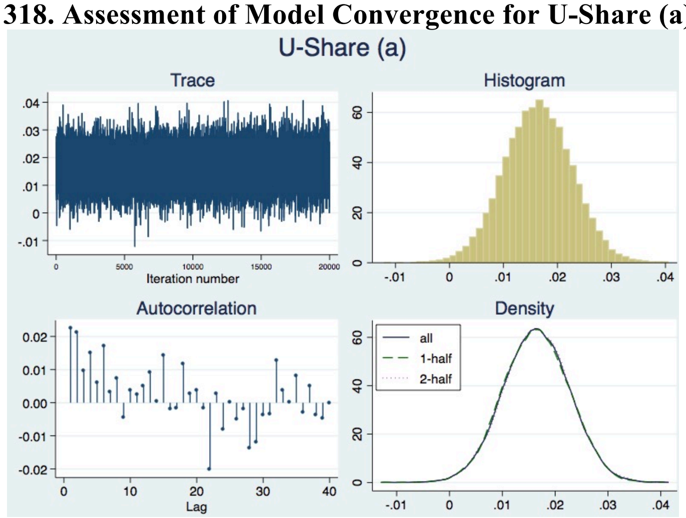


Figure 319. Assessment of Model Convergence for C-U-Share (a) (Group 2)

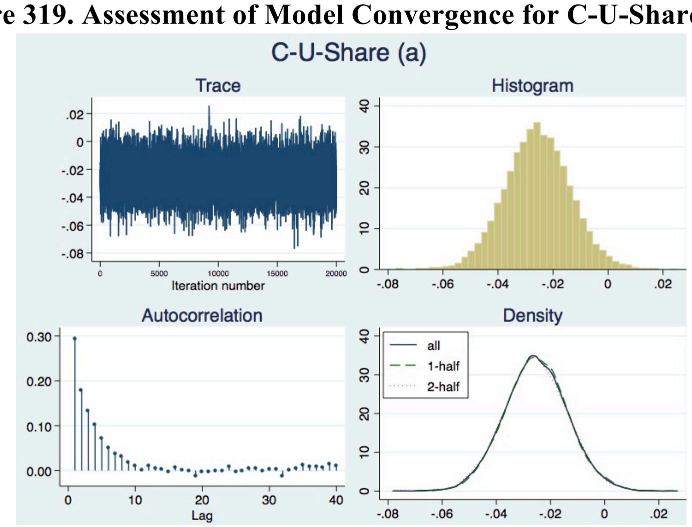


Figure 320. Assessment of Model Convergence for TD-Post (c) (Group 2)

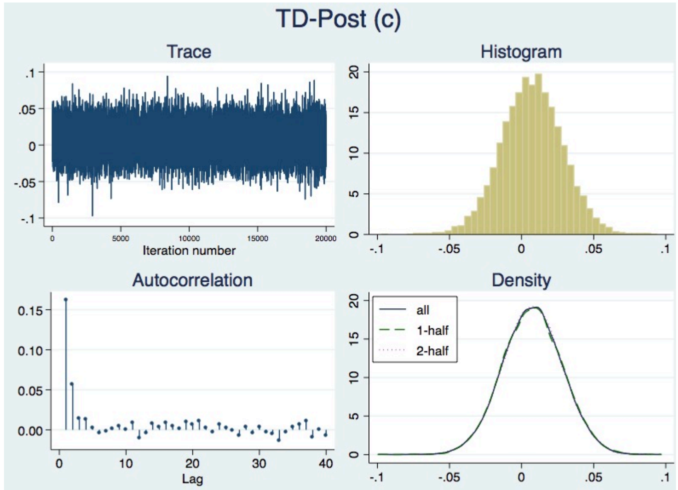


Figure 321. Assessment of Model Convergence for C-TD-Post (c) (Group 2)

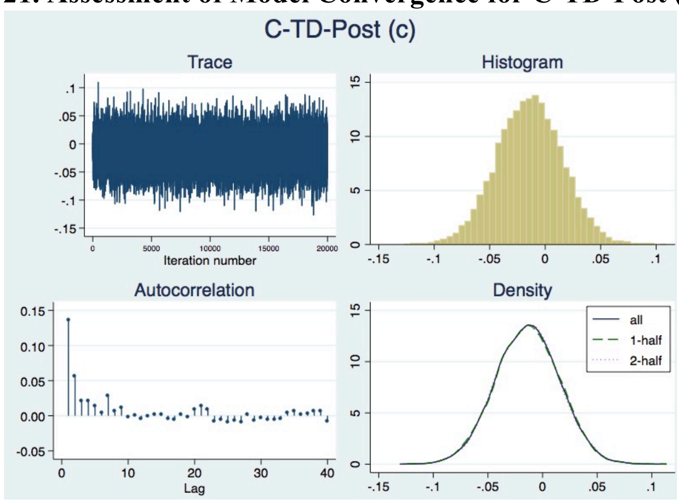


Figure 322. Assessment of Model Convergence for TMS (Group 2)

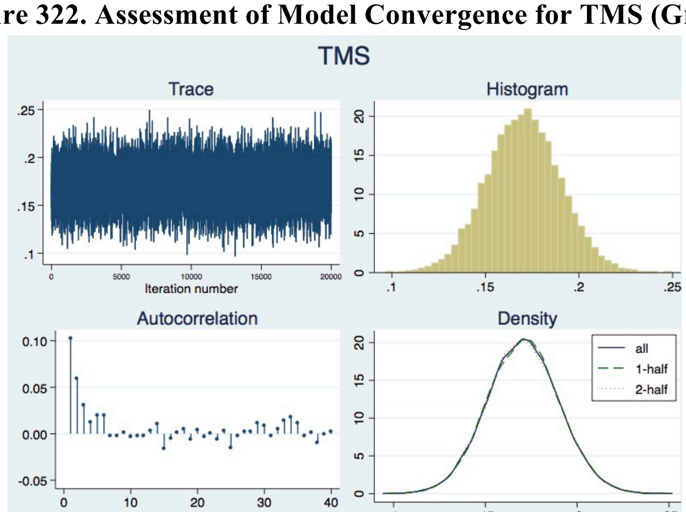


Figure 323. Assessment of Model Convergence for Price (Group 2)

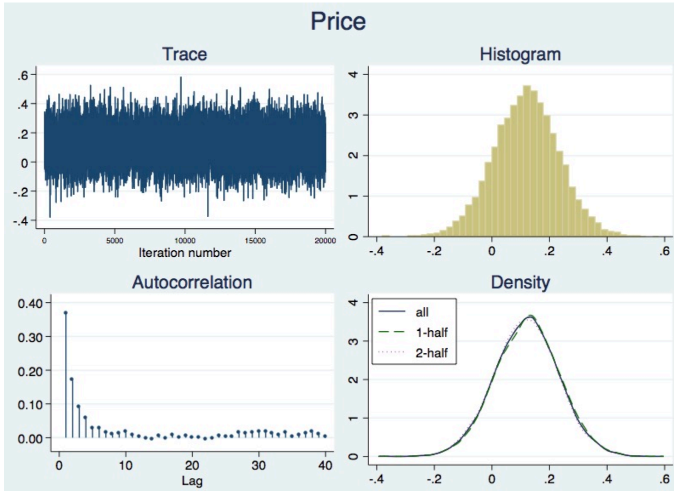


Figure 324. Assessment of Model Convergence for GT (Group 2)

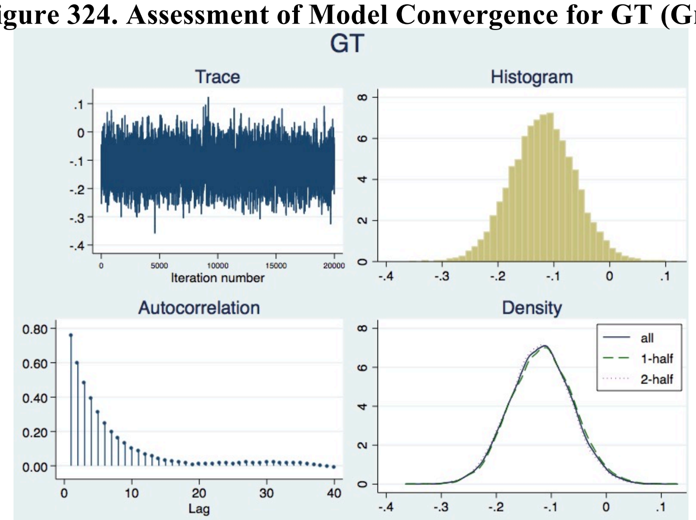


Figure 325. Assessment of Model Convergence for GPI (Group 2)

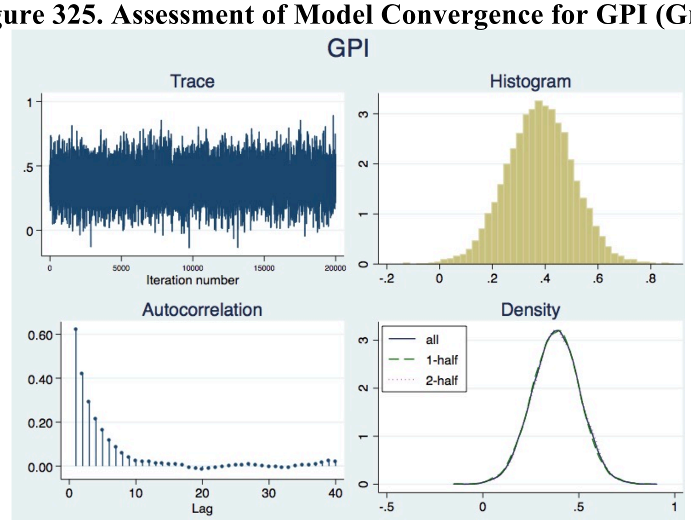


Figure 326. Assessment of Model Convergence for CCI (Group 2)

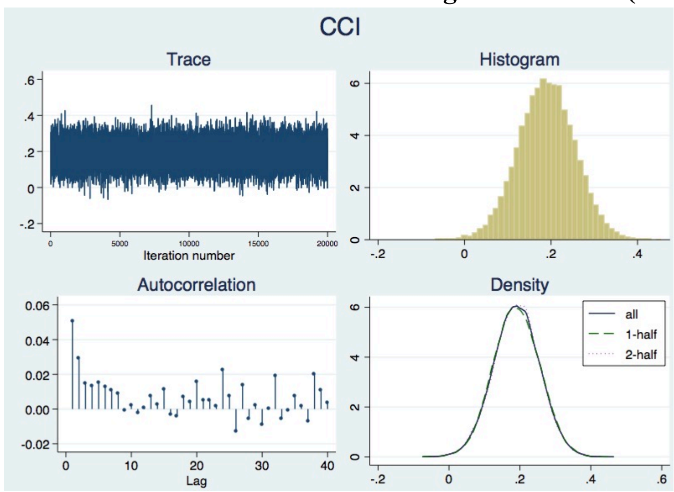


Figure 327. Assessment of Model Convergence for F-Share (a) (Group 3)

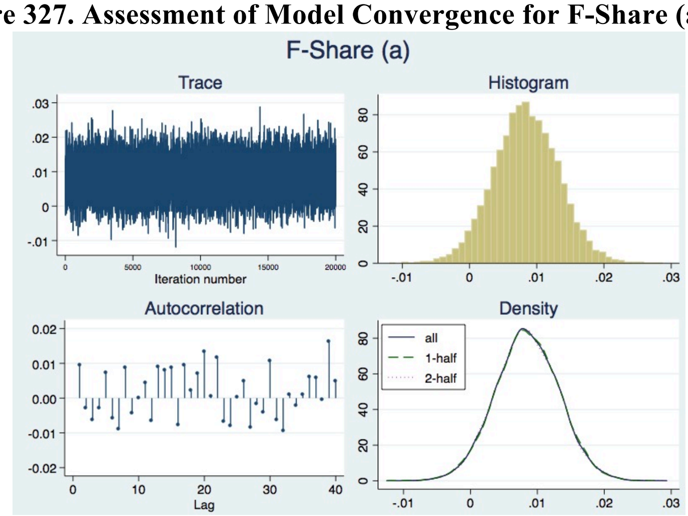


Figure 328. Assessment of Model Convergence for C-F-Share (a) (Group 3)

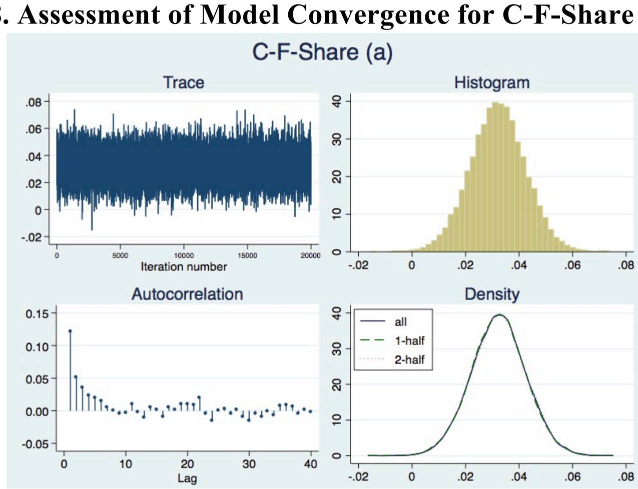


Figure 329. Assessment of Model Convergence for U-Share (a) (Group 3)

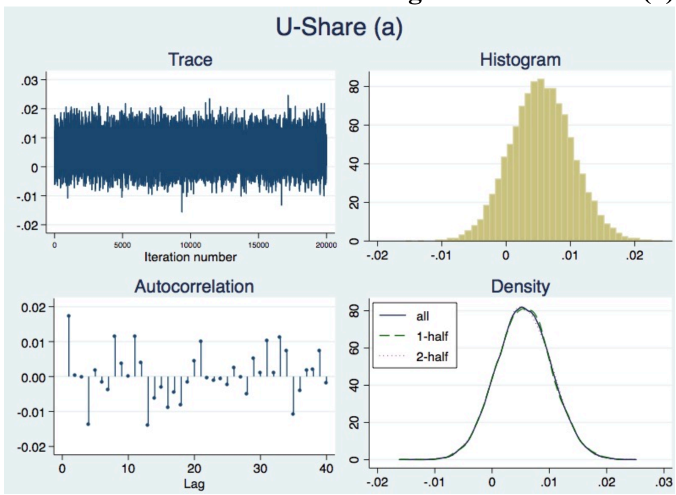


Figure 330. Assessment of Model Convergence for C-U-Share (a) (Group 3)

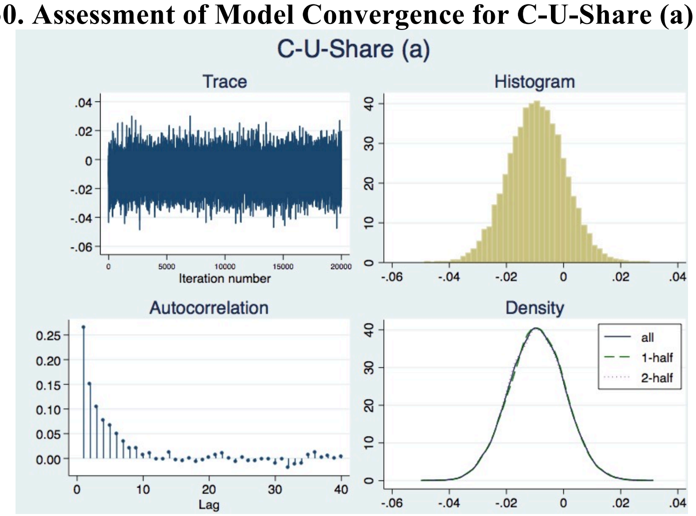


Figure 331. Assessment of Model Convergence for TD-Post (c) (Group 3)

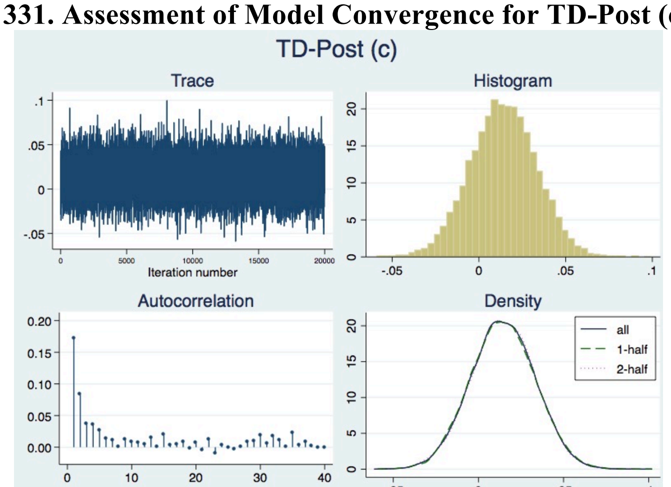


Figure 332. Assessment of Model Convergence for C-TD-Post (c) (Group 3)

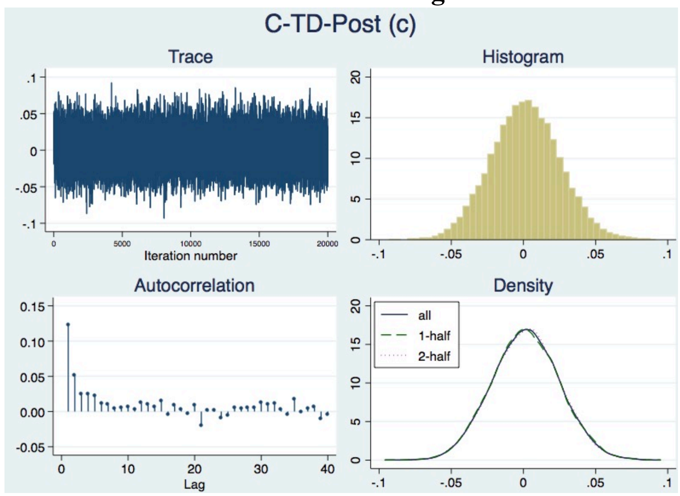


Figure 333. Assessment of Model Convergence for TMS (Group 3)

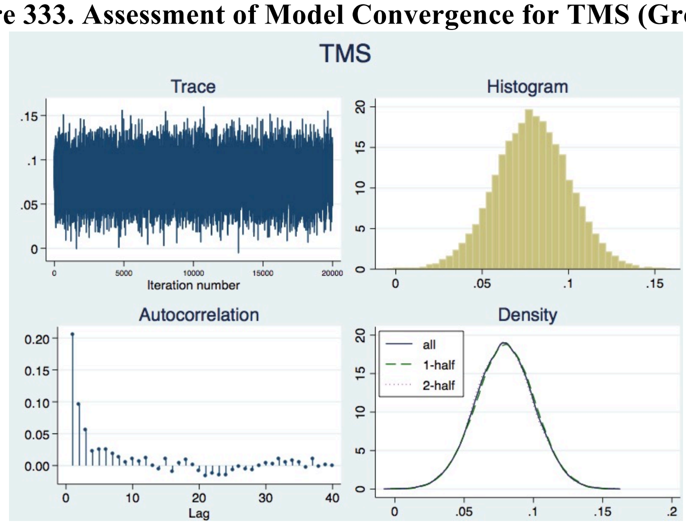


Figure 334. Assessment of Model Convergence for Price (Group 3)

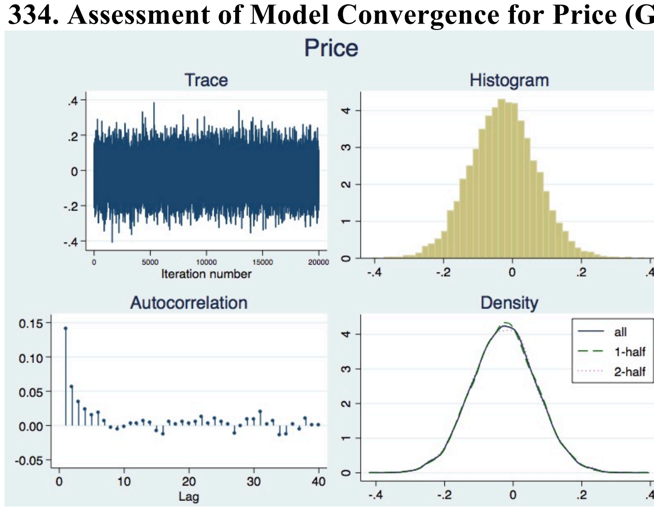


Figure 335. Assessment of Model Convergence for GT (Group 3)

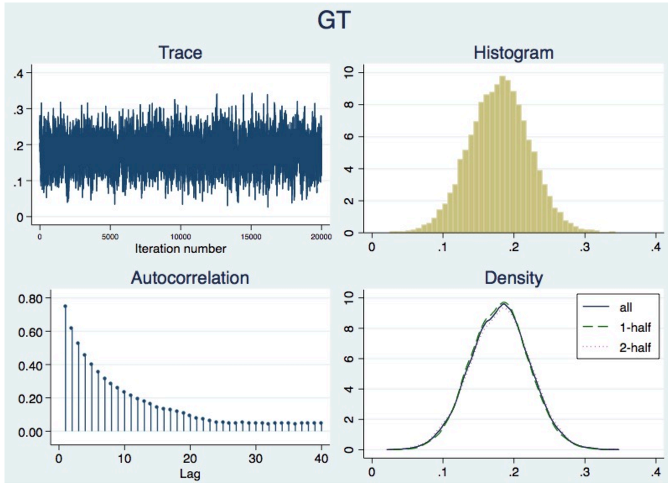


Figure 336. Assessment of Model Convergence for GPI (Group 3)

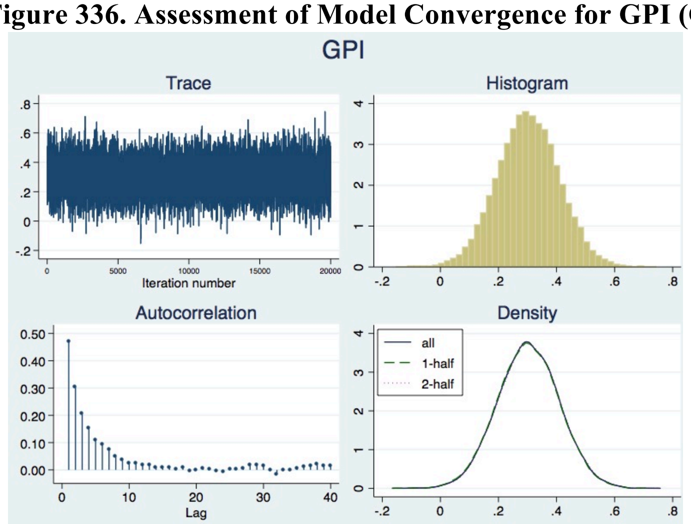
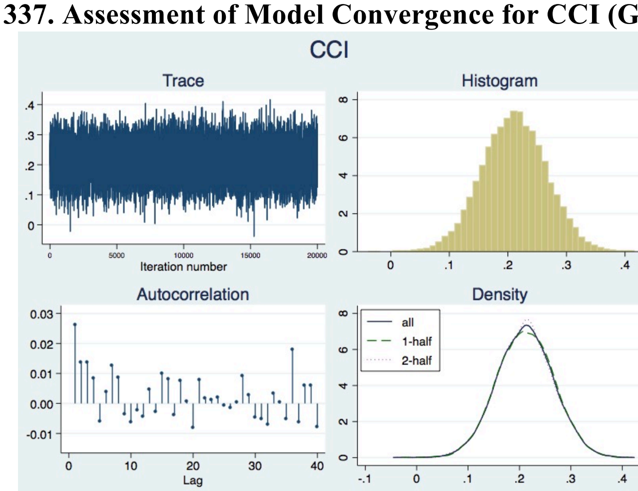


Figure 337. Assessment of Model Convergence for CCI (Group 3)



3.5.4 Sample Split Bayesian Analysis Results on Luxury and Non-Luxury Brands

Previous research on WOM has provided evidence that consumers' motivation to engage in online WOM differs across brands, and that consumers may be particularly inclined to converse about high-regarded or high-quality brands, about luxury goods, or about brands with a high degree of differentiation (Lovett et al., 2013). Such differences in online WOM activity may naturally affect the informativeness of social media data for perdition (Geva et al., 2017). I, therefore, examine whether and how the luxury versus non-luxury category[20] may vary dynamics of online WOM in the current study. Tables 75 and 76 show descriptive statistics for luxury and non-luxury group, respectively.

Table 75. Descriptive Statistics for Luxury brands

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	800	11221.53	7948.68	97	37,399
F-Post (a)	800	30.50	24.7	0	436
C-F-Post (a)	800	927.75	406.43	64	2,584
F-Like (a)	800	115851.5	199947.3	0	1,100,000
C-F-Like (a)	800	2,266,860	2,101,807	4,230	6,000,000
F-Comment (a)	800	2146.45	2445.04	0	15,943
C-F-Comment (a)	800	66019.67	38378.31	861	152,429
F-Share (a)	800	8182.67	16276.19	0	115,372
C-F-Share (a)	800	174978.8	173358.8	83	578,089
U-Post (a)	800	281.24	409.66	0	9,624
C-U-Post (a)	800	12722.51	4424.98	853	22,520
U-Like (a)	800	8745.22	30559.04	0	560,219
C-U-Like (a)	800	307365.1	387251.3	561	2,500,000
U-Comment (a)	800	442.67	895.59	0	11,461
C-U-Comment (a)	800	25968.61	16172.53	670	109,163
U-Share (a)	800	56.15	358.91	0	5,283
C-U-Share (a)	800	2478.32	3971.74	0	21,905
TD-Post (c)	800	139.54	152.18	5	1,595
C-TD-Post (c)	800	7119.08	4998.62	1,983	35,072
TMS	800	17976444.25	12746535.05	65,200	75,000,000
Price	800	49494.1	12755.88	28,800	90,775
GT	800	61.51	16.05	26	100
GPI	800	3.40	0.39	2.31	3.98
CCI	800	66.17	12.88	40.9	94.1

[20] **Luxury:** Acura, Audi, BMW, Buick, Cadillac, Infiniti, Jaguar, Land Rover, Lexus, Lincoln, Mercedes-Benz, Porsche, Saab, and Volvo**; Non-Luxury:** Chevrolet, Chrysler, Dodge, FIAT, Ford, Honda, Hyundai, Jeep, KIA, Mazda, Mitsubishi, Nissan, Scion, Subaru, Toyota, and Volkswagen

Table 76. Descriptive Statistics for Non-Luxury brands

Variable	No. of obs.	Mean	Std. dev.	Min	Max
Sale	989	60260.79	55507.96	500	244,501
F-Post (a)	989	35.39	40.8	0	1,042
C-F-Post (a)	989	907.93	408.54	48	2,605
F-Like (a)	989	54474.84	78756.19	0	722,146
C-F-Like (a)	989	2,312,127	2,161,215	3,093	6,000,000
F-Comment (a)	989	2519.67	3130.35	0	26,648
C-F-Comment (a)	989	64858.59	38966.45	420	153,749
F-Share (a)	989	4763.35	7856.64	0	62,457
C-F-Share (a)	989	177261.6	176295.6	27	580,559
U-Post (a)	989	592.91	586.58	0	4,918
C-U-Post (a)	989	12210.44	4409.6	647	22,539
U-Like (a)	989	12537.61	31007.68	0	463,332
C-U-Like (a)	989	300836.7	387,759	254	2,500,000
U-Comment (a)	989	1294.46	2271.28	0	36,118
C-U-Comment (a)	989	24776.21	16061.45	480	108,721
U-Share (a)	989	111.64	612.16	0	16,400
C-U-Share (a)	989	2399.58	3870.65	0	21,905
TD-Post (c)	989	336.09	408.59	13	3,771
C-TD-Post (c)	989	6854.49	4836.52	1,862	35,106
TMS	989	47563335.39	40493361.94	238,700	200,000,000
Price	989	23922.2	4076.61	14192.5	33783.9
GT	989	49.47	20.53	7	100
GPI	989	3.39	0.4	2.31	3.98
CCI	989	66.06	12.89	40.9	94.1

Tables 77 to 78 show my sample split Bayesian estimation results at the post level (i.e., Facebook post and test drive post) for luxury and non-luxury group, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (Figures 338 to 359) also suggested the model specification converged for each relationship.

First, at the stage of awareness, I observe that for the luxury group, F-Post (a) is not effective in influencing office line car sales of the focal brand, rejecting H1, while C-F-Post (a) has the positive impact on offline car sales of the focal brand, supporting H2. On the other hand, both H1 and H2 are supported for posts by the focal firm and its competitors. I also observe another interesting patterns for posts associated with the focal brand's user posts and its competitors' user posts (U-Post (a)) and (C-U-Post (a)) for the non-luxury group. Although I find the statistically significant effects for these two mechanisms, they show the opposite effects as hypothesized. Namely, both U-Post (a) and C-U-Post (a) have the negative impact on offline car sales of the focal brand, thereby rejecting both H1 and H2. Finally, for online WOM at the stage of consideration, I only find H3 and H4 supported for the luxury-group. It provides further evidence that customers from these two different groups appreciate test drive experience posts dramatically different to help them make purchase decisions.

Table 77. Bayesian Estimation Results for Posts (Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	0.007 (0.009)	(-0.024, 0.038)
C-F-Post (a) $_{J, t-1}$	**0.165 (0.03)**	**(0.11, 0.225)**
U-Post (a) $_{A, t-1}$	0.007 (0.009)	(-0.01, 0.025)
C-U-Post (a) $_{J, t-1}$	-0.04 (0.026)	(-0.091, 0.011)
TD-Post (c) $_{A, t-1}$	**0.035 (0.017)**	**(0.002, 0.068)**
C-TD-Post (c) $_{J, t-1}$	**-0.061 (0.023)**	**(-0.1, -0.016)**
TMS $_{A, t-1}$	**0.121 (0.013)**	**(0.094, 0.147)**
Price $_{A, t-1}$	-0.075 (0.1)	(-0.28, 0.127)
GT $_{A, t-1}$	-0.033 (0.066)	(-0.161, 0.097)
GPI $_{A, t-1}$	-0.046 (0.11)	(-0.265, 0.173)
CCI $_{A, t-1}$	**0.285 (0.153)**	**(0.164, 0.41)**

Table 78. Bayesian Estimation Results for Posts (Non-Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Post (a) $_{A, t-1}$	**0.028 (0.009)**	**(0.009, 0.047)**
C-F-Post (a) $_{J, t-1}$	**0.167 (0.022)**	**(0.124, 0.21)**
U-Post (a) $_{A, t-1}$	**-0.021 (0.008)**	**(-0.038, -0.004)**
C-U-Post (a) $_{J, t-1}$	**-0.039 (0.019)**	**(-0.076, -0.002)**
TD-Post (c) $_{A, t-1}$	-0.001 (0.015)	(-0.032, 0.03)
C-TD-Post (c) $_{J, t-1}$	-0.034 (0.019)	(-0.073, 0.004)
TMS $_{A, t-1}$	**0.12 (0.02)**	**(0.091, 0.15)**
Price $_{A, t-1}$	0.032 (0.074)	(-0.11, 0.176)
GT $_{A, t-1}$	**0.19 (0.037)**	**(0.12, 0.264)**
GPI $_{A, t-1}$	**0.303 (0.082)**	**(0.14, 0.462)**
CCI $_{A, t-1}$	**0.194 (0.047)**	**(0.1, 0.286)**

Figure 338. Assessment of Model Convergence for F-Post (a) (Luxury)

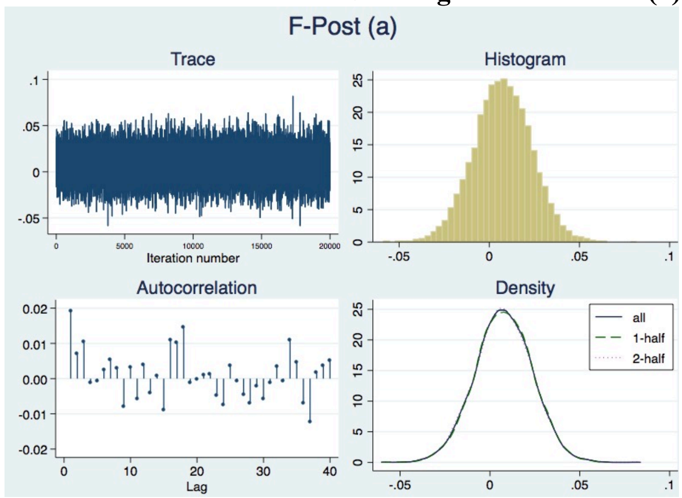


Figure 339. Assessment of Model Convergence for C-F-Post (a) (Luxury)

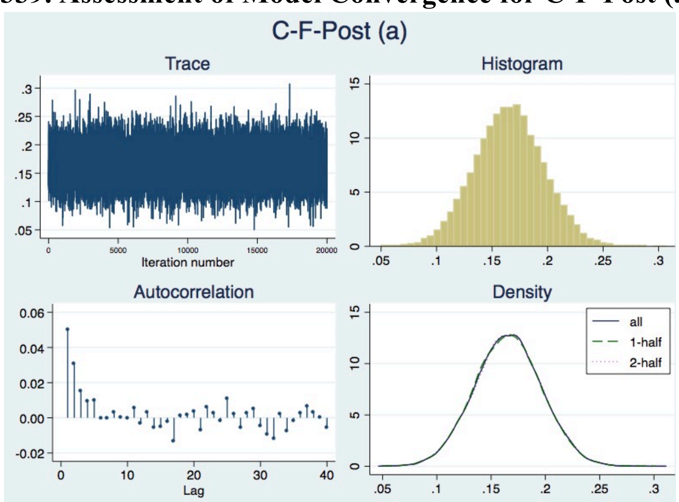


Figure 340. Assessment of Model Convergence for U-Post (a) (Luxury)

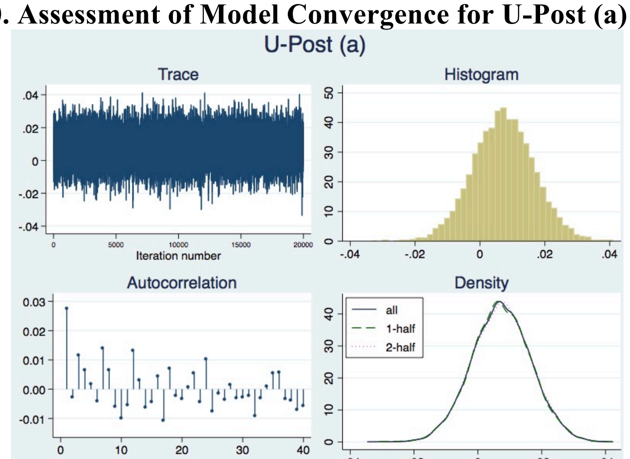


Figure 341. Assessment of Model Convergence for C-U-Post (a)

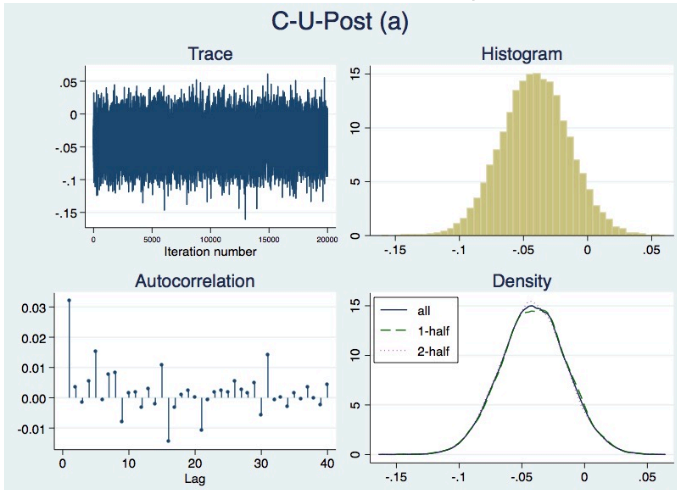


Figure 342. Assessment of Model Convergence for TD-Post (c) (Luxury)

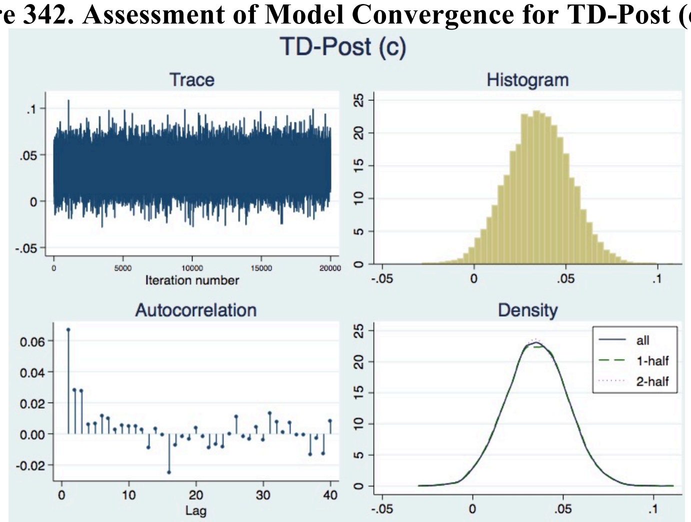


Figure 343. Assessment of Model Convergence for C-TD-Post (c) (Luxury)

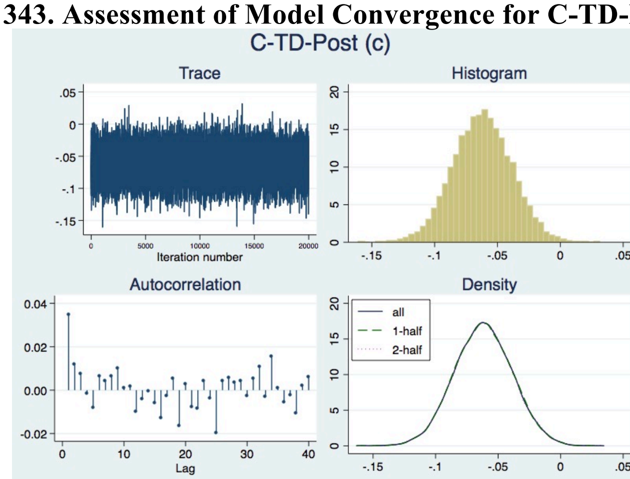


Figure 344. Assessment of Model Convergence for TMS (Luxury)

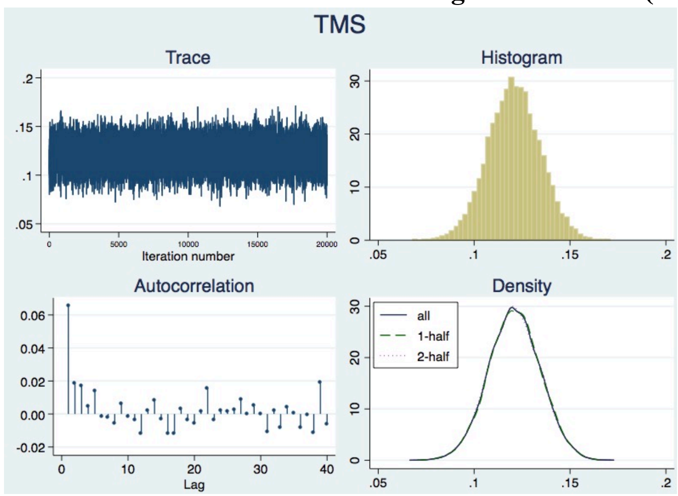


Figure 345. Assessment of Model Convergence for Price (Luxury)

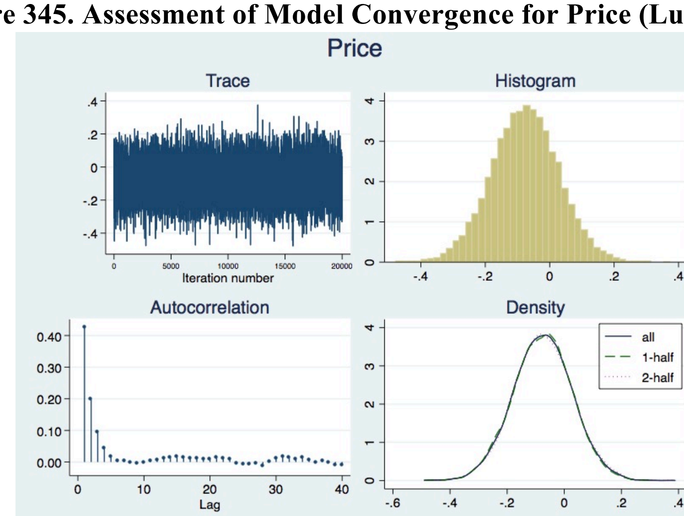


Figure 346. Assessment of Model Convergence for GT (Luxury)

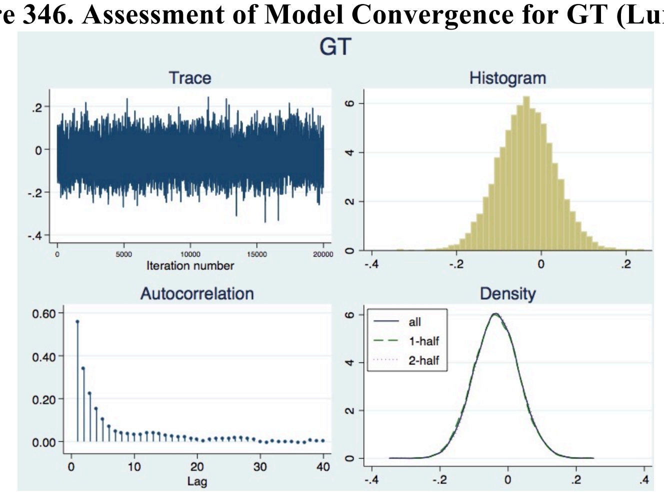


Figure 347. Assessment of Model Convergence for GPI (Luxury)

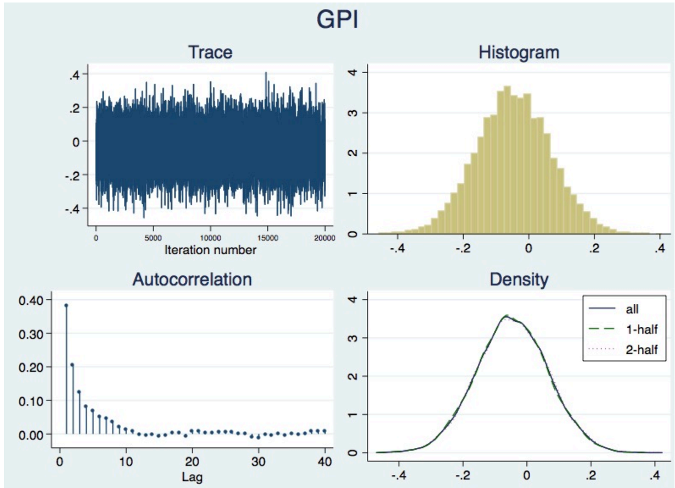


Figure 348. Assessment of Model Convergence for CCI (Luxury)

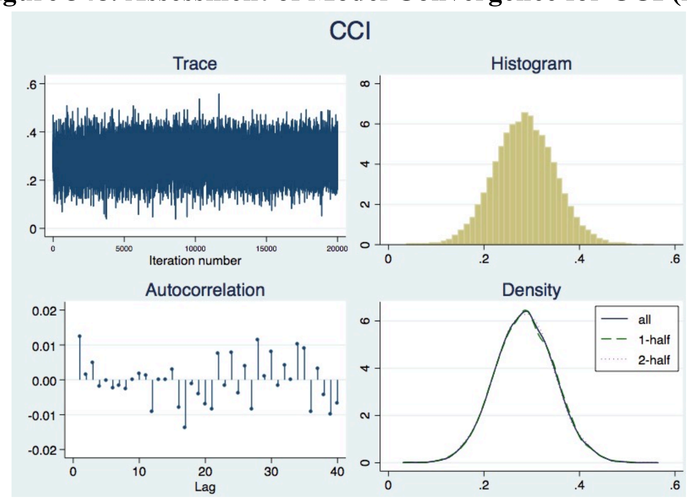


Figure 349. Assessment of Model Convergence for F-Post (a) (Non-Luxury)

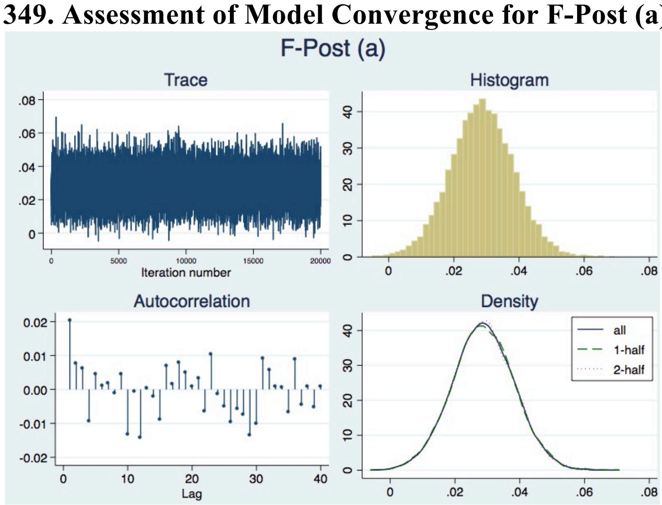


Figure 350. Assessment of Model Convergence for C-F-Post (a) (Non-Luxury)

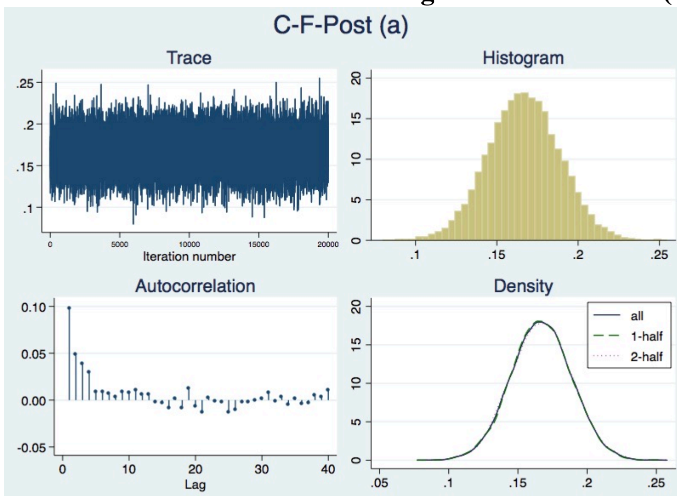


Figure 351. Assessment of Model Convergence for U-Post (a) (Non-Luxury)

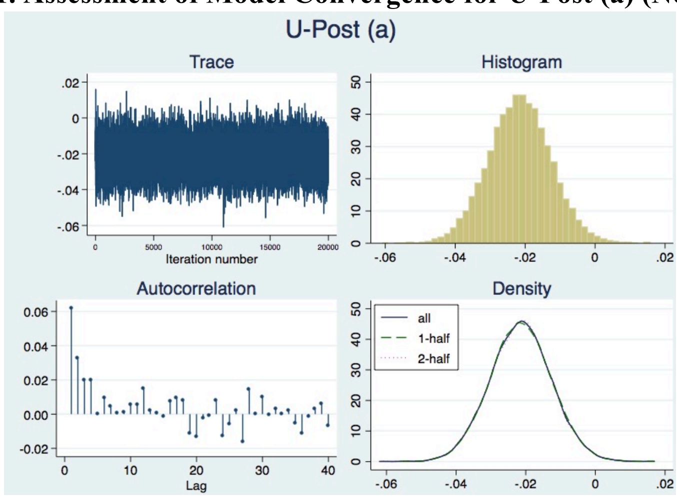


Figure 352. Assessment of Model Convergence for C-U-Post (a) (Non-Luxury)

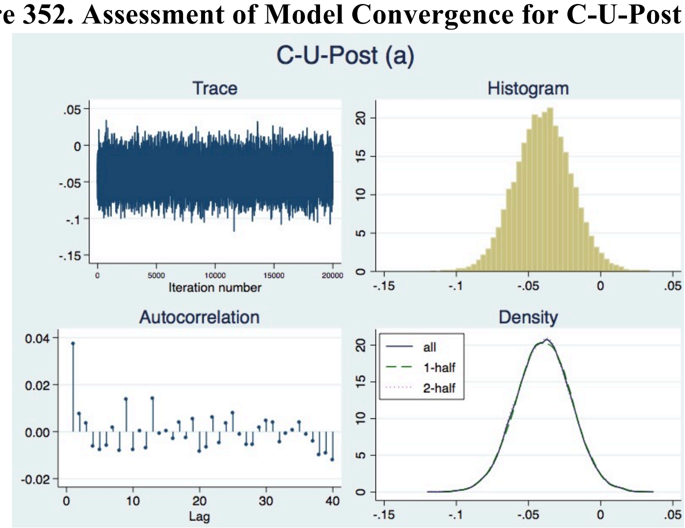


Figure 353. Assessment of Model Convergence for TD-Post (c) (Non-Luxury)

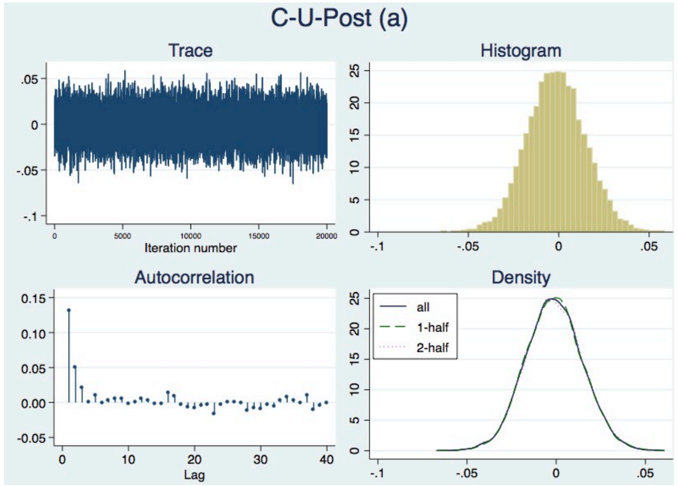


Figure 354. Assessment of Model Convergence for C-TD-Post (c) (Non-Luxury)

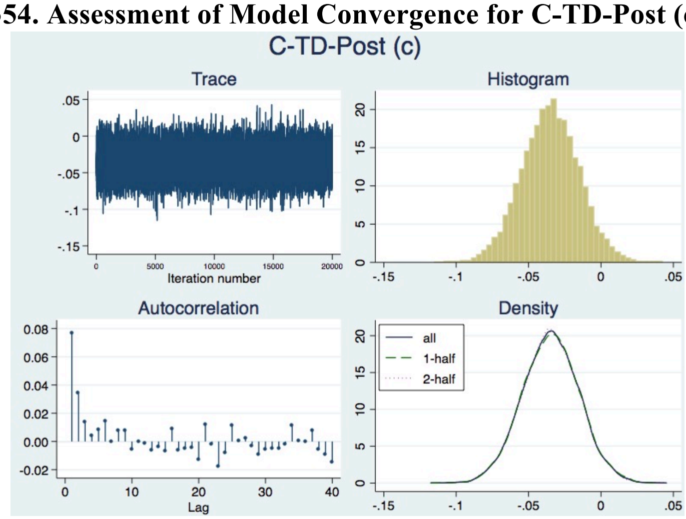


Figure 355. Assessment of Model Convergence for TMS (Non-Luxury)

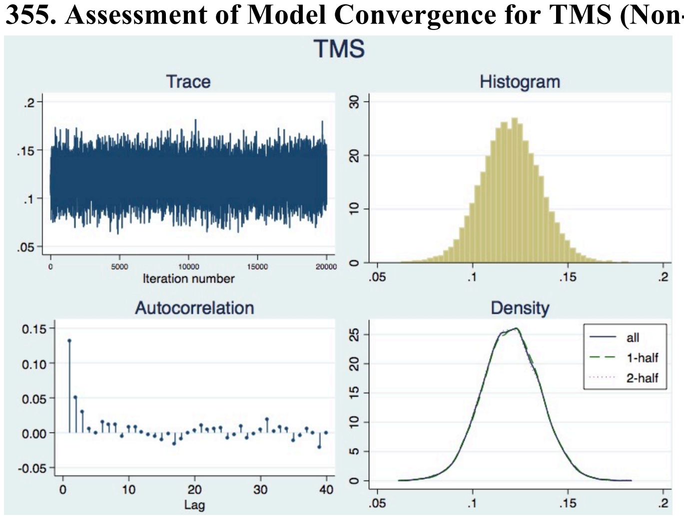


Figure 356. Assessment of Model Convergence for Price (Non-Luxury)

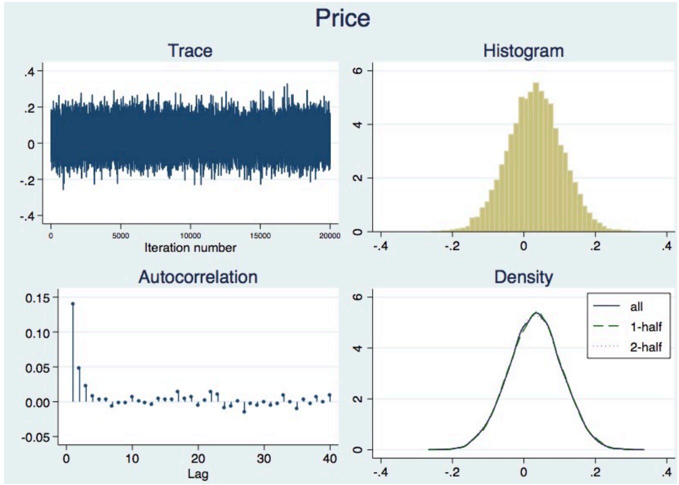


Figure 357. Assessment of Model Convergence for GT (Non-Luxury)

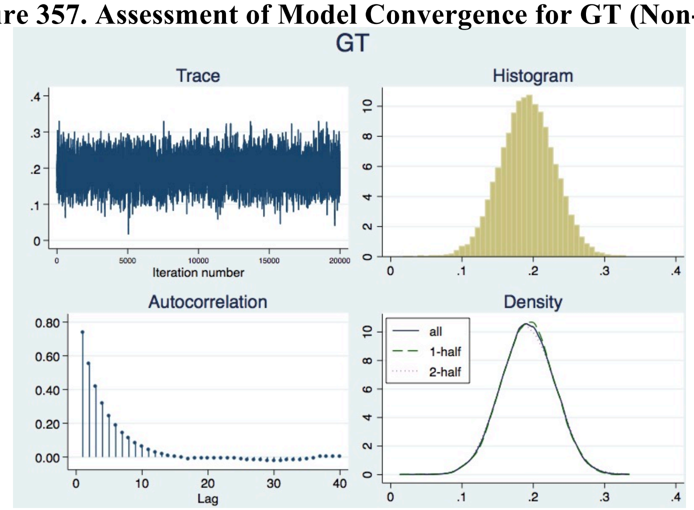


Figure 358. Assessment of Model Convergence for GPI (Non-Luxury)

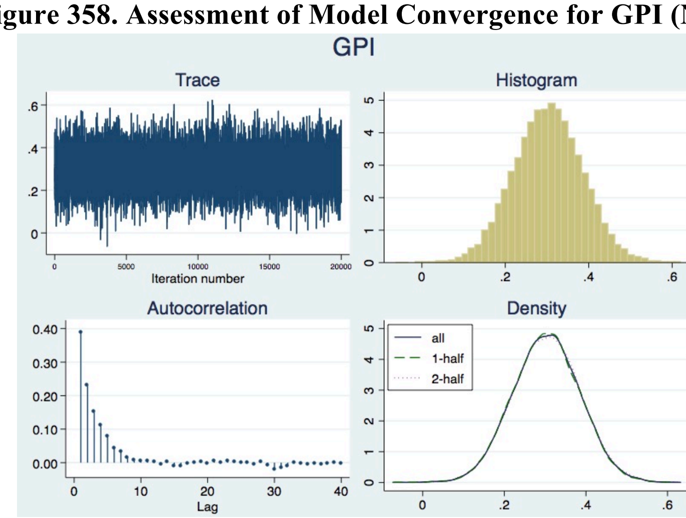
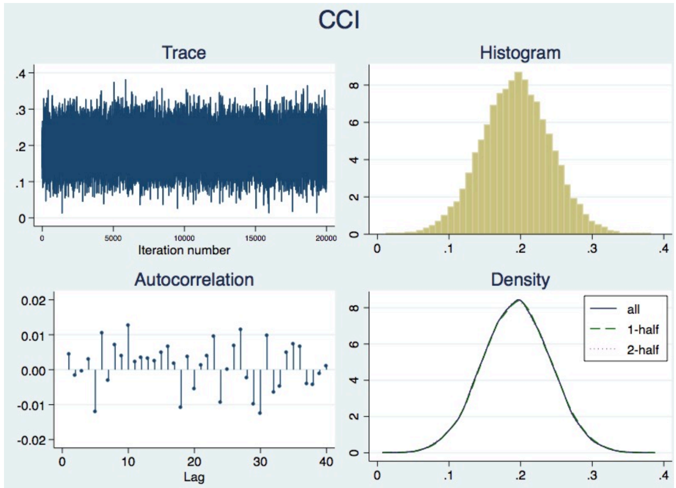


Figure 359. Assessment of Model Convergence for CCI (Non-Luxury)



Tables 79 to 80 show my sample split Bayesian estimation results at the like level (i.e., "Like" associated with posts at Facebook and test drive post) for luxury and non-luxury groups, respectively. In these models, I also ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 360 to 381) suggested that the model specification converged for each relationship.

In this set of analysis, I find that C-F-Like (a) has positive spillover effects on offline car sales of the focal brand for two groups, supporting my H2. For the luxury group, U-Like (a) also has the positive impact on offline car sales of the focal brand, supporting my H1. On the other hand, C-U-Like (a) also shows positive spillover effects on offline car sales of the focal brand, supporting H2. Finally, online WOM at the stage of consideration is not very effective in this particular relationship.

Table 79. Bayesian Estimation Results for Likes (Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	-0.011 (0.007)	(-0.025, 0.003)
C-F-Like (a) $_{J, t-1}$	**0.077 (0.016)**	**(0.046, 0.1)**
U-Like (a) $_{A, t-1}$	**0.016 (0.005)**	**(0.006, 0.026)**
C-U-Like (a) $_{J, t-1}$	-0.006 (0.015)	(-0.035, 0.023)
TD-Post (c) $_{A, t-1}$	0.024 (0.016)	(-0.008, 0.055)
C-TD-Post (c) $_{J, t-1}$	-0.028 (0.021)	(-0.069, 0.013)
TMS $_{A, t-1}$	**0.11 (0.013)**	**(0.09, 0.141)**
Price $_{A, t-1}$	-0.045 (0.1)	(-0.242, 0.153)
GT $_{A, t-1}$	-0.004 (0.064)	(-0.131, 0.122)
GPI $_{A, t-1}$	-0.172 (0.1)	(-0.37, 0.023)
CCI $_{A, t-1}$	**0.137 (0.064)**	**(0.012, 0.263)**

Table 80. Bayesian Estimation Results for Likes (Non-Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Like (a) $_{A, t-1}$	-0.0007 (0.006)	(-0.013, 0.011)
C-F-Like (a) $_{J, t-1}$	**0.061 (0.012)**	**(0.037, 0.084)**
U-Like (a) $_{A, t-1}$	**-0.012 (0.004)**	**(-0.021, -0.003)**
C-U-Like (a) $_{J, t-1}$	**0.04 (0.011)**	**(0.017, 0.062)**
TD-Post (c) $_{A, t-1}$	0.005 (0.02)	(-0.02, 0.035)
C-TD-Post (c) $_{J, t-1}$	-0.029 (0.018)	(-0.065, 0.007)
TMS $_{A, t-1}$	**0.11 (0.014)**	**(0.085, 0.141)**
Price $_{A, t-1}$	-0.038 (0.072)	(-0.177, 0.1)
GT $_{A, t-1}$	**0.239 (0.035)**	**(0.169, 0.31)**
GPI $_{A, t-1}$	0.05 (0.072)	(-0.09, 0.19)
CCI $_{A, t-1}$	0.045 (0.048)	(-0.049, 0.139)

Figure 360. Assessment of Model Convergence for F-Like (a)

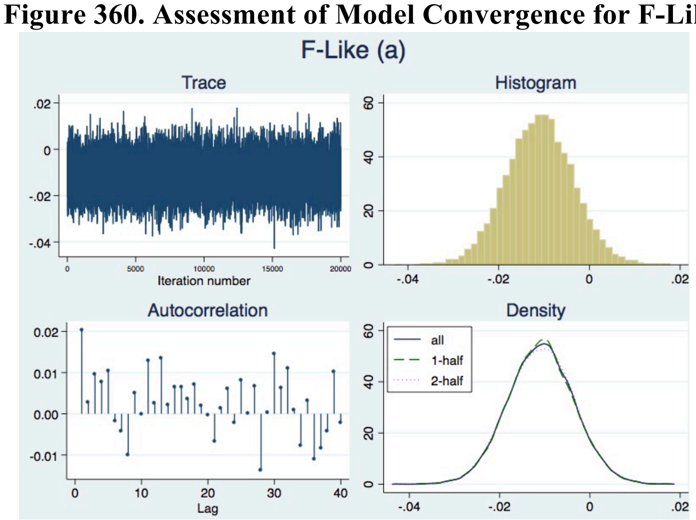


Figure 361. Assessment of Model Convergence for C-F-Like (a)

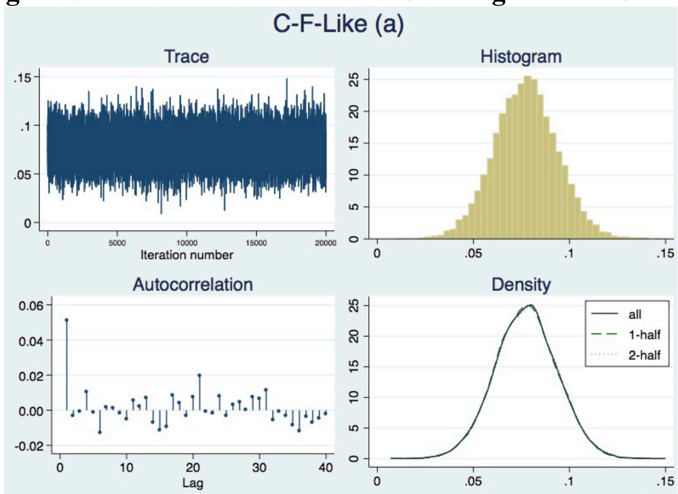


Figure 362. Assessment of Model Convergence for U-Like (a)

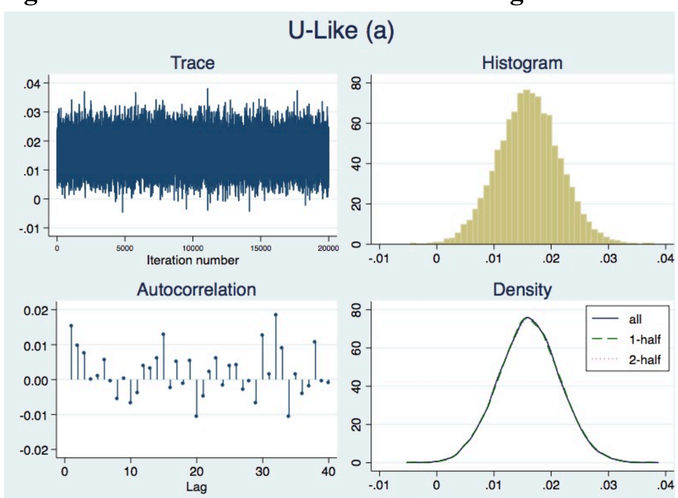


Figure 363. Assessment of Model Convergence for C-U-Like (a)

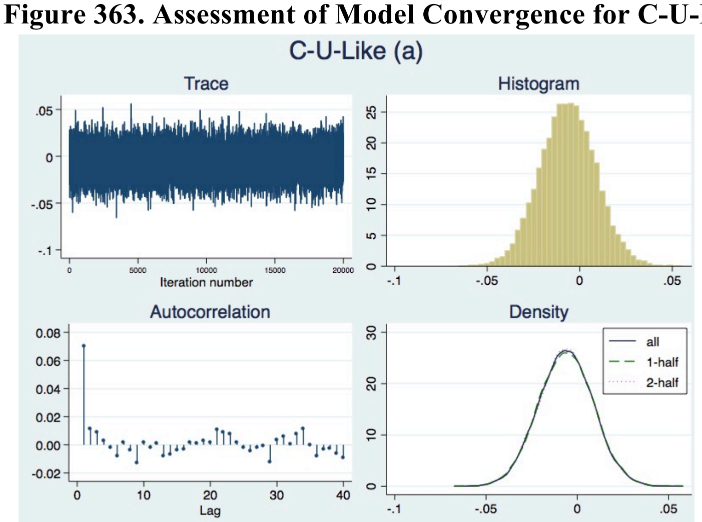


Figure 364. Assessment of Model Convergence for TD-Post (c) (Luxury)

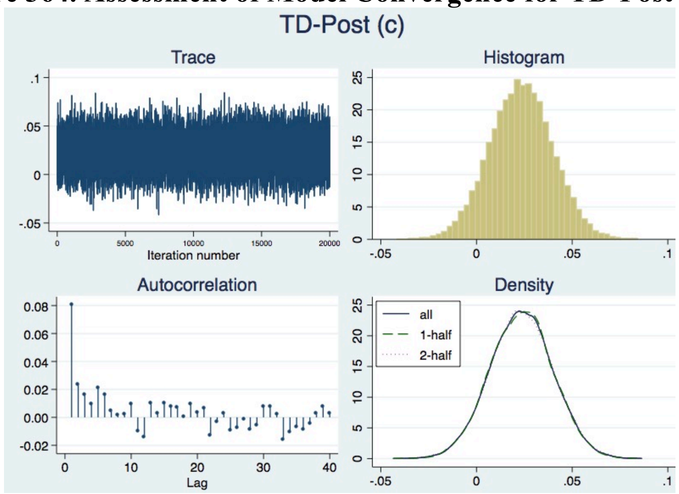


Figure 365. Assessment of Model Convergence for C-TD-Post (c)

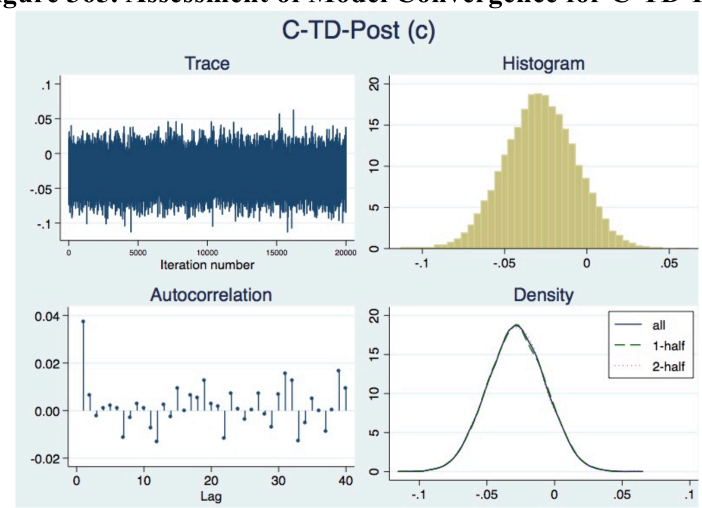


Figure 366. Assessment of Model Convergence for TMS (Luxury)

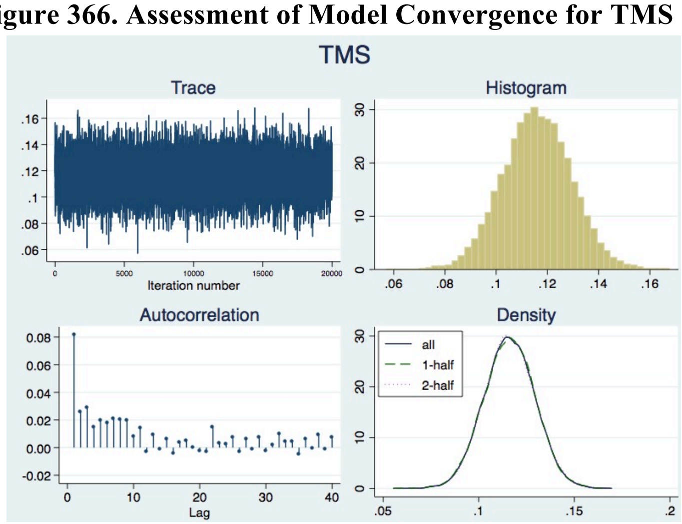


Figure 367. Assessment of Model Convergence for Price (Luxury)

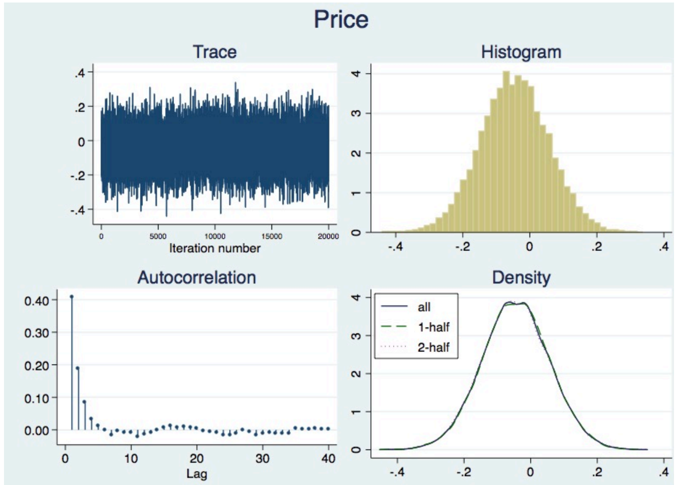


Figure 368. Assessment of Model Convergence for GT (Luxury)

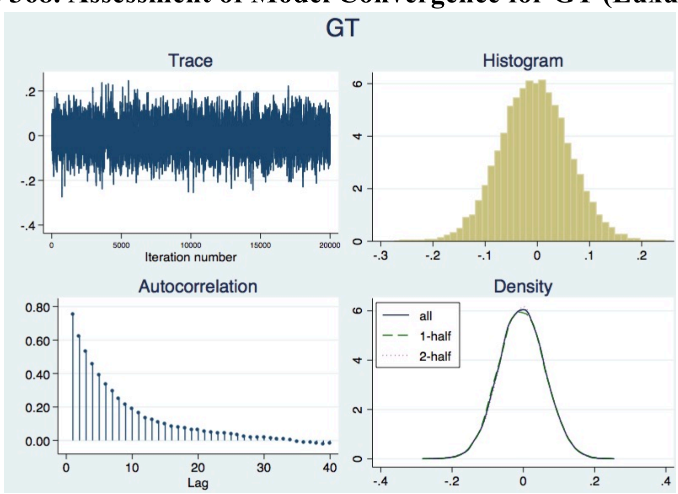


Figure 369. Assessment of Model Convergence for GPI (Luxury)

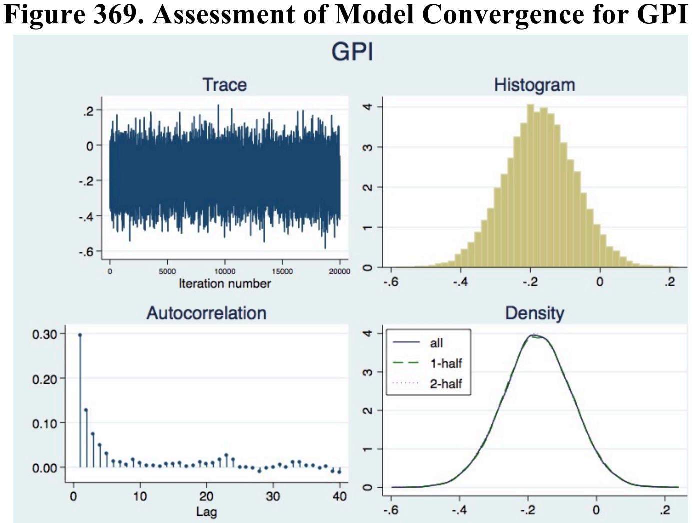


Figure 370. Assessment of Model Convergence for CCI (Luxury)

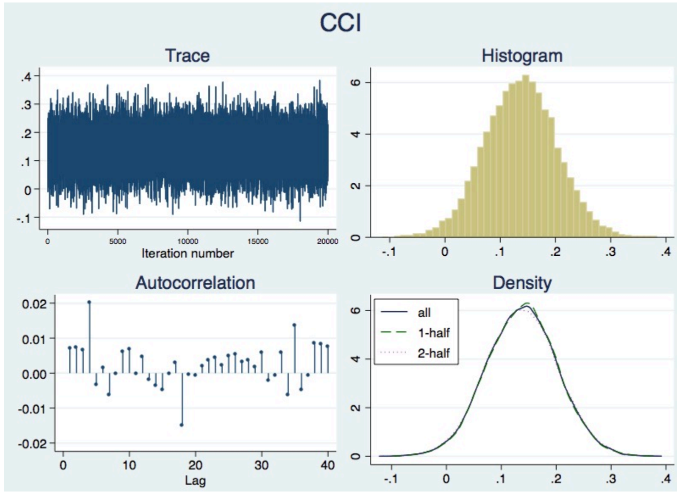


Figure 371. Assessment of Model Convergence for F-Like (a) (Non-Luxury)

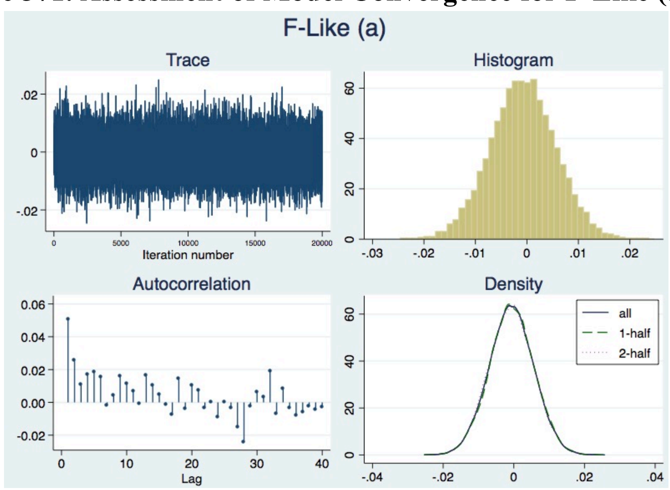


Figure 372. Assessment of Model Convergence for C-F-Like (a) (Non-Luxury)

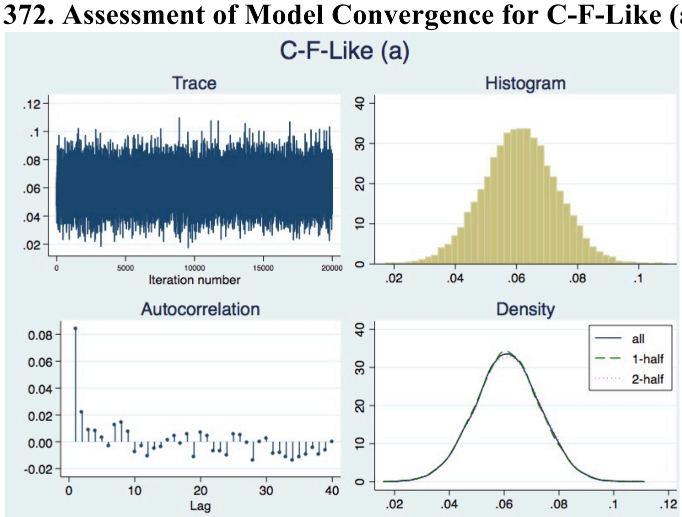


Figure 373. Assessment of Model Convergence for U-Like (a) (Non-Luxury)

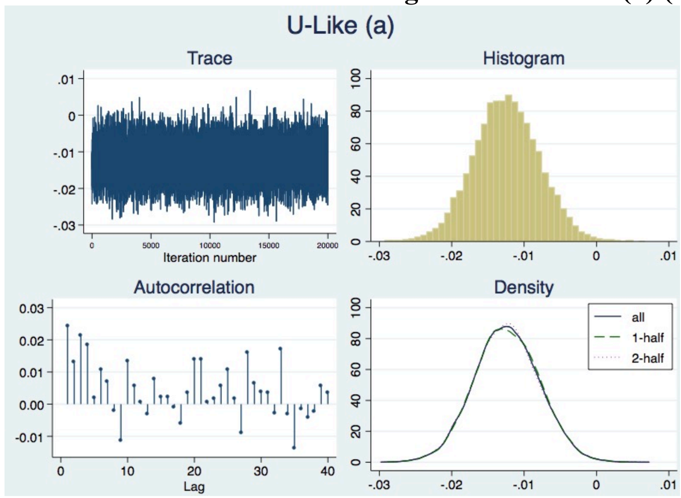


Figure 374. Assessment of Model Convergence for C-U-Like (a) (Non-Luxury)

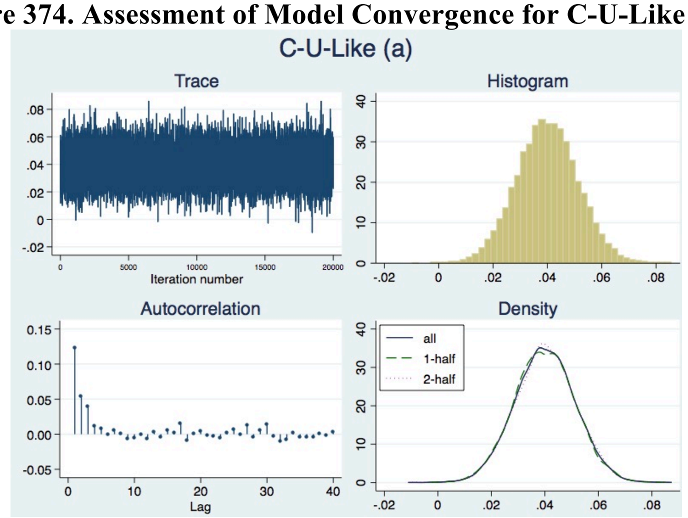


Figure 375. Assessment of Model Convergence for TD-Post (c) (Non-Luxury)

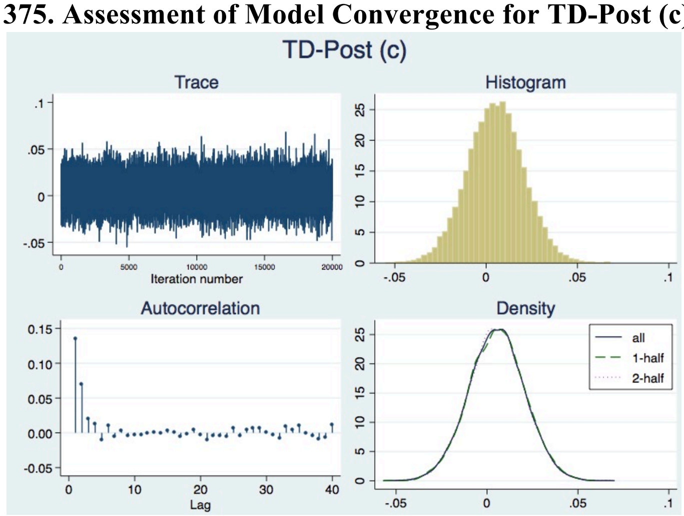


Figure 376. Assessment of Model Convergence for C-TD-Post (c) (Non-Luxury)

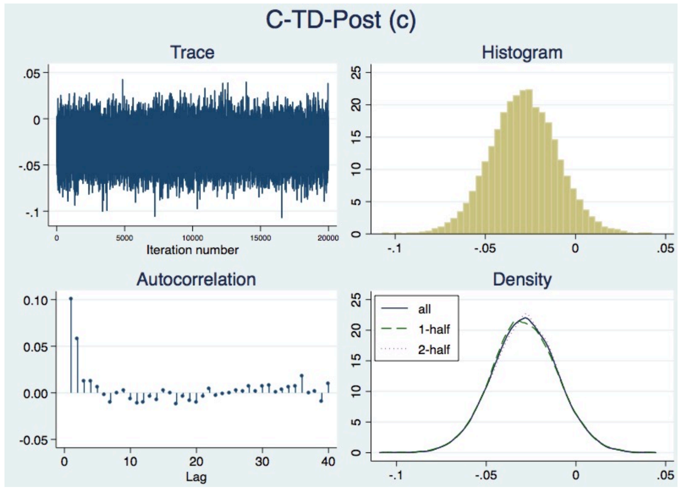


Figure 377. Assessment of Model Convergence for TMS (Non-Luxury)

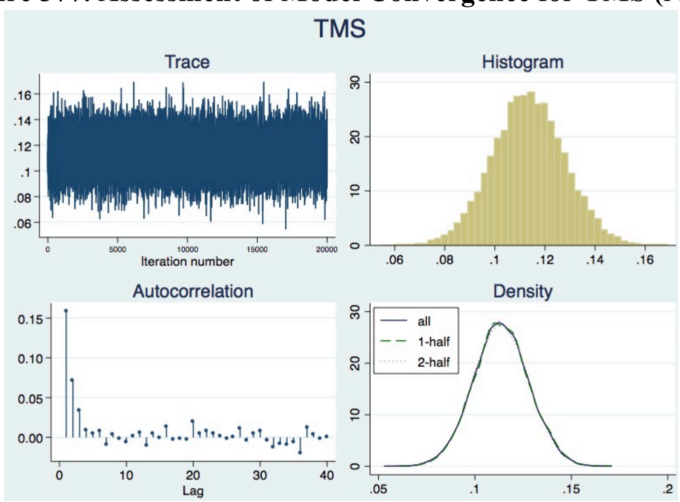


Figure 378. Assessment of Model Convergence for Price (Non-Luxury)

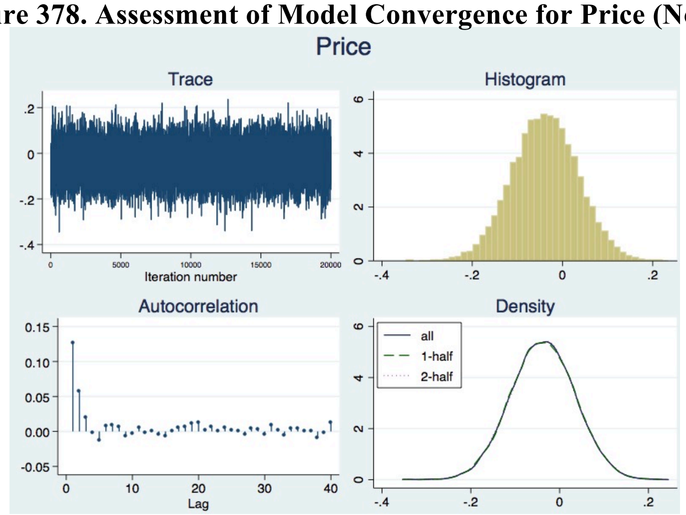


Figure 379. Assessment of Model Convergence for GT (Non-Luxury)

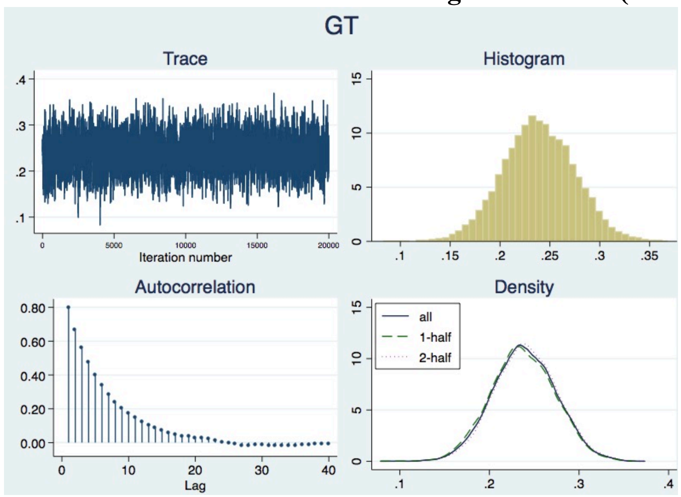


Figure 380. Assessment of Model Convergence for GPI (Non-Luxury)

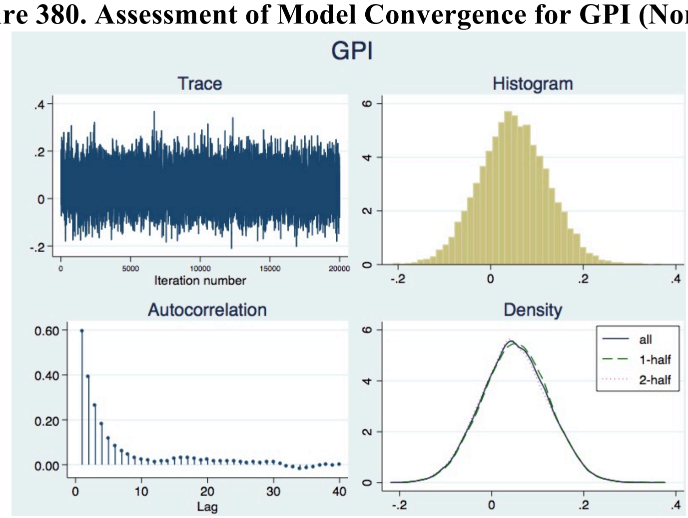
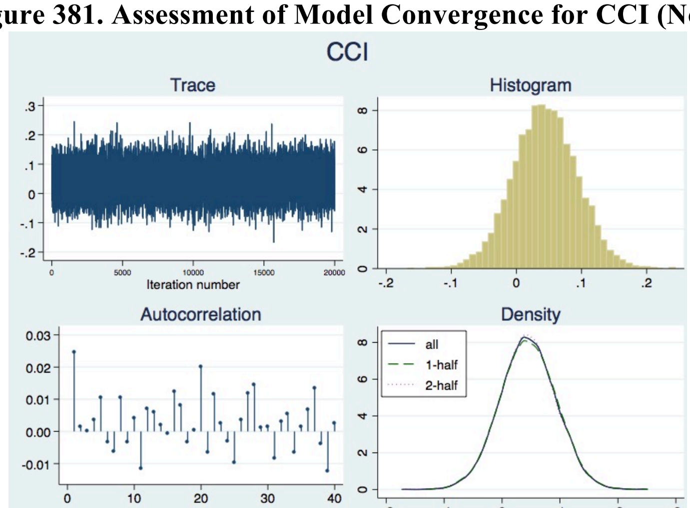


Figure 381. Assessment of Model Convergence for CCI (Non-Luxury)



Tables 81 to 82 show my sample split Bayesian estimation results at the comment level (i.e., “Comment” associated with posts at Facebook and test drive post) for luxury and non-luxury group, respectively. I ran the MCMC chain for 1,849,921 iterations and, I discarded the first 250,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every eightieth iterations for the remaining iterations. The assessment of model convergence (see Figures 382 to 403) suggested that the model specification converged for each relationship.

The results in the comment level are consistent with main results (see Table 43) with some differences. For example, I find that for the luxury group, the volume of comment associated with competitors’ user posts (U-Comment (a)) has the positive impact on offline car sales of the focal brand, supporting H1. Furthermore, I also observe that C-U-Comment (a) has positive spillover effects on offline car sales of the focal brand for the non-luxury group only, supporting my H2. Regarding online WOM at the stage of consideration, similar to main results, I find negative spillover effects (C-TD-Post (c) for these two different groups.

Table 81. Bayesian Estimation Results for Comments (Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	-0.013 (0.008)	(-0.03, 0.002)
C-F-Comment (a) $_{J, t-1}$	**0.124 (0.019)**	**(0.088, 0.161)**
U-Comment (a) $_{A, t-1}$	**0.018 (0.007)**	**(-0.014, 0.014)**
C-U-Comment (a) $_{J, t-1}$	-0.009 (0.02)	(0.004, 0.032)
TD-Post (c) $_{A, t-1}$	0.018 (0.016)	(-0.013, 0.049)
C-TD-Post (c) $_{J, t-1}$	**-0.048 (0.021)**	**(-0.09, -0.007)**
TMS $_{A, t-1}$	**0.115 (0.013)**	**(0.089, 0.141)**
Price $_{A, t-1}$	-0.077 (0.1)	(-0.28, 0.11)
GT $_{A, t-1}$	0.001 (0.064)	(-0.12, 0.13)
GPI $_{A, t-1}$	-0.089 (0.091)	(-0.26, 0.09)
CCI $_{A, t-1}$	**0.22 (0.059)**	**(0.1, 0.336)**

Table 82. Bayesian Estimation Results for Comments (Non-Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Comment (a) $_{A, t-1}$	0.008 (0.007)	(-0.005, 0.021)
C-F-Comment (a) $_{J, t-1}$	**0.09 (0.014)**	**(0.063, 0.12)**
U-Comment (a) $_{A, t-1}$	**-0.019 (0.006)**	**(-0.03, -0.008)**
C-U-Comment (a) $_{J, t-1}$	**0.027 (0.014)**	**(0.0002, 0.053)**
TD-Post (c) $_{A, t-1}$	0.0009 (0.015)	(-0.029, 0.032)
C-TD-Post (c) $_{J, t-1}$	**-0.043 (0.027)**	**(-0.08, -0.006)**
TMS $_{A, t-1}$	**0.114 (0.015)**	**(0.085, 0.143)**
Price $_{A, t-1}$	0.031 (0.073)	(-0.11, 0.174)
GT $_{A, t-1}$	**0.23 (0.038)**	**(0.157, 0.306)**
GPI $_{A, t-1}$	**0.31 (0.068)**	**(0.173, 0.443)**
CCI $_{A, t-1}$	**0.189 (0.046)**	**(0.097, 0.279)**

Figure 382. Assessment of Model Convergence for F-Comment (a) (Luxury)

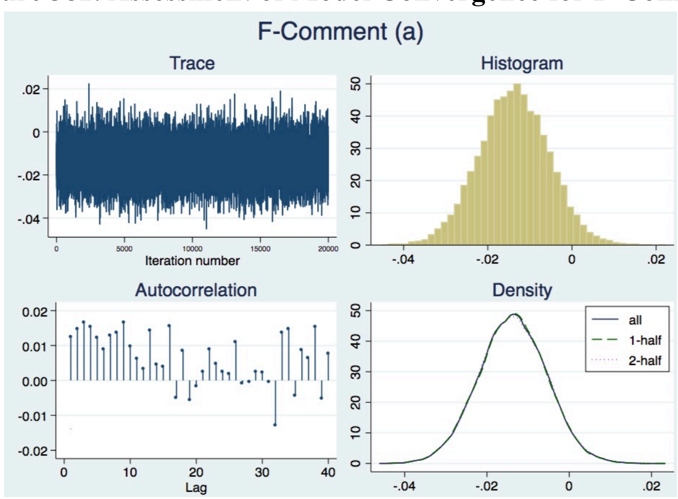


Figure 383. Assessment of Model Convergence for C-F-Comment (a) (Luxury)

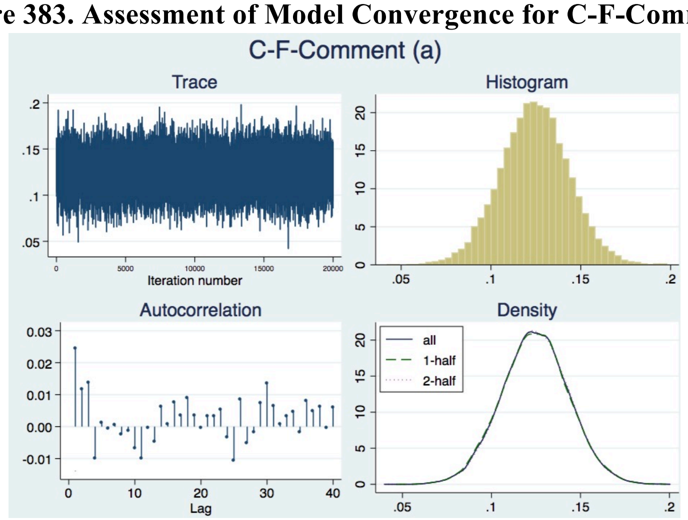


Figure 384. Assessment of Model Convergence for U-Comment (a) (Luxury)

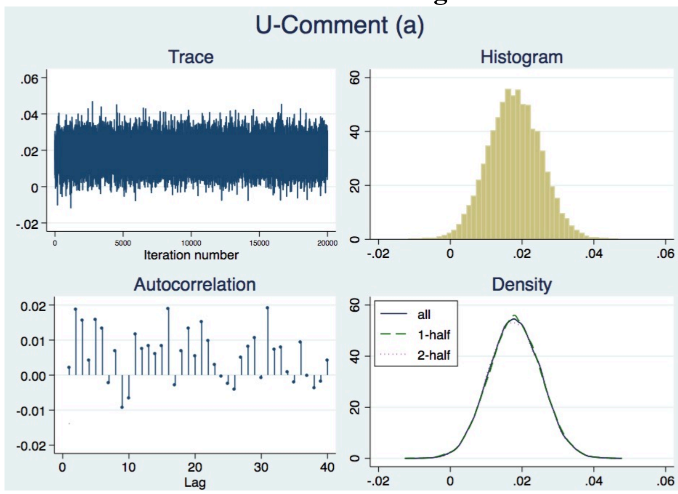


Figure 385. Assessment of Model Convergence for C-U-Comment (a) (Luxury)

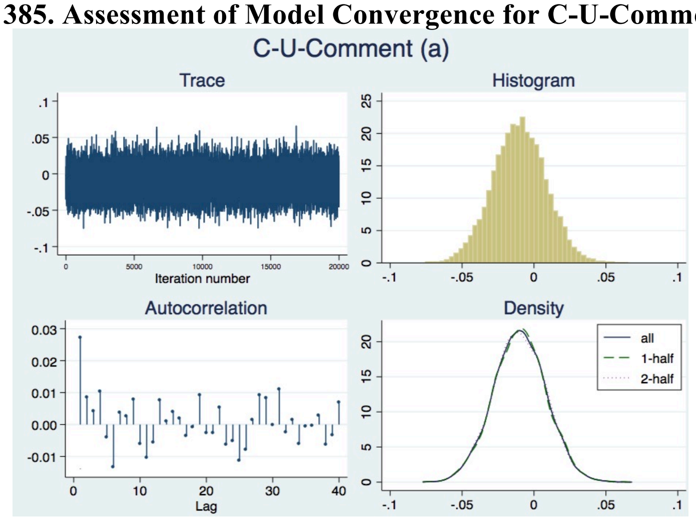


Figure 386. Assessment of Model Convergence for TD-Post (c) (Luxury)

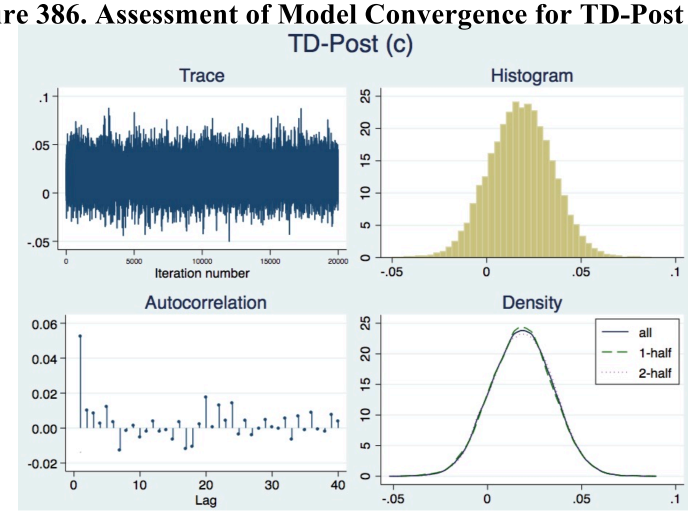


Figure 387. Assessment of Model Convergence for C-TD-Post (c) (Luxury)

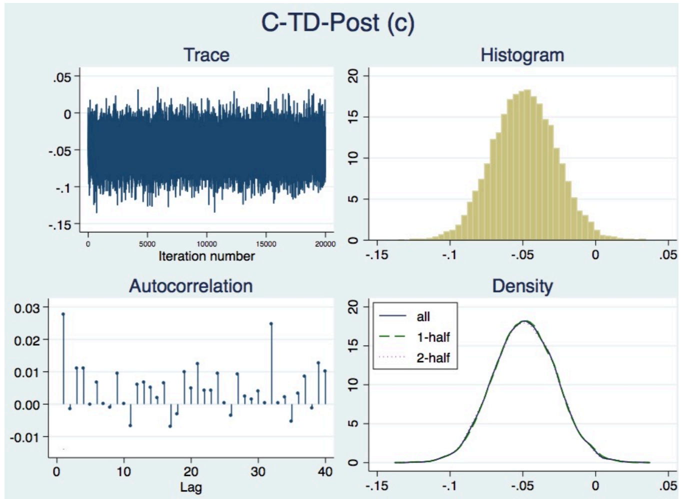


Figure 388. Assessment of Model Convergence for TMS (Luxury)

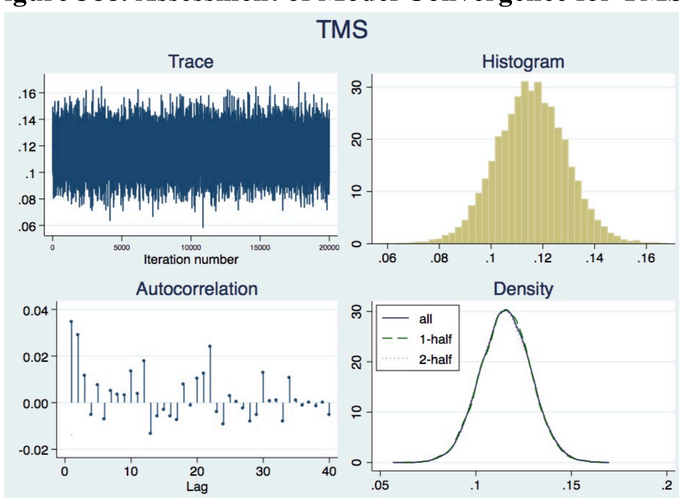


Figure 389. Assessment of Model Convergence for Price (Luxury)

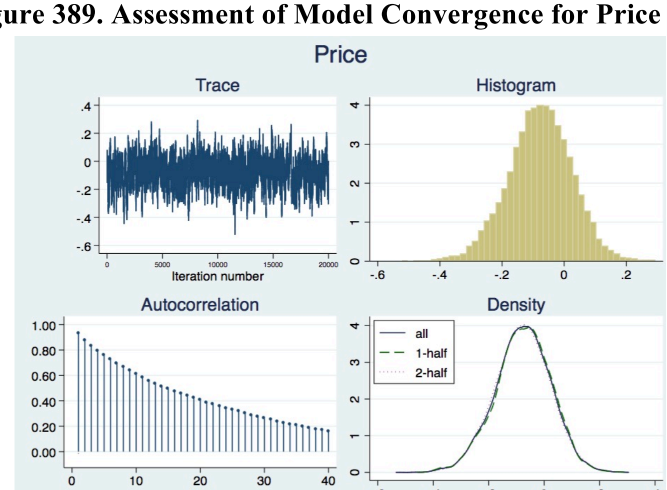


Figure 390. Assessment of Model Convergence for GT (Luxury)

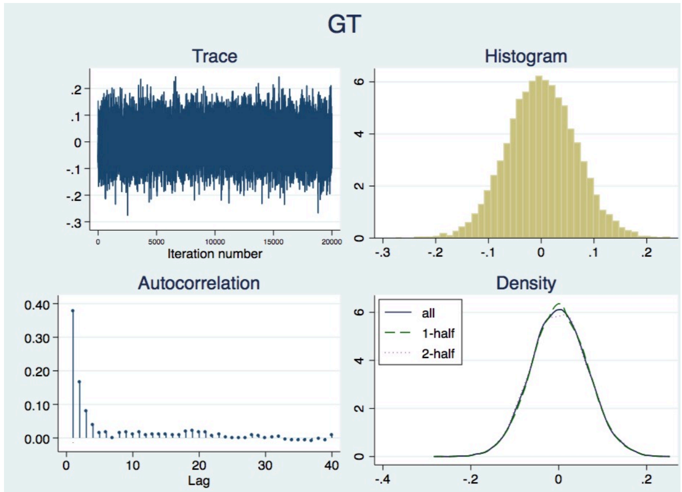


Figure 391. Assessment of Model Convergence for GPI (Luxury)

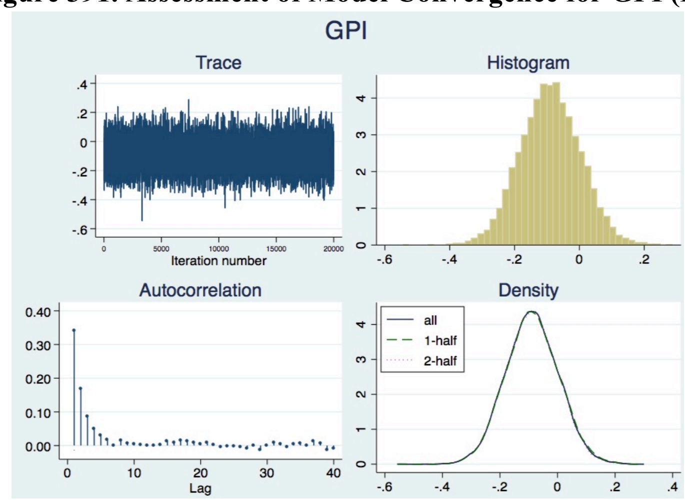


Figure 392. Assessment of Model Convergence for CCI (Luxury)

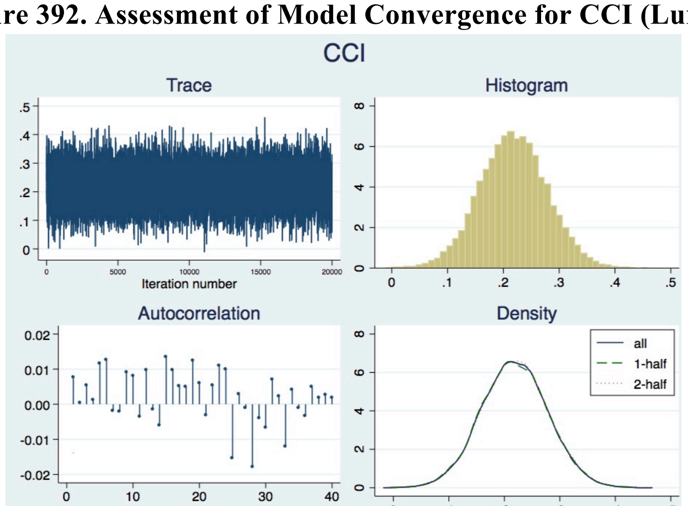


Figure 393. Assessment of Model Convergence for F-Comment (a) (Non-Luxury)

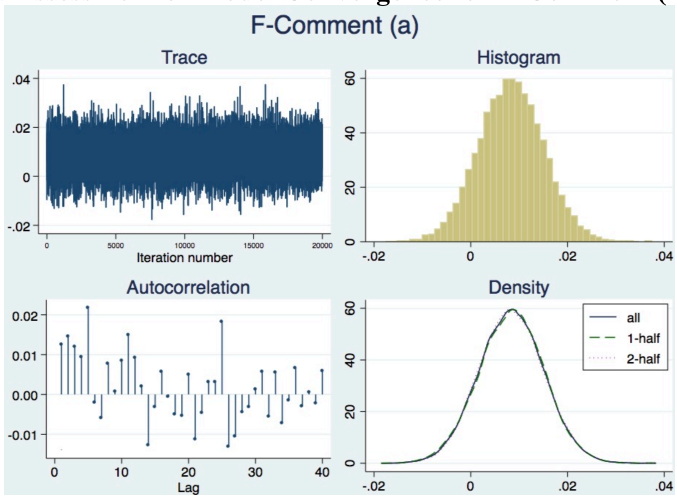


Figure 394. Assessment of Model Convergence for C-F-Comment (a) (Non-Luxury)

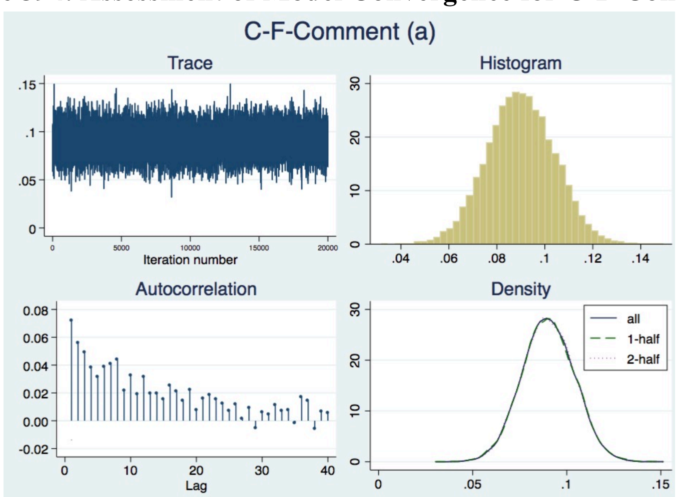


Figure 395. Assessment of Model Convergence for U-Comment (a) (Non-Luxury)

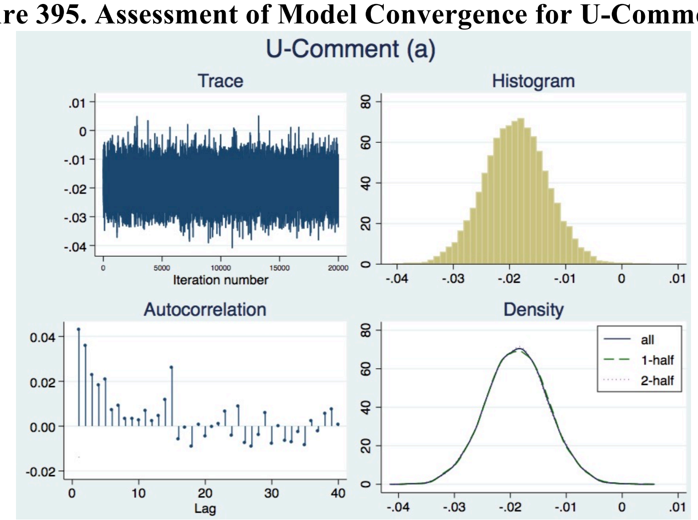


Figure 396. Assessment of Model Convergence for C-U-Comment (a) (Non-Luxury)

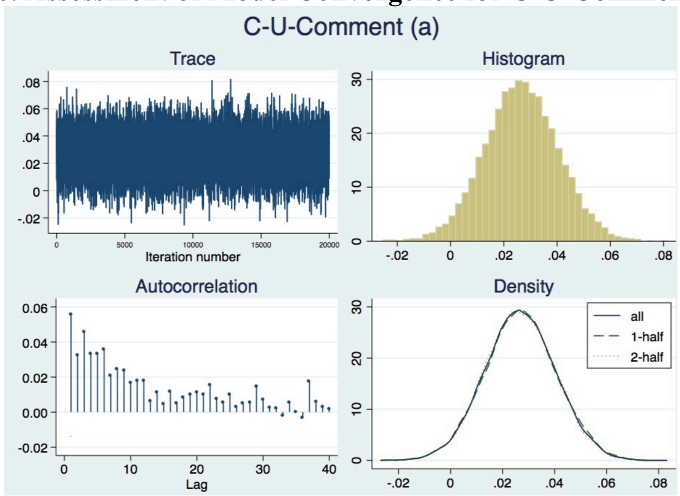


Figure 397. Assessment of Model Convergence for TD-Post (c) (Non-Luxury)

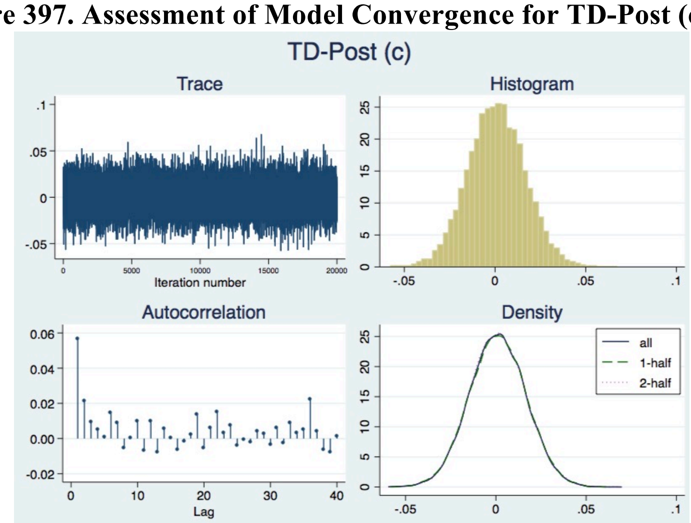


Figure 398. Assessment of Model Convergence for C-TD-Post (c) (Non-Luxury)

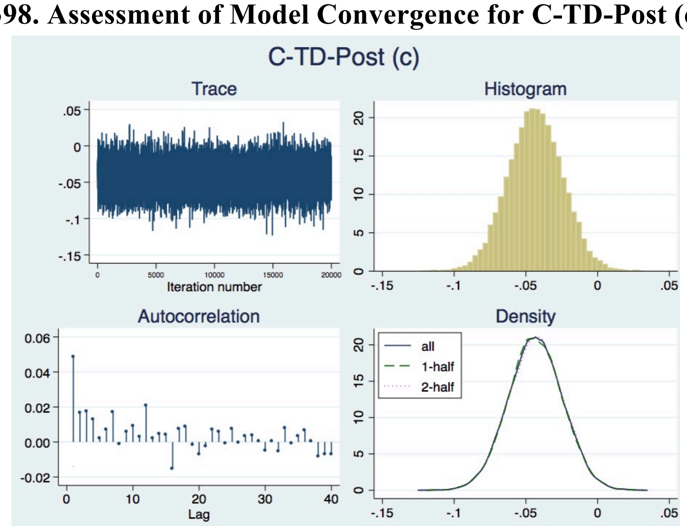


Figure 399. Assessment of Model Convergence for TMS (Non-Luxury)

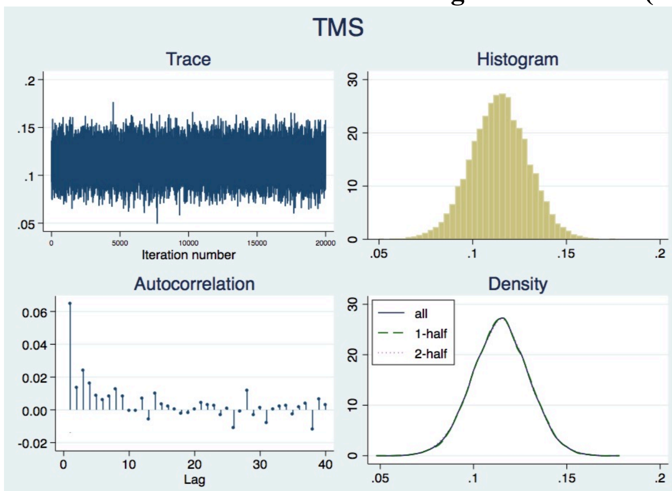


Figure 400. Assessment of Model Convergence for Price (Non-Luxury)

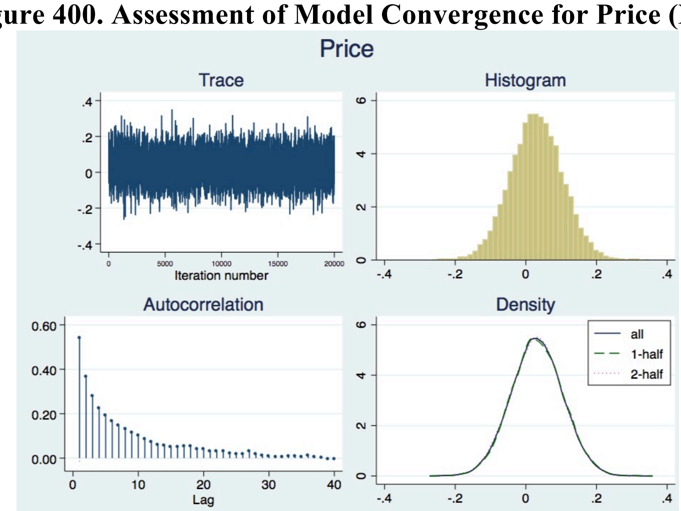


Figure 401. Assessment of Model Convergence for GT (Non-Luxury)

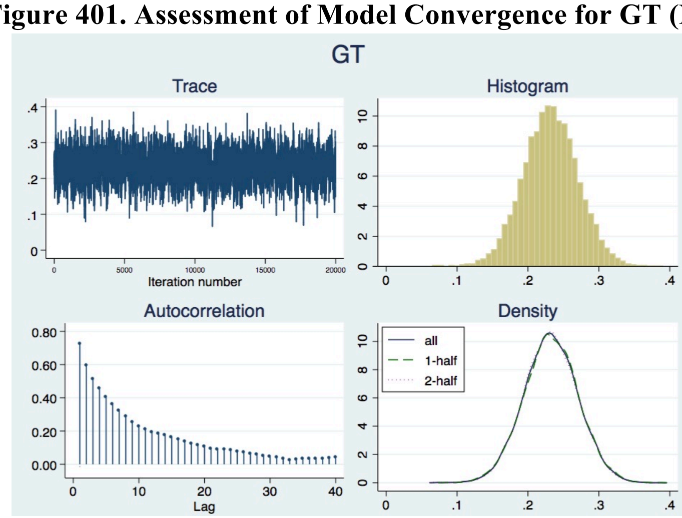


Figure 402. Assessment of Model Convergence for GPI (Non-Luxury)

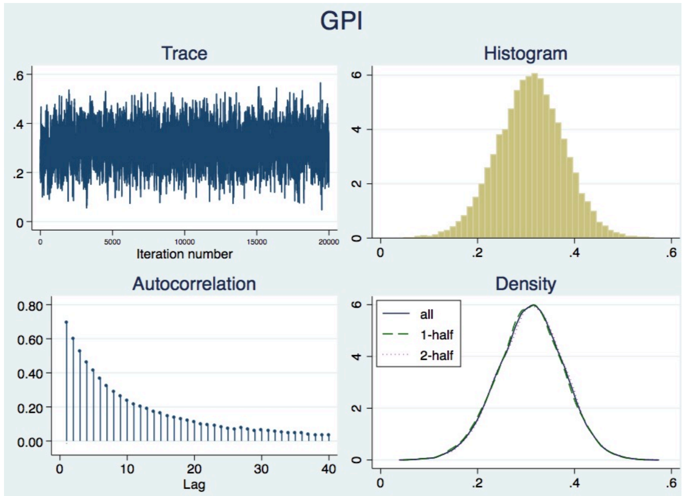
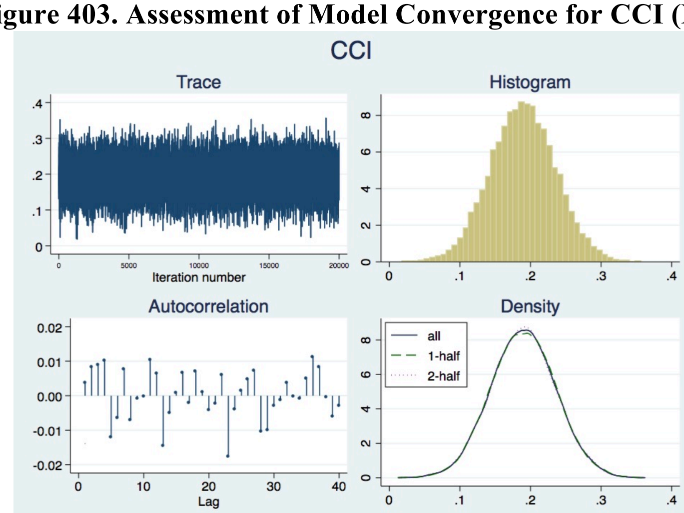


Figure 403. Assessment of Model Convergence for CCI (Non-Luxury)



Tables 83 to 84 show my sample split Bayesian estimation results at the share level (i.e., "Share" associated with posts at Facebook and test drive post) for luxury and non-luxury group, respectively. In these models, I ran the MCMC chain for 999,961 iterations and, I discarded the first 200,000 iterations to ensure convergence. Because of the high auto-correlation of parameter posterior draws, I thinned the sampling chain and kept one from every fortieth iterations for the remaining iterations. The assessment of model convergence (see Figures 404 to 425) suggested that the model specification converged for each relationship.

First, I find that the results for the luxury group are consistent with main results (see Table 44). That is, C-F-Share (a) has positive spillover effects on offline car sales of the focal brand and TD-Post (c) also positively influences offline car sales of the focal brand, thereby supporting both H2 and H3. However, for the non-luxury group, I only observe that C-F-Share (a) has positive spillover effects on offline car sales of the focal brand, supporting H3.

To summarize, a set of split analysis suggests that when leveraging online WOM to help purchase decisions, origin of brand, market structure of brand, and price factor of brand do vary dynamics between online WOM about the focal brand, online WOM about competitors, and offline car sales of the focal brand. Furthermore, the results provide further evidence that no every mechanism at Facebook (i.e., post, like, comment, and share) has the equal impact on offline car sales and these different mechanisms also influence how customers appreciate online WOM at the stage of consideration. Table 85 shows the summarized results of this study.

Table 83. Bayesian Estimation Results for Shares (Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	-0.006 (0.006)	(-0.017, 0.004)
C-F-Share (a) $_{J, t-1}$	**0.052 (0.011)**	**(0.03, 0.073)**
U-Share (a) $_{A, t-1}$	0.0009 (0.006)	(-0.011, 0.013)
C-U-Share (a) $_{J, t-1}$	-0.02 (0.011)	(-0.043, 0.002)
TD-Post (c) $_{A, t-1}$	**0.039 (0.016)**	**(0.005, 0.071)**
C-TD-Post (c) $_{J, t-1}$	-0.023 (0.024)	(-0.007, 0.025)
TMS $_{A, t-1}$	**0.12 (0.014)**	**(0.095, 0.148)**
Price $_{A, t-1}$	-0.052 (0.105)	(-0.257, 0.155)
GT $_{A, t-1}$	0.003 (0.067)	(-0.136, 0.137
GPI $_{A, t-1}$	**0.243 (0.118)**	**(0.01, 0.472)**
CCI $_{A, t-1}$	**0.283 (0.06)**	**(0.166, 0.401)**

Table 84. Bayesian Estimation Results for Shares (Non-Luxury)

Parameters	Sales $_{A, t}$	
	Posterior Mean	95% Credible Level
F-Share (a) $_{A, t-1}$	0.004 (0.004)	(-0.003, 0.011)
C-F-Share (a) $_{J, t-1}$	**0.045 (0.008)**	**(0.029, 0.059)**
U-Share (a) $_{A, t-1}$	0.007 (0.006)	(-0.0009, 0.015)
C-U-Share (a) $_{J, t-1}$	-0.013 (0.008)	(-0.028, 0.002)
TD-Post (c) $_{A, t-1}$	0.003 (0.015)	(-0.026, 0.033)
C-TD-Post (c) $_{J, t-1}$	-0.002 (0.019)	(-0.039, 0.036)
TMS $_{A, t-1}$	**0.11 (0.015)**	**(0.084, 0.141)**
Price $_{A, t-1}$	-0.024 (0.072)	(-0.165, 0.118)
GT $_{A, t-1}$	**0.178 (0.036)**	**(0.11, 0.248)**
GPI $_{A, t-1}$	**0.311 (0.083)**	**(0.144, 0.474)**
CCI $_{A, t-1}$	**0.179 (0.044)**	**(0.091, 0.265)**

Figure 404. Assessment of Model Convergence for F-Share (a) (Luxury)

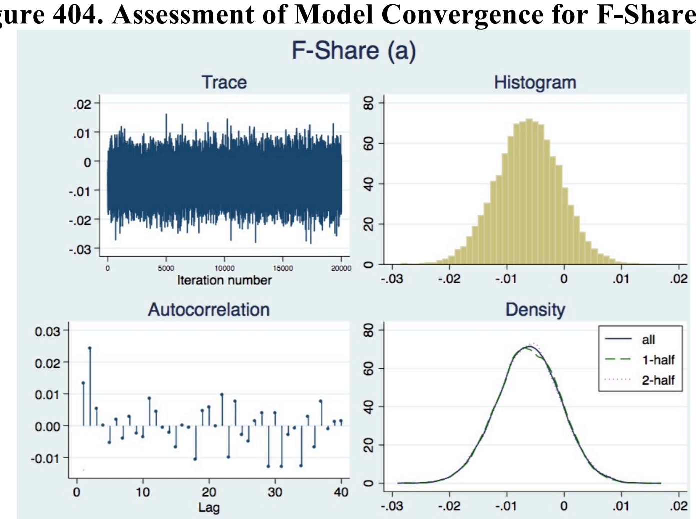


Figure 405. Assessment of Model Convergence for C-F-Share (a) (Luxury)

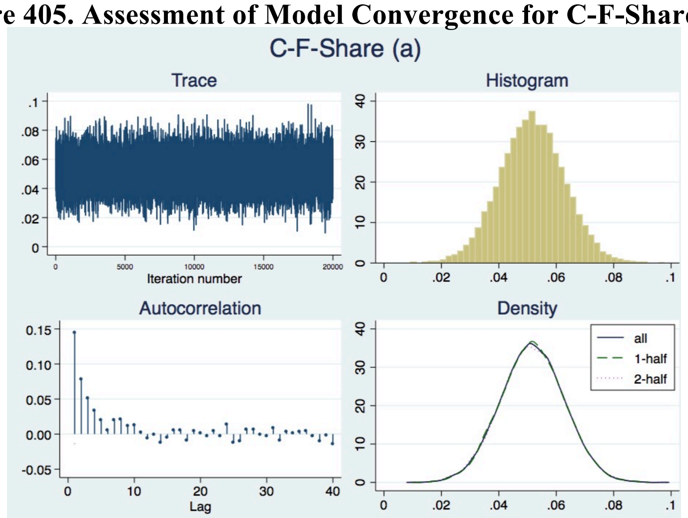


Figure 406. Assessment of Model Convergence for U-Share (a) (Luxury)

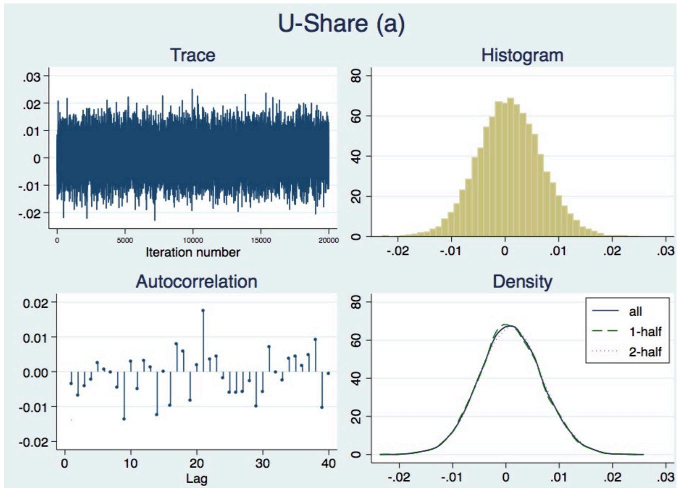


Figure 407. Assessment of Model Convergence for C-U-Share (a) (Luxury)

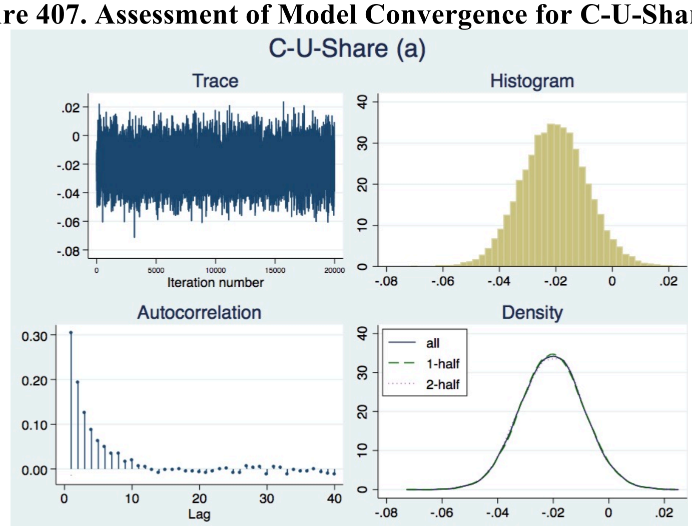


Figure 408. Assessment of Model Convergence for TD-Post (c) (Luxury)

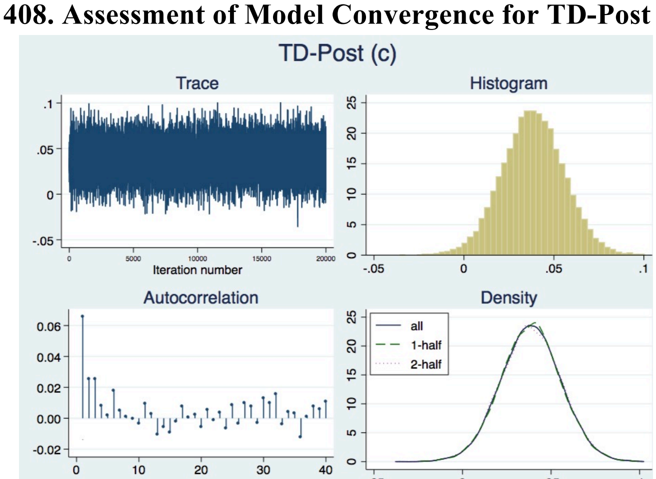


Figure 409. Assessment of Model Convergence for C-TD-Post (c) (Luxury)

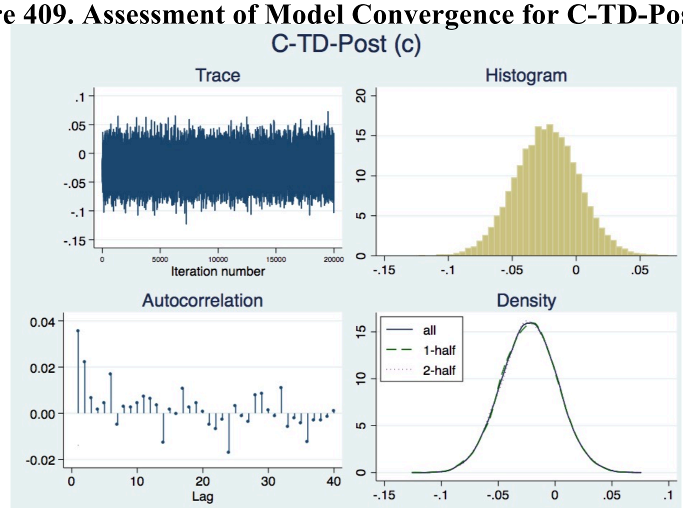


Figure 410. Assessment of Model Convergence for TMS (Luxury)

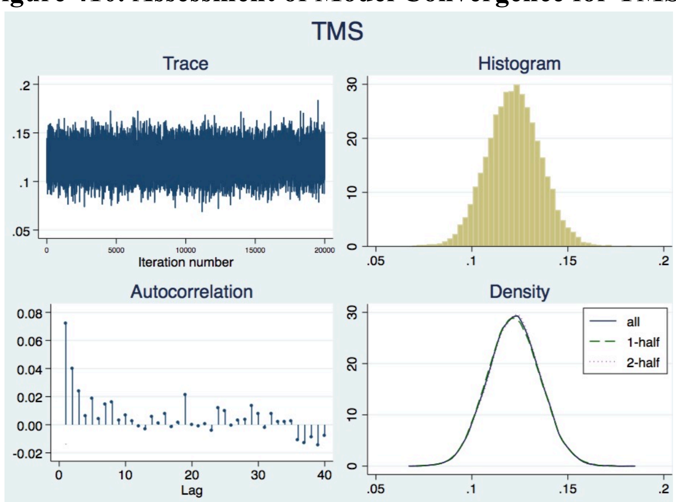


Figure 411. Assessment of Model Convergence for Price (Luxury)

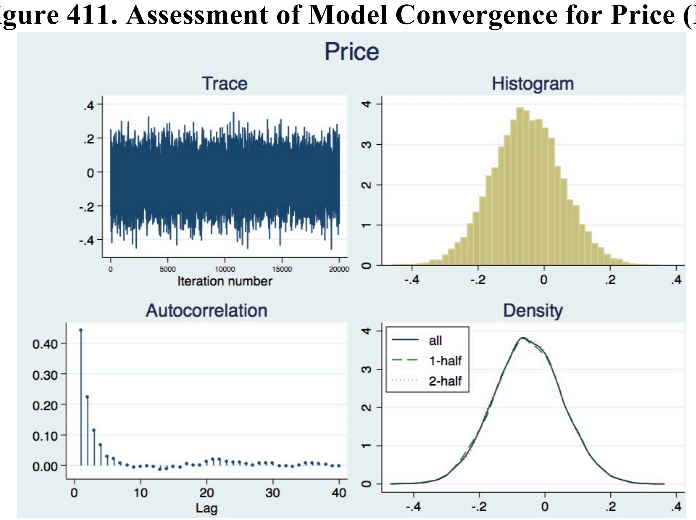


Figure 412. Assessment of Model Convergence for GT (Luxury)

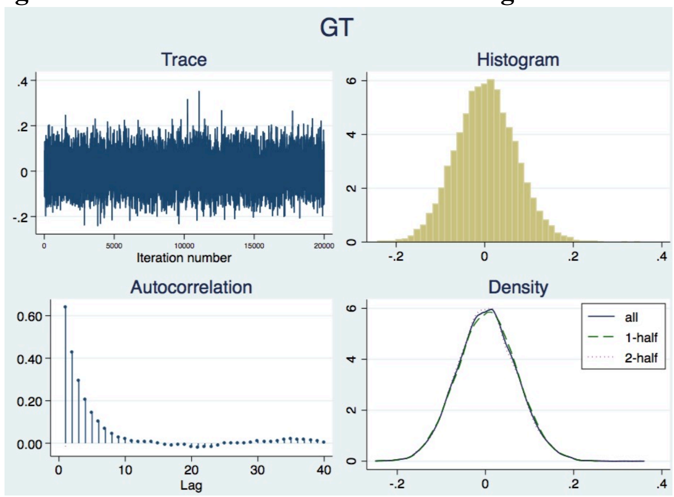


Figure 413. Assessment of Model Convergence for GPI (Luxury)

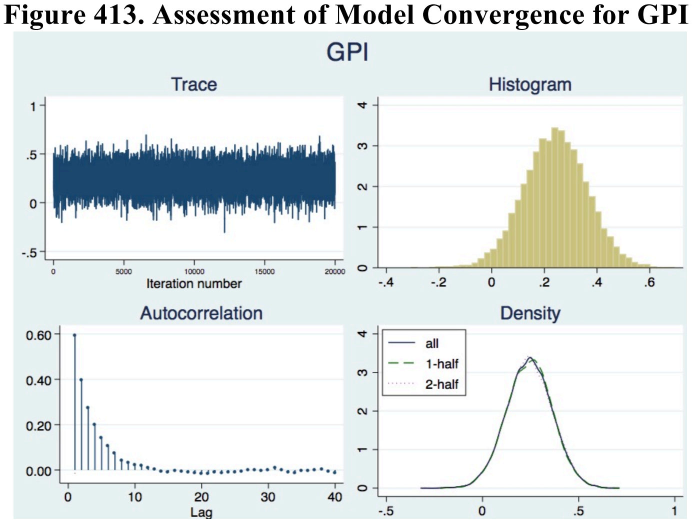


Figure 414. Assessment of Model Convergence for CCI (Luxury)

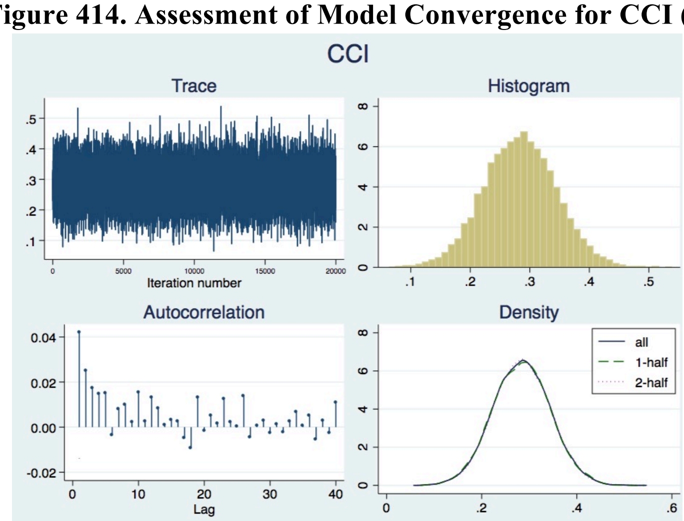


Figure 415. Assessment of Model Convergence for F-Share (a) (Non-Luxury)

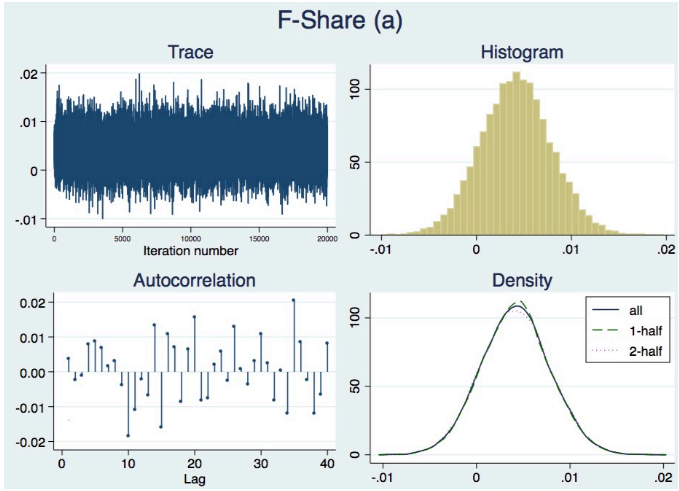


Figure 416. Assessment of Model Convergence for C-F-Share (a) (Non-Luxury)

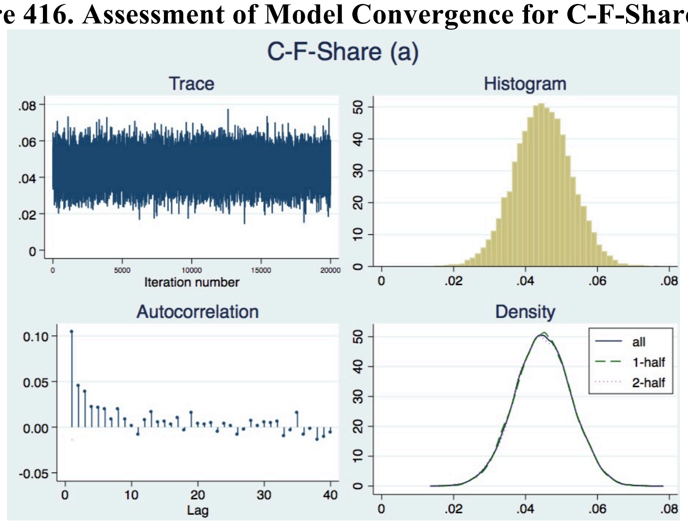


Figure 417. Assessment of Model Convergence for U-Share (a) (Non-Luxury)

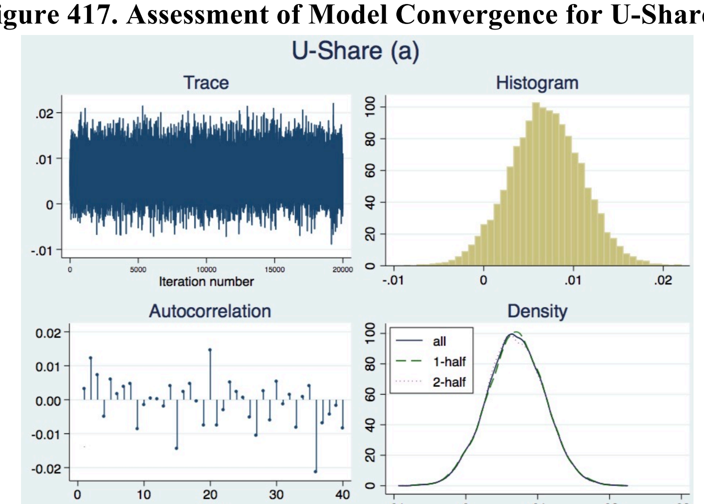


Figure 418. Assessment of Model Convergence for C-U-Share (a) (Non-Luxury)

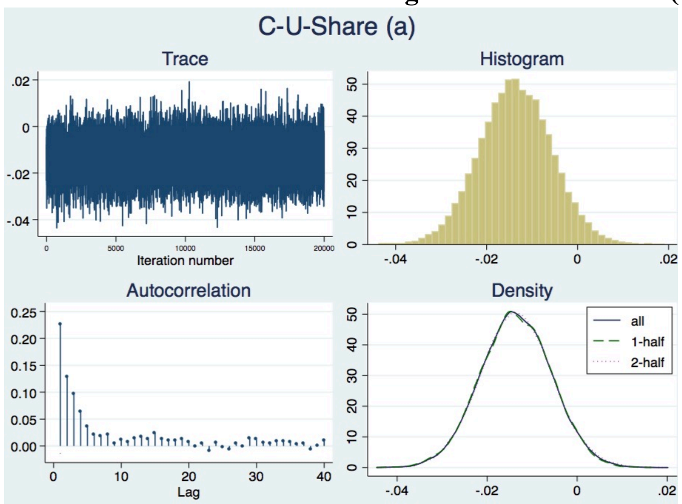


Figure 419. Assessment of Model Convergence for TD-Post (c) (Non-Luxury)

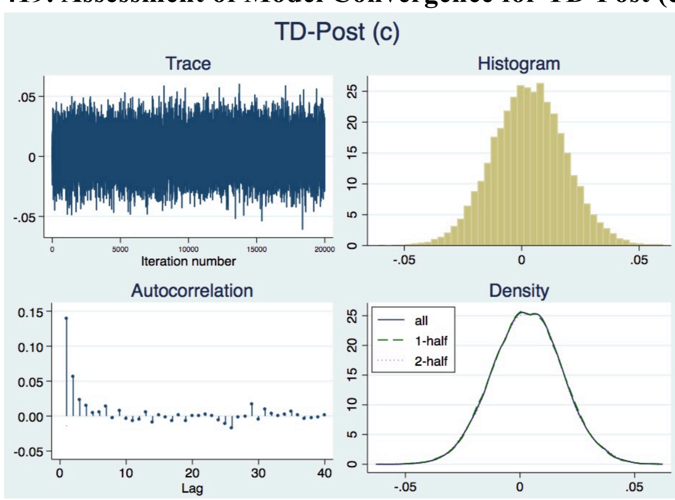


Figure 420. Assessment of Model Convergence for C-TD-Post (c) (Non-Luxury)

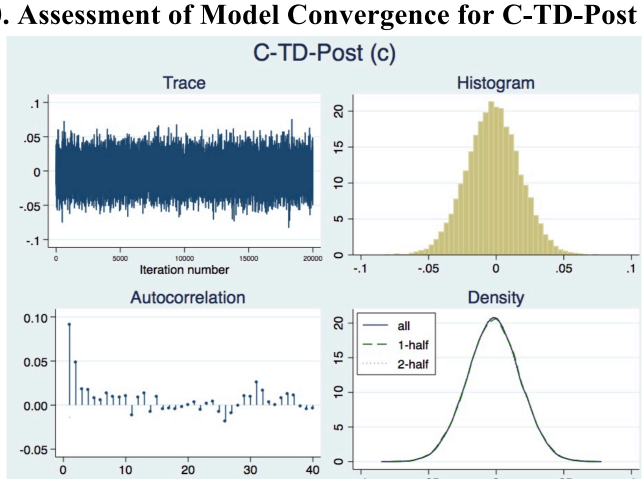


Figure 421. Assessment of Model Convergence for TMS (Non-Luxury)

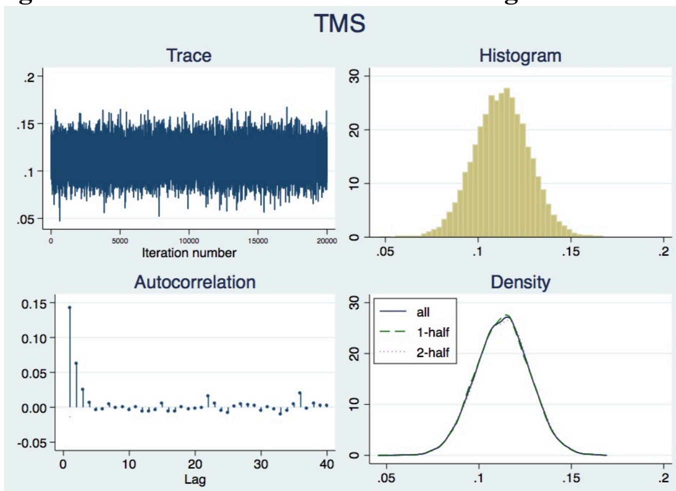


Figure 422. Assessment of Model Convergence for Price (Non-Luxury)

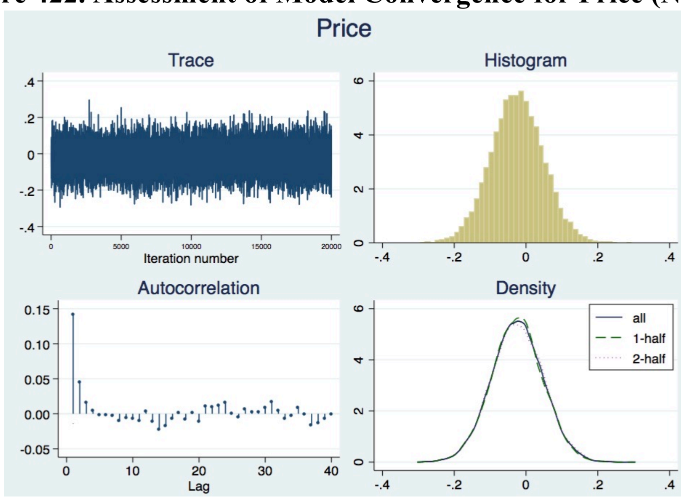


Figure 423. Assessment of Model Convergence for GT (Non-Luxury)

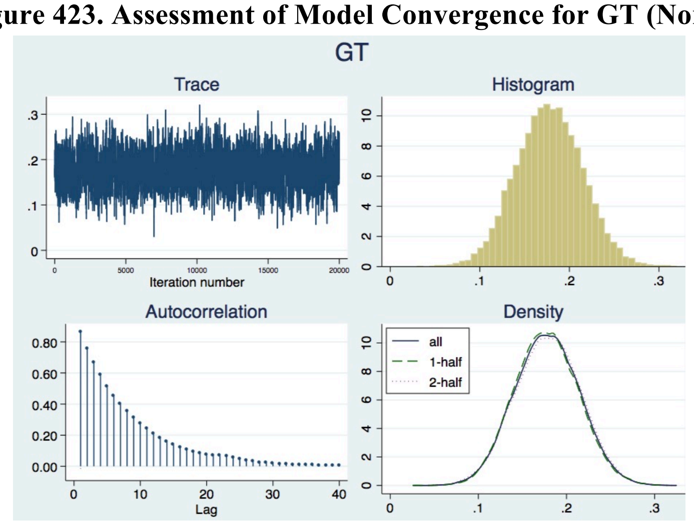


Figure 424. Assessment of Model Convergence for GPI (Non-Luxury)

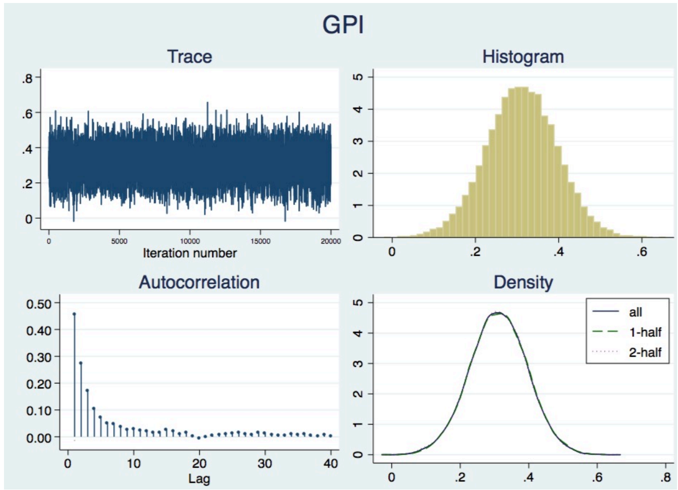


Figure 425. Assessment of Model Convergence for CCI (Non-Luxury)

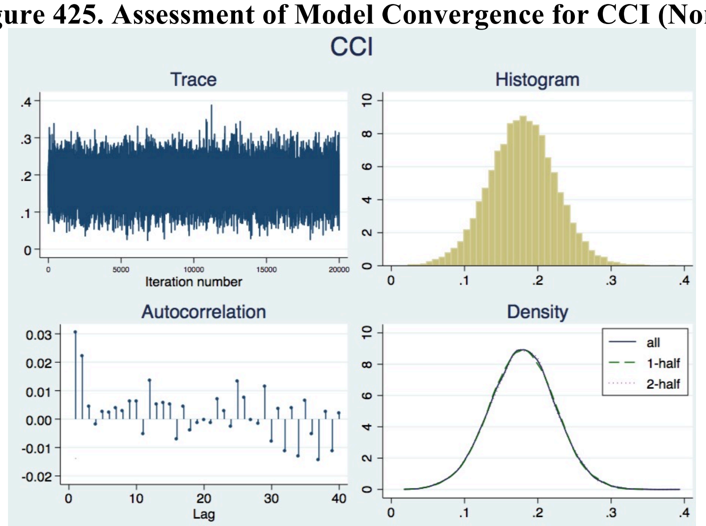


Table 85. Summary of Results

Analysis level	Results
Whole Sample	
Post	H1 (F), H2 (F), H3, and H4
Like	H2 (F), H3, and H4
Comment	H2 (F) and H4
Share	H2 (F) and H3
Sample Split on Origin of Brand	
Post	**Asian:** H2 (F), H3, and H4; **European:** H1 (F) and H2 (F); **US:** H2 (F)
Like	**Asian:** H2 (F); **European:** H2 (F); **US:** H2 (F) and H2 (U)
Comment	**Asian:** H2 (F) and H4; **European:** H1 (U), H2 (F), and H4; **US:** H2 (F) and H2 (U)
Share	**Asian:** H2 (F) and H3; **European:** H2 (F) and H3; **US:** H2 (F)
Sample Split on Market Structure	
Post	**Group 1:** H2 (F), H3, and H4; **Group 2:** H2 (F); **Group 3:** H1 (F) and H2 (F)
Like	**Group 1:** H1 (U), H2 (F), and H3; **Group 2:** H2 (F) and H2 (U); **Group 3:** H2 (F)
Comment	**Group 1:** H4; **Group 2:** H2 (F) and H2 (F); **Group 3:** H1 (F) and H2 (F)
Share	**Group 1:** H2 (F) and H3; **Group 2:** H1 (U) and H2 (F); **Group 3:** H2 (F)
Sample Split on Price Factor	
Post	**Luxury:** H2 (F), H3, and H4; **Non-Luxury**: H1 (F) and H2 (F)
Like	**Luxury:** H1 (U) and H2 (F); **Non-Luxury:** H2 (F) and H2 (U)
Comment	**Luxury:** H1 (U), H2 (F), and H4; **Non-Luxury:** H2 (F), H2 (U), and H4
Share	**Luxury:** H2 (F) and H3; **Non-Luxury:** H2 (F)

Notes: (F) refers to metrics initiated by firms at the stage of awareness (e.g., F-Post (a), F-Share (a), or C-F-Post (a)); (U) refers to metrics initiated by users at the stage of awareness (e.g., U-Post (a), U-Share (a), or C-U-Post (a)).

3.6 DISCUSSION

Online WOM plays an important aspect in consumers' purchase decisions (Chen et al., 2015) and provide a means for firms to learn about customers and the marketplace (Borah & Tellis, 2016). Despite the richness of research on online WOM, prior research on the dynamics of online WOM and its spillover effects is very scarce with few exceptions (e.g., Borah & Tellis, 2016; Chae et al., 2017; Sabnis & Grewal, 2015). More importantly, although prior research indicates that customers may experience a multi-stage process before making purchase decisions (i.e., awareness, consideration, and final decision) (Bettman, 1979; De Bruyn & Lilien, 2008; Hauser & Wernerfelt, 1990; Shocker et al., 1991), our knowledge on the relative effects played by online WOM at the stage of awareness and consideration is still not clear. Therefore, the objective of this paper is to examine the dynamics of online WOM and its spillover effects by considering their relative effects at the stages of customer awareness and consideration in the U.S. automobile industry.

Generally, the results indicate that (1) online WOM at the stage of consideration has the stronger effect on offline car sales than online WOM at the stage of awareness, (2) spillover effects exist across both stages of awareness and consideration, though effects are heterogeneous in direction: positive spillover effects at the stage of awareness while negative spillover effects at the stage of consideration, and (3) at the stage of awareness, online WOM initiated by firms is more effective in influencing offline car sales than online WOM initiated by users. Furthermore, not every mechanism at Facebook (i.e., post, like, comment, and share) has the equal impact on offline car sales and these different mechanisms also influence how customers appreciate online WOM at the stage of consideration. Finally, the results vary significantly across origin of brand, market structure, and price factor. These varied results imply that (1) customers might use these pre-existed attributes to make similar inferences for brands that belong to the same pre-existed group and (2) depending upon their belonging groups, firms should leverage different mechanism to strategically drive offline sales.

3.6.1 Theoretical Implications

There are several key contributions from this research. First, the current study is the first study that examines the relative effects played by online WOM and its spillover effects across two stages of customer awareness and consideration on offline car sales. Recent research has noted the need to account for competition as means to extend our understanding on different aspects of online WOM (Dou, Niculescu, & Wu, 2013) and has provided evidence of online WOM spillover effects in some settings (e.g., Borah & Tellis, 2016; Chae et al., 2017; Sabnis & Grewal, 2015). Examining online WOM and its spillover effects across two stages of decision process, I find a variation in the sign of the results that though the effects of online WOM about competitors is statistically significant, the precise nature of the effect depends on whether online WOM provides sufficient or concrete information to help customers make purchase decisions. Therefore, the current study contributes to the consumer choice literature by showing different role of online WOM played across stages of awareness and consideration. In addition, this study sheds new lights on the effectiveness of online WOM and the competition nature of online WOM (e.g., Borah & Tellis, 2016; Chae et al., 2017; Sabnis & Grewal, 2015) and shows how the competition nature may vary across different stages of consumer decision process. Furthermore, my examination on the effect of online WOM on high-involvement products also responds to the call for more research regarding the impact of online WOM on different types of products (e.g., Goh et al., 2013; Stephen & Galak, 2012).

Second, the approach of quantifying the relative effectiveness of online WOM initiated by firms and online WOM by users at the stage of awareness (i.e., firm’s Facebook page) also echoes the call for more research on how firm’s media channels should operate as a system (e.g., Dewan & Ramaprasad, 2014; Luo et al., 2013). The predominant emphasis of prior research focuses on the isolated impact of either online WOM initiated by firms or online WOM initiated on online sales of media or low-involvement products such as movie or music. The current contributes to this stream of the literature by showing the relative effectiveness of these two sources of online WOM at the stage of awareness. Furthermore, our findings also suggest that not every mechanism at Facebook has the equal impact on offline car sales and these different mechanisms influence how customers appreciate online WOM at the stage of consideration and its corresponding impact. Thus, my study sheds lights on decision-making and marketing literature by demonstrating how firms could utilize the combinations of different mechanisms to strategically enhance firm performance.

Finally, my split sample analysis on origin of brand, market structure, and price factor offers very interesting insights regarding how customers may attribute to their pre-existed attributes to make similar inferences for brands that belong to the same pre-existed group. For example, at the post level (posts at Facebook pages and test drive posts), online WOM at the stage of consideration has the positive impact on offline car sales of the focal brand and online WOM has negative spillover effects on offline car sales of the focal brand for the Asian-based group. However, these relationships cannot observe for the European-based group. Therefore, this study contributes to the current literature by showing different patterns of how firms from different pre-existed groups could develop their marketing efforts more effectively to leverage online WOM.

3.6.2 Managerial Implications

The study also provides important managerial implications. Practitioners have considered online WOM as one of important tools to influence customer decision-making. The current study has shown that the need to consider online WOM across different stages of customer decision process and that the effect of online WOM and its spillover effects vary differently across stages. Therefore, in the competitive marketplace, practitioners not only need to observe online WOM regarding their own brand but also need to monitor online WOM regarding their competitors. More importantly, they need to realize that online WOM has different aspects and that depending on the sufficient degree that online WOM may provide (i.e., abstract information versus concern information) firms need to place different weights to better understand consumer perceptions and predict performance.

Second, when leverage their Facebook pages, firms should pay special attention on different mechanisms provided by Facebook. My results indicate that the volume of post at Facebook is more effective in influencing offline car sales than the volume of like or the volume of comment does. Thus, given the limited resource each firm may have, firms could leverage my findings to better allocate their resource and effort to leverage online WOM. Finally, my examination on the relative effect of online WOM initiated by firms and online WOM initiated by users at the stage of awareness also provides insights to managers to better understand how they could operate their marketing channel as a whole system and the individual effect within the system.

3.6.3 Limitations and Future Research

This study does have some limitations. First, when considering online WOM at the stage of awareness, I only focus on firms Facebook fan pages. It is very likely that firms also leverage other social media channels to enhance their customer awareness and then make profits. Due to data limitations, I am not able to study these cross-channel effects at the stage of awareness. Second, the current study only focuses on the U.S. automobile industry. Although this setting allows me to echo the call for more research on the impact of online WOM on high-involvement products, scholars should be still cautious of the unique characteristics of the automobile industry. Thus, it would be worthwhile to investigate the generalizability of the results to other high-involvement product categories.

Finally, the current study only explores the volume of online WOM across two stages of decision process. It may be interesting for future research to apply some machine learning approaches to extract aspects such as emotions embedded in online WOM and examine their corresponding impact.

3.7 CONCLUDING REMARKS

Despite the richness of research on online WOM, prior research on the dynamics of online WOM and its spillover effects is very scarce. Particularly, our knowledge on the role played by online WOM at the stages of customer awareness and consideration is very limited. This paper attempts to examine the dynamics of online WOM and its spillover effects by considering their relative effects at the stages of customer awareness and consideration in the U.S. automobile industry. The findings show that spillover effects are heterogeneous in direction across two stages and that different mechanisms at the stage of awareness would influence how customers appreciate online WOM at the stage of consideration. Furthermore, the dynamics of online WOM vary across origin of brand, market structure, and price factor.

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