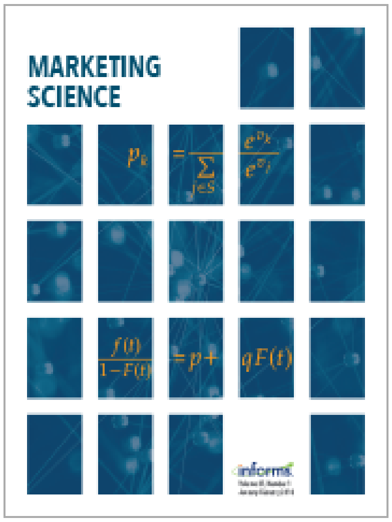

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Minimum Advertised Pricing: Patterns of Violation in Competitive Retail Markets

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Manufacturers in many industries frequently use vertical price policies, such as minimum advertised price (MAP), to influence prices set by downstream retailers. Although manufacturers expect retail partners to comply with MAP policies, violations of MAP are common in practice. In this research, we document and explain both the *extent* and the *depth* of MAP policy violations. We also shed light on *how retailers vary* in their propensity to violate MAP policies, and the depth by which they do so.

Our inductive research approach documents managerial wisdom about MAP practices. We confront these insights from practice with a large empirical study that includes hundreds of products sold through hundreds of retailers. Consistent with managerial wisdom, we find that authorized retailers are more likely to comply with MAP than are unauthorized partners. By contrast to managerial wisdom, we find that authorized and unauthorized markets are largely separate, and that violations in the authorized channel have a small association with violations in the unauthorized channel. Last, we link our results to the literatures on agency theory, transaction cost analysis, and theories of price obfuscation.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0933.

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1. Introduction

Minimum advertised pricing (MAP) policies are a type of vertical pricing policy often used by manufacturers to influence the downstream prices of channel partners, such as retailers and distributors. Under a MAP policy, a manufacturer unilaterally states a minimum price for a specific stock keeping unit (SKU) that holds equally for all authorized retailers. Those that comply may receive benefits such as cooperative marketing money or preferential product access and those that violate the MAP price (i.e., advertise prices *below* the MAP price) may face penalties, such as denial of product access.

These policies are very common in many industries, including electronics (e.g., Sony, Bose, Samsung), cameras (e.g., Olympus), video games (e.g., Nintendo), housewares (e.g., Viking, Sub-Zero), sporting goods (e.g., Callaway, TaylorMade), computers (e.g., Hewlett-Packard (HP)), toys (e.g., Activision Blizzard, LeapFrog), marine equipment (e.g., JL Marine), motor sports (e.g., GPR Stabilizer), and plumbing (e.g., Brasstech). Manufacturers seek MAP compliance from all authorized retailers, but MAP violations are, in fact, quite common in practice. Monitoring and enforcing these violations is one of the major problems faced by manufacturers using MAP policies. In this research, we therefore seek to document and explain both the *extent* and the *depth* of violations of MAP policies, as well as shed light on *how resellers vary* in their propensity to violate MAP policies, and the depth by which they do so.

There is little theoretical or empirical academic research that predicts the extent and depth of MAP violations. This is in part because the prior analytic literature analyzes equilibrium models in which optimal design of the MAP policy results in no violations. Empirical evidence on MAP largely consists of anecdotes in the popular press that document violations (Pereira 2008) and a single lab experiment (Charness and Chen 2002). To our knowledge, our paper provides the first extensive, empirical analysis of MAP pricing.

Given the lack of prior research, we take an inductive point of view in our investigation. We conduct a series of interviews with managers to establish their empirical beliefs concerning the extent and depth of MAP violations. We then confront this managerial wisdom with empirical analysis that includes a large variety of products that are sold through hundreds of authorized and unauthorized retailers. Our entire data set contains more than one million unique observations, which allows for a broad characterization of the empirical phenomenon. As our results unfold, we carefully relate our findings to predictions from the academic literatures on agency theory and price obfuscation, as well as posing other possible explanations.

Reassuringly, many of our findings are consistent with managerial beliefs about MAP. Managers believe that authorized retailers are less likely to violate MAP than unauthorized retailers. For the manufacturer that is the focus of this study, we find that authorized retailers offer prices below MAP 14.7% of the time, while unauthorized retailers offer prices below MAP 53.5% of the time. When we include seven other manufacturers in our analysis, we find that violations are 22% for authorized retailers versus 46% for unauthorized retailers. We conclude that this finding is very robust.

Managers also believe that MAP violations lead to a cascading effect among retailers, i.e., a violation by one retailer is expected to be associated with other retail violations. Indeed, we find support for this belief in our data. Violations by authorized retailers are strongly associated with violations by other authorized retailers; violations by unauthorized retailers are strongly associated with violations by other unauthorized retailers.

However, two widely held managerial beliefs were not supported by our empirical analysis. First, managers we spoke with believe that unauthorized retailers are often the root cause of poor MAP compliance among all retailers. Our data do not support this belief. We find only a weak association between violations of authorized retailers and unauthorized retailers. This result is important because managers who seek to bring the channel into compliance often focus on unauthorized retailers. Our results suggest that this will have a minimal effect on noncomplying authorized retailers.

A second widely held belief among managers is that retailers are more likely to violate MAP when they sell through Amazon.com or eBay.com than otherwise. In our data, many retailers sell their products through their own site as well as one of these sites. Although there is some support for this belief in our univariate analysis, there is little support for it in our complete, multivariate analysis.

Finally, there is much consistency between our empirical findings and predictions from associated academic literatures in agency theory (Bergen et al. 1992, Heide and Miner 1992, Jap and Anderson 2003) and consumer search theory (Stigler 1961, Ellison and Ellison 2009). We find that authorized retailers that offer a broader assortment of a manufacturer's product line are less likely to violate MAP compared with authorized retailers that offer a smaller assortment of products. By contrast, we find that assortment breadth has no effect on the MAP compliance of unauthorized retailers. These results are broadly consistent with the concept of posting a bond in agency theory. An authorized retailer that carries a broad assortment is making a deeper commitment to a manufacturer and in turn may receive greater benefits than one carrying a narrower assortment. At the same time, the authorized retailer is implicitly posting a bond with the manufacturer because retailers recognize that a MAP violation on one product often results in punishment over the entire manufacturer product line that the retailer offers. Together, these increased benefits and costs discourage MAP violations among authorized retailers that offer broad assortments. By contrast, we expect no such mechanism to operate among unauthorized retailers since there is no formal relationship through which the manufacturer can offer rewards or penalties.

Our results also indicate that, although free shipping is very common, retailers that charge for shipping are more likely to violate MAP. We conjecture that because violating MAP means lowering prices and hence margins, violators may use shipping charges to recoup those lost margins in a way that is not completely obvious to the consumer. Interestingly, the practice of charging for shipping when one violates MAP occurs among both authorized and unauthorized retailers. The results are consistent with price obfuscation behavior by violating retailers that offer seemingly low prices but slip in shipping charges at the end of the electronic shopping process.

Managing MAP policies to coordinate distribution channels with authorized and unauthorized sellers is a complicated task for manufacturers. A further contribution of our paper is to provide tools to assist managers. First, we provide a graphical chart and numeric index that allows one to summarize both whether and how much retailers violate MAP. We call this a MAP Violation Index (MVI). We have noted that managers in this area have found the MVI chart and index extremely useful for interpreting vast amounts of data. A second managerial contribution is to assist managers with prioritizing their MAP enforcement efforts based on varying objectives. For example, we show that managers who want to reduce violation rates among authorized retailers should direct enforcement efforts towards authorized retailers and not unauthorized retailers. To an outsider, this may seem obvious but the recommendation contradicts conventional wisdom that the way to bring the authorized channel into compliance is to reduce violations of unauthorized retailers.

The remainder of the paper is organized as follows. In §2 we review the related literature. In §3 we provide institutional facts about MAP and develop predictions based on managers' beliefs. In §4 we discuss our raw data, operationalize our predictions, and present empirical regularities in the data. In §5 we present an empirical data analysis testing our hypotheses and discuss our findings. In §6 we conclude and discuss future research and managerial implications.

2. Literature Review

MAP policies are now widespread among durable goods manufacturers, yet little empirical work has been published on this topic. To our knowledge, the only published empirical study on MAP was conducted by Charness and Chen (2002), who use a controlled laboratory experiment in HP laboratories. Their study includes several types of MAP contracts, such as contracts with forward-looking penalties versus penalties with retroactive components, contracts in which penalties denied retailer access to the product versus those with only monetary punishment, and contracts with a linked-product design where violation on one product triggers a penalty on other products. They find that (1) A forward-looking penalty is less effective than retroactive penalties; (2) More severe penalties are associated with higher retail margins; and (3) Linked-MAP is less effective than individual-product MAP. To our knowledge, our paper is the first real-world, empirical field study of MAP pricing.

In a recent working paper, Israeli (2016) uses a quasi experiment prompted by changes in a manufacturer's channel policies to examine whether manufacturers can influence MAP compliance. By contrast, our paper focuses on the patterns of MAP violations among authorized and unauthorized retailers, and not on improving compliance. Israeli (2016) extends our paper by studying how to effectively implement MAP policies. She finds that manufacturers can improve compliance rates among authorized retailers by sending email notices of MAP violations, improving price monitoring, and modifying channel policies. While these changes improve compliance among authorized retailers, there are no substantial changes in compliance among unauthorized retailers. This complements our finding that the authorized and unauthorized markets are largely separate.

Two analytical studies, Kali (1998) and Cetinkaya (2009), compare the properties of MAP and Resale Price Maintenance (RPM). Kali (1998) views MAP as a vertical restraint that closely resembles RPM, and models MAP as a combination of RPM and a cooperative advertising subsidy. He shows that each instrument alone cannot maximize a channel's profit, while the combined use of RPM and MAP does maximize the channel's profit. Conversely, Cetinkaya (2009) models MAP and RPM as different instruments. His analysis focuses on social welfare and horizontal service externalities. In his model, MAP ensures optimal levels of retail service and duplicates the welfare outcome of vertical integration regardless of the level of service externality, whereas RPM leads to suboptimal levels of retail service if used without another vertical restraint (such as a franchise fee).

While the academic literature on MAP is quite limited, there is a large literature on RPM. From a legal perspective, MAP and other pricing policies have been legal for over 90 years.[1] Conversely, RPM agreements have been per se illegal since 1911, and became legal only in 2007 in the controversial "Leegin" ruling. The illegal status of RPM spurred an academic discussion on the economic optimality of RPM and its ability to coordinate the retail channel (Yamey 1952; Telser 1960; Gould and Preston 1965; Marvel and McCafferty 1984, 1985; Mathewson and Winter 1984; Klein and Murphy 1988; Winter 1993; Deneckere et al. 1996, 1997; and others). The literature typically treats RPM as a dictated price from the manufacturer, without considering violations, as if there were a self-enforcing agreement mechanism (Telser 1980) in place (although such a mechanism was not explicitly assumed or derived). Appropriately-designed RPM and MAP policies are predicted to provide incentives for retailers to provide service, improve retailing quality, and control profit-reducing retail discounting. However, this literature does not typically focus on retailers' incentives to violate the vertical restraint policy or explicitly consider imperfect monitoring and control mechanisms, which are widespread in practice.

Because RPM agreements were illegal, there are few empirical studies of RPM, and such studies usually use lawsuits involving allegations of vertical price fixing (Gilligan 1986, Ippolito 1991, and Bailey and Leonard 2010). Ippolito (1991) examines over 200 lawsuits between 1976–1983. She finds that collusion alone cannot be the primary explanation for RPM and that many of the lawsuits are consistent with several RPM theories. Gilligan (1986) conducts an event study using 43 antitrust complaints and finds that, on average, an antitrust challenge reduced the return to a firm over the announcement period by 1.4%. More recently, Bailey and Leonard (2010) use a natural experiment (i.e., a statute that prohibited RPM in Maryland) to analyze the effect of RPM on prices, and find that the prohibition did not affect prices of video games. Yet their analysis is limited because they cannot observe whether the video games were subject to RPM policies to begin with.

After presenting our descriptive MAP findings, we interpret them through the lenses of agency theory, consumer search theory, and other possible explanations, such as selection. Agency theory has been widely applied in the marketing channels literature to understand how issues such as commitment, moral hazard, and adverse selection affect channel partners

[1] The federal antitrust statute of the Sherman Act (1890) prohibits agreements in restraint of trade. In 1919, in a case called "Colgate," the Supreme Court ruled that a manufacturer can establish policies under which it will do business with retailers and cease selling through those that fail to comply (Henry and Zelek 2003). That is, MAP and other pricing policies are legal as long as they are unilateral. Because MAP policies are unilateral, they are not subject to the Sherman Act.

behavior (see for example Anderson and Weitz 1992, Heide and Miner 1992, Stump and Heide 1996, and Jap and Anderson 2003). Agency theory fits naturally with our empirical setting, which has nonaligned goals, limited commitment, and monitoring/enforcement concerns (see Bergen et al. 1992 for a review of the use of agency theory in marketing). While agency theory offers strong predictions on mechanisms that should deter cheating (see the seminal paper by Ross 1973, and others), the decision to cheat is often an out-of-equilibrium behavior.

Consumer search theory acknowledges that search is costly, and thus consumers might not engage in search or might limit their consideration set when searching for low prices.[2] Ellison and Ellison (2009) show how retailers strategically obfuscate prices and make it more difficult for consumers to find the final transaction price. For example, online retailers may postpone the revelation of shipping and handling costs, taxes or other add-on fees in the online buying process. This allows retailers to attract consumers by advertising lower product prices, even though the full transaction price could be considerably higher due to additional hidden costs. This is consistent with the finding in Yao and Zhang (2012) that free shipping is associated with higher base price charges. Yao and Zhang (2012) also find that when shipping charges are higher or when the base price is lower, the probability of on-time delivery is lower. Retailers that charge for shipping offer lower base prices and provide less service. Desai et al. (2010) analyze the strategic competitive implications of retailers who do not advertise their prices and find that low service retailers are more likely not to advertise their prices than high service retailers.

When interpreting our findings, we caution that some may be driven by selection effects. For example, how manufacturers select retailers and which products retailers choose to sell may also explain the effects we identify. We elaborate on this in §5.4.

3. Institutional Facts and Managerial Hypotheses

In this section, we begin with an overview of institutional details on MAP. Our overview is based on the legal literature, and discussions with a legal expert, manufacturer partners, and Channel IQ. This institutional knowledge and industry beliefs about MAP and MAP compliance are then used to construct managerially-based hypotheses about expected behavior in the marketplace, which we test in this paper.

[2] For theoretical and empirical research modeling pricing in the presence of search costs or empirically estimating search cost, see among others Stigler (1961), Stahl (1989, 1996), Hong and Shum (2006), and Mehta et al. (2003).

3.1. Institutional Facts[3]

MAP is a promotional policy in which a manufacturer unilaterally declares a minimum price below which a complying retailer should not advertise the product. In return for compliance, a retailer may receive monetary benefit from the manufacturer, e.g., co-op advertising funds. Even when a MAP policy is promulgated by a manufacturer, each retailer remains free to set its actual retail price above, below or at the MAP level. If a retailer chooses to price below the MAP price (that is, the retailer chooses to violate the MAP policy), it foregoes the benefits associated with MAP compliance. MAP policies may also specify penalties for violation by an authorized retailer, e.g., temporary or permanent withdrawal of access to one or more of the manufacturer's products. For example, a retailer that violates MAP on a single TaylorMade golf driver may lose access to all TaylorMade products (Henry and Zelek 2003).

While MAP covers only *advertised* prices, the definition of an "advertised price" is idiosyncratic to each manufacturer's MAP policy. For example, a MAP policy may specify that advertised prices include those communicated via television, radio, and print, but may exclude in-store prices. Under such a MAP policy, a retailer may be able to negotiate with a consumer in person, offer a price below MAP, and still be classified as complying with the policy. The emergence of online markets led manufacturers to broaden the definition of advertised price. For example, some manufacturers define all online prices as advertised prices (see the marked section of Veterinary Ventures' MAP policy in Online Appendix B (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0933)). Others may define prices displayed "in shopping cart" or those that require a "click for price" as nonadvertised prices (see the marked section of Panasonic's MAP policy in Online Appendix B). If a manufacturer's MAP policy indicates that all online prices are advertised prices, then, from a practical perspective, MAP is equivalent to a "Minimum Price Requirement" in online markets.

Some manufacturers use a Unilateral Pricing Policy (UPP) to control pricing in their distribution channel. Unlike MAP, the price in the UPP policy refers to advertised and retail prices, and all retailers are required to set the same price. In addition, UPP policy is not associated with any co-op advertising funds. Note that in an online market a UPP can be viewed as a special case of a MAP policy in which there are no advertising funds and the definition of "advertised price" refers to any prices. In this paper we focus on MAP policies.

[3] The information in this section is based on conversations with Eugene F. Zelek Jr, an antitrust lawyer; manufacturer partners; and Channel IQ.

Manufacturer rationales for MAP policies include controlling downstream prices, controlling and coordinating the retail channel, controlling the product's perceived brand image, and preventing products from being used as loss-leaders. Effective price restraints maintain higher retail prices, which protects retailer gross margins and thus allows retailers to give service and augment basic product profitably. Such restraints are, therefore, effective in battling discount retailers that may offer low prices but not the services required to sustain the brand. From a consumer point of view, the retail price may be higher when the product is subject to vertical restraints. Yet the higher price can be acceptable to those consumers who value broader product availability, increased service, and product augmentation. In addition, vertical price restraints can be used for positioning and supporting new products. By setting a minimum downstream price through MAP, the manufacturer informs the retailer about its valuation of the new product and signals the appropriate retail pricing strategy. Moreover, early in the product life cycle, more technical training and sales help is often required, which in turn requires a higher retail gross margin. This explains the value of MAP policies for new products.

A MAP policy is set unilaterally by the manufacturer and applies to all of its authorized dealers and distributors. A common practice by manufacturers is to first have the downstream partners sign an authorized distribution agreement, which acknowledges them as partners and describes their benefits and obligations. These agreements would also include a clause that indicates that the authorized retailer must adhere to the manufacturer's policies, which may include a MAP policy. The MAP policy is typically a separate document that specifies the rationale for MAP, the definition of MAP, specific instructions for brick and mortar versus online prices, and the benefits and consequences of adhering or violating the policy (see MAP policy examples in Online Appendix B). Under U.S. law, the penalties are typically invariant across class of retail trade.

A manufacturer publishes its MAP price for each SKU and the dates when the MAP price applies. In our interviews with manufacturers, we learned that key drivers of the MAP price are competitor's prices, demand considerations, and perceived brand value. The MAP price is relatively stable due to the costs of coordinating the authorized retailers. Changes to MAP are announced in advance so that retailers have time to respond and plan for the new MAP price. For example, the stereo manufacturer Bose may announce a price promotion event and lower the MAP price for a short period of time during this event. Some manufacturers are transparent with their MAP prices while others treat these as highly confidential communications between themselves and authorized retailers. This confidentiality contributes to the lack of empirical studies on this topic.

The structure of the MAP policy creates incentives for the authorized dealers to comply with MAP. Authorized retailers fear losing distribution and product support if they violate MAP. However, the MAP policy does not apply to unauthorized retailers since, as illegitimate channel partners, the manufacturer cannot exact a penalty against them. Instead, manufacturers can try to prosecute trademark or intellectual property-related cases to prevent unauthorized retailers from advertising or selling a manufacturer's products. For simplicity, we use the term "MAP violation" to include cases wherein unauthorized retailers advertise prices below MAP as violations although the unauthorized retailers are never bound by the policy.

For unauthorized retailers, the manufacturer's threats are indirect. Unauthorized retailers often obtain their inventory through a legitimate, authorized retailer or distributor. If the manufacturer becomes aware of an unauthorized retailer, and can trace the product from the unauthorized outlet to the authorized partner, then there may be repercussions for the authorized partner such as termination of distribution. Such repercussions can impair the supply relationship between the authorized partner and the unauthorized retailer, which may lose supply indirectly. Such considerations could dampen an unauthorized retailer's incentive to set its price far below MAP.

MAP compliance is very difficult to monitor. The marketing vice president of one electronic goods manufacturer whom we interviewed said that his staff was manually monitoring just three SKUs for MAP violations across all of its *authorized* retailers. This fraction of the total line was all he could manage with current staffing and their other job duties. Thus, even monitoring authorized retailer's prices is a daunting task.

When products are sold online, monitoring is also difficult. At first glance, it may seem that monitoring would be easier as information online is more transparent. Yet managers had exactly the opposite experience and refer to the online channel as the "Wild West." Most manufacturers have limited visibility of the vast number of unauthorized retailers selling their products online. Indirect monitoring does happen: Retailers may report or complain about other retailers (authorized or unauthorized) that violate MAP. However, when an unauthorized retailer is detected and found to be a MAP violator, the manufacturer still faces an enforcement problem: There is no MAP policy under which to penalize violations by these retailers.

Because of the difficulty of monitoring MAP violations, many manufacturers enlist the help of third-party companies, e.g., Channel IQ or Market Track, that track and monitor MAP prices on the Internet. These firms scan the Web to find all instances of sale of a product, and identify authorized and unauthorized retailers and the advertised prices for the product in a process that reveals new websites and new retailers over time. The monitoring is spread equally across all websites and retailers, authorized and unauthorized, and is done independently of the MAP price or the extent of SKU violations. Our data provider, Channel IQ, provides violation reports to manufacturers who can then contact the violating retailers and follow the warning and penalty steps mentioned in the manufacturer's policy.

In practice, authorizing a set of retailers, choosing which products are covered by MAP, defining the MAP policy, and successfully implementing the policy is a complicated and multistep process. As academics, we initially thought about these as a complex set of joint decisions. Yet in our work with companies we have learned that these are more accurately characterized as independent decisions that unfold over time. The manufacturer first decides on the strategy and brand, then chooses whether to establish a MAP policy, and then determines how to implement this policy. Enforcement must be equal across all retailers by law, and the equal treatment requirement restricts a manufacturer's ability to respond in a customized way to MAP violations. Furthermore, one might think that the MAP price chosen should be optimally linked to the enforcement of MAP violations, but this is also not the case. From a legal point of view, once any MAP policy is established, the manufacturer has an obligation to enforce it equally across any and all retailers, regardless of retailer type. Our research interviews reveal that the decision of whether to impose a MAP policy on a product has no logical link to the actual MAP price set. Likewise, the choice of how assiduously to enforce the MAP policy has no logical link to the MAP price level.

3.2. Managerial Hypotheses

In this subsection, we form a series of hypotheses motivated by managerial intuition. The approach is based on real-world practice and belief rather than academic theory. These hypotheses thus capture how managers themselves believe the market functions.

Manufacturers believe that unauthorized retailers are to blame for most MAP violations, and therefore seek to protect their authorized retail partners from unauthorized competition. For example, Samsung monitors unauthorized sales and tracks MAP violations to support its approved dealer network. Tim Baxter, president of the consumer electronics division of Samsung Electronics, was recently quoted as saying: "Samsung greatly values the strong relationship it has with its network of authorized dealers and resellers that help ensure consumers receive excellent customer service. We will continue to be vigorous in protecting our authorized partners, our brand and products and addressing the actions of unauthorized dealers" (Wolf 2010). Managerial beliefs about the differences between authorized and unauthorized retailers lead us to our first hypothesis:

Hypothesis 1 (H1). *Authorized retailers are less likely to violate MAP than unauthorized retailers.*

As part of this research, we conducted interviews with a number of different manufacturers that corroborate this perspective. For example, we had the opportunity to observe a conference call between a manufacturer and its sales representatives. During the call, the manufacturer stated: "Remember, your priority is to eliminate unauthorized dealers and support the ones you trust." Another interviewee who had worked for several decades in the electronics industry told us: "Once you bring online retail into the equation the game becomes even tougher. The black sheep among them—those who are not authorized partners—speed up the downward trend of the prices since the other retail partners constantly check competitor prices and set prices based on the Internet. We need to dry out the unauthorized distribution."

Both the popular press and our interviews confirm a widely held belief: Unauthorized retailers are to blame for the cascade of MAP violations throughout their channel. Violations are believed to originate with unauthorized retailers who cannot be held accountable for MAP violations. The violations spread from a few unauthorized retailers until eventually, a product may suffer from widespread noncompliance by many retailers.

We translate these managerial beliefs about retail pricing behavior into the following hypotheses:

Hypothesis 2 (H2). *MAP violations by authorized retailers are associated with MAP violations by unauthorized retailers.*

Hypothesis 3 (H3). *MAP violations by an authorized retailer are associated with MAP violations by other authorized retailers.*

Hypothesis 4 (H4). *MAP violations by authorized retailers are more strongly associated with MAP violations of unauthorized retailers rather than violations of other authorized retailers.*

Another theme that emerged from our interviews with manufacturers is their belief that the presence of Amazon and eBay exacerbates MAP violations through the hosting of third-party retailers on their websites.[4]

[4] Barr (2012) also documents this phenomenon and further describes: "Some brands, including German chef knife maker Wüsthof, said they stopped selling goods on Amazon after the company priced some products below the minimum advertised price. When Wüsthof

As a result of these concerns, manufacturers believe that MAP violations are more severe in online retailing platforms.

Hypothesis 5 (H5). *A retailer is more likely to violate MAP on its third-party Amazon or eBay website than on its own website.*

The academic literature provides little guidance on most of these managerial hypotheses. The literature on agency theory relates to Hypothesis H1, although it is not specifically developed with regard to MAP policy. Agency theory provides solutions to moral hazard problems and provides theoretical support for Hypothesis H1. These ideas are reflected in marketing studies of channel relationship management from a transaction cost analysis perspective.[5] For example, the basis for cooperation in an agency relationship may involve future as well as current considerations, as Heide and Miner (1992) investigate. They consider the "shadow of the future," meaning the future value of a relationship, as an asset whose value is best protected by cooperative channel behavior today. The agency theory literature also investigates channel members' ability to preserve performance outcomes in the face of incentives for opportunistic behavior by other channel members (see for example Stump and Heide 1996 and Jap and Anderson 2003). The transaction cost analysis concept of opportunism (self-interest seeking with guile) is analogous to the threats to performance resulting from a divergence in channel members' interests, combined with unobservability of channel partners' performance levels, in the agency-theoretic paradigm. Jap and Anderson (2003) show that even at high levels of opportunism, bilateral idiosyncratic investments by the channel partners over time, analogous to the agency-theoretic concept of the posting of a bond, continue to preserve performance outcomes and the expectation of future benefits from the channel relationship.

An agency-theoretic approach further suggests that manufacturers can influence the pricing behavior of their downstream retailers through rules that are backed by monitoring, incentives, the posting of bonds or all of these. All are applicable for manufacturers when they aim to manage MAP in their retail channel. In particular, compared with unauthorized retailers, authorized retailers are easier to monitor, suffer greater and more certain punishment for violations, and make more investments in the manufacturer relationship. Therefore, when applying these concepts to our setting, the prediction is that authorized retailers will be less likely to violate MAP, as stated in Hypothesis H1.

The notion of free riding in economics also informs Hypothesis H1. If unauthorized retailers are viewed as the free riders, this literature predicts that they will compete on prices, thus charging lower prices than service-providing retailers. Shin (2007) shows that free riding can soften price competition in the presence of heterogeneous buyers. However, the free riding models usually do not consider pricing under MAP or RPM. Furthermore, RPM and MAP are proposed as tools that eliminate free riding problems (e.g., Telser 1960, Cetinkaya 2009). Carlton and Chevalier (2001) examined online pricing across authorized and unauthorized retailers for 34 brands of DVD players and found that authorized retailers charge 11% higher prices compared to unauthorized retailers. During the period of their sample, RPM was per se illegal (that is, illegal under any conditions), and therefore the authors do not have information about RPM or MAP practices among these DVD manufacturers. They suggest that the differences between authorized and unauthorized retailers can be attributed to manufacturer price restrictions or reputation benefits enjoyed by authorized retailers. This finding is consistent with Hypothesis H1. Our unique database, which includes MAP prices, allows us to directly measure violation rates for both groups. To our knowledge, our other managerial hypotheses have not been addressed in the literature.

4. Data

Channel IQ provided the data for this study. Channel IQ monitors MAP policies and collects data about actual online prices for their manufacturer clients. The database includes one manufacturer[6] with two main product categories (electronics and music), that sells 226 unique product SKUs[7] through 959 different online retailers[8] (130 of which were authorized retailers) over the period January 25, 2010–January 24, 2011. In all, the database includes 1,281,903 daily observations of 10,303 different *SKU* × *retailer* × *marketplace* combinations.[9]

complained, Amazon cited competition from third-party sellers, according to Todd Myers, Wüsthof's vice president of sales in the United States. Myers said Amazon told Wüsthof to crack down on these third-party sellers itself."

[5] A full review of the marketing literature on distribution channel relationships is beyond the scope of this paper, but the references here exemplify the issues and insights that are applicable to our research focus.

[6] For confidentiality reasons, we cannot reveal the identity of this manufacturer.

[7] Initially, there are 258 unique SKUs; however after dropping cases where the MAP price was 0, only 226 SKUs are left.

[8] Initially, there are 1,866 unique sellers; however, after dropping observations where the condition of the item is not new or where there were data collection errors, only 1,095 retailers remain. Limiting SKUs to cases where the MAP price is greater than 0 yields 959 retailers.

[9] Initially, the data include 1,744,622 observations; however, after the initial cleanup of cases where the condition of the item is not new, or where the MAP price is zero or where there were data collection errors, 1,608,935 observations are left. After collapsing the data into daily observations, 1,281,903 observations are left.

Table 1 Variable Definitions

Variable name	Description
MAP	Manufacturer-set MAP price for the certain product
SKU	SKU identifier of the product
Retailer name	Name of the retailer selling the product
Price	Price that appears on the retailer's website for this product
Condition	Product condition—New, Used, Refurbished, etc.
Price available	A TRUE/FALSE dummy indicating whether the price is available as is on the website (TRUE) or the user has to actively ask for the price by adding it to a cart, for example (FALSE)
Marketplace	Website where the product is sold—Retailer's own website, Amazon, eBay, etc.
Shipping rate	Shipping rate for the product
Authorized	A TRUE/FALSE dummy indicating whether the retailer is an authorized distributer of the product
Web link	Web link where the specific quote for the product and retailer was found
Date and time	Date and time of the quote

Note. Each observation in the raw database describes a quote of a price for a certain product by a certain retailer, and has the above mentioned variables.

The manufacturer-set floor price in the database is called the "MAP price." Other information included in the database is the marketplace where the product is offered (Amazon, eBay or a retailer's own website); the condition of the product (new, used or refurbished; we restrict our analysis to new products only); whether the retailer is authorized; shipping rates; whether the price is available to consumers before selecting the product; and the Web link from which the data were taken. A detailed explanation of the variables available in the database is provided in Table 1.

Channel IQ collects its information by scanning the Internet for websites that sell a manufacturer's SKUs. In addition, they receive information from the manufacturer about MAP prices and the identity of authorized dealers. Their Internet search also uncovers unauthorized retailers of the manufacturer's SKUs. Some price information is collected every few hours, while other information is collected once a day. To balance the data, we aggregate data up to the daily level.[10] We define each observation to be $SKU \times retailer \times marketplace \times day$ rather than $SKU \times retailer \times day$ as this allows us to measure how pricing varies among outlets (own online store; sales through Amazon; and sales through eBay), on the same day, for a specific retailer and SKU. Each of our 959 retailers might be selling on its own online website; on Amazon; on eBay or on all three. Thus, if a retailer uses all three online retail outlets to sell a specific SKU on a particular day, its sales of that SKU would have three observations, i.e., one for the own online outlet, one for the Amazon outlet, and one for the eBay outlet. Of our 959 retailers, 855 of them sell through only one outlet; 81 of them sell through two outlets; and 23 of them sell through all three outlets. While the data provide information on prices for used or refurbished products, we include only new products in our data analysis, since the manufacturer's pricing policies apply only to new products.

For much of our analysis, we collapse the daily data into a single observation for each $SKU \times retailer \times marketplace$ combination. This leads to 10,303 observations. We chose this aggregation of the data because for over 92% of our observations there is no temporal variation in compliance behavior. Therefore, MAP compliance for a $SKU \times retailer \times marketplace$ combination varies little over time. As a robustness check, we also estimate our models on the nonaggregated, daily data. Our main findings continue to hold.

The database includes a binary variable that indicates whether the price of a product is available to consumers before selecting the product. As mentioned above, some manufacturers allow retailers to post prices below MAP when the price is not on the main Web page but can be seen if a consumer takes some action (such as calling the retailer or placing the product in the shopping cart) to observe the price (Desai et al. 2010). Overall, fewer than 1% of the observations are flagged to indicate this type of price offer.[11] Because of the very infrequent occurrence we have omitted this variable from our analysis.

While there is very little temporal variation in the data, there is a substantial variation in products, retailers, and channel characteristics: 31% of the SKUs in our sample are in the electronics category, an average SKU is sold by 40 retailers, and an average retailer carries 10 SKUs on average. Free shipping is the norm in the sample, with 76.4% of the observations offering it. Sixty-three percent of the observations are from a retailer's own website, 26% are from retailers on Amazon, and 11% are from retailers on eBay. While authorized retailers represent only 13.5% of retailers, they represent 58.5% of the observations.

4.1. Variable Definitions and Operationalization

We compute a variety of measures from our raw data. We first define a MAP violation as occurring if an observed price is below the MAP price. In the aggregated data, we compute the percent of violations

[10] If there are two or more observations in the same day from the same $SKU \times retailer \times marketplace$ combination with different prices, we choose the lowest price of that day. That is, since we are interested in retailers' daily behavior and the daily probability of a violation, the "worst" behavior in the day is of interest.

[11] The percent of "unavailable price" observations was less than 0.77% before collapsing the data into daily observations. Among daily observations, only 0.72% reported an "unavailable price." Only 22 of 959 retailers ever used the "unavailable price" option, with 20 of the 22 using it only on Amazon.com (one of the 20 being Amazon itself).

over the entire period of the database, for each *SKU* × *retailer* × *marketplace* combination. For example, if a particular *SKU* × *retailer* × *marketplace* combination has 300 observations over the period of a year, and 60 of them presented a price below MAP, we record a violation rate for that observation of 20%. Similarly, the depth of violation is the number of percentage points below MAP at which the product was priced.[12] In the aggregated data, the depth of violation is averaged only over noncomplying observations. The average percentage of violations in the database is 30.8%, and the average depth of violations is 13.4%.

We also define measures that capture SKU-specific and product-specific characteristics. We define the distribution intensity of each SKU as the total number of retailers that hold that SKU. We obtain SKU category information from Amazon.com and the manufacturer website, to determine whether the product is in the electronics or the music category.

We also define and collect measures that capture retailer-specific characteristics. For each *retailer*, we define assortment size as the total number of SKUs that a specific retailer sells. We also identify the top retailers in terms of size: We collected measures of (a) the 100 largest retailers overall, (b) the top 40 online retailers, (c) the top 10 electronics retailers, and (d) two separate top 10 retailers lists in the music category.[13] Among our 959 retailers, 24 were included in at least one of the top retailer lists, 20 of which were authorized retailers. The majority of the top retailers in each product category sell the manufacturer's products, as our data includes at least 75% of the top retailers list of each category. We also create a dummy variable that indicates whether the retailer has a brick and mortar store or a showroom. Of the 959 retailers, 137 have a showroom or a store. Finally, we also count the number of days that a retailer appears in our database.

We define a dummy variable that indicates whether there are shipping fees for the specific *SKU* × *retailer* × *marketplace* combination. In addition, we identify for each retailer, SKU, and marketplace whether they always charge for shipping or only sometimes charge for shipping based on the shipping charges for each daily observation. Additionally, we measure the number of clicks required to find out whether there is a charge for shipping and what the shipping rate is when applicable.[14] While on shopping platforms such as Amazon or eBay, shipping charges are revealed immediately or within one click (depending on whether the retailer belongs to a special shipping program); the majority of the observations (63%) are from other websites that vary in the number of clicks required to reveal shipping charges (2.4 clicks on average).

From these raw data, we create variables that describe MAP violation behavior. For each *SKU* × *retailer* × *marketplace*, we compute the average violation rates and depths among all authorized and unauthorized retailers other than that retailer (i.e., "*self*"). That is, we construct four variables that describe the average rate of violations for authorized retailers other than self, the average rate of violations for unauthorized retailers other than self, the average depth of violations for authorized retailers other than self, and the average depth of violations for unauthorized retailers other than self. We use these variables to test Hypotheses H2–H4.

Our database also allows us to operationalize variables that capture *monitoring*, *bonding*, *price obfuscation*, and *service level perception*, which are key constructs from agency theory and consumer search theory. We interpret the breadth of distribution, the number of unauthorized retailers in a specific market, the assortment size, the number of days the retailer sells a specific SKU in a certain market, and the showroom indicator variables as proxies for agency theory constructs in our discussion and the shipping related variables as proxies for consumer search theory constructs.

Our models include MAP price, an indicator of being on a top retailer list, and a product category dummy variable (Electronics) for the SKU as controls. While we do not have any strong a priori theoretical predictions about these variables, they do help to explain some of the variation in MAP violations. We also include a dummy variable to identify authorized versus unauthorized retailers. We expect authorized retailers to be more compliant with MAP, as stated in Hypothesis H1; when a retailer violates MAP, we expect authorized retailers to have a shallower depth of violation. Finally, we include marketplace dummy variables (Amazon, eBay) to test Hypothesis H5.

[12] For the example above, suppose that the MAP price is $100, and that 30 of the violations are priced at $95 and the other 30 violations are priced at $85. We have a 20% violation rate (60/300). To calculate the violation depth conditional on violation, we use the 60 violating observations to arrive at an average violation depth of 10%. Thus, for this example, the violation *rate* is 20%, and the violation *depth* is 10%.

[13] Sources: top 100 overall: http://www.stores.org/2012/Top-100-Retailers; top 40 online retailers: http://www.foreseeresults.com/research-white-papers/_downloads/us-top-40-e-retail-satisfaction-index-holiday-2011-foresee.pdf; top 10 electronic retailers: http://www.cognizant.com/InsightsWhitepapers/Understanding-US-Consumer-Electronics-Retailing.pdf; top 10 music retailers: http://www.musictrades.com/top200.html and http://musical-instruments.toptenreviews.com/musical-instruments-stores-review/. All lists were accessed August 1, 2013.

[14] Some retailers' websites are no longer available, and thus we were unable to measure the number of clicks required to find out the shipping rate. Of the 6,522 observations in "own website" we obtained the number of clicks for 5,680. For Amazon and eBay, prices are revealed within 0 or 1 clicks, depending on whether the retailer belongs to a special shipping program. For own website the number of clicks vary between 0 and 10, with a mean of 2.4 and a standard deviation of 2.8.

Table 2 Summary Statistics

Variable	Mean	Median	SD	Min	Max
Percent of overall violations	0.308	0	0.440	0	1
Average depth of violations	0.134	0.100	0.137	1.25E–05	0.965
Violation depth: Authorized	0.091	0.052	0.114	1.25E–05	0.91
Violation depth: Unauthorized	0.163	0.129	0.143	1.59E–05	0.97
Violation rate: Authorized	0.147	0	0.316	0	1
Violation rate: Unauthorized	0.535	0.944	0.487	0	1
Assortment size	51.1	41	41.8	1	163
Distribution intensity	62.8	55	40.2	1	216
% Unauthorized	0.415	0.370	0.217	0	1
Charge for shipping = TRUE	0.236	0	0.425	0	1
Always charge for shipping = TRUE	0.067	0	0.250	0	1
Sometimes charge for shipping = TRUE	0.168	0	0.374	0	1
Showroom = TRUE	0.368	0	0.482	0	1
Authorized = TRUE	0.585	1	0.493	0	1
MAP price ($)	654	370	837	35.0	9,999
Number of days selling SKU	134	103	98.4	1	269
Top retailer	0.197	0	0.397	0	1
Electronics = TRUE	0.309	0	0.462	0	1
Market = AMAZON	0.258	0	0.437	0	1
Market = EBAY	0.114	0	0.318	0	1
Market = OWN WEBSITE	0.628	1	0.483	0	1

Notes. Each observation is a *SKU × retailer × marketplace* combination. Percent of overall violations is the percent of violations across the database for each *SKU × retailer × marketplace* combination. Average depth of violations is the average depth of discount below MAP. Percent of overall violations and average depth of violations take values between 0 and 1, corresponding to 0% and 100%. While all other measures are based on a sample of 10,303 observations, the depth of violation figures include only the 4,044 violating observations. Violation Depth/Rate for Authorized/Unauthorized is the average depth of violations among all other authorized/unauthorized selling this *SKU* in this *marketplace*. Assortment size is the number of products a retailer holds. Distribution intensity is the number of retailers that hold a certain SKU. Percent unauthorized is the percent of unauthorized retailers selling the SKU in the market. Charge for shipping is true if there was a shipping charge for the *SKU × retailer × marketplace* combination. Always charge for shipping is true if there is always a shipping charge for the *SKU × retailer × marketplace*, sometimes charge for shipping is true when only some of the observations have a shipping charge. Showroom is true if the online retailer also has a brick and mortar store or a showroom. Authorized indicates whether the retailer is an authorized dealer. MAP price is the manufacturer-set floor price in dollars. Number of days selling SKU indicates the amount of days in the data that the retailer was observed selling a specific SKU. Top retailer is true if the retailer appeared in one of the top retailers' lists. Electronics indicates the product category and Market defines the specific marketplace.

Table 2 displays the summary statistics of the above measures and other variables in the database. Table A1 in Online Appendix A displays a correlation matrix of these variables and measures.

4.2. Descriptive Statistics

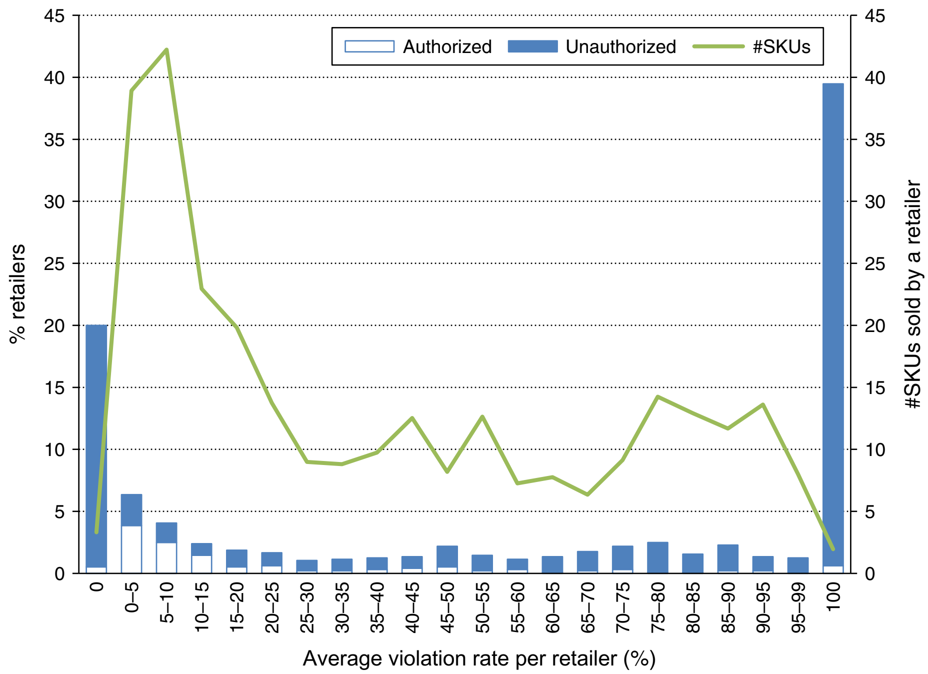
Figure 1 plots the distributions of (i) MAP violations by retailers (bars) and (ii) the number of products sold (line) as a function of the MAP violation rate. To interpret Figure 1 it is helpful to look at the extreme cases. The far left bar indicates that 20% of retailers in our sample never violate MAP on any SKU; the far right bar indicates that nearly 40% of retailers in our sample always violate MAP on all SKUs that they sell. As indicated by the line, these retailers sell an average of 2–3 SKUs, which is very low. Between these extremes, we group retailers by their percentage of MAP violations. Because there is little temporal variation in violations, these groupings can be loosely interpreted as the percentage of SKUs with a MAP violation. For example, a retailer that always violates on 1 SKU and never violates on 19 SKUs would be classified into the 0%–5% bin.

The picture that emerges from Figure 1 is that violation rates are lower among retailers that offer more SKUs. In addition, larger assortment size, as represented by the number of SKUs offered by a retailer, is associated with lower violation rates.

To compare violations of authorized and unauthorized retailers, we split each of the vertical bars in Figure 1 into authorized and unauthorized parts. This reveals two key differences between authorized and unauthorized retailers: (i) Authorized retailers sell on average more products than unauthorized retailers, and (ii) Authorized retailers' distribution of MAP violations is skewed toward lower violation rates. Most of the authorized retailers have 0%–25% violation rates. On the other hand, most of the unauthorized retailers never violate or always violate, and there are few observations with a violation percentage strictly between 0% and 100%. This suggests that there are two unauthorized retailer segments, i.e., one that offers low prices (the MAP violators) and another that attempts to compete in the market while charging the MAP price. Overall, the average violation rate among authorized retailers tends to be lower than that of unauthorized retailers, which is consistent with Hypothesis H1.

The retailers with a violation rate strictly between 0% and 100% are those that sometimes violate and

Figure 1 (Color online) Retailer Violation Rates



Notes. The figure plots the distribution of violations for retailers as well as the corresponding number of products offered by the retailer, for the 959 retailers. Percent retailers indicates what fraction of the retailers have the specific average violation rate, and #SKUs sold by a retailer indicates the average number of SKUs sold by retailers with the specific violation rate. Average violation rate for retailer is the average violation rate of that retailer across all observations. For example, 20% of the retailers always comply (0% violation rate), and these retailers hold 3.3 SKUs on average. While the height of the bars indicate the fraction of retailers at a specific average violation rate, the white part of the bars indicate the authorized retailers in that group, and the blue part of the bar indicates the unauthorized retailers. For example, 6% of the retailers are in the 0%–5% violation group; of these retailers, 61% are authorized.

sometimes comply with the MAP policy. While not shown in the figures, additional analysis shows that these are generally multiproduct retailers that choose a subset of products for compliance and a subset of products for violation. Specifically, 60% of the SKUs of those in this group are always in compliance and 22% are always in violation.

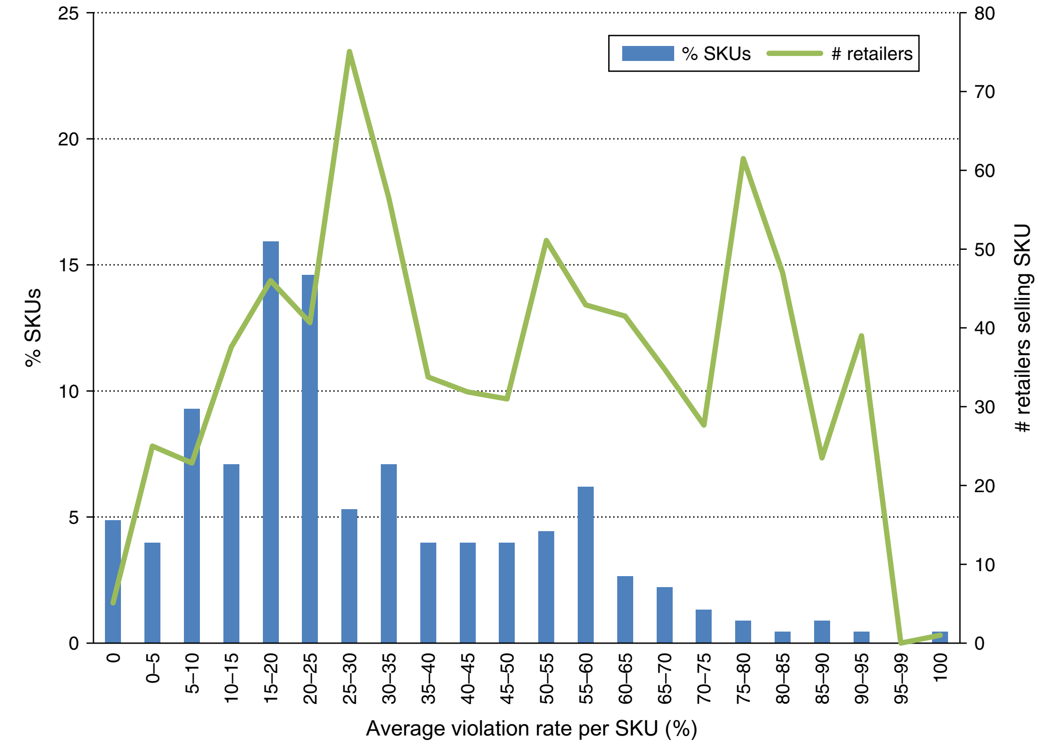
Analogous to Figure 1, Figure 2 plots the distributions of (i) the mean MAP violation rate by SKU; and (ii) the number of retailers selling those SKUs as a function of the MAP violation rate. Scanning the x-axis from left to right, we see that there are very few SKUs that have more than a 60% violation rate. The density of our data can be approximated by multiplying the numeric values indicated by the bars with the numeric values indicated by the line. For example, while there are over 60 retailers selling SKUs with a violation rate of 75% to 80%, this group accounts for less than 1% of SKUs. Hence, they represent a fraction of the overall data. By contrast, among SKUs with violation rates of 20%–25%, the number of retailers averages over 40 and more than 16% of SKUs fall into this category (and about 17% of the data). Indeed, the greatest fraction of our data (about 70%) lies in the regions with 5% to 35% violation rates (i.e., the left half of the figure). Within this region, we see that products that are sold by a greater number of retailers have a higher violation rate. By contrast to Figure 1, where we observed 3 main groups of retailers (violators, non-violators, and sometimes violators), the SKU violation rates in Figure 2 do not show this extreme behavior. In particular, we do not see large mass points at 0% and 100% SKU violation. This suggests that MAP compliance behavior is not driven by SKUs alone.[15]

4.3. Definition of Violations

One of the challenges in our data is to define a MAP violation. To this point in the discussion, we have defined a violation in the strictest manner possible, i.e., any price below MAP. When we relax the MAP violation criterion to categorize any price at least 1% below MAP as a violation, we find that the average

[15] We have also examined these same figures for authorized and unauthorized retailers, but for ease of exposition we omit them from the paper. Similar to Figure 1, the main difference between authorized and unauthorized retailers is that the authorized retailers' violations are skewed towards zero. When looking at authorized retailers only, most of the SKUs they sell have 0%–30% violation rates. On the other hand, the observations in the plot of SKUs using only unauthorized retailers are more evenly distributed over the full range of violations. Interestingly, while 15% of the SKUs sold by unauthorized retailers are always in compliance with MAP, there are almost no SKUs sold by unauthorized retailers with violation rates between 0% and 10%. This implies that, on average, unauthorized retailers that choose to violate MAP pricing do so by more than 10%.

Figure 2 (Color online) SKU Violation Rates



Notes. The figure plots the distribution of violations for SKUs as well as the corresponding number of retailers selling that SKU, for the 226 SKUs. Percent SKUs indicates what fraction of the SKUs have the specific violation rate, and # retailers selling SKU indicates what the average number of retailers that offer the SKU with the specific violation rate is. Average violation rate for SKU is the average violation rate for that SKU across all observations. For example, 4.9% of the SKUs have no violations (0% violation rate), and are offered by 5.1 retailers on average.

violation rate decreases from 30.8% to 25.1%. Some of the reasons for such a substantial change could be price endings (e.g., MAP was set to \$X.99 and the retailer used \$X.90), retailers being uninformed of the MAP price or perhaps believing that such a small deviation would not be noticed or acted on by the manufacturer.

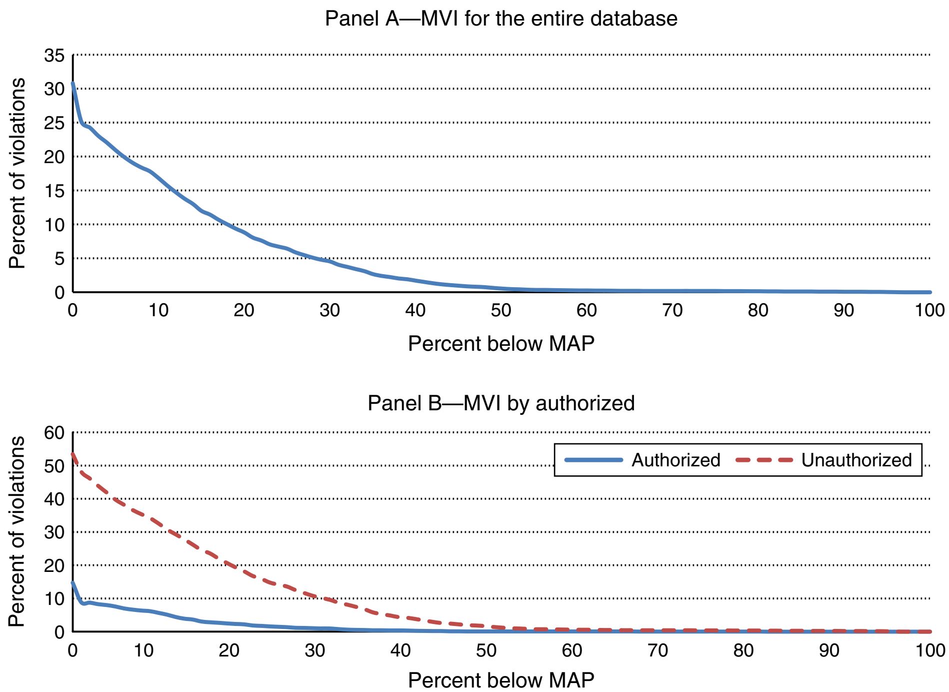
To gain a better understanding of the violation behavior, we construct a measure that demonstrates how the rate and depth of violations change when the definition of violation changes. We name this measure the MVI. The index is displayed as a figure (see for example MVI computed for the entire data set in Panel A of Figure 3), where the horizontal axis is "percent below MAP" and the vertical axis is "percent of violations." Each point in the graph indicates the violation rate if we are willing to categorize up to an X percent deviation below MAP price as a *non*-violation. For example, the MAP price of an item might be \$100. At $X = 0$, we compute the percent of prices that are below \$100; at $X = 10\%$, we compute the percent of prices that are below \$90 (\$100 × (1%–10%)). Performing this calculation for all values of X allows us to create an MVI chart.

To quantify the MVI chart information, and compare the data temporally and across different data subsets, we generate an MVI score that represents the area below the curve (i.e., we numerically integrate the area below the MVI curve). The MVI score assigned to the reference chart is 100; all other MVI scores are defined as the ratio between the area below that curve and the area below the curve of the reference chart. A lower MVI score indicates a smaller area below the curve which in turn suggests fewer violations in rate and/or depth.

An advantage of this approach is that we can study a variety of data cuts, for any subset of SKUs or retailers, as demonstrated in Figure 3. When analyzing the figure, we are interested in the shape of the curve as this informs us about many aspects of MAP violations. For example, if the MVI chart is horizontal from $X = 0$ to $X = X^*$, this implies that there are no observed pricing violations in this range. This shows that if a retailer violates MAP, the depth of violation is always large. By contrast, a steep, vertical slope around $X = 0$ shows that there are many small MAP violations. Finally, the maximum depth of MAP violation is the point where the MVI curve first intersects the x-axis (i.e., the point where violations are zero). Thus, the MVI charts allow us to summarize the depth and frequency of MAP violations.

While we can construct MVI charts for any set of characteristics, we only display the MVI chart of the

Figure 3 (Color online) MAP Violation Index (MVI) Charts



Notes. The horizontal axis is "percent below MAP" and the vertical axis is "percent of violations." Panel A plots the MVI for the full dataset and Panel B plots a separate MVI for authorized and unauthorized retailers. Each point in the plot indicates the percent of violations in the data, if we assume that the manufacturer tolerates an up-to-*X* percent deviation below MAP without categorizing it as a violation. For example, in Panel A, zero is the actual percent of violations in the data (30.8%); 1% deviation below MAP reduces the percent of observations categorized as violations to 25.1%. At a threshold of 50% deviation below MAP, only 1% of observations would be categorized as violating MAP.

complete database and the MVI chart splitting authorized and unauthorized retailers in this paper. Figure 3, Panel A reveals some interesting facts. First, we clearly see that the substantial change in violation rate between 0% and 1% allowed deviation below MAP price. Second, beyond 1%, the line continues to decrease quite smoothly. This indicates that retailer MAP violations occur at many price levels. If retailers "bunched" in the sense that they chose the same percent violation (e.g., 5% below MAP) then the MVI curve would exhibit discontinuities. We do not observe this in the data.

Figure 3, Panel B plots MVI for authorized versus unauthorized retailers. The percent of violations in the authorized-retailers data is 14.7%, compared to 53.5% for unauthorized retailers. In other words, authorized retailers have much higher compliance rates than unauthorized, which is expected (Hypothesis H1). In this plot, we see that the depth of violations across the groups is very different. While the violation rate of the authorized group is close to zero starting about 40% deviation below MAP, for the unauthorized group the violation rate drops to zero only close to 80% deviation below MAP. The average depth of violation in each group is 9.1% for authorized retailers and 16.3% for unauthorized.

While we find that unauthorized retailers tend to violate MAP much more than authorized retailers, it is perhaps surprising that their violation rate is only 53.5% and not 100% since the manufacturer holds no direct authority over these retailers. One reason for unauthorized retailers to comply with MAP is to avoid being traced and eliminated by the manufacturers. A quote by Ted Cohen, eBay's vice president of global government relations, supports this conclusion. In a 2008 *Wall Street Journal* article (Pereira 2008), Cohen states: "They [manufacturers and price enforcing agencies] take down the Web sites only of the unauthorized resellers that are selling at discount, but don't bother unauthorized sellers if they're selling at MAP. This suggests manufacturers are only interested in keeping prices up…"

Using Panel A of Figure 3, we assign an MVI score of 100 to the area below the curve of the entire sample and compute MVI scores of the other data cuts relative to the entire sample. When the data are not discrete, we use a median split to divide the sample into two groups. The third column of Table 3 displays the MVI scores for different variables. Note that the MVI score contains information about both the depth and rate of violation. Therefore, we loosely use the term "more severe violation" when comparing two MVI scores (instead of saying that "one group violates more than the other"). To gain a better understanding of the violation rates, Table 3 also includes a sensitivity analysis

Table 3 MVI Scores and Various Violation Rates

			% violations at *X*% below MAP				
Category	Subset	MVI score	0	1	5	10	20
All data	All data	100	30.8	25.1	20.9	16.8	8.8
Assortment size	Above median	31	13.7	9.5	6.8	5.5	2.5
	Below median	165	46.7	39.8	34.0	27.4	14.7
Distribution intensity	Above median	72	29.5	22.7	17.7	13.1	5.0
	Below median	126	32.0	27.4	23.9	20.3	12.4
Charge for shipping	No shipping	80	27.0	21.1	17.1	13.7	7.0
	Shipping	205	50.8	46.0	40.6	32.9	18.3
Showroom	Showroom	43	17.4	11.2	9.5	7.4	3.4
	Online only	133	38.6	33.3	27.5	22.3	12.0
Dealership authorization	Authorized	30	14.7	8.8	7.5	5.6	2.2
	Unauthorized	199	53.5	48.1	39.7	32.6	18.2
Price	Above median	75	27.9	21.3	17.0	12.8	5.8
	Below median	124	33.6	28.8	24.6	20.7	11.6
Product category	Electronics	210	44.4	41.5	38.9	34.6	22.9
	Music	51	24.7	17.8	12.9	8.9	2.5
Marketplace	Own website	79	27.5	21.8	17.3	13.6	6.8
	Amazon	120	33.1	28.0	24.3	19.7	10.9
	eBay	170	44.0	37.1	33.2	28.1	15.2

Notes. We split the data into different subsets and plot MVI charts (see Figure 3) for each cut. This table displays the MVI scores assigned to each split based on the area below the curves. An MVI score of 100 was assigned to the full sample MVI; other MVI scores are assigned based on the ratio between the area below the curve and the area below the curve of the full sample. We also display violation rates at 0%, 1%, 5%, 10%, and 20% violation tolerance values below MAP. Assortment size is the number of products a retailer holds. Distribution intensity is the number of retailers that hold a certain SKU. Charge for shipping is true if there was a shipping charge for the *SKU* × *retailer* × *marketplace* combination. Showroom is true if the online retailer also has a brick and mortar store or a showroom. Dealership authorization indicates whether the retailer is an authorized dealer. Price is the manufacturer-set floor price. Product category indicates the product category and Marketplace defines the specific marketplace.

wherein we vary the definition of a MAP violation (e.g., 1% below MAP) and compute the percentage of actual prices below this threshold.

Table 3 shows that violations are more severe for below-median assortment size, below-median distribution intensity[16] and below-median MAP prices. Consistent with Hypothesis H1, it shows that authorized retailers violate less than unauthorized retailers. It also shows that the retailers that charge for shipping have more severe violations compared to those that do not charge for shipping, and that retailers that also have a showroom comply more compared with those that have only an online shop. As to product category, electronics has much more severe violations compared to music. Finally, in terms of marketplace, the violations are more severe on eBay compared to Amazon, and they are the least severe on the retailer's own website, as predicted by Hypothesis H5.

The right columns of Table 3 provide more information on the shape of the MVI curves. First, we see the steep difference between the violations at 0% and 1% below MAP across the various cuts. Second, we see that for most of the cuts, the depth of violations is above 20% for fewer than 15% of the observations.

[16] For distribution intensity the effect is reversed if we examine cutpoints other than the median. For example, when distribution intensity is defined as "fewer than 10 retailers," we find that MAP compliance is very high.

To complete our exploratory analysis, we estimated univariate models for each of the variables of interest in our main database. The results of this analysis are provided in Tables A2 and A3 in Online Appendix A. These univariate results are consistent with the findings uncovered in our MVI plots.

4.4. Violations Across Multiple Manufacturers

To further test Hypothesis H1, that authorized retailers are less likely to violate MAP than unauthorized retailers, we report summary statistics for seven additional manufacturers from various industries who also use MAP policies in their online channel. Table 4 shows average daily violation rates among authorized and unauthorized retailers for each manufacturer for a period of one year (October 2012—September 2013).

The first column of Table 4 defines a violation as any case wherein the advertised price was lower than the MAP price. Because MAP policies often allow a price leeway of $1 below MAP or 1% below MAP when defining violations, we also display mean violation rates for these two other definitions of violations. In Column 2 an advertised price is considered to violate MAP if it is more than $1 below MAP, and in Column 3 if it is more than 1% below MAP. Regardless of how we define a MAP violation, we find support for Hypothesis H1. On average, authorized retailers are less likely to violate MAP than are unauthorized retailers.

Table 4 Average Violation Rates for Authorized and Unauthorized Retailers—Various Manufacturers

	Price < MAP		Price < MAP − \$1		Price < 99%MAP	
	Authorized (%)	Unauthorized (%)	Authorized (%)	Unauthorized (%)	Authorized (%)	Unauthorized (%)
1	69.0	59.5	12.6	52.6	13.5	51.1
2	21.1	48.8	8.5	36.9	9.1	36.0
3	14.9	31.8	14.2	28.7	14.4	28.8
4	28.0	42.6	24.3	42.2	12.1	34.2
5	60.7	63.3	55.2	60.9	22.2	57.7
6	62.7	58.5	55.7	57.0	27.3	48.1
7	72.0	72.2	71.8	71.8	70.8	71.4
8	14.7	53.5	5.4	41.7	8.8	48.1
Total	42.89	53.78	30.96	48.98	22.28	46.93

Notes. This table displays the average violation rates for authorized and unauthorized retailers for eight different manufacturers.[a,b] The figures represent the fraction of retailers in each group that violated MAP for a specific product on a day, for the period October 2012–September 2013. There are three different definitions of violations for which these fractions are calculated. Column 1 defines any advertised price below MAP as a violation. In Column 2 any advertised price lower than \$1 below MAP is defined as a violation, and in Column 3 any price lower than 1% below MAP is a violation. All of the differences between the groups are statistically different at $p < 0.01$ except for manufacturer 7, column 1, which is statistically significant at $p < 0.05$, and manufacturer 7, column 2, which is insignificantly different.

[a]Manufacturer 8 is the main manufacturer in our study (note that the time period is different).

[b]The average is computed with equal weights for each manufacturer.

5. Data Analysis

We now turn to a series of multivariate models that allow us to jointly control for many different variables. We estimate the following model:

$$\begin{aligned} y_{rsm} = {} & \alpha + \theta Unauth_r + \beta^{aa} Auth_r \times AuthVioDepth_{sm} \\ & + \beta^{au} Auth_r \times UnauthVioDepth_{sm} \\ & + \gamma^{aa} Auth_r \times AuthVioRate_{sm} \\ & + \gamma^{au} Auth_r \times UnauthVioRate_{sm} \\ & + \beta^{ua} Unauth_r \times AuthVioDepth_{sm} \\ & + \beta^{uu} Unauth_r \times UnauthVioDepth_{sm} \\ & + \gamma^{ua} Unauth_r \times AuthVioRate_{sm} \\ & + \gamma^{uu} Unauth_r \times UnauthVioRate_{sm} \\ & + \sum_{\mathbf{i}} \delta_i^a Auth_r \times X_{irsm} \\ & + \sum_{\mathbf{i}} \delta_i^u Unauth_r \times X_{irsm} + \epsilon_{rsm}, \end{aligned} \tag{1}$$

where the dependent variable, y_{rsm}, is either the percent of violations or the depth of violations for SKU s, retailer r, and market m. The independent variable $Unauth_r$ indicates whether retailer r is an unauthorized dealer of the manufacturer and $Auth_r$ indicates whether retailer r is an authorized dealer of the manufacturer. The variables of type $AuthVioDepth_{sm}$ and $UnauthVioDepth_{sm}$ are the average depth of violation of authorized (*Auth*) and unauthorized (*Unauth*) retailers with the exception of retailer r in market m for SKU s. The variables of type $AuthVioRate_{sm}$ and $UnauthVioRate_{sm}$ are the average rate of violation for those groups. The interactions between these variables and $Unauth_r$ and $Auth_r$ allow us to assess the marginal effect of violation depth (β coefficients) and rate (γ coefficients) for both types of retailers. If r is an authorized retailer, then $Unauth_r = 0$ and this part of the model is shut down; if r is an unauthorized retailer, then $Auth_r = 0$ and this part of the model is shut down. Because the dependent variable is the percent of violations or the depth of violations, this model is similar to a price reaction function, whereby one retailer's price is a function of other retailers' prices. This type of model exhibits a simultaneity problem since prices that appear on the left-hand side (LHS) of an equation also appear on the right-hand side (RHS) of other equations in the regression. We address this issue by estimating two-stage least squares (2SLS) regression when appropriate; we provide the details of the estimation below.

We include a number of independent variables in the vector X_{irsm}. The $Assort_r$ variable is the assortment size of retailer r; the $Dist_s$ variable is the distribution intensity for SKU s; the $Unauthorized\%_{sm}$ variable indicates the percentage of unauthorized retailers in market m selling SKU s; the $Shipping_{rsm}$ variable indicates whether there is a shipping charge for SKU s and retailer r in market m. In some of the models we decompose $Shipping_{rsm}$ into the variables $AlwaysShipping_{rsm}$ and $SometimeShipping_{rsm}$ that indicate whether a retailer always or sometimes charges for shipping on a SKU. The $Showroom_{rsm}$ variable indicates whether retailer r has a showroom. The X_{irsm} vector also includes controls for MAP price, number of days retailer r sells SKU s, a top retailer indicator if the retailer appeared in one of the top retailers' lists, a category indicator, and market indicator. Finally, ϵ_{rsm} is the error term. We begin with an analysis of the violation rate and then turn to the depth of violation.

5.1. Violation Rate

As the dependent variable, percent violations, ranges from 0 to 1, we estimate a linear probability model using OLS. We estimate four versions of the OLS model and cluster the standard errors by retailer. Across these four variations we incrementally add parameters of others' violation behavior. For the two models that include violation rates of others (Models 3 and 4), we also estimate a 2SLS regression. Table 5 presents our main results for the percent of MAP violations. In Panel A of Table 5, we present the OLS regression using the specifications of Models 1 and 2. The left two columns are labeled "Authorized Interactions" and show β^{aa}, β^{au}, and δ_i^a coefficients from each model. The right two columns are labeled "Unauthorized Interactions" and show the β^{ua}, β^{uu}, and δ_i^u coefficients for each model. Thus, the results from a single model, Model 1, are shown in two columns. The variable $Unauth_r$ is included in the model as a noninteracted dummy variable; the coefficient appears in the lower panels of Table 5. Panel B presents both the OLS and 2SLS estimation of Models 3 and 4, and is structured similarly to Panel A, such that the results from a single model are shown in two columns and in the appropriate column in the bottom panel. In addition to

Table 5 MAP Violation Rate Using Annual Observations

Panel A—OLS results				
	Authorized interactions		Unauthorized interactions	
	Model 1	Model 2	Model 1	Model 2
Violation depth: Authorized		1.5***		0.47***
		(0.21)		(0.14)
Violation depth: Unauthorized		0.1		1.2***
		(0.095)		(0.12)
Assortment size	−0.0014***	−0.0014***	−0.00051	−0.0006
	(0.00031)	(0.00031)	(0.0016)	(0.0016)
Distribution intensity	0.00018	0.00036	0.00023	0.00055**
	(0.00025)	(0.00024)	(0.00026)	(0.00026)
% Unauthorized	0.087**	0.015	0.31***	0.098
	(0.043)	(0.044)	(0.067)	(0.071)
Always charge for shipping	0.26***	0.23***	0.1*	0.11**
	(0.088)	(0.086)	(0.054)	(0.051)
Sometimes charge for shipping	0.056**	0.05**	0.093**	0.1**
	(0.025)	(0.025)	(0.042)	(0.041)
Showroom = TRUE	−0.023	−0.024	−0.2**	−0.19**
	(0.023)	(0.023)	(0.082)	(0.079)
MAP price	−0.00002***	−0.000014**	−0.000011	1.9e−06
	(5.3e−06)	(5.4e−06)	(0.000016)	(0.000015)
Number of days sell SKU	−0.0006***	−0.00051***	−0.00057**	−0.00058**
	(0.00011)	(0.00011)	(0.00026)	(0.00026)
Top retailer	−0.059***	−0.059***	−0.24*	−0.23*
	(0.023)	(0.022)	(0.12)	(0.13)
Electronics = TRUE	−0.06***	−0.087***	0.24***	0.14***
	(0.02)	(0.022)	(0.041)	(0.038)
Amazon marketplace	−0.0084	0.0015	−0.078*	−0.069
	(0.023)	(0.022)	(0.047)	(0.046)
eBay marketplace	−0.016	−0.0055	−0.025	−0.0082
	(0.04)	(0.04)	(0.041)	(0.041)
	Model 1	Model 2		
Unauthorized	0.14*	0.16**		
	(0.078)	(0.078)		
Constant	0.24***	0.25***		
	(0.027)	(0.028)		
R-squared	0.31	0.34		
N cases	10,303	10,303		

Notes. Panel A of Table 5 shows the results of Equation (1) under two different model specifications (Models 1 and 2), where the dependent variable is the average percent of annual violations at 0% deviation below MAP. The top panel contains coefficients for interactions between the authorized dummy and independent variables (β^{ai}, δ^{ai}), as well as those for interactions between the unauthorized dummy and independent variables (β^{ui}, δ^{ui}). The bottom panel of the table provides the estimates for the constant (α), the unauthorized dummy (θ), and the R^2 for each of the models. Standard errors are clustered by retailer.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5 (Continued)

Panel B—Accounting for simultaneity

	Authorized interactions				Unauthorized interactions			
	OLS		2SLS		OLS		2SLS	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Violation depth: Authorized		0.12 (0.22)				0.15 (0.17)		
Violation depth: Unauthorized		0.01 (0.12)				0.73*** (0.15)		
Violation rate: Authorized	0.57*** (0.06)	0.55*** (0.065)	1.1*** (0.22)	0.67*** (0.078)	0.11** (0.05)	0.12** (0.058)	0.15 (0.36)	0.067 (0.086)
Violation rate: Unauthorized	0.054*** (0.019)	0.051** (0.023)	−0.065 (0.062)	0.0032 (0.035)	0.41*** (0.05)	0.25*** (0.062)	0.88*** (0.12)	0.78*** (0.08)
Assortment size	−0.0015*** (0.00031)	−0.0015*** (0.00031)	−0.0015*** (0.00033)	−0.0015*** (0.00032)	−0.00034 (0.0017)	−0.00044 (0.0016)	0.00009 (0.0017)	−0.00012 (0.0017)
Distribution intensity	−1.8e−06 (0.00024)	0.000019 (0.00024)			0.000076 (0.00025)	0.00032 (0.00025)		
% Unauthorized	−0.00079 (0.04)	−0.0035 (0.041)			0.13* (0.07)	0.071 (0.072)		
Always charge for shipping	0.2** (0.087)	0.2** (0.087)	0.15 (0.093)	0.19** (0.085)	0.11** (0.052)	0.11** (0.051)	0.092* (0.054)	0.094* (0.055)
Sometimes charge for shipping	0.051** (0.026)	0.05* (0.026)	0.054* (0.028)	0.053** (0.026)	0.1** (0.041)	0.11*** (0.041)	0.084** (0.039)	0.083** (0.039)
Showroom = TRUE	−0.026 (0.023)	−0.026 (0.023)	−0.031 (0.024)	−0.027 (0.024)	−0.19** (0.083)	−0.19** (0.081)	−0.16** (0.083)	−0.17** (0.083)
MAP price	−9.5e−06* (5.3e−06)	−9.3e−06* (5.4e−06)			1.1e−06 (0.000015)	4.3e−06 (0.000015)		
Number of days sell SKU	−0.00045*** (0.00011)	−0.00045*** (0.00011)	−0.00032*** (0.0001)	−0.00039*** (0.0001)	−0.00049* (0.00027)	−0.00052** (0.00026)	−0.00048* (0.00028)	−0.00054** (0.00026)
Top retailer	−0.06*** (0.022)	−0.06*** (0.022)	−0.06*** (0.022)	−0.057*** (0.022)	−0.27** (0.13)	−0.26* (0.14)	−0.27* (0.15)	−0.25* (0.14)
Electronics = TRUE	−0.047** (0.021)	−0.05** (0.021)			0.14*** (0.039)	0.12*** (0.038)		
Amazon marketplace	0.0028 (0.023)	0.0032 (0.023)			−0.065 (0.046)	−0.063 (0.045)		
eBay marketplace	−0.011 (0.04)	−0.01 (0.041)			−0.011 (0.042)	−0.0048 (0.041)		

	OLS		2SLS	
	Model 3	Model 4	Model 3	Model 4
Unauthorized	0.18** (0.079)	0.18** (0.078)	0.22*** (0.075)	0.22*** (0.073)
Constant	0.24*** (0.027)	0.24*** (0.027)	0.22*** (0.024)	0.22*** (0.023)
R-squared	0.35	0.36	0.31	0.33
N cases	10,303	10,303	10,303	10,303

Notes. Panel B of Table 5 shows the results of the OLS and the 2SLS estimation of Equation (1) under two different model specifications (Models 3 and 4), where the dependent variable is the average percent of annual violations at 0% deviation below MAP. The table displays both the OLS and the 2SLS results for the two models. The endogenous variables are the violation rate of other retailers; the estimated coefficients of their fitted values are displayed. The top panel provides coefficients for interactions between the authorized dummy and independent variables (β^{ai}, γ^{ai}, δ^{ai}), as well as those for interactions between the unauthorized dummy and independent variables (β^{ui}, γ^{ui}, δ^{ui}). The bottom panel of the table provides the estimates for the constant (α), the unauthorized dummy (θ), and the R^2 for each of the models. Standard errors are clustered by retailer.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the above coefficients, it includes estimates for the γ coefficients.

As expected, and consistent with Hypothesis H1, we find that authorized retailers are less likely to violate MAP. This can be seen from the coefficient on unauthorized retailers in the lower panels of Table 5. The MAP violation rate is 14%–22% lower for authorized than for unauthorized retailers, which is one of the largest effects in the data.

In Model 2 we include four variables for violation depth of other retailers. All four coefficients are positive. Yet we see an asymmetry in these coefficients. Among authorized retailers there is a large positive association of violation depth of other authorized retailers ($\beta^{aa} = 1.5$, $p < 0.01$) with own violation rates; but the impact of unauthorized retailers violation depth is positive and insignificant. Among unauthorized retailers, there is a large positive association of violation depth of other unauthorized retailers ($\beta^{uu} = 1.2$, $p < 0.01$) with own violation rates; but the impact of authorized retailers violation depth is much smaller in magnitude ($\beta^{ua} = 0.47$, $p < 0.01$). Given the small standard errors, these coefficients (1.5 versus 0.11 and 1.2 versus 0.47) are statistically different from each other.

In Models 3 and 4 the average violation rates of other retailers selling the same SKU s in market m are used as RHS variables, while the dependent variable is violation rates of a specific retailer r in market m selling SKU s. These specifications generate a simultaneous equations model since the RHS variable "average violation rates" for observation i is the average of LHS variables of other observations $(-i)$. To address the arising simultaneity, we estimate Models 3 and 4 using a 2SLS specification in Panel B of Table 5. In the first stage, we regress the four endogenous average violation rate variables on all of the market- and SKU-specific independent variables. In the second stage, we regress the rate of violations on all retailer-specific variables and the fitted values of the endogenous variables. Note that in Model 4, because the average depth of violations is a market and SKU characteristic, it is used only in the first stage.

Panel B of Table 5 presents results of the OLS and the 2SLS specification for Models 3 and 4. Reassuringly, the pattern of asymmetry is replicated: Authorized retailers' violation rates are associated with other authorized retailers' violation rates, while unauthorized retailers' violation rates are associated with other unauthorized retailers' violation rates. In these specifications, only the within-group coefficients (γ^{aa} for authorized and γ^{uu} for unauthorized) are statistically different from zero ($p < 0.01$). In addition, other retailer-specific variable coefficient estimates are consistent in size and magnitude with those of the OLS regression.

In Model 3 we include only the four variables for violation rates of other retailers. Again, we see a large asymmetry. Among authorized retailers there is a large positive association of violation rate of other authorized retailers ($\gamma^{aa} = 0.57$, $p < 0.01$ in the OLS regression and $\gamma^{aa} = 1.1$, $p < 0.01$ in the 2SLS regression) with own violation rates; but the impact of unauthorized retailers' violation rate is one-tenth the magnitude ($\gamma^{au} = 0.054$, $p < 0.01$) in the OLS regression and is statistically not different from zero in the 2SLS regression. Among unauthorized retailers, there is a large positive association of violation rate of other unauthorized retailers ($\gamma^{uu} = 0.41$, $p < 0.01$ in the OLS regression and $\gamma^{uu} = 0.88$, $p < 0.01$ in the 2SLS regression); but the impact of authorized retailers' violation rate is one-fourth the magnitude ($\gamma^{ua} = 0.11$, $p < 0.05$) in the OLS regression and is statistically not different from zero in the 2SLS regression.

For authorized retailers, the coefficients for the violation rates of authorized retailers are positive and significantly different from zero in both specifications. This is consistent with Hypothesis H3, which predicts that a MAP violation by an authorized retailer is associated with MAP violations among other authorized retailers. Hypothesis H2, which predicts that MAP violation by an unauthorized retailer is associated with a violation among an authorized retailer, is only supported in the OLS specification. The asymmetry we observe in the data suggests that we should reject Hypothesis H4, however. According to this hypothesis, we would expect the association between violation rates of unauthorized retailers and those of authorized retailers (γ^{au}) to be greater in magnitude than the association between violation rates of authorized retailers and those of other authorized retailers (γ^{aa}) for authorized retailers. However, we observe the opposite in the data.

In Model 4, we combine depth and rate variables in the same model. This allows us to assess whether violation rates are driven by competing retailers' depth or rate of violation. Among authorized retailers, the violation depth variables become small and statistically insignificant in the presence of the violation rate variable: Compliance of authorized retailers is associated with the violation rate of competing authorized retailers. Meanwhile, among unauthorized retailers, we see that compliance is associated with rate and depth of violations among other unauthorized retailers.

Again, we find a large asymmetry in Model 4. Among authorized retailers there is a large positive association of violation rate of other authorized retailers ($\gamma^{aa} = 0.55$, $p < 0.01$ in the OLS regression and $\gamma^{aa} = 0.67$, $p < 0.01$ in the 2SLS regression) with own violation rates; but the impact of unauthorized retailers' violation rates is one-tenth the magnitude ($\gamma^{au} = 0.051$, $p < 0.05$) in the OLS regression and is statistically not different from zero in the 2SLS regression. These are the same pattern and effect sizes seen in Model 3, which is consistent with Hypotheses H2 and H3, but which rejects Hypothesis H4. Among unauthorized retailers, there is a large positive association of violation rate of other unauthorized retailers ($\gamma^{uu} = 0.25$, $p < 0.01$ in the OLS regression and $\gamma^{uu} = 0.78$, $p < 0.01$ in the 2SLS regression) with own violation rates; but the impact of authorized retailers' violation rate is half the magnitude ($\gamma^{ua} = 0.12$, $p < 0.05$) in the OLS regression and is statistically not different from zero in the 2SLS regression. The estimation with depth and rate of violation of other retailers (Model 4) can be seen only in the OLS version of Model 4. In this specification, there is a large positive association of violation depth of other unauthorized retailers ($\beta^{uu} = 0.73$, $p < 0.01$) with own violation rates, but the coefficient for the depth of authorized retailers is statistically insignificant.

Table 5 also presents results on our other variables of interest. We organize the discussion on these variables by first detailing the direction of the findings and then specifying the effect size for the largest effects in our data. For authorized and unauthorized retailers, offering free shipping, carrying the product for a longer period of time, and being "top retailers" are associated with higher compliance rates. For authorized retailers, those that always charge for shipping are more likely to violate MAP than are authorized retailers that sometimes charge for shipping. In addition, higher assortment size is associated with fewer violations for authorized retailers. We further find that unauthorized retailers that had a showroom had a violation rate that was lower than unauthorized retailers without a showroom. We also find that authorized and unauthorized retailers have lower compliance rates for electronics versus music products.

The effect sizes of charging for shipping and for being a top retailer are large. Authorized retailers that charge for shipping are 20% more likely to violate MAP; unauthorized retailers that charge for shipping are 8%–11% more likely to violate MAP. The difference in these effect sizes surprised us. One might have inferred that charging for shipping is a nefarious practice of the unauthorized channel; but the data suggest that it is common for all retailers and that the effect size is largest for authorized retailers. Additionally, authorized top retailers' violation rates are 6% lower compared to those of authorized retailers that are not top retailers; unauthorized top retailers' violation rates are 26% lower than those of unauthorized retailers that are not top retailers.

Recall that in the MVI analysis, we found initial support for Hypothesis H5, which predicts that the violation rates of retailers selling on Amazon and eBay will be greater than those on the retailer's own website. After controlling for other factors in our models, we no longer find support for this hypothesis. Together, these results suggest that there are important, observable differences in the SKUs, retailers, and behaviors on third-party websites that account for the variation in violations we observed in Table 3.

We conduct a sensitivity analysis using different threshold definitions of MAP violation. Specifically, we use definition of violations as starting at more than 1%, more than 2.5%, and more than 5% below the MAP price (see Table 3). The rationale for this sensitivity analysis is that a manufacturer may only enforce large violations. For example, a one cent violation of MAP may not be enforced. The results for these regressions are presented in Table A4 in Online Appendix A and are broadly consistent with those in Table 5 in terms of direction and magnitude. This demonstrates that our main findings are robust to alternative definitions of a MAP violation. Specifically, we still find support for Hypotheses H1–3; we reject Hypothesis H4; and we find no support for Hypothesis H5.[17]

In Table A5 in Online Appendix A, we also estimate this model in logit and probit frameworks, wherein we model the probability of a violation and treat the dependent measure as binary. More specifically, if the price is greater than or equal to MAP, then $y = 0$ (no violation); otherwise $y = 1$. We estimate the same series of models as in the OLS models presented here. We also estimate this model in a Tobit framework where we limit the LHS variable to between $y = 0$ and $y = 1$. Overall, our main results from the OLS model replicate in these models as well.

5.2. Violation Depth

To analyze the depth of violation, we estimate Equation (1), but the dependent variable is now the average violation depth. The results are presented in Table 6 and are formatted in a manner similar to Table 5. In this case, Panel A displays the OLS results for Models 1 and 3 (the models that do not include the violation depth of other retailers), and Panel B displays both the OLS and the 2SLS results for Models 2 and 4 (which do include the violation depth of other retailers). In these models we only consider the 4,044 observations where the observed price is less than the MAP price. In this subsample, 60% of the observations are of unauthorized retailers. Because we limit our subsample, we also compute the variables of other retailers' rates and depths of violations, limiting the scope only to those that appear in the subsample.

Surprisingly, while the raw data reveal a difference in violation depth between authorized and unauthorized retailers, we find no evidence of this in our four models once we control for other variables. This can be seen by examining the unauthorized coefficient in the lower panels of Table 6. After controlling for all of the variables in our models, we see that authorized and unauthorized retailers' depths of violation are statistically not different from each other. Thus, the differences in the violation depth of authorized and unauthorized retailers can be explained by the variables we include in the model.

[17] One difference is that when violations are defined as prices more than 5% below MAP, unauthorized retailers that carry a larger assortment are less likely to violate MAP, similar to the authorized retailers, while under other definitions of MAP there was no statistically significant relationship between assortment size and violations for unauthorized retailers. This finding suggests that as the price violation is larger in magnitude, unauthorized retailers with a higher assortment size comply more with MAP compared with those with a lower assortment size. One explanation could be that unauthorized retailers with a larger assortment try to stay "under the radar" to prevent manufacturers from targeting them.

Table 6 Average MAP Violation Depth using Annual Observations

Panel A—OLS results

	Authorized interactions		Unauthorized interactions	
	Model 1	Model 3	Model 1	Model 3
Violation rate: Authorized		0.005 (0.014)		0.016 (0.011)
Violation rate: Unauthorized		0.0066 (0.015)		0.061*** (0.016)
Assortment size	0.00033** (0.00015)	0.00033** (0.00016)	−0.00026 (0.0002)	−0.00023 (0.0002)
Distribution intensity	−0.00036*** (0.00011)	−0.00036*** (0.00011)	−0.00032*** (0.000071)	−0.00036*** (0.000072)
% Unauthorized	0.04* (0.021)	0.034 (0.023)	0.11*** (0.019)	0.11*** (0.02)
Always charge for shipping	0.029* (0.016)	0.029* (0.017)	0.03** (0.013)	0.032** (0.013)
Sometimes charge for shipping	0.028** (0.011)	0.028** (0.012)	0.025** (0.011)	0.027** (0.01)
Showroom = TRUE	0.0029 (0.0098)	0.0029 (0.0097)	0.02 (0.017)	0.022 (0.018)
MAP price	−4.8e–06 (4.3e–06)	−4.6e–06 (4.2e–06)	−0.000012* (7.1e–06)	−8.8e–06 (7.1e–06)
Number of days sell SKU	−0.00022*** (0.000038)	−0.00021*** (0.00004)	−0.00017*** (0.000048)	−0.00015*** (0.000048)
Top retailer	0.021 (0.014)	0.021 (0.014)	−0.14*** (0.018)	−0.15*** (0.018)
Electronics = TRUE	0.064*** (0.01)	0.066*** (0.011)	0.072*** (0.0099)	0.069*** (0.01)
Amazon marketplace	−0.03*** (0.0093)	−0.028*** (0.0096)	−0.015 (0.0096)	−0.0096 (0.0097)
eBay marketplace	0.014 (0.02)	0.015 (0.02)	−0.0063 (0.012)	0.00081 (0.012)
	Model 1	Model 3		
Unauthorized	0.016 (0.013)	0.016 (0.013)		
Constant	0.079*** (0.011)	0.077*** (0.011)		
R-squared	0.26	0.27		
N cases	4,044	4,044		

Notes. Panel A of Table 6 shows the results of Equation (1) under two different model specifications (Models 1 and 3), where the dependent variable is the average depth of annual violations at 0% deviation below MAP, only for observations with MAP violations. The top panel shows coefficients for interactions between the authorized dummy and independent variables (γ^{ai}, δ^{ai}), as well as those for interactions between the unauthorized dummy and independent variables (γ^{ui}, δ^{ui}). The bottom panel of the table provides estimates for the constant (α), the unauthorized dummy (θ), and the R^2 for each of the models. Standard errors are clustered by retailer.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

While the average depth of violation may be similar, we still find evidence of asymmetric spillovers between authorized and unauthorized retailers. While these are in line with our hypotheses, we do not have a priori predictions about the effect of one retailer group's depth of violations on that of other groups. The OLS estimation of Models 2 and 4 shows that authorized retailers' violation depth is associated with authorized and unauthorized violation depth, but that unauthorized retailers' violation depth is more responsive to other unauthorized retailers violation depth than to other authorized retailers. In Model 4, the violation rates of other retailers have either a negative correlation with violation depth or the coefficient is statistically not different from zero. The 2SLS results display the asymmetric pattern we have seen throughout the paper. Among authorized retailers there is a large positive association of violation depth of other authorized retailers ($\beta^{aa} = 1.1$, $p < 0.01$ or $\beta^{aa} = 0.57$, $p < 0.01$) with own violation depth; but the impact of unauthorized

Table 6 (Continued)

Panel B—Accounting for simultaneity

	Authorized interactions				Unauthorized interactions			
	OLS		2SLS		OLS		2SLS	
	Model 2	Model 4	Model 2	Model 4	Model 2	Model 4	Model 2	Model 4
Violation depth: Authorized	0.24***	0.26***	1.1***	0.57***	0.083**	0.092***	0.087	0.065
	(0.057)	(0.056)	(0.23)	(0.13)	(0.032)	(0.033)	(0.099)	(0.071)
Violation depth: Unauthorized	0.26***	0.27***	0.00055	0.19**	0.71***	0.75***	0.89***	0.8***
	(0.081)	(0.086)	(0.12)	(0.094)	(0.049)	(0.051)	(0.073)	(0.058)
Violation rate: Authorized		−0.021**				−0.013		
		(0.011)				(0.0098)		
Violation rate: Unauthorized		−0.014				−0.05***		
		(0.015)				(0.014)		
Assortment size	0.00032**	0.00033**	0.0002	0.0003**	−0.00033	−0.00036	−0.00019	−0.0002
	(0.00015)	(0.00015)	(0.00016)	(0.00015)	(0.00022)	(0.00022)	(0.0002)	(0.00021)
Distribution intensity	−0.00019*	−0.00016*			−0.00011*	−0.00007*		
	(0.0001)	(0.0001)			(0.000062)	(0.000063)		
% Unauthorized	−0.02	−0.013			0.021	0.016		
	(0.02)	(0.021)			(0.018)	(0.02)		
Always charge for shipping	0.021	0.022	0.0073	0.017	0.038***	0.037***	−0.00028	−0.00029
	(0.015)	(0.014)	(0.019)	(0.015)	(0.011)	(0.011)	(0.00022)	(0.00023)
Sometimes charge for shipping	0.022*	0.021*	0.018	0.018	0.037***	0.036***		
	(0.013)	(0.012)	(0.014)	(0.013)	(0.0087)	(0.0089)		
Showroom = TRUE	7.8e−06	0.000024	−0.0056	−0.00091	0.016	0.014		
	(0.0098)	(0.0097)	(0.011)	(0.011)	(0.015)	(0.015)		
MAP price	−3.0e−06	−3.5e−06			4.6e−06	2.8e−06	0.034***	0.032***
	(4.5e−06)	(4.5e−06)			(5.6e−06)	(5.4e−06)	(0.011)	(0.011)
Number of days sell SKU	−0.00019***	−0.0002***	−0.00013**	−0.00018***	−0.0002***	−0.0002***	0.032***	0.032***
	(0.000038)	(0.000038)	(0.000053)	(0.000043)	(0.000039)	(0.00004)	(0.0084)	(0.0083)
Top retailer	0.019	0.02	0.018	0.018	−0.13***	−0.13***	0.016	0.015
	(0.013)	(0.013)	(0.013)	(0.012)	(0.015)	(0.015)	(0.013)	(0.014)
Electronics = TRUE	0.035***	0.029**			0.016	0.015		
	(0.011)	(0.012)			(0.0097)	(0.0098)		
Amazon marketplace	−0.019**	−0.022**			−0.014	−0.018*		
	(0.0092)	(0.0094)			(0.0096)	(0.0098)		
eBay marketplace	0.018	0.016			0.0046	−0.00032		
	(0.022)	(0.022)			(0.011)	(0.011)		

	OLS		2SLS	
	Model 2	Model 4	Model 2	Model 4
Unauthorized	0.025*	0.022	0.019	0.02
	(0.014)	(0.014)	(0.014)	(0.013)
Constant	0.086***	0.09***	0.095***	0.097***
	(0.011)	(0.011)	(0.012)	(0.011)
R-squared	0.43	0.44	0.35	0.41
N cases	4,044	4,044	4,044	4,044

Notes. Panel B of Table 6 shows the results of the OLS and the 2SLS estimation of Equation (1) under two different model specifications (Models 2 and 4), where the dependent variable is the average depth of annual violations at 0% deviation below MAP, only for observations with MAP violations. The table displays both the OLS and the 2SLS results for the two models. The endogenous variables are the violation depth of other retailers, and the estimated coefficients of their fitted values are displayed. The top panel provides coefficients for interactions between the authorized dummy and independent variables (β^{ai}, γ^{ai}, δ^{ai}), as well as those for interactions between the unauthorized dummy and independent variables (β^{ui}, γ^{ui}, δ^{ui}). The bottom panel of the table provides the estimates for the constant (α), the unauthorized dummy (θ), and the R^2 for each of the models. Standard errors are clustered by retailer.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

retailers' violation rates is statistically not different from zero in Model 2 and smaller in magnitude in Model 4 ($\beta^{au} = 0.19$, $p < 0.05$). Among unauthorized retailers, there is a large positive association of violation depth of other unauthorized retailers ($\beta^{uu} = 0.9$, $p < 0.01$ or $\beta^{uu} = 0.8$, $p < 0.01$) with own violation depth; but the impact of authorized retailers' violation depth is statistically not different from zero in the 2SLS regression.

With regard to the effect of other retailers' violation rates as displayed in Model 3, the only coefficient that is different from zero is that of the association between violation depth of unauthorized retailers and the violation rates of other unauthorized retailers ($\gamma^{uu} = 0.61$, $p < 0.01$).

As noted in the previous paragraph, the coefficient for violation rate is sometimes negative and statistically different from zero. We believe that these unexpected negative effects in Model 4 are largely driven by the lack of independent variation of violation depth and rate. In the data, the correlation between violation rate and depth is 0.55 for authorized retailers and 0.74 for unauthorized retailers, respectively. These correlations are quite high and explain why it may be difficult to disentangle violation rate from depth, as retailers that have higher violation rates also have a high depth of violations.

Table 6 also presents results on our other variables of interest. We find that authorized retailers that charge for shipping have a higher depth of violations. In terms of magnitude, the violation depth of authorized retailers that sometimes charge for shipping is about 2% higher than those that do not charge for shipping. Among unauthorized retailers, those that charge for shipping, either sometimes or always, have about 3% higher depth of violation compared to unauthorized retailers that do not charge for shipping.

We find that authorized retailers with larger assortments tend to have a higher depth of violations. Previously we found that large assortment size deters authorized retailers from violating MAP. This shows that large assortments are associated with fewer, but deeper, MAP violations. When a product is more intensely distributed we observe a smaller depth of violation. Empirically, we find that the depth of violations decreases 0.2%–0.4% for every 10 additional retailers that sell the product. We also find that the depth of violations is lower when the product is sold on Amazon compared to the retailer's own website or eBay.[18] In addition, among unauthorized retailers, the depth of violations for top retailers is 12%–18% lower than for other retailers.

We also find that the depth of violation is lower for retailers that sell a SKU for a longer period of time, and when the product is in the music category. These findings exist for authorized and unauthorized retailers. Finally, in several of the models, the percent of unauthorized retailers is associated with a higher depth of violations.

[18] One reason for the lower depth of violation on Amazon.com may be the seller fees incurred by retailers selling products on Amazon.com, which would cause retailers to try to shore up their margins by charging higher (i.e., MAP) prices. However, since eBay uses a similar seller fee structure, we would expect a similar result for the eBay marketplace, which we do not find.

5.3. Daily Results

Our results thus far are descriptive and we are unable to make direct, causal claims. To examine the issue of causality more directly, we estimate an analogous model and use daily observations where the dependent variables are violation occurrence and the depth of violation. We include *SKU* × *retailer* × *marketplace* fixed effects in the model due to the high inertia and lack of dynamics in the data. Additionally, we use one day lagged versions of the violation variables. Thus, our empirical identification strategy relies on temporal antecedence. Does a violation by other retailers yesterday affect a retailer's compliance today? Does the depth of violation by other retailers yesterday affect a retailer's depth of violation today? A detailed discussion of these analyses and the results is provided in Online Appendix C.

The results of our daily violation rate variable provide convergent evidence of the asymmetric spillovers we observe in the annual data (see Table C1 in Online Appendix C). The asymmetric pattern for the violation depth variables (e.g., Models 2 and 4 in Table C4 in Online Appendix C) replicate in some instances, but are less robust.

We note that our daily analyses are limited by a lack of temporal variation in the data. The daily models includes *SKU* × *retailer* × *marketplace fixed effects*, hence empirical identification relies on changes in violation behavior within *SKU* × *retailer* × *marketplace*. For the violation depth model, we further condition our data on a violation occurring. For example, if a retailer violates at 10% below MAP and never changes this price, then this observation contributes no information to the parameters of interest. Our model requires a change in violation depth (e.g., from 10% to 15%) within a *SKU* × *retailer* × *marketplace*, which is a strong empirical requirement. We speculate that our results for daily violation depth are less robust because we are stretching the data to its limits.

5.4. Explanation of Findings

We summarize our main findings in Table 7. In this subsection, we offer possible explanations for these findings. We are cautious about making causal interpretations of our results since such statements assume that the various variables are exogenous, which is not the case. While this paper is descriptive in nature, future research is needed to distinguish between the different theories.

There is overwhelming evidence that authorized retailers are less likely to violate MAP than are unauthorized retailers. This main effect guides much of the practitioner wisdom cited in §1; unauthorized retailers violate MAP much more frequently. One interpretation of this robust finding is that authorization confers gains on a retailer; the higher the gains from compliance, the

Table 7 Findings Table

General empirical finding	Empirical facts from this study
Managerial hypotheses	
Compliance rate is higher among *Authorized* retailers compared to *Unauthorized* retailers	*Authorized* retailers violate MAP 22% of the time on average, compared to 47% of the time among *Unauthorized* retailers.
MAP violations by *Authorized* retailers are associated with MAP violations by *Unauthorized* retailers	For a given SKU and market, an increase of 1% in *Unauthorized* retailer violation rate is associated with up to a 0.05% increase in an *Authorized* retailer violation rate.
MAP violations by an *Authorized* retailer are associated with MAP violations by other *Authorized* retailers	For a given SKU and market, an increase of 1% in other *Authorized* retailer violation rate is associated with a 0.55%–1.1% increase in an *Authorized* retailer violation rate.
MAP violations by an *Unauthorized* retailer are associated with MAP violations by other *Unauthorized* retailers	For a given SKU and market, an increase of 1% in other *Unauthorized* retailer violation rate is associated with a 0.25%–0.88% increase in an *Unauthorized* retailer violation rate.
MAP violations by an *Unauthorized* retailer are associated with MAP violations by *other Authorized* retailers	For a given SKU and market, an increase of 1% in *Unauthorized* retailer violation rate is associated with up to a 0.12% increase in an *Authorized* retailer violation rate.
Academic theories	
Compliance rate is higher among *Authorized* retailers who offer more of a manufacturer's products	1.5% lower violation rates for each 10 additional products an *Authorized* retailer carries.
Compliance rate is higher among retailers who offer a SKU for a longer period of time	4% lower violation rates for every 100 days that a SKU is offered.
Compliance rate is higher among *Unauthorized* retailers with a showroom, compared to those without a showroom	16%–20% higher among *Unauthorized* retailers with a showroom.
Compliance rate is higher for retailers who offer free shipping	10%–20% higher, for both *Authorized* and *Unauthorized* retailers.

higher we expect MAP compliance to be. Note that authorization status is not given randomly, but is a choice of the manufacturer and the retailer. Therefore, another explanation could be that the manufacturers' pre-select retailers that are known to be more likely to comply with their policies.

Overall, we find asymmetric spillovers across authorized and unauthorized retailers with regard to MAP violations. That is, each group of retailers' behavior is more correlated with its own group and to a lesser extent with the other group. Managers often believe that this relationship is causal, and that the behavior of a group of retailers affects the behavior of a specific retailer. Thus, one interpretation of our findings is that authorized retailers observe the violation behavior of other authorized retailers and respond accordingly. Similarly, unauthorized retailers engage in MAP violations based on the behavior of other unauthorized retailers. The fact that we find smaller or no effects across the groups may suggest that each group of retailers views itself as a separate group and makes violation decisions based on in-group behavior. The different compliance rates for authorized and unauthorized retailers for different product categories further highlights the differences between authorized and unauthorized retailers' MAP compliance. Finally, our analysis of daily violation rates supports this causal interpretation.

Another possible explanation for the asymmetric spillovers is that products' characteristics, which are unobserved by researchers, have different effects on the violation behavior of authorized and unauthorized retailers. For example, suppose that the leakage in the distribution of products is such that unauthorized retailers are highly likely to obtain certain products. If so, they can heavily violate MAP for this subset of products, while an authorized retailer chooses not to violate MAP for them or not to carry such products.

Agency theory predicts that violation rates should be lower if a retailer makes a larger commitment to a manufacturer (see, for example, Anderson and Weitz 1992). In some cases, the basis for cooperation may depend on future as well as current outcomes, as Heide and Miner (1992) investigate. They consider the "shadow of the future," meaning the future value of a relationship, as an asset whose value is best protected by cooperative channel behavior today. A broad assortment implies a large bond posted by the retailer, whose penalty value is the future profit stream from selling the manufacturer's products over the penalty period (including the foregone financial value of the promotional incentives offered by the manufacturer to compliant retailers).[19] An authorized retailer who violates MAP risks losing the assortment temporarily or permanently. We find that among authorized retailers the coefficient for

[19] Jap and Anderson (2003) show that even at high levels of opportunism, bilateral idiosyncratic investments by the channel partners over time, analogous to the agency-theoretic concept of the posting of a bond, continue to preserve performance outcomes and the expectation of future benefits from the channel relationship.

assortment size is negative, but assortment size has no association with compliance of unauthorized retailers. Both of these results are consistent with predictions from agency theory. Because the manufacturer has no legitimate authority over the unauthorized channels, we would be surprised to see that assortment affects compliance. Yet among authorized retailers we see greater compliance when a retailer offers a broader assortment.

Note that assortment size may also be a proxy for a retailer's scale in the category, rather than a proxy for bonding. In that case, retailers with a broader assortment may have higher prices than retailers with a large volume of few SKUs. In turn, higher prices would suggest lower violations. This explanation would be convincing if we would exhibit the same negative relation between assortment size and violation rates among authorized and unauthorized retailers. However, the lack of significant relationship between assortment size and violations among unauthorized retailers suggests that the commitment interpretation may be more compelling. In addition, we try to control for retailer scale using the top retailer indicators. We find that top retailers have lower violation rates than other retailers. This finding is consistent with the notion that larger scale retailers may have a lower need to discount their prices compared to smaller scale retailers.

Another measure of retailer commitment is the number of days that a retailer has offered a SKU. We find that retailers that offer a SKU for longer periods are less likely to violate MAP. We speculate that some retailers may obtain excess inventory that periodically appears in the supply chain or may invest in lower levels of initial inventory. Either behavior would manifest itself in our data as a lower number of days offered for a SKU. These retailers may offer prices below MAP because they are less vested in a long-term relationship with a manufacturer. By contrast, retailers that have a stronger, ongoing relationship with a manufacturer will consistently offer inventory to consumers. In this sense, the observed relationship between the number of days a SKU is offered and violation rates is consistent with predictions from agency theory. An alternative explanation is that a retailer's decision to carry a SKU for more days reflects other unobserved product characteristics (i.e., a selection effect).

We anticipated that retailers with a showroom may be less likely to violate MAP because they have made larger investments in infrastructure compared to online retailers. The results surprised us. Among authorized retailers, the presence of a showroom had no impact on violation rates. Yet unauthorized retailers with a showroom had a violation rate that was 16%–20% lower than unauthorized retailers without a showroom. One explanation for this difference could be that, when choosing authorized partners, a manufacturer chooses a group that is expected to adhere to policies regardless of the presence or absence of a showroom. If so, the average violation rate should be the same for authorized retailers with versus without a showroom. However, unauthorized retailers self-select into selling the manufacturer's products. An unauthorized retailer with a showroom may have a higher incentive to comply with MAP and maintain high profit margins due to higher expenses such as trained personnel, inventory, and rent or due to its higher visibility compared to an unauthorized retailer without a showroom.

When a product is more intensely distributed we observe a smaller depth of violations. This is somewhat counter to what one might expect, i.e., that intense distribution may lead to greater competition among retailers and greater depth of violation. One possible explanation for our result is that retail intensity may imply more price-elastic demand. In other words, retailers of intensely distributed SKUs may sell more popular items for which customers are very price-sensitive. If true, then small MAP violations may be very effective and a retailer may not need to offer a large discount to attract consumers.

Our results on shipping charges are consistent with the findings of Ellison and Ellison (2009) and Yao and Zhang (2012) on price obfuscation. Most of our retailers (77% of observations—see Table 2) offer free shipping, which would lead consumers to expect free shipping if not informed otherwise. Therefore, a retailer could try to engage in price obfuscation by hiding the shipping fee or postponing the revelation of the shipping fee to a late step in the search and shopping process. Retailers that charge for shipping tend to violate MAP more than those that do not charge for shipping.

Our interpretation of this as "price obfuscation" is admittedly somewhat speculative. To examine this interpretation more closely, our analysis also includes the number of clicks required to see the shipping charge. In some cases, shipping fees are known in advance ("free shipping") but in others it takes several clicks to see a shopping cart and learn the shipping fee. This analysis revealed that among the retailers that charge for shipping, a greater number of clicks is associated with a higher shipping fee (see Table A6 in Online Appendix A). We interpret this result as convergent evidence that retailers that charge for shipping are engaging in price obfuscation. If a retailer plans to surprise a customer with a shipping charge, then it is logical to make this unexpected fee more difficult to find.

An alternative explanation is that shipping charges are associated with perceptions of low service levels (see §2). Thus, we include a dummy variable indicating that there are always shipping charges as a proxy for a lower perceived level of service. We find support for this explanation as well. Retailers may also use shipping charges due to their overall lower level of service.

We do not find support for what one may call the "leaky bucket" theory of distribution. That is, when products are in broad distribution and leak into the hands of many unauthorized retailers, then we might have expected MAP violations to increase. Yet by contrast, our analysis shows that unauthorized retailers are relatively compliant. One might expect these retailers to violate on 100% of their prices since they are not authorized outlets. However, our data reject this extreme behavior. What forces are causing these unauthorized retailers to comply with MAP remains an open question.

6. Conclusions

To our knowledge, this study provides the first empirical investigation of MAP policies in practice. MAP policies are widely used among practitioners as a key component of brand management and channel management, but have received little attention by academics. The empirical findings, based on a sample of hundreds of retailers and a large variety of products, advance our understanding of this important topic.

Our inductive approach yields many new, interesting findings. Specifically, we find that managers correctly conclude that authorized retailers are far more compliant than unauthorized retailers. Yet further tests suggest managers may be too quick to conclude that simply bringing the unauthorized channel into compliance will also bring the authorized channel into compliance. Further research by Israeli (2016) confirms this prediction: The authorized and unauthorized markets operate independently.

In Online Appendix D, we offer simulation-based findings that manufacturers can cautiously use to help improve MAP compliance. In particular, manufacturers should be wary of violation behavior for authorized and unauthorized retailers and should try to target both groups to improve overall MAP channel compliance.

Many of our findings are consistent with predictions from agency theory and consumer search theory. These include results on the depth of assortment, breadth of assortment, and shipping fees. While the results are consistent with theory, we are careful not to infer a causal interpretation. To this end, we provide alternative explanations that should be considered. Disentangling these various explanations is an important topic for future research.

Manufacturers have used MAP policies for nearly 100 years in the United States. Today MAP is extremely widespread. The area of vertical price restraints has been studied theoretically for decades but virtually no systematic empirical analysis exists of vertical pricing policies and MAP. Analytic models of RPM and MAP often assume an equilibrium in which cheating never occurs. Yet the reality that most manufacturers face today requires that they understand the extent of MAP violations to bring errant channel partners into compliance. Our findings offer a rich description of market behavior that helps managers achieve the goal of better understanding this widespread problem. Of particular significance, our empirical evidence challenges conventional wisdom and this may lead managers to develop more effective channel management policies.

This research was spurred by the availability of extensive new data and by the urgent need of managers to understand an evolving marketplace. As data like these become more widespread, we anticipate that empirical analysis of vertical price restraints will become an important area of future research for academics, managers, and policy makers.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0933.

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