4-18-2014

Three Essays on Decision Making Strategies

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University of Connecticut, 2014

Abstract

This dissertation consists of three essays on decision making strategies. In the first essay, we analyze the determinants of expansions and contractions of shopping centers using a unique dataset of property level data for shopping centers in eleven metropolitan areas over the period from 1995 through 2005. We find that shopping centers with large operating costs are less likely to expand and are more likely to contract. Higher expected revenue increases the likelihood of expansion and decreases the likelihood of contraction. We find weak support for Grenadier's theory that a larger number of competitors reduces the value of option to wait and increases the likelihood of both expansion and contraction. The market share of competitors reduces the likelihood of increasing the number of stores as suggested by the theory of strategic positioning.

In the second essay, we examine the intra-metropolitan location decisions of retail stores by focusing on the opening of a comprehensive list of department ("anchor") stores in the United States. The nonparametric K-density procedure shows that new stores are more dispersed than existing stores; their locations depend on existing competitive conditions. By applying a conditional logit model (CLM), we find that the location choices of new anchors can be explained by zoning, population, CBD and highway proximity, potential revenue and revenue growth, cannibalization, competition and localization economies. The CLM-based K-density confidence intervals effectively explain actual location patterns within three miles.

In the third essay, we find that the probability of intentional accounting misstatements (irregularities) increases with the level of investor beliefs about business conditions but decreases when the beliefs are sufficiently positive. Further, the proportion of independent directors with

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accounting expertise is a decreasing function of investor beliefs, and the likelihood of irregularities is decreasing in the proportion of independent directors with accounting expertise. Finally, stock market reaction to accounting restatements is positively related to the proportion of independent directors with accounting expertise. These findings underscore the effectiveness of accounting expertise of independent directors in reducing the incidence and severity of corporate misconduct.

Three Essays on Decision Making Strategies

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University of Connecticut, 2014

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2014

APPROVAL PAGE

Doctor of Philosophy Dissertation

Three Essays on Decision Making Strategies

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Acknowledgements

I would like to express the deepest appreciation to my committee chair, Professor John M. Clapp for his guidance, inspiration, patience, and continuous support. Not only have I learned how to become a good researcher, but also I have gained a profound understanding in what it means to be a researcher. His enthusiasm, attitude towards research and pursuit of excellence will undoubtedly benefit my whole career. Professor Clapp is an extraordinary person. He is one of the greatest mentors in my life and one of the people whom I respect the most in the world – professionally and personally.

I am grateful to Professor Shantaram Hegde for incredibly valuable advice and support. I consider myself very fortunate to have had the opportunity to work with Professor Hegde. I express sincere gratitude to Professor John Glascock, who has been always supportive and generous. I would like to thank Professor Joseph Golec, the best and most responsible PhD program coordinator, for his continuous support during the past five years. I would also like to thank Professors Assaf Eisdorfer and Stephen Ross for their time serving as my committee members and providing valuable comments. I am grateful to all the finance PhD students, especially Chongyu Wang, Di Huang, Yihong Xiao, Le Sun, Fan He, Reilly White, Alain Krapl, Scott Roark, Shantanu Namjoshi, Stephen Rush and Charles Clarke, for being always supportive.

Foremost, I am indebted to faculty members at University of Macau, especially Professors Rose Lai and Ricardo Siu, for inspiring me, for shaping who I am, and for paving the way for my graduate study.

I am blessed to have the kindest and most caring parents and husband on Earth. They always offer tremendous encouragement and unconditional support to me. They have been staying by my side through all the challenges. Our lovely cats, Nick and Ellie, have always been genuine and make every day wonderful.

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Essay 1

Expansions and Contractions of Major US Shopping Centers

1. Introduction

Shopping centers play a vital role in the U.S. economy. Seventy percent of U.S.'s GDP is attributed to consumer spending and forty percent of consumer spending is conducted at shopping centers.[1] One of the most important economic decisions made by a developer of a shopping center is the irreversible decision to expand or to contact. However, academic literature that examined redevelopment of shopping centers is very limited. To the best of our knowledge, only one study (Peng and Thibodeau (2011)) examines property level redevelopment decision for commercial real estate; it finds that their model is not significant for retail properties.[2] We contribute to the literature by analyzing the determinants of expansions and contractions of shopping centers using a unique dataset of property level data for shopping centers in eleven metropolitan areas over the period from 1995 through 2005.

Our study of the contraction decision is particularly timely: even before the global financial crisis (GFC) investment professionals noted a trend away from regional and super-regional centers with full line department stores and towards smaller "life style" centers emphasizing a small town or village shopping experience. In some cases this involved converting enclosed malls with high Heating, Ventilating, and Air Conditioning (HVAC) costs to open air centers. In other cases regional centers have been replaced by "power centers" characterized by big box retailers.[3] This is sometimes referred to as "demalling." Our study is further motivated by the GFC. Higher unemployment and reduced retail spending has caused discussion of too much retail space per customer. One way to deal with the high operating costs generated by excess retail space is to reduce the size of the centers.

We examine two types of irreversible decisions: substantial change in the number of stores and in Gross Leasable Area (GLA thereafter). Since the change in GLA involves greater degree of irreversibility, this analysis provides one method of controlling for the cost of changing the center.[4]

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[1] The 40% estimate is based on Bureau of Labor Statistics numbers analyzed by Fanning (2005).

[2] Other empirical studies examine new construction rather than capital expenditures for existing properties. See Peng and Thibodeau (2011) for detailed review of this stream of literature.

[3] Morris Newman (1999), writing for *The Los Angeles Times* says "As shoppers find other ways to buy merchandise, several traditional shopping centers--including that famous playground for Valley girls, the former Sherman Oaks Galleria--are being converted to such new hybrids as entertainment centers, "big box" retail centers, office buildings, schools and even housing."

[4] Change in the number of stores is associated with relatively small costs of repositioning of walls. However, it

We separately analyze large and small shopping centers since it is likely that large shopping centers are above equilibrium size and small shopping centers are below equilibrium size. Moreover, large shopping centers provide greater agglomeration economy for consumers. Furthermore, shopping centers might build excess capacity to signal the ability to attract customers and the willingness to compete for market share and thus deter the entry of competitors. Therefore, determinants of expansion and contraction decisions might differ for small and large shopping centers.

Large shopping centers in our sample have higher operating costs and higher expected revenue than small shopping centers. Large shopping centers have more stores (113 versus 33), however store size of larger shopping centers is less than half of that of small shopping centers. Although large shopping centers have more competitors, the market share of the competition is smaller than that of the competitors of small shopping centers.

We rely on several theoretical frameworks to guide our empirical analysis. Real options theory is one of the most widely researched theories applied to the analysis of the irreversible investment decisions. The purchase of real estate includes embedded real options to alter the bundle of structural characteristics. Value derives from the flow of utility and/or rents from the existing property characteristics and from the right but not the obligation to alter the structure. The call (put) option is the right but not the obligation to increase (reduce) the scale of investment at a given location (McDonald and Siegel, 1986). Location is not subject to alteration: ownership of land confers the right but not the obligation to make changes to the structure. Dixit (1989) provides a simple theoretical framework, in which a fixed cost can be paid to go out of business and eliminate operating losses. If the factory is not operating, a different cost can be paid to re-enter. Thus there are two states for the investment: operating or not operating. The former gives rise to the put option, which is in the money when variable costs are above revenues, while the latter has value for the call, which is in the money when value exceeds the cost of entry.[5] Real options theory predicts that the increase in costs

requires costly and irreversible renegotiation of leases. Change in GLA involves high construction costs. Both types of redevelopment involve disruption of existing retailing.

[5] The literature contains numerous empirical studies of the call option for housing: i.e., the option to tear down and rebuild a larger or more luxurious structure, or to substantially renovate. The tear down option is the subject of Rosenthal and Helsley (1994); Dye and McMillen (2007); Rosenthal (2008); Clapp and Salavei (2010); Clapp, Bardos and Wong (2011). Vacant land (zoned commercial and residential) has been studied by

and (or) a decrease in expected revenue lower the value of call option but increase the value of put option.

Bulan, Mayer and Somerville (2009) point out that it can be difficult to distinguish the exercise of an option at the point in time when NPV=0 from the exercise after a delay, when NPV>0. In real option theory, the NPV=0 point corresponds to a certainty world, where risk is zero and therefore the value of option to wait is zero. In contrast, when uncertainty is greater than zero the exercise takes place when NPV>0 and the option to delay is valuable; risk is important empirically. We show that a real options theoretical framework is more general than the NPV framework: i.e., the NPV rule is a special case of a barrier control policy.[6]

Our data are not well suited to distinguishing whether expansions and contractions take place when NPV=0 or NPV>0. Therefore, most of our analysis focuses on the determinants of the trigger point net of the value of option to wait, such as revenue and costs. However, our general framework allows us to separately consider some evidence supporting the role of uncertainty in delaying investment decisions.

We find that an increase in operating costs and a decrease in revenue lower the probability of expansion but increase the probability of contraction. Small shopping centers with large stores are more likely to provide greater variety of stores to customers while leaving the footprint in place. Large shopping centers with large stores adjust with both decreases of the footprint and increase in the number of store. This suggests that large shopping centers have greater flexibility in responding to changing market conditions. For small shopping centers the decision to change GLA is largely driven

Quigg (1993); theory derives from the seminal work of Titman (1985). Commercial property call option exercise has been studied by Childs, Riddiough and Triantis (1996) and by Schwartz and Torous (2007). Empirical studies of put option have focused on mine openings and closings (Brennan and Schwartz 1985; Moel and Tufano 2002). The salient point here is the relatively high operating costs that can be saved by shutting down. Most housing and office properties would bear substantial operating costs (property taxes, insurance, security) even if shuttered, so an owner with an over-improved property has little choice but to wait for depreciation to reduce the value of the investment. Glaeser and Gyorko (2005) study asymmetrical investment decisions in housing.

[6] Dixit and Pindyck (1994, pp 139-40) point out that real option theory is relevant in a certainty world because the flexibility to delay a project has value. Certainty is a special case of the real options model: when risk approaches zero, then the NPV rule becomes the only relevant consideration. When risk is significantly greater than zero, then the NPV determinants (costs and revenues) are still relevant.

by potential revenue, while the decision to change the number of stores is mainly a function of cost. These results are consistent with the certainty case of classical real options model (e.g. Dixit (1989)).

If the value of option to delay is non-zero, then the trigger point for expansion will increase by the value of call option and the trigger point for contraction will decrease by the value of put option. For provide some support for the presence of non-negative put and call options. First, we find that both expansion and the contraction in GLA are less likely for large malls in MSAs with greater uncertainty about real estate prices. Second, Grenadier (1996) suggests that the value of both call and put option is reduced by competition: i.e., any value to the delay option is reduced as decision making is forced towards the NPV rule. An industry leader will exercise her option earlier than implied by real options framework to reap the additional profits from leadership. We find support for Grenadier (1996) in our univariate analysis. Shopping centers that expand in GLA, but not the number of stores, have more competitors than the rest of the sample. Contractions in both GLA and number of stores have more competitors. The coefficient on number of competitors in multivariate analysis is only marginally significant in some models, but is of expected sign: the number of competitors reduces the value of option to wait and increases the likelihood of both expansion and contraction. The result is stronger for small shopping centers.

Lastly, we examine whether strategic deterrence (see, for example, Salvo (2010)) can explain shopping center renovation decisions. Shopping centers may expand in anticipation of competitive entry and contract in response to entry. We find support for this theory for large shopping centers: market share of competition reduces the likelihood of exercise of both call and put options. The result is stronger for expansions.

Overall, our hypotheses better explain contractions for large shopping centers and expansions for small shopping centers, suggesting that large shopping centers are above equilibrium size and small shopping centers are below equilibrium size.

The paper contributes to the literature in several ways. First, this paper provides first evidence on the determinants of redevelopment decisions for shopping centers. Second, our analysis uses a unique dataset of geographically diverse property level data that spans a ten year time period. Third, we

simultaneously examine both expansions and contractions. Finally, our analysis focuses on redevelopment rather than new construction, which has received considerably more attention in the literature.

The paper proceeds as follows. Next section reviews relevant theoretical framework and develops hypotheses. Section 3 discusses the data. Section 4 presents univariate analysis. Multivariate analysis and robustness tests are discussed in Section 5, and the role of the delay option is explicitly addressed. Section 6 concludes the paper.

2. Theoretical Background and Hypotheses

A number of theories provide a framework for evaluating expansion and contraction decisions of US shopping centers. We include several relevant theoretical perspectives because the study of shopping center expansions and contractions is a new area of inquiry, without previous theory or empirical work that is directly relevant.[7] These theories provide a basis for identifying relevant explanatory variables and functional forms; these allow us to explore our database.

2.1 Classical Option Exercise Model

Dixit (1989) proposes a theoretical framework analyzing entry and exit decisions. Investment decisions are irreversible and entail sunk costs. Suppose there is a project with avoidable operating cost w per unit of time. The investment requires a sunk cost k to enter. If the investment is made, the abandonment requires a one-time sunk cost l to exit. ρ is the rate of interest. P is the revenue of the project per unit of time. If the firm believes that P will be unchanged, it should invest if $P > w + \rho \cdot k$, where the right hand side is the annualized full cost of the investment. Similarly, if the project starts operation, it should be abandoned as soon as P satisfies the following inequality: $P < w - \rho \cdot l = W_L, where W_L > 0$. This is the NPV rule, which holds under certainty. The costs of

[7] Cho and Shilling (2007) examines the real option applications on shopping center leases. Peng and Thibodeau (2011) examine the association between interest rate changes and capital expenditures for retail properties and find it to be insignificant.

investment provide the “irreversible” component to the investment decisions.[8]

In the NPV framework of Dixit (1989), it must be true that $0 < W_L < P < W_H$. If P falls below W_L then the put option is rationally exercised and the supply of the product falls.[9] If P rises above W_H then the call option is rationally exercised and the supply of the product increases. Most of our evidence focuses on the determinants of P, W_H and W_L; as such, it is consistent with this certainty model.

In this certainty model we have the following two equations:

$$Expand\ if: P = (w + \rho \cdot k) = W_H \tag{1}$$

$$Contract\ if: P = (w - \rho \cdot l) = W_L \tag{2}$$

Dixit's model with a valuable option to delay

Equations (1) and (2) are special cases of Dixit's general model where risk is significantly greater than zero. When uncertainty is added in the form of a stochastic process for P, Dixit shows that a rational investor will follow a barrier control policy. P_H and P_L are two trigger values of investment and abandonment, where $P_H > P_L$. The investment should be made as soon as $P > P_H$ and abandoned as soon as $P < P_L$. The trigger value of investment is higher than the full cost because the value of delay is sacrificed when the real option is exercised.

$$Expand\ if: P = W_H + D_H = P_H \tag{3}$$

Here, $D_H > 0$ is a measure of the value of the option to delay expansion because of uncertainty.

Similarly, the trigger value of abandonment is lower than the full cost when we consider that stochastic increases in price may make the project profitable in the future.

$$Contract\ if: P = W_L - D_L = P_L > 0 \tag{4}$$

Here, $D_L > 0$ is a measure of the value of the option to delay contraction because of uncertainty.

[8] I.e., the firm can go in and out of business depending on *P*, but the costs imply that the firm may not enter the market even when it is profitable for existing firms, and may not exit even when price is below variable costs.

[9] A change in supply is one of the distinguishing features between real options and financial options. In this regard, real options are like stock warrants.

The model assumes that P is varying stochastically between the two barriers, P_L and P_H. Changes in supply together with boundary assumptions ensure that price does not stray outside this range.

As a result, there is a "hysteresis" where an idle firm does not invest and an active firm does not exit when price is between P_H and P_L. This area of inaction gets larger the higher the variance of the stochastic process and it responds in known ways to other parameters of the model.

In this study, we focus on how different characteristics affect the trigger values W_H and W_L. Note that the NPV rule implies a band of inaction when price falls between the two trigger points; inaction arises because of the irreversible costs of expansion and contraction. Empirically it is difficult to distinguish whether exercise occurs when NPV=0 (equations (1) and (2)) or when NPV>0 (equations (3) and (4)) and the value of option to delay is positive. We provide limited evidence regarding the presence of option to delay in section 5.3.

As the scale of operation for a given type of shopping center[10] increases, cost increases and marginal revenue decreases because the existing shopping center might be at an optimal scale. We expect that an increase in *w* and (or) a decrease in *P* lower the likelihood of expansion but increase the likelihood of contraction. As a result, we expect a negative (positive) relation between shopping center scale and the probability of expansion (contraction).

In this paper, the dependent variables are constructed based on the change of GLA and number of stores. This allows us one measure of the cost of option exercise: it is costlier to change GLA than to change number of stores holding GLA constant. Construction costs for changing number of stores by moving internal partitions are not high. However, the cost of negotiating and renegotiating leases is high, and changing the number of stores disrupts existing business. Changing the amount of GLA, on the other hand, requires obtaining permits, pouring foundations and other construction costs as well as disrupting existing tenants. Thus, we hypothesize that both changes involve irreversibility but that the amount of irreversibility is greater for GLA change.

[10] Shopping center types (e.g., community, regional or superregional) will be discussed below.

When shopping centers add or subtract GLA or stores they are exercising exchange options: i.e., they are exchanging the existing configuration of the real asset for another.[11] A major cost of the exchange is the sacrifice of revenue from existing space or stores. We proxy this cost – i.e., a portion of W_H and W_L in equations (1) and (2) – with average size: GLA/store (*store_size*). I.e., we divide the total GLA in the center by number of stores.

Our *store_size* variable is in addition to the cost control we obtain by separating GLA change from store change. A third control for cost is provided by the enclosed dummy (*enclosed*).[12] This allows us to evaluate evidence for the "demalling" trend: enclosed malls are said to reduce HVAC costs by converting to open air ("lifestyle" or "power") centers. These shopping center types typically have less GLA and fewer stores.

Because *store_size* has GLA in the numerator and number of stores in the denominator,[13] its effect on GLA expansion will be different than its effect on store expansion. An increase in *store_size* increases the cost of GLA expansion because GLA is already relatively large; the exchange of the revenues from the existing GLA for the revenues from the new expanded GLA is likely to result in relatively small net gain. The reverse is true for expanding stores because the relatively large GLA can be more readily subdivided to allow for more stores. This reasoning leads to:

H1-Expansion: *Store_size* is negatively (positively) associated with the probability of expansion in GLA (number of stores). *Enclosed* is negatively associated with the probability of expansion in both GLA and number of stores.

H1-Contraction: *Store_size* is positively (negatively) associated with the probability of contraction in GLA (number of stores). *Enclosed* is positively associated with the probability of contraction in both GLA and number of stores.

We use ordered logit as the main empirical specification for testing our hypotheses, in which contraction is coded is -1 and expansion is coded as +1.

Ordered logit implications of H1: *Store_size* is negatively (positively) associated with the

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[11] The internal configuration of the shopping center (i.e., mix of stores and placement of stores within the structure) has received some attention in the literature. See, for example,: Shulz and Stahl (1996), Carter (2009) and Benjamin, Boyle and Sirmans (1990 and 1992).

[12] Enclosed is considered as one of the features of the shopping center design in Sirmans and Guidry (1993).

[13] Both are measured at the beginning of the period.

dependent for GLA (number of stores). *Enclosed* is negatively associated with the dependent for both GLA and number of stores.

Our proxy for revenue (WATS) is based on the trade area of each shopping center: i.e., the geographical area providing most customers.[14] The trade area will depend on the size and type of the shopping center as discussed below.

H2-Expansion: WATS is positively associated with the probability of expansion in GLA and number of stores.

H2-Contraction: WATS is negatively associated with the probability of contraction in GLA and number of stores.

Ordered logit implications: WATS is positively associated with the dependent, regardless of whether it is change in GLA or number of stores.

2.2 Strategic Option Exercise - Grenadier

Grenadier (1996) suggests that an industry leader tries to exercise the option earlier and reap the additional profits from leadership. This reduces the value of both call and put option: i.e., it moves the market towards the NPV point. The value of waiting ("hysteresis" in Dixit's model) is reduced.

Grenadier's theory implies that the number of competitors in the trade area is a relevant variable. i.e., the theory starts with the classic predictions; increased competition tends to set the C and A values in equations (1) and (2) to zero. The theory is based specifically on number of competitors (Compet_ttl).[15]

H3-Expansion: Number of competitors in the trade area is positively associated with the probability of expansion in GLA and number of stores.

H3-Contraction: Number of competitors in the trade area is positively associated with the probability of contraction in GLA and number of stores.

Ordered logit implications: offsetting effects imply insignificant coefficients regardless of

[14] WATS is the weighted average market share within a trade area. See the Appendix for detailed calculations. Benjamin, Boyle and Sirmans (1992), Pashigan and Gould (1998) and Carter (2009) show a positive relation between sales per sq ft and rent per sq ft. Mejia and Benjamin (2002).

[15] Bulan, Mayer and Somerville (2009) use the number of competing residential projects as the measure of competition in their real option framework.

whether we are evaluating changes in GLA or number of stores.

2.3 Strategic Positioning

We use the term "strategic positioning" to refer to expansions in anticipation of competitive entry or contractions in response to entry. Game theory has yielded an extensive literature predicting strategic entry deterrence. In this branch of the literature, capacity expansion by an incumbent provides a credible threat for prospective entrants. By paying the cost of the expansion, the incumbent firm signals that they have the capacity to attract customers and the willingness to compete for market share.

Salvo (2010) develops a model applying strategic deterrence to a domestic monopolist (or group of oligopolists) facing the threat of entry by a foreign firm. The domestic firms will expand production to satisfy the entire domestic market at a price point just below the price that would invite entry. Production will be expanded and contracted in response to demand shocks, but price will remain at the point of deterrence. This is relevant to shopping centers, where a center with relatively large amount of retail square footage can expand or contract retail lines (i.e., reconfigure existing space) in response to demand shocks. Positive demand shocks can lead to more GLA in an effort to saturate the market before competitors can gain entry. It takes a strong negative demand shock, perceived as permanent, to reach the abandonment point for GLA indicated by equation (2).[16]

Seminal theory related to entry deterrence is provided by Stahl (1982). Shopping centers are generated endogenously simply by introducing a fixed cost (or other non-convexity) into the transportation costs of consumers. It follows that the one stop shopping provided by shopping centers is valuable to consumers, and they are willing to pay more for it. In effect, shopping centers provide a valuable agglomeration economy for consumers. An immediate implication for our research is that potential revenue per square foot of retail space, P in the model, increases with the size of the shopping center, and it will depend on bundling different types of goods together in a way that is valuable to consumers. For example, neighborhood centers might be anchored by a grocery store and

[16] Note that the ρl cost term can drive the abandonment point far below variable costs.

include shoe repair (or other personal services) and a beauty salon. A larger community center might be anchored by a junior department store and include a pharmacy or home improvement center. In both cases, bundling is designed to increase P.

These agglomeration economies have been directly related to entry deterrence by Choi and Stefanadis (2006). The way in which a firm bundles its goods and services can provide significant barriers to competitive entry. They show the application to Microsoft's attempt to bundle software so as to discourage entry and GE's proposed merger with Honeywell. Here, we propose that shopping centers accomplish the same thing by building excess space that can be occupied by a changing mix of tenants.[17]

Another example of the strategic placement game is termed "predatory (or competitive) placement." A center will enter, expand or reconfigure so as to cut off the flow of traffic to a competing center. I.e., by providing attractive intervening opportunities it obtains shoppers who formerly went to the rival center. This is just one example of the kind of market-filling placement discussed by Stahl (1982) and by Salvo (2010).

Empirically, we model strategic positioning with a variable measuring the market shares of rivals within the subject's trade area.[18] We measure the market share of competing centers at the beginning of the observation period – i.e., before the subject decides to expand or contract. The logic of strategic positioning predicts a negative relationship between the market share of competitors within the trade area and the subject's probability of expansion, and a positive effect on the probability of contraction. The logic is that a prior space filling move by competitors, measured by market share, will limit the probability that the subject center will expand, and possibly force a contraction.

H4-Expansion: the market share of competitors in the trade area is negatively associated with the probability of expansion in GLA and number of stores.

H4-Contraction: the market share of competitors in the trade area is positively associated with the probability of contraction in GLA and number of stores.

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[17] Smith and Hay (2005) have an interesting application to the agglomeration economies of independent owners ("streets" of independent retailers), shopping centers and "supermarkets," defined as a single store that offers many different product lines (e.g., butcher, baker, pharmacy and bank) within the store.

[18] Of course, we control for center type (e.g., regional or community).

Ordered logit implications: the market share of competitors in the trade area is negatively associated with the dependent, regardless of whether it is based on change in GLA or number of stores.

Note that H4 is differentiated from H3 by emphasizing market share, not number of competitors. Grenadier's theory (H3) deals specifically with number of competitors which drive the market away from oligopoly and towards strategic competition. On the other hand, H4 is based on agglomeration economies associated with market share.

It might be argued that number of competitors and market share of competitors are highly correlated, obviating the theoretical distinction between number of competitors and market share of competitors. In this case, the signs of the expected coefficients differentiate the two sets of hypotheses. Grenadier's theory predicts a positive sign on the call option and it has no prediction for ordered logit, whereas strategic positioning predicts a negative association with the likelihood of expansion and on the ordered logit coefficient. Both predict a positive association with the likelihood of contraction.

2.4 Alternative Hypotheses

Our discussions with real estate professionals suggest a large number of hypotheses intended to explain expansion and contraction of shopping centers. Most of these are consistent with the above hypotheses. For example, one common hypothesis is that the trend away from enclosed malls and towards power centers or lifestyle centers is motivated by a desire for cost savings. Effective rental cost for tenants is their base rent, possibly a percentage of sales, and common area (CAM) charges. CAM can be a large part of total rent.

The desire to reduce CAM is just one aspect of the real options theories, H1 – H4; *w* in equations (1) and (2). Thus, we assert that the theoretical framework we have provided has richer implications than institutional hypotheses.

Our research is motivated by our unique database, allowing us to analyze expansion and contraction decisions. If the hypotheses H1-H4 yield incorrect or inconclusive predictions, then the data may suggest an alternative explanation supported by the professional retail literature. Any results

supporting our hypotheses will be conservative since there are many impediments, such as delays in obtaining permits and neighborhood opposition, to shopping center owners acting in their best economic interests.

3. Data

We test our hypotheses using shopping center data from the Directory of Major Malls (directory or DMM thereafter). DMM reports shopping center characteristics for over 50 Metropolitan Statistical Areas (MSAs) for shopping centers with GLA of more than 250,000 square feet. We analyze 343 shopping centers in eleven MSAs. We choose MSAs that are included in the Case and Shiller price index and have the greatest number of shopping centers. We define that a shopping center is located in a particular MSA based on the Standards for Defining Metropolitan and Micropolitan Statistical Areas published by The Office of Management and Budget (OMB) in 2000.[19] We obtain directories for the following years: 1995, 2000, 2002 and 2005.[20] For 223 (65%) of shopping centers in our sample the first record appears in 1995 directory, for 76 (22%) shopping centers the first record appears in 2000 directory and for remaining 44 (13%) shopping centers – in 2002 directory. DMM reports name, location, design (open-air or enclosed), GLA, number of stores, site area, year opened, year of last renovation, etc. Some information, such as proposed expansion data, is self-reported by the managers and is considered subjective so we do not include it in our analysis.

For each shopping center we require at least 2 entries in directories so that we can determine whether an expansion or a contraction took place. It should be noted that some shopping centers are missing in some directories. Unless demolished before 2005, shopping centers with year opened before 1995 should be recorded in all four directories, shopping centers with year opened between 1995 and 2000 should appear in 2000, 2002 and 2005 directories, and so forth. We check all the

[19] The 11 MSAs include (1) Boston-Cambridge-Quincy, MA-NH Metropolitan Statistical Area; (2) Charlotte-Gastonia-Concord, NC-SC Metropolitan Statistical Area; (3) Cleveland-Elyria-Mentor, OH Metropolitan Statistical Area; (4) Denver-Aurora, CO Metropolitan Statistical Area; (5) Las Vegas-Paradise, NV Metropolitan Statistical Area; (6) Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area; (7) San Diego-Carlsbad-San Marcos, CA Metropolitan Statistical Area; (8) San Jose-Sunnyvale-Santa Clara, CA Metropolitan Statistical Area; (9) Seattle-Tacoma-Bellevue, WA Metropolitan Statistical Area; (10) Tampa-St. Petersburg-Clearwater, FL Metropolitan Statistical Area; and (11) Portland-Vancouver-Beaverton, OR-WA Metropolitan Statistical Area.

[20] We used the 2002 Directory to verify and revise variables from the 2000 Directory.

observations to ensure that our results are not affected by survivorship bias.[21] We focus on a stacked sample of two five-year time intervals: 1995-2000 and 2000-2005. In that way, we assume that each observation come to our sample independently, although one shopping center might be counted at most twice from 1995-2000 and 2000-2005. This assumption is reasonable because, even for a same shopping center, a stacked sample captures changes in the local market environment from one time period to the next.

We collect the latitudes and longitudes for all the shopping centers using the geographic information system (GIS). We then use Haversine formula to calculate the distances between shopping centers to surrounding census tracts and shopping centers to its competitors. Distances based on Haversine formula are great arc distances instead of road distances. Road distances vary with topographical conditions and methods of transportation and hence are more difficult to measure.

4. Summary Statistics

Table 1 describes the variables collected and calculated from the DMM, the US Census and S&P. We use the latitude and longitude coordinates for each shopping center in the GIS system to define the trade area. Trade area is the geographical area from which most sales originate. The shopping center size and characteristics are major factors that delimit the trade area. An exact trade area is difficult to define because it relies on a complex of parameters such as uniqueness of retailer, variety of transportation, consumer perception, etc. Our classification comes principally from the International Council of Shopping Centers (ICSC thereafter), which is a leading global trade association of the shopping center industry. We define a shopping center as "large" if it has a GLA greater than 600,000 sq ft and number of stores greater than 40, which is the upper bound of a community center. The remaining malls are classified as "small".[22] Similarly, a trade radius is assigned to each shopping

[21] It means that all the shopping centers were not demolished in 2005. We do not consider the change of ownership as a failed case. The directory assigns an identification number to each shopping center. The identification number does not change as the owner or name changes.

[22] ICSC clearly defines the range of GLA and number of stores, and trade areas for different types of shopping centers. The ICSC definition is different from Carter (2009). Some papers, such as Gatzlatt, Sirmans and Diskin (1994) and Carter and Vandell (2005) only focus on certain types of shopping centers.

center based on its type according to the ICSC standard.[23]

We use store size (scaled by 1,000 sq ft) and enclosed dummy as proxies for cost of renovation in H1. Competition is captured by the number of competitors within trade areas in order to address Grenadier's model of strategic option exercise, which is stated in H3-Expansion and contraction hypotheses. In addition, we calculate the average market shares for competitors within 5 miles to test H4-Expansion and contraction.

Table 2 shows the summary statistics of a pooled sample of five-year spans of 1995-2000 and 2000-2005.[24] Panel A includes continuous variables. Panel B presents statistics for dummy and MSA-level variables. Panels C through E compare the differences between two sub-samples: large and small shopping centers, expansions in GLA and contractions in GLA, expansions in number of stores and contractions in number of stores. Panel F compares each type of renovation with no change. Chi-square tests are used to test the independence of the sub-samples. To define expansion and contraction, we compare the first and the last observation of the sample period and construct four renovation dummies, a dummy equal one if GLA increased (decreased) by 10% or more (*GLA_exp* and *GLA_con*, respectively) and zero otherwise; a dummy equal to one if the number of stores increased (decreased) by 10% or more (*store_exp* and *store_con*, respectively). All changes are calculated by comparing the first and the last observation of the time span; level variables are for the first year. For example, GLA and number of stores in Table 2 Panel A are from DMM 1995 for 1995-2000 time span observations and are from DMM 2000 for 2000-2005 observations. We focus on the first year we observe the shopping center so that prior shopping center characteristics can be allowed to predict subsequent renovation.

Table 2 Panels A and B show descriptive statistics for the sample. As shown in Panel A, an average shopping center in our sample is classified as a large shopping center with GLA of 612,115 sq ft and 76 stores. Mean shopping center increased GLA but decreased the number of stores, however the median shopping center did not change either GLA or the number of stores. The average store size

[23] We apply 6 miles for community centers, 5 miles for power centers, 15 miles for regional shopping centers and 25 miles for super regional shopping centers. Note that community centers are power centers are classified as small shopping centers and regional and superregional malls are classified as large shopping centers.

[24] Our results are similar when we use 5-year spans of 1995-2000 and 2000-2005, a 10-year span of 1995-2005 and a pooled sample of 5-year spans of 1995-2000 and 2000-2005.

is 11,950 square feet. WATS mean suggests that the potential revenue per sq ft from an average household within trade areas is about $1.84. An average shopping center competes with twelve shopping centers in its trade area.

Table 2 Panel B shows that forty six percent of shopping centers are enclosed. Slightly more than half of our sample consists of large shopping centers. Our sample includes 113 expansions (55 in GLA and 53 in the number of stores) and 175 contractions (58 in GLA and 117 in the number of stores). In general, investors are equally likely to change GLA and number of stores for expansions but more likely to change number of stores for contractions as suggested by much greater proportion of store contractions in all the sub-samples. The imbalance in the irreversible investments indicates that investors are ambitious in expansion by changing the shopping center footprint but conservative in contraction by only altering the tenant profile. This phenomenon could be explained by strategic deterrence because, once the scale-indication investment is made, it has value in deterring competitive entry. I.e., it poses a credible threat of high attractive power (agglomeration economies) and low prices due to scale economies.

MSA-level variables show that our observations are fairly equally distributed across eleven MSAs. Comparatively, the distributions of renovations show more variations. For example, some MSAs, such as Minneapolis and Boston have a greater percentage of expansions and contractions. Case Shiller growth rate (*growth5*) and standard deviation (*std5)* variables are used to test the basic prediction of uncertainty version of Dixit's model. They are available only at MSA level. Because we pool two five-year sample periods, we choose the annualized Case-Shiller growth rate and standard deviation in the middle year of the first and last observations. We use the alternatives of 1-year, 3-year and 5-year average within the middle year. As a result, each MSA has 2 observations for annualized growth and standard deviation. MSAs, such as Cleveland and San Diego, with higher growth rates also have higher risks.

Panel C compares sub-samples of small and large shopping centers. It is likely that many large shopping centers are above equilibrium size while many small shopping centers are below equilibrium. As a result, large shopping centers might be more likely to contract and small shopping centers might

be more likely to expand. Therefore, we analyze large and small shopping centers separately. T-test and Wilcoxon test are used to test the differences in sample mean and median of continuous variables, respectively. Chi-square test is used to test the independence of two sub-samples for binary variables.

In Panel C, an average small shopping center has GLA of 346,000 sq ft and 33 stores and an average large shopping center has GLA of 847,000 sq ft and 113 stores. A greater store size of small shopping centers, together with a greater fraction of store contractions in large shopping centers, is consistent with the current trend of power center conversions.[25] Large shopping centers have more competitors and capture greater market share so they have smaller average weighted average market share of competitors within 5 miles (*compet_share*). A proxy for revenue per sq ft, *WATS*, is much greater for large shopping centers than small shopping centers.[26] The difference of *WATS* between small and large shopping centers is consistent with the retail agglomeration economies theories in Ghosh (1986) and West, Von Hohenbalkon and Kroner (1985). Large shopping centers are much more attractive to shoppers, so they have higher sales volume per sq ft.[27] A smaller *store_size* together with a higher *WATS* of large shopping centers is also consistent with Carter (2009) and Pashigan and Gould (1998) that smaller stores tend to have higher sales and rent per sq ft. Chi-square tests show that there is a significantly higher proportion of enclosed malls among large shopping centers. Large shopping centers are more likely to renovate except for store expansion. In conclusion, the differences in characteristics between small and large shopping centers highlight the importance of controlling for shopping center type in the regression analysis.

Table 2 Panels D and E examine sub-samples by type of renovation. Our hypothesis, H1-Expansion, is supported by a significantly smaller *store_size* of GLA-expansion shopping centers when compared to shopping centers that experienced contraction (Panel D). Shopping centers that have large store sizes as measured by GLA/store face lower revenue loss from contraction.[28] Turning

[25] Power centers became quite common in recent years. A power center usually refers to a shopping center with 200,000 to 800,000 square feet of gross leasable areas that contains three or more big-box retailers or department stores and a number of smaller retailers. Movie center conversion refers to the renovation in which the shopping center owners take the movie center out and add more retailers.

[26] We present both the absolute value and the log value of WATS. While we use log value of WATS in regressions, the results are similar when we use absolute value.

[27] Benjamin, Boyle and Sirmans (1992) also conclude that the larger the centers, the higher the rents.

[28] This is an exchange option, so revenue loss from any change is part of the cost of exercise.

to expansion in number of stores compared to contraction in number of stores (Panel E), we find that relation for the cost of exercise is reversed: it is relatively inexpensive to expand stores (expensive to contract) when store size is large. Panel E confirms that this is a significant effect, supporting H1. Enclosed proportions support hypothesis 1 only for expansion in number of stores but not expansion in GLA because the proportion of enclosed shopping centers for GLA expansions is not significantly greater than for GLA contractions. This might be explained by the agglomeration economies in enclosed shopping centers. Sirmans and Guidry (1993) find that enclosed shopping centers have higher rents because they provide more variety and thus have higher ability to attract customers. However, expansions on store scale do not have significant effects on boosting rental revenue. In that way, enclosed shopping centers have higher incentives to expand their GLA scale instead of store scale.

H2-Expansion and H2-Contraction predict that proxy for revenue per sq ft is positively (negatively) associated with the probability of expansion (contraction) in GLA and number of stores. As shown in Panels D and E, GLA-expansion and store-expansion shopping centers WATS is greater than that for the full sample, which is consistent with H2-Expansion. Although we do not find a smaller *WATS* in store-contraction shopping centers, *WATS* in GLA-contraction shopping centers is smaller than for the full sample consistent with H2-Contraction. Consistent with H3-Expansion and H3-Contraction, we find that number of competitors is greater in each type of renovations than the whole sample. Because of the offsetting effect, the mean and median are not significantly different between expansion and contraction sub-samples in both cases. The coefficients of *compet_share* provide little evidence on the strategic positioning as most of the tests on mean and median differences are insignificant.

The offsetting effect highlights the importance of comparing each type of renovation with no change in Panel F. Consistent with H1, *store_size* is significantly negative in GLA expansion and store contraction and significantly positive in store expansion. Consistent with H1, proportion of enclosed shopping centers is higher in store contraction than in no change sub-sample. A higher proportion of enclosed shopping centers in the GLA-expansion sub-sample seems to contradict H1 but can be

explained by agglomeration economies. Although *WATS* is insignificantly different for contractions when compared to no change, it is significantly higher for expansions on both GLA and number of stores as predicted in H2. Competition is higher for both expansions and contractions than no change sub-sample, supporting H3. Lastly, market share (*compet_share)* does not differ for the sub-samples.

Overall, Panels D and E suggest that renovation decisions on GLA and number of stores should be examined separately. The decisions on renovation of GLA and number of stores might be explained by different factors in different ways. For example, *store_size* is significantly smaller in GLA-expansion than GLA-contraction but significantly greater in store-expansion than store-contraction. In addition, *WATS* difference is significant in GLA change but not in store change sub-samples.

5. Results

In this section we perform multivariate tests of our hypotheses. We employ three types of logistics regressions: ordered, multinomial and simple logit.[29] Ordered and multinomial logit allow us to jointly consider expansions and contractions. The dependent variable in these models equals -1 for contractions and +1 for expansions. Ordered logit is the most appropriate model for our analysis because there is a natural order to our dependent variable: when put option is in the money the call option is out of the money and vice versa. Similarly, even when the value of option to wait is zero, W_H and W_L are not equal. Therefore, when a shopping center hits upper bound W_H it will be above lower bound W_L. Moreover, the results are easy to interpret. Multinomial model lifts some restrictions by allowing for asymmetric effect of explanatory variables on decision to expand or contract. However, multinomial model does not consider the order of the dependent variable, and it assumes independence of irrelevant alternatives (IIA).

[29] Prior literature also used hazard models to examine the determinants of time between renovations (Bulan, Mayer and Somerville (2000)). Our data is not well suited for such tests because we observe a shopping center only at three points during a ten year interval. Moreover, the directory does not provide reliable data on the year built and year since last renovation, variables essential to hazard analysis.

5.1. Multivariate analysis – Ordered logit

Table 3 shows ordered logistic regression for the stacked sample of 1995-2000 and 2000-2005. Since changing number of stores is less costly than changing the amount of GLA, we separately analyze change in GLA and change in the number of stores to better control for cost of irreversible decision. The dependent variable in the analysis of changes in GLA is *gla_reno* and equals -1 if GLA decrease by 10% or more and +1 if GLA increase by 10% or more during the observation period; and zero otherwise. The *store_reno* variable is constructed in the same manner for store size.

In Model 1, we focus on testing the implications of irreversible investment theory (hypotheses 1 and 2). To test hypothesis 1, we include two measures of cost in our model: *store_size* and *enclosed*. We expect negative association between these variables and *gla_reno*, and positive association with *store_reno*. To test hypothesis 2, we include *WATS*, which proxies for revenue per square foot. We expect positive association of *WATS* with both *gla_reno* and *store_reno*. We allow for different effect for large and small shopping centers by including large dummy and interacting it with *WATS* and *store_size*. All continuous variables are standardized to the mean of zero and the variance of one. Therefore, the coefficients show change in the likelihood of expansion or contraction given a one standard deviation change in explanatory variable. The marginal effects of each coefficient for large shopping centers are shown at the bottom of Table 3.

We find that for both small and large shopping centers the sign of the coefficient on *store_size* is as predicted by hypothesis 1: negative for *gla_reno* and positive for *store_reno*. However, for large shopping centers this coefficient is significant only in *gla_reno* regression while for small shopping centers it is significant only in *store_reno* regression.[30] When stores are large, the cost of developing additional GLA is high, whereas the cost of reconfiguring GLA for additional stores is relatively small. The results suggest that small shopping centers are more likely to increase the number of stores the bigger the initial store size, whereas this variable has no significant effect on change in GLA. I.e., costs and benefits are such that small shopping centers with big stores optimize by leaving their footprint unchanged while subdividing the space so as to give customers a greater variety of stores.

[30] See marginal effects for large shopping centers in Table 3.

Large shopping centers, on the other hand, are more likely to decrease GLA as store size gets bigger, reducing their footprint. For large shopping centers, the response of number of stores to the store size variable is the same as small shopping centers. Thus, large shopping centers adjust with both GLA decreases and with store increases whereas small shopping centers only use the latter. These results are consistent with hypothesis 1. Although the coefficient on the enclosed dummy is not significant in either model, the sign is negative and consistent with H1 that enclosed malls are less likely to expand and more likely to contract.

We find support for hypothesis 2. For small shopping centers a proxy for revenue per square foot, *WATS,* is positive and significant in *gla_reno* regression and is positive but insignificant in *store_reno* regression.[31] Combined with the findings for *store_size,* this suggests that for small shopping centers the decision to change GLA is largely driven by potential revenue, while the decision to change the number of stores is largely a function of cost. For large shopping centers both the decision to increase GLA and the decision to increase number of stores is positively associated with *WATS*, suggesting that expected revenue is an important consideration for expansion decisions. Note that for large shopping centers the decision to change GLA is determined by both costs and revenue (as suggested by negative coefficients on *store_size* and *WATS*). However, only expected revenue proxy (*WATS*) and not the cost proxy (*store_size* and *enclosed*) are significant at explaining the decision to change number of stores for large shopping centers. Overall, the results suggest that large shopping centers have more room to maneuver than small shopping centers and respond to changing market conditions by altering both number of stores and the footprint of the shopping center.

Model 2 tests whether predictions of Grenadier's theory can help explain the decision to redevelop. We include *compet_ttl* and its interaction with *large* to Model 1. We find that total competition does not explain decision to change GLA or number of stores for either small or large shopping centers, rejecting hypothesis 3. The rest of the results remain robust to inclusion of these variables.

To tests hypothesis 4, we include the average of the *WATS* of competitors within 5 miles of the

[31] Note that the p-value is .26, suggesting that an increased sample size will produce a significant positive sign.

subject shopping center (*compet_share*) and interaction of *compet_share* with large dummy (see Model 3). Since *compet_share* and *compet_ttl* are likely correlated, we exclude *compet_ttl* from Model 3. We find support for hypothesis 4 only for large shopping centers in *store_reno* regression. The coefficient on *compet_share* is negative and significant; this suggests that large market share of competitors increases the probability of contraction of the number of stores. This follows from central place theory which says that a larger share for competitors shrinks the customer base and reduces optimal size. The rest of the results are unaffected with an exception of the negative coefficient on enclosed dummy becoming significant in *store_reno*, providing further support for hypothesis 1.

Table 4 shows separate analysis for large and small shopping centers. For large shopping centers, positive coefficient on *store_size* becomes significant in *store_reno* regression (Models 1 and 2), and enclosed dummy becomes significant in Model 2, providing support for hypothesis 1. For small shopping centers results in Table 4 are similar to those in Table 3.

Overall, we find the decision of a shopping center to expand or contract is best explained by classical theory of irreversible reinvestment, rather than by number of competitors and the market share of the competition.[32]

5.2. Multivariate analysis – multinomial and simple logit

So far our analysis employed ordered logistic regression. The advantage of this approach is that we were able to simultaneously consider the exercise of both expansions and contractions and account for natural ordering of put and call decisions. However, ordered logit does not allow for asymmetric effect of explanatory variables. Moreover, the IIA assumption is required. In this section, we replicate Table 4 using multinomial logistic regression, which produces separate coefficient for expansions and contractions, while considering these decisions simultaneously.

Table 5 suggests that the effect of all explanatory variables on *gla_reno* and *store_reno* differs for NPV put and NPV call options. One new result in Table 5 is that large shopping centers are more likely to contract: the total effect for large dummy is positive and significant for contractions for both

[32] Section 5.4 discusses the evidence supporting the presence of option to wait.

gla_reno and store_reno regressions in all three models. However, the total effect for large dummy is not significant for expansions, suggesting that large shopping centers are equally likely to expand as small shopping centers. Interestingly, none of the variables are significant in explaining contractions of small shopping centers in Table 5. At the same time, the results for expansions of small shopping center in multinomial logit (Table 5) are very similar to results using ordered logit (Table 4): revenue proxy *WATS* is increasing the likelihood of expansion in GLA and cost proxy *store_size* is increasing the likelihood of expansion in number of stores. This suggests that the significance in ordered logit comes from the relation of *WATS* and *store_size* with expansion but not the contractions of the small shopping centers. Similarly, for large shopping centers we find that there is more significance in expansion rather than contraction models (see net effects for *WATS* and *store_size*). Overall, multinomial logit suggests that theory of irreversible investment better explains contraction decisions of large shopping centers and expansion decisions of small shopping centers, suggesting that large shopping centers are above equilibrium size and small shopping centers are below equilibrium size.

Table 6 performs multinomial logit analysis separately for large and small shopping centers. For large shopping centers *WATS* and *store_size* are highly significant in explaining contraction in both GLA and number of stores in the direction predicted by hypothesis 1. *WATS* decreases the likelihood of GLA and number of store contraction, suggesting that higher expected revenue makes the shopping center less likely to contract. Consistent with Hypothesis 2, *store_size* increases the probability of contraction on GLA but decreases the probability of contraction on number of stores. Total competition becomes marginally significant at 9% in the GLA contraction model, suggesting that greater number of competitors makes the contraction more likely. This supports hypothesis 3.

Interestingly, for large shopping centers none of the variables are significant in the expansion on GLA model, although the p-values are all below 30% suggesting that a larger sample size might result in more power. In Table 5 *WATS* is positive but *WATS* for large shopping centers is much higher than small shopping centers so the effect becomes not as prominent as in general model.

In Models 2 and 3 negative coefficient on *store_size* becomes significant in GLA expansion model, supporting hypothesis 1: large shopping centers with high operating costs are less likely to

expand. *Store_reno* regressions for expansions provide support for hypotheses 1 and 2: enclosed malls are less likely to expand number of stores; shopping centers with high expected revenue are more likely to expand number of stores as suggested by positive coefficient on *WATS*. We also find support for hypothesis 4: higher market share of competitors decreases the likelihood of expansion on the number of stores.

The decision to contract for small shopping centers is explained only by number of competitors – greater number of competitors forces small shopping centers to increase the probability of contraction (Table 6, Panel B). The decision to expand for small shopping centers is associated with more variables: expansion in GLA is positively associated with *WATS* and *compet_ttl*; expansion in number of stores is positively associated with *store_size*. Overall, multivariate logit shows that for large shopping centers our hypotheses better explain contractions while for small shopping centers our hypotheses better explain expansions, supporting our contention that large shopping centers are above equilibrium and small shopping centers are below equilibrium.

5.3 Evidence for the value of the option to delay

Equations (3) and (4) apply to the more realistic assumption of a stochastic process for price, P. In this case, the higher the variance of the process, the higher the "wedge" between the NPV rule and the real option rule. This wedge is represented by D_H (expansion option) and D_L (contraction option). The purpose of this section is to summarize the evidence pertaining to the role of uncertainty in adding value to the option to delay.

Our data is not well suited to directly test the predictions of real options theory of positive association of uncertainty and the value of options to expand and contract because we do not have property level measure of uncertainty. However, we are able to provide some limited evidence that suggests the presence of option to wait to redevelop. First, we re-estimate models in Tables 3 and 4 replacing MSA dummies with MSA level measures of drift (*growth5*) and variance (*std5*) of house prices obtained from Case and Shiller Indexes. We find that for large malls the coefficient on std5 is negative and significant in gla models, suggesting that higher uncertainty about real estate prices

delays redevelopment. Coefficient on growth5 is positive but not significant for large malls in any of the models. Coefficient on neither variable is significant for small malls.

Second, as discussed earlier, we find some support for Grenadier's model: greater number of competitors increases the likelihood of contraction, especially for small malls. Grenadier's model assumes that the value of option to delay is non-negative and that competition reduces the value of this option forcing the exercise.

5.4 Robustness tests

In this section we perform several robustness tests. We estimate simple logit regressions, which consider the decision to expand and contract independently. In terms of Dixit's theory, this is supported if the call option is deep out of the money when the put option is in the money, and vice versa. As a robustness test, simple logit avoids the IIA assumption made by multinomial logit: simple logit assumes the independence of two decisions whereas multinomial logit assumes dependence.

Tables 7 and 8 show simple logit results. The dependent variable in the first column is *gla_exp*, which equals one if GLA increased by 10% or more and zero otherwise. Note that contractions are assigned the value of zero in this model. Similarly, in *gla_con* model, decrease in GLA of more than 10% is assigned a value of one and the rest of the observations, including expansions, are coded as zeros. The results in Table 7 are similar to those in Table 5, suggesting that our inference is not affected by whether decision to expand and contract are considered as independent or jointly determined. The results in Table 8 differ just slightly from the results in Table 6: coefficient on *WATS* and *store_size* in GLA expansion regression becomes significant in all models, providing further support for hypotheses 1 and 2.

We perform several other robustness tests. First, we change the threshold for major renovation from 10% to 5% and 3%. Our results remain robust to these alternative definitions of expansions and contractions. Second, we perform analysis on continuous measures of renovation: percent change in GLA and percent change in number of stores and obtain similar results. We report results using 10% in the body of the paper because high threshold allows us to focus on major renovations and minimizes the

influence of noisiness in the data.

6. Conclusion

To summarize, we find the decision to expand or contract is best explained by standard theory of irreversible investment. Shopping centers with large operating costs are less likely to expand and are more likely to contract. Higher expected revenue increases the likelihood of expansion and decreases the likelihood of contraction. For small shopping centers the decision to change GLA is largely driven by potential revenue, while the decision to change the number of stores is largely a function of cost. We find weak support for Grenadier's theory that large number of competitors reduces the value of option to wait and increases the likelihood of both expansion and contraction. The result is stronger for small shopping centers. Market share of competition reduces the likelihood of increasing the number of stores as suggested by the theory of strategic positioning (Salvo, 2010). Our hypotheses best explain contraction decisions of large shopping centers and expansion decisions of small shopping centers, suggesting that large shopping centers appear to be above equilibrium size and small shopping centers are smaller than equilibrium. Our results are robust to estimating expansions and contractions jointly or independently.

References

Benjamin, J.D., G.W. Boyle, and C.F. Sirmans. 1990. Retail Leasing: The Determinants of Shopping Center Rents. *Journal of the American Real Estate and Urban Economics Association* 18: 302-12.

___. 1992. Price Discrimination in Shopping Center Leases. *Journal of Urban Economics,* 1992, 32: 299-317.

Brennan, M. J., and E. S. Schwartz. 1985. Evaluating Natural Resource Investments, *Journal of Business* 58, 2: 135-157.

Bulan, L., C. Mayer, and C.T. Somerville. Irreversible Investment, Real Options, and Competition: Evidence from Real Estate Development. *Journal of Urban Economics,* 2009, 65: 237–51.

Carter, C.C. 2009. What We Know about Shopping Centers. *Journal of Real Estate Literature* 17: 165-180.

Carter, C.C. and K.D. Vandell. 2005. Store Location in Shopping Centers: Theory and Estimates. *Journal of Real Estate Research* 27: 237-65.

Childs, P., T. Riddiough and A. Triantis. 1996. Mixed Uses and the Redevelopment Option. *Real Estate Economics* 24: 317–339.

Cho, H. and J.D. Shilling. 2007. Valuing Retail Shopping Center Lease Contracts. *Real Estate Economics* 35: 623-49.

Choi, J.P. and C. Stefanadis. 2006. Bundling, Entry Deterrence, and Specialist Innovators, Journal of Business 79: 2575-2594.

Clapp, J.M., K. S. Bardos and S.K. Wong. 2011. Empirical Estimation of the Option Premium for Residential Redevelopment. WP.

Clapp, J.M. and K. Salavei. 2010. Hedonic pricing with redevelopment options: A new approach to estimating depreciation effects. *Journal of Urban Economics* 67:362-377.

Dixit, A. 1989. Entry and Exit Decisions under Uncertainty. *Journal of Political Economy* 97: 620-638.

Dixit, A.K. and R.S. Pindyck. 1994. *Investment under Uncertainty*. Princeton University Press: Princeton, N.J.

Dye, R.F. and D.P. McMillen, 2007. Teardowns and Land Values in the Chicago Metropolitan Area, *Journal of Urban Economics* 61: 45-63.

Fanning, S. 2005. *Market Analysis for Real Estate*. Appraisal Institute, Chicago, IL.

Gatzlaff, D.H., G.S. Sirmans, and B.A. Diskin. 1994. The Effect of Anchor Tenant Loss on Shopping Center Rents. *Journal of Real Estate Research* 9: 99-110.

Ghosh, A. 1986. The Value of a Mall and Other Insights from a Revised Central Place Model. *Journal of Retailing* 62: 79-97.

Glaeser, E. and J. Gyourko. 2005. Urban decline and durable housing. *Journal of Political Economy*. 113: 345–375.

Grenadier, S. 1996. The Strategic Exercise of Options: Development Cascades and Overbuilding in Real Estate Markets. *Journal of Finance* 51: 1653-1679.

McDonald, R. and D. Siegel, 1986. The Value of Waiting to Invest. *Quarterly Journal of Economics* 101, 707-727.

Mejia, L.C. and J.D. Benjamin. 2002. What Do We Know About the Determinants of Shopping Center Sales? Spatial vs. Non-Spatial Factors. *Journal of Real Estate Literature* 10: 3-26.

Moel, A. and P. Tufano. 2002. When are Real Options Exercised? An Empirical Study of Mine Closings. *Review of Financial Studies*. 15: 35-64.

Pashigan, B.P. and E.D. Gould. 1998. Internalizing Externalities: The Pricing of Space in Shopping Malls. *Journal of Law and Economics*, XLI, 115-42.

Peng, L. and T.G. Thibodeau. 2011. Interest Rate and Investment under Uncertainty: Evidence from Commercial Real Estate Capital Expenditures. WP.

Quigg, L. 1993. Empirical Testing of Real Option-Pricing Models. *Journal of Finance* 48: 621–640.

Rosenthal, S. 2008. Old Homes, Externalities, and Poor Neighborhoods: A Dynamic Model of Urban Decline and Renewal, *Journal of Urban Economics*, 63: 816-840.

Rosenthal, S. and R. Helsley. 1994. Redevelopment and the Urban Land Price Gradient. *Journal of Urban Economics*, 35: 182-200.

Salvo, A. 2010. Inferring market power under the threat of entry: the case of the Brazilian cement industry. *RAND Journal of Economics* 41: 326–350.

Schwartz, E. and Torous W. 2007. Commercial Office Space: Testing the Implications of Real Options Models with Competitive Interactions. *Real Estate Economics* 35: 1–20.

Schulz, N. and K. Stahl. 1996. Do Consumers Search for the Highest Price? Oligopoly Equilibrium and Monopoly Optimum in Differentiated-Products Markets. *RAND Journal of Economics* 27: 542-562.

Sirmans, C.F. and K.A. 1993. Guidry. The Determinants of Shopping Center Rents. *Journal of Real Estate Research*, 8: 107-15.

Smith, H. and D. Hay. 2005. Streets, Malls, and Supermarkets. *Journal of Economics & Management Strategy* 14: 29–59.

Stahl, K. 1982. Location and Spatial Pricing Theory with Nonconvex Transportation Cost Schedules. *The Bell Journal of Economics* 13: 575-582.

Titman, S. 1985. Urban Land Prices Under Uncertainty. *American Economic Review* 75: 505–514.

West, D.S., B. Von Hohenbalken, and K. Kroner. 1985. Tests of Intraurban Central Place Theories. *The Economic Journal* 95: 101-17.

Appendix: Calculation of WATS

To test the implications of potential revenue on the expansion and contraction decision (Hypothesis 2) we first calculate WAMS (weighted average market share within a trade area) as the sum of income adjusted gravity potential for each tract in shopping center's trade area. We assume the following trade area for different types of shopping centers: a 40 mile radius for that superregional shopping centers, a 20 mile radius for regional shopping centers, and a 10 mile radius for community.

We calculate gravity potential for each tract j in each shopping center's i trade area.

$$\text{Gravity potential}_{\text{ij}} = \text{GP}_{\text{ij}} = \frac{\dfrac{\text{GLA}_{\text{i}}}{\text{distance}_{\text{ij}}}}{\displaystyle\sum_{i=1}^{N} \frac{\text{GLA}_{\text{i}}}{\text{distance}_{\text{ij}}}}$$

where distance is the distance between the shopping center and the center of the tract. If the distance is less than 1 mile, then it is set to 1 mile. Otherwise the distance equals the actual distance. *N* is the number of shopping centers competing for tract *j*. For example, when there are 3 shopping centers (Shopping center 1, Shopping center 2, and Shopping center 3) and 3 tracts (Tract A, Tract B and Tract C), and Shopping centers 1 and 2 compete for Tract A, then the formula for the gravity potential for Shopping center 1 Tract A is as follows:

$$\text{Gravity potential}_{\text{1A}} = \text{GP}_{\text{1A}} = \frac{\dfrac{\text{GLA}_1}{\text{distance}_{\text{1A}}}}{\dfrac{\text{GLA}_1}{\text{distance}_{\text{1A}}} + \dfrac{\text{GLA}_2}{\text{distance}_{\text{2A}}}}$$

In this example there are only two shopping centers competing for tract A's sales. So the denominator should have only two terms. Note that gravity potentials for each tract will add up to one. Next, we adjust gravity potential by tract's scaled net income.

$$\text{Income Adjusted GP}_{\text{ij}} = \text{GP}_{\text{ij}} * \left(\frac{\text{TI}_{\text{j}}}{\displaystyle\sum_{\text{j=1}}^{\text{Mi}} \text{TI}_{\text{j}}} \right)$$

TI_j is the total income for tract *j* from 2000 decennial Census. M_i is the number of tracts in shopping center *i*'s trade area. If in our example Shopping center 1 is competing for all three tracts (Tract A, B and C), then *Income Adjusted GP_{1A}* is calculated as follows.

$$\text{Income Adjusted}\,\mathrm{GP}_{1A} = \mathrm{GP}_{1A} * \left(\frac{\mathrm{TI}_A}{\mathrm{TI}_A + \mathrm{TI}_B + \mathrm{TI}_C} \right)$$

WAMS is then calculated as the sum of *Income Adjusted GP_{ij}* across all tracts in shopping center *i*'s trade area:

$$\text{Weighted Average Market Share}_i = \mathrm{WAMS}_i = \sum_{j=1}^{M_i} \text{Income Adjusted}\,\mathrm{GP}_{ij}$$

In our example, WAMS for Shopping center 1 is calculated as follows:

$$\mathrm{WAMS}_1 = \text{Income Adjusted}\,\mathrm{GP}_{1A} + \text{Income Adjusted}\,\mathrm{GP}_{1B} + \text{Income Adjusted}\,\mathrm{GP}_{1C}$$

Our proxy for potential revenue per sq ft for a shopping center, WATS, is WAMS multiplied by population weighted household income in the trade area and then divide by its GLA. WATS simply measures how much per sq ft does an average household within the trade area will spend in shopping center *i*.

Table 1: Variable Definition

This table summarizes variable definitions. Shopping center characteristics and renovations are estimated and tracked from Directory of Major Malls (DMM). Trade areas are delineated from the geographic information system (GIS). Demographic data are collected from the US Census Bureau.

Variable Name	Variable Definition	Source of data
Explanatory variables		
gla	Gross leasable area (sq ft)	DMM
gla_change	Percentage change of GLA between the first and last observations	DMM
number_stores	Number of stores	DMM
store_change	Percentage change of number of stores between the first and last observations	DMM
year_opened	Year the shopping center was opened	DMM
store_size (1,000 sq ft)	GLA divided by number of stores then divided by 1,000	DMM
enclosed	Indicator variable: 1 if the shopping center is enclosed, 0 if the shopping center is open	DMM
WATS	Weighted average trade area income per sq ft, a proxy for revenue generated per sq ft. Log of total population-weighted median household income multiplied by weighted average market share within a trade area and then divided by GLA. Latitudes and longitudes for all the shopping centers are hand-collected by using the geographic information system (GIS). Haversine formula is used to estimate the distance between the shopping center and surrounding tracts within its trade area. Median household income is from the US Census.	DMM, US Census, GIS
type_large	Indicator variable: 1 for regional (GLA from 400,000 to 800,000 sq ft and number of stores from 40 to 80) and super regional shopping centers (GLA greater than 800,000 sq ft and number of stores greater than 80), 0 for community center (GLA from 200,000 to 400,000 sq ft; number of stores from 15 to 40) and power center (GLA less than 400,000 and number of stores less than 15 or GLA from 400,000 to 600,000 and number of stores from 15 to 40)	DMM
compet_ttl	Total number of competitors within the trade area. Latitudes and longitudes for all the shopping centers are hand-collected by using the geographic information system (GIS). Haversine formula is used to calculate the distances between shopping centers to surrounding census tracts and shopping centers to its competitors.	DMM, GIS

compet_share	Weighted average market share of the competitors within 5 miles. Latitudes and longitudes for all the shopping centers are hand-collected by using the geographic information system (GIS). Haversine formula is used to calculate the distances between shopping centers to surrounding census tracts and shopping centers to its competitors.	DMM, US Census, GIS
growth5	5-year average of annualized Case-Shiller growth rates around the mid-year of the observation period	S&P
stdev5	5-year average of annualized Case-Shiller standard deviations around the mid-year of the observation period	S&P

Renovation variables

gla_exp	Dummy variable: 1 if GLA increased by 10%, or more 0 otherwise	DMM
gla_con	Dummy variable: 1 if GLA decreased by 10% or more, 0 otherwise	DMM
store_exp	Dummy variable: 1 if number of stores increased by 10% or more, 0 otherwise	DMM
store_con	Dummy variable: 1 if number of stores decreased by 10% or more, 0 otherwise	DMM
gla_reno	Categorical variable: -1 if GLA decreased by 10% or more and +1 if GLA increased by 10% or more, 0 otherwise	DMM
store_reno	Categorical variable: -1 if number of stores decreased by 10% or more and +1 if number of stores increased by 10% or more, 0 otherwise	DMM

Table 2: Summary Statistics

The summary statistics are based on a pooled sample of 1995-2000 and 2000-2005. Variables are computed from the DMM 1995, 2000, 2002 and 2005. Panel A includes continuous variables. Panel B presents dummy and MSA-level variables. HH-income is the average household income for census tracts around our sample shopping centers according to the US Census 2000. Growth5 and Stdeb 5 is 5-year Case Shiller growth rate and standard deviation around the mid-year of our observations. Panel C to E compare sub-samples by type, GLA renovation and store renovation. Panel F provide t-statistics and Wilcoxon statistics based on the comparison between each type of renovation and no change. *t*-tests and Wilcoxon tests are used to test the differences in sample mean and median, respectively. Chi-square tests the independence of two samples. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Variable	**Mean**	**Median**	**Lower Quartile**	**Upper Quartile**	**Std Dev**	**N**
Panel A: Continuous variables						
gla (sq ft)	612,115	456,337	310,000	875,604	379,927	599
gla_change (%)	0.94	0	-0.19	0.57	18.05	599
number _stores	75.61	56	30	118	56.29	599
store_change (%)	-0.97	0	-1.88	0	24.76	598
store_size (1,000 sq ft)	11.95	8.13	6.30	12.11	12.85	599
year_opened	1978.15	1979	1967	1990	13.64	599
WATS (absolute)	1.84	1.46	0.77	2.47	1.68	599
WATS (log)	0.35	0.38	-0.26	0.9	0.71	599
compet_ttl	11.55	9	3	19	9.05	599
compet_share	0.08	0.07	0.05	0.1	0.07	599

Panel B: Dummy and MSA-level variables

Variable	**#**	**%**
enclosed	273	46%
type_large	318	53%
gla_exp	55	9%
gla_con	57	10%
store_exp	53	9%
store_con	110	18%

MSA	#	%	HH-Income Mean	Growth5 Mean	Std5 Mean	gla_exp # (%)	gla_con # (%)	store_exp # (%)	store_con # (%)
Portland	26	4%	57,206.55	9.78%	2.21%	5 (9.09%)	1 (1.82%)	4 (7.27%)	6 (10.91%)
LasVegas	35	6%	50,948.81	3.47%	1.46%	4 (7.27%)	3 (5.45%)	4 (7.27%)	1 (1.82%)
Minneapolis	57	10%	47,053.99	3.76%	1.49%	6 (10.91%)	9 (16.36%)	3 (5.45%)	21 (38.18%)
Charlotte	48	8%	52,897.72	6.63%	1.33%	6 (10.91%)	5 (9.09%)	3 (5.45%)	7 (12.73%)
Cleveland	57	10%	46,528.88	12.77%	2.25%	5 (9.09%)	9 (16.36%)	6 (10.91%)	10 (18.18%)
Boston	83	14%	54,647.51	8.37%	1.62%	8 (14.55%)	7 (12.73%)	8 (14.55%)	21 (38.18%)
Denver	56	9%	49,270.20	7.30%	1.56%	2 (3.64%)	4 (7.27%)	4 (7.27%)	15 (27.27%)
SanDiego	56	9%	52,889.73	13.77%	2.22%	4 (7.27%)	1 (1.82%)	6 (10.91%)	5 (9.09%)
SanJose	73	12%	65,571.23	12.72%	2.70%	2 (3.64%)	8 (14.55%)	2 (3.64%)	16 (29.09%)
Seattle	47	8%	53,699.98	8.75%	1.58%	7 (12.73%)	8 (14.55%)	9 (16.36%)	8 (14.55%)
Tampa	61	10%	40,829.78	10.88%	1.42%	6 (10.91%)	3 (5.45%)	4 (7.27%)	7 (12.73%)

Panel C: Difference in means and median for large and small shopping centers								
	Small shopping centers(N=281)			Large shopping centers (N=318)			t-test	Wilcoxon test
Variable	Mean	Median	Std	Mean	Median	Std	*t-*	*Z*
gla (sq ft)	346,075	310,000	127,600	847,200	841,000	373,812	-22.47***	-18.05***
gla_change (%)	1.26	0	18.49	0.65	0	17.67	0.41	-0.72
number _stores	32.83	30	19.62	113.42	114.5	50.82	-26.16***	-19.83***
store_change (%)	2.02	0	29.06	-3.62	0	19.88	2.74**	3.53***
store_size (1,000 sq ft)	16.71	11.24	17.42	7.74	7.28	2.37	8.56***	8.76***
year_opened	1982.41	1987	12.98	1974.38	1974	13.12	7.52***	7.40***
WATS (absolute)	0.95	0.79	0.61	2.63	2.27	1.91	-22.85***	-17.20***
compet_ttl	4.38	3	3.71	17.89	18	7.51	-28.41***	-18.52***
compet_share	0.09	0.08	0.09	0.08	0.07	0.06	2.32**	2.54**
	#	%		#	%		Chi-square	
enclosed	46	16.37%		227	71.38%		***	
large	0	0.00%		318	100.00%		***	
gla_exp	15	5.34%		40	12.58%		***	
gla_con	15	5.34%		42	13.21%		***	
store_exp	24	8.54%		29	9.12%			
store_con	29	10.32%		81	25.47%		***	

Panel D: Difference in means and median for GLA expansion and contraction								
	GLA expansion (N=55)			GLA contraction (N=57)			t-test	Wilcoxon test
Variable	Mean	Median	Std	Mean	Median	Std	*t-*	*Z*
gla (sq ft)	606,710	500,000	314,041	763,625	670,000	404,751	-2.3**	-1.93*
gla_change (%)	33.93	17.83	40.44	-23.3	-20.16	12.43	10.05***	9.12***
number _stores	90	80	50.45	87.12	85	47.32	0.31	0.25
store_change (%)	11.14	0	49.47	-9.13	0	23.76	2.75**	2.46**
store_size (1,000 sq ft)	9.36	6.60	12.01	10.29	8.91	7.50	-0.49	-3.35***
year_opened	1977.67	1978	14.75	1973.77	1972	15.97	1.34	1.46
WATS (absolute)	2.56	2.11	2.58	1.77	1.63	1.14	2.79**	2.27**
compet_ttl	14.09	13	8.73	15.42	16	8.64	-0.81	-0.91
compet_share	0.08	0.07	0.06	0.08	0.06	0.07	0.00	0.13
	#	%		#	%		Chi-square	
enclosed	32	58.18%		31	54.39%			
large	40	72.73%		42	73.68%			
store_exp	18	32.73%		5	8.77%		***	
store_con	15	27.27%		19	33.33%			

Panel E: Difference in means and median for Store expansion and contraction								
	Store expansion (N=53)			Store contraction (N=110)			t-test	Wilcoxon test
Variable	Mean	Median	Std	Mean	Median	Std	*t*-	*z*
gla (sq ft)	602,732	470,000	375,452	700,344	612,500	400,399	-1.52	-1.84**
gla_change (%)	14.51	3.59	33.52	-1.99	0	13.15	3.46***	3.61***
number _stores	67.04	67	48.37	96.75	86	64.67	-3.28**	-2.89***
store_change (%)	44.86	30.43	52.45	-27.41	-21.88	17.15	9.78***	10.31***
store_size (1,000 sq ft)	17.30	9.86	20.45	8.71	7.13	6.30	2.99***	2.73***
year_opened	1981.62	1989	14.19	1972.76	1972	13.14	3.82***	4.00***
WATS (absolute)	2.17	1.66	2.54	1.92	1.77	1.21	0.67	0.25
compet_ttl	12.79	13	9	14.75	15	9.25	-0.53	-0.68
compet_share	0.08	0.07	0.09	0.09	0.07	0.09	-1.29	-1.46
	#	%		#	%		Chi-square	
enclosed	22	41.51%		69	62.73%		***	
large	29	54.72%		81	73.64%		**	
gla_exp	18	33.96%		15	13.64%		***	
gla_con	5	9.43%		19	17.27%			

Panel F: Difference in means and median for renovation and no change

	GLA-exp = 1 (N=55) *versus* GLA-exp = 0 (N=544)			GLA-con = 1 (N=57) *versus* GLA-con = 0 (N=542)			store-exp = 1 (N=53) *versus* store-exp = 0 (N=546)			store-con = 1 (N=110) *versus* store-con = 0 (N=489)		
Variable	t-test	Wilcoxon test		t-test	Wilcoxon test		t-test	Wilcoxon test		t-test	Wilcoxon test	
gla (sq ft)	-0.13	0.55		2.99***	3.42***		-0.19	-0.35		2.59**	3.10***	
gla_change	6.65***	12.78***		-14.93***	-12.99***		3.2***	4.86***		-2.36**	-0.64	
number _stores	2.19**	2.63***		1.89*	2.47***		-1.33	-1.21		3.91***	4.54***	
store_change	1.98*	2.11**		-2.71***	-2.27**		6.96***	13.29***		-16.79***	-18.05***	
store_size	-1.67*	-3.87***		-1.6	0.94		2.06**	1.67*		-4.58***	-3.58***	
year_opened	-0.25	-0.03		-2.21**	-2.29**		1.87*	2.27**		-4.73***	-4.69***	
WATS	4.15***	3.78***		-0.19	0.23		1.82*	1.71*		1.37	1.46	
compet_ttl	2.26**	2.41**		3.54***	3.58***		1.05	0.87		4.05***	4.09***	
compet_share	-1.12	-1.44		-1.08	-1.15		-0.38	-1.39		0.48	-1.22	
	GLA-exp =1 # (%)	GLA-exp =0 # (%)	Chi-sq	GLA-con =1 # (%)	GLA-con =0 # (%)	Chi-sq	store-exp =1 # (%)	store-exp =0 # (%)	Chi-sq	store-con =1 # (%)	store-con =0 # (%)	Chi-sq
enclosed	32 (58%)	241 (44%)	**	31 (54%)	242 (45%)		22 (42%)	251 (46%)		69 (63%)	204 (42%)	***
large	40 (73%)	278 (51%)	***	42 (74%)	276 (51%)	***	29 (55%)	289 (53%)		81 (74%)	237 (48%)	***
gla_exp	55 (100%)	0 (0%)	N.A.	0 (0%)	55 (10%)	N.A.	18 (34%)	37 (7%)	***	15 (14%)	40 (8%)	*
gla_con	0 (0%)	57 (10%)	N.A.	57 (100%)	0 (0%)	N.A.	5 (9%)	52 (10%)		19 (17%)	38 (8%)	***
store_exp	18 (33%)	35 (6%)	***	5 (9%)	48 (9%)		53 (100%)	0 (0%)	N.A.	0 (0%)	53 (11%)	N.A.
store_con	15 (27%)	95 (17%)	*	19 (33%)	91 (17%)	***	0 (0%)	110 (20%)	N.A.	110 (100%)	0 (0%)	N.A.

Table 3: Ordered Logistic Regression – Full Sample

Ordered logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. Variables are computed from the DMM 1995, 2000, 2002 and 2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. gla_reno equals -1 if GLA decreased by 10% or more and +1 if GLA increase by 10% or more during the observation period and 0 otherwise. store_reno equals -1 if number of stores decreased by 10% or more and +1 if number of stores increase by 10% or more during the observation period and 0 otherwise. Total effect of large shopping centers equals the sum of all standardized coefficients associated with large shopping centers multiplied by the median value of the non-standardized variable. Net effect tests whether the sum of a standardized coefficient and its large-shopping center dummy equals zero. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. /cut1 is the estimated cutpoint on the latent variable used to differentiate contraction from no change and expansion when values of the predictor variables are evaluated at zero. /cut2 is the estimated cutpoint on the latent variable used to differentiate contraction and no change from expansion when values of the predictor variables are evaluated at zero. *p*-values are reported in parentheses.* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

	(1)		(2)		(3)	
	gla_reno	store_reno	gla _reno	store_reno	gla _reno	store_reno
enclosed	-0.08	-0.42	-0.01	-0.44	-0.13	-0.50*
	(0.79)	(0.12)	(0.97)	(0.11)	(0.65)	(0.07)
type_large	-2.20***	-0.71	-1.90***	-0.68	-2.27***	-0.80*
	(0.00)	(0.12)	(0.00)	(0.22)	(0.00)	(0.08)
WATS	0.65***	0.22	0.69***	0.24	0.67***	0.23
	(0.01)	(0.26)	(0.00)	(0.23)	(0.01)	(0.24)
WATS*large	0.15	0.62***	0.15	0.59**	0.16	0.65***
	(0.61)	(0.01)	(0.61)	(0.01)	(0.58)	(0.01)
store_size	-0.02	0.26**	0.00	0.27***	-0.02	0.27**
	(0.82)	(0.01)	(0.97)	(0.01)	(0.81)	(0.01)
store_size*large	-3.76***	0.89	-3.69***	0.83	-3.92***	0.70
	(0.00)	(0.36)	(0.00)	(0.40)	(0.00)	(0.48)
compet_ttl			-0.27	-0.11		
			(0.47)	(0.80)		
compet_ttl*large			0.10	0.17		
			(0.81)	(0.70)		
compet_share					0.02	-0.05
					(0.80)	(0.73)
compet_share*large					-0.35	-0.33
					(0.19)	(0.11)
/cut 1	-3.32***	-2.59***	-3.07***	-2.52***	-3.39***	-2.69***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
/cut 2	1.67***	1.67***	1.93***	1.74***	1.63***	1.60***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3 (continued)

Total effect (Large shopping centers)	-32.71*** (0.00)	6.76*** (0.00)	-30.94* (0.01)	7.82 (0.11)	-34.10*** (0.00)	5.11*** (0.00)
Net effect						
WATS	0.80*** (0.00)	0.84*** (0.00)	0.84*** (0.00)	0.83*** (0.00)	0.83*** (0.00)	0.88*** (0.00)
store_size	-3.78*** (0.00)	1.15 (0.23)	-3.69*** (0.00)	1.10 (0.24)	-3.94*** (0.00)	0.97 (0.31)
compet_ttl			-0.17 (0.44)	0.06 (0.99)		
compet_share					-0.33 (0.21)	-0.38** (0.04)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Pseudo R2	0.075	0.079	0.077	0.079	0.079	0.085
Obs	599	599	599	599	599	599

Table 4: Ordered Logistic Regression by Size Category

Ordered logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. Variables are computed from the DMM 1995, 2000, 2002 and 2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. Panel A includes only large shopping centers (regional and super regional) and Panel B includes only small shopping centers (community and power centers). Gla_ reno equals -1 if GLA decreased by 10% or more and +1 if GLA increase by 10% or more during the observation period and 0 otherwise. Store_ reno equals -1 if number of stores decreased by 10% or more and +1 if number of stores increase by 10% or more during the observation period and 0 otherwise. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. /cut1 is the estimated cutpoint on the latent variable used to differentiate contraction from no change and expansion when values of the predictor variables are evaluated at zero. /cut2 is the estimated cutpoint on the latent variable used to differentiate contraction and no change from expansion when values of the predictor variables are evaluated at zero. *p*-values are reported in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Panel A - Large shopping centers						
	(1)		(2)		(3)	
	gla_reno	store_reno	gla _reno	store_reno	gla _reno	store_reno
enclosed	-0.35	-0.49	-0.27	-0.59*	-0.43	-0.62*
	(0.28)	(0.12)	(0.43)	(0.07)	(0.19)	(0.05)
WATS	0.78***	0.94***	0.80***	0.93***	0.82***	1.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
store_size	-2.97***	1.62*	-2.87***	1.49	-3.11***	1.44
	(0.00)	(0.07)	(0.00)	(0.10)	(0.00)	(0.12)
compet_ttl			-0.16	0.2		
			(0.45)	(0.25)		
compet_share					-0.28	-0.39**
					(0.19)	(0.01)
/cut 1	-1.23**	-2.29***	-1.27**	-2.24***	-1.28**	-2.38***
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
/cut 2	3.03***	1.55***	3.00***	1.61***	3.01***	1.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Pseudo R2	0.0798	0.0950	0.0813	0.0973	0.0853	0.1064
Obs	318	318	318	318	318	318

Panel B - Small shopping centers						
	(1)		(2)		(3)	
	gla_ reno	store_ reno	gla_ reno	store_ reno	gla_ reno	store_ reno
enclosed	0.32	-0.87	0.34	-0.86	0.32	-0.87
	(0.52)	(0.13)	(0.54)	(0.14)	(0.52)	(0.13)
WATS	0.85**	0.39	0.86**	0.41	0.85**	0.39
	(0.04)	(0.18)	(0.04)	(0.17)	(0.04)	(0.18)
store_size	-0.024	0.33***	-0.014	0.33***	-0.025	0.33***
	(0.89)	(0.00)	(0.93)	(0.00)	(0.89)	(0.00)
compet_ttl			-0.12	-0.08		
			(0.87)	(0.88)		
compet_share					0.01	-0.02
					(0.96)	(0.91)
/cut 1	-4.37***	-2.70***	-4.25***	-2.63***	-4.37***	-2.71***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
/cut 2	2.18***	2.38***	2.30*	2.44***	2.18**	2.37***
	(0.01)	(0.00)	(0.05)	(0.00)	(0.01)	(0.00)
Prob>chi2	0.10	0.00***	0.08*	0.00***	0.13	0.00***
Pseudo R2	0.1043	0.0828	0.1045	0.0829	0.1042	0.0828
Obs	281	281	281	281	281	281

Table 5: Multinomial Logistic Regression – Full Sample

Multinomial logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. Variables are computed from the DMM 1995, 2000, 2002 and 2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. Gla_ reno equals -1 if GLA decreased by 10% or more and +1 if GLA increase by 10% or more during the observation period and 0 otherwise. Store_ reno equals -1 if number of stores decreased by 10% or more and +1 if number of stores increase by 10% or more during the observation period and 0 otherwise. Total effect of large shopping centers equals the sum of all standardized coefficients associated with large shopping centers multiplied by the median value of the non-standardized variable. Net effect tests whether the sum of a standardized coefficient and its large-shopping center dummy equals zero. *p*-value is reported below coefficient estimates. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. *p*-values are reported in parentheses.* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Full Sample						
	(1)		(2)		(3)	
	gla_reno	store_reno	gla_reno	store_reno	gla _reno	store_reno
-1						
enclosed	-0.17	0.32	-0.37	0.29	-0.15	0.38
	(0.62)	(0.29)	(0.32)	(0.37)	(0.67)	(0.21)
type_large	2.48***	1.31***	1.44*	0.66	2.57***	1.40***
	(0.00)	(0.01)	(0.06)	(0.26)	(0.00)	(0.01)
WATS	-0.1	-0.2	-0.28	-0.53	-0.12	-0.22
	(0.84)	(0.62)	(0.60)	(0.25)	(0.81)	(0.61)
WATS*large	-0.88	-0.74*	-0.85	-0.45	-0.86	-0.77*
	(0.11)	(0.09)	(0.14)	(0.34)	(0.11)	(0.09)
store_size	-0.13	-0.29	-0.23	-0.36	-0.1	-0.34
	(0.65)	(0.34)	(0.47)	(0.23)	(0.68)	(0.31)
store_size*large	2.48***	-1.25	2.40***	-1.14	2.61***	-1.05
	(0.00)	(0.15)	(0.00)	(0.18)	(0.00)	(0.25)
compet_ttl			1.08*	1.15**		
			(0.07)	(0.03)		
compet_ttl*large			-0.55	-1.12**		
			(0.42)	(0.04)		
compet_share					-0.33	0.15
					(0.26)	(0.29)
compet_share*large					0.47	0.11
					(0.27)	(0.62)
intercept	-3.78***	-3.37***	-2.96***	-2.66***	-3.82***	-3.50***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 5 (continued)

Total effect	22.31***	-9.13***	15.68**	-18.86***	23.50***	-7.42***
(Large shopping centers)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)
Net effect						
WATS	-0.98***	-0.94***	-1.13***	-0.98***	-0.98***	-0.99***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
store_size	2.35**	-1.54*	2.17***	-1.5*	2.51***	-1.39*
	(0.00)	(0.05)	(0.00)	(0.06)	(0.00)	(0.10)
compet_ttl			0.53*	0.03		
			(0.10)	(0.87)		
compet_share					0.14	0.26
					(0.27)	(0.62)
0	base outcome					
+1	(1)		(2)		(3)	
	gla_reno	store_reno	gla _reno	store_reno	gla _reno	store_reno
enclosed	-0.3	-0.51	-0.43	-0.61	-0.38	-0.61
	(0.42)	(0.23)	(0.27)	(0.15)	(0.32)	(0.15)
type_large	-0.76	0.33	-1.45*	-0.37	-0.76	0.24
	(0.34)	(0.64)	(0.09)	(0.66)	(0.32)	(0.72)
WATS	1.34***	0.37	1.29***	0.26	1.33***	0.38
	(0.00)	(0.22)	(0.00)	(0.45)	(0.00)	(0.21)
WATS*large	-1.05**	0.11	-1.03**	0.19	-1.03**	0.11
	(0.02)	(0.75)	(0.02)	(0.63)	(0.02)	(0.76)
store_size	-0.11	0.33***	-0.21	0.26**	-0.11	0.33***
	(0.62)	(0.00)	(0.32)	(0.03)	(0.62)	(0.00)
store_size*large	-2.83*	0.098	-2.94*	-0.1	-2.84*	-0.12
	(0.07)	(0.95)	(0.06)	(0.95)	(0.05)	(0.92)
compet_ttl			0.73	0.65		
			(0.14)	(0.30)		
compet_ttl*large			-0.49	-0.31		
			(0.35)	(0.64)		
compet_share					-0.03	0.07
					(0.89)	(0.70)
compet_share*large					-0.36	-0.54
					(0.30)	(0.11)
intercept	-2.11***	-2.41***	-1.44*	-1.83**	-2.04***	-2.37***
	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)
Total effect	-24.17	1.17	-30.15	-3.9	-24.27	-0.73
	(0.96)	(0.55)	(0.48)	(0.57)	(0.84)	(0.56)
<u>Net effect</u>						
WATS	0.29*	0.48*	0.26	0.45	0.3	0.49**
	(0.05)	(0.05)	(0.25)	(0.09*)	(0.16)	(0.04)
store_size	-2.94	0.428	-3.15**	0.16	-2.95**	0.21
	(0.19)	(0.77)	(0.04)	(0.91)	(0.04)	(0.88)
compet_ttl			0.24	0.34		
			(0.34)	(0.21)		
compet_share					-0.39	-0.47
					(0.30)	(0.11)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Pseudo R2	0.1378	0.1201	0.1473	0.1264	0.1431	0.1270
Obs	599	599	599	599	599	599

Table 6: Multinomial Logistic by Size Category

Multinomial logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. Variables are computed from the DMM 1995, 2000, 2002 and 2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. Panel A includes only large shopping centers (regional and super regional) and Panel B includes only small shopping centers(community and power centers). Gla_ reno equals -1 if GLA decreased by 10% or more and +1 if GLA increase by 10% or more during the observation period and 0 otherwise. Store_ reno equals -1 if number of stores decreased by 10% or more and +1 if number of stores increase by 10% or more during the observation period and 0 otherwise. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. *p*-values are reported in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Panel A - Large shopping centers						
	(1)		(2)		(3)	
	gla_reno	store_reno	gla _reno	store_reno	gla _reno	store_reno
-1						
enclosed	0.07	0.3	-0.21	0.29	0.13	0.38
	(0.89)	(0.42)	(0.68)	(0.44)	(0.79)	(0.31)
WATS	-1.06***	-1.06***	-1.21***	-1.05***	-1.09***	-1.11***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
store_size	2.48***	-1.66**	2.27***	-1.66**	2.69***	-1.52*
	(0.00)	(0.04)	(0.01)	(0.04)	(0.00)	(0.08)
compet_ttl			0.60*	0.01		
			(0.09)	(0.99)		
compet_share					0.17	0.28
					(0.61)	(0.13)
intercept	-2.39**	-2.26***	-2.68***	-2.26***	-2.38**	-2.32***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
0	Base outcome					
1						
enclosed	-0.47	-0.88*	-0.57	-1.12**	-0.58	-1.06**
	(0.30)	(0.07)	(0.21)	(0.02)	(0.21)	(0.03)
WATS	0.26	0.56**	0.24	0.63**	0.29	0.62**
	(0.28)	(0.04)	(0.32)	(0.03)	(0.22)	(0.02)
store_size	-2.38	1.33	-2.54	1.09	-2.45*	1.03
	(0.12)	(0.38)	(0.10)	(0.50)	(0.09)	(0.46)
compet_ttl			0.19	0.46		
			(0.46)	(0.14)		
compet_share					-0.38	-0.52*
					(0.19)	(0.06)
intercept	-2.88***	-1.25	-2.94***	-1.41	-2.80***	-1.25
	(0.01)	(0.18)	(0.00)	(0.13)	(0.01)	(0.16)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Pseudo R2	0.1470	0.1190	0.1566	0.1226	0.1539	0.1301
Obs	318	318	318	318	318	318

Panel B - Small shopping centers						
	(1)		(2)		(3)	
	gla_reno	store_reno	gla _reno	store_reno	gla _reno	store_reno
-1						
enclosed	-1.45	0.67	-1.83*	0.48	-1.48	0.69
	(0.15)	(0.20)	(0.08)	(0.41)	(0.13)	(0.19)
WATS	0.12	-0.21	-0.2	-0.58	0.06	-0.2
	(0.87)	(0.60)	(0.84)	(0.25)	(0.94)	(0.62)
store_size	-0.06	-0.27	-0.27	-0.33	-0.05	-0.31
	(0.84)	(0.35)	(0.46)	(0.27)	(0.86)	(0.33)
compet_ttl			1.65*	1.18**		
			(0.06)	(0.05)		
compet_share					-0.43	0.11
					(0.26)	(0.46)
intercept	-2.40***	-2.84***	-1.11	-2.09**	-2.39***	-2.93***
	(0.01)	(0.00)	(0.32)	(0.02)	(0.00)	(0.00)
0	Base outcome					
1						
enclosed	-0.32	-0.1	-0.82	-0.14	-0.34	-0.13
	(0.68)	(0.91)	(0.41)	(0.88)	(0.68)	(0.88)
WATS	1.17**	0.62	1.03**	0.47	1.14**	0.64
	(0.01)	(0.16)	(0.02)	(0.35)	(0.02)	(0.17)
store_size	-0.03	0.36***	-0.28	0.29**	-0.03	0.36***
	(0.92)	(0.00)	(0.34)	(0.04)	(0.92)	(0.00)
compet_ttl			1.67*	0.67		
			(0.08)	(0.31)		
compet_share					-0.12	0.08
					(0.52)	(0.66)
intercept	-1.43*	-2.86***	0.26	-2.21*	-1.40*	-2.90***
	(0.07)	(0.01)	(0.83)	(0.06)	(0.09)	(0.01)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.0***
Pseudo R2	0.1873	0.1268	0.2123	0.1384	0.1927	0.1284
Obs	281	281	281	281	281	281

Table 7: Logistic Regression – Full Sample

Logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. gla_exp equals 1 if GLA increased by 10% or more during the observation period and 0 otherwise. gla_con equals 1 if GLA decreased by 10% or more during the observation period and 0 otherwise. store_exp equals 1 if number of stores increased by 10% or more during the observation period and 0 otherwise. store_con equals 1 if number of stores decreased by 10% or more during the observation period and 0 otherwise. Total effect of large shopping centers equals the sum of all standardized coefficients associated with large shopping centers multiplied by the median value of the non-standardized variable. Net effect tests whether the sum of a standardized coefficient and its large-shopping center dummy equals zero. *p*-value is reported below coefficient estimates. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. *p*-values are reported in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

	(1)				(2)				(3)			
	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con
enclosed	-0.26	-0.14	-0.56	0.37	-0.37	-0.32	-0.66	0.35	-0.35	-0.11	-0.67	0.44
	(0.47)	(0.69)	(0.18)	(0.22)	(0.33)	(0.37)	(0.12)	(0.27)	(0.36)	(0.75)	(0.12)	(0.15)
type_large	-1.07	2.55***	0.13	1.28***	-1.68**	1.56**	-0.5	0.7	-1.07	2.66***	0.04	1.39***
	(0.17)	(0.00)	(0.85)	(0.01)	(0.04)	(0.04)	(0.56)	(0.24)	(0.14)	(0.00)	(0.96)	(0.01)
WATS	1.33***	-0.2	0.39	-0.24	1.30***	-0.38	0.3	-0.56	1.32***	-0.22	0.4	-0.25
	(0.00)	(0.68)	(0.20)	(0.56)	(0.00)	(0.46)	(0.39)	(0.22)	(0.00)	(0.64)	(0.19)	(0.55)
WATS*large	-0.93**	-0.81	0.26	-0.75*	-0.90**	-0.78	0.33	-0.46	-0.91**	-0.79	0.26	-0.78*
	(0.03)	(0.13)	(0.44)	(0.08)	(0.03)	(0.17)	(0.39)	(0.32)	(0.03)	(0.13)	(0.45)	(0.08)
store_size	-0.1	-0.12	0.35***	-0.33	-0.19	-0.22	0.29**	-0.41	-0.11	-0.1	0.34***	-0.39
	(0.65)	(0.67)	(0.00)	(0.26)	(0.37)	(0.49)	(0.02)	(0.17)	(0.65)	(0.71)	(0.00)	(0.25)
store_size	-3.17**	2.79***	0.36	-1.25	-3.26**	2.73***	0.16	-1.11	-3.19**	2.93***	0.11	-1.02
*large	(0.03)	(0.00)	(0.80)	(0.15)	(0.03)	(0.00)	(0.91)	(0.19)	(0.02)	(0.00)	(0.94)	(0.26)
compet_ttl					0.66	1.04*	0.55	1.08**				
					(0.19)	(0.08)	(0.38)	(0.05)				
compet_ttl					-0.46	-0.53	-0.22	-1.08*				
*large					(0.37)	(0.44)	(0.74)	(0.05)				
compet_share									-0.02	-0.32	0.06	0.15
									(0.92)	(0.27)	(0.74)	(0.28)
compet_share									-0.38	0.5	-0.57*	0.15
*large									(0.27)	(0.24)	(0.08)	(0.47)
intercept	-2.11**	-3.91**	-2.41***	3.46***	-1.51**	-3.13**	-1.90**	-2.82***	-2.04***	-3.96***	-2.36***	-3.61***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 7 (continued)

	(1)				(2)				(3)			
	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con
Total effect	-27.2	24.92*	3.16	-9.17***	-32.67	18.69	-1.05	-18.22**	-27.38	26.22***	0.99	-7.19***
(large shopping centers)	(0.72)	(0.06)	(0.94)	(0.00)	(0.25)	(0.21)	(0.46)	(0.01)	(0.85)	(0.00)	(0.79)	(0.00)
<u>Net effect</u>												
WATS	0.40**	-1.01***	0.65***	-0.99***	0.40*	-1.16***	0.63**	-1.02***	0.41**	-1.01***	0.66***	-1.03***
	(0.04)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.01)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
store_size	-3.27**	2.67***	0.71	-1.58**	-3.45**	2.51***	0.45	-1.52	-3.3**	2.83***	0.45	-1.41
	(0.02)	(0.00)	(0.62)	(0.04)	(0.02)	(0.00)	(0.76)	(0.05)	(0.01)	(0.00)	(0.73)	(0.09*)
compet_ttl					0.2	0.51	0.33	0.01				
					(0.44)	(0.11)	(0.21)	(0.98)				
compet_share									-0.40	0.18	-0.51*	0.30*
									(0.18)	(0.56)	(0.06)	(0.08)
Prob>chi2	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Pseudo R2	0.1250	0.1460	0.0829	0.1444	0.1290	0.1599	0.0891*	0.1497	0.1322	0.1498	0.0919	0.1508
Obs	599	599	599	599	599	599	599	599	599	599	599	599

Table 8: Logistic Regression by Size Category

Logistic regressions are based on a pooled sample of 1995-2000 and 2000-2005. See Table 1 for variable definitions. Continuous variables are normalized with zero mean and unit standard deviation. *p*-value is reported below coefficient estimates. Robust variance estimator is used to adjust data clustering. Fixed effect in MSA level is used. MSA dummy coefficients are not reported in the table. *p*-values are reported in parentheses. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Panel A Large shopping centers

	(1)				(2)				(3)			
	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con
enclosed	-0.45	0.14	-0.91*	0.38	-0.51	-0.12	-1.16**	0.39	-0.57	0.21	-1.10**	0.47
	(0.30)	(0.76)	(0.07)	(0.30)	(0.25)	(0.81)	(0.02)	(0.30)	(0.21)	(0.65)	(0.03)	(0.20)
WATS	0.41*	-1.10***	0.75***	-1.11***	0.42*	-1.25***	0.82***	-1.10***	0.44**	-1.14***	0.81***	-1.16***
	(0.06)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)
store_size	-2.80*	2.80***	1.65	-1.78**	-2.92*	2.62***	1.39	-1.76**	-2.88**	3.03***	1.31	-1.62*
	(0.06)	(0.00)	(0.28)	(0.03)	(0.05)	(0.00)	(0.39)	(0.03)	(0.04)	(0.00)	(0.35)	(0.07)
compet_ttl					0.14	0.58	0.5	-0.04				
					(0.60)	(0.11)	(0.12)	(0.87)				
compet_share									-0.4	0.22	-0.58**	0.32*
									(0.17)	(0.51)	(0.03)	(0.08)
Intercept	-3.18***	-2.42***	-1.41	-2.46***	-3.23***	-2.70***	-1.57*	-2.45***	-3.09***	-2.42***	-1.39	-2.53***
	(0.00)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.01)	(0.12)	(0.00)
Prob>chi2	0.08*	0.00***	0.09*	0.00***	0.04**	0.00***	0.09*	0.00***	0.03**	0.00***	0.00***	0.00***
Pseudo R2	0.1051	0.1702	0.0905	0.1167	0.1062	0.1868	0.1024	0.1168	0.1161	0.1735	0.1102	0.1257
Obs	318	304	318	301	318	304	318	301	318	304	318	301

Panel B Small shopping centers

	(1)				(2)				(3)			
	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con	gla_exp	gla_con	store_exp	store_con
Enclosed	-0.21	-1.38	-0.23	0.69	-0.64	-1.69*	-0.26	0.51	-0.21	-1.39	-0.27	0.71
	(0.79)	(0.17)	(0.79)	(0.19)	(0.51)	(0.10)	(0.77)	(0.37)	(0.79)	(0.15)	(0.75)	(0.17)
WATS	1.16**	-0.05	0.63	-0.26	1.03**	-0.33	0.5	-0.62	1.12**	-0.13	0.65	-0.25
	(0.01)	(0.95)	(0.15)	(0.52)	(0.02)	(0.73)	(0.31)	(0.22)	(0.02)	(0.84)	(0.16)	(0.54)
store_size	-0.02	-0.04	0.37***	-0.31	-0.25	-0.24	0.32**	-0.38	-0.02	-0.03	0.37***	-0.35
	(0.93)	(0.89)	(0.00)	(0.27)	(0.39)	(0.54)	(0.02)	(0.19)	(0.94)	(0.92)	(0.00)	(0.26)
compet_ttl					1.54*	1.54*	0.56	1.10*				
					(0.10)	(0.08)	(0.39)	(0.06)				
compet_share									-0.11	-0.41	0.07	0.11
									(0.55)	(0.29)	(0.68)	(0.48)
intercept	-1.52*	-2.69***	-2.92***	-2.93***	0.07	-1.45	-2.37**	-2.26**	-1.51*	-2.72***	-2.96***	-3.01***
	(0.05)	(0.00)	(0.01)	(0.00)	(0.96)	(0.20)	(0.04)	(0.01)	(0.06)	(0.00)	(0.01)	(0.00)
Prob>chi2	0.02**	0.77	0.02**	0.19	0.00***	0.77	0.03**	0.08*	0.01**	0.64	0.03**	0.29
Pseudo R2	0.1702	0.0763	0.1324	0.0750	0.1951	0.1016	0.1376	0.0902	0.1717	0.0851	0.1333	0.0772
Obs	216	216	254	258	216	216	254	258	216	216	254	258

Essay 2

The Location of New Anchor Stores within Metropolitan Areas

1. Introduction

The retail sector is a dynamic sector, with new construction and expansion occurring side-by-side with high vacancy, bankruptcy and liquidation of leading retail chains. Wal-Mart, Target and wholesale club chains have expanded aggressively over the past 25 years, introducing new technology such as sophisticated distribution centers and systems, tight cost control and related internet sales. Foster, Haltiwanger and Krizan (2006) use establishment level data from the Census of Retail Trade to explore substantial increases in productivity in the retail sector.[33] These changes are associated largely with the entry and exit of retail establishments. They find that entry into local markets by large, multi-establishment retailers have displaced smaller retailers such as those with a single establishment over the 1987-97 decade. Moreover, they find that "the enormous restructuring of the retail trade sector towards large, national chains has been at the core of productivity gains in the retail sector (p. 749)."[34]

In this paper, we examine intra-metropolitan retail patterns by focusing on the opening of large, full-line department ("anchor") stores in the United States. We identify and test factors that make a particular location more attractive to a particular chain among these large retailers. This is an important topic because the entry of a new multi-line, multi-store retail chain into a local market has the potential to change the retail landscape for smaller stores, causing some to thrive and others to go out of business. These changes may play out over a decade or more.

We focus on anchors for two reasons. First, data collection, while still difficult, is manageable whereas any attempt to model the entire retail sector would have to deal with its enormous size and complexity. Second, as suggested by previous literature, these stores lead the retail sector. Any new shopping center requires a commitment from one or more anchors, and the economics of clusters of independent retail is changed by the opening of an anchor store.[35] By understanding the changing

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[33] An establishment is a single physical location where economic activity takes place.

[34] In a recent study, Haltiwanger, Jarmin and Krizan (2010) examine the negative impact of Big-Box entry on small retail establishments within the DC metro area. Hausman and Leibtag (2007) find efficiency gains for consumers following the entry of a Wal-Mart. They ignore adjustments in the labor market.

[35] Kramer (2008) defines the Wal-Mart shadow as open air strip shopping centers built in conjunction with a large Wal-Mart store. She says that "several chain stores, notably Dollar Tree, Cato and Shoe Show, make it their stated corporate objective to follow Wal-Mart's path (p 46)." Kramer gives other examples of smaller stores that locate near Wal-Mart and compete directly with some of Wal-Mart's lines.

location pattern of anchor stores, we gain insight into the dynamics of a large segment of the retail industry.[36]

This paper tests the hypothesis that anchor locations can be largely explained by the location of population. The suburbanization of populations and income has been a dominant trend in the US. Only if we control adequately for access to population and income then we can isolate the role of retail clustering in location decisions. It is our goal to understand localization economies, the benefits associated with a cluster of retail stores. But clustering implies costs associated with traffic congestion and competition among stores selling close substitutes. We want to model localization economies and separate them from negative competitive effects.

Our data are well-suited to the issues we address. Our sample includes 36 metropolitan statistical areas (MSAs) across East, Central, Midwest and Southwest regions in the US. By compiling data on all anchor stores each year from the beginning of 2005 to the end of 2011, we work with the universe of all anchors within these markets: there are 54 anchors in our data. We further classify all the chains into three categories, high-price, mid-price and low-price to control for price and quality variables. See Appendix 1B for details on our classification method based on Vitorino (2012) and Gould, Pashigian and Prendergast (2005).

Wal-Mart is a particularly visible anchor store that has been the subject of some scholarly research (Pope and Pope, 2013; Ellickson and Grieco, 2013; Holmes, 2011; Neumark, Zhang and Ciccarella, 2008; Jia, 2008; Hausman and Leibtag, 2007; Basker, 2005). Our low-price category includes Wal-Mart Supercenters and its major competitors – Target, Costco, and Kmart – as well as Sears Grand, Sears Essentials, Meijer, Shopko, BJ's Wholesale Club and Sam's Club (a Wal-Mart subsidiary). We model Wal-Mart as just one among many competitors because, with about 20 percent of openings, it does not dominate the data.[37]

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[36] Anchors generate traffic to a shopping center or retail cluster because customers can economize on transportation costs by making multipurpose shopping trips. Stahl (1982) and Schulz and Stahl (1996) develop the importance of nonconvex transportation costs. Additional theory is provided by Brueckner (1993), Pashigan and Gould (1998) and Salvo (2010). Konishi and Sandfort (2003) argue that stores with substantial advertising reduce uncertainty about product quality. Shopping centers and retail clusters attract customers because easy price and quality comparison implies low prices, good service and higher product variety.

[37] We exclude three of Wal-Mart's formats (Wal-Mart discount, Wal-Mart Market and Wal-Mart Express) because they do not satisfy our definition of a multiline department store. Target has about 15 percent of

Our analysis starts with a comparison of the location pattern of existing and new stores using a nonparametric approach proposed by Duranton and Overman (2005), and developed by Klier and McMillen (2008) and Billings and Johnson (2012). This K-density method estimates the density of distances separating each store location. We conclude that the location pattern of new stores is more dispersed than that of existing stores, i.e., there is less density at the short distances (e.g., three miles) of interest to decision makers. In all regions, the confidence intervals based on population-weighted probabilities poorly predict the location pattern of new stores, especially within three miles. We conclude the same results by investigating each of the three price types. As a result, the simple suburbanization hypothesis – that openings are simply following population – is rejected. This motivates a multivariate econometric model to explain the location pattern of openings as a function of localization and competitive effects.

Next, we apply the conditional logit model (CLM) to anchor location decisions.[38] We find that, consistent with the revenue hypothesis, new openings are affected by location proximity to Central Business District (CBD) and highway, potential revenue and growth. Most important, we find a strong negative cannibalization effect (i.e., competition from an existing store owned by the same chain) as well as a positive localization effect. There is also heterogeneity among different regions, where openings in Southwest are more influenced by population and hence least affected by localization. Zoning is taken into account with proxy variables such as the presence of existing retail establishments and proximity to a limited access highway.

To test whether the CLM effectively explains the location pattern of openings, we use the predicted probabilities from the model to calculate K-density measures of concentration. We find that the CLM-based confidence intervals perform considerably better than do population-based confidence intervals, especially within the important threshold of three miles between anchors. We present evidence that the CLM successfully captures the possibility of zoning constraints with the proxy variables included. By separating into three price types, we find that the K-densities based on CLM perform better than the aggregate level, indicating that decision makers can accurately explain

openings, leaving about two-thirds spread out among many competitors.

[38] The CLM is central to much of industrial location literature (see Arauzo-Carod, Liviano-Solis, and Manjón-Antolín, 2010).

location patterns if they disaggregate by price type. Most importantly, the model by matched type (i.e., when the price-type and chain of an opening are matched to existing stores to capture the mix of types and chains; hereafter, “matched type”) also has significant explanatory power. This means that the model has the potential to explain the location pattern of openings from the point-of-view of a particular retailer, a useful result for any decision maker.

Our paper contributes to the literature in several ways. First, it is the first location choice paper to focus on anchor store openings and to extend the concept of localization economies to include clusters of anchors of different types.[39] Second, our data are far more comprehensive than that used in other retail studies since we cover all anchors, existing and newly-opened, inside shopping centers and freestanding, in a broad range of MSA sizes over the period 2005-2011.[40] We develop a new way of collecting data at the business establishment level, using CoStar and company web sites with 10K reports and a database of mergers and acquisitions. Third, this is the first paper we know of to apply CLM to a retail establishment database. Our application of the Duranton and Overman (2005) K-density method is also the first to a retail database. Most importantly, this paper develops a model suitable for adaptation by public policy officials, large retailers such as one of the anchors in our sample, and smaller retailers who might be displaced by anchor openings.

The remainder of this paper is organized as follows. The next section develops our main hypotheses. Section 3 describes the data collection method and our unique data set, and presents descriptive statistics. Section 4 analyzes the spatial pattern of anchor stores and tests the hypothesis that retail follows population by using the nonparametric K-density method. Section 5 discusses the CLM results. Section 6 tests whether the CLM effectively explains the location pattern of openings. Section 7 concludes the discussion.

[39] In the context of industrial firm and plant location decisions, localization economies are usually defined as sharing of inputs such as specialized labor and technology (Arauzo-Carod, Liviano-Solis, and Manjón-Antolín, 2010). Our extension to the retail sector includes the benefits from comparison shopping and multi-purpose shopping trips. For example, the clustering of stores selling high-value differentiated goods (e.g., jewelry and automobiles) is explained by this concept of localization economies.

[40] For example, Hausman and Leibtag (2007) focus on supermarket competition only; Holmes (2011) studies Wal-Mart only; Jia (2008) evaluates Wal-Mart and Kmart competition in counties with small population; Vitorino (2012) works with nine anchor stores in regional shopping centers in 2006. By way of contrast, we have 54 anchors in 36 MSAs, and these MSAs represent all but the smallest and largest markets.

2. Do Anchor Locations Passively Follow Population and Income?

The purpose of this section is to elaborate on the idea that retail is an uninteresting sector because it serves the needs of local population. The hypothesis that retail locations passively follow household locations (referred to as the suburbanization hypothesis) serves as a useful point of departure for our model, which introduces the possibility that retail locations are influenced by localization economies and by competitive conditions. A finding that suburbanization explains the location pattern of anchors would imply no need to add more variables.

If customers are the major driver of retail productivity, the location pattern of retail establishments could be well-predicted by the location of households or population. We make this simple idea more plausible by introducing three types of anchor stores: low-price, mid-price and high-price. Incomes of the population may not be important if department stores can choose the format suitable to income in the local area. Therefore, the point of departure for our analysis is the hypothesis that location patterns of these three types will be indistinguishable from the location patterns of households and population modified by income. If so, then the potential of retail to lead local economic development, as suggested by Hausman and Liebtag (2007) and by Foster, Haltiwanger and Krizan (2006), is irrelevant to spatial patterns.

We elaborate the suburbanization hypothesis with profit maximization, which predicts spatial clustering by adding variables such as potential revenue, revenue growth and urban transportation systems. For example, a location near limited-access roads expands the market catchment area. We refer to this group of variables as testing the revenue hypothesis.

We add localization economies, the benefits associated with a cluster of retail stores of all types.[41] Stahl (1982) assumes nonconvex transportation costs for consumers and declining marketing costs for retailers. A simple representation for consumers is a fixed cost of a shopping trip; this may be spread over multiple purchases. When differentiated products are introduced, then comparison shopping motivates clustering of retailers selling substitute products; localization economies may outweigh competitive effects. From the retailer’s perspective, a fixed setup cost allows costs to

[41] The concept of agglomeration (localization and urbanization) economies has been considered as the most studied determinant of industrial location (Arauzo-Carod, Liviano-Solis and Manjon-Antolin, 2010).

decline with the volume of sales and the number of products sold; economies of scope are realized by larger retailers.

Konishi and Sandfort (2003) extend Stahl's (1982) framework to allow for brand names established by department stores. Advertising allows customers to develop a high degree of certainty about the items for sale and their pricing, as opposed to smaller "in-line" retailers that do not have as much advertising and selection or that have higher prices. The different brand identification, together with greater variety at the department store, generates benefits from co-location. We refer to these as a form of localization economies. As in the industrial location literature, localization economies would also derive from specialized labor pools and easier access to technology such as inventory control and supply-chain management systems.

A strand of the economics literature views the location choices of anchor stores as a strategic game: see Jia (2008), Holmes (2011), Fershtman and Pakes (2012) and Vitorino (2012).[42] This approach emphasizes the negative effects of competition, suggesting that spatial patterns will be dispersed as anchors seek to avoid competition or enter in a way designed to preclude competition (Salvo, 2010). One form of competition is cannibalization: anchors have a strong aversion to locating too close to another of their own stores; empirical support for cannibalization has been found by Holmes (2011).

We test competition and cannibalization hypotheses as one of several explanations of spatial patterns of retail. To summarize the most elaborate hypothesis, we test if spatial patterns of anchor store openings can be explained by competition (including cannibalization), localization economies, revenues (income and income growth) and by the location of population. The suburbanization hypothesis that households drive retail locations is nested within the revenue hypothesis since income and income growth will not have additional explanatory power if household location explains everything. Likewise, competition and localization economies elaborate the revenue hypothesis.

The intra-metropolitan location of anchor stores is constrained by zoning, which commonly

[42] We find this line of reasoning problematical because it requires improbably complex calculations once the number of competitors increases from some small number. By adding constraints to optimization, Vitorino (2012) increases the number of competitors in her model to nine, whereas we consider all anchors of a given type as competitors.

provides for retail districts and accommodates shopping centers to serve the needs of the local population. Zoning might account for retail patterns that are more concentrated than that of households.[43]

3. Data

3.1. Sample Construction

Anchor stores are defined by their functions and these differ across the central place hierarchy.[44] We develop a rigorous definition of anchors for large shopping centers: i.e., department stores where shoppers can find different categories of products including clothing, footwear, bedding, furniture, jewelry, beauty products, and housewares, as well as different brands within each category.[45] We choose a sample of leading retail firms which operate department stores, discount stores, hypermarkets and wholesale clubs based on "Leading Retail Chains" listed in Directory of Major Malls (DMM).[46] We also require the minimum store square footage be greater than 20,000 sq ft. Panel A of Appendix 1 contains the list of 54 department stores.[47] Based on Vitorino (2012) and Gould, Pashigian and Prendergast (2005), we control for price and quality variables by classifying all the chains into three categories, high-price, mid-price and low-price. Panel B of Appendix 1 includes the classification methods.

Since manual date collection is quite time-consuming, we start with a list of metropolitan statistical areas (MSAs) with population more than 750,000 in 2005. Based on the rationale of retail

[43] Similarly, the industrial location literature has sought to determine the influence of public policy: see, for example, Crozet, Mayer and Mucchielli (2004) and Arauzo-Carod, Liviano-Solis, and Manjón-Antolín (2010).

[44] The Directory of Major Malls (DMM) reports anchor stores for each shopping center. For regional and super regional shopping centers, anchor stores are normally department stores such as Macy's, Sears and Nordstrom. For small-scale centers, anchor stores could be apparel chain stores such as Gap and Bob's store. For power centers featured with big box retailers, anchor stores are normally discount stores (TJ Max and Marshalls), hypermarkets (Wal-Mart and Target) and wholesale clubs (BJ's and Costco). Leading apparel chains such as the Gap are anchor stores for community centers but not for regional centers or larger.

[45] This is essentially consistent with the hypothesis of Konishi and Sandfort (2003) that consumers with preference uncertainty can economize their travel costs. Following the same logic, discount stores, hypermarkets and wholesale clubs play a similar function and are normally anchor stores for large power centers and lifestyle centers.

[46] The definition of department store in DMM is different from ours. A subject store is included in our sample based on the variety of products and brands. For example, TJ Maxx, Marshalls, Burlington Coat Factory and Ross Dress For Less are classified as apparel chains according to DMM. But we treat them as representatives of anchor stores because they provide a variety of products as well as different brands within each category. We do not include GAP and Abercrombie & Fitch because they offer only apparel of their own brands.

[47] We initially include more than 60 retail chains but some of them are not within the 36 MSAs.

clustering and the function of anchor stores, customers economize their transportation costs through multipurpose shopping. In the US, shoppers often drive from store to store within a retail district. Downtown shopping, on the other hand, typically involves walking from store to store; it is more akin to shopping within a suburban shopping center, except that it is harder to identify the relevant cluster of stores. As a result, we delete all MSAs with heavy or light rail transportation systems. This leaves us with MSA's that do not have mass transit systems in 2010.[48] We end up with 36 MSAs defined in 2010 Census. We further classify the MSAs into 4 regions: East, Central, Midwest and Southwest. There are 14 MSAs in East, 9 in Central, 6 in Midwest and 7 in Southwest.

Panel A of Figure 1 shows that the 36 MSAs group logically into four regions, consistent with Census regions and divisions. Panel B of Figure 1 focuses on the 7 MSAs in the Southwest, showing that the anchors do follow population as suggested by the suburbanization hypothesis. In all MSAs except Las Vegas, the map shows that anchors, especially those opened since early 2005, often locate away from the CBD.

For store openings, we search in Factiva to collect related news articles. Factiva applies Intelligent Indexing® in order to assign unique company codes to Dow Jones News Search (DJNS) articles that represent the companies that are the subject of the articles. Because of Intelligent Indexing, Factiva is considered effective in identifying articles relevant to specific companies. By conducting rigorous search in major news and business publication sources and press release wires, we gather 14,400 articles related to our universe of anchor store openings from 01/01/2005 to 01/01/2012.[49]

The objective of the search is to identify all articles related to anchor store openings driven by market demand as well as competition. By reading through the articles, we find the reasons behind those openings. We focus on new stores that require substantial sunk costs and thus may have large strategic impact on development within the MSA. As a result, we exclude rebranding, expansions and

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[48] The source of transportation mode for each MSA is a listing by the American Public Transportation Association (APTA). As our sample period ends in December 2011 and transportation systems change over time, we use the 2011Q4 APTA report in order to guarantee the list of cities we selected do not have heavy and light rail transportation system during the whole sample period.

[49] We search articles in headlines and leading paragraphs by using *(store or stores or *center or center*) near10 (move* or relocate* or relocation or expand* or expansion* or open or opens or opened or opening or unveil* or dispose* or disposal or cut* or shut* or close or closes or closing or closed or closure)*

renovations. But we account for store relocations because relocation requires new construction that involves substantial sunk cost. We carefully investigate false announcements and censored observations because some announced openings did not actually take places. Our final sample includes 806 new stores opened from 2005 to 2011.

The decision to open a new store is conditioned on the mix of pre-existing stores in the same local market. To identify existing anchors at any point in time, we manually collect all the existing stores as of September 2012 on retailers' websites. We exert discretion to ensure that we select all stores within the list of MSAs.[50] Our interest lies on the ownership of the store at both chain-level and company-level. Starting with stores existing in 2012, we then track backwards by identifying stores closed or those with an ownership change. Closings are tracked through news articles, CoStar, DMM and various website searches.[51] Mergers and acquisitions are tracked from news articles, 10K reports, CoStar and Thompson One Banker database of mergers and acquisition at property level.

For each chain, we start with September 2012 anchor locations and use the following equation to track existing stores backwards to the beginning of each year:

 # stores at the beginning of year t = # stores at the end of year t - # stores acquired during year t - # stores opened during year t + # stores closed during year t + # stores sold during year t

As January is a big month for new store openings, an annual observation begins February 1 and ends January 31 (Holmes, 2011).[52] To avoid the bias that some companies might have higher incentive to announce openings, we cross check openings with CoStar and DMM.[53]

Information on headquarters and distribution centers is collected from news articles, 10-K reports

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[50] In store locator websites, we enter the names of the cities and collect the addresses for all stores that show up on the webpage. Some retailers such as Belk show all the stores by states. In that case we will collect stores locations based on states. Some retailers such as Bon Ton ask us to specify the radius on their store locator websites. We always choose the widest radius. However, in that way, we might over-select stores. So we match zip codes with MSAs in the next steps.

[51] CoStar does not explicitly provide store closing information but might provide ownership information through tenancy and property transaction records.

[52] Using Macy's as an example, we collected all the current stores from Macy's store locator website in September 2012. Based on the news articles on openings, closing, mergers and acquisitions from February 2011 to September 2012, we use the above equation to track the number of Macy's as of February 2011.The data collection period of the current existing store was from June to October 2012. In order to ensure the data accuracy, we collect news articles up to December 2012.

[53] For example, CoStar Properties provides "Year Built" and CoStar Tenants provides "Move-in date". If the property where the subject store located was built between 2005 and 2011, as indicated in CoStar Properties, or the earliest move-in date of the subject store is between 2005 and 2011, as indicated in CoStar Tenant, we treat it as a new opening.

and CoStar. We exclude e-commerce fulfillment centers from traditional distribution centers. We also consider the openings and closings of distribution centers, headquarter relocations and changes on distribution centers of multi-chain companies.[54]

We manually search for detailed addresses of existing and new stores, in the form of "number, street, city, state, zip code" and categorize them into different MSAs based on "HUD USPS ZIP Code Crosswalk Files". We only keep openings in our sample of 36 MSAs.[55] Appendix 2 includes the distribution of openings by MSA. We obtain latitude and longitude of all the openings, existing stores, headquarters and distribution centers. Information is further verified based on various sources such as Google and GIS system.

3.2. Descriptive Statistics

Table 1 presents summary statistics at the MSA level. Panel A shows the socioeconomics characteristics of 36 MSAs by region based on Census 2010. The East MSAs have the fewest households but the highest median household income while the Central MSAs have the most households but the lowest income.[56] Demand is defined as the total number of households multiplied by median household income. On average, the East MSAs have the highest demand density while the Southwest MSAs have the lowest demand density. Turning to demand growth, the Central MSAs exhibit the slowest demand growth while the Southwest MSAs exhibit the fastest growth in the recent 20 years.[57]

Panel B includes summary statistics of 2,380 existing stores as of 2005, the beginning of our sample period. By breaking down into three price types, we find evidence supporting the

[54] Some distribution centers serve more than one chain but some do not. For example, TJ Maxx and Marshalls under TJX do not share distribution centers while Sam's club and Wal-Mart do.

[55] We match zip code with counties/MSAs based on HUD 2010 definition. Correspondently, we should make two match files (MSA-CY and ZIP-CY) consistent. So we should use the 2010 MSA-CY definition as well. But the latest is the OMB 2009 definition. The 2010 definition has not been released. As a result, we use the OMB 2009 definition.

[56] We use households instead of population because it is a better unit of measurement for consumption.

[57] Because MSA definition changes over time, we use the Census 2010 definitions: 12,346 census tracts in the 36 MSAs. Demand in a local area (LA) around each tract is calculated for a three-mile radius from 2010 centroids, effectively controlling for changes over time in tracts and in MSA definitions. Demand Growth 1990-2000 is defined as annualized percentage growth of inflation-adjusted demand from 1990 to 2000. We use demand growth from 1990 to 2000, which is more than 10 years before the beginning of our sample period because a new opening normally takes more than five years to plan and construct.

suburbanization hypothesis that income may not be important because the anchors choose the format suitable to income in the area. For instance, the Central MSAs have the largest number of low-price existing stores due to the largest population and the lowest income. The East MSAs have the largest number of mid-price per capita and a high number of high-price per capita, corresponding to high income and demand density in the East. The number of high-price and mid-price anchors per capita in the Southwest MSAs corresponds well to the fact that it has median household income very close to the East. When we scale existing anchors by demand, much of the disparity across regions disappears. This suggests that the mix of stores varies systematically with local market conditions, a hypothesis we will explore further with CLM.

Panel C presents statistics of 806 openings from 2005 through 2011. When we scale openings by households, the Midwest ranks the highest in all three price segments, suggesting that its high demand growth (Panel A) is balanced across demand segments. The Southwest, with demand growth of over 4.5% per year, has a relatively large concentration of mid-price openings, suggesting that middle income groups are the fastest growing. As with existing anchors, when we scale new anchors by demand, we get a much more even distribution across regions.

Next, we analyze within-MSA location choices by using randomly chosen tract centroids as a counterfactual that allows us to evaluate existing and new locations. The reason of using this counterfactual is that a significant number of these areas have no new or existing stores; comparison shows how the chosen locations differ from the rejected ones.[58] In addition, because there are more census tracts in more densely populated neighborhoods, randomly chosen centroids represent the suburbanization hypothesis that the anchors follow population.

In Table 2, we bore down to demand and growth variables in local market areas (LAs) most relevant to the success of an anchor store, the three-mile radius around the store. The use of three-mile radius around each tracts centroid is justified by discussions with real estate professionals[59] and by

[58] In unreported results, at least 25% of counties have neither new nor existing stores. Our counterfactual methodology is similar to those used by Duranton and Overman (2005) and Billings and Johnson (2012).

[59] Fanning (2005, page 192) uses three to five miles or a 5-10 minute drive on local roads as the boundary between shopping centers anchored by supermarkets and junior department stores and those anchored by the multiline department stores we study. Moreover, a three-mile radius is consistent with the sizes of submarkets defined by CoStar and other vendors.

the fact that larger areas would potentially comprise too much of a typical metropolitan area, depriving location choices of sufficient intra-metropolitan variation. Moreover, three mile areas have the advantage of encompassing enough area to obviate the need for distance weighted variables such as those used by Crozet, Mayer and Mucchielli (2004) and by Woodward Figueiredo and Guimarães (2006).[60]

In all regions, demand is much higher in LAs of existing stores, in comparison with random LAs as well as LAs of openings. However, demand growth is much higher in LAs of openings, in comparison with random LAs and LAs of existing stores. This suggests that new stores are accepting lower immediate revenues than existing in exchange for higher demand in the future. New stores are likely less profitable on a current basis. This is also consistent with the revenue hypothesis in which potential revenue and growth help explain the opening decisions of new anchor stores.

4. The Spatial Pattern of Anchor Stores

4.1. An Example of Spatial Pattern within MSAs

Since our analysis is based on choices within MSAs, we are interested in a general spatial pattern across a typical MSA. To illustrate a general pattern, Figure 2 compares Albany-Schenectady-Troy, NY (Panel A) with Oklahoma City and Tulsa, OK (Panel B). Both maps demonstrate a strong spatial clustering observed in all our MSAs. The anchors tend to locate in the most densely populated parts of the MSAs, where census tracts have smaller areas.[61] Existing anchors as of January 2005 tend to cluster around limited access roads (not shown). On the other hand, openings are somewhat more disbursed, avoiding the CBD. The generality of this conclusion is demonstrated previously by Table 2, which shows a random (i.e., population weighted) choice of location compared to actual locations.

The three MSAs have similar total populations (about 350,000 households in Tulsa and Albany, 471,000 in Oklahoma City), but Albany has over twice the density of Tulsa and 1.5 times that of

[60] Spatial autoregressive techniques are not well developed in the CLM context. Despite the advantages of using three-mile LAs, we are aware of the Modifiable Areal Unit Problem (MAUP) and so we provide sensitivity tests of the three mile assumption.
[61] In the US, census tracts are designed to contain residential locations of about 4,000 people on average. Therefore, the area will be smaller and the centers of the tracts ("centroids") will be closer together in more densely populated areas.

Oklahoma City.[62] The different scales on the two maps provide a visual representation of the relatively spread-out pattern in Tulsa and Oklahoma City. As a result, separate analysis of each of the four regions is motivated by Figure 2.

4.2. Duranton and Overman (2005) Method for Evaluating Spatial Patterns

Next, we use the Duranton and Overman (2005) K-density method to test the suburbanization hypothesis and examine spatial patterns of existing and new stores. Appendix 3 includes computation details. Our application of the K-density method is motivated by the question "can the CLM model explain the spatial clustering of new anchors better than the suburbanization hypothesis?" To build on the previous findings that existing stores exhibit more spatial clustering than openings, we plot the densities of distances between existing anchors (E2E) compared to the density between opening of new stores and existing stores (O2E).

By using existing locations as counterfactuals, we deal with the dartboard problem discussed by Ellison and Glaeser (1997) and Billings and Johnson (2012). The problem is that random locations will exhibit patterns that might be mistaken for intentional clustering. Our comparison of O2E to E2E simply describes the way openings compare to existing locations.[63]

Figure 3 plots the spatial pattern of E2E and O2E by region. The solid line without cross shows the pattern of E2E. The solid line with cross marks shows the pattern of O2E. The horizontal axis is target distance from zero to 50 miles; 51 target points. We use 50 miles as threshold because the 90th percentile of E2E distances is about 50 miles.[64] The East region has a sharp peak because older cities typically have dense CBDs and there are stronger controls on new constructions.

The two dashed lines plot the global confidence interval for a random choice of tract centroid

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[62] The Albany MSA had about 123 households per square mile in 2010, whereas the Tulsa MSA had about 58 and Oklahoma City about 85.

[63] There are other reasons for using E2E and O2E. Duranton and Overman (2005) use existing locations as counterfactuals because it is known that existing establishments have zoning permissions, and existing establishments likely found locations attractive from a profit maximizing point-of-view after considering many factors unobserved by the econometrician. In addition, comparing E2E with O2O would lack a reliable benchmark. For example, if new stores opened in a recently emerged shopping district located far away from traditional central business district (CBD), one might falsely conclude that openings exhibit clustering compared with existing anchors.

[64] Duranton and Overman (2005) use the median distance between all pairs of manufacturing establishments in the whole UK. We focus on individual MSAs, which are much smaller but relatively densely populated geographical areas. As a result, we use the 90th percentile instead of median.

(i.e., a population weighted location choice). The first (second) numbers in parentheses is the number of O2E densities at 51 target distances (four target distances within three miles) outside the 95% global confidence intervals. This approach is similar to Duranton and Overman (2006), Klier and McMillen (2008) and Billings and Johnson (2012) who suggest global intervals to test for choices across multiple locations. We use the centroids of census tracts as counterfactuals and assume that the probability that a census tract is chosen as a new store location is equal within a MSA. Graphically, a cluster pattern (i.e., more spatially concentrated than population) is detected when the actual K-density lies above the upper confidence band and a dispersed pattern is detected when the actual K-density lies below the lower confidence band. We find that, except in the Midwest, O2E is well-above the 95 percent global confidence interval from distance of zero to three miles. The numbers in parentheses show that, except in the Southwest, most of actual O2E densities are outside the population-weighted global confidence intervals, especially at the four target distances within three miles. In unreported figures, we plot O2E densities by price type. Again, the global confidence intervals based on population weighting do not predict any of the three types of openings.

The clustered pattern of openings relative to a population weighted pattern could be explained by zoning, but the differences between E2E and O2E suggest that there is more to the story: i.e. O2E is more dispersed than E2E for all regions, consistent with findings reported in Tables 1 and 2.[65] The comparison of O2E with E2E suggests that anchors have had some success in finding locations closer to population, and perhaps farther from competition, than existing anchors.

Localization and competition hypotheses suggest that anchors have higher incentive to locate near existing stores of different price categories. For example, Target might prefer a location near Macy’s rather than Wal-Mart, subject to zoning constraints. To directly test competition and localization hypotheses, we aggregate existing stores into four categories defined from the perspective of an opening of a given price type and chain. The matched type variables are defined as the locations of existing anchors that are: same-chain-same-company (SCS), different-chain-same-company (DCS), same-type-different-company (SD) and different-type-different-company (DD) relative to a given

[65] The endogeneity of zoning (see Glaeser, Gyourko and Saiz, 2008) suggests that local governments often comply with profit maximizing imperatives. This assumption is particularly plausible for the retail sector.

opening. We hypothesize that cannibalization is measured by SCS stores and localization is measured by DD stores. Figure 4 plots K-densities of O2SCS, O2SD and O2DD defined analogously to O2E with the existings broken down into the SCS, SD and DD categories. We omit O2DCS because of insufficient observations.

In Figure 4, O2SCS lies well below O2SD and O2DD, consistent with cannibalization.[66] As shown by the numbers in parentheses, most of densities are outside the population-weighted global confidence intervals. More importantly, O2SCS is more dispersed than the lower band, supporting the fact that zoning does not dictate location choices. Likewise, in a recent study of Big Box stores, Schuetz (2013) concludes that zoning does not appear to drive store clustering.

The major conclusions of Figure 3 and 4 are that, consistent with descriptive statistics, the location pattern of openings cannot be fully explained by either existing locations or by population. This motivates a multivariate econometric model to explain the location pattern of openings.

5. A Conditional Logit Model (CLM) of Anchor Store Openings

5.1. Conditional Logit Model

The CLM has been one of the most popular methods for industrial location literature, so it is a reasonable point of departure for a study of retail locations.[67] The CLM we develop models the intra-metropolitan location of anchor store openings as a function of measurable supply and demand. A significant contribution of applying CLM is to use existing store locations, and choices near limited-access highways, to control for omitted variables. Appendix 4 gives details of the CLM method, which is based on profit maximizing location choices.

For an opening in a particular MSA, we assume that the decision maker faces a set of finite potential location choices (tract centroids) within the same MSA. We follow the methods used by Ben-Akiva and Lerman (1985) and by Klier and McMillen (2008) to deal with the problem of a large choice set and to obtain consistent estimators that are more efficient than a multinomial logit (MNL)

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[66] In unreported figures, we plots K-densities of O2SCS, O2SD and O2DD by region and conclude the same results.

[67] Table 1 in Arauzo-Carod, Liviano-Solis, and Manjón-Antolín (2010) lists nineteen studies using CLM and they compare discrete choice to count data models.

model. To ensure the choices are finite, we replace the locations of actual openings by the closest census tract centroid. Each opening is paired with five non-overlapping LAs randomly select without replacement in order to ensure that the choices are independent and mutually exclusive.[68] The resulting dataset has N openings and 6N observations; the dependent variable equals 1 for the selected market and 0 for the rejected markets. Time is not a factor in our CLM model because we evaluate each decision relative to initial characteristics at the beginning of each year. Hence, CLM allows us to control all time-invariant unobservable characteristics of decision makers.

Our CLM model is a reduced form, cross sectional solution designed to explain the spatial pattern better than a model that omits our supply and demand variables. The explanatory power of CLM should be better than either the population weighted K-density of tracts or the K-density for E2E. Controlling for factors such as distance to highways and CBD, significant coefficients for SCS and DD variables indicate that they can explain spatial patterns.

5.2. Explanatory variables

Our explanatory variables include location specific variables (*X* variables) and location-decision specific variables (*Z* variables). A set of *X* variables to test the suburbanization hypotheses includes a CBD dummy for any location within three miles of the CBD (*CBD_3mile*), distance of the location from the CBD (*dis2CBD*) and distance squared. Movements of population and income over the sample period have typically been away from the CBD and towards more outlying suburbs. Consequently, we expect a negative sign on *CBD_3mile*, a positive sign on *dis2CBD* and an indeterminate sign on the squared term.

To test the revenue hypothesis, we make the LA's more flexible by including dummies for locations within half a mile of a limited-access road (*hwy_half_mile*).[69] Then we add another dummy for locations more than half a mile but less than two miles from highways (*hwy_half2two_mile*). The omitted category is all other tract centroids. If these variables do, in fact, measure access to demand,

[68] Guimarães, Figueirdo, Woodward et al (2003) suggest Poisson regressions as an alternative to CLM. Since our IIA tests cannot reject the null hypothesis, we do not pursue the Poisson method here.
[69] All anchors will locate on a major road, suggesting that the limited access designation is a reasonable first approximation to better access to demand. We use the terms "highway" and "limited-access roads" interchangeably.

then we expect a positive coefficient on *hwy_half_mile* and a smaller positive coefficient on *hwy_half2three_mile*. The *hwy_half_mile* variable also captures a positive effect of zoning, which typically encourages retail locations near limited access highways.

The most important variable for testing the revenue hypothesis is *expected demand* (demand in 2000 multiplied by demand growth from 1990 to 2000 within a three-mile LA).[70] However, anchors may position themselves in growth markets even when current demand is low. In this case, our expected demand variable may not give sufficient weight to growth. We also test models separating demand (2000) and growth (1990-2000). In order to make a direct comparison, we standardize demand variables with mean of zero and standard deviation of one.

To test cannibalization and localization hypothesis, the *Z* vector contains three location-decision specific variables. *existing_scs* captures the cannibalization effect and takes on a value of one if the number of same chain, same company stores within the local area is above the median for the MSA, otherwise zero.[71] For localization economies, *existing_sd* (same type, different company) and *existing_dd* (different type, different company) is constructed in the same way as *existing_scs*. It is important to note that *existing_sd* not only captures localization effects but also competition effects.

For completeness, we add *existing_dcs* (different chain, same company).[72] We also add additional *Z* variables to control for distance to headquarters and distance to the closest distribution centers. Because these variables are highly right skewed, we use dummy variables to control the non-normality. All the *Z* variables are calculated based on the median values within the same MSA.[73]

We can interpret coefficients as the change in probability relative to a base case, as suggested by Ben-Akiva (see Chapter 9). The base is a given amount of demand in the area around a tract. Then the shift in probability of opening given by the coefficients on the competition and localization variables is relative to the base that demand is the only driver of location. i.e., high values of SCS, SD and DD

[70] Census tract centroids within the three-mile LA radius are used to obtain 1990 and 2000 numbers. This adjusts for tract splits and mergers.
[71] Note that this variable is based on the number of matched type anchors within an LA. The number of stores is calculated at the beginning of the year before opening. We choose the dichotomous variable because the distribution of number of stores in an LA is highly skewed left.
[72] Because of few observations, we present the different-chain-same-company variable just for completeness.
[73] We only present results by using dummies for median. In unreported estimates, we use dummies for upper quartile. The results are similar.

indicate conditions (including omitted variables) that change the probability of opening. Significant values explain spatial clustering patterns. The efficacy of the CLM location model can be tested with K-density confidence bands for the probability of an opening.

6. Results

6.1. CLM Results

Table 3 presents three CLM models for all MSAs and by region. Panel A presents the base model with expected demand. Consistent with the suburbanization hypothesis, negative and significant coefficients on *CBD_3mile* indicate that new openings are less likely to locate in CBD areas, which have negative or slow population growth. The Southwest is an exception, but only in that the coefficient is not different from zero. Capturing population movements away from the inner suburbs, *dis2CBD* is positive and the squared term is negative except that the Southwest has insignificant signs on both variables.

Consistent with the revenue hypothesis, positive coefficients of dummies for proximity to highways suggest that new openings prefer locations with better access to demand and available locations. Again, this pattern is less significant in the Southwest. In addition, large positive coefficients of *expected demand* are consistent with the revenue hypothesis. In Panel B, both demand and growth have positive impact but demand has a larger impact than growth. Immediate revenues are preferred to deferred revenues. In unreported results, we interact expected demand with dummies for proximity to highways. Interaction coefficients are negative and significant in all MSAs, East and Central regions, indicating that trade areas are expanded by highway access. New stores near limited access highways require less demand within three miles. These findings suggest that the demand can come from much larger areas if the store has good highway access.

Our *Z* variables measure how decision makers respond to competition and localization. We observe a strong cannibalization effect as indicated by large negative coefficients of *existing_scs*. The East MSAs have the largest coefficient. This is consistent with descriptive statistics that the East region has the largest number of existing stores per households and per demand. The coefficients of *existing_sd* are positive but only significant in all MSAs and East while the coefficients of *existing_dd*

are positive and highly significant in all MSAs. In comparison with *existing_sd*, *existing_dd* has a larger magnitude as well as a higher statistical significance. This is consistent with localization economies because *existing_dd* captures the localization effect while *existing_sd* captures both competition as well as localization. Separating by region, the localization effect is the highest in Midwest. As we concluded in Table 1, the Midwest has the smallest number of existing stores per household and per demand. This suggests that localization plays a more important role when demand is less densely distributed.

For other control variables, *existing_dcs* is insignificant. This might be affected by limited observations because most of companies in our sample do not operate multi-chains.[74] Because we construct Z variables based on median value within an MSA, it is difficult to get enough variation on variables of distance to headquarters and distance to distribution centers. Coefficients of these two variables are not significant, except distance to headquarters in Central.

We have omitted variables, notably precise measures of zoning and of competition among local jurisdictions for new anchor stores. We have noted that SD and DD variables should be positively associated with prior local public policies and including them should partially control for public policy.[75] Coefficients on these variables cannot be interpreted as causal relationships, but we can exploit the plausible assumption that both DD and SD respond in the same way to omitted factors.

To interpret the SD minus DD coefficient we have the following: the SD coefficient includes the sum of competitive effects, localization economies and omitted variables whereas the DD coefficient includes the sum of the last two only. Moreover, we expect greater localization benefits from DD since it represents greater variety in the choices of anchors available to shoppers. It follows that the SD – DD coefficient is the sum of the negative competitive effect and the extra localization benefits associated with DD: i.e., the difference can be interpreted as a lower bound on the absolute value of

[74] For some companies that operate multi-chains, there might be no opening that took place within our sample areas and sample period.

[75] Duranton and Overman (2005) recognize this, which is why they (and we) use existing locations to measure spatial clustering. An additional proxy for zoning in our study includes distance to limited access highways. Moreover, zoning may not be binding, or may be endogenous, because local governments need revenue from anchors and prefer to serve the needs of their local populations.

competitive effects assuming that omitted variables have identical effects on DD and SD.[76]

The difference between SD and DD for all MSAs implies a lower bound estimate of -30% (=exp(.36-.71) – 1) on the probability of opening for a one unit change in the SD variable; this difference is statistically significant at the 5% level. The difference is negative in each region taken separately, providing evidence that the negative competition effect is always of larger magnitude than the extra localization effect associated with DD. The difference is large and significant in the Midwest (a 76% reduction in probability) and Southwest (a 29% reduction). The difference is much smaller in magnitude and statistically insignificant in East and Central regions. A likely cause is more restrictive public policies in these regions, but full investigation of this would require more study.

6.2. Robustness tests

In a robustness test, we investigate the possibility that a high correlation between SD and DD is driving our results: i.e., the collinearity issue. We calculate correlation coefficients in all MSAs and by region. The correlation varies from 0.38 (East and Central) to 0.41 (Southwest). We also run separate models by including only *existing_sd* and only *existing_dd*. In SD-only results, we find that the estimated coefficients are positive in all regions. They are significant in all MSAs, East and Central. In DD-only results, we find that the estimated coefficients are positive and significant in all MSAs and in all four regions. Comparing the magnitude to coefficients when both of the variables are in the regression, SD coefficients are bigger and DD about unchanged when they are alone in the regression. This supports our interpretation of the SD – DD coefficients.

We perform several addition tests for robustness. We replace the *Z* variables based on median values with alternatives based on upper quartiles and conclude similar results. We also apply a different classification of competition based on Company reports by Gale Business Insights (GBI). The classification is shown in Appendix 1 Panel C. Instead of classifying into different price categories, GBI reports major competitors of each firm. Hence, we revise our competition variables accordingly. *existing_sd* (*existing_dd*) equals one if number of existing competing (non-competing)

[76] It may be objected that the competitive effect differs for a low-priced anchor when compared to another type. But, our SD and DD variables include competition as viewed by each type. Our lower bound for the absolute value of the competitive coefficient may be interpreted as an average over all anchor types.

stores is greater than the median for the MSA and zero otherwise. We conclude that our results are robust by using variables constructed based on the GBI classification. Because we have omitted variables which might vary across decision makers, we apply a random effect model to the specifications in Table 3. The results are similar in terms of sign and significant level.[77] To deal with MAUP, we also try five-mile radius around tract centroids; we find very similar CLM coefficients.

6.3. Is the CLM Model Effective in Estimating the Location Pattern of Openings?

In Figure 5, we apply the estimated probabilities from CLM as the basis for K-density confidence intervals.[78] The difference between the CLM-based intervals and the population-based intervals plotted in Figure 3 is that the former uses model results to estimate the probability that any tract centroid is chosen, whereas the later selects each centroid with probability 1/n. If the CLM model accurately estimates the location pattern of openings, then the actual O2E K-densities should lie within the 95% confidence interval implied by the estimated probabilities.

Shown by the numbers in parentheses, we find that the CLM-based confidence bands successfully capture the cluster pattern within three miles; none of the actuals fall outside the confidence bands. The three-mile distance is more important to decision makers than long distances. From a practitioner's perspective, distances of 10 to 12 miles, the peak of the actual distribution, are too long to be within the same submarket. Comparing with the numbers in parentheses in Figure 3 (three of the four points within three miles are outside the bands), we conclude that the CLM model explains the actual location pattern much better than population weighted distances. For example, for all MSAs, the CLM confidence bands include 44 of the 51 actuals, whereas the population weighted confidence bands include only 22 out of 51.

The actual O2E is still below the five percent lower band from four miles to the peak. This says that the actual is somewhat more dispersed than predicted by the model, but only at distances beyond

[77] One cannot compare the magnitude because the random effect model contains an intercept term.

[78] Our approach is similar to Klier and McMillen (2008), except that they use probability estimates from a simple logit model. We randomly draw without replacement from the set of *n* census tracts in the same MSA. The calculation of global confidence interval is shown in Appendix 3. With *n* existing stores and *n* census tract centroids, there are n^2 distance pairs. For each location choice to a particular decision maker, we calculate the probabilities based on CLM estimates. The predicted probability is given by Appendix Equation (A4).

those of most interest to decision makers.

In Figure 6, we find that the CLM-based confidence bands perform better by different price types than at the aggregate level (Figure 5, panel A), indicating that decision makers can accurately explain location patterns if they disaggregate by price type using our model. In Panel A, high-price densities at all the target distances fall within the confidence bands estimated by CLM. Low- and mid-priced anchor openings are well-explained within three mile distances. In Panel B, although results by matched type are not as good as in Panel A, the model still explain most of the 51 target distances for SD and DD, and all four target distances within three miles for SCS. Again, we conclude that, from a particular retailer chain's point of view, the model offers a better explanation of a general location pattern than the population-weighted method. Plots by region (not shown) reveal similar results.

In conclusion, the CLM model effectively explains location patterns of new anchor stores. Even in the Southwest, where the hypothesis that retail follows population did the best (42 out of 51 target points were explained) the CLM produced better explanations (all 51 points were within a 95% global confidence band). The model offers a better explanation of location patterns by different price types (Figure 6A), in comparison with the aggregate level (Figure 5A). Most importantly, the explanatory power of the model by matched type (Figure 6B) suggests that, even from the point-of-view of a particular retailer, our model explains spatial patterns as well as the aggregate (Figure 5A).[79]

7. Conclusion

This paper examines the intra-metropolitan location decisions of retail stores by focusing on the opening of a comprehensive list of anchor stores in the United States. We develop a method for using CoStar, Factiva, 10K reports and other sources to track retail establishments and their ownership over time. The nonparametric K-density procedure shows that new stores are more dispersed than existing stores. It shows substantial differences in retail location patterns across regions. Anchors classified by

[79] For same-chain-same-company, the model does not do a good job of predicting the tendency to widely separate these stores. Future research might refine the model to better account for cannibalization.

price type and by relationship to competition have different location patterns. K-density analysis rejects the suburbanization hypothesis that anchors passively follow population, motivating the introduction of variables designed to account for zoning, revenue potential, competition and localization economies.

By applying the CLM approach, we can account for the effects of several explanatory variables. The probability of opening is negatively related to CBD location but positively related to distance to CBD as suggested by the suburbanization trend occurring during our sample period. Highway proximity has a strong positive impact on probability of opening. Openings are more likely to locate in areas with higher potential revenue as well as revenue growth. The model is particularly effective in explaining openings within three miles of existing anchors, an approximation to the spatial scale of most relevance to decision makers such as anchor stores, government officials and smaller retailers.

Consistent with cannibalization, openings are much less likely to locate near an existing store owned by the same chain. Most importantly, localization economies play a significant positive role in the opening decisions by anchor stores. Localization economies appear to be more important than the competitive effects associated with the existence of a concentration of the same type of store owned by a different chain. Using the difference between two coefficients (same type, different chain minus different type, different chain), we estimate a lower bound on the effect of competition on the probability of opening, assuming that omitted factors have the same effect on the two variables. The lower bound is negative in all regions and significantly negative for all MSAs, the Midwest and Southwest.

Further research might explore reasons for small competitive effects in the East and Central regions, and apply our method to alternative MSA classification schemes. We present evidence that zoning is not strongly binding, but further research might reveal a bigger effect in the East and Central than other regions we study.

References

Arauzo-Carod, J.-M., Liviano-Solis, D., Manjón-Antolín, M., 2010. Empirical Studies in Industrial Location: An Assessment of Their Method and Results. *Journal of Regional Science*, 50, 685-711.

Basker, E., 2005. Selling a Cheaper Mousetrap: Wal-Mart's Effect on Retail Prices. *Journal of Urban Economics* 58, 203-229.

Ben-Akiva, M., Lerman, S., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, MA: MIT Press.

Billings, S., Johnson, E., 2012. A Non-parametric Test for Industrial Specialization. *Journal of Urban Economics*, 71, 312-331.

Brueckner, J., 1993. Inter-store Externalities and Space Allocation in Shopping-centers. *Journal of Real Estate Finance and Economics*, 7, 5-16.

Crozet, M., Mayer, T., Mucchielli, J.-L., 2004. How do Firms Agglomerate? A Study of FDI in France. *Regional Science and Urban Economics*, 34, 27-54.

Duranton, G., Overman, H., 2005. Testing for Localisation using Microgeographic Data. *Review of Economic Studies*, 72, 1077–1106.

Ellison, G., Glaeser, E.L., 1997. Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach. *Journal of Political Economy* 105, 889-927

Ellickson, P., Grieco, P., 2013. Wal-Mart and the Geography of Grocery Retailing. *Journal of Urban Economics* 75, 1-14.

Fanning, S., 2005. *Market Analysis for Real Estate: Concepts and Application in Valuation and Highest and Best Use*. Appraisal Institute.

Fershtman, C., Pakes, A., 2012. Dynamic Games with Asymmetric Information: A Framework for Empirical Work. *Quarterly Journal of Economics* 127, 1611-1661.

Foster, L., Haltiwanger, J., Krizan, C. 2006. Market Selectin, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s. *Review of Economics and Statistics*, 88, 748-758.

Glaeser, E., Gyourko, J., Saiz, A., 2008. Housing Supply and Housing Bubbles. *Journal of Urban Economics*, 64, 198-217.

Gould, E., Pashigian, B., Prendergast, C., 2005. Contracts, Externalities, and Incentives in Shopping Malls. *Review of Economics and Statistics*, 87, 411-422.

Guimarães, P., Figueirdo, O., Woodward, D., 2003. A Tractable Approach to the Firm Location Decision Problem. *Review of Economics and Statistics*, 85, 201-204.

Haltiwanger, J., Jarmin, R., Krizan, C.J., 2010. Mom-and-Pop Meet Big-Box: Complements or Substitutes? *Journal of Urban Economics* 67, 116-134

Hausman, J., Leibtag, E., 2007. Consumer Benefits from Increased Competition in Shopping Outlets: Measuring the Effect of Wal-mart. *Journal of Applied Econometrics*, 22, 1157-1177.

Holmes, T., 2011. The Diffusion of Wal-mart and Economies of Density. *Econometrica*, 79, 253-302.

Jia, P., 2008. What Happens when Wal-mart Comes to Town: An Empirical Analysis of the Discount

Retailing Industry. *Econometrica*, 76, 1263-1316.

Klier, T., McMillen, D., 2008. Evolving Agglomeration in the U.S. Auto Supplier Industry. *Journal of Regional Science*, 48, 245-267.

Konishi, H., Sandfort, M., 2003. Anchor stores. *Journal of Urban Economics,* 53, 413-435.

Kramer, A., 2008. Retail Development Handbook (Development Handbook Series), fourth ed. Urban Land Institute.

Neumark, D., Zhang, J., Ciccarella, S., 2008. The Effects of Wal-Mart on Local Labor Markets. *Journal of Urban Economics* 63, 405-430.

Pashigian, B., Gould, E., 1998. Internalizing Externalities: The Pricing of Space in Shopping Malls. *Journal of Law & Economics*, 41, 115-142.

Pope, J., Pope, D., 2013. When Walmart Comes to Town: Always Low Housing Prices? Always? Working Paper.

Salvo, A., 2010. Inferring Market Power under the Threat of Entry: The Case of the Brazilian Cement Industry. *Rand Journal of Economics*, 41, 326-350.

Schuetz, J., 2013. Why Are Wal-Mart and Target Next-Door Neighbors? paper presented at the Weimer School Session Program, Weimer School for Advanced Studies in Real Estate and Land Economics, West Palm Beach FL.

Schulz, N., Stahl, K., 1996. Do Consumers Search for the Highest Price? Oligopoly Equilibrium and Monopoly Optimum in Differentiated-products Markets. *Rand Journal of Economics*, 27, 542-562.

Stahl, K., 1982. Location and Spatial Pricing Theory with Nonconvex Transportation Cost Schedules. *Bell Journal of Economics*, 13, 575-582.

Vitorino, M., 2012. Empirical Entry Games with Complementarities: An Application to the Shopping Center Industry. *Journal of Marketing Research*, 49, 175-191.

Woodward, D., Figueiredo, O., Guimarães, P., 2006. Beyond the Silicon Valley: University R&D and High-technology Location. *Journal of Urban Economics*, 60, 15-32.

Appendix 1

Panel A: List of 54 Department Stores (Anchors)

List of Retail Chains	Company	Public / Private	Note
Barneys New York	Barneys New York	Private	
Boscov's	Boscov's	Private	Filed for bankruptcy in 2008. Exited bankruptcy in 2009.
Lord & Taylor	Hudson's Bay Company	Public	Belongs to Federated Department Store before 2006
Von Maur	Von Maur	Private	
Bealls (Florida)	Bealls	Private	
Bealls Outlet	Bealls	Private	Outlet format store of Bealls (Florida)
Belk	Belk	Public	
Bloomingdale's	Macy's	Public	
Bloomingdale's outlet	Macy's	Public	Outlet format store of Macy's
Macy's	Macy's	Public	Former name is Federated Department Store
Filene's	Macy's	Public	Converted to Macy's in 2006
Strawbridge's	Macy's	Public	Converted to Macy's in 2006
Robinsons-May	Macy's	Public	Converted to Macy's in 2006
Bon-Ton	Bon-ton Stores	Public	
Elder-Beerman	Bon-ton Stores	Public	
Bergner's	Bon-ton Stores	Public	Sold by Saks to Bon-ton Stores in 2005
Boston Store	Bon-ton Stores	Public	Sold by Saks to Bon-ton Stores in 2005
Carson Pirie Scott	Bon-ton Stores	Public	Sold by Saks to Bon-ton Stores in 2005
Herberger's	Bon-ton Stores	Public	Sold by Saks to Bon-ton Stores in 2005
Parisian	Bon-ton Stores	Public	Sold by Belk to Bon-ton in 2006
Younkers	Bon-ton Stores	Public	Sold by Saks to Bon-ton Stores in 2005
Dillard's	Dillard's	Public	
Gottschalks	Gottschalks	Public	Filed for bankruptcy and liquidated in 2009. All stores were closed.
Kohl's	Kohl's	Public	
May Department Store	May Department Stores	Public	

Appendix 1 (continued)

Mervyn's	Sun Capital Partners	Private	Filed for bankruptcy and liquidated in 2008. All stores were closed.
Peebles	Stage Stores	Public	
Bealls	Stage Stores	Public	
Stage	Stage Stores	Public	
JCPenney	JCPenney	Public	
Saks Fifth Avenue	Saks	Public	
Off 5th Saks Fifth Avenue Outlet	Saks	Public	Outlet format store of Saks Fifth Avenue
Nordstrom	Nordstrom	Public	
Nordstrom Rack	Nordstrom	Public	Outlet format store of Nordstrom
Neiman Marcus	Neiman Marcus	Public	
Bergdorf Goodman	Neiman Marcus	Public	
Neiman Marcus last call	Neiman Marcus	Public	Outlet format store of Neiman Marcus
Sears	Sears	Public	
Meijer, Inc.	Meijer	Private	
Burlington Coat Factory	Burlington Coat Factory	Private	
Pamida	Shopko	Private	Operated by Shopko from 1999 to 2007. Merged with Shopko in 2012.
Shopko	Shopko	Private	
Kmart	Sears	Public	
Target	Target	Public	
TJ Max	TJX	Public	
Marshalls	TJX	Public	
AJ Wright	TJX	Public	Defunct in 2011. All stores were closed by TJX.
Ross	Ross Stores	Public	
Stein Mart	Stein Mart	Public	
BJ's	BJ's	Public	
Costco	Costco	Public	
Sam's club	Wal-Mart	Public	
Walmart Supercenters	Wal-Mart	Public	

Note: this is the universe of all multiline department stores operating in the 36 MSAs during the years 2005-2012. See text for full definition.

Panel B: Classifications of Retail Chains (Anchors)

Classification in Gould, Pashigian and Prendergast (2005) pp.414

"*Type 1: Prestige/fashion department stores. These stores usually operated in only one or a few markets until recently, when they expanded into more regional and national markets, often by entering into existing malls.*

Type 2: High- to moderate-quality department stores with national reputations since the 1950s and 1960s. These stores were usually in the mall right from the beginning and were eagerly recruited by developers to establish the mall.

Type 3: Lower-quality department stores with mostly local or regional reputations. (30% of anchor stores.)

Type 4: Department stores that are members of very well-known national chains that have long operated in many markets. These stores were also usually in the mall right from the beginning and were eagerly recruited by developers to establish the mall.8 (41% of anchor stores.)"

Classification in Vitorino (2012) pp.177

"*Upscale department stores: These stores generally sell designer merchandise above an average price level. When their items are on sale, their prices resemble those of averagepriced items at a lower-scale department store. Upscale department stores typically provide checkout service and customer assistance in each department. Examples include Dillard's, Macy's, and Nordstrom.*

Midscale department stores: These stores sell brand names and non–brand names but do not sell upscale brand names. Compared with upscale department stores, midscale stores usually do not have perfumes and beauty supplies at the main entrance and do not have cosmetic specialists. Examples include JCPenney, Mervyn's, and Kohl's.

Discount department stores: These stores encompass retail establishments selling a variety of merchandise for less than conventional prices. Target, Sears, Wal-Mart, and Kmart are examples. Most discount department stores offer wide assortments of goods; others specialize in merchandise such as jewelry, electronic equipment, or electrical appliances. Discount stores are not dollar stores, which sell goods at a dollar or less. Discount stores differ because they sell branded goods, and prices vary widely among products. Compared with midscale department stores, discounters sell fewer major brand names and offer a wider variety of products. Stores in the discount department store category typically have fewer sales workers, relying more on self-service features, and have centrally located cashiers."

Classification of Direct Competitors to Department Stores by Gale Business Insights

Chain	Direct Competitors
Macy's	Saks Fifth Avenue, Nordstrom, Dillard's, JCPenney
Nordstrom	Saks Fifth Avenue, Neiman Marcus, Dillard's, Macy's, JCPenney, Sears
Neiman Marcus	Barneys New York, Macy's, Bon-Ton Stores, Dillard's, Nordstrom, Saks Fifth Avenue, Von Maur
Saks Fifth Avenue	Barneys New York, Bloomingdale's, Neiman Marcus, Macy's, Dillard's, Nordstrom
Bealls	Kohl's, Target, Wal-Mart
Belk	Saks Fifth Avenue, Dillard's, JCPenney, Macy's
Von Maur	Macy's, Nordstrom
Bergdorf Goodman	Barneys New York, Saks Fifth Avenue, Nordstrom, Bloomingdales
Dillard's	Burlington Coat Factory, Kohl's, Macy's, Neiman Marcus, Nordstrom, Saks Fifth Avenue
Elder-Beerman	Boscov's, Macy's, Kohl's, Sears
Gottschalks	JCPenney, Mervyns, Dillard's, TJ Maxx, Marshalls, AJ Wright
Parisian	Boscov's, Macy's, Kohl's, Sears
Bealls outlet	Sears, Wal-Mart
Neiman Marcus last call	Nordstrom Rack, Saks Fifth Off
Nordstrom Rack	Neiman Marcus last call, Saks Fifth Off
Saks Off 5th	Nordstrom Rack, Neiman Marcus last call
JCPenney	Kohl's, Sears, Target, Wal-Mart, Dillard's, Nordstrom, Bon-Ton Stores
Kohl's	Wal-Mart, Target, JCPenney, Sears, Mervyn's, TJ Maxx, Marshalls, AJWright, Ross Stores, Macy's
Burlington Coat Factory	Ross Stores, TJ Maxx, Marshalls, AJ Wright, Target
Marshalls	Kohl's, JCPenney, Target, Macys
Ross Dress for Less	TJ Maxx, Marshalls, AJ Wright, Kohl's, Target, Burlington Coat Factory, JC Penney, Stein Mart, Goody's
Stein Mart	JC Penney, TJ Maxx, Marshalls, AJ Wright, Macy's
T.J. Maxx	Kohl's, JCPenney, Target, Macys
BJ's	Sam's club, Costco
Costco	Sam's club, BJ's
Meijer	Wal-Mart, Target
Sam's club	BJ's, Costco
Shopko	Wal-Mart, Target, Kmart
Target	Costco, Macy's, JCPenney, Kohl's, Sears, Wal-Mart
Wal-Mart Supercenter	Costco, Target, Kmart
Sears Essentials	Wal-Mart, Target, JCPenney, Kohl's
Sears Grand	Wal-Mart, Target, JCPenney, Kohl's

Source: http://www.cengagesites.com/literature/782/gale-business-insights-global-essentials/
Note: Based on GBI reports, *existing_sd* (*existing_dd*) equals to 1 if number of existing competing (non-competing) stores is above the median for the MSA, otherwise zero. The number of existing competing (non-competing) stores is calculated at the beginning of the year before opening.

Appendix 2: Openings by MSA

MSA	Region	Number of Openings
Albany-Schenectady-Troy, NY	East	7
Albuquerque, NM	Southwest	13
Allentown-Bethlehem-Easton, PA-NJ	East	16
Austin-Round Rock, TX	Midwest	46
Bakersfield, CA	Southwest	6
Birmingham-Hoover, AL	Central	23
Bridgeport-Stamford-Norwalk, CT	East	4
Cincinnati-Middletown, OH-KY-IN	Central	29
Columbus, OH	Central	24
Dayton, OH	Central	8
Detroit-Warren-Livonia, MI	Central	64
Fresno, CA	Southwest	10
Grand Rapids-Wyoming, MI	Central	11
Hartford-West Hartford-East Hartford, CT	East	6
Indianapolis-Carmel, IN	Central	21
Jacksonville, FL	East	35
Kansas City, MO-KS	Midwest	37
Las Vegas-Paradise, NV	Southwest	38
Louisville-Jefferson County, KY-IN	Central	15
Milwaukee-Waukesha-West Allis, WI	Central	24
Nashville-Davidson--Murfreesboro, TN	East	28
New Haven-Milford, CT	East	11
Oklahoma City, OK	Midwest	20
Omaha-Council Bluffs, NE-IA	Midwest	17
Orlando-Kissimmee, FL	East	48
Oxnard-Thousand Oaks-Ventura, CA	Southwest	9
Providence-New Bedford-Fall River, RI-MA	East	15
Raleigh-Cary, NC	East	28
Richmond, VA	East	19
Riverside-San Bernardino-Ontario, CA	Southwest	53
Rochester, NY	East	15
San Antonio, TX	Midwest	35
Tucson, AZ	Southwest	16
Tulsa, OK	Midwest	18
Virginia Beach-Norfolk-Newport News, VA-NC	East	27
Worcester, MA	East	10

Note: We do not include Honolulu, HI because it is not in the continental US, so it does not fit into our regional classification of MSAs.

Appendix 3: Non-parametric Based Measure of Localization by Duranton and Overman (2005)

K-densities of Actual Locations

The K-density method proposed by Duranton and Overman (2005) takes all pairs of anchor locations within the same MSA and calculates the distances between them. The existing to existing (E2E) density of bilateral distances at any target distance *d* is calculated by using Silverman's (1986) reflection method as:

(A1) $$K(d) = \frac{2}{n(n-1)h}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left[f(\frac{d-d_{i,j}}{h}) + f(\frac{-d-d_{i,j}}{h})\right] \text{ for d > 0}$$

$$K(d) = 0 \text{ for d} \leq 0$$

where $d_{i,j}$ is the straight line distance between existing store *i* and existing store *j* in the same MSA, *h* is the bandwidth, and *f* is the kernel function. With *n* existing stores, there are *n(n-1)* distance pairs. We use a standard Guassian kernel with an optimal bandwidth proposed by Silverman (1986).

The opening to existing (O2E) density of bilateral distances at any target distance *d* is calculated similar to (A1) except that $d_{i,j}$ is the straight line distance between opening *i* and existing store *j* in the same MSA.

Local and Global Confidence Intervals

To calculate local and global confidence intervals for population-weighted choices of locations, we use a bootstrap re-sampling procedure by following Duranton and Overman (2005) and Klier and McMillen (2008). We make *m* draws without replacement from the set of census tract centroids to construct a set of *n* locations. The distance between every existing store and the randomly chosen set of locations is calculated. The K-density is:

(A2) $$K(d) = \frac{1}{n^2 h}\sum_{i=1}^{n}\sum_{j=1}^{n}\left[f(\frac{d-d_{i,j}}{h}) + f(\frac{-d-d_{i,j}}{h})\right]$$

where $d_{i,j}$ is the distance between existing store i and random chosen location j in the same MSA. With n existing stores and n census tract centroids, there are n^2 distance pairs. We apply this bootstrap re-sampling procedure 1,000 times and generate 1,000 estimates of the K-density functions. Because our target distance is from 0 mile to 50 miles, we estimate K-density at each of the 51 target distances. At each target distance, we rank K-density and take the 2.5 percentile (lower band) and 97.5 percentile (upper bound) as local confidence interval. The global confidence interval, constructed to ensure that no more than 95 percent of the estimated density functions have even a single value that lies outside at any of the target distances, controls for the multiple alternative hypotheses being tested.

Appendix 4: Conditional Logit Model (CLM)

Opening decisions can be based on either chooser-specific or choice-specific explanatory variables. In our research setting, chooser-specific factors such as financing condition, investment plan and business strategy are largely unobservable. CLM allows us to control all time-invariant unobservable characteristics of decision makers (department store chain): the likelihood function is constructed as a ratio for each chooser, so these variables drop out.

Our explanatory variables include location specific variables (X variables) and location-chain specific variables (Z variables). The profit derived from an opening decision *i* in market *j* is

$$\text{(A3)}\quad \pi_{ij} = \beta_x^{'} x_{ij} + \beta_z^{'} z_{ij} + \varepsilon_{ij}$$

where $i = 1, \ldots N$ represents opening decisions and $j = 1, \ldots J$ represents markets or trade areas. x_{ij} is a vector of location-specific variables which does not depend on decision makers. β_x is a vector of unknown parameters of x_{ij}. z_{ij} is a vector of location-specific variables which depends on decision makers. β_z is a vector of unknown parameters of z_{ij}. ε_{ij} is a random term. The profit from decision *i* of locating at *j* is composed of a deterministic and a random component. Given an opening decision, the investor will choose a market that will yield the highest expected profit. If the ε_{ij} is the usual (i.i.d.) stochastic term assumed to have an extreme type value I distribution. Then, following McFadden, the probability of that opening *i* locates at *j* is

$$\text{(A4)}\quad p_{ij} = \frac{\exp(\beta_x^{'} x_{ij} + \beta_z^{'} z_{ij})}{\sum_{j=1}^{J} \exp(\beta_x^{'} x_{ij} + \beta_z^{'} z_{ij})}$$

If we let $d_{ij} = 1$ if opening *i* locates in area *j* and $d_{ij} = 0$ otherwise, the log likelihood of the conditional logit model is

$$\text{(A5)}\quad \log L_{CLM} = \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} \log p_{ij}$$

Table 1: Descriptive Statistics

Panel A – MSA Composition and Characteristics

	All	East	Central	Midwest	Southwest
Number of MSAs	36	14	9	6	7
Number of Households per MSA	548,172	474,335	681,009	567,374	508,599
Demand per MSA (mil $2010)	31,307	28,600	37,467	31,129	28,954
Number of Households per sq. miles	114.35	183.96	194.96	95.92	51.18
Median Household Income ($2010)	52,211	55,963	49,248	50,171	53,214
Demand Growth 1990-2010 (annualized %)	2.13%	2.02%	0.35%	3.20%	4.53%

Notes: Mean values are presented. Demand is defined as the total number of households multiplied by median household income.

Panel B – Descriptive Statistics on Existing Stores as of the beginning of 2005

		All	East	Central	Midwest	Southwest
Number of Existing Stores	Total	2380	876	721	364	419
	Low-price	1026	343	355	154	174
	Mid-price	877	359	234	135	149
	High-price	477	174	132	75	96
Number of Existing Stores per 100,000 Households	Total	12.06	13.19	11.76	10.69	11.77
	Low-price	5.20	5.17	5.79	4.52	4.89
	Mid-price	4.44	5.41	3.82	3.97	4.19
	High-price	2.42	2.62	2.15	2.20	2.70
Number of Existing Stores Per $mil Demand	Total	2.11	2.19	2.14	1.95	2.07
	Low-price	0.91	0.86	1.05	0.82	0.86
	Mid-price	0.78	0.90	0.69	0.72	0.74
	High-price	0.42	0.43	0.39	0.40	0.47

Panel C – Descriptive Statistics on Opening of New Stores from 2005 to 2011

		All	East	Central	Midwest	Southwest
Number of Openings	Total	806	219	269	173	145
	Low-price	382	125	126	73	58
	Mid-price	380	85	131	83	81
	High-price	44	9	12	17	6
Number of Openings per 100,000 Households	Total	4.08	3.30	4.39	5.08	4.07
	Low-price	1.94	1.88	2.06	2.14	1.63
	Mid-price	1.93	1.28	2.14	2.44	2.28
	High-price	0.22	0.14	0.20	0.50	0.17
Number of Openings per $mil Demand	Total	1.45	1.40	1.25	2.06	1.45
	Low-price	0.69	0.80	0.59	0.87	0.58
	Mid-price	0.68	0.54	0.61	0.99	0.81
	High-price	0.08	0.06	0.06	0.20	0.06

Table 2: Demographic Characteristics and Market Conditions of Openings, Existing Stores and Randomized Local Market Areas

		All MSAs		East		Central		Midwest		Southwest	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Demand 2000 (mil $2005)	Opening	25.14	30.79	23.27	29.86	27.45	35.95	20.64	26.76	31.91	36.53
	Existing	38.22	47.16	33.27	39.88	40.53	49.09	41.17	57.85	43.09	52.51
	Random	25.93	40.99	23.24	36.32	33.27	42.77	21.89	35.08	26.48	39.96
Opening minus Existing		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Random minus Existing		<.0001	<.0001	<.0001	0.0004	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001
Random minus Opening		0.4742	<.0001	0.986	0.011	0.0194	<.0001	0.5681	0.0186	0.0611	0.7837
Growth 1990-2000	Opening	3.71%	2.78%	3.79%	3.15%	2.51%	2.19%	5.07%	3.70%	3.85%	1.94%
	Existing	2.51%	1.60%	2.27%	1.50%	2.20%	1.53%	3.30%	2.31%	2.84%	1.38%
	Random	2.56%	1.63%	2.12%	1.55%	1.60%	0.97%	3.64%	2.50%	3.61%	2.07%
Opening minus Existing		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Random minus Existing		0.6918	0.403	0.5204	0.8394	0.0018	<.0001	0.2141	0.1621	0.0363	0.0104
Random minus Opening		<.0001	<.0001	<.0001	<.0001	0.0008	<.0001	0.0026	0.0018	0.693	0.9577
Number of Low-price Existing	Opening	1.40	1.00	1.49	1.00	1.31	1.00	1.12	0.00	1.70	1.00
	Existing	2.46	2.00	2.41	2.00	2.38	2.00	2.27	2.00	2.89	3.00
	Random	1.17	0.00	1.06	0.00	1.17	0.00	1.12	0.00	1.43	1.00
Opening minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Opening		0.0004	0.0004	< .0001	< .0001	0.2402	0.2433	0.9856	0.8252	0.1155	0.1239

Table 2 (con't)

Number of Mid-price Existing	Opening	0.79	0.00	0.70	0.00	0.72	0.00	0.77	0.00	1.08	0.00
	Existing	1.74	1.00	1.66	1.00	1.50	1.00	1.79	1.00	2.26	2.00
	Random	0.72	0.00	0.66	0.00	0.59	0.00	0.82	0.00	0.91	0.00
Opening minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Opening		0.0633	0.0041	0.6213	0.0196	0.2053	0.1963	0.7239	0.9879	0.229	0.0416
Number of High-price Existing	Opening	1.43	1.00	1.26	1.00	1.47	1.00	1.29	1.00	1.83	1.00
	Existing	2.09	2.00	1.81	2.00	2.01	2.00	2.27	2.00	2.65	2.00
	Random	1.20	1.00	1.04	1.00	1.23	1.00	1.17	1.00	1.50	1.00
Opening minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Existing		< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001	< .0001
Random minus Opening		< .0001	< .0001	0.0021	0.0011	0.0058	0.0022	0.1919	0.0193	0.0278	0.0015

Notes: Demand 2000 (in million constant 2005 dollars) is defined as the number of households in 2000 multiplied by median household income in 2000. Demand Growth 1990-2000 is defined as annualized percentage growth of inflation-adjusted demand from 1990 to 2000. Opening minus Existing, Random minus Existing and Random minus Opening show *p*-value of two-sample *t*-test for mean and Wilcoxon Rank-Sum test for median.

Table 3: Conditional Logit Model

Panel A - Model with Expected Demand

Variable	All MSAs	East	Central	Midwest	Southwest
CBD_3mile	-1.2398***	-1.4381***	-1.627***	-2.6805***	0.1025
	(0.2318)	(0.4173)	(0.629)	(1.0477)	(0.3847)
hwy_half_mile	0.7526***	0.6375***	0.7871***	1.2896***	0.632**
	(0.1272)	(0.2333)	(0.2696)	(0.281)	(0.2766)
hwy_half2two_mile	0.4825***	0.6509***	0.7835***	0.8514***	-0.0581
	(0.1007)	(0.1793)	(0.2031)	(0.2195)	(0.2482)
dis2CBD	0.0653***	0.0536**	0.1305***	0.1326***	0.0241
	(0.0122)	(0.0244)	(0.0264)	(0.0419)	(0.018)
*dis2CBD*dis2CBD*	-0.0007***	-0.0004	-0.0014***	-0.0028***	-0.0002
	(0.0002)	(0.0005)	(0.0005)	(0.0011)	(0.0002)
exp_demand	0.3926***	0.5398***	0.5361***	0.3236***	0.5731***
	(0.0637)	(0.1145)	(0.1433)	(0.1379)	(0.1679)
distance to HQ	0.0306	0.1549	-0.3442**	0.0952	0.1485
	(0.0895)	(0.1631)	(0.1755)	(0.21)	(0.2148)
distance to DC	0.0318	0.0264	0.0485	0.0227	0.00797
	(0.0958)	(0.1703)	(0.1841)	(0.2188)	(0.226)
existing_scs	-1.9121***	-2.5567***	-2.2509***	-2.2517***	-1.1741***
	(0.168)	(0.3648)	(0.3513)	(0.4062)	(0.2981)
existing_dcs	-0.3132	-0.5192	-0.4996	-1.1115*	-0.2481
	(0.2186)	(0.3575)	(0.3709)	(0.5391)	(0.5639)
existing_sd	0.3621**	0.4230	0.5108	-0.2775	0.1505
	(0.161)	(0.2712)	(0.3369)	(0.4022)	(0.3497)
existing_dd	0.7099***	0.5429***	0.5694***	0.8381***	0.4939*
	(0.1189)	(0.1962)	(0.2293)	(0.3083)	(0.2701)
Pseudo-R2	0.1665	0.2158	0.223	0.2468	0.1289

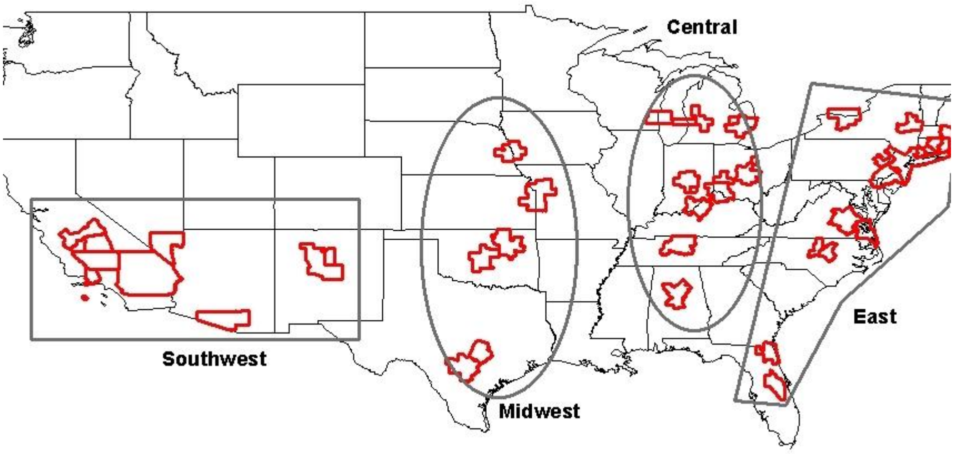
Panel B – Model with Growth and Demand

Variable	All MSAs	East	Central	Midwest	Southwest
CBD_3mile	-1.238***	-1.3939***	-1.5958***	-2.764***	0.0684
	(0.2318)	(0.4032)	(0.6301)	(1.0502)	(0.3898)
hwy_half_mile	0.7742***	0.7175***	0.7747***	1.3224***	0.5956**
	(0.128)	(0.236)	(0.2701)	(0.283)	(0.2843)
hwy_half2two_mile	0.4972***	0.7564***	0.7684***	0.8203***	-0.0953
	(0.1013)	(0.1836)	(0.2042)	(0.221)	(0.257)
dis2CBD	0.0574***	0.0354***	0.1404***	0.0903**	0.0263
	(0.0132)	(0.0161)	(0.0295)	(0.0455)	(0.019)
*dis2CBD*dis2CBD*	-0.0006***	-0.0003	-0.0016***	-0.0022**	-0.0002
	(0.0002)	(0.0002)	(0.0005)	(0.0011)	(0.0002)
growth	0.2202***	0.3974***	0.0896	0.3286***	0.1452
	(0.0557)	(0.0835)	(0.1106)	(0.1095)	(0.1401)
demand	0.3259***	0.3872***	0.6128***	0.1232	0.5723***
	(0.072)	(0.1257)	(0.1655)	(0.1604)	(0.184)
distance to HQ	0.0256	0.1295	-0.3452**	0.0689	0.1585
	(0.0895)	(0.1632)	(0.1755)	(0.2117)	(0.2157)
distance to DC	0.0289	0.018	0.0383	-0.0251	0.00444
	(0.0958)	(0.17)	(0.1845)	(0.2202)	(0.2263)
existing_scs	-1.9031***	-2.5785***	-2.2575***	-2.2338***	-1.1865***
	(0.1683)	(0.3653)	(0.3515)	(0.41)	(0.2992)
existing_dcs	-0.305	-0.4765	-0.4981	-1.0253**	-0.2497
	(0.2187)	(0.3618)	(0.3703)	(0.539)	(0.5642)
existing_sd	0.3814**	0.4295	0.5018	-0.1823	0.1343
	(0.1615)	(0.275)	(0.3372)	(0.4069)	(0.3506)
existing_dd	0.7277***	0.6494***	0.5594***	0.9325***	0.4766*
	(0.1195)	(0.2013)	(0.2299)	(0.3141)	(0.2722)
Pseudo-R2	0.1672	0.2276	0.2239	0.2577	0.1297

Notes: The dependent is one if a new anchor opened in the tract, otherwise zero. The omitted category is locations beyond 2 miles from the highway. Standard errors are in parentheses. *Significant at 10%. **Significant at 5%. ***Significant at 1%.

Figure 1: Distribution of Anchor Stores in 36 MSAs and A Close-Up in Southwest

Panel A: Regional Classifications of 36 MSAs.



Panel B: A Close-Up in Southwest.

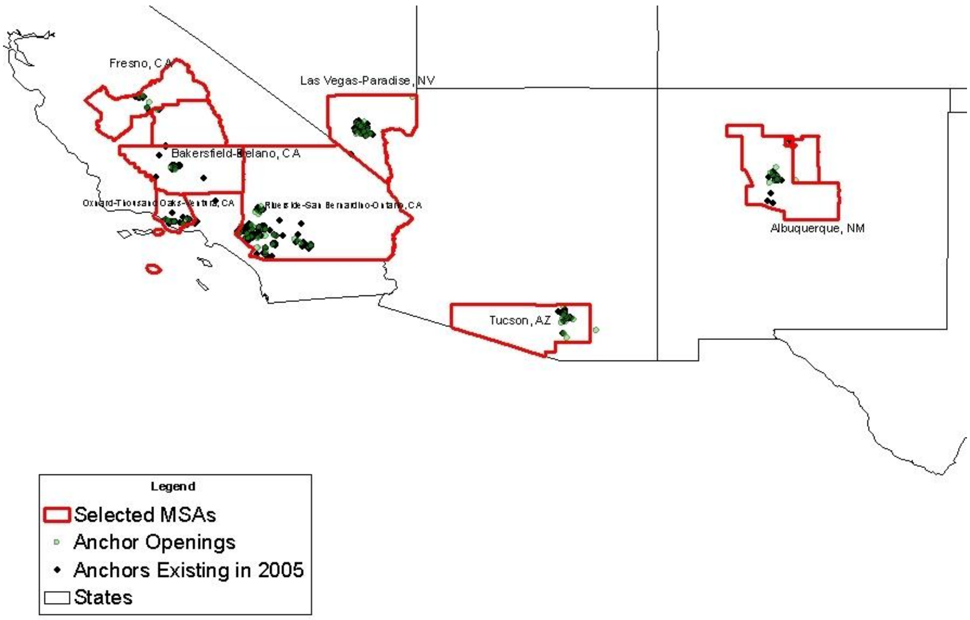
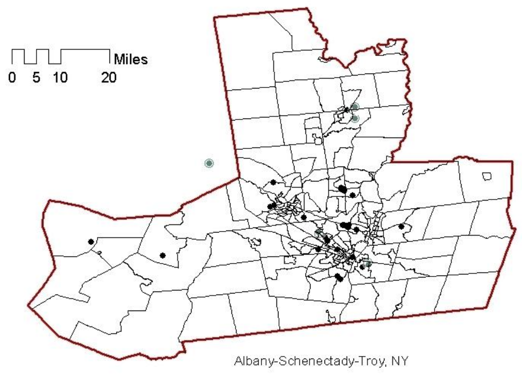
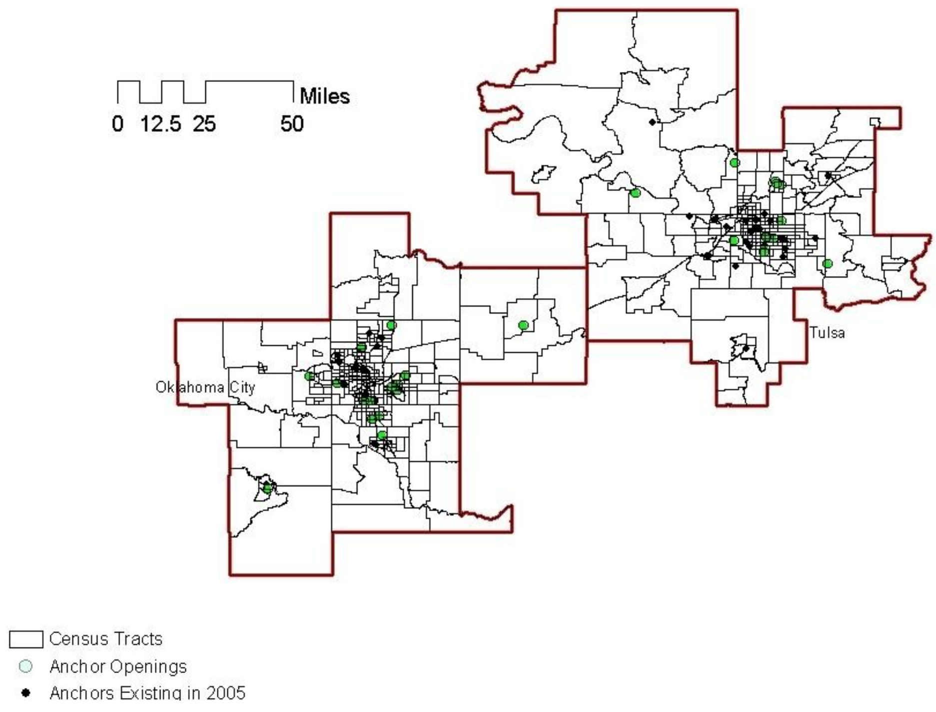


Figure 2: Examples of the Sample MSAs – Similar Population but Divergent Location Pattern.

Panel A: Albany-Schenectady-Troy, NY.



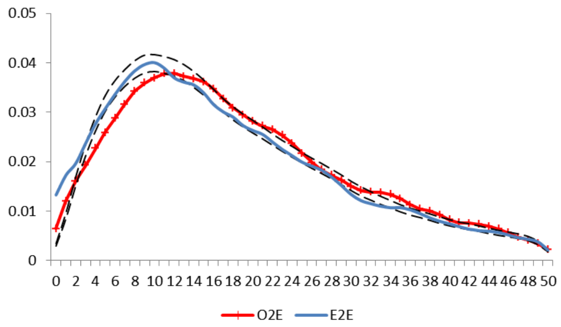
Panel B: Oklahoma City and Tulsa, OK.



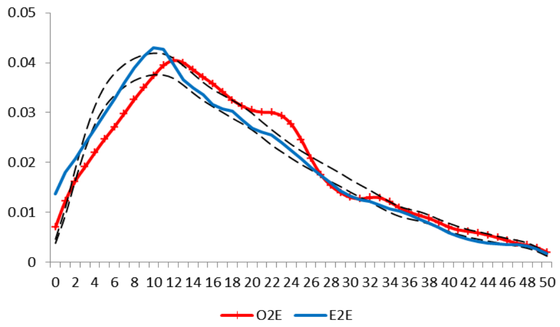
Note: There are different mileage scales for Oklahoma City and Tulsa, OK compared to Albany-Schenectady-Troy, NY

Figure 3: Densities for Distance from Existing to Existing Stores (E2E) and Distance from New to Existing Stores (O2E), and Population-weighted Confidence Interval

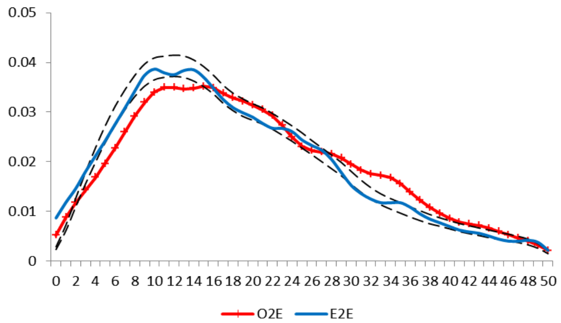
Panel A: All MSAs
(22, 1)



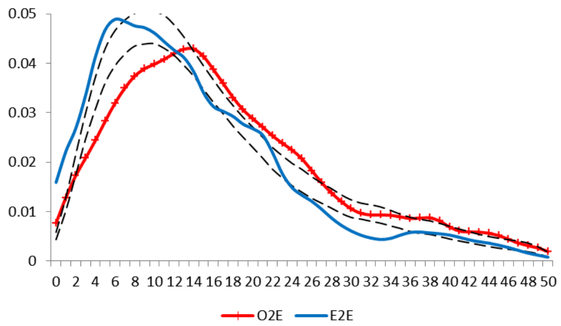
Panel B: East
(26, 1)



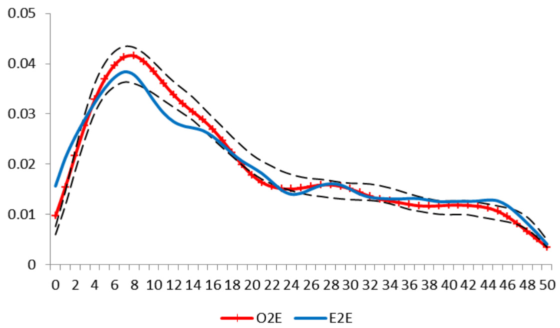
Panel C: Central
(18, 1)



Panel D: Midwest
(15, 0)

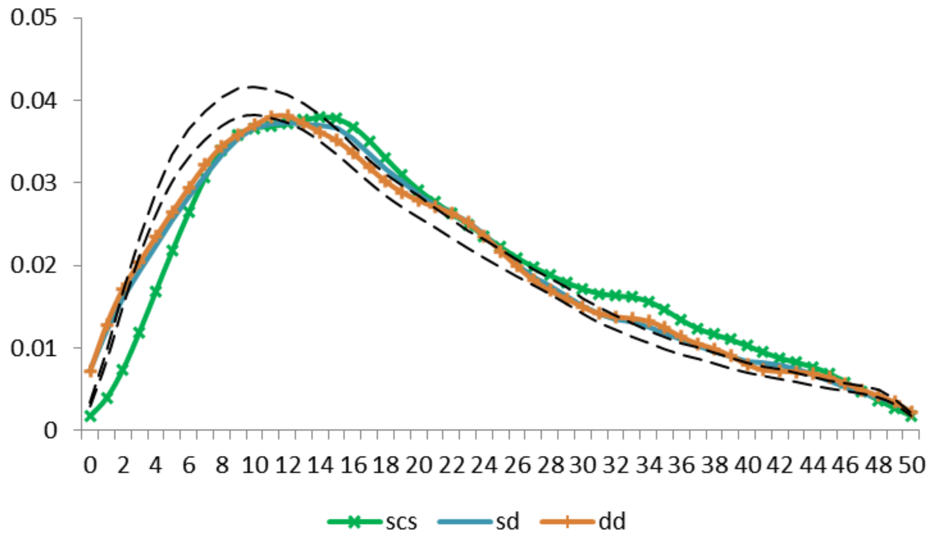


Panel E: Southwest
(42, 2)



Notes: The solid line without cross shows the pattern of K-densities of existing stores to existing stores (E2E). The solid line with cross marks shows the pattern of K-densities of openings to existing stores (O2E). The two dashed lines plot the global confidence interval for a random choice of tract centroid (i.e., a population-weighted location choice). The horizontal axis is target distance from zero to 50 miles; 51 target points. The first (second) numbers in parentheses is the number of O2E densities at 51 target distances (4 target distances within 3 miles) inside the 95% global confidence intervals.

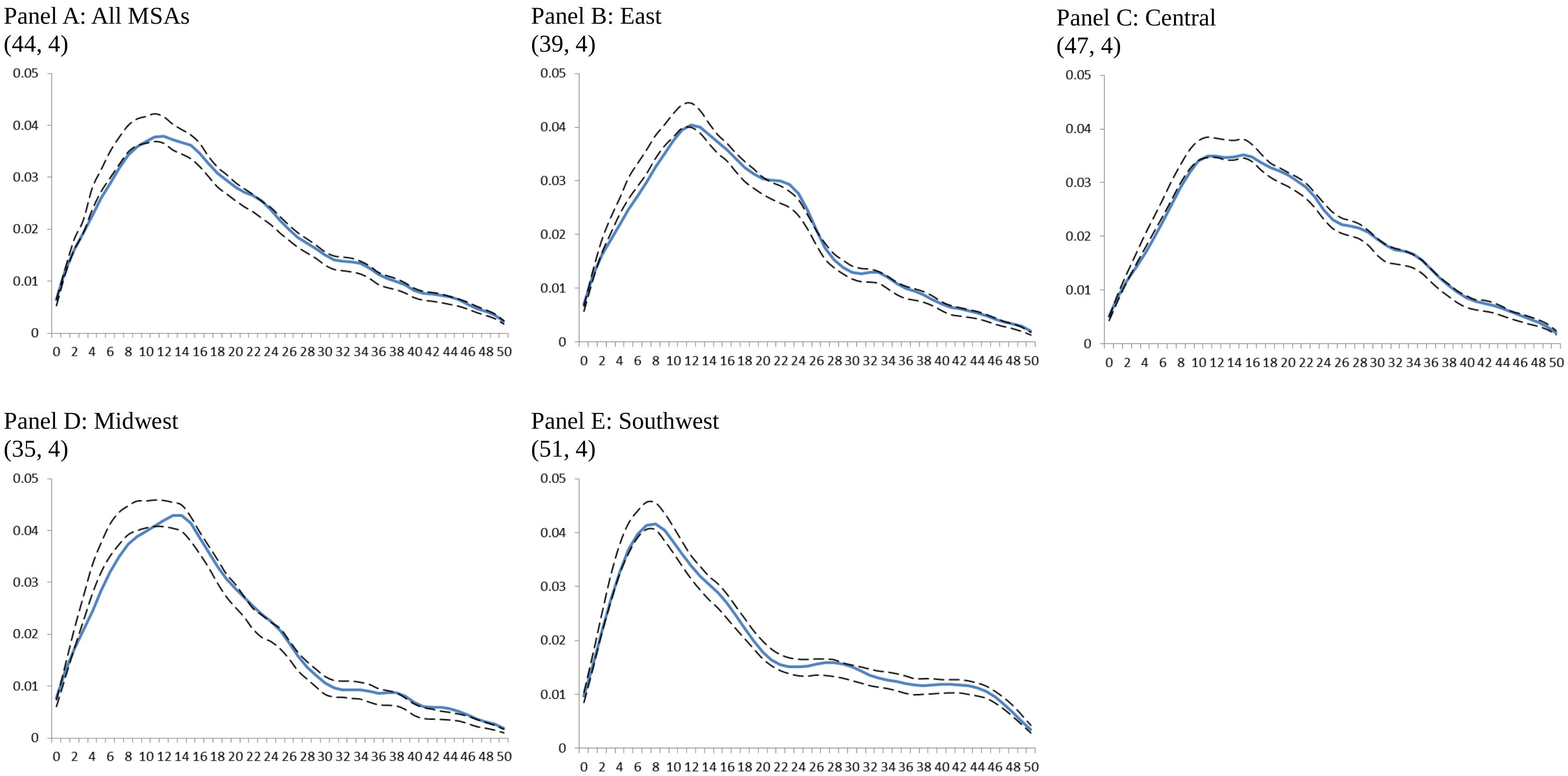
Figure 4: Densities for Distance from New to Existing Stores (O2E) by Matched Type, and Population-weighted Confidence Interval – All MSAs



SCS: (4, 0); SD: (15, 1); DD: (24, 0)

Notes: The solid line with cross marks shows the pattern of K-densities of same-chain-same-company openings to existing stores (scs). The solid line without mark shows the pattern of K-densities of same-type-different-company openings to existing stores (sd). The solid line with vertical marks shows the pattern of K-density of different-type-different-company openings to existing stores (dd). The two dashed lines plot the global confidence interval for a random choice of tract centroid (i.e., a population weighted

Figure 5: Densities for Distance from New to Existing Stores (O2E), and Confidence Interval Based on CLM.

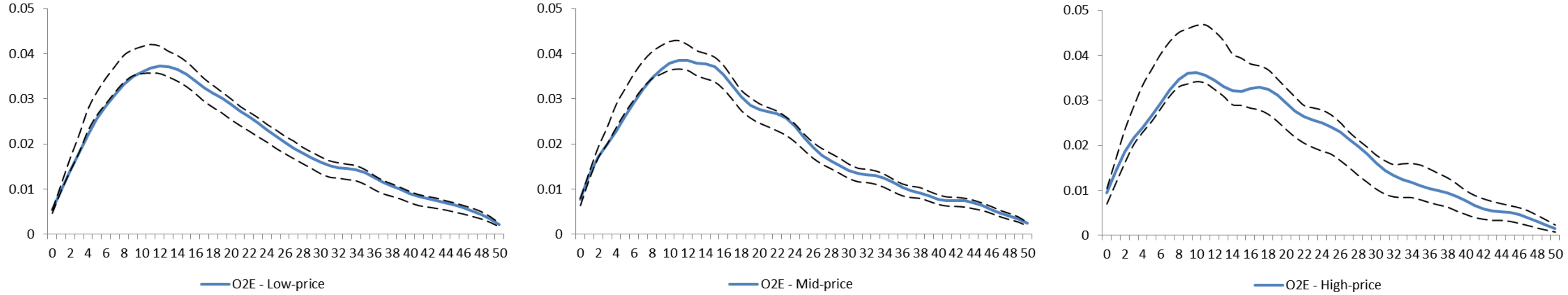


Notes: The solid line shows the pattern of K-densities of openings to existing stores (O2E). The two dashed lines plot the global confidence interval based on predicted probability from CLM estimates. The horizontal axis is target distance from zero to 50 miles; 51 target points. The first (second) numbers in parentheses is the number of O2E densities at 51 target distances (4 target distances within 3 miles) inside the 95% global confidence intervals.

Figure 6: Densities for Distance from New to Existing Stores (O2E) for all MSAs by Price Type and Matched Type, and Confidence Interval Based on CLM

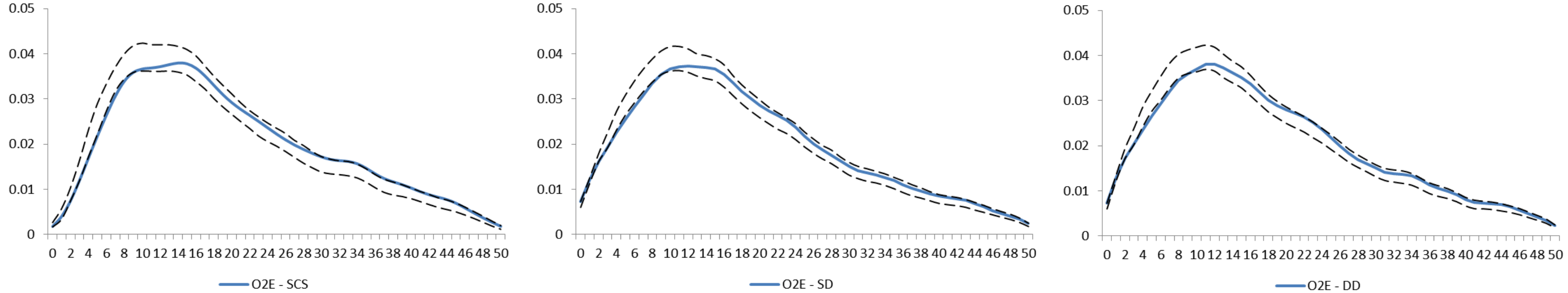
Panel A: By Price Type

(45, 4) (47, 4) (51, 4)



Panel B: By Matched Type

(35, 4) (45, 4) (45, 4)



Notes: In Panel A, the solid line shows the pattern of K-densities of openings to existing stores by low-price, mid-price and high-price. In Panel B, the solid line shows the pattern of K-densities of openings by same-chain-same-company (SCS), same-type-different company (SD) and different-chain-different-company (DD). The two dashed lines plot the global confidence interval based on predicted probability from CLM estimates. The horizontal axis is target distance from zero to 50 miles; 51 target points. The first (second) numbers in parentheses is the number of O2E densities at 51 target distances (4 target distances within 3 miles) inside the 95% global confidence intervals.

Essay 3

Accounting Expertise of Directors and Accounting Irregularities

1. Introduction

Although there exists a fairly large literature on the causes and consequences of accounting misconduct, we still donot have a good understanding of what factors affect a firm's incentives to misreport accounting performance, why accounting scandals vary across industries and over time, and what factors are effective in regulating fraudulent behavior. Povel, Singh and Winton (2007; PSW, hereafter) indicate that incentives to commit fraud are affected by two major mechanisms, investors' prior beliefs about business conditions and their monitoring costs. Drawing on these insights, we test the effect of investor beliefs and the monitoring effectiveness of independent directors with accounting expertise (AE) on the incidence of intentional accounting misstatements (irregularities). In addition, we investigate whether investor optimism decreases the proportion of independent directors with accounting expertise serving on the board. We focus on irregularities instead of accounting fraud because *intentional* misrepresentations are necessary but not sufficient conditions for classifying misconduct as accounting fraud. That is, an accounting fraud is an irregularity, but an irregularity is not necessarily a fraud. Hence, an analysis of irregularities allows us to study a broader class of accounting misconduct.[1]

We use a sample of U.S. firms that committed irregularities as well as *unintentional* accounting misstatements (which are labelled as errors henceforth) from 1996 to 2010. Our first finding is that the probability of committing irregularities is hump-shaped in investor beliefs about industry business conditions, first increasing as beliefs improve and decreasing when beliefs are sufficiently high. However, investor beliefs do not affect the likelihood of errors, consistent with our expectation.

PSW also predict that investors do not monitor a firm with positive public information carefully when their priors are fairly optimistic, suggesting a negative link between investor beliefs about business conditions and their monitoring intensity. More optimistic beliefs about business conditions

[1] The legal definition of fraud is "an intentional misrepresentation of material existing fact made by one person to another with knowledge of its falsity and for the purpose of inducing the other person to act, and upon which the other person relies with resulting injury or damage." (http://definitions.uslegal.com/f/fraud/) For a detailed discussion of differences in fraud terminology in law, finance, and accounting, see Karpoff, Koester, Lee, and Martin (2012), Appendix E. Hennes, Leone and Miller (2008) are among the first in distinguish errors from irregularities. Most studies on irregularities focus on financial restatements instead of accounting fraud. An accounting fraud is an irregularity. But an irregularity is not necessarily a fraud. We focus on "intentional" misinterpretations, so we include both irregularities and accounting fraud. Data on irregularities are obtained from General Accounting Office (GAO) and Audit Analytics (AA), while accounting frauds are collected from US SEC Accounting and Auditing Enforcement Releases (AAER) and Securities Class Action Clearinghouse (SCAC). Karpoff, Koester, Lee, and Martin (2012) note that the Federal Securities Regulation (FSR) database is considered more comprehensive compared with AAER and SCAC.

lead to lower monitoring, encouraging financial misconduct.[2] Whereas many monitoring mechanisms would influence fraudulent behavior of firms, we focus on the AE of independent members of the board of directors, which should play a salient role in mitigating accounting misstatements. We investigate whether optimistic investor beliefs about business conditions lower the proportion of independent directors with AE and find that the latter is decreasing in investor beliefs. Next, we analyze the effect of AE of independent directors on the board on the incidence of accounting misstatements (which covers both irregularities and errors). PSW suggest that decreasing monitoring costs shift the incidence of corporate fraud toward higher investor beliefs. An alternative explanation proposed by Sherman (1990) suggests that a decrease in monitoring costs reduces the likelihood of fraud regardless of investor beliefs because of legal liability and reputational concerns. We expect that accounting expertise lowers monitoring costs faced by independent directors over accounting reports issued by firms, thus enhancing the directors' monitoring effectiveness. Consistent with Sherman (1990), we find that stronger AE of independent directors is associated with less irregularities overall. In addition, this pattern also appears in accounting errors. In addition, the level of investor beliefs on irregularity continues to have a hump-shaped impact on the incidence of irregularity, suggesting that the monitoring mechanism is not the full explanation. In contrast, the predicted monitoring does not explain the incidence of errors.

To provide further insight on the monitoring mechanism of independent directors' AE on fraudulent behavior, we also investigate whether stock market reaction to financial restatements varies with AE. Consistent with previous literature, we find that investor reactions to irregularities are more negative, compared with their reactions to errors. More importantly, market reactions to the announcement of irregularities are positively related to the proportion of independent directors who are accounting experts. In addition, we find that investors react positively to the independent directors' AE measured when misstatements are committed, not only when misstatements are detected. Finally, we find that an improvement in AE from the time of commission of misstatements to their detection has a positive impact on market reactions.

[2] A large volume of literature addresses the link between investors' optimism and monitoring, see Shleifer and Vishny (1997) for a survey on this topic.

This study makes three important contributions. First, although there is considerable research on the various factors underlying fraudulent accounting behavior, this is the first study to focus on the impact of investor prior beliefs about business conditions on the incidence of financial misstatements. Wang, Winton and Yu (2010; WWY, hereafter) test PSW's model by using a sample of IPO firms. A few papers, such as Harris and Bromiley (2006), Kedia and Philippon (2007) and Davidson (2011), show that the incidence of accounting scandals varies with macroeconomic conditions. However, most papers focus on realized (*ex post*) economic conditions, instead of investors' *ex ante* beliefs about business prospects. Furthermore, previous studies investigate a linear relation between fraud and business cycle, while our study shows that consistent with recent models of corporate fraud there is a non-linear relation between fraud and investor beliefs.

Second, although there is a large body of literature on the relation between accounting or financial expertise and quality of financial reporting (for example, Abbott, Parker, and Peters, 2004; Agrawal and Chadha, 2005; Keune and Johnstone, 2012; Erkens and Bonner, 2013), none of these studies investigate whether investors' prior beliefs about business conditions influence how many independent directors with AE are appointed to board.[3] WWY analyze the role of venture capitalists in IPO fraud and conclude that, in the presence of venture capitalists, fraud is less likely in bad times but more likely in good times. In contrast to venture capitalists, underwriters care about their reputation and try to detect fraud regardless of the level of investor beliefs. Given that the interaction between monitoring costs and investor prior beliefs explains the fraudulent behavior, it is important to investigate more deeply the monitoring mechanisms linking investor prior beliefs to the incidence of irregularities. Our results suggest that a) investor optimism lowers the proportion of independent directors with accounting expertise, and b) monitoring by independent directors with AE is effective regardless of the level of investor beliefs in reducing the likelihood of accounting irregularities.

Third, there is considerable research on market reactions to accounting restatements, with many papers examining restatement features and firm characteristics that explain the magnitude of the stock

[3] Most of existing studies focus on the AE of audit committees. Bedard, Chtourou and Courteau (2004) find that audit committee AE is associated with less earnings management. Anderson, Mansi and Reeb (2004) conclude that audit committee AE lowers cost of debt. DeFond, Hann, and Hu (2005) find a positive abnormal stock price reaction upon appointment to the audit committee. Erkens and Bonner (2013) investigate the effect of firm status on the appointment of accounting experts to audit committees. They find that higher status firms (larger, better connected and more admired firms) are less likely to appoint accounting experts.

price reaction (Palmrose, Richardson and Scholz, 2004; Files, Swanson, and Tse, 2009). However, there exist few studies on the impact of accounting or financial expertise on the market reaction to restatement announcements. An exception is Carcello, Neal, Palmrose and Scholz (2011) who find no relation between the financial expertise of audit committee (measured as of the first year of misstatements) and market reaction to a restatement announcements.[4] Yet none of the studies differentiate the impact of accounting expertise measured when misstatements are committed from that measured when misstatements are detected. We expect that investors pay attention to the level of monitoring by the board of directors measured when the managerial misconduct begins (i.e., the date of commission) and when the misconduct is announced (i.e., date of disclosure or detection). Furthermore, Carcello, Neal, Palmrose and Scholz (2011) only examine the financial expertise of audit committee, which is typically but a subset of independent members of the broad of directors. In contrast, we measure accounting expertise of all independent directors on the broad, which is arguably a more comprehensive measure of the effectiveness of board monitoring. As expected, our results suggest that both the measurements of directors' AE (i.e., at the time of commission and at detection) are associated with less negative market reactions to restatements. In addition, the improvement in the accounting expertise of independent directors from the time of commission of misstatements to their detection helps mitigate negative stock price reaction to irregularities.

2. Development of Hypotheses

2.1 Investor Beliefs and Propensity for Irregularities

In PSW, a manager controls a firm and seeks funding. A firm can be either good or bad. A funded firm generates control benefits for the manager, regardless of firm type. The firm type is private information to the investors, who incur monitoring costs to discover it. Investors have prior beliefs about business conditions and take actions of no investment (A1), investment with monitoring (A2), and investment without monitoring (A3). They consider three threshold points about investor beliefs

[4] In Carcello, Neal, Palmrose and Scholz (2011), the definition of financial expertise is the same as our definition of accounting expertise. In a related study, Kouwenberg and Phunnarungsi (2013) conclude that there is no significant difference in market reaction to violations of rules and regulations between firms with high and low corporate governance scores in Thai listed firms.

about business conditions and five regimes: fund-everything regime, optimistic regime, trust-signal regime, skeptical regime and no-trust regime. In fund-everything regime and no-trust regime, there is no incentive to commit fraud because investors would take actions of either A1 or A3. In PSW proposition 4, the probability of fraud increases in prior beliefs about business conditions in the skeptical regime and decreases in prior beliefs in optimistic regime and trust-signal regime. Thus, the probability of fraud is hump-shaped in the prior beliefs of investors about macroeconomic conditions.

In this study, we focus on accounting irregularities instead of fraud. Irregularities are similar to fraud in terms of a firm's incentives to engage in accounting misconduct. However, irregularities are not necessarily fraud. Fraud signifies stronger perverse incentives whereas irregularities denote generally milder incentives to misreport. Fraud implies that the perpetrator intended to deceive stakeholders, and intent to deceive requires a higher burden of proof than is necessary to bring charges of financial misrepresentation. Accounting fraud is defined as a case as involving fraud if the Securities and Exchange Commission (SEC) or Department of Justice (DOJ) file charges alleging the violation of: (i) Section 17(a) of the 1933 Securities Act for fraudulent interstate transactions related to the issuance of a security; or (ii) Section 10(b) of the 1934 Securities Exchange Act for manipulative and deceptive devices related to the trading of an already issued security (Karpoff, Koester, Lee and Martin, 2012; Young and Peng, 2013). Further, Hennes, Leone and Miller (2008) highlight the importance of distinguishing between (unintentional) accounting errors and (intentional) irregularities. Since we are interested in studying a firm's incentives to engage in a broader class of accounting misconduct, we examine not only accounting fraud but also intentional misstatements that are not regarded as fraud as well as accounting errors. We formulate the following hypothesis based on PSW's prediction.

Hypothesis 1: *The likelihood of irregularities should be a hump-shaped function of investor beliefs about business conditions. But the likelihood of errors should be unrelated to investor beliefs about business conditions.*

2.2 Monitoring Costs and Propensity for Irregularities

In PSW, investor monitoring of the firms is affected by their beliefs about the state of the economy. When investor beliefs are high (i.e., optimistic), firms are funded without monitoring. This is consistent with prior studies on the relation between monitoring and financing.[5] These studies indicate that more optimistic beliefs about business conditions lead to lower investor monitoring of managers. Independent directors with AE are one of the most direct and important (delegated) monitoring mechanisms that can affect intentional misstatements. An independent director with AE is defined as an independent director with CPA and/or experience as a public accountant, auditor, principal or chief financial officer, controller, or principal or chief accounting officer. Our definition of AE is the same as that of accounting financial experts defined by SEC 2002, which is considered as more effective compared with the SEC 2003 definition.[6] Recent literature suggests that the broader definition of SEC 2003 does not capture the essential monitoring power (Carcello, Hollingsworth, Klein, and Neal 2009; Zhang, Zhou, and Zhou 2007; Krishnan and Visvanathan 2008).[7] Defond, Hann and Hu (2005) find a positive market reaction to the appointment of accounting financial experts but no reaction to nonaccounting financial experts assigned to audit committees. Krishnan and Visvanathan (2008) find that accounting conservatism is positively related to accounting financial expertise but not related to non-accounting financial expertise and nonfinancial expertise.

The Sarbanes-Oxley Act of 2002 mandates that a firm must *disclose* whether *at least* one member of the audit committee is a financial expert. If not, the firm has to explain why. Further, the listing stock exchanges, such as NYSE and MASDAQ, *require* that *at least* one member of the audit committee have accounting or related financial management expertise and/or experience (Krishnan and Visvanathan (2008)). These rules suggest that investors can influence how many additional

[5] Shleifer and Vishny (1997) summarize previous literature on the relation among external financing, investors' optimism and monitoring.

[6] SEC 2002 originally proposed that accounting financial experts are individuals who have knowledge of GAAP that has been obtained through direct experience in accounting and/or auditing positions, which would have only included individuals with experience as a public accountant, auditor, principal or chief financial officer, controller, or principal or chief accounting office. In SEC 2003, it relaxed the range and allowed for individuals who have obtained knowledge of GAAP by supervising or otherwise monitoring the performance of others who are directly engaged in accounting and/or auditing functions to qualify.

[7] The majority of accounting literature focuses on the accounting financial expertise of audit committee while our focus is on the AE of independent members of the board of directors. Audit committee is part of the board of directors. Committee members are drawn from members of the company's board of directors. The independent directors are expected to serve as the overall monitors of management activities while the audit committee is specifically charged with the oversight of financial reporting.

independent directors with accounting expertise, over and above the minimum set by the regulatory and listing provisions, are appointed to the board depending on their beliefs about business conditions. Specifically, we would expect that investors would appoint fewer (subject to the minimum of one) independent directors with AE when they feel more optimistic. This intuition leads us to advance the following hypothesis:

Hypothesis 2A: *The proportion of independent directors with accounting expertise decreases when investor beliefs about business conditions are relatively optimistic.*

In PSW, investor prior beliefs about business conditions and the cost of monitoring are the two key determinants of a firm's incentives to commit fraud. Prior beliefs affect fraud propensities as monitoring costs decrease. Investors do not monitor fraud per se; instead, they use monitoring to make investment decisions. In bad times, investor monitoring focuses on firms reporting strong performance to weed out bad firms. The presence of (some) investors with lower monitoring costs decreases the likelihood of fraud. In good times, monitoring focuses on firms reporting weak performance to pick out undervalued investment opportunities. The presence of investors with lower monitoring costs increases the likelihood of fraud. Consistent with PSW's prediction, WWY find that the presence of venture capitalists increases the probability of IPO fraud when investor beliefs are optimistic but decreases the probability of fraud when investor beliefs are pessimistic. In our study, The fiduciary duties of independent directors require them to act on behalf of investors and monitor managerial behavior. Therefore, we expect to find the monitoring role of independent directors with AE to differ from that of venture capitalists in WWY.

WWY also test an alternative model proposed by Sherman (1999) and analyze underwriters' incentives in IPOs. Because of legal liability and concerns over loss of reputation, underwriters certify whether an issuing firm has good prospects as accurately as they can, regardless of investor beliefs. Consistent with Sherman (1999), WWY find that underwriters' industry specialty is negatively and significantly associated with the probability of fraud regardless of the level of investor beliefs. In our study, an independent director is subject to fiduciary duties and obligated to act in the reasonable

belief that her actions are in the best interests of shareholders. We argue that accounting expertise lowers monitoring costs faced by independent directors over accounting reports issued by firms, thus enhancing the directors' monitoring effectiveness. In addition, the board of directors would face substantial costs if the firm engages in fraudulent behavior (Srinivasan, 2005; Helland, 2006; Fich and Shivdasani, 2007). Therefore, we expect that independent directors would act in a similar fashion as underwriters in Sherman (1999) and WWY. These arguments lead us to the following hypothesis.

Hypothesis 2B: *The likelihood of accounting irregularities decreases as the proportion of independent directors (on the board) with accounting expertise increases, regardless of investor beliefs about business conditions.*

2.3 Market Reactions

Numerous studies document an economically and statistically significant negative market reaction to restatement announcements and an even more negative market reaction to irregularities or fraud (see, for example, Palmrose, Richardson and Scholz, 2004; Hribar and Jenkins, 2004). However, only a couple of studies examine the relation between financial or accounting expertise of directors and market reactions. Carcello, Neal, Palmrose and Scholz (2011) predict that an audit committee with financial experts might mitigate negative stock price reaction to restatement announcements. Kouwenberg and Phunnarungsi (2013) suggest that if governance is fully discounted in stock prices, the market reacts more negatively when firms with better governance violate the exchange listing rules. Moreover, both of these studies do not find any significant impact of monitoring by the broad of directors on market reactions to the announcement of financial misstatements and misconduct.

Carcello, Neal, Palmrose and Scholz (2011) posit a positive relation between market reaction and audit committee expertise, measured as of the first year of misstatement, because a firm with good corporate governance is viewed as less prone to systematic failure. In our second hypothesis, we consider the accounting expertise of independent directors when misstatements are *committed* rather than *detected*. However, when a firm announces a restatement investors learn about the directors' accounting expertise not only as of the date when accounting misstatements begin (say, time *t*-1) but

also at the time of announcement of an accounting restatement (say, at time *t*). The time-gap between these two critical event dates is typically two or more years. If a higher proportion of independent directors with AE indicates better corporate governance and more effective monitoring over a firm's incentives to commit irregularities, it is important to investigate whether investors react to the AE of independent directors measured as of the date when misstatements are detected, in addition to when they are committed. We should expect that investor reaction to the restatement announcement would be more positive the higher the percentage of independent directors with accounting expertise at time *t*-1 (commission) as well as time *t* (detection). In addition, an improvement in the proportion of directors with accounting expertise from the date of commission to detection should be positively associated with market reaction to restatements. These arguments lead us to the following hypothesis:

Hypothesis 3: *Investors react more negatively to the announcement of accounting irregularities as compared to accounting errors. However, market reaction to financial misstatements increases with the proportion of independent directors with accounting expertise measured when misstatements are committed as well as detected.*

3. Empirical Design

3.1 Bivariate probit model

Investors are unaware of financial misstatements at the time when they are actually committed (*t*-1), they come to learn about the beginning of misconduct only at a later time if and when the misstatements are disclosed or detected (*t*). Therefore, the occurrence of financial misconduct is only partially observable to investors. We follow WWY and use a bivariate probit model to address the partial observability (incomplete detection) concern. There are two latent variables, whether firms intentionally misstate financial statements (M) and whether the misconduct is disclosed or detected (D). We only observe misstatements that have been committed and detected/restated. That is, both M and D equal one. In addition, the probability of observed misstatements is different from the probability of committed misstatements if the detection/disclosure process is not perfect. Bivariate probit model is designed to address those issues.

For each firm *i*, *Mi* is the incentive to intentionally misstate financial reports and *Di* is the potential disclosure conditional on having misreported. The reduced form model is

$$M_i = \boldsymbol{x}_{M,i}\boldsymbol{\beta} + u_i$$

$$D_i = \boldsymbol{x}_{D,i}\boldsymbol{\gamma} + v_i$$

where $\boldsymbol{x}_{M,i}$ is a row vector with elements that explain firm *i*'s incentives to issue intentional misreports, and $\boldsymbol{x}_{D,i}$ is a row vector with elements that explain firm *i*'s incentives for potential disclosure. u_i and v_i are zero-mean disturbances with a bivariate normal distribution. ρ represents the correlation between u_i and v_i.

We only observe disclosed accounting irregularities but not undisclosed ones. $Z_i = M_i D_i$, where Z_i = 1 if firm *i*'s irregularities are detected, and Z_i = 0 if firm *i* does not commit any irregularity or does commit an irregularity but that has not been detected. The bivariate standard normal cumulative distribution function is Φ. Then

$$P(Z_i = 1) = P(M_i D_i = 1) = \Phi\big(\boldsymbol{x}_{M,i}\boldsymbol{\beta}, \boldsymbol{x}_{D,i}\boldsymbol{\gamma}, \rho\big)$$

$$P(Z_i = 0) = P(M_i D_i = 0) = 1 - \Phi\big(\boldsymbol{x}_{M,i}\boldsymbol{\beta}, \boldsymbol{x}_{D,i}\boldsymbol{\gamma}, \rho\big)$$

The log-likelihood function for the model is

$$L(\beta, \gamma, \rho) = \sum_{Z_i=1} \log\big(P(Z_i = 1)\big) + \sum_{Z_i=1} \log\big(P(Z_i = 0)\big)$$

$$= \sum_{i=1}^{N} \{Z_i \log\big[\Phi\big(\boldsymbol{x}_{M,i}\boldsymbol{\beta}, \boldsymbol{x}_{D,i}\boldsymbol{\gamma}, \rho\big)\big] + (1 - Z_i)\log[1 - \Phi\big(\boldsymbol{x}_{M,i}\boldsymbol{\beta}, \boldsymbol{x}_{D,i}\boldsymbol{\gamma}, \rho\big)]\}$$

Our objective is to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$**.** To test our first hypothesis about the impact of investor beliefs about business conditions on the likelihood of accounting irregularities we use the following bivariate probit models:

Commission of Misstatements Equation:

M = {Proxies for Investor Beliefs, Proxies for Investor Prior Beliefs Squared, Proxies for AE, *ST Compensation/LT Compensation ROA, Leverage, External Financial Need, Insider Ownership, Big Auditors, M&A, Capital Expenditure, R&D, Log Assets, Analyst Coverage, SOX* }

Detection of Misstatements Equation:

D = {*M&A, Capital Expenditure, R&D, Log Assets, Analyst Coverage, Abnormal Restate Risk, Disastrous Stock Return, Abnormal Volatility, Abnormal Turnover, SOX* }

Our second hypothesis posits a negative relation between the likelihood of accounting irregularities and the proportion of independent directors (on the board) with accounting expertise. To examine this hypothesis, we add measurements of AE in the commission model and interact them with investor beliefs about industry prospects. Variable definitions, including data sources, are provided in Appendix A.[8] In the commission model, we analyze market sentiment at the time when misstatements begin, instead of the time when misstatements are detected or announced. In the irregularity detection model, variables are constructed when misstatements are detected or announced. To mitigate endogeneity concerns, we exclude firms with misstatements when computing these proxies for investor beliefs.

3.2 Proxies for investor beliefs

Following WWY, we construct two time-varying measurements for investors' prior beliefs about business conditions at the Fama-French 49 industry level. We use the industry median analyst forecast of a firm's annual EPS growth (*Ind. ESP Growth*), and industry median Tobin's Q (*Ind. Q*). *Ind. ESP Growth* captures the consensus of analysts for a particular industry. *Ind. Q* reflects investors' expectation on the growth opportunities for an industry.

Our first hypothesis predicts a hump-shaped relation between investor prior beliefs and the firm's propensity to issue intentional misstatements. Therefore, we expect to find positive coefficients on *Ind. ESP Growth* and *Ind. Q* and negative coefficients on their squared terms.

3.3 Proxies for Monitoring Costs

Greater accounting expertise of independent directors (higher *%AE*) should lower the monitoring

[8] We winsorsize all continuous variables at 1% and 99% to remove the effects of outliers in our model estimations.

costs of investors. We construct three proxies for the monitoring of managerial behavior by independent directors with AE. The first variable, *AE dummy*, equals one if there is at least one independent director with AE for a given firm-year and zero otherwise. It captures the presence of AE on the board of directors. However, this measurement is highly correlated with the size of the board, and it fails to capture how many independent directors possess accounting expertise. Therefore, we construct another variable, *%AE*, measured as the number of independent directors with AE divided by the total number of independent directors for a given firm-year. Because some industries entail complex accounting practice, *%AE* might be closely related to industry characteristics (Bills, Jeter and Stein, 2013). To mitigate this potential concern, we construct the third proxy, *Excess AE*, which equals one if *%AE* is greater than industry median *%AE* for a given firm-year.

Our second hypothesis predicts a negative relation between the likelihood of accounting irregularities and the proportion of independent directors with accounting expertise. So we expect negative regression coefficients on all three monitoring proxies discussed above.

3.4 Control Variables in Misstatement Commission

We construct our *ex ante* control variables in the misstatement commission regression following Wang (2013) and Wang and Winton (2014). The *ex-ante* variables are measured prior to the commission. All variable definitions and data sources are summarized in Appendix A. We measure performance by return on assets (*ROA*) because previous studies find that manipulating firms had strong financial performance prior to the misstatements (see Crutchley, Jensen and Marshall, 2007; Dechow, Ge, Larson and Sloan, 2010; Wang, 2013; Wang and Winton, 2014). Beasley (1996) finds that companies reporting repeated losses are more likely to engage in financial fraud. Kinney and McDaniel (1989) find that less profitable companies are more likely to misreport. But Summers and Sweeney (1998) find a positive association between misstatements and profitability, and Erickson, Hanlon and Maydew (2006) find insignificant or mixed evidence.

We control for leverage based on the debt covenant hypothesis (DeFond and Jiambalvo; 1994, Sweeney, 1994; Dichev and Skinner, 2002). However, the empirical evidence on the impact of leverage is mixed (DeAngelo, DeAngelo, and Skinner, 1994; Dechow, Sloan and Sweeney, 1996;

DeFond and Jiambalvo, 1991; Dechow, Larson and Sloan, 2011).

High external financing needs affect earnings management as well as the commission of accounting misstatements (Dechow, Sloan and Sweeney, 1996; Teoh, Welch and Wong, 1998; Wang, 2013; Wang and Winton, 2014). As our analysis focuses on accounting misstatements instead of fraud, we construct this measurement based on Dechow, Sloan and Sweeney (1996).[9] *Ext. Fin. Need* is a dummy variable equal to one if the firm's free cash flow is less than –0.5 and zero otherwise. Dechow, Sloan and Sweeney (1996) suggest that, as free cash flow becomes more negative (i.e., the firm is closer to exhausting its internal funds), the firm is more likely to manipulate earnings. For example, when free cash flow is equal to -0.5, a firm will consume all of its available current assets within two years. Free cash flow is defined as cash from operations minus average capital expenditures during the previous three years and then divided by prior year current assets. Cash from operations equals earnings minus accruals. Accruals is changes in current assets minus changes in current liabilities minus changes in cash/cash equivalents plus changes in debt included in current liabilities, and minus depreciation and amortization expense.

Warfield, Wild, and Wild (1995) find that greater insider ownership is associated with greater earnings informativeness and better accruals quality. However, Goldman and Slezak (2006) and Denis, Hanouna and Sarin (2006) suggest that a positive relation between firm performance and insiders' compensation can induce misreporting. Previous studies (such as Bhattacharya and Marshall, 2012; Agrawal and Cooper, 2014) generate mixed results. We construct this proxy using the percentage of shares owned by insiders.[10]

We control for M&A expenditure. Kinney, Palmrose, and Scholz (2004) suggest that acquisitions may increase the probability of a misstatement because of new accounting issues and possible business integration problems. We also add capital expenditure (*CAPX*), R&D expenditure and analyst coverage following Wang (2013) and Wang and Winton (2014).

Since we analyze accounting misstatements, we also include a dummy variable for big 4 or big 5

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[9] Wang (2013) and Wang and Winton (2014) focus on accounting fraud.

[10] Armstrong, Jagolinzer and Larker (2010) suggest potential selection bias because of missing observations in ExecuComp. We do not have access to the Compact Disclosure database. We hence construct FF 49 industry median for each fiscal year and replace missing observations with industry median.

auditors to control for audit firm quality. We also include *Log Assets* as the logarithm of book value of total assets, and *SOX* as a dummy variable that equals one for misstatements committed in 2002 or after and zero otherwise.

Hertzberg (2005) posits that positive investor beliefs lead to more short-term executive compensation, which, in turn, increases the likelihood of fraud. Consistent with these arguments, WWY find a positive and significant relation between short-term managerial compensation and a firm's fraud propensity. Yet, investors' prior beliefs (emphasized by PSW) remain robust in their tests after controlling for the compensation effect. In addition, Burns and Kedia (2006) report that the sensitivity of the CEO's option portfolio to stock price is significantly positively related to the propensity to misreport.[11] Therefore, we add the following two executive compensation variables as controls: *ST Compensation* (industry median short-term incentive defined as (salary + bonus + other annual compensation)/ (total expected compensation) and *LT Compensation* (industry median long term incentive measured as (restricted stock grants + option awards)/ (total expected compensation)).

3.5 Determinants of the Probability of Misstatement Detection

Similar to Wang (2013) and Wang and Winton (2014), we include a set of *ex-ante* detection factors as well as a set of *ex-post* detection factors. The *ex-ante* variables are measured prior to the detection, and the *ex-post* variables are measured as of the year of detection.[12] All variable definitions and data sources are summarized in Appendix A.

Our ex-ante determinants of misstatement detection include mergers and acquisitions expenditures (*M&A*), R&D expenditures (*R&D*), capital expenditures (*CAPX*), number of analysts following (*Analyst Coverage*), firm size (*Log Asset*) and *SOX* dummy. Wang (2013) suggests that R&D investment, capital expenditure and mergers and acquisitions tend to affect the likelihood of detection. Dyck, Morse and Zingales (2010) suggest that analysts are important external monitors of firms. We hence include *Analyst Coverage* as the number of stock analysts that follow an industry.

[11] Related studies on the impact of compensation on misconduct incentives include Hass, Muller and Vergauwe (2014) and Li (2014).

[12] As a robustness test, we also follow Wang (2014) and test our model by using information at year t-1 to construct ex-ante factors of detection and t+1 to construct ex-post factors of detection, given year t is the beginning year of misstatement. The results are similar.

Similar to WWY and Wang (2013), we include firm size and SOX dummy.

Our ex-post determinants of misstatement detection follow WWY and Wang (2013). We replace litigation risk in WWY by misstatement risk (defined as the logarithm of the sum of the market value of restated firms in an industry) to control for industry misstatement intensity. *Abnormal Restatement Risk* is the yearly deviation from the industry average restatement intensity. Regulators and investors pay more attention to a particular industry which has more misstatements. Firms that experience large negative returns, high stock turnover and high return volatility are more likely to be watched by investors and shareholders. *Disastrous Stock Return* is an indicator variable equals one if the firms' stock return is in the bottom 10% of all the firm-year return observations in the COMPUSTAT-CRSP merged database.[13] *Abnormal Return Volatility* is the difference between the yearly standard deviation of the firm's returns and its time-series average. Similarly, *Abnormal Stock Turnover* is the difference between the monthly share turnover from the firm's time-series average.

4. Data and Sample Construction

Our misstatement sample is collected from three sources, Federal Securities Regulation (FSR) (provided by Karpoff, Koester, Lee and Martin (2012)), General Accounting Office (GAO) and Audit Analytics (AA).[14] This sample is more comprehensive than GAO or AA (or both) used by most of the previous literature GAO published two reports, one in 2002 and the other in 2006. The two GAO reports contain financial restatements from January 1997 to September 2006. AA includes restatements from January 2000. The FSR data is based on any violations of 13(b) provisions of the Securities and Exchange Act of 1934, which we consider as more relevant to our analysis of accounting irregularities.[15] We cross-check the three databases and delete duplicate cases. As one case might be associated with more than one event, we carefully investigate each case and only keep the earliest event. Our sample consists of unique firm-year observations.

Our sample includes financial misstatements occurring between 1996 and 2010. We restrict our

[13] We also test for other cutoff points such as the bottom 5%, 15% and 20% and obtain similar results.
[14] We are grateful to Jonathan M. Karpoff, Allison Koester, D. Scott Lee and Gerald S. Martin who generously shared with us the FSR database they used in their paper, Karpoff, Koester, Lee and Martin (2012).
[15] Karpoff, Koester, Lee and Martin (2012) find that 87.5% of cases in GAO and 97.8% of cases in AA are non-misconduct cases, compared with 0% in FSR.

sample to misstatements after 1996 because the passage of the Private Securities Litigation Reform Act in 1995 might affect a firm's incentives to engage in fraudulent behavior. For each misstatement, we collect information on both the year of commission and the dates of detection. Since the median length of the misstated period (from commission to detection) in our combined sample of irregularities and errors is about two years in our sample, our commission and detection sub-samples terminate in years 2010 and 2012, respectively. Following Hennes, Leone and Miller (2008), we classify each case of misstatement into either an irregularity or an error.[16] The final misstatement sample includes 830 accounting irregularities and 4,360 accounting errors.

Our control sample includes all firms in the COMPUSTAT-CRSP merged database except firms that are in the misstatement sample. We also delete firms with the two-digit SIC code equal to 99 because these firms are shell holding companies and acquisition vehicles whose characteristics change dramatically after acquisition. Since our control sample is based on the population of COMPUSTAT firms for which data are available, we address the concern over matched sample problem raised by Jones, Krishnan, and Melendrez (2008) and Burns, Kedia, and Lipson (2010). The control sample includes 64,734 firm-year observations. After we delete missing observations of control variables, the control sample drops to 39,801 firm-year observations.

To test our (second) hypothesis on the monitoring role of accounting expertise of independent directors, we hand collect AE data from proxy statements. Since manual data collection is quite time-consuming, we focus on S&P1500 firms to generate a reasonable sample on accounting expertise. This choice reduces the sample used in firm-level analyses of monitoring by independent directors with AE to 174 accounting irregularities, 828 accounting errors, and 8,707 control (with no misstatement) firm-year observations. In order to utilize the best available sample, we test our hypotheses using the full sample of all firms in the COMPUSTAT-CRSP merged database (with about 25,000 firm-year observations on all variables used in our multivariate tests).

[16] The GAO data on the classification of errors versus irregularities was generously provided by Professor Andrew J. Leone (http://sbaleone.bus.miami.edu/) In AA dataset, there are two variables help us distinguish irregularity from errors. One is "Res_fraud", which equals 1 if the restatement identified financial fraud, irregularities and misrepresentations. The other is "Res_sec_investigation", which equals 1 if the restatement disclosure identified that the SEC, PCAOB or other regulatory body is investigating the registrant. Including "Res_sec_investigation" is consistent with the procedure to distinguish irregularities from errors by Hennes, Leone and Miller (2008), where the first step is self-disclosure of irregularity or fraud, the second step is SEC investigation and the third step is non-SEC investigation. (pp.1494 of Hennes, Leone and Miller 2008).

5. Results

5.1 Summary Statistics

Panel A of Table 1 reports the annual frequency of accounting irregularities and errors in the full sample, both measured as of the year of commission. There is a declining trend in the incidence of both irregularities and errors after 2000, but the drop-off appears more pronounced in intentional misstatements.

Panel B reports the annual frequency and percentage of independent directors with AE *(%AE*) in the S&P 1500 sub-sample. Entries in the "N" column indicate the number of firms with accounting irregularities and those in the "Mean" column represent the average percentage of independent directors with accounting expertise. For example, there are 10 firms in the S&P 1500 sub-sample reporting irregularities beginning in 1996. On average, only 4.07% of independent directors of these firms have accounting expertise. The remaining entries show that only a small fraction of independent directors on the board qualifies as accounting experts. For both irregularities and errors commission, we find that *%AE* increases after the passage of SOX in 2002.

Panel A of Table 2 presents the mean and median of variables for the three sub-samples, control (no-misstatements), irregularities and errors. The test results on the differences in means and medians of the key outcome and test variables between the sub-samples are shown in Panel B. Industry median EPS growth in the irregularities sample (13%) is significantly higher relative to the control (11%) and error (11%) sub-samples. We find a similar pattern for industry median Q. These base-level test results are supportive of our first hypothesis that more positive investor beliefs about industry prospects lead to higher incidence of accounting irregularities. Unreported results show that, among firm-years with no misstatements, 52.6% have accounting expertise on average, as compared with only 38.77% of firm-years with irregularities. The difference in means is highly significant as shown by the *t*-test in Panel B. Further, the industry median percentage of independent directors with accounting expertise (*% AE*) is 4 among firm-years with irregularities, which is significantly lower than 7% for firm-years without misstatements. We find similar results with respect to *Excess AE*, with 30% of firm-years with irregularities having excess AE, compared with 39% of firm-years with errors

and 39% of firm-year without misstatements. Overall, these univariate tests indicate that firms committing accounting irregularities are marked by fewer independent directors with accounting expertise.

Compared with the control sample, firms associated with irregularities and errors have higher M&A expenditures, higher ROA, higher leverage, higher external financing needs, higher M&A expenditure, higher capital expenditure, lower R&D expenditure, lower analyst coverage, larger size, higher industry restatement risk and higher likelihood of being audited by the 5 largest auditing firms. Turning to the executive compensation variables, firms associated with irregularities are marked by higher but insignificant short-term incentives and lower long-term incentives, consistent with Hertzberg (2005). However, we find a similar pattern in the subsamples on no-misstatements and errors.

5.2 Investor Beliefs and Propensity for Irregularities

Panel A (irregularities) and Panel B (errors) of Table 3 report the regression results for our first hypothesis. Bivariate probit model is used to mitigate the partial observability problem. Our test variables are the investor belief proxies and their squared terms in the commission equation (P(M)). P(D|M) includes variables in detection equation. The dependent variable in P(M) is a latent variable equal to one if a firm committed an accounting misstatement, and zero otherwise. The dependent variable in P(D|M) is a latent variable equal to one if a firm committed an accounting misstatement and then restated or got caught, and zero otherwise. For each regressor, coefficient estimates and standard errors (in parentheses) are reported. Standard errors are clustered at firm level.

The investor belief proxy in Models 1 is industry median EPS growth rate. In Panel A, the probability of committing an irregularity is significantly positively related to the level of prior investor beliefs about business conditions (with a coefficient estimate of 0.4750), but significantly negatively related to the squared term (-0.6660). We find that the predicted probability of fraud peaks at the industry median EPS growth forecast of 0.36. For any industry median EPS growth forecast exceeding 0.36, a higher level of investor beliefs is associated with a lower probability of fraud. In Panel B, the probability of committing an accounting error is insignificantly related to both industry

median EPS growth and its squared term, suggesting that the likelihood of errors is unrelated to investor beliefs about business conditions. When we replace industry median EPS growth with industry median Q to represent investor beliefs, we find similar results in Models 2.

The remaining estimates with respect to our control variables in the commission of irregularities and errors (P(M=1)) model are consistent with the previous literature. *ROA* is significantly positive, in line with Summers and Sweeney (1998) who note that firms with higher profitability are more likely to misstate their financial reports. Consistent with Kinney, Palmrose, and Scholz (2004), *M&A Expenditures* is positive and significant. Leverage is positive and insignificant in the irregularity sub-sample but significantly positive in errors sub-sample, suggesting that the debt covenant hypothesis has explanatory power for the variable in accounting errors across firm-years but not for irregularities. Similar to leverage, external financing need is also positive and insignificant in the irregularity sub-sample, and significantly positive in the error sub-sample. Consistent with Wang and Winton (2014), firms with higher insider ownership tend to have a higher likelihood of fraud commission. In addition, larger capital expenditure, smaller size and less analyst coverage tend to increase the probability of misstatement commission.

All variables in the detection model (P(D=1|M=1)) have the expected signs. Opposite to commission, smaller capital expenditure, larger size and more analyst coverage tend to increase the probability of misstatement detection. Abnormal restatement risk is positive and highly significant. In addition, disastrous stock return increases the probability of being watched because of investors' concerns about potential investment losses. Abnormal return volatility is positive but insignificant. A high turnover means more investors are affected and hence it increases the detection risk. A positive and significant coefficient on SOX dummy suggests that the incidence of disclosure of misconduct increases after SOX. We find a similar pattern in the determinants of detection in the error sub-sample.

5.3 Monitoring Costs and Propensity for Irregularities

Although PSW predict that lower monitoring costs of investors are on average associated with higher fraud propensity in good times, our second hypothesis posits that monitoring by independent

directors (who are obligated to act in the best interests of shareholders) should lower the likelihood of misconduct, consistent with Sherman (1999).

To test this hypothesis, we first repeat the tests in Table 3 while adding the percentage of independent directors with accounting expertise (*% AE*) as a proxy for monitoring by independent directors. In unreported results, we find that the coefficient estimate on *Ind. EPS Growth* is positive and significant and that on the squared term is negative and significant in the irregularities sub-sample. By contrast, both coefficient estimates are insignificant in the errors sub-sample. These results show that our first hypothesis remains robust after controlling for the percentage of accounting experts on the board of directors. In Model 1, the coefficients on *% AE* are negative (-1.3802 and -1.6127) and significant at 1% in both the irregularities and errors sub-samples. These findings suggest that the probability of misstatements decreases with the proportion of independent directors with AE.[17]

PSW and Shleifer and Vishny (1997) suggest that more optimistic beliefs about business conditions lead to lower investor monitoring of managers, encouraging financial misconduct. To investigate whether investor monitoring through the appointment of independent directors with AE is the underlying mechanism affecting the relation between irregularity propensity and investor beliefs, we utilize a two-stage regression approach. In the first-stage, we regress firm-level *%AE* of independent directors against investor beliefs for the entire Risk Metrics database. We construct other control variables following Agrawal and Chadha (2005) and Krishnan and Visvanathan (2008) which examine the determinants of monitoring by accounting experts.

We include board size because larger boards are more likely to include a board member of any type. G Index, developed by Gompers, Ishii, and Metriek (2003), measures the strength of a firm's governance system and is constructed based on a simple counting of 24 corporate governance provisions. Since the data on G Index is not available after 2008, we use the 2008 index data for 2009 as well 2010 – the last two years in our sample period. A low (high) G Index is associated with a strong (weak) governance system. Previous literature (see, for example, DeFond, Hann and Hu, 2005 and Krishnan and Visvanathan, 2008) suggests a negative relation between the appointment of a

[17] In unreported results, we find similar results when we replace % AE with AE dummy.

financial expert and the G Index.[18]

Agrawal and Chadha (2005) predict that firms that are more capital intensive are likely to have a greater need for financial expertise on the board. We measure capital intensity as total assets scaled by number of employees. We include *Debt* and *Prior ROA* because more leveraged firms with poor performance are likely to have a greater need for external financing, which requires boardroom financial expertise. Agrawal and Chadha (2005) also predict that firms with greater earnings volatility tend to face greater asymmetric information problems in raising external finance. We measure *Earnings Volatility* as the standard deviation of earnings per share including extraordinary items for the past five years. Following Agrawal and Chadha (2005), and Krishnan and Visvanathan (2008), we include *Sales Growth*, measured as annual percentage change of sales, and *Size*, measured as log of assets. In order to capture regulatory change, we include *SOX* dummy. All variable definitions and data sources are summarized in Appendix A. All firm characteristics are lagged. We control for firm fixed effect and cluster standard errors at firm levels.

In Panel A of Table 4, we observe a negative relation (significant at 1%) between investor beliefs about business condition and firm-level *%AE* (our proxy for monitoring by independent directors on behalf of investors), consistent with our Hypothesis 2A. When prior beliefs are fairly optimistic, investors do not seem to monitor firms carefully. The coefficient estimates of control variables suggest that there is more *%AE* when the firm has larger size, larger board size, better corporate governance, poor prior performance and lower sales growth. More mature firms tend to have more *%AE* on the board. The presence of AE and the percentage of AE tend to increase significantly after SOX. The R-squared is over 65% in Model 1 and over 82% in Model 2.

In the second stage (Panel B of Table 4), we include the industry median predicted percentage AE calculated from the first stage. Similar to WWY, we include industry median compensation variables. Hertzberg (2005) posits that positive investor beliefs lead to more short-term executive compensation, which increases the likelihood of fraud. Consistent with Hypothesis 2B, the coefficient estimates of *Predict % AE* suggests a negative and significant impact of AE on a firm's irregularity propensity. The economic significance is quite large. In unreported results, the marginal effect of *Predicted % AE* in

[18] We find similar results by replacing G Index with BCF Index, developed by Bebchuk, Cohen and Ferrell (2009).

Model 1 (Panel B of Table 4) is -0.1032 with a predicted conditional probability of 0.0517 at the mean values of the regressors. It means that 10% increase in *Predicted % AE* reduces the predicted conditional probability by 19%.[19] The level of investor beliefs about the state of the economy continues to have a hump-shaped impact on the incidence of irregularity, suggesting that the monitoring mechanism, together with investor beliefs, plays an important role in explaining intentional financial misconduct. There is an important interplay between investor beliefs and monitoring. Neither can provide a complete explanation to irregularity propensity. Furthermore, we find a significantly positive (negative) relation between actual industry median predicted ST compensation (industry median predicted LT compensation) and the probability of misstatements. In contrast, the coefficient estimates of *Predict % AE* are insignificant in the error sub-sample.

Reverse causality is a potential concern. It is possible that firms with incentives to manipulate financial statements intentionally reduce the number of independent directors with accounting expertise before issuing misleading reports. We argue that our results are not likely driven by reverse causality because (1) we use predicted *%AE* instead of actual *%AE*; (2) predicted *%AE* is *ex ante;* (3) predicted *%AE* in year *t* is calculated by using ex ante information in year *t*-1; (4) we use industry median measurements of *AE* instead of firm-level measurements. We also perform robustness tests by using two-year, three-year and four-year lagged measurements of %*AE*. In unreported results, the level of investor beliefs continues to have a hump-shaped impact on the incidence of irregularity. More important, the coefficient estimates (*p*-value) of %*AE* are -0.902 (0.091) for lagged-two-year, -1.292 (0.035) for lagged-three-year and -1.219 (0.055) for lagged-four-year.

Since PSW suggest that the impact of monitoring costs varies with the degree of investor prior beliefs, we construct an indicator variable for each quintile of investor beliefs and interact it with predicted *% AE*. The first (fifth) quintile corresponds to the lowest (highest) level of investor beliefs. In addition, we control for the level of investor beliefs and compensation. In Panel A of Table 5, the coefficient estimates on the interaction terms are negative in all the quintiles and significant in most of the quintiles. They suggest that, consistent with our Hypothesis 2B, monitoring by independent

[19] Because the industry median %*AE* is essentially categorical instead of continuous, the traditional interpretation of economic significance using one-standard-deviation change of independent variables is inappropriate.

directors with AE is effective across different levels of investor beliefs. The likelihood of irregularities decreases as the proportion of independent directors with AE increases, regardless of the level of investor beliefs. We still find a significantly negative impact of AE on irregularity propensity, even after controlling for the mechanism between investor beliefs and monitoring. We do not find a similar pattern for errors in Panel B. Coefficient estimates of control variables in the misstatement commission model (P(M=1)) and those in the detection model (P(D=1|M=1)) are consistent with Table 3 and Table 4.

To assess the sensitivity of the above estimates to our approach to constructing predicted proportion of directors with accounting expertise, we replace *Predicted % AE* with *Excess AE*, an indicator variable that takes a value of 1 for *% AE* greater than the industry median and 0 otherwise, in Table 6. Since *Excess AE* is based on firm-level observations, our sample size drops to about 7,000 firm-year observations. We use the same control variables in commission and detection equation as in previous tables. To save space, coefficient estimates of control variables are suppressed. Similar to results in Panel A of Table 5, the coefficient estimates on *Excess AE* (Model 1) and the interactions between *Excess AE* and quintile dummies of investor beliefs (Model 2) continue to be negative and significant in the irregularity sub-sample in Panel A of Table 6, though not always significant. It is possibly due to a much smaller sample size. In contrast, the coefficient estimates become insignificant in the error sub-sample in Panel B. In summary, our findings suggest that an increase in the proportion of independent directors with accounting expertise is associated with a lower propensity of intentional accounting misreporting after controlling for investor beliefs about industry prospects and standard regulatory, firm and industry characteristics. The negative impact of AE of independent directors on irregularity propensity still persists even after controlling for investor beliefs.

5.4 Compensation, Monitoring Costs and Propensity for Irregularities

Hertzberg (2005) posits that positive investor beliefs lead to more short-term executive compensation, which, in turn, increases the likelihood of fraud. WWY test the link between investor beliefs and firm's fraud incentives and find that more optimistic beliefs lead to more short-term compensation. Further, to scrutinize whether compensation is the dominant mechanism, they run a

two-stage regression by examining the relationship between investor beliefs and the structure of executive pay in the first stage and then use the predicted compensation in the second stage.

In a similar fashion, we run a two-stage regression and report our results in Appendix B. In the first-stage, we regress the firm-level short- and long-term executive compensation against industry median investor beliefs (Ind. EPS Growth) for the entire ExecuComp database, and calculate the predicted firm-level short- and long-term compensation. We then calculate industry median pedicted ST compensation and industry median predicted LT compensation, which are industry median predicted compensation in the commission equation of the bivariate probit analysis.

In Panel A of Appendix B, we observe that more optimistic beliefs are associated with more short-term compensation (Model 1) and less long-term compensation (Model 2). These findings are consistent with Hertzberg (2005) and WWY. In Panel B, we find that industry median predicted ST compensation (industry median predicted LT compensation) is positively (negatively) associated with the probability of misstatements, including both irregularities and errors. After controlling for executive incentives, we still observe a hump-shaped relation between investor beliefs and irregularity propensity, consistent with our first hypothesis. More important, *%AE* is still negative and significant in both the irregularity commission model and the error commission model, suggesting a salient monitoring role of independent directors with accounting expertise.

5.5 Market Reactions

Table 7 reports preliminary results on our third hypothesis predicting negative investor reactions to the announcement of accounting restatements and positive reactions to the proportion of independent directors with accounting expertise. Since we collect firm-level proxies for AE in S&P 1500 firms, our sample of market reactions includes all accounting restatements announced by those firms from 1996 to 2012.[20] After we merge with the CRSP market data, our sample includes 1,005 restatement announcement dates. We subtract the CRSP market index return (equally weighted, with dividends) from a company's daily stock return to estimate its daily abnormal return. The daily abnormal returns are summed over the event window to obtain the cumulative abnormal returns (CAR)

[20] We only look at restatements from GAO and AA and exclude misstatements from FSR.

for each firm.

In Panel A of Table 7 we examine CAR over the (-2,2) and (-1,1) windows for the sub-samples of irregularities and errors. The average three-day abnormal returns is about -6% for irregularities, compared with roughly -1% for errors. The differences in means and medians are highly significant. This evidence is consistent with our third hypothesis that investors react more negatively to the announcement of irregularities as compared with errors. Since we limit our sample to S&P 1500 firms, the mean abnormal returns are less negative compared with previous papers which include both small and big firms. This is consistent with the existing evidence indicating that large firms tend to have smaller market reaction to restatements (Collins, Kothari and Rayburn, 1987; Freeman, 1987; Bhushan, 1989; O'Brien and Bhushan, 1990; El-Gazzar, 1998).

Panel B of Table 7 compares CAR for firms with above-median *% AE* with firms with below-median *% AE*. Carcello, Neal, Palmrose and Scholz (2011) suggest that an audit committee with financial experts indicates good corporate governance and hence might mitigate negative stock price reaction to restatement announcements. However, they fail to find any significant relation between investor reactions and the audit committee financial expertise. We broaden the measure of accounting expertise by covering all independent directors on the board with AE, not just those independent directors who serve on the audit committee. In addition, Carcello et al measure financial expertise of independent directors as of the date when firms begin misreporting their accounts. As noted previously, in our combined sample of irregularities and errors the median time-gap between the beginning of misconduct and its subsequent detection is about two years.[21] Given this wide window, the proportion of independent directors with AE can vary between the date of commission and the subsequent detection of misconduct. Hence, it is important to investigate whether investors react differently to AE as of the date of disclosure of restatements, and whether any potential improvement from commission to disclosure in the proportion of independent directors with accounting expertise helps mitigate negative market reaction. Therefore, we look at *%AE* when misstatements begin and when misstatements are detected separately. When we compare firms with (1) below-median *%AE*

[21] In the irregularities sample, the median (mean) length from commission to detection is 2.64 (2) years and the upper (lower) quartile is 4 (1) years. In the errors sample, the median (mean) length from commission to detection is 2.17 (2) years and the upper (lower) quartile is 3 (1) years.

with (2) those with above-median *%AE* measured when misstatements begin in both cases, we find that investors react more negatively to firms with lower *%AE*. Both mean and median differences are highly significant.

Next we compare firms with (3) below-median *%AE* with (4) their peers with above-median *%AE* measured in both cases when misstatements are disclosed. Again, investors seem to react more negatively to firms with lower *%AE*. However, only the five-day mean difference in CARs is significant. Overall, consistent with our third hypothesis, these mean difference test results indicate that market reaction to financial misstatements increases with the proportion of independent directors with accounting expertise measured when misstatements begin as well as when they are detected.

Panel A of Table 8 reports the results of multivariate regressions. Since we include the change in the proportion of independent directors with accounting expertise from the date of commission to disclosure of misstatements, we exclude observations on AE that we can measure only at the time of commission or detection. This reduces the number of observations to 981. There are four main test variables: *IRR*, a dummy variable equal to one for misstatements that are irregularities and zero otherwise, *AE_commit* (percentage of AE when misstatements begin), *AE_detect* (percentage of *AE* when misstatements are detected), *AE_change* (change in the percentage of *AE* between the time of detection and commission of misstatements). In addition, we consider interactions between the three *AE* variables and *IRR*. Consistent with the univariate analysis presented in Table 7, the coefficient estimates on *IRR* are all negative and highly significant, indicating that investors react more negatively to intentional misstatements. Both *AE_commit* and *AE_detect* are positive and significant. These estimates suggest that a high percentage of independent directors with AE mitigate the average negative market reaction to restatements. However, the interaction terms are not significant.

When we track the change in the percentage of AE between detection and the beginning of misconduct, the coefficient estimate of *AE_change* is not significant but its interaction with *IRR* is positive and marginally significant. This evidence suggests that an improvement in the proportion of independent directors with accounting expertise between the time of detection and the beginning of misconduct serves to mitigate negative reaction to the disclosure of irregularities.

The coefficient estimates on control variables are consistent with those reported by previous

literature. Palmrose, Richardson, and Scholz (2004) find that more negative returns are associated with restatements attributed to auditors or management but not to the SEC.[22] We find positive and highly significant coefficients on the SEC dummy (which flags restatements prompted by SEC). Also, we find positive and highly significant coefficients on firm size, consistent with Collins, Kothari and Rayburn (1987), Freeman (1987), Bhushan (1989), O'Brien and Bhushan (1990), and El-Gazzar (1998) who report that stock price reactions to earnings news is attenuated for large firms and magnified for small firms.

To verify the robustness of the above results, we construct two alternative measures of accounting expertise: dummy variables of excess accounting expertise relative to the industry median measured when misstatements are committed and when they are subsequently detected. The estimates presented in Panel B indicate that both *Excess AE_commit* and *Excess AE_detect* are positive and significant but their interactions with *IRR* are not significant.[23]

Overall, the above results offer strong support for our third hypothesis which predicts negative market reactions to the announcement of accounting irregularities but positive reactions to the percentage of independent directors with accounting expertise when misstatements begin as well as when they are detected.

6. Conclusion

The causes and consequences of accounting misconduct have been widely studied, but our understanding of what factors influence a firm's incentives to issue misleading reports and the effectiveness of various monitoring mechanisms is rather limited. This paper empirically tests two key determinants of intentional accounting misconduct proposed by Povel, Singh and Winton (2007), investors' prior beliefs about business conditions and monitoring costs. We use industry medians of Tobin's Q and analyst growth forecasts of earnings per share to capture investor beliefs and the industry median proportion of independent directors with accounting expertise on the board as our

[22] Table 4 in Palmrose, Richardson, and Scholz (2004) show that the average market reaction is -18% if the restatement is attributed to auditor, -13% if the restatement is attributed to company and -4% if the restatement is attributed to SEC.
[23] Numbers of observations (N) in Panel B of Table 8 (1,037 in Models 1 and 2, and 1,083 in Models 3 and 4) are greater than those in Panel A (981) because we do not exclude observations on AE that we can measure only at the time of commission or detection.

primary proxy for monitoring on behalf of investors.

Using a sample of U.S. firms which intentionally misstate their financial reports from 1996 to 2010, we find that the probability of accounting misconduct is hump-shaped in investor beliefs about business conditions, increasing in the level of investor beliefs but decreasing when beliefs are sufficiently positive. However, this pattern does not exist in (unintentional) accounting errors. Turning to monitoring mechanisms, we present strong evidence indicating that optimistic investor beliefs about business conditions lower the proportion of independent directors with accounting expertise. In addition, the incidence of irregularities decreases with the proportion of independent directors with accounting expertise regardless of investor prior beliefs about business conditions. This highlights the important interplay between investor beliefs and monitoring.

Finally, consistent with previous literature, we find that the stock market reacts more negatively to announcement of irregularities. More importantly, the magnitude of market reaction to restatements is positively correlated with the percentage of independent directors with accounting expertize, measured when misstatements begin as well as when they are disclosed. These findings highlight the effectiveness of monitoring by independent directors with accounting expertise in reducing the incidence and severity of accounting misconduct.

References

Abbott, L.J., S. Parker, and G. F. Peters. 2004. Audit Committee Characteristics and Restatements. *Auditing: A Journal of Practice & Theory* 23, 69-87.

Agrawal, A., and S. Chadha. 2005. Corporate Governance and Accounting Scandals. *Journal of Law & Economics* 48, 371-406.

Agrawal, A., and T. Cooper. 2014. Insider Trading Before Accounting Scandals. Working paper presented at the CFA-JCF-Schulich Conference on Financial Market Misconduct.

Anderson, R.C., S.A. Mansi, and D.M. Reeb. 2004. Board Characteristics, Accounting Report Integrity, and the Cost of Debt. *Journal of Accounting and Economics* 37, 315-342.

Armstrong, C.S., A.D. Jagolinzer, and D.F. Larcker, 2010. Chief Executive Officer Equity Incentives and Accounting Irregularities. *Journal of Accounting Research* 48, 225-271.

Beasley, M. 1996. An Empirical Analysis of the Relation between the Board of Director Composition and Financial Statement Fraud. *The Accounting Review* 71, 443–65.

Bebchuk, L.A., A. Cohen, and A. Ferrell. 2009. What Matters in Corporate Governance. *Review of Financial Studies* 22:783–827.

Bédard, J., S.M. Chtourou, and L. Courteau. 2004. The Effect of Audit Committee Expertise, Independence, and Activity on Aggressive Earnings Management. *Auditing: A Journal of Practice & Theory* 23, 13-35.

Bhattacharya, U. and C.D. Marshall, 2012. Do they do it for the money? *Journal of Corporate Finance* 18, 92-104

Bhushan, R., 1989. Collection of Information about Publicly Traded Firms: Theory and Evidence. *Journal of Accounting & Economics* 11, 184–206.

Bills, K.L., D. C. Jeter and S. E. Stein. 2013. Auditor Industry Specialization and Evidence of Cost Efficiencies in Homogenous Industries. Working Paper. Available at SSRN: http://ssrn.com/abstract=2321741 or http://dx.doi.org/10.2139/ssrn.2321741

Burns, N. and S. Kedia. 2006. The Impact of Performance-based Compensation on Misreporting. *Journal of Financial Economics* 79, 35–67.

Burns, N., S. Kedia, and M. Lipson. 2010. Institutional Ownership and Monitoring: Evidence from Financial Misreporting, *Journal of Corporate Finance* 16, 443-455.

Carcello, J.V., C.W. Hollingsworth, A. Klein, and T. L. Neal. 2009. The Role of Audit Committee Financial Experts in the Post-SOX Era: Have Smaller Public Companies Benefited Disproportionately? Working paper, The University of Tennessee.

Carcello, J.V., T.L. Neal, Z.V. Palmrose, and S. Scholz. 2011. CEO Involvement in Selecting Board Members, Audit Committee Effectiveness, and Restatements, *Contemporary Accounting Research* 28, 396-430.

Collins, D.W., S.P. Kothari and J.D. Rayburn. 1987. Firm Size and the Information Content of Prices with respect to Earnings. *Journal of Accounting & Economics* 9, 111–138.

Crutchley, C.E., M. Jensen and B.B. Marshall. 2007. Climate for Scandal: Corporate Environments that contribute to accounting fraud. *Financial Review* 42, 53-73.

Davidson, R. 2011. Accounting Fraud: Booms, Busts, and Incentives to Perform, Working Paper.

DeAngelo, H., L. DeAngelo, and D.J. Skinner. 1994. Accounting Choice in Troubled Companies. *Journal of Accounting and Economics* 17, 113–43.

Dichev, I.D., and D.J. Skinner. 2002. Large-sample Evidence on the Debt Covenant Hypothesis. *Journal of Accounting Research* 40, 1091–123.

Dechow, P.M., W.L. Ge, C.R. Larson, and R.G. Sloan. 2010. Predicting Material Accounting Misstatements. *Contemporary Accounting Research* 28, 17-82.

Dechow, P.M., R.G. Sloan, and A.P. Sweeney. 1996. Causes and Consequences of Earnings Misstatement: An Analysis of Firms Subject to Enforcement Actions by the SEC. *Contemporary Accounting Research* 13, 1–36.

Defond, M.L., R.N. Hann, and X.S. Hu. 2005. Does the Market Value Financial Expertise on Audit Committees of Boards of Directors? *Journal of Accounting Research* 43, 153-193.

DeFond, M.L., and J. Jiambalvo. 1994. Debt Covenant Violation and Misstatement of Accruals. *Journal of Accounting and Economics* 17, 145–76.

Denis, D.J., Hanouna and P., Sarin, A., 2006. Is there a dark side to incentive compensation? *Journal of Corporate Finance* 12, 467-488

Dyck, A., A. Morse, and L. Zingales. 2010. Who Blows the Whistle on Corporate Fraud? *Journal of Finance* 65, 2213-2253

El-Gazzar, S.M. 1998. Pre-disclosure Information and Institutional Ownership: A Cross-sectional Examination of Market Revaluations during Earnings Announcement Periods. *The Accounting Review* 73, 119–129.

Erkens, D.H., and S.E. Bonner. 2013. The Role of Firm Status in Appointments of Accounting Financial Experts to Audit Committees. *The Accounting Review* 88, 107-136.

Erickson, M., M. Hanlon, and E. Maydew. 2006. Is There A link between Executive Incentives and Accounting Fraud? *Journal of Accounting Research* 44, 113–43.

Files, R., E. Swanson and S. Tse. 2009. Stealth Disclosure of Accounting Restatements. *The Accounting Review* 84, 1495–1520.

Fich, E.M. and A. Shivdasani. 2007. Financial Fraud, Director Reputation, and Shareholder Wealth. *Journal of Financial Economics* 86, 306-336.

Freeman, R.N. 1987. The Association between Accounting Earnings and Security Returns for

Large and Small Firms. *Journal of Accounting & Economics* 9, 195–228.

General Accounting Office (GAO). 2002. Financial Statement Restatements — Trends, Market Impacts, Regulatory Responses, and Remaining Challenges (GAO-03-138). Washington, DC: Report to Congressional Committees.

General Accountability Office (GAO). 2006. Financial Restatements: Update of Public Company Trends, Market Impacts, and Regulatory Enforcement Activities (GAO-06-678). Washington, DC: Report to Congressional Committees.

Goldman, E. and S. Slezak. 2006, An Equilibrium Model of Incentive Contracts in the Presence of Information Manipulation. *Journal of Financial Economics* 80, 603-626.

Gompers, P., J. Ishii, and A. Metrick. 2003. Corporate Governance and Equity Prices. *Quarterly Journal of Economics* 118, 107–55.

Harris, J.D. and P. Bromiley. 2006. Incentives to Cheat: The Influence of Executive Compensation and Firm Performance on Financial Misrepresentation. *Organization Science* 18, 350–67.

Hass, L.H., M.A. Muller and S. Vergauwe. 2014. Promotion-Based Incentives and Corporate Fraud. Working paper. presented at the CFA-JCF-Schulich Conference on Financial Market Misconduct.

Helland, E. 2006. Reputational Penalties and the Merits of Class Action Securities Litigation. *Journal of Law & Economics* 49, 365–396.

Hennes, K.M., A.J. Leone, and B.P. Miller. 2008. The Importance of Distinguishing Errors from Irregularities in Restatement Research: The Case of Restatements and CEO/CFO Turnover. *The Accounting Review* 83, 1487-1519.

Hertzberg, A. 2005. Managerial Incentives, Misreporting, and the Timing of Social Learning: A Theory of Slow Booms and Rapid Recessions. Working Paper, Northwestern University.

Hribar, P., and N.T. Jenkins. 2004. The Effect of Accounting Restatements on Earnings Revisions and the Estimated Cost of Capital. *Review of Accounting Studies* 9, 337-356.

Jones, K.L., G.V. Krishnan, and K.D. Melendrez. 2008, Do Models of Discretionary Accruals Detect Actual Cases of Fraudulent and Restated Earnings? An Empirical Analysis. *Contemporary Accounting Research* 25, 499-531.

Karpoff, J., A. Koester, D. Lee and G. Martin. 2012. An Analysis of Database Challenges in Financial Misconduct Research. Working Paper.

Kedia, S. and T. Philippon. 2009. The Economics of Fraudulent Accounting. *Review of Financial Studies* 22, 2169-2199.

Keune, M.B., and K.M. Johnstone. 2012. Materiality Judgments and the Resolution of Detected Misstatements: The Role of Managers, Auditors, and Audit Committees. *The Accounting Review* 87, 1641-1677.

Kouwenberg, R., and V. Phunnarungsi. 2013. Corporate Governance, Violations and Market Reactions. *Pacific-Basin Finance Journal* 21, 881-898.

Kinney, Jr, W.R., and L.S. McDaniel. 1989. Characteristics of Firms Correcting Previously Reported Quarterly Earnings. *Journal of Accounting and Economics* 11, 71–93.

Kinney, Jr, W.R., Z.V. Palmrose, and S. Scholz. 2004. Auditor Independence, Non-audit Services, and Restatements: Was the U.S. Government Right? *Journal of Accounting Research* 42, 561–88.

Krishnan, G.V., and G. Visvanathan. 2008. Does the SOX Definition of An Accounting Expert Matter? The Association between Audit Committee Directors' Accounting Expertise and Accounting Conservatism. *Contemporary Accounting Research* 25, 827-857.

Li, Z. 2014. Mutual Monitoring and Agency Problems. 2014. Working paper presented at the CFA-JCF-Schulich Conference on Financial Market Misconduct.

O'Brien, P. and R. Bhushan. 1990. Analyst Following and Institutional Ownership. *Journal of AccountinFg Research* 28, 55–76.

Palmrose, Z.V., V.J. Richardson and S. Scholz. 2004. Determinants of Market Reactions to Restatement Announcements. *Journal of Accounting & Economics* 37, 59-89.

Povel, P., R. Singh and A. Winton. 2007. Booms, Busts, and Fraud. *Review of Financial Studies* 20, 1219-1254.

Sherman, E. 1999. Underwriter Certification and the Effect of Shelf Registration on Due Diligence. *Financial Management* 28, 5–19.

Srinivasan, S. 2005. Consequences of Financial Reporting Failure for Outside Directors: Evidence from Accounting Restatements and Audit Committee Members. *Journal of Accounting Research* 43, 291-334.

Shleifer, A., Vishny, R.W., 1997. A Survey of Corporate Governance. *Journal of Finance* 52, 737-783.

Summers, S.L. and J.T. Sweeney. 1998. Fraudulently Misstated Financial Statements and Insider Trading: An Empirical Analysis. *The Accounting Review* 73, 131-46.

Sweeney, A.P. 1994. Debt-covenant Violations and Managers' Accounting Responses. *Journal of Accounting and Economics* 17, 281–308.

Teoh, S.H., I. Welch and T.J. Wong. 1998. Earnings Management and the Underperformance of Seasoned Equity Offerings. *Journal of Financial Economics* 50, 66-99.

U.S. Securities and Exchange Commission (SEC). Proposed Rule: Disclosure Required by 404, 406 and 407 of the Sarbanes-Oxley Act of 2002. U.S. Securities and Exchange Commission, 2002.

U.S. Securities and Exchange Commission (SEC). Final Rule: Disclosure Required by Sections 406 and 407 of the Sarbanes-Oxley Act of 2002. U.S. Securities and Exchange Commission, 2003a.

U.S. Securities and Exchange Commission (SEC). Final Rule: Standards Relating to Listed Company Audit Committees. U.S. Securities and Exchange Commission, 2003b.

Wang, T.Y. 2013. Corporate Securities Fraud: Insights from a New Empirical Framework. *Journal of Law, Economics and Organization* 29 (3), 535-568.

Wang, T.Y., A. Winton and X.Y. Yu. 2010. Corporate Fraud and Business Conditions: Evidence from IPOs. *Journal of Finance* 65, 2255-2292.

Wang, T.Y. and A. Winton. 2014. Product Market Interactions and Corporate Fraud. Working Paper. University of Minnesota.

Warfiled, T.D., J.J. Wild, and K.L. Wild. 1995. Managerial Ownership, Accounting Choices and Informativeness of Earnings. *Journal of Accounting and Economics* 20, 61-91.

Young, S. and E. Peng. 2013. An Analysis of Accounting Frauds and the Timing of Analyst Coverage Decisions and Recommendation Revisions: Evidence from the US, Working Paper.

Zhang, Y., J. Zhou and N. Zhou. 2007. Audit Committee Quality, Auditor Independence, and Internal Control Weaknesses. *Journal of Accounting and Public Policy* 26, 300–327.

Appendix A: Variable Definitions

Variable	Source	Definition
Ind. EPS Growth	I/B/E/S	= Industry median forecasted EPS growth. EPS growth = (Forecasted annual EPS / prior year realized EPS) – 1 Industries are defined based on the Fama–French 49 industry classification
Ind. Q	COMPUSTAT	= Industry median Tobin's Q. Q = (book value of assets + market value of equity−book value of equity) / book value of assets
% AE	Proxy Statements	= Industry median % of independent director with accounting expertise
Excess AE	Proxy Statements	= 1 for firm-level % AE greater than industry median; = 0 otherwise
ROA	COMPUSTAT	= Net income before extraordinary items / total assets.
Leverage	COMPUSTAT	= Long-term debt / total assets
Ex. Fin. Need	COMPUSTAT	= 1 if the firm's free cash flow is less than –0.5; = 0 otherwise. Free cash flow = (cash from operations – average capital expenditures during the previous three years) / current assets Cash from operations = earnings – accruals Accruals = change in current assets – change in current liabilities – change in cash/cash equivalents + change in debt included in current liabilities – depreciation and amortization expense
Insider Ownership	ExecuComp	% of shares owned by officers
Big N	COMPUSTAT	= 1 if the firm is audited by Big4 or Big5 auditors; = 0 otherwise.
M&A	COMPUSTAT	= M&A expenditure / total assets.
CAPX	COMPUSTAT	= Capital expenditure / total assets
R&D	COMPUSTAT	= R&D expenditure / total assets.
Log Asset	COMPUSTAT	= log (total book assets)
Analyst Coverage	I/B/E/S	= log (1 + total number of analyst following)
SOX		= 1 for 2002 and after; = 0 otherwise

Abnormal Restatement Risk	Audit Analytics GAO FSR	= yearly deviation from the average restatement risk in an industry. Restatement Risk = log (total market value of misstated firms in an industry-year)
Disastrous Stock Return	CRSP	= 1 if stock return is in the bottom 10% of all the firm-year return observations in the COMPUSTAT database; = 0 otherwise.
Abnormal Return Volatility	CRSP	= the difference between the yearly standard deviation of the firm's stock returns and its time-series average.
Abnormal Turnover	CRSP	= the difference between the monthly share turnover of the firm's stock returns and its time-series average.
ST-Compensation	ExecuComp	= Industry median short-term incentive. Short-term incentive = (salary + bonus + other annual compensation) / total expected compensation Total expected compensation = salary, bonus, other annual income + value of restricted stock granted + value of stock option grants + long-term incentive payouts + and all other total income
LT-Compensation	ExecuComp	= Industry median long-term incentive. Long-term incentive = (value of stock option grants + value of restricted stock granted) / total expected compensation
Prior ROA	COMPUSTAT	= Prior three-year average return on assets
Debt	COMPUSTAT	= Long-term debt / total assets
Sales Growth	COMPUSTAT	= Annual percentage change in sales
Board Size	Risk Metrics	= Natural logarithm of number of directors in the board
Capital Intensity	COMPUSTAT	= Total assets / number of employees
G Index	Risk Metrics	= An index developed by Gompers, Ishii, and Metriek (2003), measures the strength of a firm's governance system and is constructed based on a simple counting of 24 corporate governance provisions.
Earning Volatility	COMPUSTAT	= Earnings volatility for the past five years

Age	COMPUSTAT Prof. Jay Ritter’s Website	= Age of the firm from the date of listing in number of year
%AE_commit	Proxy Statements	= percentage of AE when misstatements begin
%AE_detect	Proxy Statements	= percentage of AE when misstatements were detected/announced
%AE_change	Proxy Statements	= change in percentage of AE between misstatement detection and commission (%AE_change =%AE_ detect less %AE_ commit)
IRR	Audit Analytics GAO FSR	= an indicator variable equal to 1 if the misstatement is intentional and 0 if the misstatement is unintentional
Core	Audit Analytics GAO FSR	= an indicator variable equal to 1 if revenue and/or expense was impacted by the restatement, and 0 otherwise
Length	Audit Analytics GAO FSR	= total number of years between the beginning of misstatements and their detection
SEC	Audit Analytics GAO FSR	= an indicator variable equal to 1 if the SEC prompted the restatement, and 0 otherwise
Prior_returns	CSRP	= prior year excess returns

Appendix B: Investor Beliefs, Accounting Experts and Predicted Executive Compensation

In Panel A, the dependent variable is firm-level ST Compensation in Model (1) and (3) and firm-level LT Compensation in Model (2) and (4). Firm EPS Growth is contemporaneous. All firm characteristics are lagged. Time Trend ranges from 1 to 15, where Time Trend = 1 for 1996 and 15 for 2010. Other variables are defined in Appendix A. Panel B reports bivariate probit regression results. The dependent variable is a dummy variable equal to Z=1 if a firm committed an irregularity (error) and then got caught later, zero otherwise. The estimation of misstatement propensity is indicated by P(M=1), and the estimation of misstatement detection likelihood by P(D=1|M=1). "Ind. Predicted ST Compensation" is the industry median of predicted value of Firm ST Compensation in Model (2) of Panel B. "Ind. Predicted LT Compensation" is the industry median of predicted value of Firm LT Compensation in Model (4) of Panel B. Other variables are defined in Appendix A. Control variables in P(M=1) and in P(D=1|M=1) are the same as previous tables and suppressed. Robust standard errors are clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A Determinants of Executive Compensation

	(1) Firm ST Compensation	(2) Firm LT Compensation
Firm EPS Growth	0.0051***	-0.0039**
	(0.0016)	(0.0016)
Sales growth	-0.0130**	0.0099*
	(0.0057)	(0.0059)
ROA	-0.0854***	0.0995***
	(0.0158)	(0.0164)
Stock Return	-0.0062***	0.0086***
	(0.0022)	(0.0023)
Tobin's Q	-0.0217***	0.0244***
	(0.0015)	(0.0015)
Log Asset	-0.0426***	0.0406***
	(0.0030)	(0.0031)
Time Trend	0.0010**	-0.0010**
	(0.0004)	(0.0004)
Constant	0.9187***	0.0229
	(0.0216)	(0.0224)
Firm Fixed Effect	Yes	Yes
Number of Firms	2,914	2,914
Observations	22,889	22,889
R-squared	0.5117	0.5127

Panel B: Monitoring, Executive Compensation and Irregularity Propensity

VARIABLES	(1) P(M)	(2) P(M)
Ind. EPS Growth	0.9271***	0.9822***
	(0.1731)	(0.1743)
Ind. EPS Growth Squared	-1.3199***	-1.3725***
	(0.3290)	(0.3264)
% AE	-0.8556**	-0.7378*
	(0.3884)	(0.3887)
Predicted ST Compensation	7.8017***	
	(0.8293)	
Predicted LT Compensation		-8.8445***
		(0.8794)
Control variables in P(M=1) and in P(D=1|M=1) (suppressed)		
Log Likelihood	-2660	-2647
Observations	26,231	26,231

Panel C: Monitoring, Executive Compensation and Error Propensity

VARIABLES	(1) P(M)	(2) P(M)
Ind. EPS Growth	0.3565***	0.3904***
	(0.0653)	(0.0639)
Ind. EPS Growth Squared	-0.0953	-0.1170
	(0.0801)	(0.0796)
% AE	-1.4800***	-1.4513***
	(0.1811)	(0.1807)
Predicted ST Compensation	4.0340***	
	(0.3526)	
Predicted LT Compensation		-4.6283***
		(0.3578)
Control variables in P(M=1) and in P(D=1|M=1) (suppressed)		
Log Likelihood	-8272	-8256
Observations	28,108	28,108

Table 1: Distribution of Accounting Misstatements and Percentage of Independent Directors with Accounting Expertise

This table presents the distribution of accounting misstatements and percentage of independent directors with accounting expertise. Irregularities (errors) are intentional (unintentional) accounting misstatements. Panel A displays time trend in accounting irregularities and errors in the COMPUSTAT-CRSP merged sample. N is the number of firms in a given year that committed irregularities (errors). Panel B shows time trend in the percentage of independent directors with accounting expertise in the S&P 1500 sub-sample.

Panel A: Distribution of Irregularities and Errors (full sample)

	Irregularities	**Errors**
Year of Commission	N	N
1996	50	55
1997	73	133
1998	77	171
1999	98	322
2000	118	405
2001	83	486
2002	66	460
2003	57	450
2004	62	399
2005	48	321
2006	22	263
2007	18	252
2008	26	222
2009	18	237
2010	14	184
Total(firm-years)	830	4,360

Panel B: Distribution of Percentage of Independent Directors with Accounting Expertise (S&P 1500 sub-sample)

Year	Irregularities			Errors		
	% AE			% AE		
	N	Mean	Median	N	Mean	Median
1996	10	0.0407	0	13	0.0333	0
1997	28	0.0551	0	34	0.0861	0
1998	32	0.1017	0	39	0.0795	0
1999	33	0.0567	0	88	0.0575	0
2000	50	0.0898	0	94	0.0765	0
2001	21	0.0592	0	120	0.0757	0
2002	17	0.0754	0	109	0.0814	0
2003	17	0.1257	0.1169	92	0.1304	0.1111
2004	15	0.1132	0.1250	81	0.1368	0.1222
2005	8	0.0823	0.0625	62	0.1808	0.2000
2006	2	0.1667	0.1667	43	0.1887	0.1667
2007	7	0.1964	0.1964	46	0.1934	0.1667
2008	3	0.1875	0.1875	59	0.2185	0.2500
2009	3	0.2250	0.2250	52	0.2356	0.2222
2010	10	0.2095	0.2000	44	0.2483	0.2500
Total(firm-years)	246			976		

Table 2: Descriptive Statistics

This table presents mean and median of variables for the control sample with no misstatements, irregularity sample and error sample. Irregularities (errors) are intentional (unintentional) accounting misstatements. Non-misstated firm-years are taken from the COMPUSTAT-CRSP merged sample after deleting firms that commit irregularities or errors during the sample period. All variables are defined in Appendix A. Panel B presents *t* statistics (*t*-stat) for mean differences and Wilcoxon *z* statistics (*z*-stat) for median differences. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Means and medians of variables for the non-misstated sample, irregularity sample and error sample

	(1) Control (firm-years)			(2) Irregularities (firm-years)			(3) Errors (firm-years)		
Variables	N	Mean	Median	N	Mean	Median	N	Mean	Median
Ind. EPS Growth	39,801	0.08	0.11	618	0.11	0.13	3,306	0.08	0.11
Ind. Q	39,801	1.55	1.37	618	1.61	1.38	3,306	1.52	1.35
ST Compensation	39,801	0.55	0.55	618	0.55	0.55	3,306	0.55	0.55
LT Compensation	39,801	0.38	0.38	618	0.38	0.38	3,306	0.39	0.38
% AE	39,801	0.07	0.00	618	0.04	0.00	3,306	0.07	0.00
Excess AE	8,707	0.39	0.00	175	0.30	0.00	828	0.39	0.00
ROA	39,801	-0.02	0.05	618	0.02	0.07	3,306	0.00	0.05
Leverage	39,801	0.17	0.10	618	0.20	0.14	3,306	0.19	0.13
Ext. Fin. Need	39,801	0.33	0.00	618	0.41	0.00	3,306	0.38	0.00
Insider Ownership	39,801	0.02	0.01	618	0.02	0.01	3,306	0.01	0.01
Big N	39,801	0.80	1.00	618	0.87	1.00	3,306	0.81	1.00
M&A	39,801	0.03	0.00	618	0.05	0.00	3,306	0.04	0.00
CAPX	39,801	0.06	0.03	618	0.07	0.04	3,306	0.07	0.04
R&D	39,801	0.00	0.00	618	0.00	0.00	3,306	0.00	0.00
Log Asset	39,801	5.81	5.71	618	6.06	5.91	3,306	5.87	5.82
Analyst Coverage	39,801	8.18	8.34	618	8.11	8.29	3,306	8.16	8.33
Abnormal Restatement Risk	39,801	-0.99	-0.75	618	-0.78	-0.75	3,306	0.39	0.37
Disastrous Stock Return	39,801	0.00	0.01	618	-0.01	0.00	3,306	-0.01	0.01
Abnormal Return Volatility	39,801	0.12	0.00	618	0.19	0.00	3,306	0.20	0.00
Abnormal Turnover	39,801	0.69	-0.71	618	2.06	-1.10	3,306	1.20	-0.69

Panel B - Tests for differences in means and medians of variables for the control sample (1), irregularity sample (2), and error sample (3)

	(1)–(2)		(1)–(3)		(2)–(3)	
Variables	*t*-stat	*z*-stat	*t*-stat	*z*-stat	*t*-stat	*z*-stat
Ind. EPS Growth	-3.61***	-6.05***	-0.38	-1.01	-3.13***	-5.23***
Ind. Q	-2.63***	-3.00***	3.31***	1.91*	-3.99***	-3.63***
ST Compensation	-1.08	-1.22	0.97	0.39	-1.39	-1.28
LT Compensation	1.58	1.60	-0.98	-0.82	1.86*	1.82*
% AE	8.95***	9.06***	4.94***	5.03***	6.63***	6.79***
Excess AE	2.54**	2.54**	-0.04	-0.04	2.37**	2.36**
ROA	-3.55***	-3.77***	-3.13***	1.16	-2.35**	-4.29***
Leverage	-3.30***	-4.13***	-5.51***	-6.17***	-0.74	-1.20
Ext. Fin. Need	-4.088***	-4.08***	-6.63***	-6.62***	-1.00	-1.00
Insider Ownership	-0.12	-4.08***	2.39**	-1.47	-1.37	-3.49***
Big N	-5.15***	-5.73***	-4.77***	-4.67***	-2.35**	-3.22***
M&A	-4.35***	-4.35***	-1.04	-1.04	-3.72***	-3.71***
CAPX	-3.25***	-6.10***	-4.52***	-7.10***	-1.07	-2.65***
R&D	6.05***	3.83***	2.92***	2.82***	3.39***	1.96*
Log Asset	-2.71***	-2.60***	-1.57	-2.58***	-2.02**	-1.36
Analyst Coverage	1.75*	3.15***	1.05	1.54	1.21	2.25**
Abnormal Restatement Risk	-1.61	-0.72	-24.27***	-20.70***	10.37***	8.62***
Disastrous Stock Return	1.03	1.00	0.12	-2.55***	0.84	1.81*
Abnormal Return Volatility	-4.93***	-4.92***	-13.12***	-13.09***	0.77	0.77
Abnormal Turnover	-2.26**	0.09	-1.92*	-1.76*	-1.24	0.68

Table 3: Investors Beliefs and Misstatement Propensity

The dependent variable is a dummy variable, Z equal to 1 if a firm committed an irregularity (error) and then got caught later, zero otherwise. The estimation of misstatement propensity is indicated by P(M=1), and the estimation of misstatement detection likelihood by P(D=1|M=1). All variables are defined in Appendix A. Coefficient estimates and standard errors (in parentheses) are reported. Standard errors are clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Irregularities

	(1)		(2)	
VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)
Ind. EPS Growth	0.4750***			
	(0.0916)			
Ind. EPS Growth Squared	-0.6660***			
	(0.1665)			
Ind. Q			0.4079***	
			(0.1332)	
Ind. Q Squared			-0.0785***	
			(0.0291)	
ROA	0.1491**		0.2195***	
	(0.0668)		(0.0757)	
Leverage	0.0469		0.0841	
	(0.0583)		(0.0653)	
Ext. Fin. Need	0.0340		0.0381	
	(0.0228)		(0.0239)	
Insider Ownership	0.5122**		0.5824*	
	(0.2374)		(0.3011)	
Big N	0.0591		0.0586	
	(0.0370)		(0.0394)	
M&A	0.3304**	-0.1457	0.3328**	-0.1239
	(0.1418)	(0.1592)	(0.1562)	(0.1702)
CAPX	1.0080***	-1.1852***	0.9362***	-1.1203***
	(0.2783)	(0.3662)	(0.2920)	(0.3712)
R&D	1.3700	-3.6538*	1.9945	-3.4592
	(4.5624)	(2.0720)	(4.8003)	(2.2836)
Log Asset	-0.1036***	0.1239***	-0.1029***	0.1294***
	(0.0163)	(0.0152)	(0.0201)	(0.0183)
Analyst Coverage	-0.0409	0.0814***	-0.0546*	0.0771**
	(0.0293)	(0.0284)	(0.0305)	(0.0303)
SOX	-2.5092***	4.2467	-2.5228***	3.4802***
	(0.0704)	(7.3890)	(0.0948)	(1.3125)
Abnormal Restatement Risk		0.0778***		0.0835***
		(0.0151)		(0.0197)
Disastrous Stock Return		0.4323***		0.4810***
		(0.1514)		(0.1697)
Abnormal Return Volatility		0.0376		0.0648
		(0.0385)		(0.0422)
Abnormal Turnover		0.0010		0.0008
		(0.0009)		(0.0009)
Constant	0.9683***	-1.2499***	0.6803*	-1.2750***
	(0.2670)	(0.2501)	(0.3472)	(0.2788)

Log Likelihood		-1986		-2003
Observations		25,103		25,103

Panel B: Errors

	(1)		(2)	
VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)
Ind. Q	0.1317			
	(0.1873)			
Ind. Q Squared	-0.0695			
	(0.0495)			
Ind. EPS Growth			0.1011	
			(0.0726)	
Ind. EPS Growth Squared			0.0452	
			(0.0884)	
ROA	0.0005		0.0499	
	(0.0644)		(0.0636)	
Leverage	0.2904***		0.3226***	
	(0.0862)		(0.0850)	
Ext. Fin. Need	0.1349***		0.1250***	
	(0.0301)		(0.0300)	
Insider Ownership	-0.6948		-0.5702	
	(0.5197)		(0.5013)	
Big N	-0.0300		-0.0469	
	(0.0433)		(0.0428)	
M&A	0.3019**	0.4118	0.2836**	0.4118
	(0.1414)	(0.2737)	(0.1407)	(0.2737)
CAPX	0.1403	-0.3656	0.1320	-0.3654
	(0.2081)	(0.2970)	(0.2092)	(0.2970)
R&D	-14.3096**	0.7139	-10.7894*	0.7142
	(5.6239)	(5.3865)	(5.6707)	(5.3863)
Log Asset	-0.0447***	0.0330***	-0.0403***	0.0330***
	(0.0095)	(0.0113)	(0.0094)	(0.0113)
Analyst Coverage	-0.0489***	0.0573**	-0.0538***	0.0573**
	(0.0180)	(0.0248)	(0.0179)	(0.0248)
SOX	-7.1798***	6.9551***	-4.0996***	1.2329***
	(0.0194)	(0.1318)	(0.1534)	(0.1594)
Abnormal Restatement Risk		0.4101***		0.4101***
		(0.0143)		(0.0143)
Disastrous Stock Return		1.0766***		1.0766***
		(0.2790)		(0.2790)
Abnormal Return Volatility		0.1062		0.1062
		(0.0769)		(0.0769)
Abnormal Turnover		-0.0019		-0.0019
		(0.0016)		(0.0016)
Constant	6.3362***	-0.9703***	3.2938***	-0.9703***
	(0.2057)	(0.2148)	(0.2271)	(0.2148)
Log Likelihood		-7489		-7500
Observations		27,329		27,329

Table 4: Investors Beliefs, Predicted Accounting Expertise and Misstatement Propensity

Panel A reports panel regression results of monitoring by independent directors with accounting expertise. The dependent variables are a) a dummy variable equal to 1 if the firm has any independent directors with accounting expertise and 0 otherwise in Model (1); and b) firm-level percentage of independent directors with accounting expertise in Model (2). All firm characteristics are lagged, and all variables are defined in Appendix A. Standard Errors are clustered at firm level. Panel B and Panel C report bivariate probit regression results. The dependent variable is a dummy variable Z equal to 1 if a firm committed an irregularity (error) and then got caught later, zero otherwise. The estimation of misstatement propensity is indicated by P(M=1), and the estimation of misstatement detection likelihood by P(D=1|M=1). "Ind. Predicted AE" is the industry median of predicted value of Firm % AE in Model (2) of Panel A. Standard errors are clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Determinants of Monitoring

VARIABLES	(1) Firm AE Dummy	(2) Firm % AE
Ind. EPS Growth	-0.0144	-0.0208***
	(0.0252)	(0.0045)
Log Asset	0.0770***	0.0112***
	(0.0228)	(0.0027)
Prior ROA	-0.3149**	-0.0980***
	(0.1335)	(0.0151)
Debt	0.0106	-0.0231***
	(0.0738)	(0.0089)
Sales growth	-0.0478*	0.0031
	(0.0258)	(0.0034)
Board Size	0.1358**	0.0022
	(0.0687)	(0.0078)
Capital Intensity	-0.0124	0.0007
	(0.0138)	(0.0014)
G Index	-0.0177	-0.0042***
	(0.0118)	(0.0012)
Earning Volatility	-0.0064	-0.0011
	(0.0137)	(0.0019)
Age	0.2986***	0.1454***
	(0.0474)	(0.0060)
SOX	0.1156***	0.0639***
	(0.0247)	(0.0029)
Constant	-0.9029***	-0.3489***
	(0.2079)	(0.0228)
Firm Fixed Effect	Y	Y
Number of Firms	1,066	1,066
Observations	6,485	6,485
R-squared	0.687	0.8259

Panel B: Predicted Accounting Expertise and Irregularity Propensity

	(1)		(2)		(3)	
VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)	P(M)	P(D|M)
Ind. EPS Growth	0.4781***		0.4632***		0.4535***	
	(0.1181)		(0.1182)		(0.1203)	
Ind. EPS Growth Squared	-0.8186***		-0.8069***		-0.7946***	
	(0.1974)		(0.1892)		(0.1862)	
Predicted % AE	-0.9527*		-0.9874*		-1.1415**	
	(0.5773)		(0.5673)		(0.5655)	
ST Compensation			0.8858***			
			(0.2270)			
LT Compensation					-0.9843***	
					(0.2096)	
ROA	0.1630**		0.1187		0.1198	
	(0.0828)		(0.0824)		(0.0834)	
Leverage	0.1786*		0.1514		0.1439	
	(0.0965)		(0.0957)		(0.0943)	
Ext. Fin. Need	0.0288		0.0382		0.0386	
	(0.0369)		(0.0367)		(0.0365)	
Insider Ownership	10.1046***		7.0947***		7.2738***	
	(2.2240)		(2.2850)		(2.2575)	
Big N	0.0611		0.0616		0.0694	
	(0.0556)		(0.0552)		(0.0550)	
M&A	0.3198	0.0832	0.3174	0.0759	0.3148	0.0570
	(0.2290)	(0.2983)	(0.2205)	(0.2855)	(0.2194)	(0.2790)
CAPX	1.0435***	-1.2569***	1.0556***	-1.2857***	1.0035***	-1.2444***
	(0.3242)	(0.4143)	(0.3157)	(0.4091)	(0.3149)	(0.4128)
R&D	-15.2419	4.4442	-15.4920*	3.9066	-16.1128*	3.7349
	(9.5558)	(4.3149)	(9.3970)	(4.1702)	(9.4154)	(4.1481)
Log Asset	-0.0741***	0.1133***	-0.0728***	0.1114***	-0.0751***	0.1119***
	(0.0197)	(0.0167)	(0.0190)	(0.0163)	(0.0185)	(0.0161)
Analyst Coverage	-0.0347	0.0929**	-0.0178	0.1247***	0.0007	0.1209***
	(0.0316)	(0.0362)	(0.0317)	(0.0368)	(0.0320)	(0.0365)
SOX	-2.5678***	6.1722***	-2.6132***	6.3445***	-2.6037***	5.9512***
	(0.1267)	(0.8613)	(0.1187)	(0.7410)	(0.1120)	(1.4732)
Abnormal Restate Risk		0.1713***		0.1745***		0.1770***
		(0.0360)		(0.0326)		(0.0306)
Disastrous Stock Return		0.5759**		0.5178**		0.5228**
		(0.2725)		(0.2633)		(0.2613)
Abnormal Volatility		0.1261*		0.1223*		0.1236*
		(0.0654)		(0.0634)		(0.0634)
Abnormal Turnover		0.0011		0.0014		0.0014
		(0.0012)		(0.0012)		(0.0012)
Constant	1.1329***	-1.4661***	0.6015	-1.6994***	1.3891***	-1.6649***
	(0.3914)	(0.3502)	(0.3841)	(0.3512)	(0.3873)	(0.3445)
Log Likelihood		-1801		-1791		-1786
Observations		24,790		24,790		24,790

Panel C: Predicted Accounting Expertise and Error Propensity

	(1)		(2)		(3)	
VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)	P(M)	P(D|M)
Ind. EPS Growth	0.1426*		0.1474*		0.1403*	
	(0.0802)		(0.0827)		(0.0811)	
Ind. EPS Growth Squared	0.0813		0.0956		0.0829	
	(0.0868)		(0.0860)		(0.0863)	
Predicted % AE	0.0101		-0.1492		-0.1517	
	(0.5194)		(0.5337)		(0.5325)	
ST Compensation			0.4346*			
			(0.2434)			
LT Compensation					-0.2611	
					(0.2005)	
ROA	0.0084		-0.0089		-0.0021	
	(0.0651)		(0.0656)		(0.0654)	
Leverage	0.2899***		0.2844***		0.2856***	
	(0.0880)		(0.0883)		(0.0881)	
Ext. Fin. Need	0.1232***		0.1256***		0.1239***	
	(0.0318)		(0.0320)		(0.0319)	
Insider Ownership	4.0928*		3.6769		4.2134*	
	(2.3802)		(2.3836)		(2.3891)	
Big N	-0.0422		-0.0406		-0.0396	
	(0.0439)		(0.0441)		(0.0441)	
M&A	0.3137**	-0.0745	0.3192**	-0.0749	0.3190**	-0.0747
	(0.1425)	(0.4053)	(0.1427)	(0.4055)	(0.1426)	(0.4054)
CAPX	0.2668	-0.9754**	0.2819	-0.9769**	0.2676	-0.9759**
	(0.2153)	(0.4297)	(0.2154)	(0.4301)	(0.2153)	(0.4299)
R&D	-11.0862*	10.1858	-11.7331**	10.1936	-11.6227**	10.1876
	(5.6843)	(6.4930)	(5.6938)	(6.4954)	(5.6852)	(6.4940)
Log Asset	-0.0344***	0.0316*	-0.0344***	0.0316*	-0.0349***	0.0316*
	(0.0102)	(0.0162)	(0.0102)	(0.0162)	(0.0102)	(0.0162)
Analyst Coverage	-0.0518**	0.1548**	-0.0398*	0.1551**	-0.0409*	0.1549**
	(0.0202)	(0.0669)	(0.0211)	(0.0670)	(0.0219)	(0.0669)
SOX	-6.9040***	6.9405***	-4.8369***	6.9185***	-5.1342**	6.9669***
	(1.1907)	(0.2949)	(1.5966)	(0.2969)	(2.3461)	(0.3061)
Abnormal Restate Risk		0.5160***		0.5162***		0.5161***
		(0.0315)		(0.0317)		(0.0316)
Disastrous Stock Return		1.3018***		1.3029***		1.3022***
		(0.4021)		(0.4025)		(0.4023)
Abnormal Volatility		0.0497		0.0496		0.0497
		(0.1040)		(0.1040)		(0.1040)
Abnormal Turnover		-0.0032*		-0.0032*		-0.0032*
		(0.0017)		(0.0017)		(0.0017)
Constant	5.9865***	-1.5420***	3.6606**	-1.5434***	4.3058*	-1.5425***
	(1.3434)	(0.5359)	(1.7871)	(0.5362)	(2.4254)	(0.5361)
Log Likelihood		-7233		-7230		-7232
Observations		26,938		26,938		26,938

Table 5: Investors Beliefs, Accounting Expertise and Misstatement Propensity

The dependent variable is a dummy variable, Z equal to1 if a firm committed an irregularity (error) and then got caught later, zero otherwise. The estimation of misstatement propensity is indicated by P(M=1), and the estimation of misstatement detection likelihood by P(D=1|M=1). All variables are defined in Appendix A. Coefficient estimates and standard errors (in parentheses) are reported. Standard errors are clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Irregularities

	(1)		(2)	
VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)
Ind. EPS Growth	0.4384***		0.4189***	
	(0.1318)		(0.1319)	
Ind. EPS Growth Squared	-0.8125***		-0.7884***	
	(0.1792)		(0.1733)	
Predicted % AE*Q1_EPS	-0.1088		-0.2576	
	(0.8085)		(0.8098)	
Predicted % AE*Q2_EPS	-1.1578**		-1.2100**	
	(0.5750)		(0.5519)	
Predicted % AE*Q3_EPS	-0.5471		-0.5902	
	(0.6319)		(0.6214)	
Predicted % AE*Q4_EPS	-2.5011***		-2.4807***	
	(0.4824)		(0.4772)	
Predicted % AE*Q5_EPS	-1.6162***		-1.6531***	
	(0.4854)		(0.4838)	
ST Compensation	0.9354***			
	(0.2375)			
LT Compensation			-0.9440***	
			(0.2218)	
ROA	0.1315		0.1373	
	(0.0843)		(0.0865)	
Leverage	0.0788		0.0702	
	(0.1171)		(0.1179)	
Ext. Fin. Need	0.0258		0.0248	
	(0.0367)		(0.0368)	
Insider Ownership	8.8824***		9.3773***	
	(2.2833)		(2.2873)	
Big N	0.0343		0.0431	
	(0.0538)		(0.0541)	
M&A	0.3407	0.0292	0.3338	
	(0.2134)	(0.2707)	(0.2125)	
CAPX	1.1658***	-1.2938***	1.1145***	
	(0.3031)	(0.4188)	(0.3045)	
R&D	-14.8401*	3.8485	-15.6202*	
	(8.9178)	(3.8805)	(9.0202)	
Log Asset	-0.0717***	0.1110***	-0.0745***	
	(0.0190)	(0.0164)	(0.0189)	
Analyst Coverage	-0.0104	0.1204***	0.0080	
	(0.0315)	(0.0371)	(0.0320)	
SOX	-2.5915***	6.2292***	-2.5943***	5.9673***
	(0.1173)	(0.7559)	(0.1149)	(1.7044)

Table 5 Panel A (continued)

Abnormal Restatement Risk		0.1680***		0.1700***
		(0.0292)		(0.0280)
Disastrous Stock Return		0.4150		0.4156

Table 5 Panel A (continued)

		(0.2588)		(0.2604)
Abnormal Return Volatility		0.1076*		0.1093*
		(0.0627)		(0.0630)
Abnormal Turnover		0.0013		0.0013
		(0.0012)		(0.0011)
Constant	0.2046	-1.6659***	0.9511***	-1.6026***
	(0.3116)	(0.3288)	(0.2828)	(0.3232)
Log Likelihood		-1784		-1781
Observations		24,921		24,921

Panel B: Errors

VARIABLES	P(M)	P(D|M)	P(M)	P(D|M)
Ind. EPS Growth	-0.0317		-0.0336	
	(0.0964)		(0.0930)	
Ind. EPS Growth Squared	0.0452		0.0486	
	(0.0933)		(0.0921)	
Predicted % AE*Q1_EPS	-0.5773		-0.6365*	
	(0.3753)		(0.3326)	
Predicted % AE*Q2_EPS	-0.2838		-0.1770	
	(0.3668)		(0.3314)	
Predicted % AE*Q3_EPS	-0.9337***		-0.9184***	
	(0.2959)		(0.2849)	
Predicted % AE*Q4_EPS	0.1114		0.1116	
	(0.2893)		(0.2839)	
Predicted % AE*Q5_EPS	-0.3854		-0.3731	
	(0.3329)		(0.3258)	
ST Compensation	0.5681**			
	(0.2314)			
LT Compensation			-0.2731	
			(0.2313)	
ROA	-0.0258		-0.0240	
	(0.0660)		(0.0659)	
Leverage	0.2778***		0.2813***	
	(0.0888)		(0.0888)	
Ext. Fin. Need	0.1250***		0.1256***	
	(0.0315)		(0.0314)	
Insider Ownership	3.3094		3.3318	
	(2.2988)		(2.3044)	
Big N	-0.0475		-0.0470	
	(0.0440)		(0.0440)	
M&A	0.3446**	0.3139	0.3451**	0.3139
	(0.1419)	(0.3115)	(0.1419)	(0.3115)
CAPX	0.2673	-0.4287	0.2645	-0.4287
	(0.2144)	(0.3545)	(0.2142)	(0.3545)
R&D	-11.5298**	7.2496	-11.6173**	7.2508
	(5.6698)	(6.0314)	(5.6659)	(6.0312)
Log Asset	-0.0328***	0.0152	-0.0333***	0.0153
	(0.0098)	(0.0151)	(0.0098)	(0.0151)
Analyst Coverage	-0.0335	0.0318	-0.0347	0.0318
	(0.0217)	(0.0347)	(0.0216)	(0.0347)
SOX	-5.4026***	6.8977***	-5.3627***	6.7689***
	(1.5061)	(0.1624)	(1.4203)	(0.1522)
Abnormal Restatement Risk		0.5133***		0.5133***
		(0.0235)		(0.0235)
Disastrous Stock Return		0.7812**		0.7812**
		(0.3283)		(0.3283)
Abnormal Return Volatility		0.1637*		0.1637*
		(0.0847)		(0.0847)
Abnormal Turnover		-0.0024		-0.0024
		(0.0017)		(0.0017)
Constant	4.0973**	-0.6214**	4.0641***	-0.6215**
	(1.6336)	(0.2779)	(1.5473)	(0.2779)
Log Likelihood		-7096		-7095
Observations		26,888		26,888

Table 6: Investors Beliefs, Excess Accounting Expertise and Misstatement Propensity

The dependent variable is a dummy variable, Z equal to 1 if a firm committed an irregularity (error) and then got caught later, zero otherwise. The estimation of misstatement propensity is indicated by P(M=1), and the estimation of misstatement detection likelihood by P(D=1|M=1). All variables are defined in Appendix A. Coefficient estimates and standard errors (in parentheses) are reported. Control variables in P(M=1) and in P(D=1|M=1) are the same as previous tables and suppressed. Standard errors are clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Irregularities

VARIABLES	(1) P(M)	(2) P(M)
Ind. EPS Growth	0.1111**	0.1496**
	(0.0494)	(0.0741)
Ind. EPS Growth Squared	-0.2633**	-0.2236**
	(0.1120)	(0.1012)
Excess AE	-0.0145***	
	(0.0041)	
Excess AE*Q1_EPS		0.0515
		(0.0582)
Excess AE*Q2_EPS		-0.0795*
		(0.0439)
Excess AE*Q3_EPS		-0.0203**
		(0.0103)
Excess AE*Q4_EPS		-0.0067
		(0.0047)
Excess AE*Q5_EPS		-0.0233**
		(0.0118)
Control variables in P(M=1) and in P(D=1|M=1) (suppressed)		
Log Likelihood	-505	-503
Observations	6,780	6,780

Panel B: Errors

VARIABLES	(1) P(M)	(2) P(M)
Ind. EPS Growth	0.3285*	0.2577
	(0.1865)	(0.2018)
Ind. EPS Growth Squared	-0.6214	-0.6434
	(0.5046)	(0.4774)
Excess AE	0.0633	
	(0.0553)	
Excess AE*Q1_EPS		0.0159
		(0.1226)
Excess AE*Q2_EPS		0.0923
		(0.1009)
Excess AE*Q3_EPS		0.0171
		(0.1075)
Excess AE*Q4_EPS		0.0502
		(0.0888)
Excess AE*Q5_EPS		0.1355
		(0.0921)
Control variables in P(M=1) and in P(D=1|M=1) (suppressed)		
Log Likelihood	-1872	-1875
Observations	7,358	7,358

Table 7: Market Reactions to Restatement Announcements

This table presents mean and median cumulative abnormal returns (CAR) over three (five) days surrounding the announcement of restatements for the misstated firms drawn from the S&P 1500 sample. Panel A shows CAR for the misstatement sample, irregularity sample and error sample. Irregularities (errors) are intentional (unintentional) accounting misstatements. Panel B compares CAR for firms with above-median and below-median percentage of accounting expertise (AE). AE_commit is percentage of AE when misstatements begin. AE_detect is percentage of AE when misstatements are detected. N denotes the number of firm-year observations. *t*-stat is *t* statistics for mean difference. *z*-stat is Wilcoxon *z* statistics for median difference. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Abnormal Returns: Irregularities versus Errors

		N	CAR (-2,2)	CAR (-1,1)
Misstatement	Mean	1,005	-0.0196	-0.0193
Sample (1)+(2)	Median	1,005	-0.0072	-0.0075
(1) Irregularities	Mean	159	-0.0563	-0.0604
	Median	159	-0.0297	-0.0327
(2) Errors	Mean	846	-0.0126	-0.0116
	Median	846	-0.0044	-0.0044
Difference (1)-(2)	*t*-stat		-5.69***	-5.68***
	z-stat		-5.23***	-4.92***

Panel B: Abnormal Returns based on Accounting Expertise

		N	Window (-2,2)	Window (-1,1)
(1) %AE_ commit	Mean	520	-0.029	-0.027
Low	Median	520	-0.012	-0.011
(2) %AE_commit	Mean	485	-0.011	-0.003
High	Median	485	-0.010	-0.002
(3) %AE_ detect	Mean	541	-0.024	-0.023
Low	Median	541	-0.090	-0.009
(4) %AE_detect	Mean	464	-0.014	-0.015
High	Median	464	-0.005	-0.003
Difference (1)-(2)	*t*-stat		-3.02***	-2.77***
	z-stat		-3.064***	-3.113***
Difference (3)-(4)	*t*-stat		-1.94**	-1.39
	z-stat		-1.56	-1.55

Table 8: Accounting Expertise and Market Reaction to Accounting Restatements

The dependent variable is cumulative abnormal return (CAR) within 3 days around accounting restatements. All variables are defined in Appendix A. Coefficient estimates and robust standard errors (in parentheses) are reported. N denotes the number of firm-year observations. Control variables in Panel B are the same as Panel A and suppressed. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Panel A: Accounting Expertise Measured by % AE

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CAR (-1,1)	CAR (-1,1)	CAR (-1,1)	CAR (-1,1)	CAR (-1,1)	CAR (-1,1)
%AE_commit	0.0333***	0.0367***				
	(0.0120)	(0.0128)				
%AE_commit*IRR		-0.0265				
		(0.0353)				
%AE_detect			0.0221**	0.0201*		
			(0.0108)	(0.0116)		
%AE_detect*IRR				0.0151		
				(0.0321)		
%AE_change					-0.0147	-0.0297
					(0.0189)	(0.0207)
%AE_change*IRR						0.0819*
						(0.0460)
IRR	-0.0240***	-0.0222***	-0.0242***	-0.0256***	-0.0248***	-0.0263***
	(0.0040)	(0.0047)	(0.0040)	(0.0049)	(0.0040)	(0.0041)
Core	-0.0014	-0.0014	-0.0019	-0.0020	-0.0023	-0.0024
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Length	0.0001	0.0001	-0.0003	-0.0003	-0.0000	-0.0000
	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
SEC	0.0168***	0.0172***	0.0172***	0.0170***	0.0166***	0.0169***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Leverage	-0.0011	-0.0013	-0.0018	-0.0017	-0.0033	-0.0033
	(0.0084)	(0.0084)	(0.0084)	(0.0084)	(0.0084)	(0.0084)
Log_Assets	0.0031***	0.0031***	0.0030***	0.0030***	0.0030***	0.0030***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Prior_returns	0.0007	0.0006	0.0007	0.0008	0.0006	0.0007
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
Constant	-0.0369***	-0.0371***	-0.0341***	-0.0339***	-0.0315***	-0.0313***
	(0.0094)	(0.0094)	(0.0093)	(0.0093)	(0.0092)	(0.0092)
Observations	981	981	981	981	981	981
R-squared	0.0560	0.0566	0.0526	0.0528	0.0491	0.0522

Panel B: Accounting Expertise Measured by Excess AE

VARIABLES	(1) CAR (-1,1)	(2) CAR (-1,1)	(3) CAR (-1,1)	(4) CAR (-1,1)
Excess AE_commit	0.0063***	0.0074***		
	(0.0024)	(0.0026)		
Excess AE_commit*IRR		-0.0075		
		(0.0068)		
Excess AE_detect			0.0060**	0.0049*
			(0.0024)	(0.0026)
Excess AE_detect*IRR				0.0079
				(0.0067)
IRR	-0.0234***	-0.0211***	-0.0216***	-0.0243***
	(0.0038)	(0.0044)	(0.0038)	(0.0044)
Control variables (suppressed)				
Constant	-0.0339***	-0.0343***	-0.0287***	-0.0283***
	(0.0091)	(0.0091)	(0.0088)	(0.0088)
Observations	1,037	1,037	1,083	1,083
R-squared	0.0544	0.0555	0.0428	0.0441