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Authors
Kim, Young-An
Wo, James C
Hipp, John R

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Young-An Kim

James Wo

John R. Hipp

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Abstract

Although prior studies have examined the association between the presence of various types of business facilities and crime in place, less attention has been paid to how the effects of businesses can be temporally different based on their age. We focus on four consumer-facing business types: 1) retail, 2) service, 3) restaurant, and 4) food and drug stores. For each type, we construct block level measures of the number of businesses, the average business age, and the standard deviation of business age. We estimate fixed-effects negative binomial regression models to test the effects of these measures on crime in blocks, controlling for a range of factors known to be associated with crime rates. The average age of businesses was robustly associated with lower crime rates. Additionally, the crime-reducing effect of older businesses was most pronounced in blocks with a greater business presence.

Keywords: Crime; Place; Businesses; Temporal effects

Estimating Age-graded Effects of Businesses on Crime in Place

Introduction

A large body of research by criminologists has explored the relationship between the presence of businesses and levels of crime at a point in time. Whereas one school of thought posits that businesses provide crime opportunities that will result in more crime nearby, another perspective is that some shop owners can provide guardianship and thus reduce nearby crime. However, the association between businesses and crime in place may not be stable but temporally dynamic and thus the effects of newer businesses on crime may operate differently in comparison to older businesses. This possibility necessitates accounting for the age of businesses in relation to crime. A consequence is that the question of whether a business is crime-producing, or crime-reducing might be overly simplistic. Unfortunately, little research has explored the long-term effects of the presence of various types of businesses on the spatial patterns of crime.

Whereas prior studies have examined the association between the presence of various types of business facilities and crime, and found that business facilities can operate as crime generators or attractors (Bernasco & Block, 2011; Brantingham & Brantingham, 1995; Brantingham & Brantingham, 1993; J. B. Kinney et al., 2008; McCord et al., 2007) or as third places (Carr, 1992; Hickman, 2013; Oldenburg, 1991, 1999; Williams & Hipp, 2019), less attention has been paid to how the effects of businesses can be temporally different based on their age. Although a few recent studies have examined both the spatial and temporal patterns of crime (Haberman & Ratcliffe, 2015; Hipp & Kim, 2019), these studies typically focus on the short-term temporal effects, such as hours of the day and days of the week. In contrast, we focus more on the crime-enhancing (or crime-reducing) effects of business facilities over a longer period of time. This idea is based on the organizational life course literature (Kimberly & Miles, 1980; Miller & Friesen, 1983; Miller & Friesen, 1984; Quinn & Cameron, 1983; Whetten, 1987) and business life cycle literature (Adizes, 1989; Beverland & Lockshin, 2001; Churchill & Lewis, 1983; Miller & Friesen, 1984; Parnell et al., 2003; Scott & Bruce, 1987) that business facilities can undergo long-term changes of growth and decline which, in turn, might bring about changes in the business situations, and thus the surrounding landscapes.

In the current study, we examine the long-term temporal effects of consumer-facing business facilities (i.e., retail, service, restaurant, and food/drug store businesses) on crime in Census blocks while controlling for other socio-structural characteristics of blocks. Our study site is the urban area within Los Angeles County as a part of the Los Angeles-Long Beach-Anaheim Urbanized Area (UA) defined by the Census bureau. In the subsequent sections, we discuss the theoretical motivations of the current study and our methodological approach.

Business Facilities and Crime in Place

Theories of criminal opportunities suggest that different environments create different criminal opportunities due to the probability of the mixture of motivated offenders, suitable targets, and the presence or absence of capable guardians at the same time and place (Cohen & Felson, 1979; Felson, 1987; Felson & Boba, 2010). Specifically, these theories view certain business facilities as criminogenic because they induce a high volume of foot traffic which, in turn, may present a high probability for a potential offender and suitable target to converge, absent of capable guardianship. According to The Brantinghams (1984; 1995), certain types of business facilities (e.g., shopping centers, malls, schools, hotels, etc.) are seen to be crime generators because they draw a large number of people into places, some of whom may be potential offenders or victims. Other types of facilities are classified as crime attractors because of their known reputations for criminal opportunities. Previous studies have analyzed business facilities and have consistently found their crime-producing effects (Bernasco & Block, 2011; Block & Block, 1995; Brantingham & Brantingham, 1995; Brantingham & Brantingham, 2017; Brantingham et al., 2016; B. Kinney et al., 2008; Kubrin & Hipp, 2016).

Although these studies theorized and revealed the criminogenic effects of businesses at places, another body of studies argues that business facilities at places potentially contribute to *lower* crime rates through their ability to stimulate prosocial interaction and ties among residents, thereby resulting in high levels of informal social control (Carr, 1992; Carr et al., 1992; Oldenburg, 1999). Oldenburg (1999) refers to them as third places (e.g., restaurants, bars, coffee shops, cafes, ice cream parlors, pizza parlors, etc.) that afford the informal settings capable of increasing social ties and cohesion among individuals.

Previous studies have empirically found that third places can reduce crime in place (Papachristos et al., 2011; Wo, 2014). For example, in a longitudinal study, Papachristos et al. (2011) showed that third places have crime-reducing effects. Specifically, the authors determined that their measure of third places–the presence of coffee shops—is related to lower homicide rates in Chicago neighborhoods. Also, Wo (2014) constructed an index of third places by combining the number of employees of coffee shops, cafes, bagel and doughnut shops, pizza parlors, ice cream paroles, diners, and snack and beverage shops.

He hypothesized and found that neighborhoods with more third-place employees have lower crime rates in neighborhoods across nine US cities.

Long-term Temporal Dynamics: Life Course of Businesses

Although previous studies demonstrate that the presence of businesses is an important factor for understanding crime in place, there has been relatively less research investigating the timing by which businesses might have criminogenic and/or protective effects, specifically the *age* of business facilities. However, business facilities are likely to experience changes over time in terms of the type and number of customers visiting, the number of employees, financial status, or the locations (Kimberly & Miles, 1980; Miller & Friesen, 1983; Miller & Friesen, 1984; Quinn & Cameron, 1983; Whetten, 1987). Specifically, the business life cycle literature suggests that business facilities go through life courses or cycles (stages) of birth, growth, and death (Adizes, 1989; Beverland & Lockshin, 2001; Churchill & Lewis, 1983; Miller & Friesen, 1984; Parnell et al., 2003; Scott & Bruce, 1987). Therefore, businesses might differentially impact crime in place based on their age. Stated alternatively, “older” businesses might impact crime differently in comparison to “newer” businesses.

Miller and Friesen (1984) noted that there are five phases of business development over time: (1) Birth, (2) Growth, (3) Maturity, (4) Decline, and (5) Death or Revival. In the *Birth* phase, a business facility is newly established and starts providing products or services and acquiring customers. In this stage, business owners tend to manage everything related to the business with one or a few employees because the business facilities are not financially stable and less likely to have many customers yet. Business facilities go into a *Growth* phase as the number of customers and sales begin to expand. Businesses at this stage have more opportunities to emerge and draw higher volumes of customers while confronting issues such as competition and effective management, all of which requires more employees as well as systematic strategies to manage both increased sales, customers, and employees.

In the *Maturity* phase, a business has a firmly stable position in the market with loyal customers and steady sales among other competitors. A business is at the apex of the business life course in terms of the number of customers and employees and volume of sales. However, as a business grows older, without an appropriate strategy to improve productivity or if it fails to adapt in the market for changes of economy, society, or market conditions, it goes into the *Decline* phase. Businesses in the decline stage of the life cycle will face challenges such as losing customers and employees and dropping sales, although it may happen slowly.

Business owners confront the decision of whether it is time to move into the final stage (*Death*) or transition to a new-born stage (*Revival*). The *revival* phase can be characterized by the reversal of decline through reinvigorated tactics (new goods and services) to re-grow in the markets to draw customers to the business again. Finally, a business facility faces the *Death* phase when the owner is not willing or fails to revive a business with steadily declining revenues, and finally decides to shut it down.

Note that this five-stage life course might not explain all businesses given that some might very quickly fail/die. Or some might become immediately successful with hardly any decline phase until far into the future. In other words, the existing literature posits that businesses might experience all five stages or some combination of the detailed stages. Although we recognize that there may be some variations by business types, we attempt to layout a more general theoretical framework in terms of business life courses that all businesses might experience over time.

Life Course of Business and Crime in Place

Businesses might differentially impact crime in place based on their age and life course. We therefore posit that the age of businesses might have important consequences for crime rates. Age of business matters for understanding the spatial patterns of crime because criminal opportunities and capable guardianship of an area can vary with the stages/cycles of the life course. We next outline two theoretical scenarios for how the temporal dynamics of businesses can have important consequences for crime in place.

First Scenario: Criminal Opportunities Perspective

The life course of businesses may be important for understanding the *level of criminal opportunities* in place because more business activities would have more criminal opportunities given that they have more people visiting the place including potential offenders and targets at the same time and place. If businesses indeed undergo several stages of life cycles, it is critical to consider how the well-known effects of businesses on criminal opportunities can change at different business life cycles over time. Particularly, a business facility will have different numbers of customers throughout the life course, which implies that the ambient population or the volume of foot traffic visiting the business and the place can temporally vary.[1] Indeed, empirical evidence suggests that business age is associated with the business performance including annual sales, employment growth rates, and numbers of employees (Lester et al., 2008; Shim et al., 2000; Yazdanfar & Öhman, 2014). These are plausible factors closely related to the magnitude of people moving in-and-out based on the assumption that larger business facilities tend to have more employees, thus more customers visiting the places. Given the argument of criminal opportunities theories that the number of people coming in-and-out can affect the probability of the convergence of potential offenders and targets, the level of crime derived from the presence of businesses in place should vary over time.

Specifically, in the first scenario, there could be higher levels of criminal opportunities (and thus crime) if business facilities are in the *growth* or *maturity* stage given that businesses at such stages tend to have higher volume of foot traffic compared to businesses of other stages. Businesses at these stages are more likely to be active so they draw more customers for further growth by providing various types of products and services for the customers to stabilize the business environments. This increases the probability of the convergence of potential offenders and targets at the same time and place. Furthermore, over the life course these same business facilities may lose customers as they go into the *decline* or *death* stage. There may be lower foot traffic into the area, which potentially weakens the criminogenic effects of businesses in place. Therefore, we expect an inverted U-shaped association between the age of businesses and criminal opportunities (and crime) in place where crime-enhancing

[1] Our data empirically indicated that there are non-trivial changes in the average number of employees by age of businesses. Specifically, the number of business employees initially increases at a birth-to-grow stage (0-5 years). Then, it decreases as a business grows and becomes relatively older (5-10 years). However, the number of employees increases again as a business goes into the maturity stage (11-16 years).

effects can be observed as foot traffic begins slowly, increases, peaks, and then falls as businesses go through each stage of life course (birth, growth, maturity, decline, and death). Figure 1a describes this scenario. Note that Figure 1a illustrates this general theoretical scenario, which may or may not be experienced by all businesses. It implies that the crime-enhancing effect of a certain business can be different in magnitude over time, which may not be fully captured by a cross-sectionally designed study. As such, we pose the hypotheses as follows:

H1-1. An increase in business age in blocks will be associated with higher risk of crime due to more criminal opportunities from increased foot traffic.

H1-2. This crime-enhancing effect will be reduced in magnitude or even reversed in blocks with very old businesses (decline or death) due to reduced criminal opportunities from decreased foot traffic.

<<< Figure 1 about here >>>

Second Scenario: Guardianship Perspective

The life course of businesses is also potentially important for understanding the *level of guardianship* in place. Level of guardianship and natural surveillance can be consequences of the volumes of customers and employees, and these characteristics likely vary over the life course of businesses in place; the implication is that the relationship between business facilities and crime in place will likely vary over the life course of businesses. Jacobs (1961) argued that areas with high volumes of people tend to have more “eyes on the streets,” which can lower the risk of crime due to increased levels of natural surveillance. Also, busier areas with more people coming in-and-out can be a locus of public social interaction between people regularly visiting the place such as residents, business owners, and employees. Consequently, “active streets will have a web of public respect and trust formed over time from many brief public sidewalk contacts” (Jacobs, 1961:56). Moreover, in small scale social communities such as blocks (behavior settings), people know each other, get familiar with others’ routines, develop and share their own norms (Taylor, 1997; Wicker, 1987). Therefore, “on a block where residents are better acquainted with neighbors, residents experience more control, easier recognition of outsiders, and fewer problems, and they report feeling more responsible for events” (Taylor, 1997:121).

In addition, Jacobs (1961) suggested that shopkeepers can also play an active role in preventing neighborhood problems. She stated that “storekeepers and other small businessmen are typically strong proponents of peace and order themselves; they hate broken windows and holdups; they hate having customers made nervous about safety” (Jacobs, 1961:37). Indeed, studies have posited that place managers such as business employees and shopkeepers can play important roles for keeping the neighborhood safe as controllers of places particularly during working hours (Clarke, 1997; Felson & Boba, 2010). For example, Eck and Weisburd (1995) emphasized the role of a ‘place manager’ who is professionally responsible for the surveillance of a place such as a security guard, store clerk, doorman, or parking lot attendant. Clarke (1992) argued that business employees can play even more important roles than local residents for keeping the neighborhood safe during working hours. In sum, these studies implied that there would be lower risk of crime if there are more active business employees in place.

Business Age

The enhanced number of eyes on the street from more visitors and employees could facilitate the natural surveillance in the area, and thus *reduce* crime in place. As stated above, businesses at the *growth* or *maturity* stage tend to increase the potential foot traffic into the area. Unlike the theoretical proposition drawing on criminal opportunities, this would result in a reduced level of crime if a certain business is at the *growth* or *maturity* stage due to more eyes on the street from more customers visiting the area and employees to serve them. Furthermore, as businesses grow older, business customers visiting the area may tend to be more local and have closer personal relationships with the owners and employees. These customers may care more about the safety of the area where the businesses are located because the businesses would comprise a considerable portion of their daily routine activities.

Moreover, owners and employees of older businesses generally have worked longer in the same place; thus, they are more familiar with the area and the surrounding environment and know how to better monitor and regulate unwanted behavior (Kim & Hipp, 2021). Note that we do not know how long the same workers have been with a company, and our argument is only that, on average, older businesses are more likely to have long-term employees compared to newer businesses. That is, customers, owners, and employees of such businesses may be more willing to regulate the area where the businesses are located because they recognize that their interests are inextricably linked to the welfare of the neighborhood as it pertains to crime and disorder problems; the latter problems could immediately reduce the volume of customers and sales and, over several years, might even reduce property values and the reputation of businesses.

However, as the same business faces *decline* or *death*, we expect that it loses visiting customers, which leads to fewer eyes on the street and thus lower natural surveillance and guardianship in the area. If this is true, we can expect a weaker crime-reducing effect of older businesses in the maturity and/or revival stages than birth and/or growth. Figure 1b describes such scenario. We propose a U-shaped association between the age of businesses and crime in place where foot traffic starts slow, increases to a peak, and then falls as businesses go through each stage of the life course (birth, growth, maturity, decline, and death). Figure 1b illustrates this general theoretical scenario. As such, we put forth two more hypotheses:

H2-1. An increase in business age on a block will be associated with lower risk of crime due to more eyes on the street from increased foot traffic.

H2-2. These crime-reducing effects will be reduced in magnitude or even reversed in blocks with very old businesses (decline or death) due to lose of eyes on the street from decreased foot traffic.

The effect of business age on crime moderated by number of businesses

Whereas we have posited that as businesses age, they will generally provide less criminal opportunity or more guardianship capability, an implication is that this age effect can be reduced/enhanced on blocks with high business activity. For example, guardianship capability will increase with age for a business, and the more businesses in a location, this should translate into greater guardianship capability overall. Furthermore, a greater density of such businesses would presumably have a multiplier effect given the generally heightened informal social control in the area. Thus, whereas we hypothesize that a block with a single business on it that has been there a long time would provide some informal social control that might reduce crime somewhat, a block with more business activities would provide considerable informal social control and therefore have a much stronger negative effect on crime. In contrast, a potential trend is that business activities may weaken the crime-reducing effects of older businesses. For example, according to the crime generator perspective, busier areas with business activities tend to draw more foot traffic coming into the area, which may heighten the probability of the convergence of potential offenders and targets at the same time and place. This yields our third and fourth hypotheses:

H3-1: The crime-reducing effect of average age of consumer-facing businesses will be strengthened on blocks with higher business activities.

H3-2: The crime-reducing effect of average age of consumer-facing businesses will be attenuated on blocks with higher business activities.

The Current Study

We test these possible theoretical scenarios of business life course and crime in the context of criminal opportunities and the level of guardianship in place. We understand that specific businesses may undergo different developmental courses. Although Weisburd et al. (2012) suggested that business facilities are relatively stable over time in place, some businesses may fail in a short period while others become stable and operate longer (Stinchcombe, 1965). However, an important implication from our theoretical discussion is that both the level of criminal opportunities and guardianship can be temporally dynamic as business situations change over time. Therefore, it is necessary to examine how the crime enhancing/reducing effects of various types of business establishments are temporally different over time, an understudied topic. In sum, it is crucial to consider the age of businesses because it can capture changes of business characteristics over time, which potentially affect the criminal opportunities and level of guardianship in place, which may have consequences for crime rates. Accordingly, the current study examines the relationship between age of different types of business facilities and crime in census blocks in the study area.

Data and Method

Independent Variables

For the current study, the units of analysis are census blocks. We used the Census block as a spatial unit of analysis for the following reasons: (1) the Census block is the smallest spatial unit in which the U.S. Census data are available; (2) blocks are small communities that contain social and physical environmental features that have a direct relevance to explaining the spatial patterns of crime (Taylor, 2015) and thus (3) previous studies of crime and place focusing on business establishments (e.g. Bernasco and Block 2011), voluntary organizations (e.g. Wo, Hipp and Boessen 2016) and spatial imputation methodologies (e.g. Kim, 2018) widely employed the Census block as a unit of analysis (Bernasco & Block, 2011; Bernasco et al., 2016; Contreras, 2017; Haberman & Ratcliffe, 2015; Kim, 2018; Wo & Kim, 2022).[2]

[2] Street segments are also used as units of analysis in studies. Although blocks are spatially larger than segments, using blocks instead of segments results in losing very little spatial precision (Kim, 2018). However, census blocks have the advantage of providing various data sources from the Census that are not available for street segments. Thus, we believe census blocks are effectively quite similar to using street segments.

Business Age

Our study site is the urbanized area within the LA county boundary defined by the Census Bureau. 54,007 blocks from 2000 to 2010 across 80 cities in the study area were included in the analysis. For all data, we normalized to 2000 Census block boundaries by using population-weighted interpolation. To measure the age of business establishments, we used the Reference USA business data from 2000 to 2010. These data provide detailed information on each business over the study period, including address, business type according to the North American Industry Classification System (NAICS) 6-digit codes, year of establishment, and revenue, to name a few. Whereas about 80% of businesses were geocoded to the location address by Info USA, we used ArcGIS 10.2 to geocode the remaining business addresses. The final geocoding hit rate for all businesses across the study years is about 95%. We aggregated the number of businesses and computed the average business age in blocks.

We constructed five sets of business measures including *Retail* (Apparel, General Merchandise, Home Products, Personal Products, and Specialty), *Services* (Auto Services, Child Care Services, Gas Stations, Laundry, Hair Care Services, Other Personal Services, and Repair Services), *Restaurants* (Full-Service and Limited-Service), *Food/Drug Stores* (Convenience Stores, Drug Stores, Groceries, and Specialty Food), and a measure of total consumer facing business including all the four business types together.[3] We chose these

[3] Here is the list of 6-digit NAICS codes associated with the business types included in the consumer facing business measure: *Retail* (448110, 448120, 448130, 448140, 448150, 448190, 448210, 452111, 452112, 452910, 452990, 453310, 453210, 443141, 442110, 442210, 442291, 442299, 444210, 444220, 444130, 444110, 444120, 444190, 453991, 446120, 446199, 453910, 453998, 451211, 451212, 443142, 451140, 451110, 451120, 446130, 453220, 453110, 448310, 448320, 451130); *Services* (532111, 441310, 441320, 811111, 811112, 811113, 811118, 811121, 811122, 488410, 811191, 811192, 811198, 624410, 447110, 447190, 812320, 812310, 611511, 812111, 812112, 812113, 532220, 532299, 541940, 812191, 812199, 812910, 812990, 541921, 812921, 812922, 561622, 811212);

business types because they are identified as consumer-facing (Kane, Hipp, and Kim 2017; Porter 2000; Delgado, Porter, and Stern 2014) and tend to attract customers for products and services at the locations. Therefore, they have more direct relevance to foot traffic coming in-and-out of the area. Also, these consumer-facing businesses engender frequent face-to-face interactions among stakeholders including owners, employees, and customers, and thus potentially increase the level of social cohesion and ties in the area.

Then, we aggregated the number of businesses in blocks by each of the four consumer-facing business types (and the total). We also constructed the average business age in blocks for each consumer facing business type. The business age was calculated as the establishment year of a facility subtracted from the current data year. Then, the average of each consumer facing business type is computed at the block level. We also constructed the standard deviation of age in the block for each business type and included it in the models to account for the heterogeneity in business age. Essentially, every entry provided information on the year of establishment.

We control for standard covariates of aggregate crime by including measures from the U.S. Census for 2000 and 2010. Census data for the intervening years between 2000 and 2010 were linearly interpolated (Crowder et al., 2012; Sampson & Sharkey, 2008; Wo, 2014; Wo et al., 2016). Although measuring businesses block by block is reasonable given how this feature of the environment can change considerably over blocks, the socio-demographic features of the area typically do not change at such a small scale given general segregation patterns. We

Restaurants (6-digit NAICS code 722511, 722514, 722515, 722513); *Food/Drug Stores* (445120, 446110, 445110, 311811, 445210, 445220, 445230, 445291, 445292, 445299, 446191).

therefore constructed these measures with an exponential decay to account for the characteristics of focal block as well as the surrounding areas. By doing so, we posit that nearer blocks have a stronger impact on a local block than farther blocks. Specifically, we constructed each Census measure in blocks, and then weighed each block within ½ mile by the exponential decay from the focal block (with β = -0.5).[4] This equation is:

$$S_i = \sum_{j}^{J} P_j \, exp(\beta d_{ij})$$

where S is the distance-weighted measure of interest, *j* represents blocks within ½ mile of a focal block (including the focal block), P indicates the value of the measure in block *j*, d_{ij} is the distance between the two blocks, and β is set to -0.5. Thus, the focal block has a weight of 1, and surrounding blocks are weighted less as they get further away.

We constructed a *concentrated disadvantage index*, a factor score including four measures: (1) percent at or below 125% of the poverty level; (2) percent single-parent households; (3) average household income; and (4) percent with at least a bachelor's degree. The last two measures had reversed loadings in the factor score. These measures are not available at the Census block level except for the percent single-parent household. Therefore, we assigned these values to the blocks within the block group by employing the ecological inference technique (Boessen & Hipp, 2015). This strategy builds a regression model at a larger aggregate unit (such as block groups) and then combines those coefficient estimates along with block-level data to impute the variable of interest in the block. The assumption of this strategy

[4] By measuring structural characteristics in terms of a ½ mile buffer rather than the focal block itself, the estimated models do not exclude blocks absent of a residential population, but only blocks that are completely devoid of residential population in the ½ mile area that surrounds it. This effectively addresses the potential concern that our models were dropping those blocks located in primarily business areas/districts.

is that the relationship among the variables at the larger ecological unit will be the same as that at the smaller unit, which arguably is a weaker assumption than the uniform imputation strategy that assumes there is no relationship among the variables. To measure *residential stability*, we utilize the percent homeowners. The current study controls for the presence of racial/ethnic minorities in blocks as the percent African American and the percent Latino/Hispanic. To capture the level of *racial/ethnic heterogeneity*, we computed a Herfindahl index based on five racial/ethnic groups (white, African American, Latino, Asian, and other races), as one minus a sum of squares. This study also included the percent *vacant units* to measure vacancies in the area, and the measures of population (logged) and the number of business employees (logged) to capture residential and ambient population in the area.

Dependent Variables

The outcomes are the crime counts of aggravated assault, robbery, burglary, larceny, and motor vehicle theft aggregated at the block level. These are official crime data reported by the local police departments across the study area from 2000 to 2010. The crime data for this study come from the Southern California Crime Study (SCCS).[5] Many police agencies of cities in the Southern California region reported incident crime data with geographic information such as addresses or 100 blocks. SCCS classified crime events into Part 1 crimes. Crime events were geocoded for each city within the study area separately to latitude–longitude points using ArcGIS 10.2, and then aggregated to blocks. The geocoding match rate for the Los Angeles metropolitan area was 94.1 percent.

Analytic Strategy

[5] For more detailed information on the SCCS, please refer to: https://ilssc.soceco.uci.edu/category/southern-california-crime-study/

Business Age

The presence and operation of business establishments could vary by the level of crime in place, which implies a potential temporal endogeneity. To address this, we employed a longitudinal data analysis strategy using the xtnbreg command in STATA version 15. Particularly, we utilized a longitudinal data set for each of the 11 years of the study (i.e., 2000 to 2010), and estimated fixed-effects negative binomial regression models including the independent variables time-lagged by 1 year (Wo et al. 2016). We employed a fixed-effects approach that only focuses on the within-block variation in the variables over time so that we can avoid the assumption in random effects models that time-varying explanatory variables are uncorrelated with unmeasured time-invariant variables (Allison, 2005, 2009).

Given the large sample size, it is not feasible to estimate models including dummy variables for all blocks. Instead, we adopted a hybrid approach proposed by Allison (2009), in which a mean score for the time-varying independent variables for each block over the entire period was subtracted from the observed value at each time point, similar to what Wo et al. (2016) did. Additionally, we included dichotomous variables for the years and cities to account for the unmeasured year- and city-specific effects on crime. This approach allows comparing levels of crime *within* a particular city and a year rather than *across* cities and years.

Although our study site is composed of 80 cities, we consider it as one large metropolitan area in which the core city (Los Angeles) and surrounding cities are geographically, socially, politically, economically and culturally coupled and thus are tightly interdependent. Therefore, it is more plausible to treat this group of cities included in the current study as one region where residents strongly share many realms of life, rather than viewing them as 80 individual cities. We nonetheless included city-fixed effects to account for baseline differences between these cities, similar to other studies (Hipp et al., 2019b; Kane et al., 2016; Kim & Hipp, 2021).

Since the dependent variables of the current study are counts of crime events (violent and property crime), their distributions are not normally distributed. Accordingly, we employed a negative binomial regression approach to effectively deal with over-dispersion (Osgood, 2000). We included (logged) population in the buffer (after adding 1) in all models, effectively translating the outcomes to crime rates. We computed the Moran's I values of residuals from the models for the most recent year to assess if there is any additional spatial autocorrelation in the residuals, and all values were below 0.01 and mostly not significant implying that our estimated models adequately control for spatial autocorrelation.[6]

We estimate four sets of models that test the effects of four types of business facilities (i.e., *total consumer-facing businesses, retail businesses, service businesses, restaurants, and food/drug stores*), while controlling for the effects of structural characteristics. We include squared terms for the average business age measures in the models to capture non-linear relationships.[7] The longitudinal models that we estimate can be expressed as follows:

$$E(y_t) = exp(\alpha + B_1\boldsymbol{A}_{t-1} + B_2\boldsymbol{N}_{t-1} + B_3\boldsymbol{H}_{t-1} + B_4 lnP_{t-1} + B_5 lnE_{t-1} + B_6\boldsymbol{S}_{t-1} + B_7\boldsymbol{J} + B_8\boldsymbol{K}) \quad (1)$$

where y_t is the dependent variable to be explained (the number of crime events in the current year), α is an intercept, $\boldsymbol{A}_{t-1}$ represents a matrix of the average business age measures in the

[6] The Moran's I values for the crime types ranged from 0.05 to 0.14 suggesting some spatial clustering of crime events, which disappears after conditioning on the variables in the model.
[7] We tested non-linear effect of business age by including cubic terms. For all models, cubic terms were not statistically significant or do not show substantially different curvilinear patterns compared to those presented in Figures 1-2. The results are available upon request from the corresponding author.

previous year (mean deviation), $\boldsymbol{N}_{t-1}$ is a matrix of the number of businesses in the previous year (mean deviation), $\boldsymbol{H}_{t-1}$ is a matrix of the business age heterogeneity measures in the previous year (mean deviation), lnP_{t-1} is logged population in previous year (mean deviation), lnE_{t-1} is the number of total business employees in previous year (mean deviation), ***S*** is a matrix of the structural characteristic variables of the previous year (mean deviation), ***J*** is a matrix of the dummy variables for years, and ***K*** is a matrix of the dummy variables for cities. In addition, to examine whether if the effects of age of businesses are moderated by the number of businesses, we estimated a set of interaction models including the measures of business age, the number of businesses, and the interaction of them. The summary statistics for the variables included in the models are reported in Table 1.

<<< Table 1 about here >>>

Results

First, we viewed the correlations between the measures of average business age, number of businesses, and business age heterogeneity. We observed that there are very weak correlations between the business age measure and the other two measures. For example, the correlation values between the business age and the number of businesses (for all types) range from 0.01 to 0.06, while those of business age and the business age heterogeneity are 0.07-0.2. The correlation values between the number of businesses and business age heterogeneity were about 0.7.

Next, we turn to our findings from the estimated models (Table 2). The complete set of regression coefficients is presented in Table 2 for the combined measure of consumer-facing businesses and Table 3 for the four separate business types. We first discuss the findings of the number of businesses in blocks, given that this is a measure commonly used in the literature. The number of consumer-facing businesses has crime-enhancing effect for aggravated assaults (β=.012, $p < .01$), robbery (β=.012, $p < .01$) and burglary (β=.007, $p < .05$) but crime-reducing for larcenies (β=-0.006, $p < .01$) (Table 2)[8]. For instance, a one standard deviation increase in the number of consumer facing business is associated with a 1.2, 1.2 and 0.7 percent increase (exp ($\beta \times$ S.D.) – 1) in the risk of aggravated assault, robbery, and burglary, but a 0.7 percent decrease in larceny, respectively. Note that these results for these *longitudinal* models are different from the more common *cross-sectional* models in the literature, which typically find a positive relationship between the presence of more businesses and crime rates.

<<< Tables 2-3 about here >>>

The story was the same in the models for the number of businesses by various subtypes (Table 3). We detect positive effects for retail businesses that increases in retail businesses resulting in a higher risk of aggravated assault and burglary, and an increase in restaurants increasing the risk of robbery. Thus, a one standard deviation increase in the number of retail businesses is associated with a 1.2 and 0.7 percent increase in aggravated assaults and burglary, respectively, and a one standard deviation increase in the number of restaurants results in a 1.4 percent increase in robbery. However, we found evidence that retail businesses are associated with lower risk of larceny, as a one standard deviation increase in retail businesses is associated with a 0.5 percent decrease in larceny risk.

[8] We estimated a set of supplemental models with the number of businesses excluding the average age and business age heterogeneity measures. However, the results are not substantially different from the models reported in Tables 2 and 3.

Business Age

We next turn to the findings for the average age of business measures. We detect strong, significant effects for these measures, and we visually display the marginal effects of the average age of the consumer-facing business measure in Figure 2 and the four subtypes in Figure 3. Given that the patterns of the effect for the average age measures were quite similar across the various crime types, we only present the results for robberies in the text. The remaining plots for consumer-facing businesses for the other crime types are reported in Appendix Figures A1-4. In all figures, the x-axis represents the mean deviation values of the measures from the 1st to 99th percentile, while the y-axis is the predicted crime rate.

As presented in Figure 2, the average age of consumer-facing businesses demonstrates a slowing negative relationship with robberies. For example, a one standard deviation increase in the average age of consumer-facing businesses results in about a 2 percent decrease in robbery rates.[9] The figures for the other four crime types in the Appendix show the same slowing negative relationship. These patterns are consistent with hypothesis 2-1 that the presence of more businesses in the growth stage will be associated with lower risk of violent and property crime.

<<< Figure 2 about here >>>

When we split the total consumer-facing businesses into the four sub-types, we find generally similar results. All show a slowing negative relationship (although one type shows a slight uptick at the oldest age). The strongest negative relationships with

[9] Given the nonlinear relationship, our interpretations are assessed by comparing the expected log value from Figures 2-3 when increasing by one standard deviation for each of the business age measures, and then exponentiating this value to obtain these percentage changes.

robberies are for food/drug stores and retail stores, as seen in Figure 3. The negative relationship for the average age of retail businesses (the red line) or food/drug stores show that a one standard deviation increase in their average age implies about a 3.5 or 3 percent reduction in robbery rates the following year, respectively.

<<< Figure 3 about here >>>

The pattern is similar, though somewhat weaker, for service and restaurant businesses. The slowing negative relationship for the age of service businesses (the green line) implies that a one standard deviation increase in their average age is associated with about 1.5 percent fewer robberies. We observed a more pronounced non-linear (U-shaped) pattern for restaurants (the brown line). Whereas a one standard deviation increase in the average age of restaurants leads to 1.3 percent decrease in robbery rates in the following year during the earlier years of restaurants, this pattern flips and becomes crime-enhancing as they grow even older for the oldest restaurants.

Next, we observed that greater age heterogeneity of consumer facing businesses is associated with lower risk of aggravated assault, robbery, and burglary (Table 2), although there was no relationship with the other two crime types. Thus, it appears that increasing variability in the age of businesses in a block is beneficial for reducing crime. When we split the total consumer-facing businesses into the four sub-types, we found a similar pattern that age heterogeneity has crime-reducing effect, in general. For example, age heterogeneity of retail businesses tends to reduce aggravated assaults and burglary while age heterogeneity of service businesses is negatively associated with all types of crime. Only the age heterogeneity of restaurant businesses tended to exhibit a positive association with crime in blocks. In contrast, the coefficients of food/drug stores were not statistically significant.

Moderating Effects

For our final set of analyses, we tested interaction effects between the measures of average business age and the number of businesses in the block to test whether moderating effects exist. We report the interaction coefficients in Appendix Tables A1-3. We plotted the predicted crime rates for these interactions, and the patterns were generally similar. We therefore report the results for the consumer-facing businesses and robbery as a representative pattern (Figure 4). The interaction plots for the remaining measures and crime types are reported in Appendix Figures A5-20. We visually display the effect of average business age at varying levels of the number of businesses for each business type (Low = -1 SD, Med = mean, and High = +1 SD). We observed that the relationship between business age and crime can vary at different levels of the number of businesses in blocks. The consistent pattern we detect is that the crime-reducing effect of average business age is most pronounced in locations with many businesses.

The pronounced interaction effect between consumer facing business age and the number of such businesses for robbery is shown in Figure 4 in which the crime-reducing effect of business age on robberies is largest among high business areas (the blue line). Thus, a block with a high number of very young consumer-facing businesses is at the highest risk of robbery, as seen on the blue line on the left side of this graph. However, as the average age of those businesses increases, there is a monotonic decrease in robbery risk. As a consequence, in a block with many older businesses the robbery rate will be even lower if there are many such businesses (the right side of this figure). For example, among blocks with relatively young businesses, a block with many consumer facing businesses has about 2.7 percent more robberies than a block with few such businesses. However, among blocks with older businesses, a block with many consumer facing businesses has about 1.5 percent *fewer* robberies than one with few such businesses. In contrast, in neighborhoods with very few businesses, the impact of business age is quite weak (the orange line), which is consistent with our hypothesis 3 that business age will have the strongest negative effect on crime in locations with many businesses. And when we focus on the average age of business subtypes, we again see the same pattern in which the strongest negative effects for average age occur in blocks with many businesses, regardless of the type of business.

Finally, the control variables generally exhibited expected relationships with crime. One point we highlight to understand the magnitude of the effects of our variables of interest is to describe the size of effects for two measures commonly employed in ecological studies of crime. First, a one standard deviation increase in concentrated disadvantage is associated with a 3.3 percent increase aggravated assault risk, and a 1.7, 5.6, and 2.1 percent increase in the risk of burglary, larceny, and motor vehicle theft, respectively. Second, a one standard deviation increase in racial/ethnic heterogeneity results in a 2-5 percent increase in violent and property crime risk. Thus, these are similar in magnitude to our business age measures.

Discussion

Although previous studies have frequently found that business facilities can have crime-enhancing effects, less attention has focused on the temporally dynamic effects of business facilities in relation to crime. Drawing on the literatures concerning criminal opportunities, capable guardianship, and business life cycles, we highlighted the importance of examining businesses in place over time, and their resulting effect on the spatial patterns of crime. We argued that business facilities can undergo changes over time, which may alter the physical and social environment of the focal block (as well as surrounding areas). To our knowledge, the current study is one of the first to demonstrate business facilities' differential capacity to impact crime based on their age.

A major finding was that the average age of consumer-facing business facilities in blocks showed consistent evidence of a crime-reducing effect. This pattern was a very consistent slowing negative effect across all five crime types that we studied and was consistent with our hypothesizing. It was only in rare cases, for certain business types (e.g., restaurants), that we found a nonlinear U-shaped relationship in which it appeared that the pattern became crime-enhancing as business facilities grow even older. We next describe our key findings.

First, we observed that the average age of businesses initially shows a particularly strong crime-reducing effect. That is, blocks with very young businesses (*birth to growth*) are at the highest risk of crime, whereas areas with relatively older businesses (*growth* to *maturity*) pose the lowest risk. One possible explanation is that in areas with relatively older businesses, business customers visiting the areas tend to be more local, and have closer personal relationships with the owners and employees. These customers may care more about the safety of the areas where the businesses are located in because the businesses would comprise a decent portion of their daily routine activities. Moreover, owners and employees of older businesses generally have worked longer in the same place; thus, they are more familiar with the area and the surroundings, and know better how to manage and intervene to keep the area safe. In short, businesses located in an area over a relatively long period of time might facilitate trusting ties between employees, residents, and nonresidents which can be instrumentally used to informally monitor and regulate crime. It was only the case for certain types of businesses (e.g., restaurants) that we observed a modest increasing pattern for crime in blocks with very old businesses (*decline* or *death*); nonetheless, the predicted crime rate was still much lower in these blocks than those with very young businesses. This may be due to the loss of visiting customers, resulting in fewer eyes on the street and thus lower guardianship capability in the area. In sum, our results support the second scenario of guardianship in place.

Moreover, the pattern of results is consistent with previous research that has either theorized or empirically found a curvilinear relationship between eyes on the street and crime in place, posited in hypotheses 2-1 and 2-2 and Figure 1b (Browning et al., 2010; Wo, 2019a, 2019b). Jane Jacobs (1961) posited that eyes on the street can function as natural surveillance if it reaches a sufficient threshold. Otherwise, visitors would increase criminal opportunities, because some of them may pose as potential offenders in combination with anonymity, which increases the probability of the convergence of potential offenders and targets at the same time and place. Areas with very young businesses (birth) may initially increase foot traffic, and thus increase criminal opportunities. However, as they grow and mature, we suspect that the amount of foot traffic generated by local businesses will exceed the threshold that is necessary for establishing consistent monitoring on the part of multiple stakeholders (i.e. residents, local store owners and employees, and other nonresidents). These temporally dynamic aspects of business facilities in areas are typically ignored by scholars. Therefore, we encourage future research to build on the results of the current study by accounting for the timing by which business facilities are crime-producing and/or crime-reducing.

It is notable that our posited effect of the crime-reducing effect of older businesses was most pronounced in blocks with many businesses. The presence of many older businesses providing eyes on the street would be expected to reduce crime more than a block with just a few older businesses, and this is exactly what we observed. The implication is that such blocks have better guardianship capability. This highlights a needed future direction for research to empirically assess whether the presence of older businesses, particularly if there is a collection of them on a block, can indeed bring about such informal social control capability. Nonetheless, our results are strongly suggestive of this possibility. There is a further implication of this finding: blocks with many *very new* businesses are *most* at risk of high crime. This may be because of a lack of informal social control, as we hypothesized, but future research will want to focus on such locations to assess if this is really what is occurring.

Although this study has provided important new insights for understanding the relationship between the presence of business facilities and crime, we acknowledge certain limitations. First, although we proposed theoretical reasons for how business facilities differentially impact crime based on their age, we cannot definitively pinpoint the changes that businesses undergo and how they are related to crime in place. It is beyond the scope of the current study to measure the mechanisms that might bring about these relationships.

Second, although we used four business types that are consumer facing and arguably most relevant to the amount of foot traffic into place, future research may want to use more fine-grained business types if there is theoretical expectation that certain specific types are important for capturing the spatiotemporal dynamics between businesses and crime. Third, our study area is the urbanized area within the LA county boundary (CA), which means our findings may be unique to this area/region. We hope that future studies examine whether the findings of the current study are consistent across geographic units of other U.S. cities. Finally, we did not test for how crime may affect the placement of business facilities. While this does not undermine the pattern of results of the current study, we propose that the potential impact of crime on business formation is a promising direction for future research. For instance, the level of crime in place may affect the density of businesses in place at a later time point. Indeed, a recent study found that higher levels of crime are associated with business failure and mobility, and reduce the likelihood of a business locating there (Hipp et al., 2019a).

It is worth highlighting that while we have focused on the age of businesses, demographers are well aware of the general issue of age, period, and cohort effects. Our analyses have exclusively focused on age effects of businesses, given that we hypothesized such effects. Nonetheless, future work in this vein will need to consider period or cohort effects. As one example, the change in a neighborhood during a specific time period is a form of a period effect. Thus, in neighborhoods undergoing gentrification, there might be numerous changes occurring, many of which may occur in a nonlinear temporal manner. If such neighborhoods simultaneously experience considerable business turnover, this will impact the age of businesses. In such instances, our measure of business age would also be capturing such neighborhood gentrification processes. We lacked the data to tease apart such possible effects, but this should be a focus of future research. As a second example, cohort effects could occur if several businesses begin at the same time point and create an extra layer of cohesion and connectedness in the neighborhood. We did not theorize this here, though it should be an area of future research. To some extent, measuring the standard deviation of business age captured this effect. The positive relationship between this standard deviation measure and some property crimes is consistent with this possible cohort effect. Nonetheless, future research explicitly focused on this question is needed.

In conclusion, we examined the dynamic nature of the business facility and crime process in blocks. Whereas prior research has often hypothesized that businesses can increase crime opportunities, with occasional research positing that specific businesses might reduce crime, we introduced a dynamic perspective. Specifically, we theorized that the effects of businesses on crime in place should vary by age of businesses based on the organizational life course and business cycle literature, which implies that business facilities undergo various changes over time which in turn, impacts features of the physical and social landscape in the immediate and surrounding area. Using an age-graded approach, we found that all types of business facilities exhibited crime-producing *and* crime-reducing effects over the life course. We therefore maintain that it is necessary to account for the timing by which business facilities shape spatial crime patterns.

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Table 1. Summary Statistics

Variables	Mean	SD
Crime (count)		
Agg. Assault	0.54	1.67
Robbery	0.30	1.13
Burglary	0.59	1.45
Larceny	1.49	6.75
M.V. Theft	0.66	1.88
Average age		
Consumer facing businesses	2.35	4.54
Retail businesses	1.07	3.23
Service businesses	1.79	4.31
Restaurants	1.07	3.63
Stores	0.68	2.82
Number of business		
Consumer facing businesses	1.50	5.43
Retail businesses	0.52	3.24
Service businesses	0.59	1.86
Restaurants	0.25	1.05
Food/Drug Stores	0.14	0.57
Business age heterogeneity		
Consumer facing businesses	0.15	0.35
Retail businesses	0.06	0.22
Service businesses	0.08	0.18
Restaurants	0.04	0.12
Stores	0.02	0.08
Population (logged)	8.74	0.85
Number of employees (logged)	-0.83	3.90
Structural Characteristics		
Concentrated disadvantage	0.00	1.04
Racial/Ethnic heterogeneity	0.48	0.16
Percent vacant units	5.15	3.20
Percent owners	51.25	24.55
Percent Black	8.90	14.75
Percent Latino	42.73	28.41

N = 54,007 blocks. *Descriptive statistics are for all cities and years combined. Descriptive statistics are for all cities and years combined. The mean and standard deviation of the different types of businesses are in their original form (i.e., prior to group mean centering).* *ABBREVIATION: SD = Standard Deviation*

Table 2. Longitudinal Negative Binomial Regression: Business Age and Crime (Consumer-facing Businesses)

	Agg. Assault		Robbery		Burglary		Larceny		M.V. theft	
Consumer facing businesses										
Average business age	-0.004	**	-0.007	**	-0.008	**	-0.006	**	-0.007	**
	-2.687		-3.918		-6.293		-6.482		-6.228	
Average business age (squared)	0.001	**	0.002	**	0.002	**	0.001	**	0.001	**
	7.210		6.784		9.773		6.946		6.497	
Number of business	0.012	**	0.012	**	0.007	*	-0.006	**	0.001	
	3.752		3.800		2.418		-3.162		0.333	
Business age heterogeneity	-0.102	**	-0.117	**	-0.099	**	-0.001		-0.018	
	-3.454		-3.937		-3.830		-0.042		-0.740	
Population (logged)	-0.171	**	-0.209	**	-0.373	**	-0.230	**	-0.314	**
	-6.212		-5.784		-16.374		-12.723		-14.126	
Number of employees (logged)	0.007	**	0.012	**	0.008	**	0.005	**	0.001	
	3.210		3.891		3.954		2.945		0.378	
Structural Characteristics (1/2 mile Exponential decay)										
Concentrated disadvantage	0.343	**	0.086		0.081		0.519	**	0.263	**
	5.751		1.124		1.609		13.404		5.192	
Racial/ethnic heterogeneity	-1.231	**	-2.280	**	-3.283	**	-1.963	**	-3.426	**
	-4.995		-7.235		-15.908		-12.025		-16.198	
Percent vacant units	-0.042	**	-0.031	**	-0.035	**	-0.039	**	-0.062	**
	-7.758		-4.772		-7.358		-11.445		-13.363	
Percent home owners	0.013	**	0.017	**	0.014	**	0.008	**	0.010	**
	3.430		3.396		4.661		3.440		3.175	
Percent Black	0.102	**	0.077	**	0.062	**	0.113	**	0.040	**
	26.683		16.113		18.385		41.899		11.893	
Percent Latino	0.050	**	0.054	**	0.044	**	0.078	**	0.036	**
	16.708		14.345		17.891		41.901		14.669	
Intercept	-8.370	**	-8.359	**	-7.438	**	-7.749	**	-8.907	**
	-145.990		-116.035		-173.893		-185.473		-146.539	
N	54,007		54,007		54,007		54,007		54,007	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test)*

T-values below coefficient estimates.

City and year fixed effects are included but not reported in the table

Table 3. Longitudinal Negative Binomial Regression: Business Age and Crime by Various Business Types

	Agg. Assault		Robbery		Burglary		Larceny		M.V. theft	
Average business age										
Retail	-0.005	**	-0.012	**	-0.009	**	-0.005	**	-0.007	**
	-3.088		-6.283		-6.044		-4.920		-4.926	
Retail (squared)	0.002	**	0.003	**	0.002	**	0.001	**	0.002	**
	6.900		10.212		8.691		6.740		7.889	
Service	-0.001		-0.003	†	-0.002	†	-0.001		-0.003	**
	-0.954		-1.756		-1.762		-0.795		-2.782	
Service (squared)	0.001	**	0.002	**	0.002	**	0.001	**	0.001	**
	7.212		8.864		8.983		4.569		6.156	
Restaurant	-0.001		-0.001		-0.003	†	-0.004	**	-0.003	*
	-0.552		-0.527		-1.929		-3.465		-2.332	
Restaurant (squared)	0.002	**	0.003	**	0.001	**	0.001	**	0.002	**
	7.629		11.398		6.552		6.283		8.194	
Food/Drug Stores	-0.011	**	-0.011	**	-0.011	**	-0.009	**	-0.007	**
	-5.892		-5.656		-6.229		-7.024		-4.229	
Food/Drug Stores (squared)	0.002	**	0.003	**	0.002	**	0.001	**	0.001	**
	9.044		11.486		7.053		6.055		6.210	
Number of business										
Retail	0.018	**	0.005		0.011	*	-0.008	*	0.000	
	3.400		1.060		2.247		-2.459		0.073	
Service	0.012		0.014	†	0.012	†	0.003		-0.004	
	1.633		1.685		1.784		0.709		-0.660	
Restaurant	0.013		0.055	**	0.004		-0.006		0.020	†
	1.016		4.130		0.375		-0.763		1.783	
Food/Drug Stores	0.017		0.020		0.026		-0.006		-0.008	
	0.786		0.959		1.353		-0.420		-0.441	
Business age heterogeneity										
Retail	-0.128	**	0.017		-0.098	*	0.022		-0.020	
	-2.731		0.395		-2.500		0.859		-0.520	
Service	-0.203	**	-0.314	**	-0.216	**	-0.181	**	-0.090	†
	-3.250		-4.417		-3.925		-4.411		-1.685	
Restaurant	0.059		-0.293	**	0.019		0.150	*	0.124	
	0.571		-2.696		0.205		2.331		1.390	
Food/Drug Stores	-0.035		-0.020		-0.003		0.159	†	0.175	
	-0.247		-0.137		-0.022		1.730		1.479	

Business Age

Population (logged)	-0.173	**	-0.214	**	-0.375	**	-0.233	**	-0.319	**
	-6.285		-5.940		-16.461		-12.887		-14.389	
Number of employees (logged)	0.008	**	0.013	**	0.008	**	0.004	**	0.000	
	3.352		4.140		3.886		2.857		0.145	
Structural Characteristics (1/2 mile Exponential decay)										
Concentrated disadvantage	0.346	**	0.083		0.079		0.516	**	0.262	**
	5.798		1.090		1.569		13.324		5.169	
Racial/ethnic heterogeneity	-1.250	**	-2.283	**	-3.302	**	-1.976	**	-3.441	**
	-5.070		-7.230		-15.993		-12.104		-16.265	
Percent vacant units	-0.041	**	-0.031	**	-0.035	**	-0.039	**	-0.061	**
	-7.596		-4.708		-7.270		-11.364		-13.286	
Percent home owners	0.013	**	0.017	**	0.014	**	0.008	**	0.010	**
	3.386		3.352		4.667		3.347		3.071	
Percent Black	0.102	**	0.077	**	0.062	**	0.113	**	0.040	**
	26.649		15.986		18.292		41.835		11.868	
Percent Latino	0.050	**	0.053	**	0.043	**	0.077	**	0.036	**
	16.501		13.993		17.609		41.603		14.507	
Intercept	-10.261	**	-10.206	**	-8.842	**	-9.611	**	-10.787	**
	-177.373		-139.813		-201.236		-225.617		-175.505	
N	54,007		54,007		54,007		54,007		54,007	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test)*

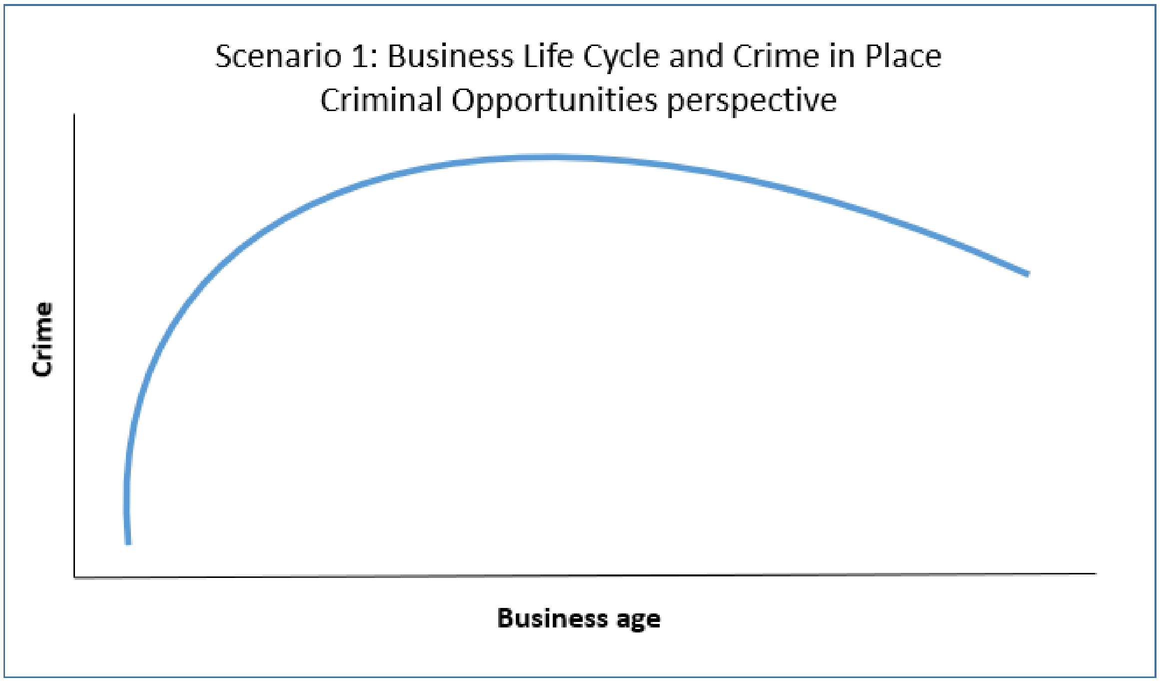
T-values below coefficient estimates.

City and year fixed effects are included but not reported in the table

Figures

Figure 1. Theoretical Models of Business Life Cycle and Crime

a. First theoretical scenario: Criminal opportunities perspetive



b. Second theoretical scenario Guardianship perstective

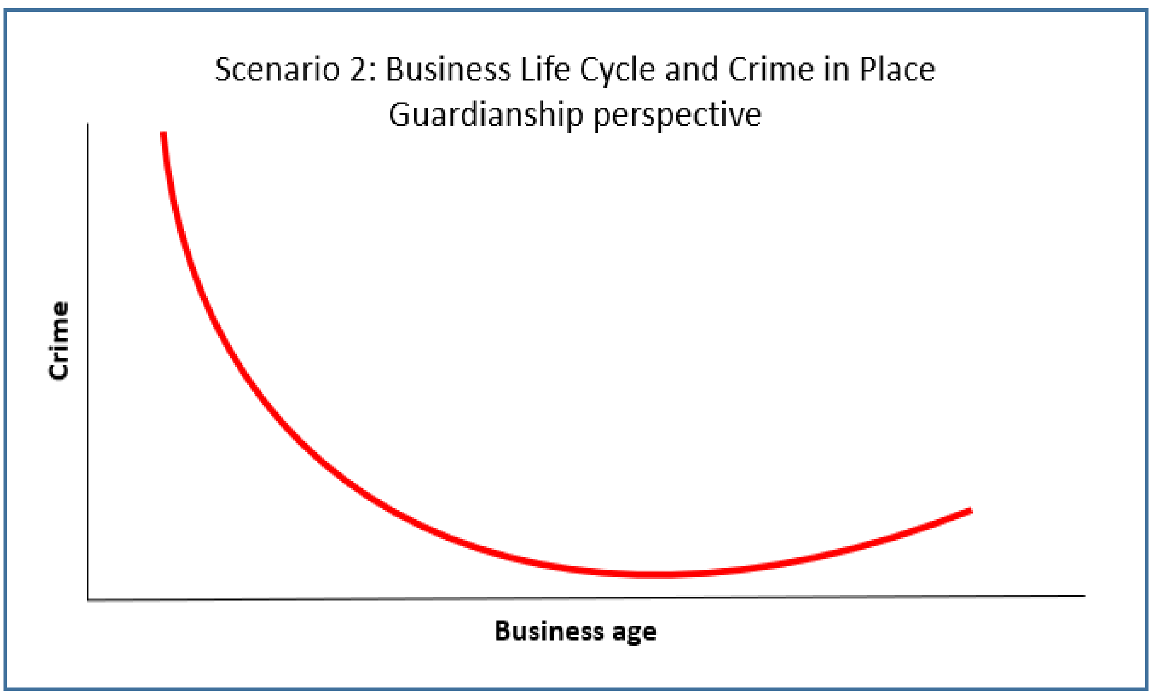


Figure 2. Age of consumer-facing businesses and crime in blocks – Robbery

Business Age

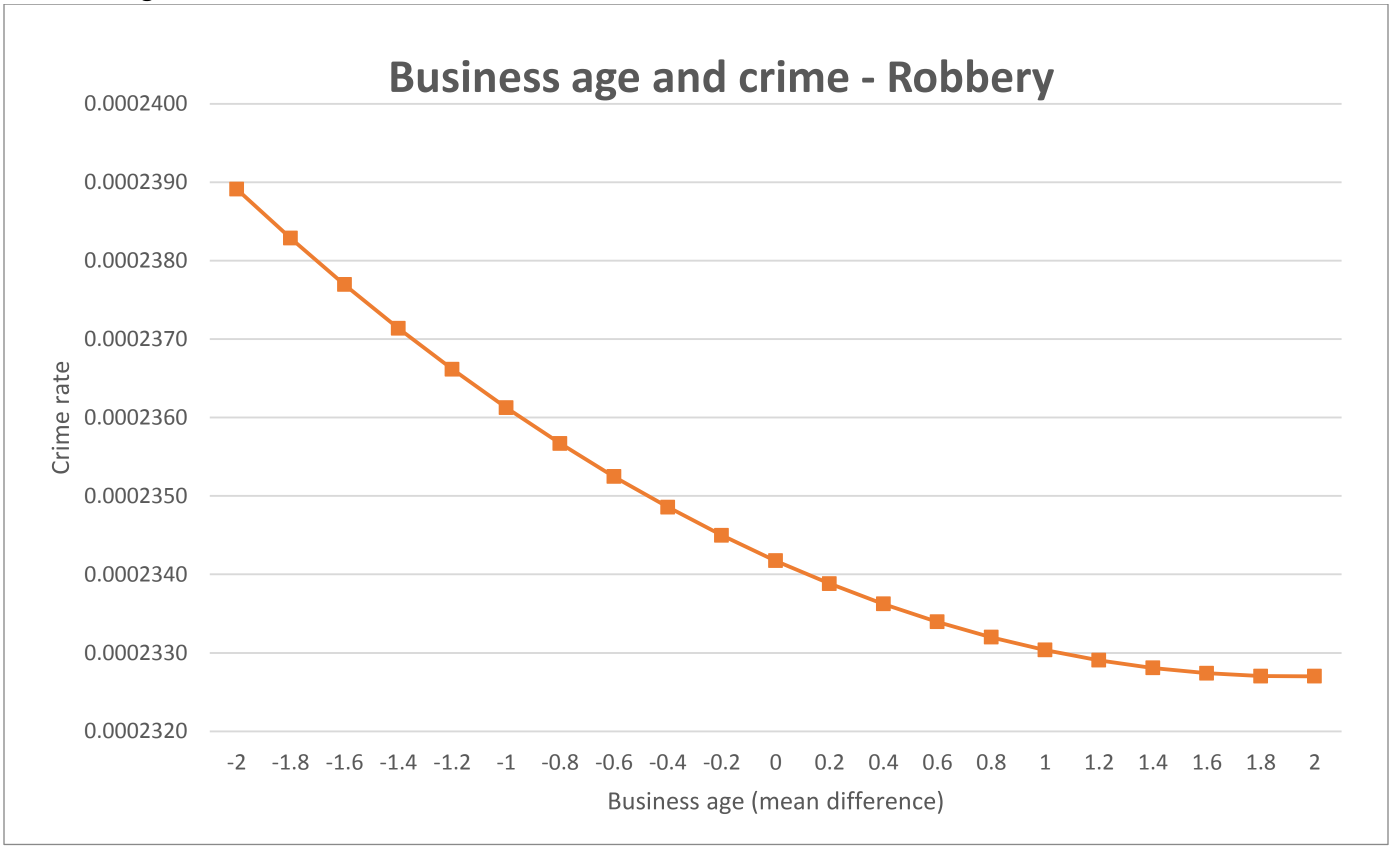
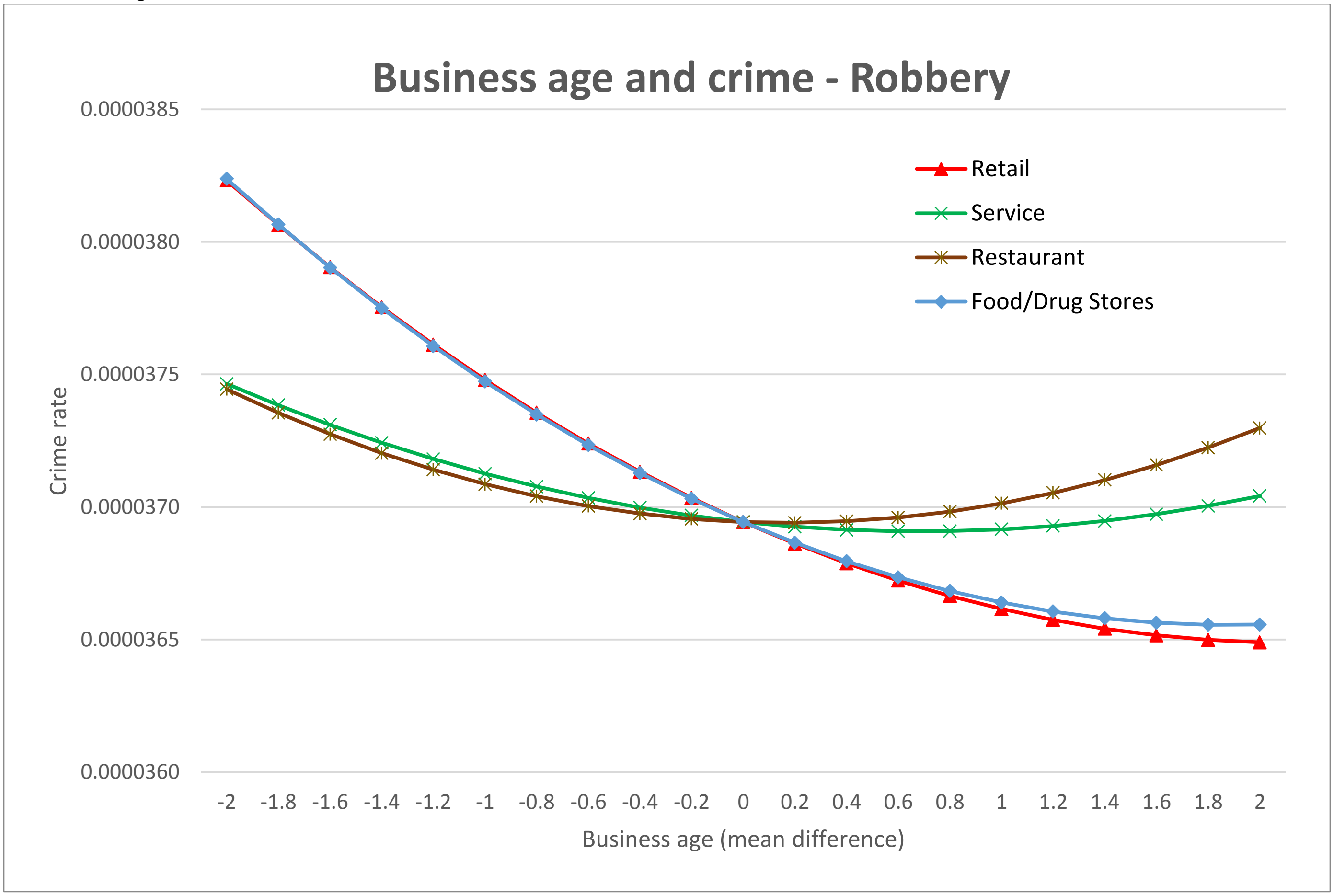


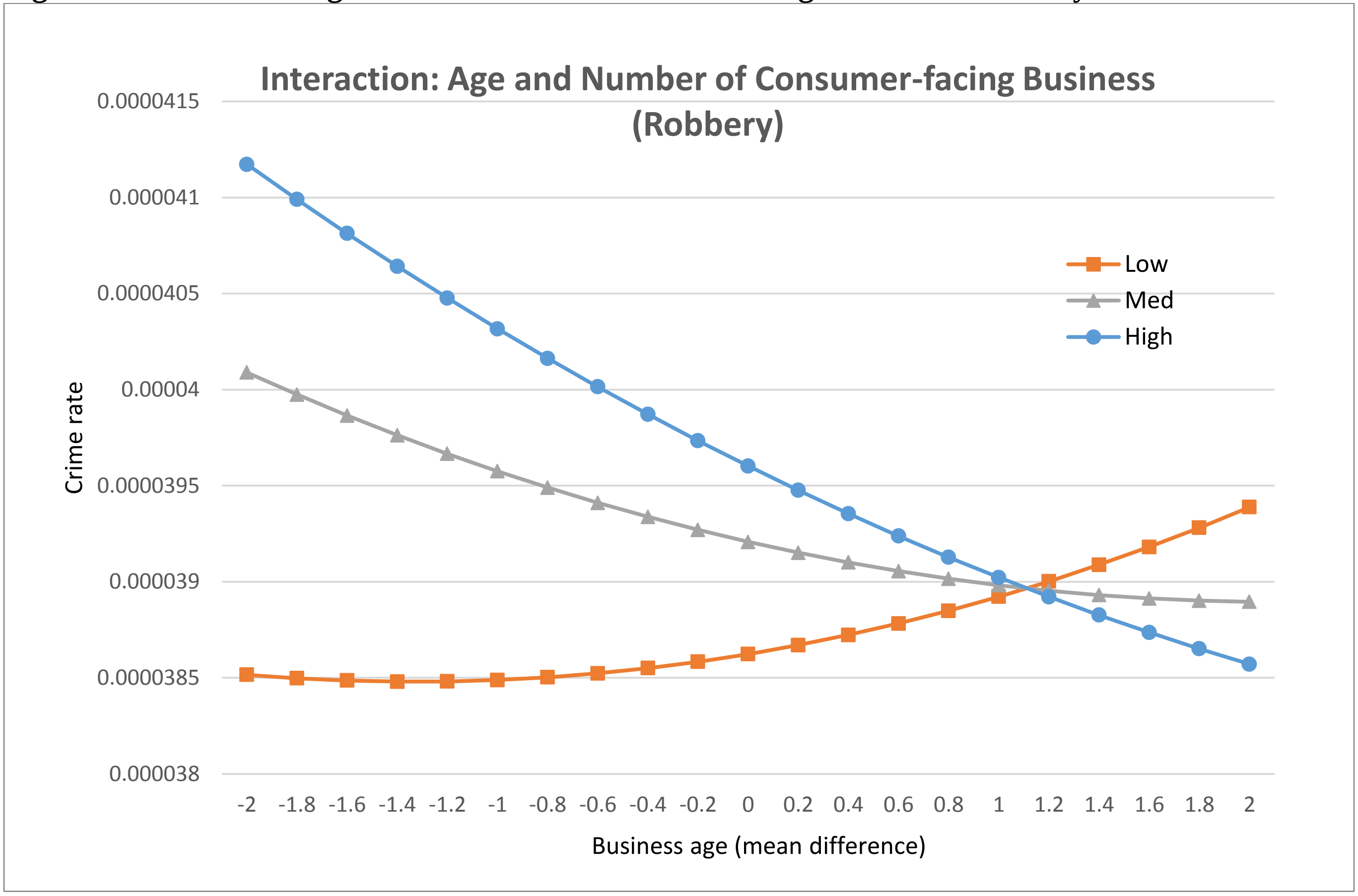
Figure 3. Age of various businesses and crime in blocks – Robbery

Business Age



Business Age

Figure 4. Interaction: Age and Number of Consumer-facing Business – Robbery



Business Age

APPENDIX A

Table A1. Interaction: Business age and the number of business (consumer-facing)

	Agg. Assault		Robbery		Burglary		Larceny		M.V. theft	
Consumer facing businesses										
Average business age	-0.004	**	-0.008	**	-0.008	**	-0.006	**	-0.008	**
	-2.915		-4.484		-6.365		-6.632		-6.464	
Average business age (squared)	0.002	**	0.002	**	0.002	**	0.001	**	0.001	**
	7.519		6.954		10.328		6.975		6.747	
Number of business	0.010	**	0.010	**	0.007	*	-0.006	**	0.000	
	3.254		3.355		2.458		-3.322		0.059	
Interactions										
Linear term	-0.005	**	-0.009	**	-0.005	**	-0.001	†	-0.004	**
	-4.202		-7.762		-5.008		-1.769		-3.780	
Squared term	0.000		0.000		0.000		0.000		0.000	
	-0.087		-1.114		-0.750		0.908		0.557	
Intercept	-10.238	**	-10.147	**	-8.829	**	-9.600	**	-10.769	**
	-176.69		-138.15		-200.67		-224.99		-174.98	
N	54,007		54,007		54,007		54,007		54,007	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test)*

T-values below coefficient estimates.

City and year fixed effects and other control variables are included but not reported in the table

Business Age

Table A2. Interaction: Business age and the number of business by business types (Violent crime)

Business Age

	Agg. Assault				Robbery			
	Retail	Service	Restaurant	Stores	Retail	Service	Restaurant	Stores
Average business age								
Retail	-0.005 **	-0.005 **	-0.005 **	-0.005 **	-0.012 **	-0.012 **	-0.012 **	-0.012 **
	-3.014	-3.049	-3.063	-3.083	-6.454	-6.231	-6.274	-6.281
Retail (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.003 **	0.003 **	0.003 **	0.003 **
	7.236	6.875	6.892	6.896	10.633	10.198	10.259	10.230
Service	-0.001	-0.001	-0.001	-0.001	-0.003 †	-0.004 *	-0.003 †	-0.003 †
	-0.933	-0.844	-0.934	-0.953	-1.730	-2.201	-1.744	-1.762
Service (squared)	0.001 **	0.002 **	0.001 **	0.001 **	0.002 **	0.002 **	0.002 **	0.002 **
	7.212	7.626	7.236	7.206	8.876	9.398	8.939	8.892
Restaurant	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.002	-0.001
	-0.491	-0.543	-0.124	-0.550	-0.433	-0.491	-0.966	-0.485
Restaurant (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.003 **	0.003 **	0.003 **	0.003 **
	7.642	7.612	8.139	7.633	11.437	11.412	12.366	11.433
Stores	-0.011 **	-0.011 **	-0.011 **	-0.011 **	-0.011 **	-0.011 **	-0.011 **	-0.012 **
	-5.861	-5.893	-5.910	-5.609	-5.622	-5.650	-5.636	-5.495
Stores (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.003 **	0.003 **	0.003 **	0.003 **
	9.056	9.050	9.015	8.134	11.505	11.514	11.440	11.305
Number of business								
Retail	0.016 **	0.017 **	0.018 **	0.018 **	0.001	0.005	0.005	0.005
	2.870	3.285	3.325	3.400	0.244	1.013	1.047	1.051
Service	0.012	0.013 †	0.012 †	0.012	0.013	0.013	0.013 †	0.014 †
	1.564	1.788	1.662	1.631	1.608	1.639	1.663	1.712
Restaurant	0.015	0.014	0.018	0.014	0.059 **	0.056 **	0.055 **	0.056 **
	1.128	1.038	1.334	1.025	4.408	4.205	4.006	4.181
Stores	0.018	0.017	0.016	0.015	0.022	0.021	0.019	0.013
	0.849	0.791	0.776	0.712	1.047	1.002	0.913	0.614
Interactions								
Linear term	-0.004 *	-0.005 **	-0.008 **	0.000	-0.007 **	-0.009 **	-0.016 **	-0.008 *
	-2.490	-3.028	-2.889	0.068	-4.127	-5.559	-5.393	-2.321
Squared term	0.000	0.000 †	-0.001 *	0.000	0.000	0.000	0.000	0.000
	-0.530	-1.768	-2.027	0.329	0.141	-0.300	0.140	0.726
Intercept	-10.262 **	-10.263 **	-10.262 **	-10.261 **	-10.209 **	-10.210 **	-10.211 **	-10.206 **
	-177.404	-177.420	-177.407	-177.350	-139.893	-139.970	-139.968	-139.832
N	54007	54007	54007	54007	54007	54007	54007	54007

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test)*

T-values below coefficient estimates.

City and year fixed effects and other control variables are included but not reported in the table

Business Age

Table A3. Interaction: Business age and the number of business by business types (Property crime)

Business Age

	Burglary				Larceny				M.V. theft			
	Retail	Service	Restaurant	Stores	Retail	Service	Restaurant	Stores	Retail	Service	Restaurant	Stores
Average business age												
Retail	-0.009 **	-0.009 **	-0.009 **	-0.009 **	-0.005 **	-0.005 **	-0.005 **	-0.005 **	-0.006 **	-0.007 **	-0.007 **	-0.007 **
	-5.774	-6.017	-6.058	-6.009	-4.620	-4.885	-4.937	-4.891	-4.499	-4.889	-4.933	-4.928
Retail (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.001 **	0.001 **	0.001 **	0.001 **	0.002 **	0.002 **	0.002 **	0.002 **
	9.176	8.675	8.708	8.687	6.698	6.719	6.744	6.718	8.053	7.858	7.892	7.896
Service	-0.002 †	-0.003 †	-0.002 †	-0.002 †	-0.001	-0.001	-0.001	-0.001	-0.003 **	-0.003 **	-0.003 **	-0.003 **
	-1.747	-1.959	-1.764	-1.769	-0.796	-0.919	-0.806	-0.787	-2.779	-2.896	-2.782	-2.785
Service (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **
	8.972	9.429	9.065	9.024	4.564	4.961	4.589	4.556	6.152	6.582	6.178	6.169
Restaurant	-0.003 †	-0.003 †	-0.004 *	-0.003 †	-0.004 **	-0.004 **	-0.004 **	-0.004 **	-0.003 *	-0.003 *	-0.004 *	-0.003 *
	-1.871	-1.906	-2.186	-1.897	-3.454	-3.446	-3.703	-3.438	-2.300	-2.315	-2.368	-2.339
Restaurant (squared)	0.001 **	0.001 **	0.002 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.002 **	0.002 **	0.002 **	0.002 **
	6.545	6.559	7.741	6.610	6.270	6.280	6.207	6.290	8.174	8.180	8.327	8.196
Stores	-0.011 **	-0.011 **	-0.011 **	-0.013 **	-0.009 **	-0.009 **	-0.009 **	-0.010 **	-0.007 **	-0.007 **	-0.007 **	-0.006 **
	-6.202	-6.235	-6.214	-6.717	-7.031	-7.033	-7.011	-7.403	-4.224	-4.224	-4.216	-3.597
Stores (squared)	0.002 **	0.002 **	0.002 **	0.002 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.002 **
	7.072	7.035	6.984	7.097	6.062	6.079	6.049	4.939	6.225	6.210	6.180	6.269
Number of business												
Retail	0.010 *	0.011 *	0.011 *	0.011 *	-0.007 *	-0.008 *	-0.008 *	-0.008 *	0.001	0.000	0.000	0.000
	2.172	2.262	2.264	2.270	-2.252	-2.462	-2.434	-2.479	0.206	0.058	0.067	0.085
Service	0.011 †	0.012 †	0.012 †	0.012 †	0.003	0.004	0.003	0.004	-0.004	-0.004	-0.004	-0.004
	1.713	1.771	1.785	1.792	0.702	0.789	0.695	0.721	-0.679	-0.597	-0.665	-0.662
Restaurant	0.006	0.005	0.005	0.005	-0.006	-0.006	-0.008	-0.006	0.020 †	0.021 †	0.020 †	0.020 †
	0.525	0.444	0.425	0.463	-0.774	-0.715	-0.966	-0.693	1.800	1.819	1.738	1.741
Stores	0.027	0.026	0.026	0.011	-0.006	-0.006	-0.006	-0.012	-0.008	-0.008	-0.008	-0.006
	1.414	1.356	1.346	0.585	-0.430	-0.421	-0.418	-0.852	-0.428	-0.427	-0.438	-0.344
Interactions												
Linear term	-0.005 **	-0.005 **	-0.013 **	-0.010 **	0.000	-0.003 **	-0.001	0.001	-0.002	-0.004 **	-0.004 †	-0.004
	-2.917	-3.678	-5.149	-3.016	0.106	-3.157	-0.673	0.598	-1.155	-3.389	-1.826	-1.400
Squared term	0.000	0.000	0.000	0.001 **	0.000	0.000	0.000	0.001 *	0.000 †	0.000	0.000	0.000
	-1.205	0.190	0.214	2.815	-0.864	-0.682	1.225	2.360	-1.716	-0.617	0.228	-0.784
Intercept	-8.843 **	-8.843 **	-8.844 **	-8.840 **	-9.611 **	-9.612 **	-9.611 **	-9.610 **	-10.788 **	-10.788 **	-10.788 **	-10.788 **
	-201.332	-201.333	-201.392	-201.166	-225.618	-225.680	-225.627	-225.560	-175.523	-175.542	-175.516	-175.511
N	54007	54007	54007	54007	54007	54007	54007	54007	54007	54007	54007	54007

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .05 (one-tail test)*

T-values below coefficient estimates.

City and year fixed effects and other control variables are included but not reported in the table

Business Age

Figure A1. Age of Consumer-facing Businesses and Crime in Blocks – Aggravated Assault

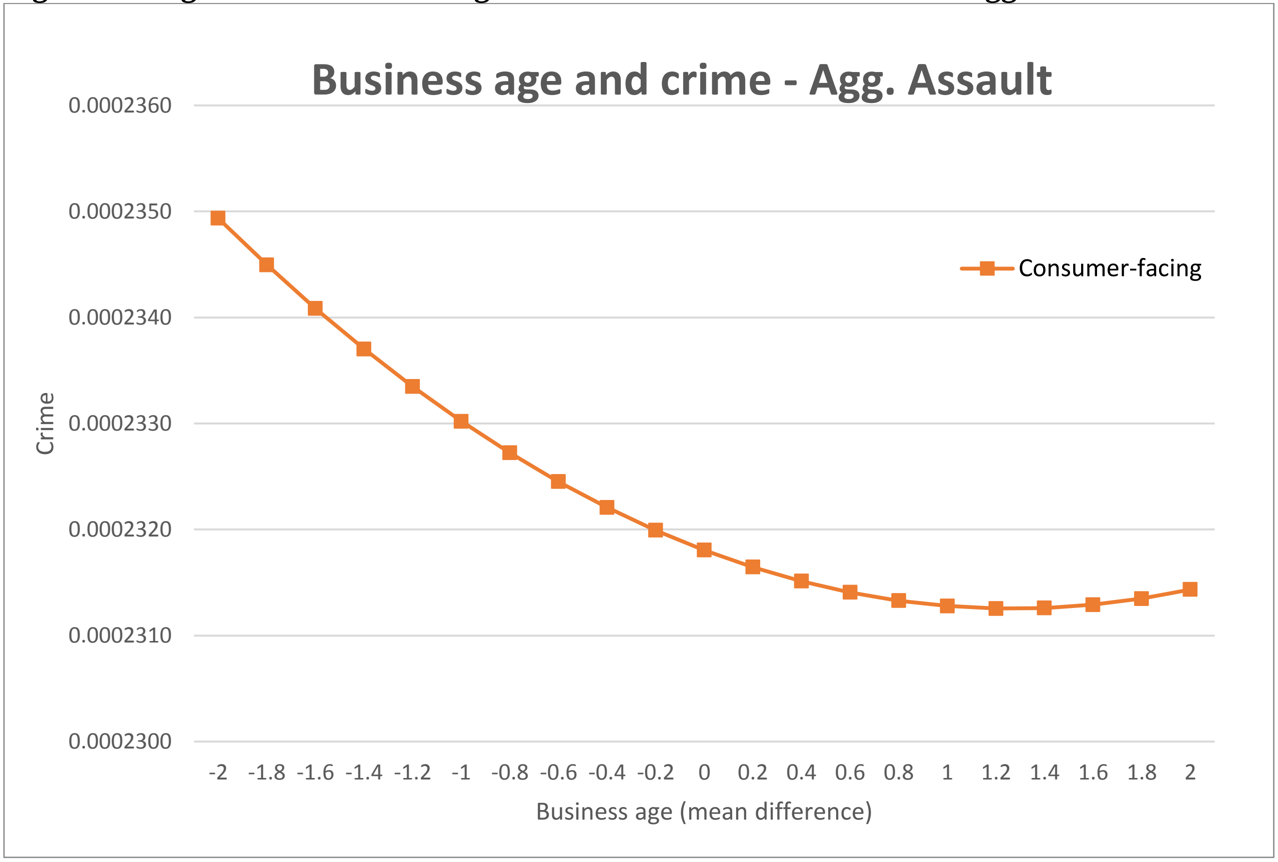


Figure A2. Age of Various Businesses and Crime in Blocks – Aggravated Assault

Business Age

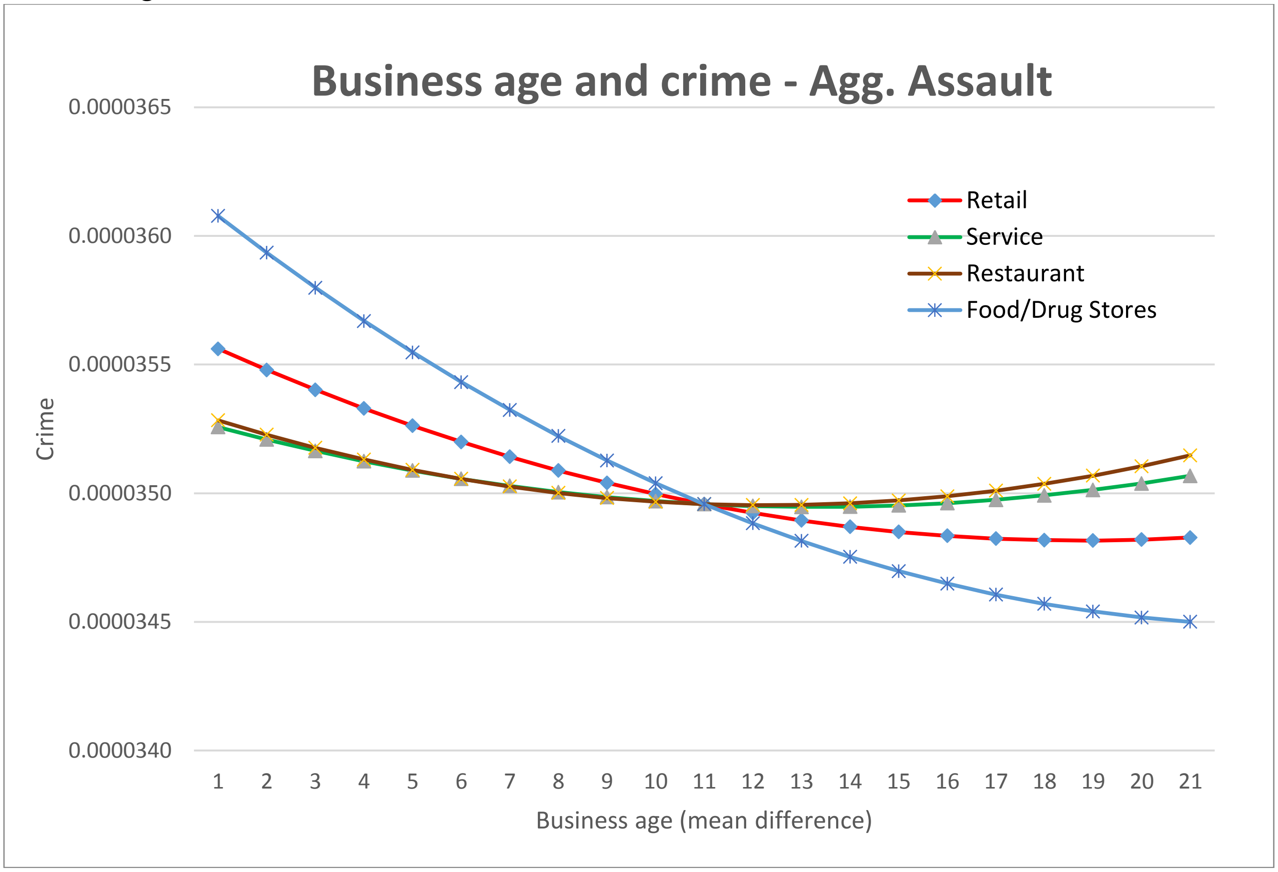
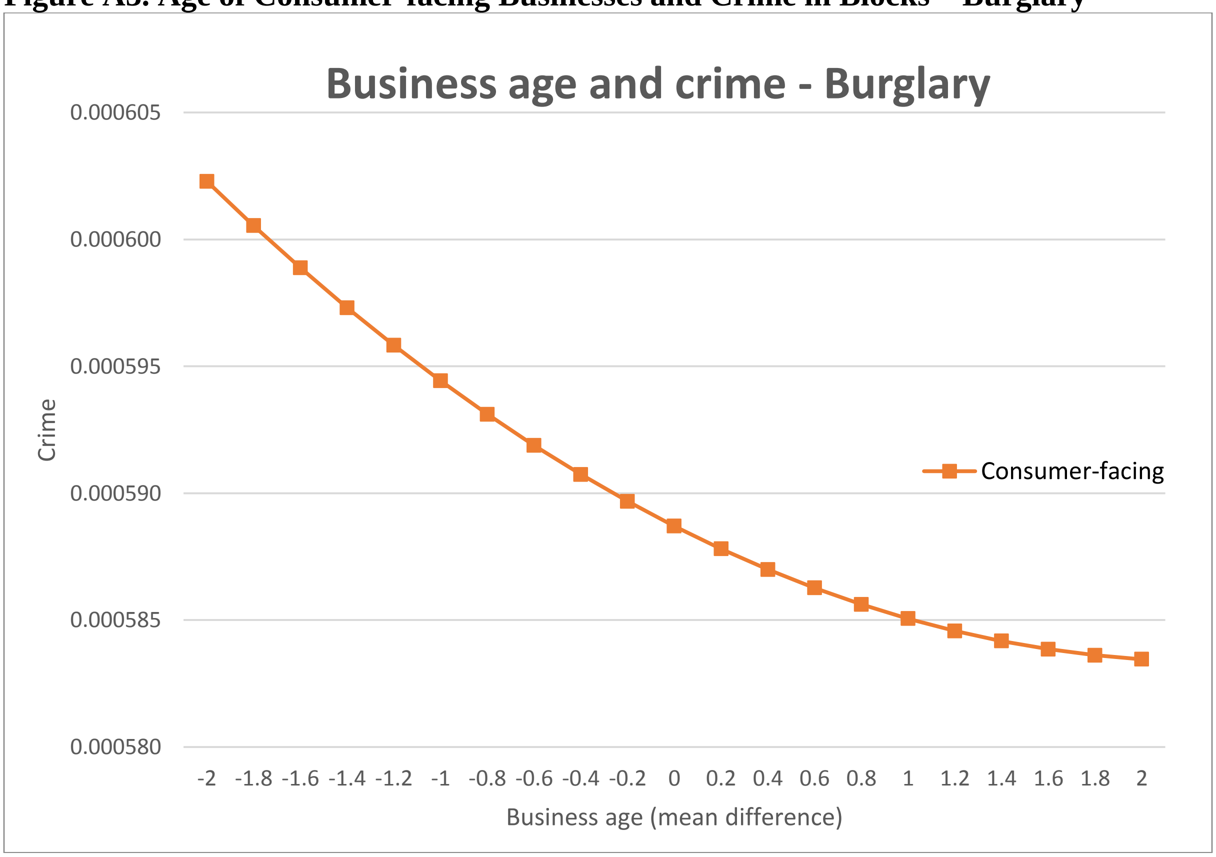


Figure A3. Age of Consumer-facing Businesses and Crime in Blocks – Burglary



Business Age

Figure A4. Age of Various Businesses and Crime in Blocks – Burglary

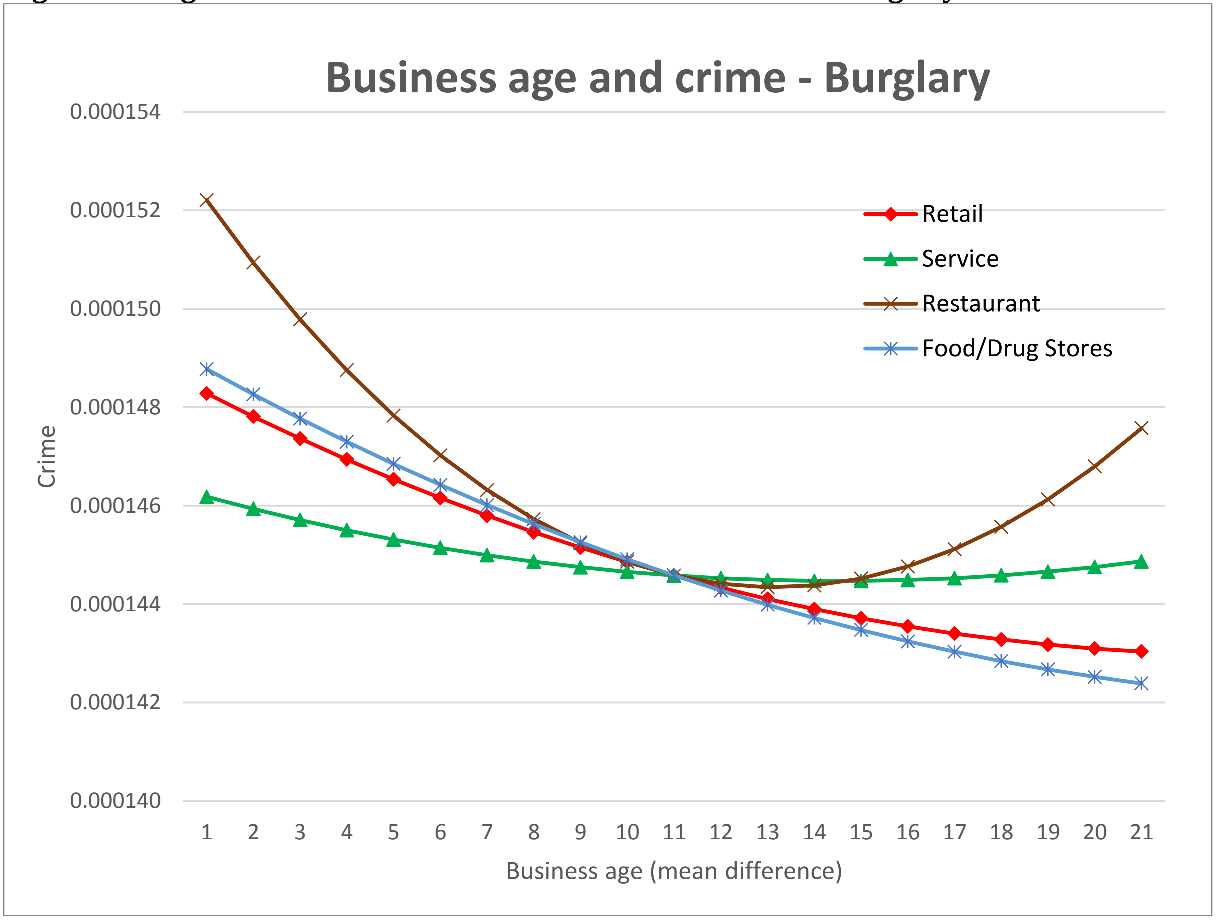


Figure A5. Age of Consumer-facing Businesses and Crime in Blocks – Larceny

Business Age

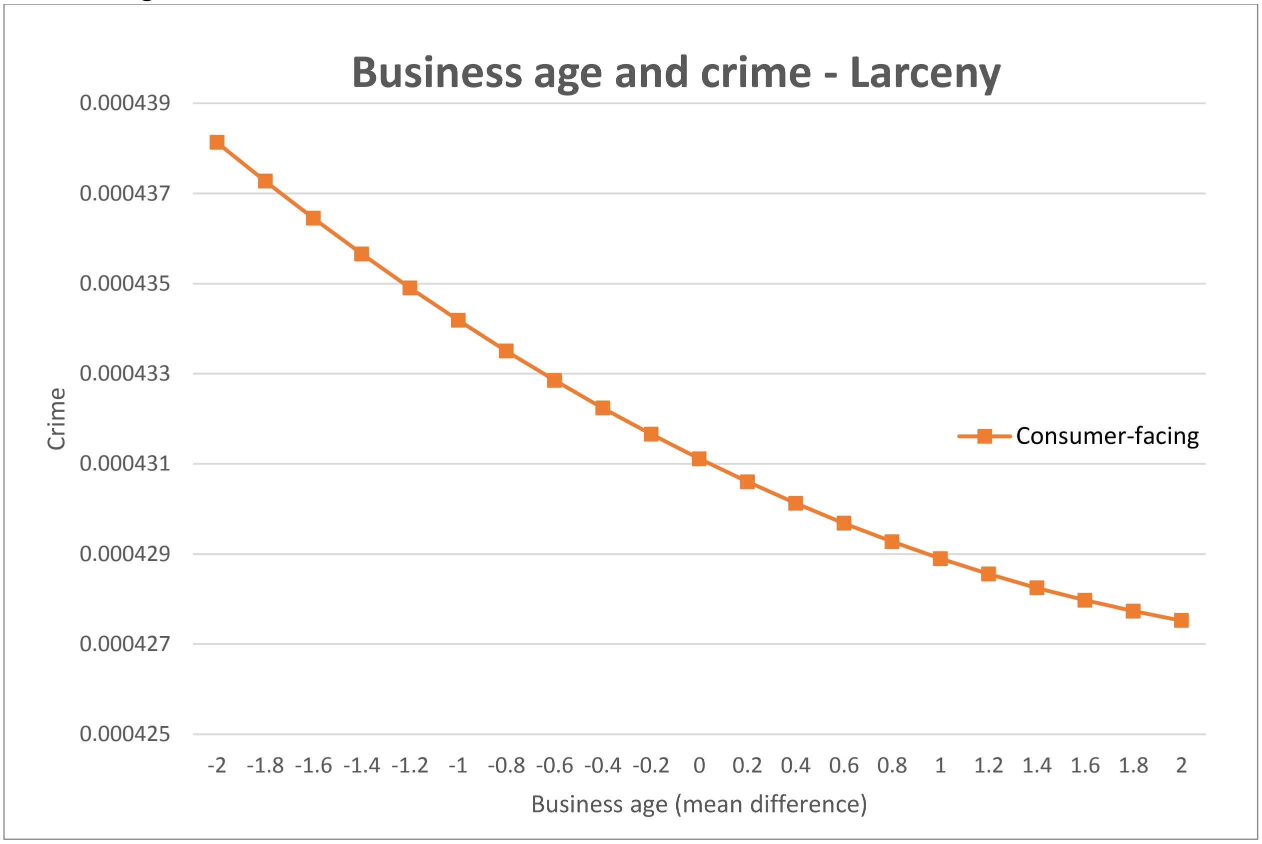
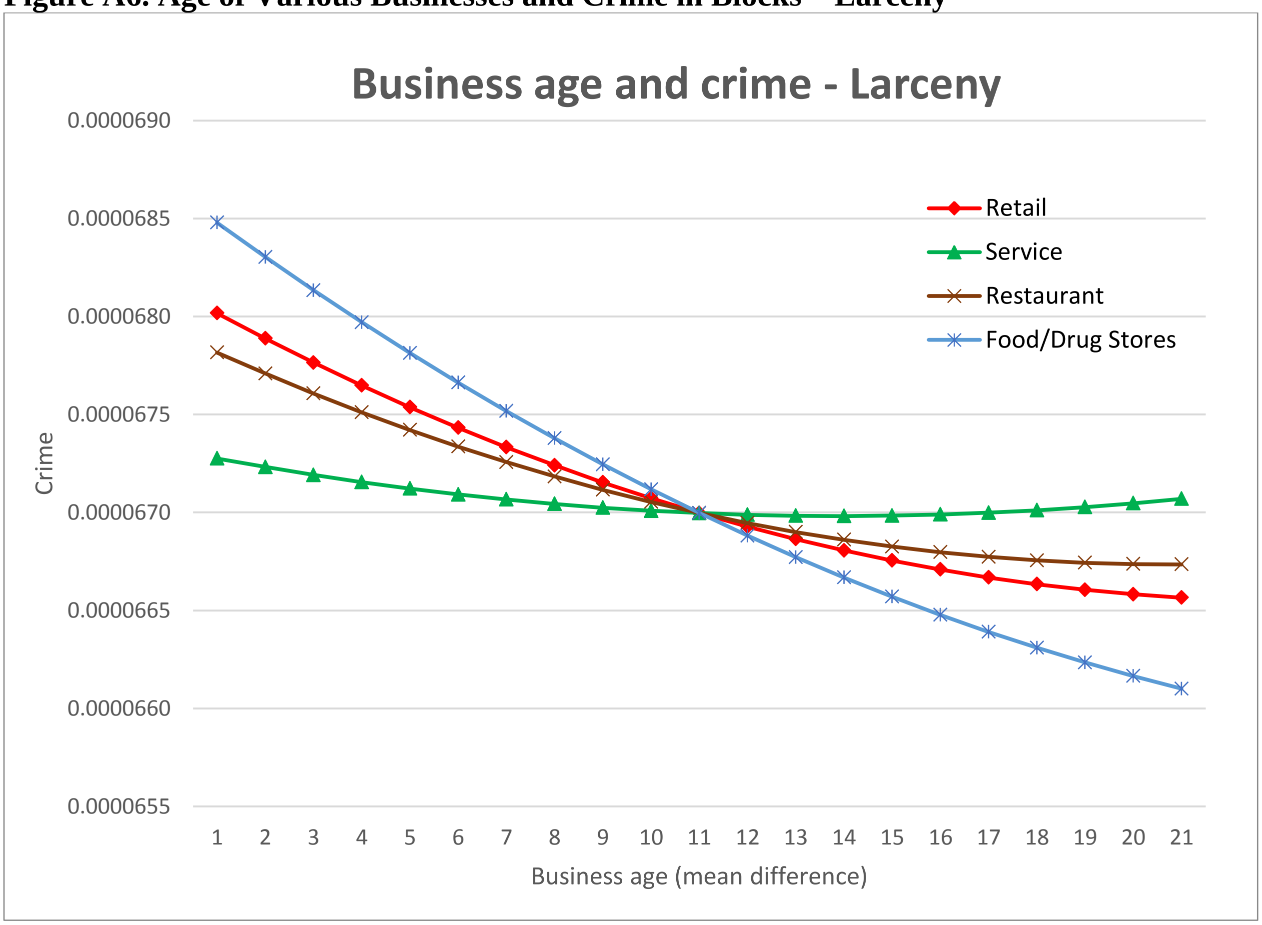


Figure A6. Age of Various Businesses and Crime in Blocks – Larceny



Business Age

Figure A7. Age of Consumer-facing Businesses and Crime in Blocks – Motor Vehicle Theft

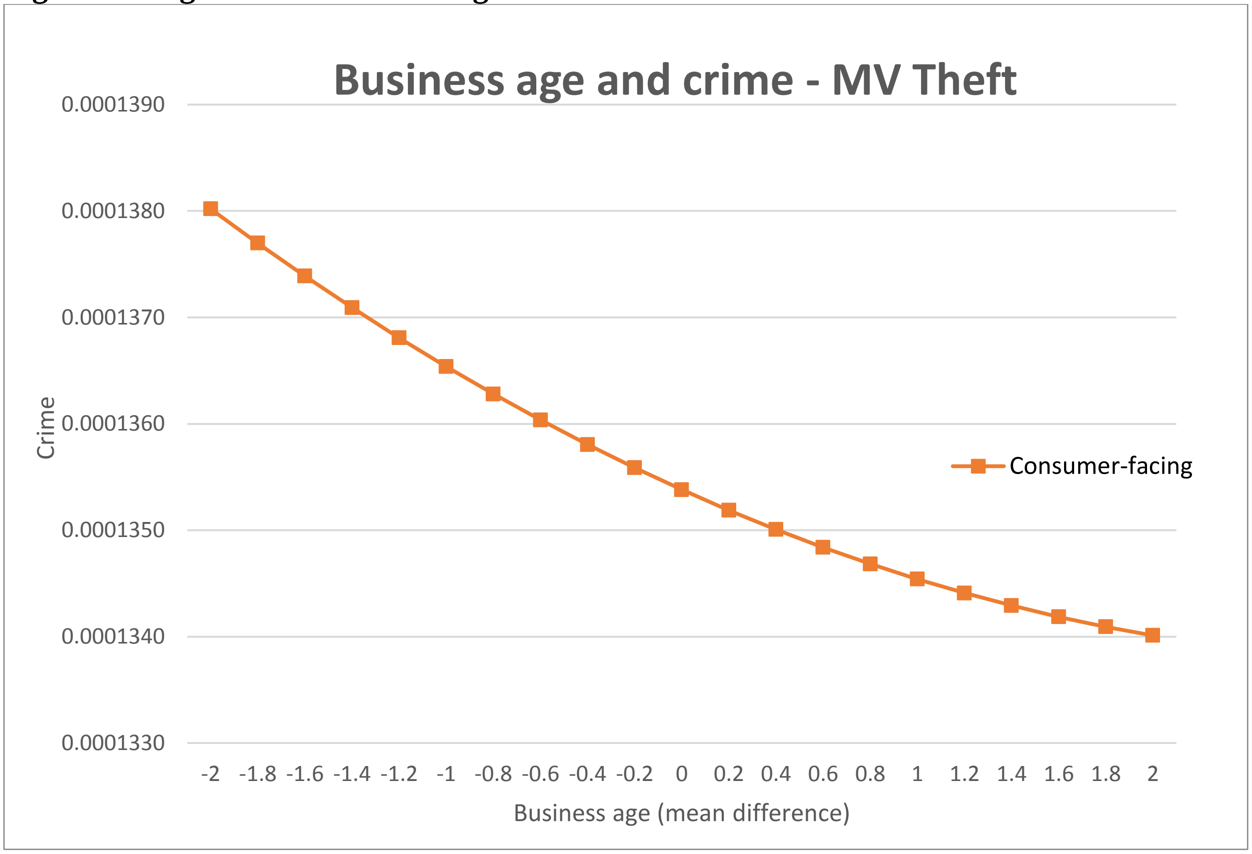
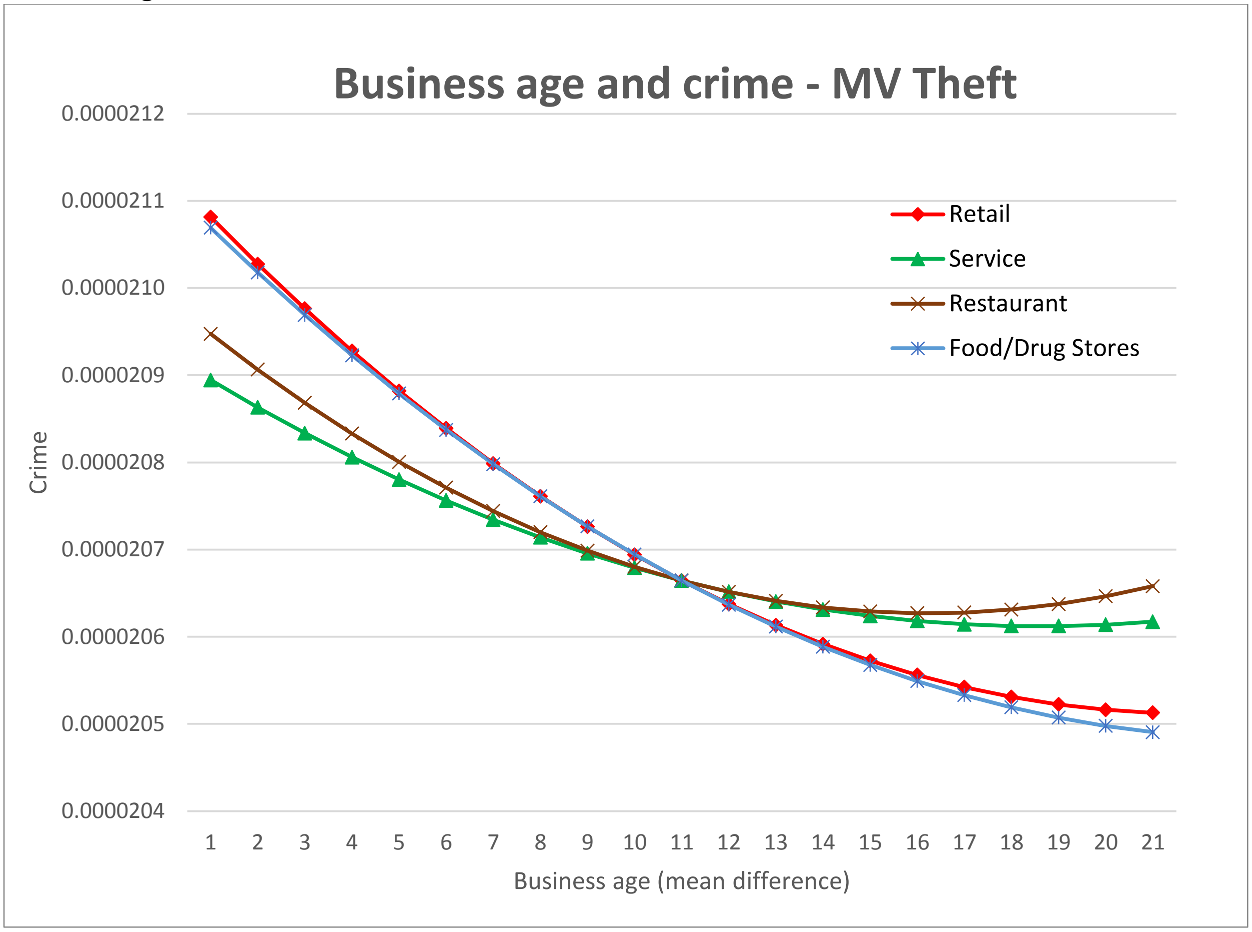


Figure A8. Age of Various Businesses and Crime in Blocks – Motor Vehicle Theft

Business Age



Business Age

Figure A9. Interaction: Age and Number of Consumer-facing Business – Aggravated assault

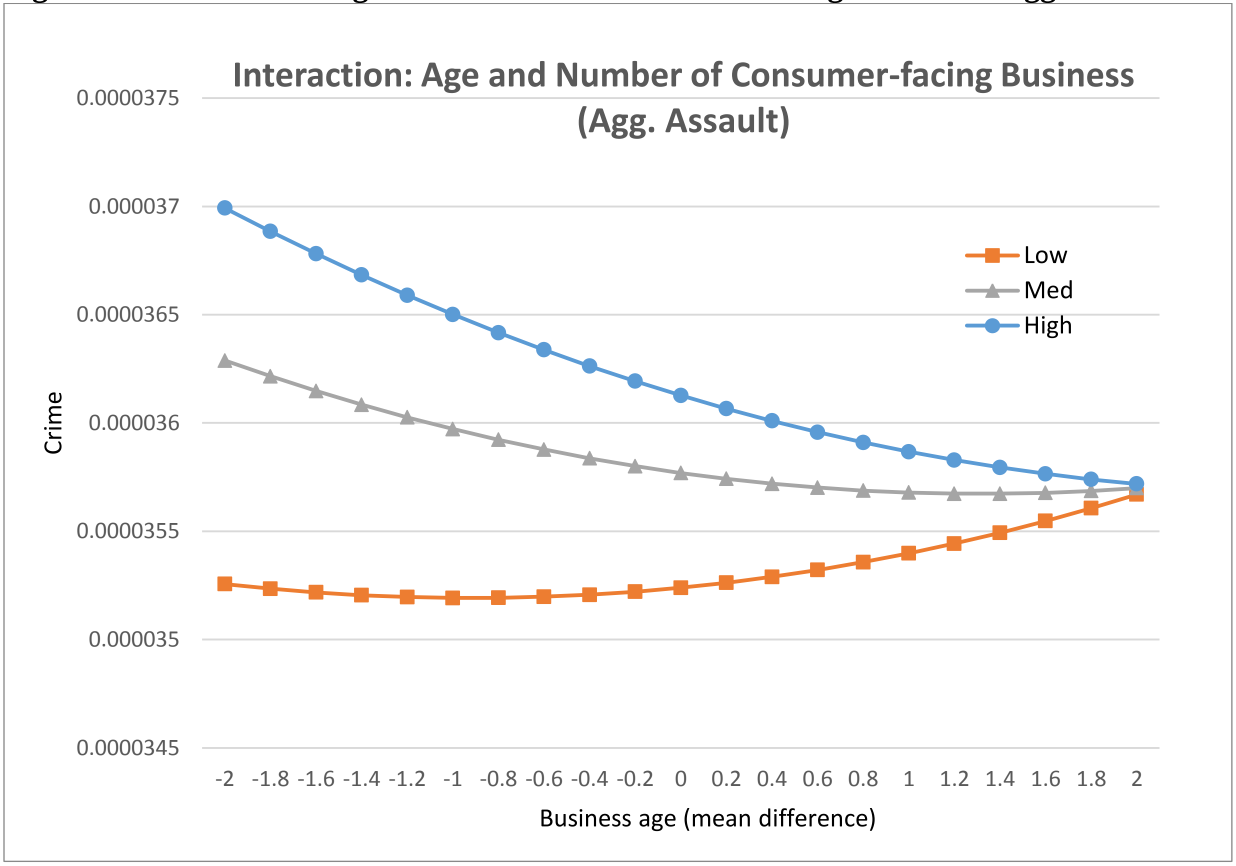


Figure A10. Interaction: Age and Number of Service Business – Aggravated assault

Business Age

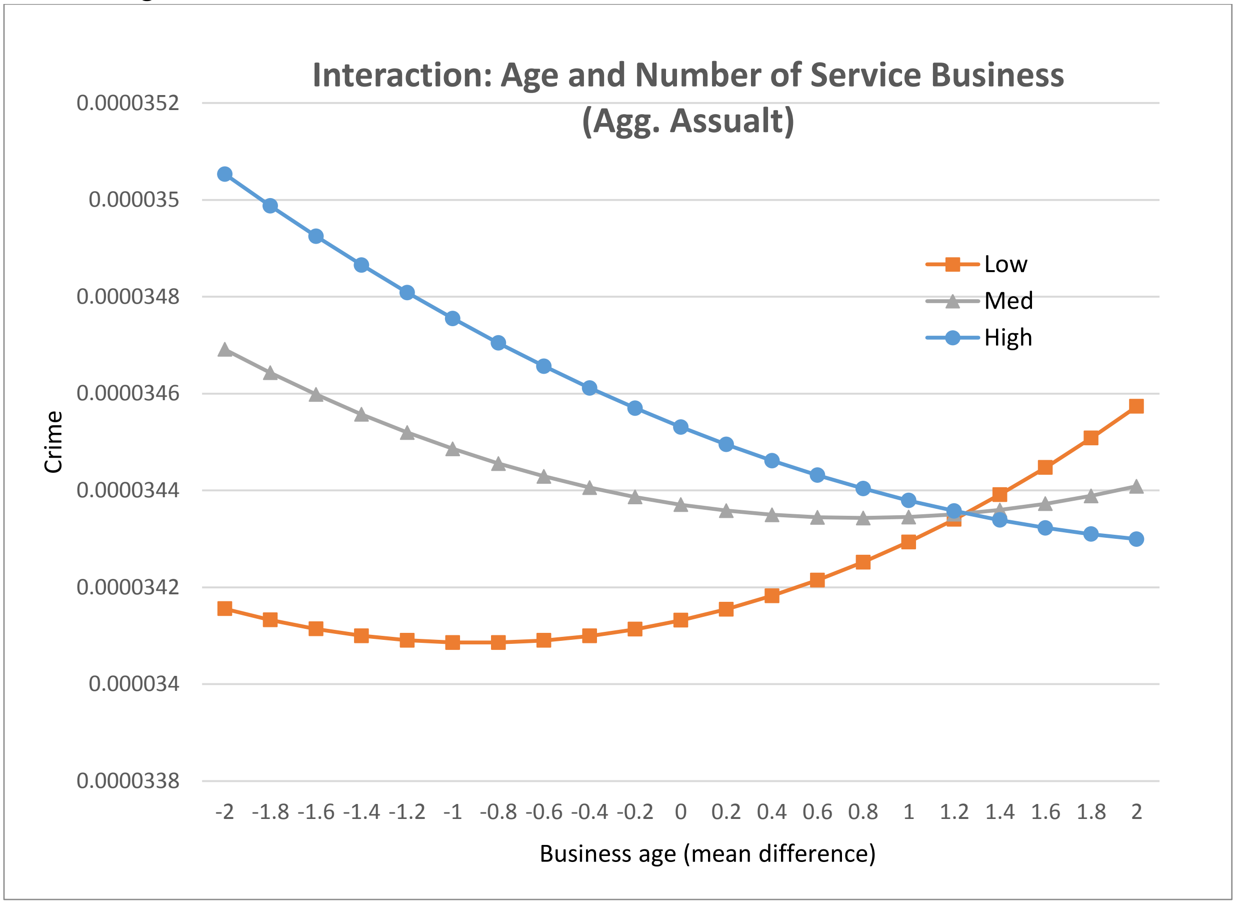


Figure A11. Interaction: Age and Number of Restaurants – Aggravated assault

Business Age

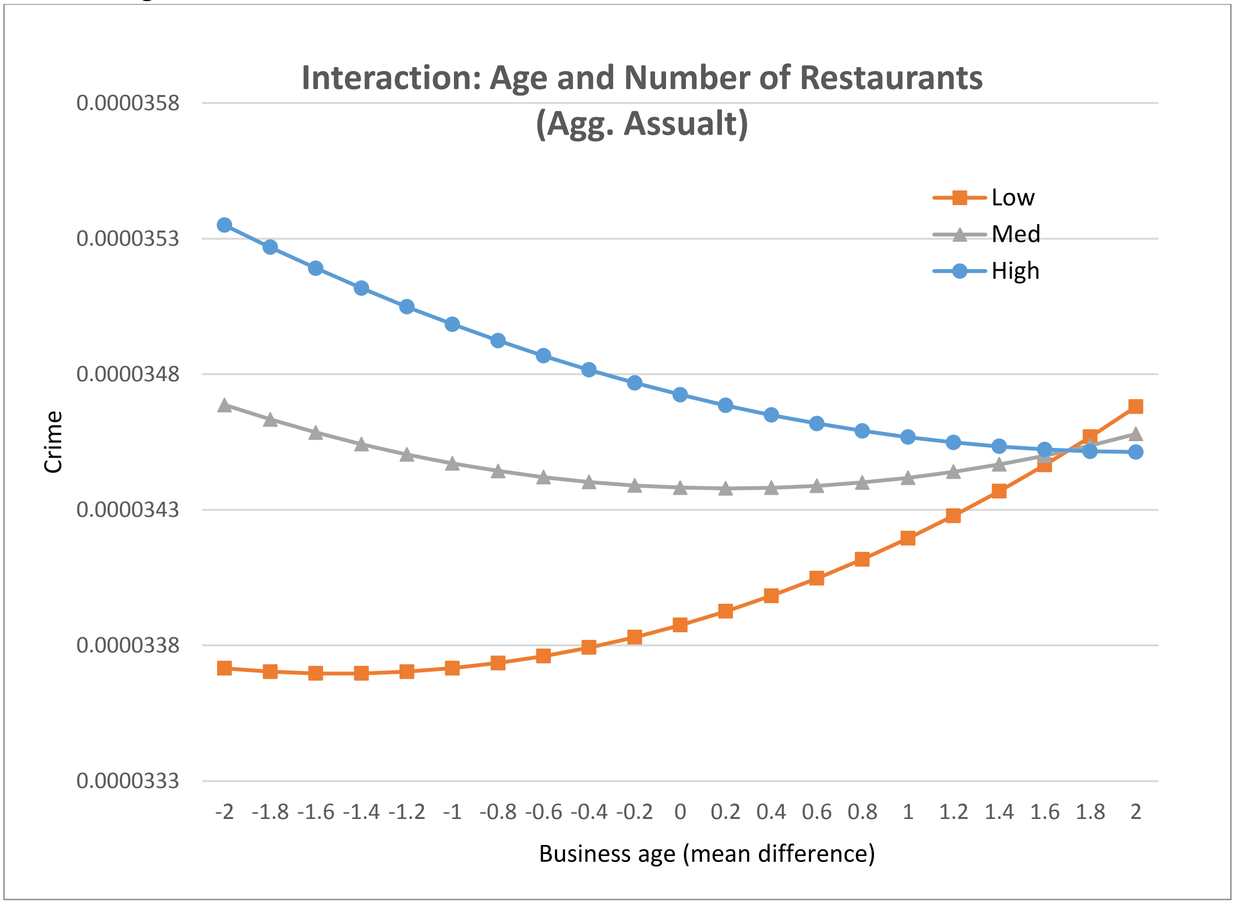


Figure A12. Interaction: Age and Number of Retail Business – Robbery

Business Age

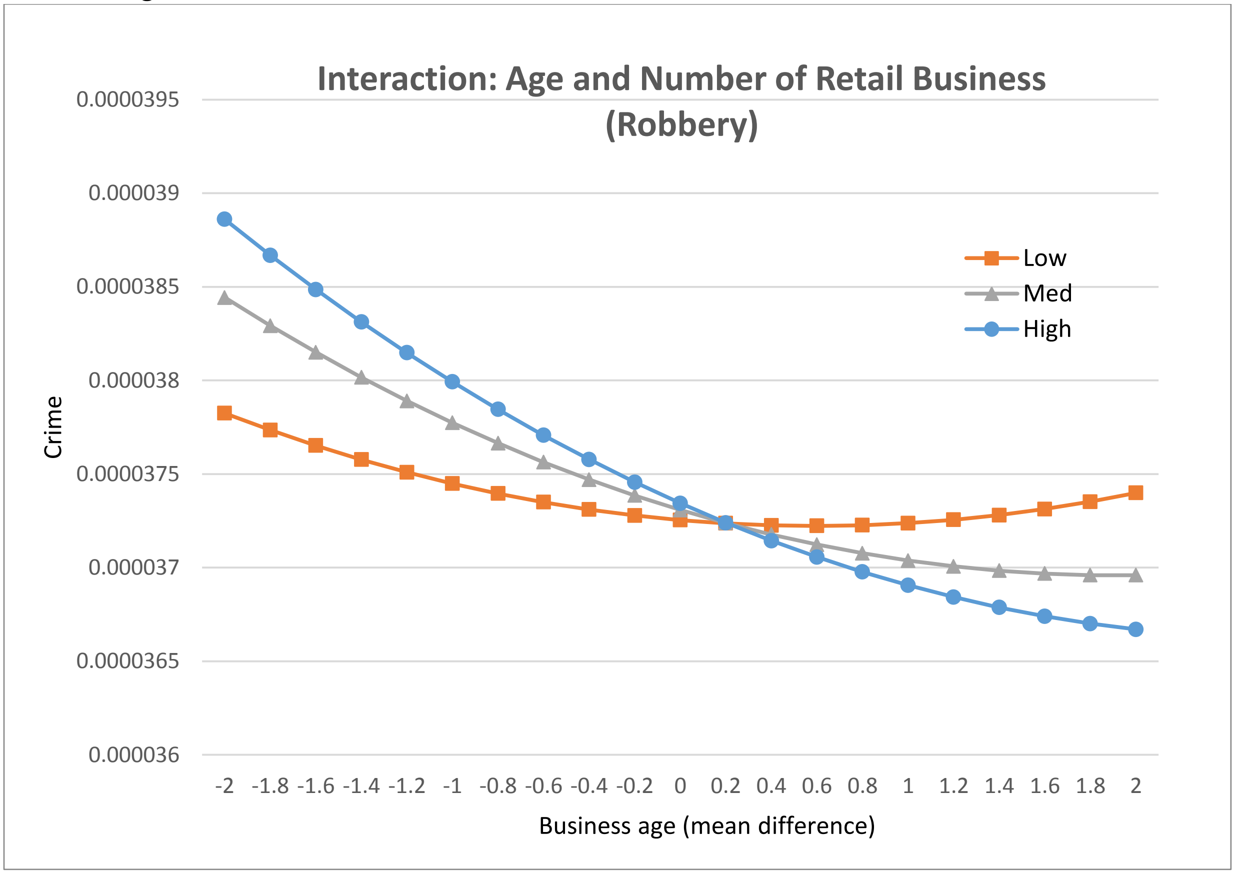
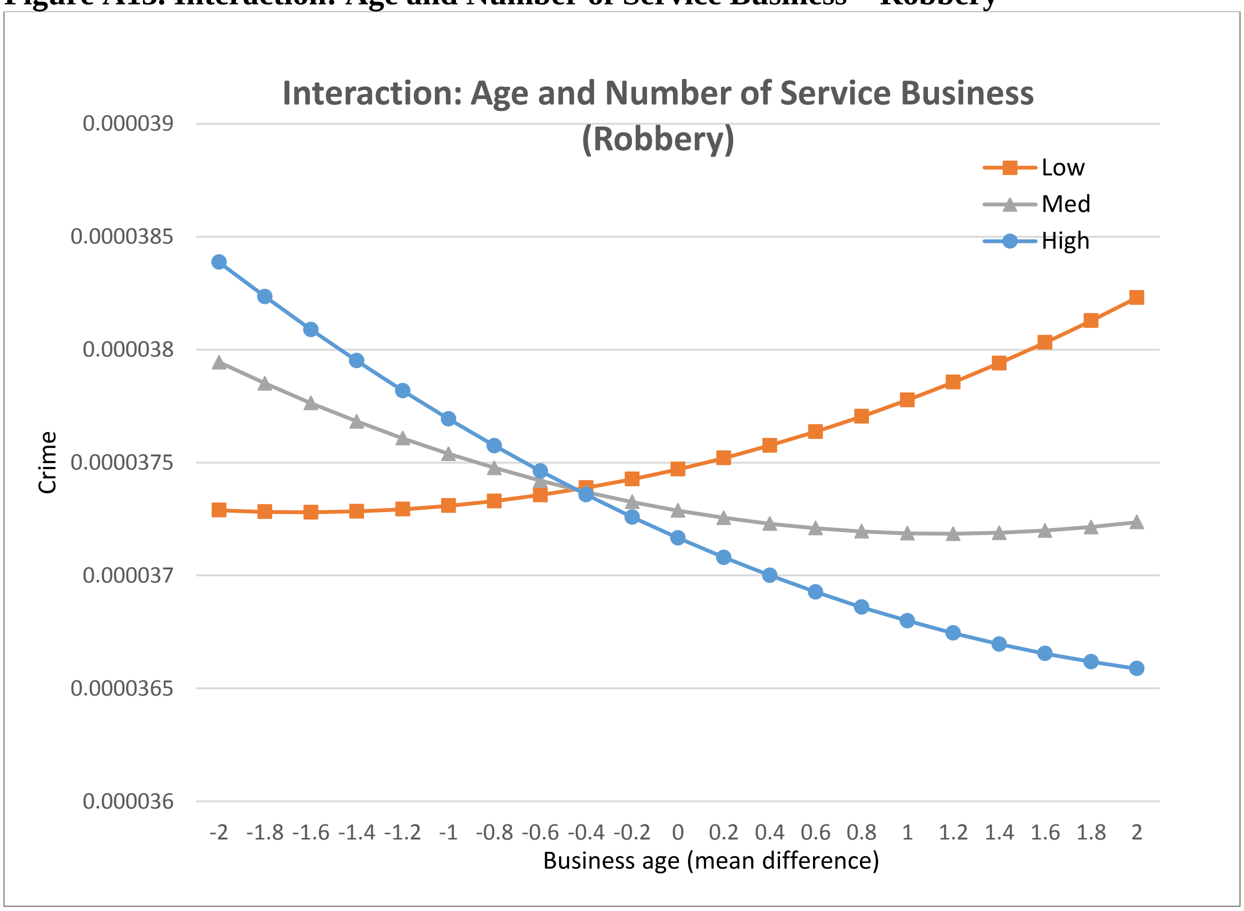


Figure A13. Interaction: Age and Number of Service Business – Robbery



Business Age

Figure A14. Interaction: Age and Number of Restaurants– Robbery

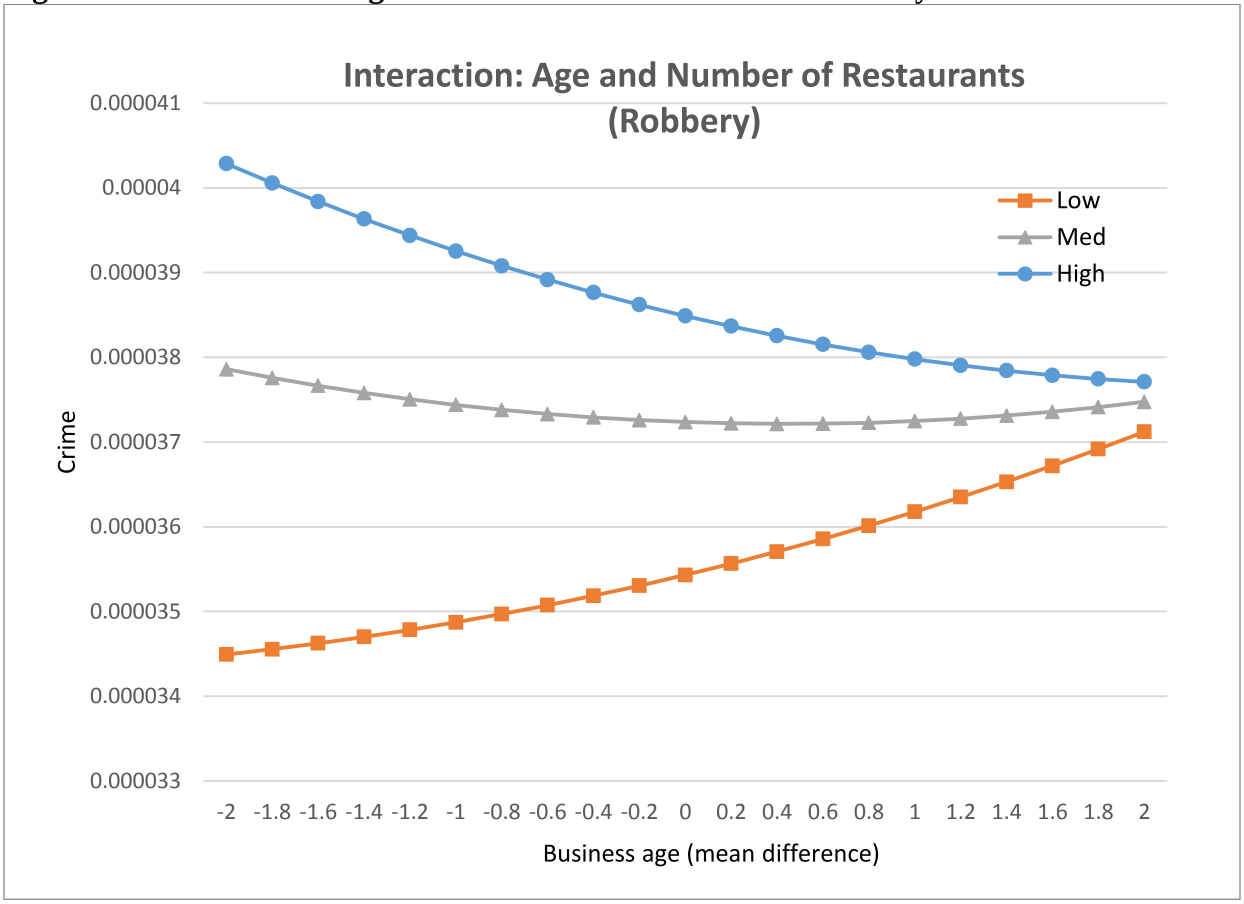


Figure A15. Interaction: Age and Number of Stores – Robbery

Business Age

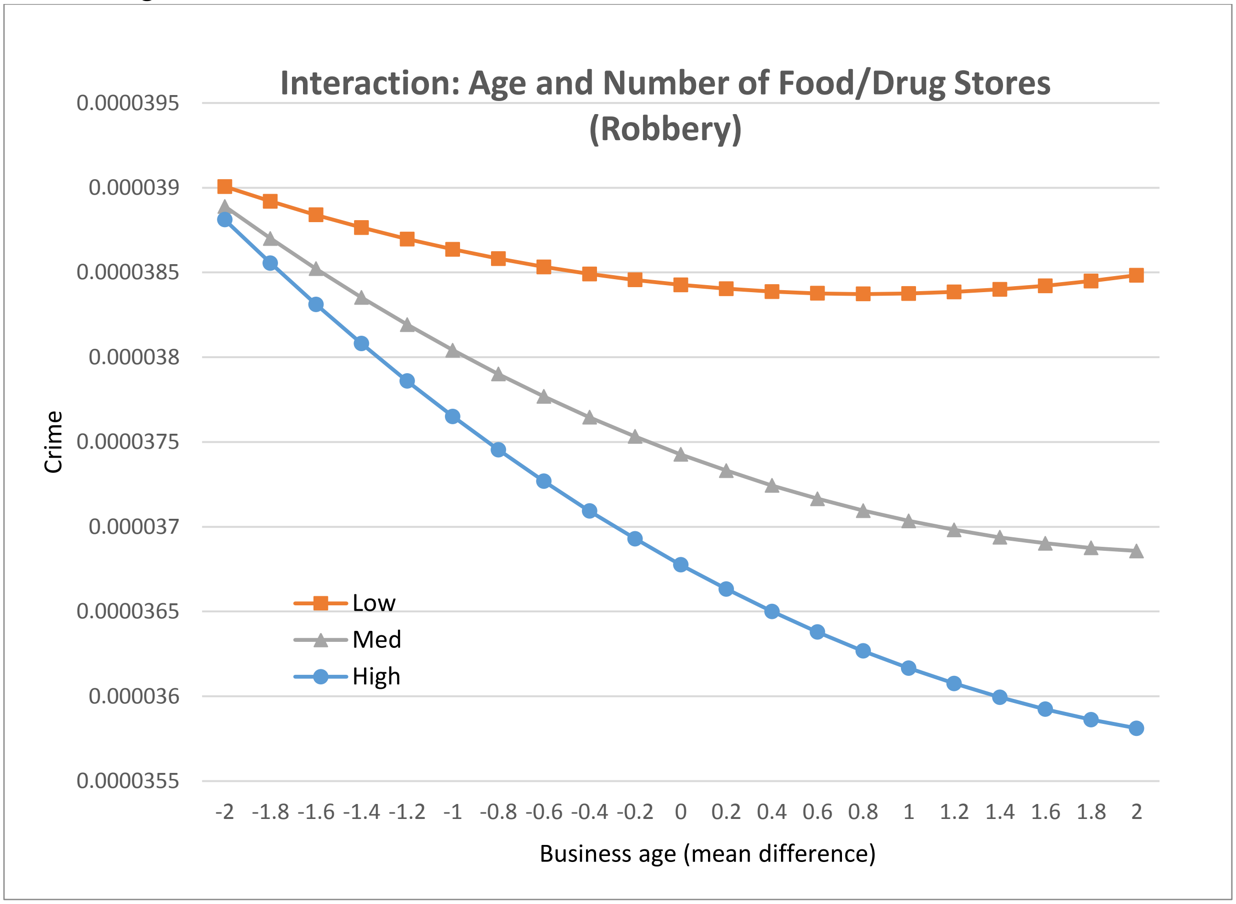


Figure A16. Interaction: Age and Number of consumer-facing business – Burglary

Business Age

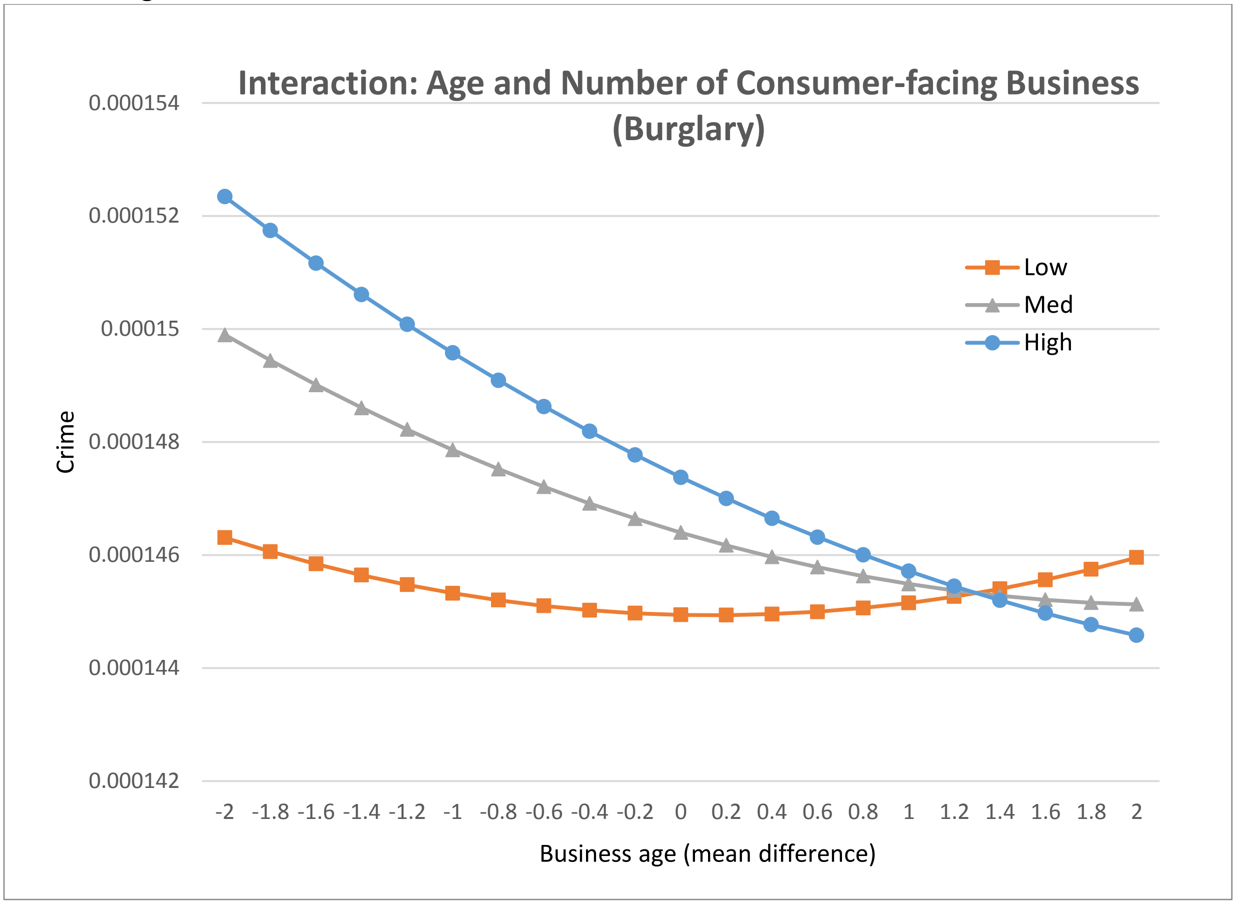
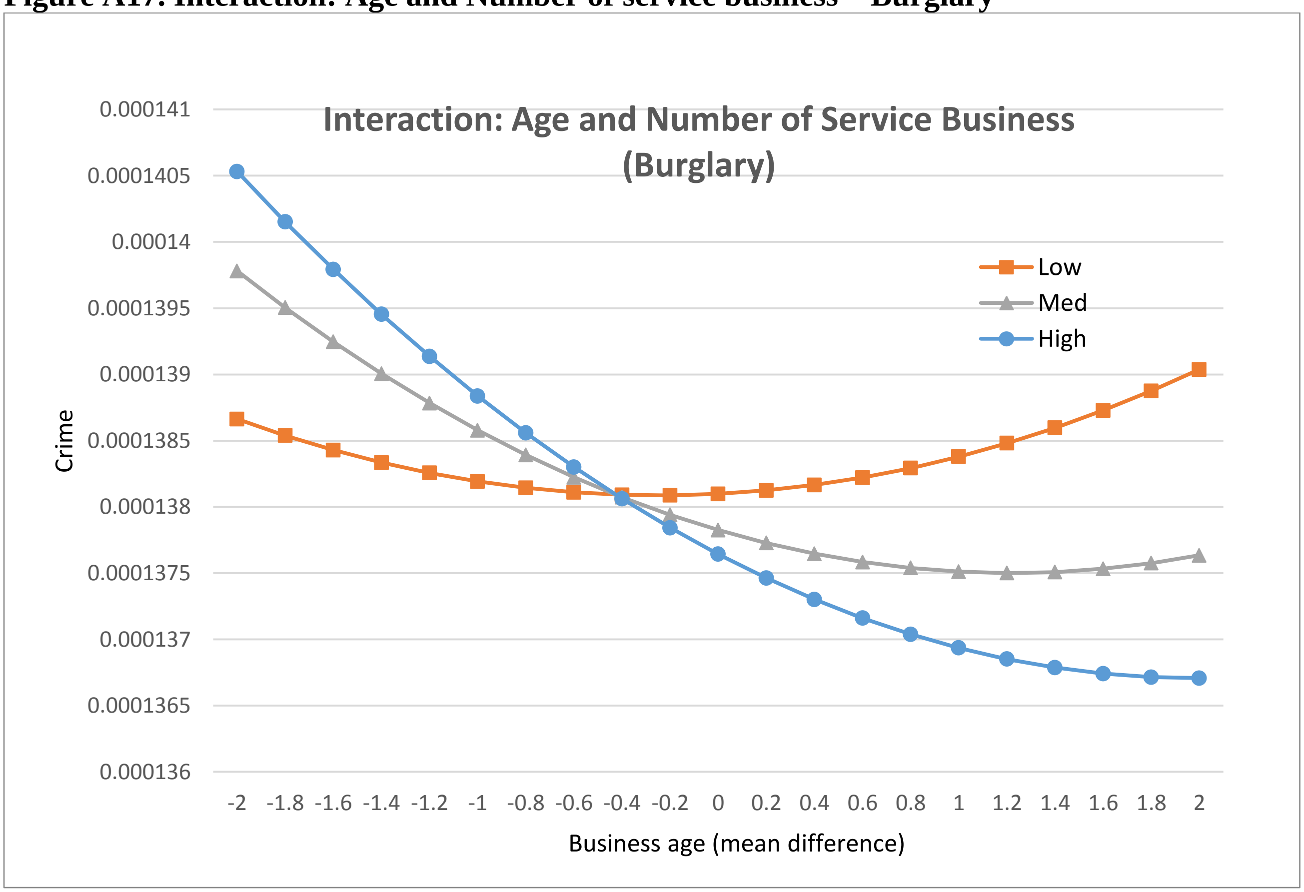


Figure A17. Interaction: Age and Number of service business – Burglary



Business Age

Figure A18. Interaction: Age and Number of restaurants – Burglary

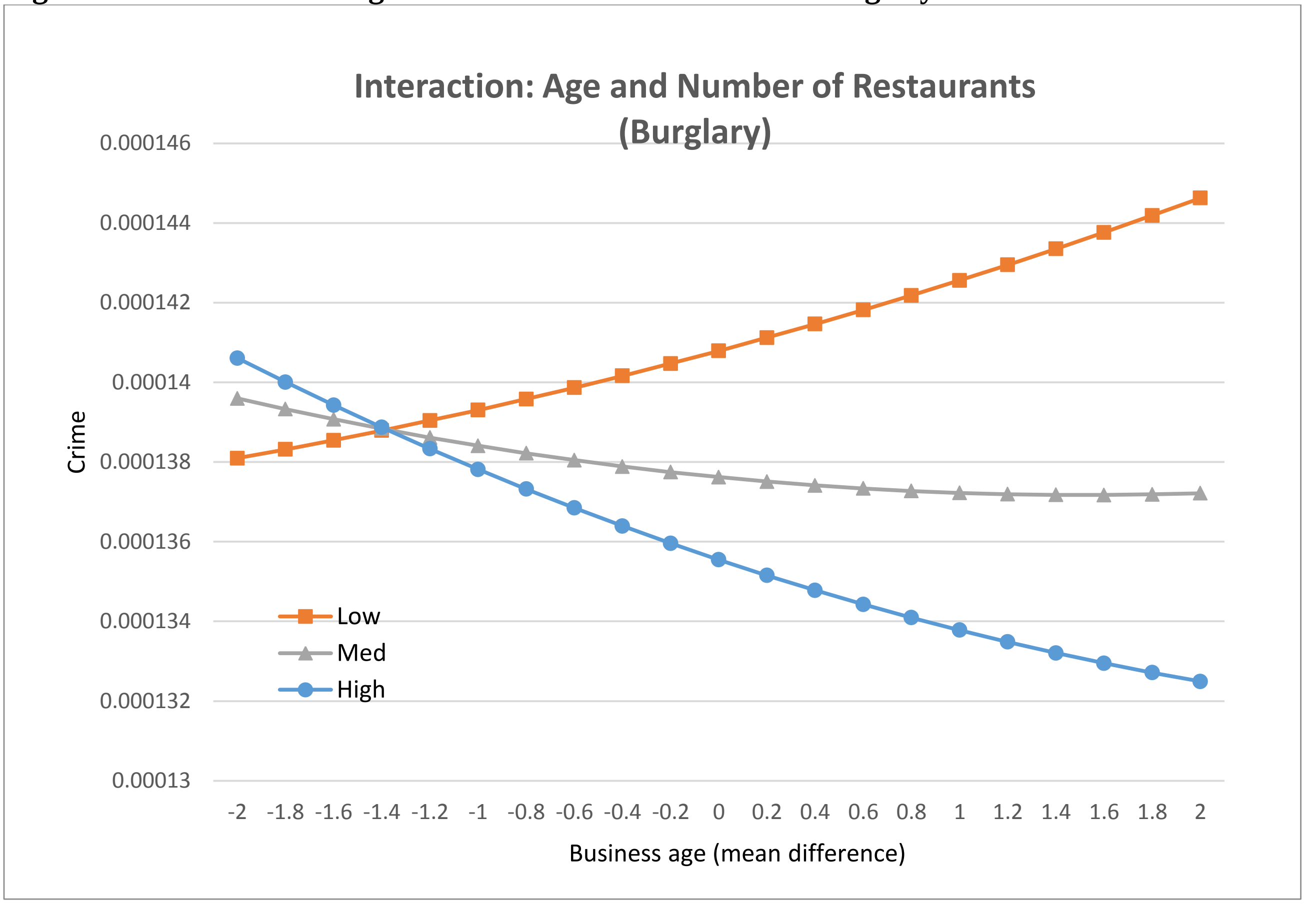


Figure A19. Interaction: Age and Number of Food/Drug stores – Burglary

Business Age

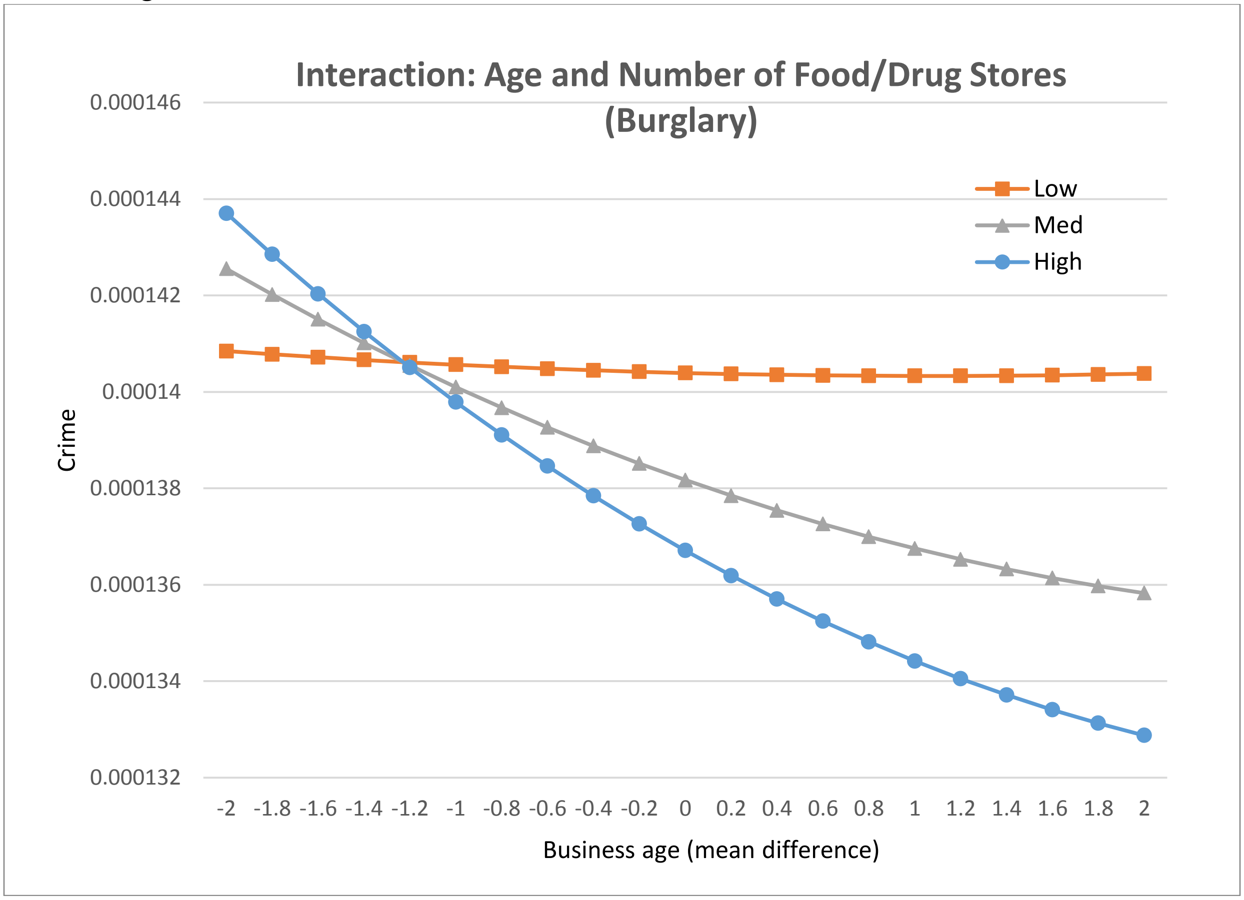


Figure A20. Interaction: Age and Number of consumer-facing business – Larceny

Business Age

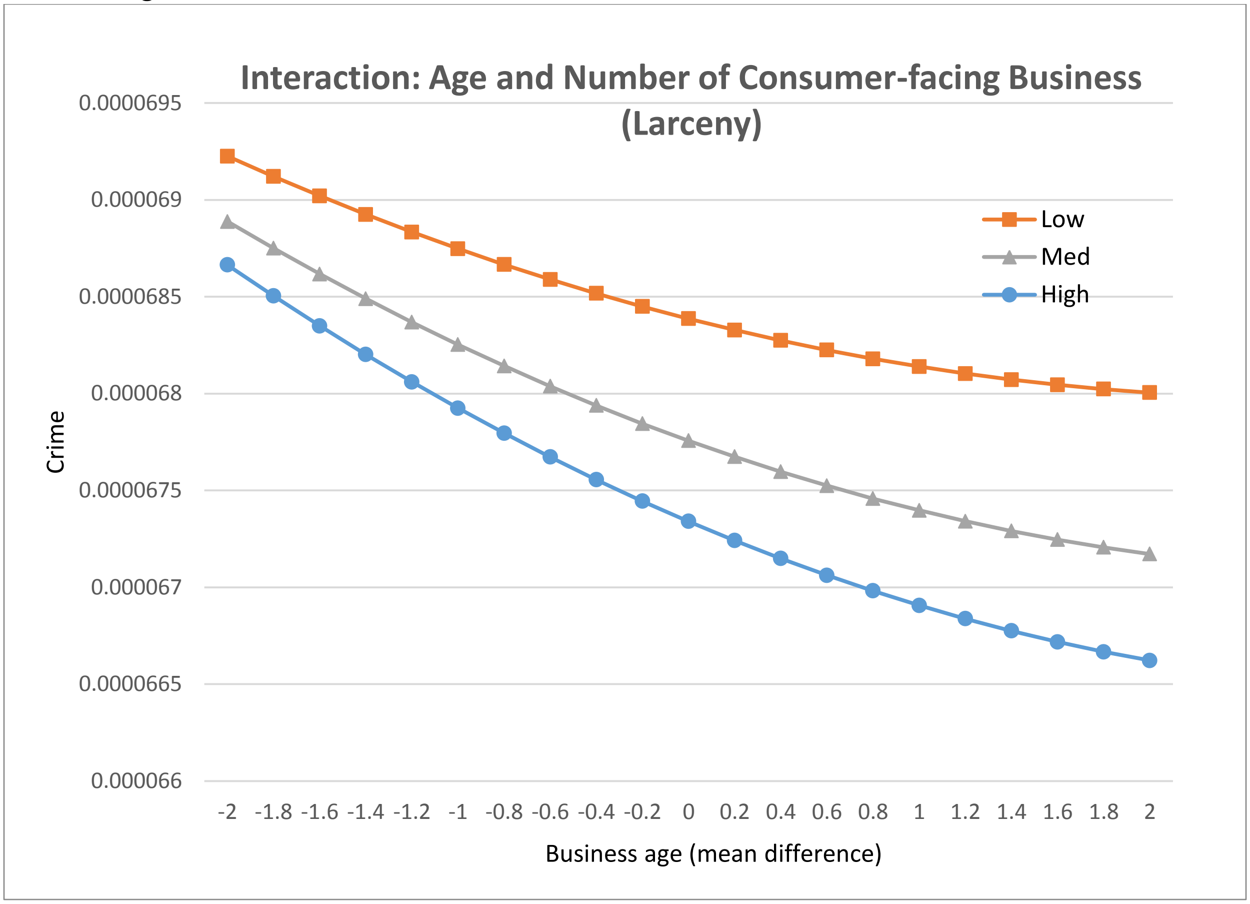
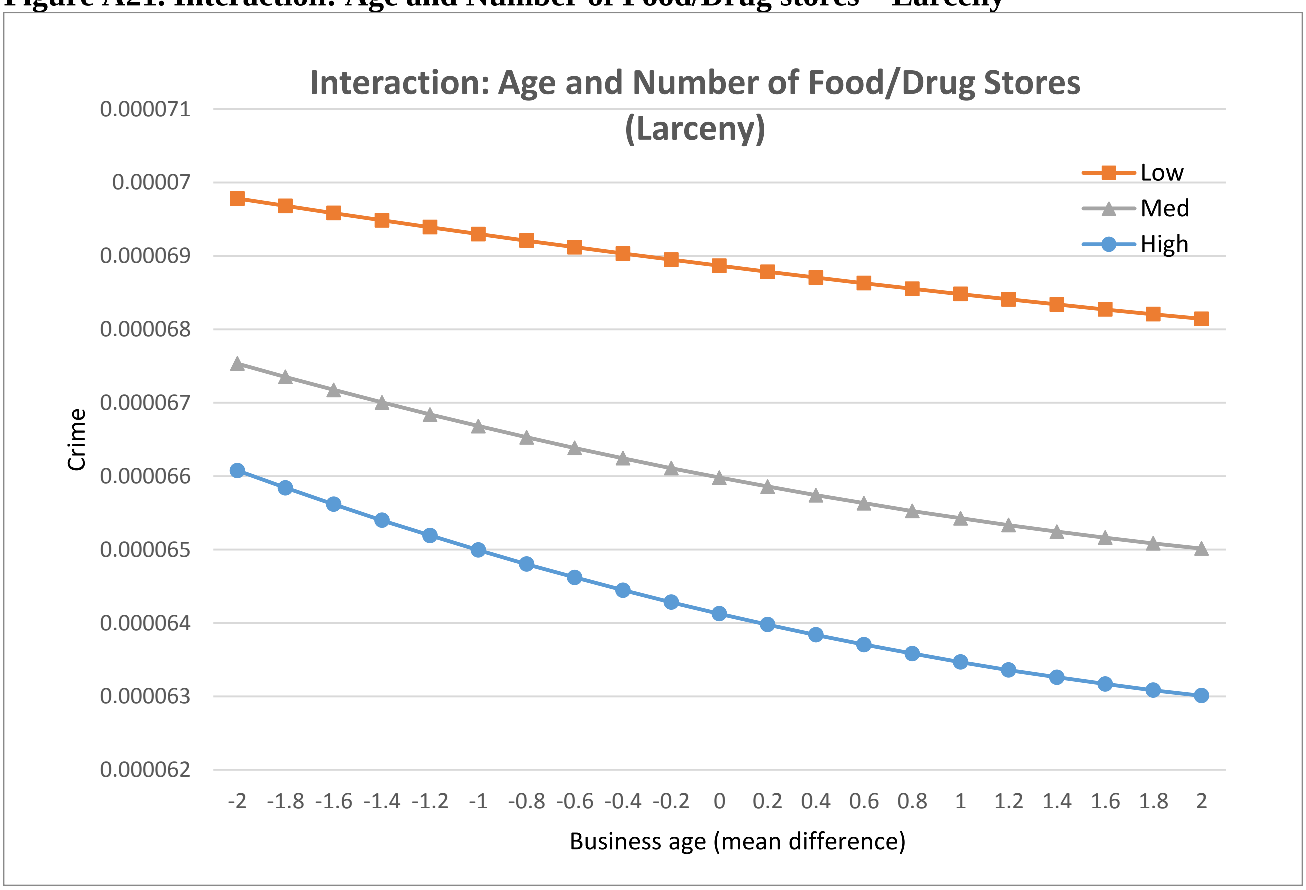


Figure A21. Interaction: Age and Number of Food/Drug stores – Larceny



Business Age

Figure A22. Interaction: Age and Number of consumer-facing business – Motor vehicle theft

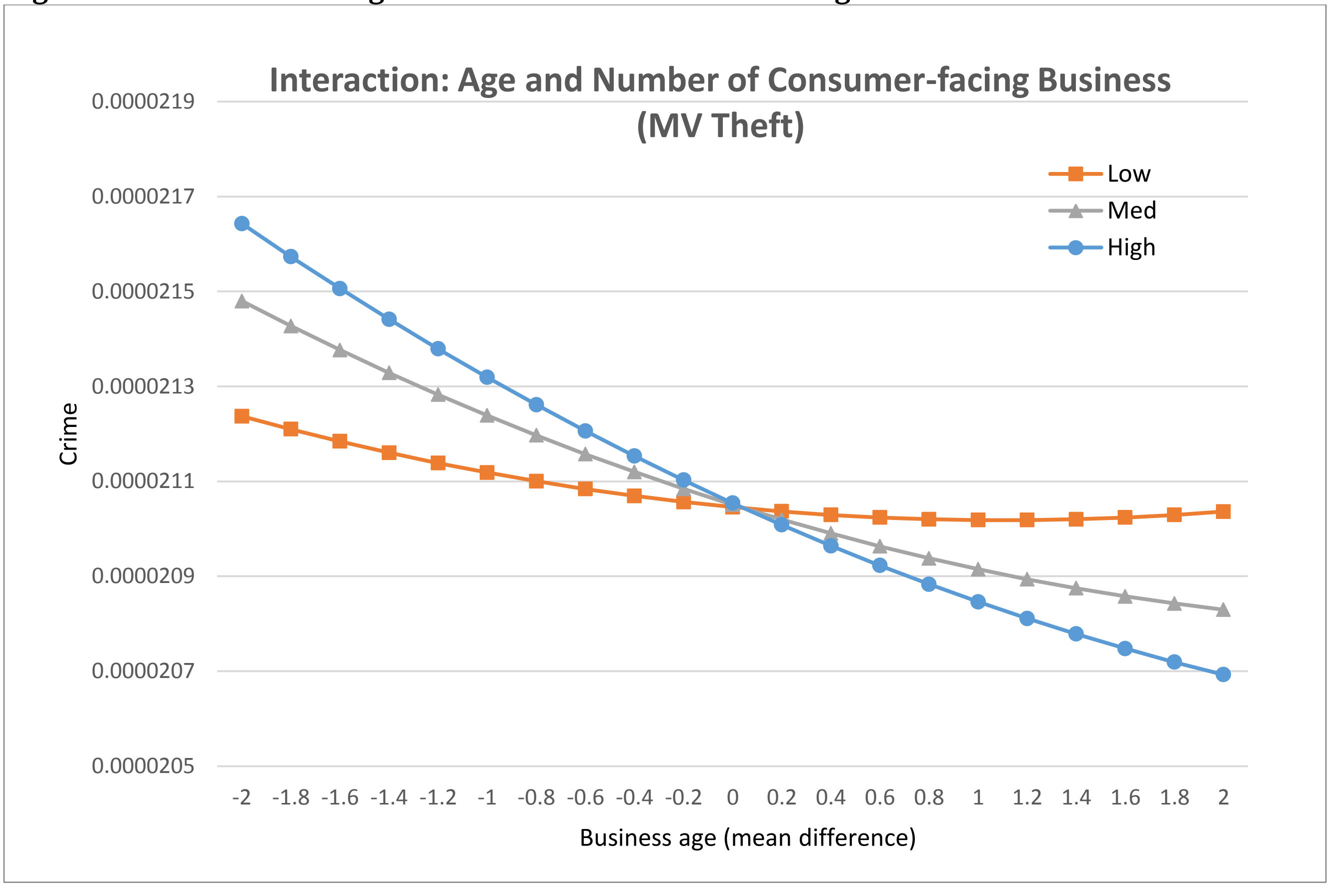


Figure A23. Interaction: Age and Number of service business – Motor vehicle theft

Business Age

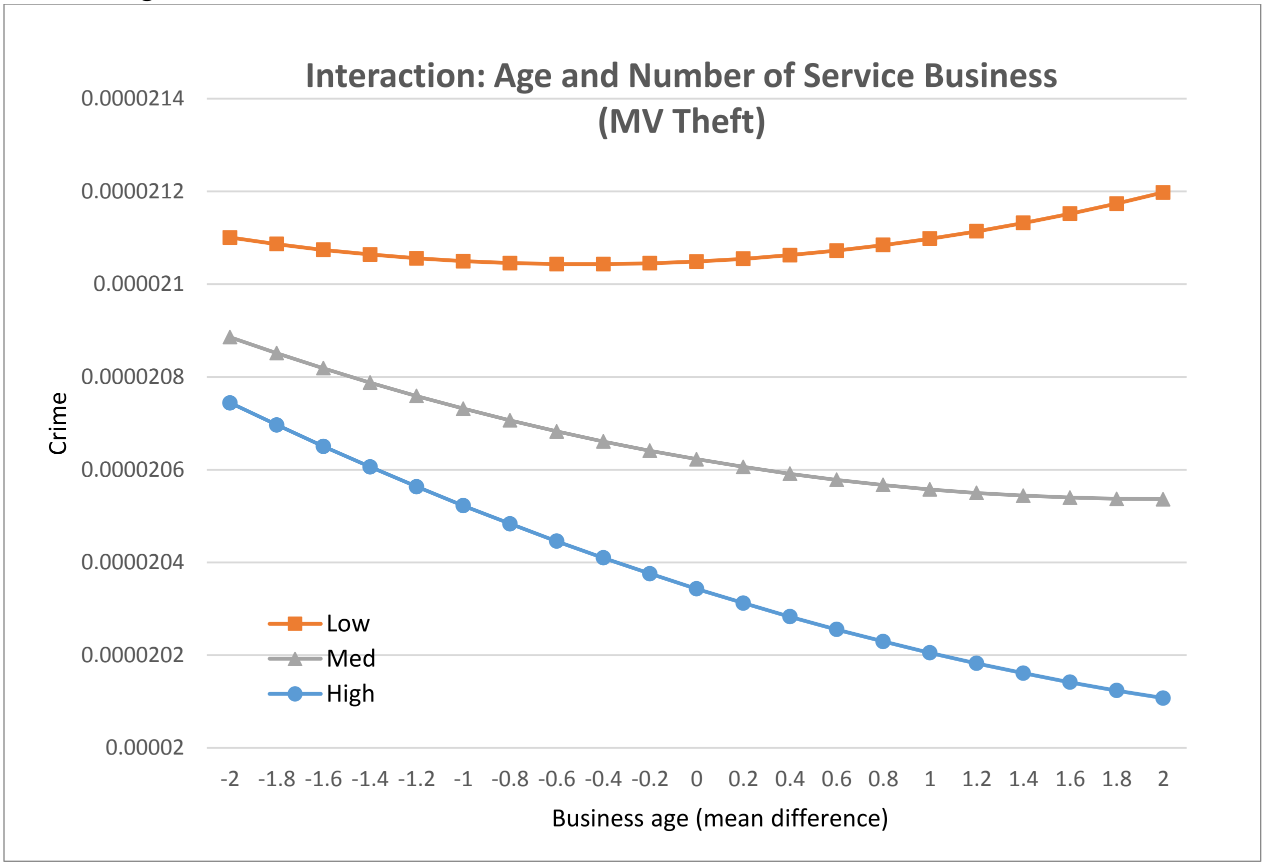


Figure A24. Interaction: Age and Number of restaurants – Motor vehicle theft

Business Age