Distribution Agreement

Signature:

______________________________ ______________

Ziqian Ju Date

U.S. Public Safety and Firm Financial Policies

By

Ziqian Ju
Master of Business Studies

Business

Jeffrey A. Busse, Ph.D.
Advisor

Francisco Barillas, Ph.D.
Committee Member

Gonzalo Maturana, Ph.D.
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

U.S. Public Safety and Firm Financial Policies

By

Ziqian Ju
B.Sc., Peking University, 2012

Advisor: Jeffrey A. Busse, Ph.D., New York University, 1998

An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Business Studies
in Business
2017

Abstract

U.S. Public Safety and Firm Financial Policies

By

Ziqian Ju

With FBI Uniform Crime Reports data on local crime rates, I find that firms in dangerous areas have more PP&E and less cash holdings. The results are robust to including various controls and to analyses of coefficient movements. Case studies and additional tests are conducted to support the findings. Small firms have stronger relation between public safety and financial policies. Overall, the evidence is consistent with the hypothesis that firms could benefit from crime rate increase.

U.S. Public Safety and Firm Financial Policies

By

Ziqian Ju
B.Sc., Peking University, 2012

Advisor: Jeffrey A. Busse, Ph.D., New York University, 1998

A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Business Studies
in Business
2017

Table of Contents

List of Tables

List of Figures

I. Introduction

Firms make financial policies based on various considerations.[1] Could public safety be one of their concerns? Intuitively, firms may prefer setting up their headquarters, branches, or plants in areas with low crime rates. When public safety condition gets worse, will firms choose to shut down their local operations and move to safer areas? If firms stay, will they change financial policies in response to the shifts of public safety? These question have not been fully investigated.

Although it is not typically viewed as a country with severe public safety issues, some areas in the US did have high crime rates during some time periods. For example, the city of Newark in New Jersey experienced high crime rate until Cory Booker, a new mayor, made great efforts in decreasing the crime rate by over 25% from 2006 to 2008. Some areas still have significantly higher crime rates than other areas, such as Pittsburgh, whose current crime rate is over 70 percent higher than Pennsylvania's average crime rate.

I develop and test two competing hypotheses about the relation between public safety and firm financial policies. Based on previous studies of urban economics, a higher crime rate may hurt local real estate market and decrease property values (e.g., Hellman and Naroff, 1979; Gibbons, 2004). Firms could benefit from worsened public safety if they could take advantage of the decreasing property prices and expand their plants or operations. If this is the case, firms should increase their investment in properties when crime rates are higher, thereby an increase in property, plant and equipment (PP&E), and a decrease in cash holdings for an expansion in investment. In contrast, firms may choose

[1] Leary and Roberts (2014) show that the characteristics of peer firms play an important role in determining corporate capital structures and financial policies. Smith (2016) finds that firms in more political corrupt areas hold less cash and have greater leverage.

to move to a safer area in order to avoid potential losses caused by increasing local crimes, including a negative impact on workplace safety (Brown, 1996; Cohn and Wardlaw, 2016). If firms plan to move away or move some branches to other safer areas, they should decrease their investment and sell their properties, thereby an increase in cash holdings and a decrease in PP&E when crime rates are higher.

To measure public safety condition, I use US Federal Bureau of Investigation (FBI) Uniform Crime Reports data on monthly crime reports from local law enforcement agencies in the US. I calculate crime rates (number of per capita crimes) with these crime data as a proxy for public safety level, assigning crime rates to firms based on headquarter locations. A large number of crime rate indicates a severe public safety condition of the firm's operating environment.

Overall, the empirical results are consistent with the hypothesis that firms change their financial policies to benefit from worsened public safety. Firms in dangerous areas have significantly more PP&E than firms in safe areas. A firm that experiences a 100 percent increase[2] in crime rate has a 1.2 percent increase in PP&E. In addition, firms in dangerous areas hold significantly less cash. A firm that has a 100 percent increase in crime rate has a 0.9 percent decrease in cash ratio. Other financial policy variables do not have significant differences.

Public safety should have a greater influence on firms that have all operations and plants located in one area, compared with firms that operate in many areas. I divide these two different kinds of firms by firm size.[3] Small firms generally have fewer branches and their

---

[2] This increase magnitude is common. For example, in an area of Newark in 1978, total crimes increased by a number more than the population of that area, then PP&E increased by 1.4 percent.
[3] Small firms are defined as firms with total asset less than 100 million US dollars.

operations are more concentrated. If there is a rise in local crime rates, small firms should be more vulnerable. Results are consistent with the overall evidence, and the magnitudes of changes in PP&E and cash holdings for small firms are slightly larger than the results for the full sample.

These findings are robust to additional tests that control for the possible bias caused by omitted variables that affect both firm financial policies and public safety simultaneously. Adding control variables associated with PP&E and cash holdings does not change the results. In addition, analysis of coefficient movements following Oster (2016) suggests the relation between firm financial policies and public safety is not driven by omitted variables. Although this paper does not find a proper instrumental variable to fully rule out the omitted variable bias, case studies with the cities of Newark and Pittsburgh provide further evidence to support the causal relation that firm financial policies are influenced by public safety.

This paper contributes to the literature on the determinants of firm financial policies and corporate structures (e.g., Leary and Roberts, 2014; Smith, 2016). It also adds to the growing cash holdings[4] and workplace safety[5] literature.

This paper also contributes to the broad literature on urban economics. Previous studies relate public safety with labor market (e.g., Cornwell and Trumbull, 1994) and real estate market (e.g., Hellman and Naroff, 1979; Gibbons, 2004), but few papers consider the influence of public safety to local firms. This paper builds up the relation between public safety and firm financial policies, especially PP&E and cash holdings.

---

[4] Foley, Hartzell, Titman, and Twite (2007), Duchin (2010), Lins, Servaes, and Tufano (2010), Hoberg, Phillips, and Prabhala (2014).
[5] Brown (1996), Cohn and Wardlaw (2016).

The remainder of the paper is organized as follows. Section II develops the two hypotheses on public safety and firm financial policies. Section III describes the data and variables used in this paper. Section IV presents the main findings. Section V provides the robustness tests. Section VI concludes.

II. Hypothesis Development

I develop and test two main competing hypotheses in this paper. In one hypothesis, a worsened public safety condition hurt firms so much that they have to shut down plants and operations and move to another place. In the other hypothesis, an increase in crime rate indirectly helps a firm by decreasing local real estate property prices and the firm could take advantage of it by increasing property investment.

Firms may suffer from an increasing local crime rate in two ways. First, their local plants or operations could be hurt by increasing property crimes, such as burglary, larceny and vehicle theft. Firms have to suffer from property loss or additional security expenditures. Second, an increase in local crimes could also hurt labor market. Residents and firm employees may have to move to other places to avoid an increase in assault, robbery, and other serious crimes[6]. Nonserious crimes, mostly property crimes, may also push residents away. Firms may find it more and more difficult to hire qualified employees.

These two reasons could make firms decide to move to a safer area, in order to avoid losses in property and human capital. Therefore, firms may decrease their investment and shut down local operations and plants, which will result in a decrease in property, plant and

[6] In the next section, I define serious crime as the combination of murder, rape, robbery and assault.

equipment (PP&E) and therefore an increase in cash holdings from a decreased PP&E (selling properties, plants or equipment). I call this hypothesis the “escape hypothesis”. The empirical predictions of the “escape hypothesis” are that the PP&E is decreasing when the crime rate is increasing, and the cash ratio (cash holdings) is increasing when the crime rate is increasing.

However, firms may also benefit from an increasing local crime rate in three ways. First, as discussed by Hellman and Naroff (1979) and Gibbons (2004), an increasing crime rate may hurt local real estate market and decrease property values. Firms may take advantage of this decreasing property pricing and increase their property investment. Therefore, firms’ PP&E will increase, and cash holdings will decrease because of the investment in properties. Second, the gains from an increasing crime rate may be more than the pains from it. Crime may not hurt local labor market that much, since the employees may probably live in other areas. This is quite common in the US. A lot of people drive more than one hour to work, and they live in safe areas like suburban districts. Therefore, firms will not suffer from a loss in labor market when local crime rates increase. Third, moving is costly. Even if they do not compensate their employees, firms’ movements involve many additional costs, including costs in finding a suitable place, moving equipment and other facilities, adapting to the new environment, and building new local relationship. As long as firms’ benefits from the decreasing local property values are larger than the losses from the increasing crime rate, firms will choose to adapt to the local crimes by changing their financial policies. I call this hypothesis the “stay hypothesis”. The empirical predictions of the “stay hypothesis” are that the PP&E is increasing when the crime rate is increasing, and the cash ratio (cash holdings) is decreasing when the crime rate is increasing.

As discussed in the next section, I match headquarters of firms with local crime rates. This matching, however, does have some limitations, since firms may have branches, plants and other operations in different areas. I assume their main operations concentrate at or near headquarter areas. I use small firms, as described in Section III and IV, to solve the issue partially, as small firms generally have a higher concentration of their operations. In addition, In addition, there is an issue of endogeneity of headquarter selection, since firms do not choose their locations randomly. I use a rich set of controls and the test of coefficient movements to mitigate this concern.

III. Data and Variables

A. Data

The initial data set of financial policies contains all US firms in Compustat from 1975 to 2012. I delete firm-year observations that have negative total assets or sales. Financial firms and utilities (standard industrial classification codes 6000-6999 and 4900-4999, respectively) are excluded from the sample. I also set missing observations of financial policy variables to zero and include an indicator to note missing observations.[7] Headquarters of firms are obtained from Compustat and missing location data are supplemented from Securities and Exchange Commission Edgar filings.

The public safety data set is obtained from US Federal Bureau of Investigation Crime Reports. The reports are monthly from 1975 to 2012, reported by over 13,000 US law enforcement agencies. Each report includes the detailed location (zip code, address, state)

[7] The results are similar if dropping missing observations.

of the law enforcement agent, the population under jurisdiction, and the number of seven major crimes (murder, rape, robbery, assault, burglary, larceny, and vehicle theft).

I aggregate the monthly data to yearly, in order to match with financial policy data set. I match yearly crime data to contemporaneous financial policy data by zip code. I also match with one-year lagged financial data, but the results are similar. After matching, I have a combined panel data set of 73,677 firm-year observations in 7,473 unique firms.

As discussed in previous sections, I construct small firm data set in order to obtain firms with operations concentrated close to their headquarters. I delete firms in the matched data set with total asset more than 100 million dollars. After deleting, I have a small firm panel data set of 43,105 firm-year observations in 5,840 unique firms.

B. Variables

As discussed in Section II, the financial policy variables of the interest are PP&E and cash holdings. I define PP&E as net property, plant, and equipment divided by total assets. Cash holdings variable is defined as cash and cash equivalents divided by total assets. In order to avoid some scaling problems (e.g., some large outlier firms carry substantially large cash ratios, such as Apple Inc.), I also use the natural log of cash divided by net assets as an additional measure of cash holdings. Other financial policy variables are calculated using the definition listed in Table A.1.

Because each law enforcement agency has various population under jurisdiction, using absolute number of crime reports may not be proper to reflect the condition of public safety of an area. Firms and residents care more about the relative number of crime reports. Therefore, I use crime rate per capita as a measure of public safety. Total crime rate is defined as the yearly total crimes of an area divided by the total population in that area. Each firm matches with a crime report agency, thus matching with a total crime rate.

Of all seven crimes reported by agencies, I find four crimes (murder, rape, robbery, and assault) are much rare compared with the other three crimes (burglary, larceny, and vehicle theft). These four crimes have a more serious social influence. Thus I define the total four crime rates of murder, rape, robbery, and assault as serious crime rate, and define the total three crime rates of burglary, larceny, and vehicle theft as nonserious crime rate. The benefit of dividing total crime rate into two categories is that it could divide the influence on residents and the influence on firms. Serious crimes may hurt residents more than firms. A sharp increase in serious crimes could force residents to move to safer areas, but firms are not hurt as much as residents are. Since property prices may decline more under serious crimes, firms may even benefit from serious crimes as discussed in Section II. On the other hand, nonserious crimes may hurt firms more than serious crimes, since firms may have to spend more in security and covering property losses.

[INSERT FIGURE 1 HERE]

Figure 1 shows the average rate of total crimes by county from 1975 to 2012. Total crime rate is calculated by the total number of crimes divided by the total population of the county. Although the firm-year observations of the panel data set use zip level crime rates, the county level heat map provides a visual representation of the data and highlights the variation in public safety by county. This variation by zip code could also be expected.[8]

[8] Both data sets (full sample and small firm sample) show the variation by zip code within each county.

In addition, Figure 1 and Table A.3 show the substantial variation in public safety by state. The average total crime rate in California is more than twice the crime rate in Georgia. The crime rate in Washington DC is the highest among all, and is more than three times the crime rate in Georgia. Because of these large cross-sectional differences, I trim the crime rates (total, serious, and nonserious) at the 1% and 99% levels. Results are similar if I winsorize the crime rates at the 1% and 99% levels.

Table A.2 shows the time serious variation in total crime rates. Although the mean values do not show much variation, the median and standard deviation values show substantial time series variation. From the median values of total crime rates, public safety of US is getting better over the years. A regression of total crime rates on indicators for full sample indicates that over 60 percent of the variation in crime rates is explained by cross-sectional variation, and less than 40 percent is explained by time series variation.

C. Summary Statistics

Table 1 displays the summary statistics for the variables of interest and control variables. Variable definitions are listed in Table A.1.

[INSERT TABLE 1 HERE]

Panel A contains all firm-year observations from 1975 to 2012 obtained from the combination of Compustat and FBI crime data sets. Observations with negative total assets or sales are deleted. Financial firms and utilities are excluded. I trim all variables at the 1% and 99 levels. In total, I obtain a full sample of 73,677 firm-year observations in 7,473 unique firms.

Panel B contains small firm observations that have asset values less than 100 million dollars. Sample selection follows the same rules in Panel A. In total, I obtain a small firm sample of 43,105 firm-year observations in 5,840 unique firms.

D. Mean Differences between Dangerous and Safe Areas

For each firm-year observation, I add a public safety indicator with the values of “dangerous” and “safe”. Firms in a year are marked as having headquarters in dangerous (safe) areas if their crime rates lie in the top (bottom) quartile of all crime rates in that year. This cross sectional comparison of crime rates is much closer to the real comparison that a firm makes than the time series comparison of crime rates, since when a firm measures the condition of public safety, a cross sectional comparison gives the firm an evaluation of whether moving to a safer place is available or not.

I calculate the statistics using the mean differences: mean values of financial variables with “dangerous” indicator *minus* mean values of financial variables with “safe” indicator. Table 2 displays the t-statistic from the difference in means test between dangerous and safe areas for the financial policy variables and control variables.

[INSERT TABLE 2 HERE]

Table 2 indicates that the differences in means of the financial policy variables are statistically large and significant. Compared to firms with headquarters in safe areas, firms with headquarters in dangerous areas have a significantly larger PP&E, a significantly smaller cash ratio[9], and significantly larger capital expenditures, on average. These results are robust for both full sample and small firm sample, and robust for all three crime rates

[9] Results are similar for ln(Cash/net assets).

(all crimes, serious crimes, and nonserious crimes). There are other financial variables showing significant differences in means, such as leverage, net working capital and R&D. However, compared with the three variables previously mentioned, these variables show much smaller magnitudes in t-statistics. In addition, after controlling for industry by matching firms with the same 3-digit SIC code and similar size, these significant differences disappear or are no more significant at the 1% level. Besides, the significance shown in capital expenditures decreases to the 5% level.

The results are consistent with the "stay hypothesis" and violate the "escape hypothesis" discussed in Section II. They indicate that firms increase PP&E and decrease cash holdings to benefit from high crime rates. Except for PP&E and cash holdings, other variables showing significant differences could be driven by crime rates, directly or indirectly. However, they could also be driven by unobserved heterogeneity between firms. In the next section, I test whether there is significant association between public safety and these financial policies.

IV. Association between Public Safety and Financial Policies

Despite Table 2 provides an intuitive comparison of firm financial policies between dangerous and safe areas, more sophisticated analysis is needed to uncover the causal relation between public safety and financial policies, i.e., how local crime rates influence firm financial variables, especially PP&E and cash holdings. In this section, I use ordinary least squares regressions to test the association between crime rates and financial variables. In next section, by doing robustness test, I try to rule out the endogeneity issue caused by omitted variables.

A. Analysis of PP&E

Table 3 displays the results of the OLS regressions estimating how PP&E varies with local crime rates. The dependent variable is PP&E. The first regression uses total crime rate as the independent variable; the second regression uses serious crime rate as the independent variable; the third regression uses nonserious crime rate as the independent variable. Column (1), (2), and (3) use the full sample with all firms; column (4), (5), and (6) use the small firm sample. All OLS regressions are heteroscedasticity-robust and have standard errors clustered by year and industry.

[INSERT TABLE 3 HERE]

For the first regression with total crime rate as the independent variable, the first model (column (1) and (4)) contains no controls except for crime rate. The coefficients for both samples are 0.012, significant at the 1% level. The second model (column (2) and (5)) contains controls, and the coefficients are 0.010 for the full sample and 0.012 for the small sample, both significant at the 1% level. The control variables includes leverage, market-to-book ratio, and EBITDA.[10] The third model (column (3) and (6)) contains controls and state fixed effects. The coefficient for the full sample is 0.006, significant at the 10% level, and the coefficient for the small sample is 0.008, significant at the 5% level. All three models include year fixed effects. The three coefficients in the small sample are all larger and more significant (have larger t-statistics) than the three coefficients in the full sample.

The adjusted R-squared of full (small) sample regression increases from 0.036 (0.037) in the first model to 0.162 (0.130) in the third model, which suggests the additional power

[10] The controls are drawn from Matsa (2010).

from control variables. According to Altonji, Elder, and Taber (2005), the increase of power added by control variables are often used as a signal of omitted variable bias. To address this concern, I conduct an analysis of coefficient movements following Oster (2015). I discuss the detailed procedure in the next section. Here I find that the selection on unobservable variables must be at least 2.9 (3.5) times as strong as selection on observable variables, in order to explain the entire association between total crime rate and PP&E for the full (small) sample. As discussed by Altonji, Elder, and Taber (2005), the results show that the relation between observable variables and the outcome is much stronger than the relation between unobservable variables and the outcome. Therefore, the association is unlikely to be driven by omitted variables.

For the second and the third regression with serious crime rate and nonserious crime rate as the independent variable, the results are similar to the first regression. The magnitudes of the coefficients for the second regression are larger than the first and the third. This is reasonable, since serious crimes (murder, rape, robbery and assault), especially murder and rape, have quite significant impact on society, compared with nonserious crimes (burglary, larceny, and vehicle theft). Therefore, firms under the same magnitude of variation in serious crimes change more of their financial policies (e.g., PP&E) than in nonserious crimes. Besides, all coefficients in small sample are larger and more significant than the coefficients in full sample.

Overall, the results indicate that for the full sample, if a firm experiences a 100 percent increase in total (or nonserious) crime rate, it will have a 1.2 percent increase in PP&E; if a firm experiences a 100 percent increase in serious crime rate, it will have a 11.5 percent increase in PP&E. Similar for the small sample. These results are consistent with the “stay hypothesis”: firms in dangerous areas have more PP&E. In addition, the coefficients obtained with the small sample are all larger and more significant than the coefficients obtained with the full sample, indicating small firms are more influenced by local crime rate change. This is consistent with the discussion in previous sections, that small firms have more concentrated operations and are more influenced by crime rate variation.

B. Analysis of Cash Holdings

Table 4 displays the results of the OLS regressions estimating how cash holdings vary with local crime rates. The dependent variable is cash ratio. The results are similar when using ln(Cash/net assets) as the dependent variable. The first regression uses total crime rate as the independent variable; the second regression uses serious crime rate as the independent variable; the third regression uses nonserious crime rate as the independent variable. Column (1), (2), and (3) use the full sample with all firms; column (4), (5), and (6) use the small firm sample. All OLS regressions are heteroscedasticity-robust and have standard errors clustered by year and industry.

[INSERT TABLE 4 HERE]

For the first regression with total crime rate as the independent variable, the first model (column (1) and (4)) contains no controls except for crime rate. The coefficient for the full sample is -0.009, significant at the 1% level; the coefficient for the small sample is -0.010, significant at the 5% level. The second model (column (2) and (5)) contains controls, and the coefficients are -0.008 for the full sample and -0.010 for the small sample, significant at the 1% level and the 5% level, respectively. The control variables includes leverage, market-to-book ratio, capital expenditures, net working capital, dividends, cash flow, R&D and acquisitions.[11] The third model (column (3) and (6)) contains controls and state fixed effects. The coefficient for the full sample is -0.012; the coefficient for the small sample is -0.016. Both significant at the 1% level. All three models include year fixed effects. The three coefficients in the small sample are all larger than the three coefficients in the full sample. Most of the coefficients of both samples have the same level of significance.

The adjusted R-squared of full (small) sample regression increases from 0.049 (0.087) in the first model to 0.127 (0.130) in the third model, which suggests the additional power from control variables. To address the same concern discussed in previous subsection, I again conduct the analysis of coefficient movements following Oster (2015). Here I find that the selection on unobservable variables must be at least 2.7 (2.9) times as strong as selection on observable variables, in order to explain the entire association between total crime rate and cash ratio for the full (small) sample. As discussed by Altonji, Elder, and Taber (2005), the results show that the relation between observable variables and the outcome is much stronger than the relation between unobservable variables and the outcome. Therefore, the association is unlikely to be driven by omitted variables.

For the second and the third regression with serious crime rate and nonserious crime rate as the independent variable, the results of all three models are similar to the first regression. The magnitudes of the coefficients for the second regression are larger than the first and the third. This is reasonable, since serious crimes (murder, rape, robbery and assault) have quite significant impact on society, compared with nonserious crimes (burglary, larceny,

---

[11] The controls are from previous studies on the determinants of cash holdings, including Opler, Pinkowitz, Stulz, and Williamson (1999), Haushalter, Klasa, and Maxwell (2007), Bates, Kahle, and Stulz (2009).

and vehicle theft). Therefore, firms under the same magnitude of variation in serious crimes change more of their financial policies (e.g., cash holdings) than in nonserious crimes.

Overall, the results indicate that for the full sample, if a firm experiences a 100 percent increase in total (or nonserious) crime rate, it will have a 0.9 percent decrease in cash ratio; if a firm experiences a 100 percent increase in serious crime rate, it will have a 9.1 percent decrease in cash ratio. Similar for the small sample. These results are consistent with the "stay hypothesis": firms in dangerous areas have less cash holdings, because they spend cash in investing properties, taking advantage of the declining real estate market hurt by the increase of local crime rates. In addition, the coefficients obtained with the small firm sample are all larger than the coefficients obtained with the all firm sample, indicating small firms are more influenced by local crime rate change. This is consistent with the discussion in previous sections, that small firms have more concentrated operations and are more influenced by crime rate variation.

C. Analysis of Capital Expenditures

In Section III, Table 2 shows that in dangerous areas, firms have more capital expenditures on average. This is reasonable because increasing capital expenditures is a vital channel in increasing PP&E, which is consistent with the "stay hypothesis". However, it is not the only channel. After controlling for industry by matching firms with the same 3-digit SIC code and similar size, the significant level shown in mean difference test of capital expenditures drops from 1% to 5%.

To investigate whether public safety could influence firm capital expenditures or not, I analyze the association between local crime rates and capital expenditures with the same regression method discussed in the previous two subsections.

[INSERT TABLE 5 HERE]

Table 5 shows the results of the OLS regressions estimating how capital expenditures vary with local crime rates. The dependent variable is capital expenditures. The first regression uses total crime rate as the independent variable; the second regression uses serious crime rate as the independent variable; the third regression uses nonserious crime rate as the independent variable. Column (1), (2), and (3) use the full sample with all firms; column (4), (5), and (6) use the small sample with only small firms. All OLS regressions are heteroscedasticity-robust and have standard errors clustered by year and industry.

For the first regression with total crime rate as the independent variable, the first model (column (1) and (4)) contains no controls except for crime rate. The coefficient for the full sample is 0.000 with p value larger than 10%; the coefficient for the small sample is 0.002, significant at the 10% level. The second model (column (2) and (5)) contains controls, and the coefficient is 0.001 for the full sample, with p value larger than 10%, while the coefficient is 0.002 for the small sample, significant at the 10% level. The control variables include market-to-book ratio, dividends, and cash flow. The third model (column (3) and (6)) contains controls and state fixed effects. The coefficient for the full sample is -0.001, while the coefficient for the small sample is 0.000, both with p value larger than 10%. All three models include year fixed effects. The three coefficients in the small sample are all larger and more significant (or at least as significant as) than the three coefficients in the full sample. The insignificance of coefficients with the full sample is consistent with the industry-adjusted results of Table 2 discussed above. The coefficients with the small sample show some weak significance, which is consistent with the “stay hypothesis”.

The adjusted R-squared of full (small) sample regression increases from 0.030 (0.031) in the first model to 0.071 (0.069) in the third model, which suggests the additional power from control variables. To address the same concern discussed in previous subsections, I conduct the analysis of coefficient movements following Oster (2015). Here I find that the selection on unobservable variables only needs to be 1.1 (1.3) times as strong as selection on observable variables, in order to explain the entire association between total crime rate and cash ratio for the full (small) sample. As discussed by Altonji, Elder, and Taber (2005), the results show that the relation between observable variables and the outcome is almost as strong as the relation between unobservable variables and the outcome. Therefore, the association driven by observable variables is not very convincing.

For the second regression with serious crime rate as the independent variable, the results of all three models for both samples are not significant. For the third regression with nonserious crime rate as the independent variable, the results of all three models are similar to the first regression. The magnitudes of the coefficients for the second regression are larger than the first and the third. This is reasonable, since serious crimes (murder, rape, robbery and assault) have quite significant impact on society, compared with nonserious crimes (burglary, larceny, and vehicle theft). Therefore, firms under the same magnitude of variation in serious crimes change more of their financial policies (e.g., capital expenditures) than in nonserious crimes. However, the insignificant coefficients make the conclusion less reliable.

Overall, the results cannot build up a convincing association between public safety and firm capital expenditures. It is partially explained by the fact that changing capital expenditures is not the only channel to influence PP&E. In addition, the weak significance in some coefficients with small sample leaves some hope that there may be some weak association. Further work can be done in exploiting more detailed samples, such as with firms concentrated in manufacturing, real estate, or testing samples in subperiods.

D. Analysis of Other Financial Policy Variables

In Table 2 of Section III, there are some other financial policy variables showing significant differences in means. These variables are leverage, market-to-book, net working capital, cash flow, R&D, and EBITDA. Compared with PP&E, cash holdings, and capital expenditures, in Table 2, these six variables show much smaller magnitudes in t-statistics. In addition, after controlling for industry by matching firms with the same 3-digit SIC code and similar size, these significant differences disappear or are no more significant at the 1% level.

Besides, it is quite difficult to build up association between public safety and these six financial policy variables consistent with either "escape hypothesis" or "stay hypothesis".

[INSERT TABLE 6 HERE]

Table 6 displays ordinary least squares regression results estimating how other variables vary with local crime rates. The results are only with the full sample, but are similar to the small sample with only small firms. Each row shows the regression results for that dependent variable. The independent variable for all six regressions is total crime rate. No controls or fixed effects are added in Table 6, but results are robust when adding controls and (year and/or state) fixed effects. All OLS regressions are heteroscedasticity-robust and have standard errors clustered by year and industry.

The coefficient estimates of all six regressions have the same signs indicated by Panel A of Table 2. For example, the regression with leverage as the dependent variable shows the coefficient on total crime rate is positive and equals to 0.009, which is consistent with the positive t-statistic 7.91 in Panel A of Table 2; when the dependent variable is market-to-book, the coefficient on total crime rate is negative and equals to -0.027, which is consistent with the negative t-statistic -5.09 in Panel A of Table 2.

However, all six coefficients are not significant. Even when adding controls and fixed effects, changing to small sample, or replacing the independent variable with serious and nonserious crime rate, the coefficients still do not show significance level higher than 10%. Only when the dependent variable is leverage or R&D, the significance level is close to the 10% level, but still not higher than that.

These results indicate that it is not convincing to build up association between public safety and the other financial policy variables. There may be some other endogenous variables that influence these financial variables other than crimes.

V. Robustness Tests

Despite the control variables and fixed effects included in the tests in Section IV, the findings could suffer from omitted variable bias. The best way to address this endogeneity concern is to use the instrumental variable approach. Unfortunately, this paper does not find a proper instrumental variable that is associated with crime rate but not associated with other variables that influence financial policies. The task to find a suitable instrumental variable is left for further work. This paper uses additional tests and case studies to address the endogeneity concern to the greatest extent.

A. Control Variables

As discussed in Angrist and Pischke (2010), except for finding a proper instrumental variable, the most straightforward approach to addressing omitted variable bias is to include appropriate selection of control variables that can be observed.

In Section IV, I include various financial controls based on previous studies.

For PP&E as dependent variable, following Matsa (2010), I include leverage, market-to-book ratio, and EBITDA as control variables. I also include sales, but the results are similar.

For cash holdings as dependent variable, following Opler, Pinkowitz, Stulz, and Williamson (1999), Haushalter, Klasa, and Maxwell (2007), Bates, Kahle, and Stulz (2009), I include leverage, market-to-book ratio, capital expenditures, net working capital, dividends, cash flow, R&D and acquisitions as control variables. I try various combination of these controls, and the results are similar.

The year and state fixed effects, as another sets of controls, help rule out the association within year and state.

Overall, these controls support the association between public safety and firm financial policies, and support the “stay hypothesis”.

B. Analysis of Coefficient Movements

Although control variables could be a good proxy for the true omitted variable in some cases, however, in most cases they are an incomplete proxy. This is due to the limitation of previous studies, and due to the limitation of data on variables that could truly capture the omitted variable.

A common approach in these cases is to analyze the sensitivity of treatment effects (coefficient movements) after including observable control variables. If a coefficient does not move much after the inclusion of observable controls, it suggests that the omitted variable bias is limited or "controlled" by control variables. The intuition is that the bias from the observable controls is informative about the bias from the full controls (perfect proxy for omitted variable), including the unobservable controls.

However, analysis of coefficient movements alone is not sufficient to evaluate bias. Oster (2016) illustrates this concern with a simple simulation example. She finds that even if some control sets may generate a very little coefficient movement, it does not mean that these control sets are perfect proxies for omitted variables. The simulation results show the other set of controls, which generate large coefficient move, produce a coefficient estimate much closer to the true coefficient, and the R-squared is also much larger. Therefore, as Oster (2016) states, omitted variable bias is proportional to coefficient movements, but only if such movements are scaled by movements in R-squared.

Previous studies, such as Altonji, Elder, and Taber (2005), provide theoretical approaches to the analysis of coefficient movements discussed above. However, these approaches are not feasible because of too restrictive assumptions. Oster (2016) extends these methods, recovers the relation between the treatment and unobservables from the relation between the treatment and observables, and generate a consistent, closed-form estimator for omitted variable bias under less restrictive assumptions. By assuming the maximum R-squared (not necessarily equals to 1) from a hypothetical regression of the outcome on treatment and both observable and unobservable controls, Oster addresses the omitted variable bias with the movement of coefficients and R-squared by adding observable controls into regression.

With the method above, I conduct analyses of coefficient movements in Section IV.

For PP&E and crime rate, the selection on unobservable controls must be at least 2.9 (3.5) times as strong as selection on observable controls, in order to explain the entire association between total crime rate and PP&E for the full (small) sample. As discussed in Altonji, Elder, and Taber (2005), the results show that the relation between observable variables and the outcome is much stronger than the relation between unobservable variables and the outcome. Therefore, the association is unlikely to be driven by omitted variables.

For cash holdings and crime rate, the selection on unobservable variables must be at least 2.7 (2.9) times as strong as selection on observable variables, in order to explain the entire association between total crime rate and cash ratio for the full (small) sample. The results indicate that the relation between observable variables and the outcome is much stronger than the relation between unobservable variables and the outcome. Therefore, the association is unlikely to be driven by omitted variables, same as the case of PP&E and crime rate.

For capital expenditures and crime rate, the selection on unobservable variables only needs to be 1.1 (1.3) times as strong as selection on observable variables, in order to explain the entire association between total crime rate and cash ratio for the full (small) sample.

Therefore, based on Altonji, Elder, and Taber (2005), the association driven by observable variables is not very convincing, because the relation between observable variables and the outcome is almost as strong as the relation between unobservable variables and the outcome.

These results address the concern of omitted variable bias, and further support the “stay hypothesis”.

C. Case Studies

In order to provide further evidence to support the causal relation that firm financial policies are influenced by public safety, I select two cities, Newark and Pittsburgh, as case study subjects, because they have clear patterns of crime rate change over time.

For the city of Newark in New Jersey, there are some apparent spikes of crime rate increase in year 1978, 1979, 1985 and 1990. In these years, total crime rate increases by over 10 percent.

I match the crime rate data of Newark with firm financial policies. I find in these spike years, the change of financial policies, especially PP&E and cash holdings, are consistent with the “stay hypothesis”. For example, in 1978, a firm’s cash ratio decreases sharply from 13.1% to 7.0%; in 1990, another firm’s PP&E increases sharply from 1.5% to 2.3%. These patterns are consistent with different firms that experienced the spike of crime rate increase.

From 2006 to 2008, thanks to the efforts from Cory Booker, a new mayor of Newark, the crime rate in Newark decreases consistently. Meanwhile, PP&E and cash holdings follow the patterns indicated by the “stay hypothesis”. For example, in 2008, a firm’s cash ratio increases from 18.4% to 5.9%; in 2007, another firm's PP&E decreases from 4.7% to 5.9%.

For the city of Pittsburgh in Pennsylvania, there are some apparent spikes of crime rate increase in year 2002, 2006, 2008 and 2011, and there are some apparent spikes of crime rate decrease in year 2001, 2007 and 2010. In these years, total crime rate increases or decreases by over 20 percent.

I match the crime rate data of Pittsburgh with firm financial policies. I find in these spike years, the change of financial policies, especially PP&E and cash holdings, are consistent with the "stay hypothesis". For example, in 2002 (an increase spike year), a firm's cash ratio decreases sharply from 24.6% to 18.4%; in 2007 (a decrease spike year), another firm's PP&E increases sharply from 1.4% to 2.4%. These patterns are consistent with different firms that experienced the spike of crime rate increase and decrease.

With these two case studies, a clear causal relation is found that firm financial policies (PP&E and cash holdings) are influenced by public safety, and the relation is consistent with the "stay hypothesis".

D. Additional Tests for "Escape Hypothesis"

Previous tests show firm financial policies follow the "stay hypothesis" when crime rate changes. However, the regression tests using firm-year observations do not consider the case that a firm moves to a new location. It might exist a situation that firms move to safer areas when local crime rate increases.

With the all firm sample and the small firm sample, I calculate the total number of unique firms and their unique headquarters (zip codes) over years.

For the full sample, of the total 73,677 firm-year observations, there are 7,473 unique firms and 7,474 unique zip codes. The only case in which one firm has two zip codes is probably due to the change of zip code system or an input error, since the detailed address of this firm is not changed.

Because the small firm sample is a subset of the full sample, there is no need to test the headquarter movement in the small sample.

However, there might be a case that firms in dangerous areas move to safe areas but change their firm name and ID. Since the firm names are also changed, there is no feasible way to identify the moved firms in this case.

I search articles on Wall Street Journal and other media about firm movement due to crime increase, but find very few articles about it. This partially rules out the possibility of firm movement because of an increase in crime rate.

As discussed in Section II, moving is costly for firms. Therefore, firms are possible to stay and try to take advantage of the crime rate increase.

E. Test of Public Safety and Market Return

From Table 2 and Table 6, when the financial policy variable is market-to-book, the negative t-statistic and coefficient estimate provide a picture that an increase in crime rate might hurt the market return of the firm's stock. This idea may not be reasonable, but I still test it to find out if the relation between public safety and market return exists.

I match stock return data with the same firm-year observations for both the full sample and the small sample. The stock return data are from CUSIP.

I run the OLS regression test, with stock return as the dependent variable, crime rate as the independent variable. I use three different crime rate: total, serious, and nonserious.

Of all three independent variables and both samples, none of the coefficients on crime rate are significant. Therefore, the relation between public safety and market return does not exist.

VI. Conclusion

This paper investigates the relation between public safety and firm financial policies. With FBI Uniform Crime Reports data, I find that firms located in dangerous areas have significantly larger PP&E and significantly smaller cash holdings. These results are consistent with the "stay hypothesis" I develop, in which firms could benefit from the increase of local crime rate, because local real estate market and property prices are hurt by the crime rate increase.

About the endogeneity issue in the association between public safety and firm financial policies, I address it with various methods.

First, I use a set of controls in the OLS regressions. These controls are based on previous studies on determinants of financial policies. The association is robust after adding the control variables and fix effects.

Second, I conduct analyses of coefficient movements, ruling out the possibility that omitted variables are responsible for the association. I find it unlikely that they are.

Third, I conduct case studies to support the causal relation between public safety and financial policies. The two cases with Newark and Pittsburgh support the causal relation under the "stay hypothesis".

Moreover, I further rule out the possibility of firm movement when crime rate increases.

Although this paper does not use an instrumental variable approach to address the omitted variable bias, the tests above provide convincing evidence that the causal relation between public safety and firm financial policies is not driven by omitted variables.

Further work can be done in finding a proper instrumental variable and conducting test in more detailed subsamples.

Reference

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools." *Journal of Political Economy* 113.1 (2005): 151-184.

Angrist, Joshua D., and Jörn-Steffen Pischke. "The credibility revolution in empirical economics: How better research design is taking the con out of econometrics." *The Journal of Economic Perspectives* 24.2 (2010): 3-30.

Bates, Thomas W., Kathleen M. Kahle, and René M. Stulz. "Why do US firms hold so much more cash than they used to?" *The Journal of Finance* 64.5 (2009): 1985-2021.

Brown, Karen A. "Workplace safety: a call for research." *Journal of Operations Management* 14.2 (1996): 157-171.

Cohn, Jonathan B., and Malcolm I. Wardlaw. "Financing constraints and workplace safety." *The Journal of Finance* 71.5 (2016): 2017-2058.

Cornwell, Christopher, and William N. Trumbull. "Estimating the economic model of crime with panel data." *The Review of economics and Statistics* (1994): 360-366.

Duchin, Ran. "Cash holdings and corporate diversification." *The Journal of Finance* 65.3 (2010): 955-992.

Foley, C. Fritz, Jay C. Hartzell, Sheridan Titman, and Garry Twite. "Why do firms hold so much cash? A tax-based explanation." *Journal of Financial Economics* 86. 3 (2007): 579-607.

Gibbons, Steve. "The costs of urban property crime. " *The Economic Journal* 114.499 (2004).

Haushalter, David, Sandy Klasa, and William F. Maxwell. "The influence of product market dynamics on a firm's cash holdings and hedging behavior." *Journal of Financial Economics* 84.3 (2007): 797-825.

Hellman, Daryl A., and Joel L. Naroff. "The impact of crime on urban residential property values. " *Urban Studies* 16.1 (1979): 105-112.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala. "Product market threats, payouts, and financial flexibility." *The Journal of Finance* 69.1 (2014): 293-324.

Leary, Mark T., and Michael R. Roberts. "Do peer firms affect corporate financial policy?" *The Journal of Finance* 69.1 (2014): 139-178.

Lins, Karl V., Henri Servaes, and Peter Tufano. "What drives corporate liquidity? An international survey of cash holdings and lines of credit." *Journal of Financial Economics* 98.1 (2010): 160-176.

Matsa, David A. "Capital structure as a strategic variable: Evidence from collective bargaining." *The Journal of Finance* 65.3 (2010): 1197-1232.

Opler, Tim, Lee Pinkowitz, René Stulz, and Rohan Williamson. "The determinants and implications of corporate cash holdings." *Journal of Financial Economics* 52.1 (1999): 3-46.

Oster, Emily. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics* (2016).

Smith, Jared D. "US political corruption and firm financial policies. " *Journal of Financial Economics* 121.2 (2016): 350-367.

Figure 1. Total Crime Rate by County

This figure shows the average rate of total crimes by county from 1975 to 2012. Total crime rate is calculated by the total number of crimes divided by the total population of the county.

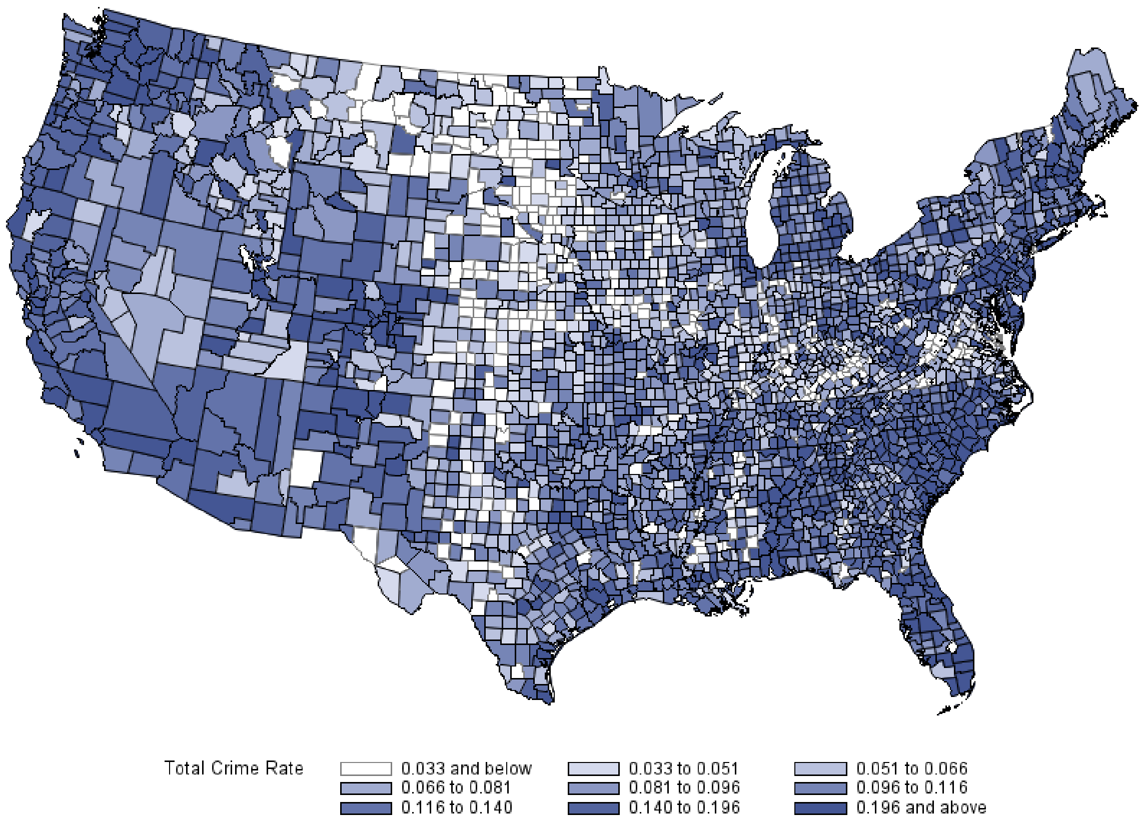

Table 1. Summary Statistics

This table displays the summary statistics for the variables of interest. Panel A contains all firm-year observations from 1975 to 2012 merged with Compustat and FBI crime datasets. Panel B contains small firm observations that have asset values less than 100 million dollars. Financial firms and utilities are excluded from the samples. Variable definitions are listed in Table A.1.

Panel A. All firms

Variables	N	Mean	Std Dev	Median	Min	Max
Crime rate (total)	73,677	0.066	0.264	0.046	0.000	19.189
Crime rate (serious)	73,677	0.002	0.026	0.001	0.000	2.358
Crime rate (nonserious)	73,677	0.063	0.245	0.045	0.000	16.830
Cash ratio	73,677	0.174	0.219	0.078	0.000	0.990
ln(Cash/net assets)	73,677	-2.441	1.977	-2.464	-12.399	4.548
Leverage	73,677	0.296	0.426	0.217	0.000	9.940
Market-to-book	73,677	2.036	2.898	1.266	0.001	49.356
Capital expenditures	73,677	0.068	0.088	0.042	-0.804	4.404
Net working capital	73,677	0.030	0.526	0.082	-9.988	0.929
Dividends	73,677	0.011	0.062	0.000	-0.014	5.361
PP&E	73,677	0.288	0.231	0.231	0.000	1.000
Cash flow	73,677	-0.068	0.517	0.053	-9.911	12.989
R&D	73,677	0.366	3.279	0.000	0.000	97.398
EBITDA	73,677	-0.002	0.490	0.105	-9.689	14.500
Acquisitions	73,677	0.018	0.071	0.000	-3.243	1.483

Panel B. Small firms

Variable	N	Mean	Std Dev	Median	Min	Max
Crime rate (total)	43,105	0.067	0.249	0.046	0.000	12.910
Crime rate (serious)	43,105	0.002	0.020	0.001	0.000	1.670
Crime rate (nonserious)	43,105	0.064	0.240	0.045	0.000	12.548
Cash ratio	43,105	0.207	0.242	0.102	0.000	0.990
ln(Cash/net assets)	43,105	-2.173	2.049	-2.176	-11.343	4.548
Leverage	43,105	0.298	0.512	0.183	0.000	9.940
Market-to-book	43,105	2.344	3.599	1.273	0.001	49.356
Capital expenditures	43,105	0.069	0.098	0.038	-0.804	4.404
Net working capital	43,105	-0.015	0.665	0.079	-9.988	0.929
Dividends	43,105	0.009	0.072	0.000	0.000	5.361
PP&E	43,105	0.263	0.228	0.197	0.000	1.000
Cash flow	43,105	-0.158	0.655	0.029	-9.911	12.989
R&D	43,105	0.531	3.975	0.000	0.000	97.398
EBITDA	43,105	-0.092	0.618	0.069	-9.689	14.500
Acquisitions	43,105	0.011	0.061	0.000	-3.243	0.976

Table 2. Mean Differences between Dangerous and Safe Areas

This table displays the t-statistic difference in means between dangerous and safe areas. Firms in one year are marked as having headquarters in dangerous (safe) areas if their crime rates lie in the top (bottom) quartile of all area crime rates in that year. The statistics are calculated using the mean differences (mean values of dangerous areas minus mean values of safe areas). *, **, and *** denote significant levels at 10%, 5% and 1%, respectively.

Panel A. All firms

	All crimes	Serious crimes	Nonserious crimes
Cash ratio	-18.73***	-8.19***	-18.48***
ln(Cash/net assets)	-19.09***	-9.51***	-19.05***
Leverage	7.91***	7.98***	8.08***
Market-to-book	-5.09***	-1.41	-4.73***
Capital expenditures	18.00***	12.56***	17.90***
Net working capital	-4.58***	-7.51***	-4.72***
Dividends	1.03	-0.97	0.99
PP&E	33.14***	21.47***	32.63***
Cash flow	3.04***	-2.20**	2.84***
R&D	-6.33***	0.85	-6.13***
EBITDA	4.17***	-1.97**	3.96***
Acquisitions	0.29	1.11	0.40

Panel B. Small firms

	All crimes	Serious crimes	Nonserious crimes
Cash ratio	-8.82***	-1.52	-8.44***
ln(Cash/net assets)	-7.57***	-0.10	-7.39***
Leverage	2.87***	3.73***	3.03***
Market-to-book	0.00	2.38**	0.38
Capital expenditures	11.66***	7.58***	11.68***
Net working capital	-3.70***	-5.84***	-3.93***
Dividends	0.88	-0.78	0.91
PP&E	17.49***	8.05***	17.29***
Cash flow	0.09	-3.69***	-0.22
R&D	-4.58***	1.60	-4.36***
EBITDA	0.80	-3.62***	0.49
Acquisitions	0.97	1.31	0.83

Table 3. PP&E and Crime Rates

This table displays the results of 18 OLS regressions estimating how PP&E varies with local crime rates. Each column shows coefficients of three OLS regressions with different independent variables. Column (1) to (3) are results with all firm sample. Column (4) to (6) are results with small firm sample. The dependent variable is PP&E. For each of the three regressions, the independent variable is total crime rate, serious crime rate, and nonserious crime rate, respectively. Control variables include leverage, market-to-book ratio, and EBITDA. The three adjusted R-squared for each column happen to be equal when rounded to three decimals. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year and industry. *, **, and *** denote significant levels at 10%, 5% and 1%, respectively.

	Dependent variable: PP&E					
	All firms			Small firms		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Crime rate (total)	0.012***	0.010***	0.006*	0.012***	0.012***	0.008**
	(3.68)	(3.16)	(1.89)	(3.74)	(3.74)	(2.55)
Crime rate (serious)	0.115***	0.093***	0.072**	0.119***	0.118***	0.094***
	(3.62)	(3.01)	(2.45)	(3.70)	(3.71)	(3.11)
Crime rate (nonserious)	0.012***	0.010***	0.006*	0.012***	0.013***	0.008**
	(3.56)	(3.07)	(1.77)	(3.62)	(3.62)	(2.40)
Controls	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	No	No	Yes	No	No	Yes
N	73,677	73,677	73,677	43,105	43,105	43,105
Adj. R-squared	0.037	0.040	0.130	0.036	0.077	0.162

Note: Each coefficient come from a separate regression (18 regressions in total).

Table 4. Cash Holdings and Crime Rates

This table displays the results of 18 OLS regressions estimating how cash holdings vary with local crime rates. Each column shows coefficients of three OLS regressions with different independent variables. Column (1) to (3) are results with all firm sample. Column (4) to (6) are results with small firm sample. The dependent variable is cash ratio. For each of the three regressions, the independent variable is total crime rate, serious crime rate, and nonserious crime rate, respectively. Control variables include leverage, market-to-book ratio, capital expenditures, net working capital, dividends, cash flow, R&D and acquisitions. The three adjusted R-squared for each column happen to be equal when rounded to three decimals. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year and industry. *, **, and *** denote significant levels at 10%, 5% and 1%, respectively.

	Dependent variable: cash ratio					
	All firms			Small firms		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Crime rate (total)	-0.009***	-0.008***	-0.012***	-0.010**	-0.010**	-0.016***
	(-2.79)	(-2.66)	(-4.21)	(-2.24)	(-2.19)	(-3.54)
Crime rate (serious)	-0.091***	-0.087***	-0.102***	-0.195***	-0.192***	-0.229***
	(-2.97)	(-2.87)	(-3.48)	(-3.39)	(-3.35)	(-4.06)
Crime rate (nonserious)	-0.009***	-0.008**	-0.013***	-0.010**	-0.008**	-0.016***
	(-2.68)	(-2.55)	(-4.15)	(-2.04)	(-1.99)	(-3.34)
Controls	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	No	No	Yes	No	No	Yes
N	73,677	73,677	73,677	43,105	43,105	43,105
Adj. R-squared	0.049	0.060	0.127	0.087	0.097	0.130

Note: Each coefficient come from a separate regression (18 regressions in total).

Table 5. Capital Expenditures and Crime Rates

This table displays the results of 18 OLS regressions estimating how capital expenditures vary with local crime rates. Each column shows coefficients of three OLS regressions with different independent variables. Column (1) to (3) are results with all firm sample. Column (4) to (6) are results with small firm sample. The dependent variable is capital expenditures. For each of the three regressions, the independent variable is total crime rate, serious crime rate, and nonserious crime rate, respectively. Control variables include market-to-book ratio, dividends, cash flow, and R&D. The three adjusted R-squared for each column happen to be equal when rounded to three decimals. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year and industry. *, **, and *** denote significant levels at 10%, 5% and 1%, respectively.

	Dependent variable: capital expenditures					
	All firms			Small firms		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Crime rate (total)	0.000	0.001	-0.001	0.002*	0.002*	0.000
	(0.47)	(0.56)	(-0.48)	(1.79)	(1.81)	(0.34)
Crime rate (serious)	0.013	0.014	-0.003	0.019	0.020	0.012
	(0.53)	(0.60)	(-0.11)	(1.60)	(1.62)	(1.01)
Crime rate (nonserious)	0.001	0.001	-0.001	0.002*	0.002*	0.000
	(0.45)	(0.53)	(-0.49)	(1.75)	(1.78)	(0.25)
Controls	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	No	No	Yes	No	No	Yes
N	73,677	73,677	73,677	43,105	43,105	43,105
Adj. R-squared	0.030	0.031	0.071	0.031	0.034	0.069

Note: Each coefficient come from a separate regression (18 regressions in total).

Table 6. Other Variables and Crime Rates

This table displays the results of six OLS regressions estimating how other variables vary with local crime rates. The results are with all firm sample. The independent variable is total crime rate. The dependent variables for the six regressions are leverage, market-to-book, net working capital, cash flow, R&D, and EBITDA, respectively. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by year and industry. *, **, and *** denote significant levels at 10%, 5% and 1%, respectively.

	Independent variable: total crime rate			
Dependent variable	Estimate	Standard Error	t-value	p-value
Leverage	0.009	0.006	1.51	0.1299
Market-to-book	-0.027	0.040	-0.66	0.5062
Net working capital	-0.006	0.007	-0.87	0.3845
Cash flow	0.005	0.007	0.68	0.4963
R&D	-0.072	0.046	-1.57	0.1163
EBITDA	0.005	0.007	0.78	0.4329

Table A.1. Variable Definitions

This table provides the definitions of variables in Table 1 to Table 6.

Variables	Definition
Cash ratio	Cash and cash equivalents divided by book assets
ln(Cash/net assets)	Natural log of cash divided by net assets
Leverage	Long-term debt plus debt in current liabilities divided by book assets
Market-to-book	Book assets – common equity + common shares outstanding * share price at fiscal year-end divided by book assets
Capital expenditures	Capital expenditures divided by book assets
Net working capital	Net working capital net of cash divided by book assets
Dividends	Cash dividends divided by book assets
PP&E	Net property, plant, and equipment divided by book assets
Cash flow	EBITDA −taxes −interest −dividends divided by book assets
R&D	Research and development expenses divided by sales
EBITDA	EBITDA divided by total assets
Acquisitions	Cash outflow related to acquisitions divided by book assets

Table A.2. Summary Statistics for Total Crime Rates by Year

This table shows the summary statistics for total crime rates of all US states by year.

Year	N	Mean	Std Dev	Median	Min	Max
1975	11,615	0.033	0.068	0.023	0.000	3.680
1976	12,038	0.033	0.068	0.024	0.000	3.883
1977	12,555	0.032	0.062	0.023	0.000	3.662
1978	12,971	0.034	0.180	0.024	0.000	19.189
1979	13,223	0.036	0.089	0.026	0.000	5.124
1980	13,397	0.038	0.129	0.028	0.000	12.910
1981	13,539	0.038	0.144	0.027	0.000	12.692
1982	13,656	0.035	0.112	0.025	0.000	9.500
1983	13,738	0.032	0.099	0.023	0.000	9.011
1984	13,835	0.032	0.122	0.022	0.000	10.831
1985	13,911	0.033	0.105	0.023	0.000	10.185
1986	14,020	0.035	0.129	0.023	0.000	11.839
1987	14,110	0.035	0.140	0.022	0.000	10.467
1988	14,180	0.032	0.122	0.021	0.000	9.798
1989	14,226	0.035	0.143	0.023	0.000	12.196
1990	14,328	0.036	0.097	0.025	0.000	7.382
1991	14,513	0.036	0.099	0.024	0.000	6.948
1992	14,613	0.036	0.091	0.024	0.000	6.860
1993	14,693	0.086	1.833	0.021	0.000	164.202
1994	14,781	0.033	0.084	0.021	0.000	6.752
1995	14,871	0.034	0.119	0.021	0.000	12.072
1996	14,908	0.032	0.100	0.020	0.000	9.880
1997	14,983	0.033	0.165	0.020	0.000	16.364
1998	15,025	0.033	0.144	0.019	0.000	14.385
1999	15,152	0.032	0.139	0.020	0.000	13.923
2000	15,243	0.030	0.101	0.020	0.000	8.450
2001	15,300	0.030	0.087	0.020	0.000	7.269
2002	15,586	0.031	0.090	0.021	0.000	7.362
2003	15,692	0.030	0.083	0.021	0.000	6.670
2004	15,792	0.031	0.076	0.021	0.000	6.426
2005	15,857	0.030	0.078	0.020	0.000	6.862
2006	15,945	0.029	0.074	0.020	0.000	6.226
2007	16,070	0.029	0.068	0.020	0.000	5.868
2008	16,146	0.030	0.061	0.021	0.000	5.756
2009	16,227	0.029	0.051	0.021	0.000	4.200
2010	16,309	0.028	0.066	0.021	0.000	6.055
2011	16,362	0.028	0.066	0.021	0.000	5.514
2012	16,436	0.028	0.070	0.020	0.000	5.577

Table A.3. Summary Statistics for Total Crime Rates by State

This table shows the summary statistics for total crime rates from 1975 to 2012 by states.

State	N	Mean	Std Dev	Median	Min	Max
AK	1,264	0.056	0.047	0.056	0.000	0.237
AL	14,518	0.032	0.048	0.017	0.000	2.476
AR	8,650	0.031	0.092	0.020	0.000	8.110
AZ	3,525	0.052	0.041	0.045	0.000	0.423
CA	19,565	0.075	0.403	0.046	0.000	12.910
CO	9,083	0.065	0.739	0.028	0.000	52.058
CT	3,867	0.032	0.029	0.028	0.000	0.645
DC	38	0.094	0.018	0.089	0.073	0.134
DE	1,644	0.066	0.090	0.046	0.000	1.033
FL	14,845	0.058	0.069	0.048	0.000	2.577
GA	19,823	0.031	0.037	0.020	0.000	1.000
HI	481	0.024	0.034	0.000	0.000	0.114
IA	8,901	0.024	0.022	0.017	0.000	0.137
ID	4,536	0.032	0.034	0.025	0.000	0.792
IL	29,784	0.018	0.032	0.000	0.000	1.061
IN	9,423	0.024	0.031	0.015	0.000	1.404
KS	12,682	0.021	0.056	0.012	0.000	3.935
KY	13,809	0.013	0.022	0.004	0.000	0.384
LA	7,643	0.032	0.056	0.021	0.000	3.859
MA	12,332	0.025	0.087	0.019	0.000	9.385
MD	4,506	0.048	0.172	0.031	0.000	9.990
ME	5,042	0.034	0.053	0.028	0.000	1.827
MI	25,057	0.035	0.047	0.027	0.000	1.174
MN	11,694	0.032	0.029	0.028	0.000	1.627
MO	15,206	0.031	0.037	0.022	0.000	1.697
MS	7,857	0.021	0.039	0.004	0.000	1.791
MT	4,279	0.019	0.025	0.011	0.000	0.241
NC	17,826	0.044	0.056	0.032	0.000	1.645
ND	3,797	0.013	0.016	0.009	0.000	0.108
NE	8,545	0.017	0.165	0.009	0.000	15.095
NH	7,775	0.023	0.222	0.003	0.000	18.925
NJ	19,536	0.046	0.124	0.033	0.000	5.143
NM	4,071	0.032	0.042	0.017	0.000	0.906
NV	1,218	0.038	0.027	0.034	0.000	0.130
NY	24,823	0.023	0.035	0.016	0.000	1.632
OH	23,257	0.027	0.063	0.019	0.000	6.024
OK	12,656	0.029	0.025	0.023	0.000	0.237

Table A.3. (Continued)

State	N	Mean	Std Dev	Median	Min	Max
OR	7,470	0.042	0.069	0.036	0.000	5.228
PA	44,953	0.030	0.905	0.014	0.000	164.202
RI	1,520	0.037	0.030	0.030	0.000	0.290
SD	4,637	0.012	0.050	0.004	0.000	3.217
TN	11,681	0.034	0.060	0.025	0.000	4.981
TX	32,233	0.039	0.043	0.031	0.000	4.000
UT	4,801	0.034	0.071	0.026	0.000	3.373
VA	9,387	0.030	0.031	0.024	0.000	1.685
VT	2,262	0.029	0.041	0.019	0.000	0.491
WA	8,717	0.069	0.969	0.046	0.000	75.019
WI	12,303	0.030	0.026	0.026	0.000	0.602
WV	9,739	0.020	0.062	0.007	0.000	3.352
WY	2,684	0.034	0.069	0.029	0.000	3.117