**Snitches *Don't* Get Stitches**

**The Impact of Per-Capita Crime on Crime Reporting Behavior in the City of Los Angeles**

by

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## 1. Introduction

The delay between when a crime occurs and when it is reported has a significant impact on the efficacy of the criminal justice system. The longer the gap between occurrence and reporting, the increased probability that evidence will be lost and witnesses' memories will fade, diminishing the ability of the criminal justice system to hold perpetrators of crime accountable for their actions. Yet from January 2010 to September 2017, 53.3% of crimes in Los Angeles have a gap between the day that the crime occurs and the day it is reported. The largest date reporting difference is 2,778 days, or over seven and a half years. This suggests that there is some psychological cost that has to be overcome in order to report the occurrence of a crime, and that this psychological cost outweighs the perceived costs of waiting to report.

Being a victim of a crime is often a traumatic experience. In addition to the actual physical or economic losses that were the direct result of the crime, crime victims often experience a loss of a sense of security, post-traumatic stress disorder, depression, and other psychological issues (Resick 1987). These conditions can be crippling, making it hard to even perform everyday functions and responsibilities. These psychological costs also make it harder to talk about the circumstances of what happened, especially to a police officer, or on cross-examination during a trial to an intimidating defense attorney.

This tension between the psychological costs of reporting and the evidentiary cost of waiting has significance for policy makers. If a goal of society is to hold perpetrators of crimes accountable for their actions, then policy makers should prioritize interventions that reduce this tension and thus bridge the gap in order to guarantee preservation of evidence and memory.

This paper explores the effect that a fear of reprisal has on crime reporting behavior. I explore this phenomena by using per-capita crime of the area in Los Angeles in which the crime was reported in as a proxy for reprisal. Controlling for aggravating aspects of the crime as well as characteristics of the victim, I regress the time gap in days between occurrence and report on the per-capita crime rate of the neighborhood. I find a statistically significant slightly negative relationship between the two. Making the generous assumption that per-capita crime of a neighborhood is a sufficient proxy for this fear, the results of my regression provide evidence against this phenomenon.

This relationship between fear of reprisal and crime reporting behavior is connected to several areas of literature. My results touch on the broader topic of the role that emotions play in economics and decision making (Loewenstein and Lerner 2003). In addition, this paper folds into the more specific field of how emotions impact crime victim behavior, specifically when it comes to reporting. Langton et al (2012) finds that 34% of crime victims who choose to report fail to do so because of a fear of reprisal.

## 1. What role does fear play in crime reporting behavior?

Loewenstein and Lerner (2003) analyze the role of emotion in decision making. They discuss two different ways that emotions can impact how individuals make decision making: *expected* emotions and *immediate* emotions. The influence of expected emotions in decision making is the agent making predictions about how decision outcomes affect emotional outcomes. Expected emotions are taken into account in standard economic models as an input to utility. Immediate emotions are felt at the time of the decision, and impact behavior by directly influencing the cognitive decision-making process or indirectly influencing by weighting how the individual feels about future events. This interaction can be visualized in the following figure.

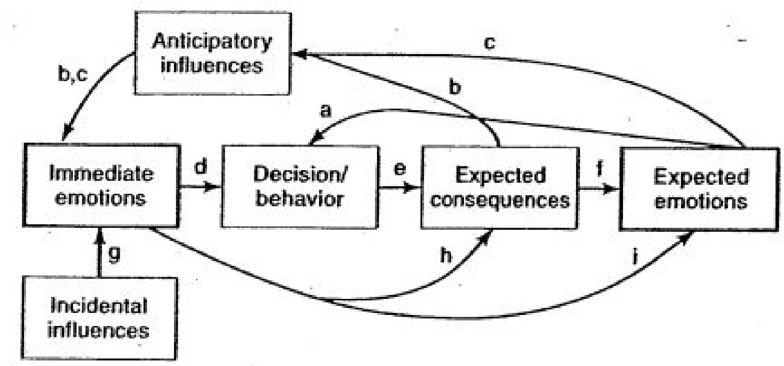


*Figure 2.1. The Impact of Emotions on Decision Making*

*Source: Loewenstein and Lerner (2003)*

This is relevant for our purposes because it allows us to hypothesize about the effect that fear has on crime reporting behavior. I hypothesize that fear in crime reporting is predominantly an expected emotion, due to the fact that crime victims are already in a traumatic state, and dread having to talk about what transpired. However, fear could also be an immediate emotion. A crime victim could feel more prepared to talk about their experience, but as they reach for the phone to call an emergency phone number or start to go to the police department, they may start to regret their decision, and ultimately decide not to go through with reporting.

Literature in economics and criminology support the notion that fear impacts reporting behavior. Langton et al (2012) studies why crime victims did not report crimes that occurred. They find that 13% of victims did not report because they were afraid of reprisal and 16% failed to report because they felt that the police could not or would not help. Severity of the crime also impacts reporting behavior (Conaway and Lohr 1994).

It is necessary to distinguish these studies from ours. In these studies, the authors examine the role of factors that contribute to whether or not a crime victim reports at all. In this paper, given that a person reports, I look at the factors that cause them to delay reporting. This subtle but significant difference lends itself to different methodologies and different explanations of human behavior and decision making. Because there are no records associated with a person refusing to report, Langton et al (2012) uses surveys of victims, whereas I look at data collected by the Los Angeles Police Department. This dichotomy leads to the difference of outcomes associated with comparing the two studies.

2. **Per-Capita Crime Should Have a Positive Correlation with Reporting Delay**

In designing this model, I pick variables that would specifically help us examine the role that fear of reprisal plays on delays in crime reporting and disentangle that from other factors that may discourage crime reporting. I choose per-capita crime to approximate the threat of reprisal. I hypothesize that per-capita crime is a sufficient proxy for reprisal because as crime is more prevalent in a neighborhood, the greater the amount of people who would care about a "snitch". Thus, per-capita crime and reporting delay should have a positive correlation; as per-capita crime increases, so too should the reporting delay because the reporter would be more wary of retaliation. I also want to control for variables that would affect the gravity of a crime. I control for the minimum sentence of the crime reported, whether a weapon was used in the commission of the crime and whether or not the crime was violent.

I use the minimum sentence of the crime as a proxy for the severity of the crime. Another factor to keep in mind is that some crimes are called "wobblers." Wobblers are crimes that can be charged as either a felony or a misdemeanor.[1] To be generous, I assume that any wobblers in the data were misdemeanors. In addition, "attempted crimes" carry a sentence of one half the sentence that the defendant would have received if they had been convicted of the underlying offense. When examining observations whose crimes were wobblers, I use the minimum sentence of the misdemeanor version of the crime in order to build a more conservative model. The addition of a weapon in the commission of a crime should also cause the difference in days of reporting to increase; a perpetrator will be incentivized to threaten or injure a witness or victim of a crime if it means not being under investigation. Therefore, a witness may be more hesitant to report. In addition, if the perpetrator is comfortable threatening an individual with a weapon for personal gain, then they will likely be comfortable threatening or injuring a witness in order to avoid the consequences of their actions. I define violence as any crime that necessitates the application of force to another human being. The presence of violence should also cause the gap between crime occurrence and crime report to increase; if the victim is the reporter, then they will probably be more traumatized and thus less likely to report. If a witness is the reporter, then they will likely be afraid that the same thing could happen to them.

I also examine factors that would impact fear stemming from characteristics of the victim. I posit that the relationship between age and the time it takes to report a crime follows a negative parabolic path. If a victim is a child, they may feel helpless and thus less likely to report. As they grow older, they may feel more confident and would then be more likely to report a crime that happened to them up to a certain age. After this age, they get older and thus feel more vulnerable, making them less likely to report a crime. Following this model, I include both

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[1] In California Law, a misdemeanor is any crime that can carry a sentence of up to and including 364 days in county jail, whereas a felony is any crime that can carry a sentence of 365 days or over in state prison.

a variable for age and the square of the age. In addition, I include a dummy variable for whether or not the victim was female. I hypothesize that the victim being female will lead to increased gaps between occurrence and report due to a feeling of being vulnerable or powerless.

Because the reporting delay is a continuous response variable and I want to examine the strength of the relationship between the per-capita crime rate and the reporting delay, I use an Ordinary Least Squares (OLS) regression. I choose a linear form for the specification, except for $Age^2$, which is in polynomial form. This is because I expect all else to have a constant slope with respect to the difference in dates of occurrence and reporting. Thus, our theoretical specification takes the form shown in the following equation:

$$dateDifference_i = \beta_0 + \beta_{perCapitaCrime} * perCapitaCrime_i + \beta_{age^2} * age_i^2 + \beta_{Age} * age_i + \\ + \beta_{minSent} * minSent_i + \beta_{violent} * violent_i + * weaponUsed_i + \beta_{female} * female + \varepsilon_i \tag{3.1}$$

**3.**

I gather my data from four sources. Summary statistics of all variables can be found in the table 3.1, which can also be found in Appendix 9.b.I.vii.

*Table 3.1*

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| victimage | 1,307,019 | 38.29737 | 15.87303 | 10 | 99 |
| violent | 1,307,019 | .4925988 | .4999454 | 0 | 1 |
| perCapitaC~e | 1,307,019 | 41.02374 | 27.15033 | 17.1 | 121.8 |
| weaponUsed | 1,307,019 | .3750688 | .4841409 | 0 | 1 |
| datediffer~e | 1,307,019 | 16.54491 | 102.1442 | 0 | 2778 |
| female | 1,307,019 | .4987915 | .4999987 | 0 | 1 |
| minSent | 1,307,019 | .2230391 | .7815377 | 0 | 100 |
| victimAge2 | 1,307,019 | 1718.641 | 1400.884 | 100 | 9801 |

The first source is a dataset cultivated by the city of Los Angeles which documents all reported crimes in the city, dating back to January of 2010. My version of the data, gathered from Kaggle.com, spans from January 2010 to September 2016. The original version of the dataset contains 1,584,316 observations, and it is from this dataset that I ascertain the age of the victim, and whether a weapon was used. The dataset reports the dates that a crime occurred and was reported. I then convert these variables into a time and date format that Stata could read and subtract the two in order to find the difference in dates between report and occurence. The relevant Stata code can be found in Appendix 9.a.I.v.

The dataset provides a variable for the description of what kind of weapon was used in the crime, if any. In order to use this information in the regression, I create a dummy variable for if a weapon was used at all. I then write a conditional statement for Stata to populate the weapon dummy variable field for that observation with “0” if the weapon description field is null and “1” if there is some text in that field. The relevant Stata code can be found in Appendix 9.a.I.ii[2]

[2] This relies on the assumption that there were no clerical errors between the officers responding to the call and to the dataset being uploaded.

The City of Los Angeles also provides a description of the crime for that particular observation. Using the Placer Group's Crime Finder application, which is widely used by attorneys in the criminal justice system, I ascertain the minimum sentence of the least severe version of the crime and then populate the minimum sentence variable with the minimum available sentence of the crime if convicted in years.

The dataset contains other variables such as the QDR number, which is a unique identifier that can be used to look up details about that individual case.[3] Other variables include modus operandi codes, which are descriptors of details about that specific incident. One variable of interest that I use is the reporting district variable, which lists which police station responded to the report. I use which police station as an approximate measure of the geographic area that the crime was reported it. I use Google to find the address of that particular police station and I then plug in that address into the Los Angeles Times' "LA Mapping" project, which collects and reports data about all of the neighborhoods in Los Angeles. One may plug an address into the website and the website then tells you which neighborhood it considers that address to be in, as well as characteristics of that neighborhood. I use this project to ascertain the per-capita crime rate of the surrounding area of the crime. The dataset also lists the actual address at which the crime was reported to have occurred. Using this address to gather per-capita crime would have been more precise but ultimately time-consuming.

There were some observations that had missing fields for certain variables. For example, several observations had the variable for the sex of the victim as null. I drop those observations. I feel comfortable doing so because of the massive size of the original dataset and thus could

[3] This would be very useful, but the LAPD charges $30 for each QDR lookup, and alas I am a broke college student. This could be fruitful if one partnered with the LAPD.

afford to lose some observations in order to make every observation able to be regressed upon. After dropping those observations I have 1,307,019 observations.

A key problem with this dataset is that it suffers from survivorship bias. This only takes into account the crimes that were reported, not the crimes that were not. If one wanted to create a fuller, more accurate picture of the factors that affect crime reporting, one would somehow have to gather data from crime victims who did not come forward. Langton et al (2012) uses surveys to gather data on victims who did not report, but if a victim was truly too scared to come forward, they would perhaps hesitate to talk to a researcher from the federal Department of Justice. In order to truly create a robust model to describe the factors that affect crime reporting, a perfect data recording mechanism would build a universal monitoring system à la *Minority Report*.

Finally, the Los Angeles Times data only goes back six months, whereas the city of Los Angeles crime data goes back six years. Therefore, the Los Angeles Time data may not accurately capture how much the city has changed in the past six years, especially when taking into account the increasing rate of gentrification.[4] This may skew the results of our regression. However, I believe the preceding six month period to be a sufficient approximation for the per-capita crime rate in the past six years. Lofstrom and Martin (2017) provides evidence that since 2010, property crimes per 100,000 residents in California have decreased slightly, but violent crimes have increased.

## 4. Per-Capita Crime Has A Slight Negative Impact On Reporting Delays

### a. Regression Results

[4] Areas undergoing gentrification have been shown to have a decreasing crime rate. See Autor et al (2017).

Running the regression discussed in section 3 gives us the following results reported in standard format, with standard errors in parentheses. All numbers are rounded to three decimal places except for t-values, because Stata only calculates the t-values for up to two decimal places.

$$
\begin{aligned}
\widehat{dateDifference}_i = \; & 38.694 - \underset{\substack{(0.003)\\ t\,=\,-4.28}}{0.016} * perCapitaCrime + \underset{\substack{(0.000)\\ 39.52}}{0.011} * age^2 - \underset{\substack{(0.025)\\ -33.70}}{0.835} * age \; + \\
& + \underset{\substack{(0.122)\\ t\,=\,11.02}}{0.933} * minSent - \underset{\substack{(0.217)\\ -81.44}}{17.457} * violent - \underset{\substack{(0.229)\\ -25.06}}{5.836} * weaponUsed + \underset{\substack{(0.180)\\ 21.57}}{3.881} * female \\
& N = 1,307,019 \qquad \overline{R}^2 = 0.013
\end{aligned}
\tag{5.1}
$$

All variables reach statistical significance at the 5% confidence level, with Stata reporting all p-values as 0.000. The results of this regression seem to run counter to the notion that fear of reprisal promotes delays in crime reporting. Per-capita crime has a slight negative relationship with the difference in days; as per-capita crime increases, the delay decreases. This provides evidence contrary to the idea that people are afraid of "snitches getting stitches," or that people are afraid of reprisal and that is why they delay reporting. However, as discussed previously, my measurements of per-capita crime are flawed and this could be causing the regression results to be biased. It is also possible that per-capita crime does not sufficiently capture the idea of the fear of reprisal.

My theory regarding victim age suggests that victim age has a negative quadratic relationship with the amount of time it takes to report. This implies that as the victim grows older, the difference between the day that the crime occurred and the day that the crime was reported diminishes up to a certain age, and then starts increasing. This is grounded in the idea that children and older people would feel vulnerable and wait to report. However, my regression shows a positive quadratic relationship between age and delay. This may be explained by the fact that the victims are not necessarily the ones that reported the crime. Other people may feel a greater sense of injustice towards crimes committed against children and the elderly, and thus report them sooner.

However, the regression does suggest that simple fear or psychological trauma does affect reporting behavior. I introduce the variable for minimum sentence as a proxy of how severe the crime is, while still being conservative. I found that as the minimum sentence goes up by one year, holding all other variables constant, the victim delays reporting the crime by an additional 1.325 days. Another factor that plays into this fear is gender. I found that if the victim is a woman, all else being equal, they will delay reporting by an additional 3.811 days.

Even though all variables reach statistical significance, the adjusted $R^2$ is very low even for data involving individuals. I will explore two potential explanations of this disconnect. One is omitted variable bias, which I will explore in section 5.b.ii. The other is a difference in population of reporters. The dataset fails to distinguish between who reported the crime: the victim or a witness? I predict that the crime reporting behavior of these two groups are fundamentally different and are then influenced by different factors. Another possible factor is that the reporters are not separated by their proximity to the crime, but by personality characteristics: there could be a *fearless* group and a *hesitant* group. The fearless group reports on the same day that the crime occurred, regardless of any factors that may contribute to their level of fear. The hesitant group is hesitant to report due to exogenous related to the characteristics of the perpetrator and the crime itself, like the actual crime committed, whether it was violent, the presence of a weapon, and other factors not explored in this examination. Endogenous factors regarding the hesitant reporter's personal characteristics also influence her decision to report or wait.

**b. Possible Econometrics Errors**

**i. Irrelevant Variable Bias**

The variable that has the smallest effect on the regression equation is $age^2$. Thus, I examine the possibility that the victim's age does not follow a parabolic path but a linear one, making $age^2$ an irrelevant variable. I use the four specification criteria: theory, a t-test, adjusted $R^2$, and bias.

1. Theory:

The theory behind a parabolic relationship between the age of the victim and the amount of hesitation of reporting does not support its inclusion in the regression. My initial hypothesis makes sense; as a person approaches becoming an adult, they feel less vulnerable and are therefore more likely to report. As a person leaves middle-age, they feel more vulnerable and less likely to report. However, because the victim is not necessarily the one who reported the crime, making the age of the victim irrelevant. Due to the results of the regression, the latter explanation is more likely, and thus provides evidence that $age^2$ should be excluded.

2. t-test: $H_0 : \beta = 0$

$$H_A : \beta \neq 0$$

By the central limit theorem, I use a normal distribution in hypothesis testing for *$age^2$* due to the large sample size. At the 95% confidence level, the t-score for a normal distribution is 1.960. We reject the null hypothesis if $|t_{age}| > 1.960$. Because the t-score of *$age^2$* is 39.37, we can safely reject the null hypothesis. Thus, a t-test provides evidence supporting the inclusion of *$age^2$*.

3. Adjusted $R^2$:

I run a regression excluding *$age^2$* to examine how the variable affects the fit of the regression line, measured by adjusted $R^2$. The results of this regression below are reported in standard format.

$$\widehat{dateDifference_i} = 21.045 - 0.015 * perCapitaCrime + 0.122 * age + 0.747 * minSent +$$

$$\begin{array}{lccc} & (0.003) & (0.122) & (0.745) \\ t = & -4.40 & 21.37 & 6.14 \end{array}$$

$$- 17.511 * violent - 5.509 * weaponUsed + 3.934 * female$$

$$\begin{array}{lccc} & (0.217) & (0.229) & (0.180) \\ t = & -80.69 & -24.09 & 21.85 \end{array}$$

$$N = 1,307,019 \qquad \bar{R}^2 = 0.0115 \tag{5.2}$$

The exclusion of *$age^2$* does negatively impact the fit of the regression, but not in a significant way, as the fit only decreases by one thousandth. Thus, the adjusted $R^2$ provides evidence in favor of *$age^2$*'s exclusion due to its irrelevance.

4. Bias:

Examining the results of the previous regression, we see that removing *$age^2$* does not significantly impact the coefficients of the other variables. The most dramatic impact that the removal had was on the variable representing minimum sentence, which changes from 0.933 to 0.747. The other variables remain largely unaffected, with slight variations to the coefficients. Thus, the lack of bias supports the exclusion of *age*$^2$. Taking the foregoing specification criteria into account, I choose to drop *age*$^2$ as an irrelevant variable.

**ii. Omitted Variable Bias**

Another explanation for the low p-values and low adjusted $R^2$ is omitted variable bias; the variables included are important in describing the factors that make someone hesitate to report, but do not tell the full story. Omitted variable bias can also cause the estimated coefficients to be inaccurate. Rabindra and Pease (1992) argue that there is a difference in reporting behavior between individuals of different ethnicities that cannot be accounted for in characteristics of that individual crime. They find evidence that non-white victims of crimes are more likely to hesitate reporting, or even not report at all. To investigate the effect that this has on my model, I create a dummy variable *POC* that is equal to 1 if the victim is non-white, and 1 if the victim is white. I drop observations which either did not report the ethnicity of the victim or whose victim's ethnicity was unknown, denoted in the original dataset by a "." or a "X," respectively. If Rabindra and Pease (1992) are correct, then *POC* should have a positive effect on *dateDifference*, and also increase $R^2$. The results of the regression can be found reported in standard format below.

$$\widehat{dateDifference_i} = \underset{t\,=\,-6.44}{\underset{(0.003)}{19.514 - 0.021}} * perCapitaCrime + \underset{21.99}{\underset{(0.006)}{0.127}} * age + \underset{5.80}{\underset{(0.123)}{0.713}} * minSent +$$

$$- 17.620 * violent - 5.900 * weaponUsed + 3.732 * female + 2.762 * POC$$

$$\begin{array}{lllll} & (0.218) & (0.231) & (0.181) & (0.208) \\ t = & -80.76 & -25.52 & 20.60 & 13.26 \end{array}$$

$$N = 1{,}298{,}665 \qquad \bar{R}^2 = 0.0117 \tag{5.3}$$

While the adjusted $R^2$ does not vary much with the inclusion of race, it does slightly increase. In addition, the relationship between reporting delay and race is statistically significant and is supported by the underlying theory in the literature. Thus, I keep race in as a variable in my final regression.

### iii. Incorrect Functional Form

One also has to examine other functional forms when building a regression model. One potential functional form would be a logistic regression, where the sigmoid function creates a threshold between observations with no reporting delay and observations with any reporting delay. This should be examined further in future studies.

### iv. Multicollinearity

In order to test for a significant influence of multicollinearity in the model, I examine the simple correlation coefficient of each possible pair of variables. These correlation coefficients can be found in 9.b.III.iii. A common heuristic is to be suspicious of a relationship between variables whose simple correlation coefficient is higher than 0.80. I use this as a quick-and-dirty, introductory check. If I find evidence of multicollinearity using this rule-of-thumb, then I run further, more in-depth tests for multicollinearity, such as a Condition number. However, using this heuristic first saves on computing time and power, and because multicollinearity does not affect the estimates, it is of less concern than other potential econometric errors. Because none of my variables have a simple correlation coefficient that come close enough 0.80 to be of concern, so I fail to find evidence that multicollinearity is skewing the results of the regression.

### v. Serial Correlation

Even though I use cross-sectional data, it may be prudent to test for serial correlation. Serial correlation may appear in cross-sectional data due to the ordering. In order to test for serial correlation, I generate a time variable *time* such that *time* = _n. The relevant Stata code can be found in Appendix 9.a.III.iv. I use the Durbin-Watson test for serial correlation, as all three assumptions of the Durbin-Watson test are met: an intercept term, the serial correlation would have to be first-order in nature, and the regression model does not use a lagged dependent variable. The Durbin-Watson d-statistic for my dataset is 1.84146. The largest available Durbin-Watson table I could find only went up to 200 observations, because most time-series studies do not have over a million observations. Therefore, using N = 200 and K = 7, dL = 1.53 and dU = 1.83. Because my Durbin-Watson statistic was greater than dU, I find no evidence of serial correlation. For completeness, I correct for serial correlation anyway using a regression model with Newey-West standard errors. I report the results of the regression below in standard format.

$$\widehat{dateDifference_i} = 19.514 - \underset{\substack{(0.003)\\ t\,=\,-6.44}}{0.021} * perCapitaCrime + \underset{\substack{(0.006)\\ 21.99}}{0.127} * age + \underset{\substack{(0.123)\\ 5.80}}{0.713} * minSent +$$

$$- \underset{\substack{(0.218)\\ t\,=\,-80.76}}{17.620} * violent - \underset{\substack{(0.231)\\ -25.52}}{5.900} * weaponUsed + \underset{\substack{(0.181)\\ 20.60}}{3.732} * female + \underset{\substack{(0.208)\\ 13.26}}{2.762} * POC$$

$$N = 1,298,665 \qquad \overline{R}^2 = 0.0117 \tag{5.3}$$

### vi. Heteroskedasticity

I use the White test to look for evidence of heteroskedasticity in the dataset, because the White test can find more types the results of heteroskedasticity than any other test. The results of the White test for my dataset can be found in Appendix 9.b.III.v, and the code can be found in Appendix 9.a.III.v. These results provide evidence in favor of unrestricted heteroskedasticity at significance level p = 0.05. Thus, we can reject the null hypothesis of homoscedasticity. I use White's robust standard errors to diminish the influence of heteroskedasticity in the model. I use White's robust standard errors as they work well with large datasets, which we have. The results of using robust standard errors can be found in Appendix 9.b.III.v. There are limitations of this test, namely that it does not test for groups of variables acting together to create multicollinearity.

## 5. Conclusion

This paper finds evidence contrary to the theory that the threat of reprisals affects reporting behavior of crime victims. While the fear of reprisal may influence the decision of whether to report at all as Langton et al (2012) argues, this fear does not affect how long it takes for an individual to report a crime, given that they have already decided to report. Other kinds of fear have a larger impact on the decision to wait instead of report.

Because the literature is minimal on empirical analysis of reporting delay, this field is ripe for review. A logit regression model may be helpful in describing the factors that lead to reporting behavior. In addition, a study that devises a method of including those who fail to report at all into the regression would potentially translate the story that the data tells much more clearly than only looking at crimes which were reported. Finally, a study that creates a closer proxy to a fear of reprisal than examining the per-capita crime rates could potentially explain more variations within the data and thus tell a more accurate story.

## 6. Conflict of Interest Disclosure

The author declares that there is no conflict of interest regarding the submission of this paper.

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