Asset Pricing with Revealed Utility

by

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DEDICATION

To my loving parents, John G. and Roxana. Thank you for encouraging my curiosity and supporting me over the years.

To my wife, Laura. You are the love of my life. I am forever grateful for your sacrifice, patience, understanding, love, and support.

To my son, Lucas. You have brought me great joy and a welcome distraction over the past nine months.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

ABSTRACT

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This dissertation consists of two essays that interpret crime as revealed marginal utility of heterogeneous consumers, and investigates its implications for asset pricing.

The first chapter proposes crime as a revealed response of individuals that derive utility from relative wealth. Using daily reported crime incidents from over 2,500 law enforcement agencies across 27 states from 1991-2012, a contemporaneous relationship between daily stock returns and various types of crimes are found. Market changes also impact investors' and non-investors' utility differently and this is interpreted as evidence in support of envy models such as Abel (1990) that individuals care about their own wealth relative to others. For example, daily stock market increases are associated with decreases in violent crimes in high

income locations, while market increases are associated with increases in violent crime in low income locations.

The second chapter builds upon using crime as revealed marginal utility. Having established a relationship between violent crime and the stock market in the first chapter, the second chapter proposes violent crime growth as a measure of revealed marginal utility growth of heterogeneous consumers in incomplete markets to price the cross-section of stock returns. Consumer heterogeneity is measured using the cross-sectional average and cross-sectional variance of crime growth exploiting a monthly panel of reported crime incidents from over 10,000 law enforcement agencies across the United States from 1975-2012. Consistent with heterogeneous consumer models such as Mankiw (1986), the cross-sectional average and variance of violent crime growth are found to explain the cross-section of stock returns. Specifically, investors pay a premium for assets that have higher betas to the violent crime growth moments.

CHAPTER 1

Taking a Beating on the Stock Market:

Crime and Stock Returns

1.1 Abstract

Using daily reported crime incidents from over 2,500 law enforcement agencies across 27 states from 1991-2012, I examine the social effects of realized stock market returns using micro-level (city/county) data. Proposing crime as a measure of revealed marginal utility, I find a contemporaneous positive and convex relationship between daily stock returns and overall crime rates. I also find that market changes impact investors' and non-investors' utility differently and interpret this as evidence in support of envy models such as Abel (1990) that individuals care about their own wealth relative to others.

1.2 Introduction

It is commonly assumed that changes in wealth drive instantaneous changes in utility, however, there is little direct evidence to support this assertion. Surveys of subjective well-being (SWB) are the standard approach to directly measure utility, but interpreting these surveys is often considered problematic. Additionally, there is mixed evidence on which types of utility functions are appropriate.[1] A popular form of utility that has had some success in explaining economic and asset return phenomena are envy forms of utility, also known as keeping up with Joneses or habit preferences (Abel, 1990; Campbell and Cochrane, 1999). In this paper I propose crime as a new measure of revealed marginal utility, and in support of envy forms of utility, I provide evidence that utility depends on relative wealth. Specifically, I find that declines in relative wealth are associated with increases in crime. This association suggests that the impact of stock market returns on marginal utility is more painful than standard models imply,[2] and indicates that changes in the stock market can drive undesirable behavior that is detrimental to society.

While interpreting crime as a measure of revealed utility is relatively novel in the finance literature, it does have precedent. An analogous assumption is made by Card and Dahl (2011) who posit that intimate partner violence (IPV) is a function of the utility of NFL game outcomes, and finds that local team losses are associated with higher rates of violence. Similarly, if poor stock market performance leads to increases in marginal utility (declines in utility) for investors,

[1] An incomplete list includes standard power utility (Hansen and Singleton, 1983), habit formation (Abel, 1990; Campbell and Cochrane, 1999), heterogeneous agents and idiosyncratic risk (Constantinides and Duffie, 1996), long run risk (Bansal and Yaron, 2004), and prospect theory (Barberis, Huang, and Santos, 2001).

[2] Under standard power utility, changes in the stock market are associated with only small changes in consumption, and by implication only small deviations in marginal utility.

these individuals may act out in ways that lead to law enforcement involvement. Using daily crime rates as a measure of marginal utility for individuals provides a causal link between stock returns and utility. The link between stock returns and utility is also made by Engelberg and Parsons (2014). They argue that hospital admissions are also a form of revealed utility, and show that declines in the stock market are associated with an increase in hospitalizations.

Utility has typically been directly measured using SWB questions such as if the individual agrees with the statement, "Much of the time during the past week I was happy." It is well documented that answers to these questions can be sensitive to wording, framing, or question order among other factors (Bertrand and Mullainathan, 2001). Additionally, surveys are typically conducted at low frequencies and generally measure SWB with respect to income, and not wealth, due to the substantial measurement error associated with the wealth data (Juster, Smith, and Stafford, 1999). Crime data provides an alternative measure of utility with several advantages over surveys. First, crime can be considered a revealed response made by individuals. Revealed preferences have long been considered preferable in studies of consumer choice. Second, crime data is standardized across regions and time. This enhances the comparability of crime across individuals that could be biased if self-reported. Third, coverage of the daily crime data is extensive and encompasses over 25% of the US population in recent periods. Finally, the daily frequency of the crime data allows us to examine if stock market returns immediately impact an individual's utility.

If relative wealth is a driver of utility, the stock market's effect on an individual's utility is expected to be different for investors and non-investors. Relative consumption models, or envy forms of utility, posit that individuals derive utility from relative consumption $u(c/\bar{c})$, rather than just from their own consumption $u(c)$. Here, $\bar{c}$ represents some measure of the average consumption of others. Envy models are well documented in the finance and economics literature (e.g., Abel, 1990; Campbell and Cochrane, 1999). If utility depends on relative consumption, then one person's increase in consumption has a negative externality on others because it lowers the relative consumption of others. Since expected lifetime consumption is a function of wealth, fluctuations in relative wealth will have similar effects.

Interpreting crime as a measure of revealed marginal utility, my findings support that stock returns impact individuals' utility and that increases in marginal utility are associated with increases in crime. Using reported crime incidents from over 2,500 law enforcement agencies across 27 states from 1991-2012, I observe a contemporaneous positive and convex relationship between daily stock returns and overall crime rates. I also find that stock market returns impact investor and non-investors differently and interpret this as evidence in support of envy or external habit models such as Abel (1990) that individuals care about their own wealth relative to others. For high income individuals, a positive market return is associated with a decrease in marginal utility (increase in utility) because high income individuals are more likely to hold stocks, and a positive market return increases their wealth relative to non-stockholders. This decrease in marginal utility corresponds to decreases (or at least no increase) in crime rates for high income individuals. Low income individuals are impacted differently by positive market returns. Because low income individuals hold less (or no) stocks as compared to high income individuals, positive market returns are associated with higher marginal utility because they are now worse off relative to high income individuals. This increase in marginal utility corresponds to an increase in crime rates for low income individuals.

Empirically I find that a one standard deviation increase in daily stock market returns corresponds to a 22.8 bps increase in overall crimes across the US. The relationship between returns and crime rates also monotonically increases from high income to low income locations. The 22.8 bps daily increase in crime is also economically meaningful and corresponds with an additional annualized 36,551 crimes across the US with an estimated annualized loss to society of $2.67 billion.

I also find a relationship between daily returns and violent crime, property crime, and white collar crime. For assaults, a one standard deviation increase in the market return is associated with a 22 bps decrease in assaults for high income locations, and a 40 bps increase in assaults for low income locations. The relationship with assaults is particularly supportive of envy models because most assaults occur at individuals' homes which ensure that our proxy for investors (high income cities) and non-investors (low income cities) are meaningful. This is in contrast to other crimes such as theft where there are presumably a number of low income individuals committing many of the thefts in high income areas. The relationship between the stock market and property crimes is also positive and strongly convex. A one standard deviation increase in the market corresponds to a 26.8 bps daily increase in property crimes. Finally, the relationship between market returns and white collar crime (fraud) is also positive and strongly convex. A one standard deviation increase in the market is associated with a 1.5% increase in fraud offenses.

I find that the relationship between crime and returns is robust to controls for common weather and celestial factors that affect both returns and crime, remains with local state returns, and is sustained when including daily fixed effects that control for common news. My results are consistent with rational asset pricing models with utility over relative wealth. Speculatively, my results suggest that high income inequality and large stock market changes can be detrimental to society through increased crime.

Although I study how asset prices affect individuals' utility, the traditional behavioral asset pricing literature has typically examined how investors' moods affect asset prices. The usual explanations of how mood affects asset prices are through risk aversion (Kliger and Levy, 2003), misattribution bias (Lucey and Dowling, 2005), and visceral factors (Loewenstein, 2000). The empirical literature relating mood to asset returns is extensive. Saunders (1993) and Hirshleifer and Shumway (2003) argue that sunshine puts investors in better moods, and this translates into higher stock returns. Cao and Wei (2005) find low temperatures are associated with higher returns. Kamstra, Kramer, and Levi (2003) find that returns are negatively associated with the onset of Seasonal Affective Disorder (SAD). Kamstra, Kramer, and Levi (2000) find lower returns following the disruption of sleep patterns due to daylight savings time. Yuan, Zheng, and Zhu (2006) observe lower returns on days around a full moon relative to returns around a new moon. Frieder and Subrahmanyam (2004) find higher returns for festive non-secular holidays and lower returns for somber holidays. Edmans, Garcia, and Norli (2007) document abnormal negative returns in the local market after a local sports team loss.

This paper makes two noteworthy contributions to the literature. First, this adds to the scarce literature that shows how stock returns can impact an individual's psychology. The closest study to mine is that of Engelberg and Parsons (2014), who find a strong inverse link between daily stock returns and hospital admissions in California, particularly for mental conditions. They argue that anticipation over future consumption directly influences an investor's instantaneous utility, and suggest this is consistent with the model of Caplin and Leahy (2001). My study differs from theirs not only through the proxy of utility, but I also take advantage of a panel data set to control for un-observables, I utilize time-varying controls that are common to both the crime and finance literature, and I cover a larger portion of the US. Most importantly, I show that stock returns impact investor (high income) and non-investor (low income) utility heterogeneously and that declines in utility not only effect the impacted individuals but also have externalities which are detrimental to society through increased crime.

While the literature relating economics and crime is vast, the literature relating finance and crime is relatively unexplored. The finance literature has typically examined effects from corporate crimes such as financial misrepresentation and managerial turnover (Karpoff, Lee, and Martin, 2008), bribery on firm value (Zeume, 2014), and insider trading (Acharya and Johnson, 2010). The literature linking finance and non-corporate crimes such as violent or property crimes is particularly sparse. Garmaise and Moskowitz (2006) find evidence of spillover effects on crime from changes in credit conditions.

The economics and criminology literature suggests that crime is a plausible measure of marginal utility because crime increases in bad economic states. Exploiting a panel of annual state GDP growth, Arvanites and Defina (2006) find that property crime has a negative relationship with state GDP growth. Rosenfeld and Fornango (2007) and Rosenfeld (2009) find that property crime and homicide exhibit a negative relationship with changes in the regional components of the University of Michigan Consumer Sentiment Index. The literature generally supports a positive relationship between unemployment and crime (Freeman, 1999), while low legal wage opportunities have also been associated with increased crime (Gould, Weinberg, and Mustard, 2002). Fajnzylber, Ledeman, and Loayza (2002) find that violent crime increases with income inequality.

Second, this paper helps identify the form of investors' utility functions and contributes to the literature on theoretical envy or external habit formation models such as Abel (1990) or Campbell and Cochrane (1999). These models have empirical support in the behavioral economics literature including experiments that find inequality aversion (Engelmann and Strobel, 2004), surveys which find an inverse relationship between self-reported satisfaction and relative income (Luttmer, 2005), and revealed choice methods (Daly, Wilson, and Johnson, 2013). Daly et al. propose suicide as a measure of utility and finds that suicide risk of individuals in the US is affected not only by their own income but also by the incomes of others in the vicinity. Consistent with these studies I provide evidence that suggests crime is a form of revealed marginal utility over relative wealth, and that declines in relative wealth increase crime.

1.3 Economic Model of Crime

1.3.1 Theoretical Model

The key assumption is that market returns generate a behavioral response that reflects a gain or loss in marginal utility. The notion that changes in wealth impact utility is standard in the literature, but has little direct empirical evidence. The assertion that crime is a behavioral response which reflects increases in marginal utility (losses in utility) is novel in the finance literature, but has precedent. An analogous assumption is made by Card and Dahl (2011) who posit that the gain-loss utility of NFL game outcomes affects the propensity of intimate partner violence. This study contrasts with theirs in that I assert that utility is derived from relative wealth.

Following Abel (1990), I assume an external habit or envy form of utility. In external habit models, each individual's habit is determined by everyone else's consumption. I assume that the utility function is $u(c/\bar{c})$, where c is an individual's consumption, $\bar{c}$ is an individual's external habit consumption (e.g., the average consumption of others), and consumption is subject to a budget constraint on wealth and income. Similarly, relative wealth w drives utility $u(w/\bar{w})$ through the budget constraint.

Theoretical models of crime typically fall into two categories. Under the standard economic model of crime, an individual optimally chooses a criminal activity based on the expected utility of that act (Becker, 1968). The utility gained could be from the monetary value of stolen goods or from the morbid pleasure of committing a violent act upon a victim. Alternatively, a crime may be committed due to a visceral factor triggering a loss of control (Loewenstein, 2000). Examples of loss of control include inducing a fight due to anger, or stealing a good because the offender believes the world is unjust and he deserves it. Consistent with either model, I posit that an increase in marginal utility (loss in utility) either leads an individual to commit a crime to restore utility to its original level or that the increase in marginal utility causes an individual to lose control and commit a crime. Specifically, similar to Card and Dahl (2011), I assume that with some probability $p \geq 0$, that the propensity of crime depends on marginal utility over relative wealth:

$$p = p^0 + \lambda u'(w/\overline{w}), \tag{1.1}$$

where p^0 is the baseline probability of crime for an individual, and λ is a scaling factor. When marginal utility increases, due to a decline in relative wealth, the probability of committing a crime increases.

Declines in marginal utility (gains in utility) do not necessarily correspond with stock market increases. A market increase can have different impacts on investors and non-investors. Although a market increase will lead to an increase in relative wealth and thus utility for investors, market increases cause non-investors to be worse off. This is because non-investors' *relative* wealth *decreases* with market increases as compared to investors. This can be clearly seen in Figure 1.1, where the propensity of crime (equivalently, marginal utility) is decreasing and convex in returns for investors, while increasing and convex for non-investors.

Although increases in the stock market may signal improvements in economic conditions that may raise incomes and job prospects for non-investors, Piketty and Saez (2003) and Saez and Zucman (2014) show that gains in income and wealth have disproportionately accrued to the top of the distribution during economic expansions. For example, they show that during the Clinton expansion from 1993-2000, income grew by 54% for the top 10% of income earners, but grew by only 16% for the bottom 90%. This suggests that although on an absolute basis non-investors (low income individuals) may be better off with economic improvements, on a relative basis they may fall behind. This is consistent with the animosity over inequality that has grown over recent years.

1.3.2 Empirical Model

Empirically, I am only able to observe the outcome of crime and not the propensity for crime. As such, the outcome variable $y_{i,s,t}$ measures the crime rate (per 100 million individuals) for location i (in state s), at time t. My empirical specification focuses on changes in wealth as proxied by stock returns and takes the form,

$$y_{i,s,t} = \beta_1 r_{s,t} + \beta_2 r_{s,t}^2 + \mathbf{\Gamma} \boldsymbol{X}_{i,t} + \theta_i + \mathbf{T}_t + \epsilon_{i,s,t}, \quad (1.2)$$

where $r_{s,t}$ is the market return (or state and non-state returns for state s of location i), $\boldsymbol{X}_{i,t}$ is a vector of controls for weather and celestial phenomena further described below, θ_i is a fixed effect for the law enforcement agency in location i, and $\mathbf{T}_t$ controls for time fixed effects including year, month of year, day of week, and holidays.[3] The primary coefficients of interest are those on the return and squared return. The squared return is included to account for the curvature of the marginal utility function, which is particularly important for those individuals that have the highest marginal utility. The location fixed effects control for the overall time invariant characteristics of the population such as average income level, demographic makeup, average education, and employment opportunities. The year fixed effects capture slow moving conditions that can affect crimes rates such as general economic conditions, income inequality, and popular culture. The month fixed effects capture the seasonality in crime rates. For example, crime rates tend to be higher in the summer months and lower in the winter months. The day of week fixed effects capture the average daily variation in crimes. For example, crime

[3] I include dummies for the day observed, the day before and the day after a holiday adjusted for weekends. Holidays where the market is closed include: Independence Day, Martin Luther King Day, President's Day, Memorial Day, Labor Day, Easter (Good Friday), Thanksgiving, Christmas, and New Year's Day. Additional holidays where the bond markets (but not stock markets) are closed include: Columbus Day and Veterans Day. I also include popular US holidays where the markets remain open: Halloween, St. Patrick's Day, Cinco de Mayo, Valentine's Day, Mother's Day and Father's Day. For completeness, I also include the Jewish and Islamic major holy days of Rosh Hashanah, Yom Kippur, Eid Al-Adha and Eid Al-Fitr.

rates tend to be highest on Fridays and lowest on Sundays. The holiday fixed effects control for the tendency of higher crime rates on national holidays such as New Years and the 4^{th} of July, or widely celebrated holidays such as Halloween and St. Patrick's Day.

There is extensive literature that documents that weather affects crime. For example, Jacob, Lefgren, and Moretti (2007) find that crime increases with temperature and decreases with precipitation, while Rotton and Frey (1985) find a negative relationship between wind speed and domestic violence, a positive relationship between sunshine and assaults, and a negative relationship with humidity and assaults. There have also been a number of studies that link weather to market returns. For example, Cao and Wei (2005) find low temperatures are associated with higher returns internationally, Saunders (1993) and Hirshleifer and Shumway (2003) find that sunshine is associated with higher stock returns, Loughran and Schultz (2004) report lower volumes for firms in blizzard-struck cities in the US, and Limpaphyom, Locke, and Sarajoti (2005) find that the bid-ask spread on the Chicago Mercantile Exchange increases on windy days.

There is also research relating behavior to celestial phenomenon such as moon phases and Seasonal Affective Disorder (SAD). Cohn (1993) finds a relationship between violent crime and moon phase, while Yuan, Zheng, and Zhu (2006) observe lower returns on days around a full moon relative to returns around a new moon. Although there appears to be no evidence for or against criminal activity and SAD, it is clinically defined as a form of major depressive disorder and depression has been linked to a greater degree of risk aversion (Eisenberg et al. 1998), and increased risk aversion could lead to a lower incidence of risky crimes. SAD has been examined in the financial literature, with Kamstra, Kramer, and Levi (2003) finding that returns are negatively associated with the onset of SAD. Because there is some evidence that weather and celestial phenomena have been found to affect both crime rates and returns, I control for them explicitly in all specifications.

Although the outcome variable is essentially count data, I utilize a linear fixed-effects model. The linear estimates are consistent, but inefficient. Furthermore, I utilize heteroskedasticity consistent standard errors clustered by time (daily) to account for the heteroskedastic nature of the count data. Clustering the standard errors by time accounts for the cross-sectional correlation of the residuals. An alternative specification that is typically applied to count data is the Poisson regression model. The advantage of using a Poisson model is that it explicitly models the non-negativity and discrete nature of count data. The standard criticism of Poisson regressions is that it assumes a Poisson distribution where the variance is equal to the mean, a condition that is typically violated. This restriction usually manifests itself by predicting fewer zeros than observed in the sample and by exhibiting grossly deflated standard errors. In the appendix, I find that a Poisson specification produces similar results as the linear specification. However, the crime data's larger variance relative to the mean (over-dispersion) leads one to interpret the Poisson specification with caution. The linear regression may be the more conservative option.

For there to be a relationship between stock market returns and crime rates, individuals must be aware of market movements to adjust their behavior. Although it is implausible that all individuals are aware of the stock market's performance on a given day, all that is required for the relationship to hold is that the behavior of some individuals is altered when made aware of the market's performance. Summaries of stock market performance are constantly provided by the media in radio, television, online, and newspaper formats. Therefore, it is not inconceivable that a significant portion of the population is made aware of the market's performance and that some of these individuals alter their crime-committing behavior in response.

1.4 Data

1.4.1 Crime

Daily crime data is from the National Incident Based Reporting System (NIBRS) which is under the jurisdiction of the Federal Bureau of Investigation (FBI).[4] NIBRS is a voluntary system used by law enforcement agencies in the US for collecting and reporting data on crime. The dataset begins in 1991 and ends in 2012. Only police agencies in a handful of states report data at the beginning of the sample, but by the end of the sample coverage grows to police agencies in 36 states that represent about 25% of the US population. The NIBRS dataset utilized is the incident-level file which contains reports of 46 major Group A crimes to individual police agencies, and are not necessarily associated with an arrest. In this study I utilize an aggregate of all 46 incidents, and separately split out property crimes, violent crimes, assaults (within violent crimes), and fraud. NIBRS supplies population data for each of the agencies, and often provides basic demographic information of the offender and victim, relationship of offender to victim, location of offense (city, county, state), location type (home, office, etc.), date and time of offense, and type of offense (homicide, assault, etc.).

[4] I utilize the dataset distributed by the Inter-university Consortium for Political and Social Research (ICPSR) available here: http://www.icpsr.umich.edu/icpsrweb/NACJD/series/128

I aggregate the daily NIBRS data to the agency level (city police force or county sheriff's office) by type of crime. Thus, the unit of interest is the reported number of incidents per day for a specific type of offense (e.g., assault) in a specific agency (e.g., Ann Arbor Police). Because not all agencies report consistently across time, I follow Dahl and DellaVigna (2009) to filter inconsistently reporting agencies annually. Specifically, for each year I first exclude agencies that do not report any offense for seven consecutive days. Next, I remove the remaining agencies that have less than 50 report days. To ensure that market movements on a given day correspond with actions that may occur during an individual's waking hours, I define a crime date *t* as beginning at 6:00 AM on calendar day *t* and ending at 5:59 AM on calendar day *t+1*. I use this date definition when merging the crime data with other datasets. In Figure 1.2 we see that between 4 AM and 6 AM is when the least number of incidents occur during the day, while midnight is when the most number of incidents occur during the day.[5] Thus 6 AM local time appears to be a reasonable start time for crime, and is before the market opens in all locations.

The increasing trend in NIBRS coverage can be seen in Figure 1.3. The start of the sample includes less than 150 agencies in only two states covering approximately 5.2 million people, but by the end of the sample it covers approximately 1,500 agencies covering roughly 67.3 million people. Over the entire sample there are approximately 3,000 unique agencies, which indicates that half the agencies drop out over the sample period. The number of incidents also increases with NIBRS coverage from approximately 1,400 crime incidents per day to 11,000 per day. To ensure that crimes are comparable across cities, I normalize the number of crimes by the population. The resulting *crime rate* is defined as the number of crime

[5] Although the spike at midnight may be due to misreporting, it is of little consequence since I classify crime day *t* to include all night-time hours through day *t*+1.

incidents each day per 100 million people. To ensure that the crime rate is not overly influenced by small populations (denominator effect) I require that the agency covers a population of at least 2,000 people to be included in the sample. The monthly crime rate can be found in Figure 1.4. The crime rate exhibits a clear cyclical pattern with a peak in July/August and a trough in January/February. The summary crime statistics by state in Table 1.1 shows that the state with the highest coverage is Michigan with an average of 164 agencies covering an average population of 6.4 million. The state with the highest overall crime rate is Georgia (although with only one agency reporting), followed by Illinois with 32,429 crimes per 100 million people per day.[6] The New England states of Connecticut and Rhode Island have the lowest crime in the sample with roughly half the rate of Illinois. Table 1.2 shows the agencies in the sample as of December 2012 with the largest population. The Fairfax County Police Department in the Washington D.C. metropolitan area has the highest population coverage. Thus, although some of the largest cities in the US are not covered (e.g., New York City or Los Angeles), there is strong coverage in moderately sized cities.

A summary of the crime rates by offense types can be found in Table 1.3. The first three columns show summary statistics for the daily time series of crime rates aggregated across all reporting agencies. Across all incidents, the aggregate crime rate across the US is 20,302 crimes per 100 million individuals per day. The two largest contributors to the overall crime rate are property crimes at 10,164 crimes per 100 million individuals and violent crime with 4,852 crimes. Within violent crimes, the largest sub-category is assault offenses with 4,298 crimes. The remaining columns show summary statistics pooled across all agencies. Although

[6] The state of Illinois drops out of the sample in 1995, with only Rockford, IL rejoining NIBRS coverage in 2006.

the pooled agency average crime rate is similar to the aggregated US rate, the agency average is generally very low in comparison to its standard deviation, suggesting a mass of zeroes and a long right tail. Indeed, many individual crime types are rare for agencies as indicated by the pooled agency median crime rate of zero in column four. This is further exemplified by the last column which shows the percent of agency-days that report at least one crime. For example, the value of 0.7% for murder indicates that on any given day in any city there was a 0.7% chance of at least one murder reported. The preponderance of zeros and the variance which is much higher than the mean indicate the assumptions underlying a Poisson regression are violated and may lead to misleading results for most crimes if used. Therefore, the linear specification may be more conservative.

1.4.2 Income

To identify offenders that are likely to have stock holdings and those that don't, I utilize the 2012 American Community Survey Public Use Microdata Sample (PUMS) from the US Census to estimate the median income for individuals within a PUMS area. PUMS areas are primarily defined at the county level, but could represent parts of counties or parts of cities that contain at least 100,000 people. For each PUMS area, I calculate the median income for full-time workers, and match the PUMS income with the NIBRS reporting city or county. I define high income agencies as those in the top tercile of income, while low income agencies are defined as those in the bottom tercile of income. Table 1.4 reports the highest income cities and counties that correspond with the agencies in the sample. The highest income agency is Issaquah in the Seattle area with a median individual income of approximately $100,000.

Issaquah is followed by a number of agencies within the Washington, D.C. metropolitan area. The lowest income cities (unreported) include Flint, MI and a number of cities in Kansas and Tennessee. Using income as a proxy for stockholder classification is consistent with Malloy, Moskowitz, and Vissing-Jorgensen (2009) who find using Survey of Consumer Finances data that the probability of holding stock is significantly higher for individuals with higher incomes. [7] Additionally, the usage of terciles on income is useful to separate stockholders from non-stockholders as they find that on average 23% of households are stockholders, with the portion of stockholders increasing over time.[8]

1.4.3 Returns

Stock returns at the US and state levels are from the Center for Research in Security Prices (CRSP). The US stock return is the value-weighted return for all US stocks in the CRSP database. State level value-weighted returns only include those companies that can be matched to Compustat and have non-missing values for the state of a company's headquarters. To be included in the regressions, I require at least 20 companies in each state to ensure proper diversification. Consistent with Engelberg and Parsons (2014) and Edmans, Garcia, and Norli (2007), all returns are standardized by dividing the daily return by its trailing one-year (252-day) standard deviation. This removes concerns of the time varying volatility of returns affecting the results. In specifications that include state and non-state returns, I first perform rolling one-year regressions of state returns on returns of firms headquartered outside of that state (non-

[7] They also find that the probability of being a stockholder is lower for non-whites, quadratically increases with age, is higher for high school and college graduates, higher for non-zero dividends, and increases with amount in checking and savings.

[8] Based on self-reported data from the Consumer Expenditure Survey (CEX) from 1982-2004.

state returns) and extract the residual. This residual represents the component of market returns that are unique to each state. As with the other returns, the residuals are divided by its trailing one-year standard deviation. It is important to note that NIBRS has daily crime data for each of the seven days in the week, while CRSP only has returns data for days that the market is open. When examining lagged daily effects of market returns on crime rates, I utilize all seven days of the crime data while appropriately accounting for market closures.

A summary of returns for each state that correspond to the available data in NIBRS is presented in Panel A of Table 1.5. Unfortunately, requiring at least 20 companies in a state will exclude a number of states for at least part of the sample. States excluded entirely include ID, ME, MS, MT, ND, RI, SD, VT, and WV. States excluded in part are AL, AR, DE, NE, and NH. As expected, average daily state returns are slightly positive but near zero, with standard deviations of one to three percent. Of the states included in the sample, MO has the highest average daily return of 7 bps, while GA has the lowest return of -1 bps. The low return for GA is at least partly due to its entrance in the data in 2004 and subsequent exit at the end of 2008, thus suffering the brunt of the financial crisis and not the following recovery. The remaining columns show the mean and standard deviation for the state residual return. Panel B of Table 1.5 displays the summary of market returns and pooled state returns. The market has an average return of 4.6 bps, and a standard deviation of 1.16%. As expected the standardized returns have standard deviations close to one. Thus in the regression results, a one unit increase in the standardized returns roughly correspond to a one percent increase in actual returns.

1.4.4 Other Controls

Data for additional controls identified in the behavioral finance and crime literature are from a number of sources. Daily weather data is from the NOAA National Climatic Data Center (NCDC),[9] and is calculated as the median value for all weather stations within 250 miles of the crime reporting agency. Average temperature is defined as the average of the maximum and minimum temperature that day measured in tenths of degrees Celsius, precipitation consists of rainfall and the liquid equivalent of any frozen precipitation in tenths of millimeters, snowfall is the amount of new snow (and other frozen types of precipitation) that fell during the day in millimeters, snow depth is the total depth in millimeters of snow on the ground at the time of observation, and wind is the average daily wind speed in tenths of meters per second. Moon fraction is from the United States Naval Observatory (USNO) and is the fraction of the moon that is illuminated at midnight.[10] Daily Seasonal Affective Disorder (SAD) data is from Lisa Kramer's website and reflects the estimated change in the proportion of subjects experiencing depression symptoms across the US.[11] Thus, higher values indicate higher depression or higher risk aversion. Changes in the VIX are from the CBOE. Analyst estimates used to calculate earnings surprises are from IBES.

[9] NCDC daily weather: http://www.ncdc.noaa.gov/cdo-web/datasets
[10] USNO moon fraction: http://aa.usno.navy.mil/data/docs/MoonFraction.php
[11] Thanks to Lisa Kramer for making the data available on her website: http://www.lisakramer.com/data.html

1.5 Market Results

1.5.1 Daily Market Relationship

I first focus on the relationship between overall market returns and overall crime rates. Panel A of Table 1.6 shows the specification where the dependent variable is the crime rate for all 46 Group A crime offenses listed in Table 1.3. The first column reports the results for all income groups together, with a positive and significant coefficient on the market return and positive yet insignificant coefficient on the squared return. This indicates an increasing and weakly convex relationship between overall market returns and overall crime rates. Specifically, a one standard deviation increase in market returns corresponds to an increase of 46.2 crimes per 100 million people per day. [12] As compared to the US daily average of 20,302 crimes per 100 million people, this corresponds to a 22.8 bps increase in overall crimes. With an estimated 314 million individuals in the US, a one standard deviation increase in returns results in an additional annualized 36,551 crimes across the US. [13] This increase is economically significant when considering that the net annual burden of crime has been estimated by Anderson (1999) to be approximately $1.7 trillion per year. Thus, a one standard deviation increase in the market translates to an estimated $2.670 billion annualized loss ($10.597 million daily loss) due to crime. [14]

The positive relationship between crime and returns seems odd if one assumes that higher returns should decrease marginal utility (increase utility) and thus decrease the

[12] Although the squared term is insignificant in a number of cases, I include them in all calculations: (linear term) + 2 × (squared term) = 35.56 + 2 × 5.316 = 46.192

[13] 46.192 × 252 × 3.14 = 36,550.81

[14] (0.00228 × 1.7 trillion) / 365 days = 10.597 million/day; 10.60 × 252 days = 2.670 billion/year

propensity for crime. However, not all individuals invest in the stock market as indicated by Malloy, Moskowitz, and Vissing-Jorgensen (2009), who estimate that only 23% of households hold stocks (including retirement plans) using the Consumer Expenditure Survey from 1982-2004. It is likely that individuals whom are more prone to commit crimes have no funds invested in the stock market and thus they are more likely to be put in sour moods when the stock market goes up and they observe others benefiting. This envy effect is consistent with models such as Abel (1990) who posit that individuals care about their own consumption relative to others. If envy from observing the "rich getting richer" is a driver of increased crime, one would expect to see higher crime rates in subgroups of the population that benefit less from market increases. Specifically, low income individuals who likely have no (or less) wealth invested in the stock market should exhibit a higher envy effect. Furthermore, because low income individuals' wealth and thus utility begins at a lower level, their marginal utility is higher, so we expect to see a higher sensitivity to market returns. To illustrate this, I partition the sample into terciles by the median income for each agency location and reproduce the results in the last three columns of Table 1.6. Indeed, I find that low income locations have the strongest positive and convex relationship with market returns, and this relationship monotonically decreases from low income locations to high income locations. For example, a one standard deviation increase in the market corresponds to a significant increase of 94.7 crimes per 100 million (46.7 bps) in low income locations, but an insignificant 2.7 crimes (1.3 bps) in high income locations.

The controls in Panel A of Table 1.6 enter the specification significantly with the expected sign. Crime increases with moon illumination, decreases with SAD induced risk aversion, increases with temperature, decreases with precipitation, decreases with snowfall and snow depth, and decreases in wind speed. The inclusion of controls provides us with additional confidence that the results are not driven by other factors in the literature that have been shown to influence both crime and returns. For conciseness, the controls in other specifications are included but with the coefficients not reported. Generally, the coefficients follow the same sign and significance across all crime categories. Exceptions include SAD and snow depth which are positive for violent crimes and assaults.

I next turn to the relationship between the stock market and significant categories of crime as defined by the FBI: property crimes, violent crimes, assaults (within violent crimes), and fraud. As shown in Table 1.3, property crimes include larceny/theft offenses, burglary/breaking and entering, and motor vehicle theft. The first column of Panel B in Table 1.6 illustrates the significantly positive and convex relationship between property crime and market returns. For example, a one standard deviation increase in market returns is associated with an increase of 27.2 property crimes per 100 million individuals (26.8 bps) per day. The significantly positive coefficient on the squared market return indicates a convex relationship between property crimes and the market. When breaking up the relationship by income in the last three columns of Panel B in Table 1.6, it appears that the overall relationship between market returns and property crimes seems to be driven by middle income locations. The lack of significant coefficients on the high and low income locations may be due to the tradeoff that thieves face between the rewards and punishment in those locations. This tradeoff is consistent with Johnson and Bowers (2004) who utilize optimal foraging theory to model criminals. In optimal foraging theory, predatory animals select hunting areas and prey, and optimize rewards by weighting the nutrition value of potential prey with the efforts and risks involved in finding, attacking, and eating it. In the same vein, thieves may be assumed to maximize their revenues by selecting neighborhoods which contain valued items with a low likelihood of being apprehended. Although high income locations likely have the highest potential rewards due to valuable goods, they are also the most likely to have the highest potential for punishment due to home security systems, security guards, and well-funded law enforcement. Conversely, low income locations are likely to have the lowest reward, but also the lowest potential for punishment. The middle income locations may be the optimal locations to perform a theft when an increase in marginal utility leads to a higher propensity for crime.

Next, I examine the relationship between the stock market and violent crimes. Violent crimes include homicide, rape offenses, assault offenses, and robbery. Although I report the results for all violent crimes in Panel C of Table 1.6, I will focus on assaults in Panel D of Table 1.6. I focus on assaults because they dominate the violent crime offenses, and the vast majority of assaults are classified as occurring at home (61%) where the victim is related to or otherwise knows the offender (87% of home assaults). Thus, we can be confident that the income groupings are meaningful for the offender. In other words, we can be confident that assaults committed by high income individuals (i.e., investors) are most likely to occur in high income locations, while assaults committed by low income individuals (i.e., non-investors) are most likely to occur in low income locations. This is in contrast to other crimes such as theft where there is presumably a large number of low income individuals committing the crimes in high income locations.

At first glance, there appears to be no relationship between stock market returns and overall assaults in the first column of Panel D of Table 1.6, but when breaking up the sample by income, it appears that the differential effects by income groups may have muddled the aggregate results. In high income locations a one standard deviation *increase* in the market is associated with a significant *decrease* of -9.4 assaults per 100 million individuals (-22 bps), while in low income locations a one standard deviation *increase* in the market is associated with a significant *increase* of 17.1 assaults (40 bps). The direction of the relationship between market returns and assaults is consistent with utility over relative wealth. For high income individuals, a higher market return is associated with a decrease in marginal utility (increase in utility) because high income individuals are more likely to hold stocks, and a higher market return increases their wealth relative to non-stock holders. This decrease in marginal utility corresponds with decreases in assaults for high income individuals. Low income individuals are impacted negatively by higher market returns. Because low income individuals are more likely to hold no stocks, higher market returns are associated with an increase in marginal utility because they are now worse off relative to high income individuals. This increase in marginal utility corresponds with an increase in crime rates for low income individuals. The empirical relationship between market returns and assaults is plotted in Figure 1.5, and is remarkably similar to the theoretical plot of market returns and crime propensity as modeled by the increasing function of marginal utility over relative wealth shown in Figure 1.1. The fact that we see the expected positive and weakly convex relationship between crime and market returns for low income locations, and the negative and weakly convex relationship for high income locations provides evidence that utility models over relative wealth are appropriate and that crime can be considered a measure of revealed marginal utility.

Finally, I report the relationship between market returns and fraud. Fraud includes false pretenses, credit card fraud, impersonation, welfare fraud, and wire fraud. Fraud is included because it is generally considered a white collar crime. Panel E of Table 1.6 indicates that the relationship between market returns and the overall fraud crime rate is significantly positive and convex. For example, a one standard deviation increase in the market return corresponds to 7.7 additional fraud offenses per 100 million individuals, or an increase of 1.5%. There is also a decreasing and monotonic relationship between market returns and fraud as we go from low income to high income locations. Specifically, a one standard deviation increase in the market is associated with a significant increase of 15.8 (3.2%) fraud offenses in low income locations, but an insignificant increase of 1.1 (23 bps) in high income locations.

1.5.2 Lagged Market Relationship

Asset pricing models assume that changes in wealth are instantaneously related to changes in utility. To examine the instantaneous assumption, I test for a delayed relationship between stock market returns and crime rates. A delayed relationship between returns and crime rates could occur due to delayed awareness or a delayed response. Delayed awareness could occur if an individual does not pay close attention to the daily movements in stock prices, but becomes aware of them over the coming days and then responds. Delayed response could occur if an individual is immediately aware of the stock market movements, but the consequences take time to manifest and perhaps are triggered by an additional event that pushes him beyond a threshold. These situations could explain if we see past returns at time t - s (for $s > 0$) having an impact on crime rates at time t.

I report the lagged relationship between the past three daily stock market returns and current crimes rates for all incidents in Table 1.7. It is important to note that the crime rates correspond to all seven days a week, while market returns only correspond to trading days. For example, the column labeled *t - 1* in includes the relationship between Saturday crime rates and Friday returns. The results indicate that the relationship between market returns and crime rates is contemporaneous. All of the coefficients on the lagged market returns are indistinguishable from zero. In other words, there does not appear to be delayed awareness or delayed response between crime rates and market returns, which supports the assumption that changes in wealth are instantaneously related to changes in utility.

1.6 State Return Results

Although fixed effects were previously added for location, year, month of year, day of week, and holidays, there still may be common variation across locations that occur on a daily frequency due to an omitted factor. To understand the extent to which unobserved heterogeneity may alter the results I exploit the home bias of US investors through the use of state returns and local crime rates, and compare specifications with and without daily fixed effects.

It is well documented that investors exhibit a home bias in their equity portfolios. French and Porterba (1991) find that investors only hold modest amounts of foreign equity. Home bias has also been shown to hold for US investors in domestic stocks. Coval and

Moskowitz (1999) show that US investment managers exhibit a strong preference for locally headquartered firms. Seasholes and Zhu (2010) show that individual US investors overweight local stocks by 18%, but still hold approximately 70% of their portfolios in non-local US stocks. This implies that the market return will be the largest driver of utility, but local returns can drive marginal differences in utility among different locations.

In order to isolate the component of returns that is unique to each state, I perform rolling one-year regressions of state returns on non-state returns and extract the state residual return. State returns are defined as the market weighted return of all firms headquartered in the state in which the police agency is located, while non-state returns are the market weighted return of all firms headquartered outside of corresponding state. The state residual return and non-state return are divided by their respective rolling one-year standard deviations. Although investors would benefit from the total state return, the state residual return has the advantage of not being confounded by the market return. Thus the state residual return provides an effective way to exploit the home bias by cleanly identifying state-only effects.

1.6.1 Daily State Return Relationship

The first column of Panel A in Table 1.8 confirms that state specific returns are related to overall crime rates. Specifically, the relationship between the overall crime rate and the state specific residual return is about two-thirds the magnitude of non-state returns with a one standard deviation increase in the state residual return associated with an increase of 30.9 crimes per 100 million individuals (15.2 bps) versus the non-state return effect of 46.1 (22.7 bps). The relationship with the non-state return is nearly identical to that of the market return in Table 1.6 of 46.2, because the non-state return includes most of the firms used to calculate the market return and is orthogonal to the state residual return. The significance of non-state returns also provides additional assurances that it is the stock market that is driving the results, and not just a local effect that could show up in the state returns. Furthermore, as with market returns, the remaining columns of Panel A in Table 1.8 show that the relationship between the state residual return and crime rates also roughly monotonically decreases from low income to high income locations. Specifically, a one standard deviation increase in the state residual return corresponds to a significant 76.2 (37.5 bps) for low income locations, which decreases to 11.8 crimes per 100 million individuals (5.8 bps) for high income locations.

Turning to the other crime categories, only property crimes follow a similar relationship with the state residual return as with market returns. Specifically, a one standard deviation increase in the state residual return corresponds to an additional 17.2 crimes per 100 million individuals (16.9 bps). Once again the relationship appears to be driven by middle income locations, which may be an optimal target for property crime given the tradeoff between rewards and punishment. The remaining crime categories of violent crimes, assaults, and fraud appear to be insignificantly related to the state residual return which indicates that the market is the primary driver in the relationship of these crimes.

1.6.2 Daily State Return Relationship with Daily Fixed Effects

To ensure that common news is not driving the relationship between stock market returns and crime rates, I use daily fixed effects to control for common variation across locations that occur at a daily frequency. For example, suppose that the Bureau of Labor

Statistics announces a weak jobs report. The prospects of high unemployment could lead to a decline in the market, and perhaps an increase in crime rates. The advantage of using daily fixed effects is that common news that may affect both the stock market and crime can be controlled. The disadvantage is that valid identifying information can be thrown out with the use of daily fixed effects. Furthermore, the use of daily fixed effects prevents identification of a relationship with the market return and only allows us to identify a relationship with local returns. This is of particular concern since investors hold most of their portfolio in non-local firms (i.e., the market portfolio), and the market return (i.e., the S&P 500, NASDAQ, or DJIA) is the most publicized form of stock performance on a daily basis.

The relationship between the overall crime rate and returns with daily fixed effects can be found in Table 1.9. The specification clearly has trouble identifying an effect from the non-state return (essentially the stock market return), likely due to the lack of variation across states. However, the state residual return can be cleanly identified, and exhibits roughly similar results to those shown without daily fixed effects in Table 1.8. For example, a one standard deviation increase in the state residual return is associated with an increase of 29.6 crimes per 100 million individuals (14.6 bps) in the daily fixed effects specification, but 30.9 (15.2 bps) without the daily fixed effects. This provides us with some assurance that the results are not driven by common news simultaneously affecting both returns and crime.

1.7 Robustness

1.7.1 Is it the VIX?

The VIX is a widely used gauge of market risk and measures the market's expectation of S&P 500 volatility over the next 30 days. If utility is affected by anxiety over the uncertainty of future consumption as in Caplin and Leahy (2001), and the VIX measures the uncertainty of future wealth, then changes in the VIX could impact utility. To ensure that anxiety over future consumption is not driving the results, as suggested by Engelberg and Parsons (2014), I explicitly control for changes in the VIX in Table 1.10. The first column shows that changes in the VIX enters insignificantly, with a one unit increase in the market corresponding to 19.4 additional crimes per 100 million individuals (9.6 bps). This provides inconclusive evidence that individuals are affected by anxiety over future returns. However, the coefficient on the market return remains highly significant with a one standard deviation increase in the market corresponding to an additional 68.6 crimes (33.8 bps). This compares to the specification without the VIX of 46.2 crimes (22.8 bps). Breaking down the results by income, changes in the VIX only enters significantly in medium income locations. Furthermore, the monotonic relationship across income groups between stock market returns and crime remains. For example, a one standard deviation increase in the market corresponds to an insignificant 6.7 crimes per 100 million individuals (3.3 bps) in high income locations, and a significant increase of 124 crimes (61.1 bps) in low income locations. The significance of the market return and remaining monotonic relationship provides assurances that the results are not driven by anxiety as measured by the VIX.

1.7.2 Earnings Surprises

If stock market returns are partly driven by the revelation of firm specific information that can influence expectations of cash flows and discount rates, then we should also expect individuals to incorporate this firm specific information in their utility over expected relative wealth. An example of firm specific information that is frequently provided to the market is earnings announcements. The difference between reported earnings and expected earnings provides new information to the stock market that could influence prices. To quantify the unexpected component of earnings, I utilize the standardized unexpected earnings (SUE) measure. Following Livnat and Mendenhall (2006), SUE is defined as the difference between reported quarterly earnings and the median of the most recent forecast for each analyst made in the 90 days prior to the report date, scaled by the quarter end price. To generate an aggregate market measure of SUE, I market cap weight the firm level SUEs for all firms that report on a given day. To be included in the sample, at least ten firms must report on that date. The empirical relationship between SUE and firm announcement returns is positive (Livnat and Mendenhall, 2006), which suggests that we should also expect a relationship between aggregate SUE and crime rates if individuals' utility over expected relative wealth changes with unexpected earnings.

The usage of SUE has the advantage that it only includes previously non-public firm information that occurred in the past, and thus is not confounded by other daily news that could simultaneously influence crime rates and returns such as macroeconomic announcements, wars/terrorist attacks, or other geo-political events. The disadvantage of using SUE is that firms do not report on all days in the sample, so approximately one-third of the observations are discarded. The results in Panel A of Table 1.11 are consistent with individuals' utility over expected relative wealth changing with unexpected earnings. The overall relationship between crime rates and aggregate SUE is positive with a one unit increase in SUE associated with a significant increase of 4.7 crimes per 100 million individuals (2.3 bps). The relationship is also stronger for low income individuals as compared to high income individuals, with a one unit increase in SUE associated with a significant 11.4 crimes (5.6 bps) in low income locations, and a significant 3.1 crimes (1.5 bps) in high income locations. Panel B of Table 1.11 confirms that the relationship between market returns and crime rates remains after controlling for SUE, suggesting that both realized returns and unexpected firm performance impact utility.

1.7.3 Falsification Test

In order to further examine if the home bias is driving the relationship between state specific returns and overall crime rates, I conduct a falsification test. In the falsification test, all police agencies within a state are assigned returns from all firms headquartered in a distant-state. If individuals exhibit a home bias for local stocks but do not exhibit a bias for distant stocks, then local residual returns can drive marginal changes in utility while distant residual returns (orthogonal to the market) will have no effect. Consistent with the local bias, a significant relationship between local overall crime rates and local-state residual returns was previously seen in Table 1.8. Similarly, if there is no bias for distant stocks, an insignificant relationship between local crime rates and distant-state residual returns is expected.

A local-state is defined as the state in which a police agency is domiciled. A distant-state is defined as any state which is at least 500 miles away from the local state[15]. To ensure that a unique distant-state's return is assigned to each local-state, the following algorithm is followed. First, local-states with the fewest distant-state options are matched to distant-states with the fewest local-state options. Second, if there are ties when selecting local or distant-states, ties a broken randomly. This process is repeated until all local-states are matched with a unique distant-state. As with the local-state returns, I perform rolling one-year regressions of the distant-state returns on non-distant-state returns and extract the residual return in order to isolate the component of returns that is unique to each distant-state. Distant-state returns are defined as the market weighted average of all firms within a distant-state, while non-distant-state returns are defined as the market weighted average of all firms outside of the distant-state. As previously, the distant-state residual return and non-distant state returns are then divided by their respective rolling one-year standard deviation.

The results in Table 1.12 are consistent with individuals showing no bias for distant stocks. The coefficients on the distant-state residual returns are all insignificant indicating that the residual return of distant stocks has no relationship with crime rates and thus utility. However, the coefficients on the non-distant-state return (essentially the stock market return) remain very similar to the coefficients on the stock market return in Table 1.6, with a one standard deviation increase in the non-distant-state return associated with 48.1 additional crimes (23.7 bps) versus the 46.2 (22.8 bps) relationship with market returns. As previously, the relationship between overall crime rates and non-distant-state returns also decreases

[15] Distance is measured from the center of one state to the next. The center of the state is defined as the average latitude and longitude for all zip codes within a state.

monotonically with income. For example, a one standard deviation increase in the non-distant-state return is associated with a significant increase of 97.8 crimes (48.2 bps) in low income locations and decreases to an insignificant 3.0 crimes (1.5 bps) in high income locations.

1.8 Conclusion

Using daily reported crime incidents from over 2,500 law enforcement agencies across 27 states from 1991-2012, I examine the social effects of realized stock market returns using micro-level (city/county) data. Proposing crime as a measure of revealed marginal utility, I find a contemporaneous positive and convex relationship between daily stock returns and overall crime rates. I also find that market changes impact investors' and non-investors' marginal utility differently and interpret this as evidence in support of envy or "keeping up with the Joneses" models such as Abel (1990) that individuals care about their own wealth relative to others. For high income individuals, a positive stock market return is associated with a decrease in marginal utility (increase in utility) because high income individuals are more likely to hold stocks, and a higher market return increases their wealth relative to non-stockholders. This decrease in marginal utility corresponds with decreases (or at least no increase) in crime rates for high income individuals. Low income individuals are impacted differently by higher market returns. Because low income individuals hold less (or no) stocks as compared to high income individuals, positive market returns are associated with higher marginal utility because they are now worse off relative to high income individuals. This increase in marginal utility corresponds to an increase in crime rates for low income individuals.

Empirically I find that a one standard deviation increase in daily stock market returns corresponds to a 22.8 bps increase in overall crimes across the US. The relationship between returns and crime rates also monotonically increases from high income to low income locations. The 22.8 bps daily increase in crime is also economically meaningful and corresponds with an additional annualized 36,551 crimes across the US with an estimated annualized loss to society of $2.67 billion.

I also find a relationship between returns and violent crime, property crime, and white collar crime. For example, a one standard deviation increase in the market return is associated with a 22 bps decrease in assaults for high income locations, and a 40 bps increase in assaults for low income locations. The relationship with assaults is particularly supportive because most assaults occur at home by an offender that is related to or otherwise known by the victim. This ensures that our proxy for investors (high income cities) and non-investors (low income cities) are meaningful.

I find that the overall relationship between overall crime rates is robust to a battery of controls, and is consistent with rational asset pricing models with utility over relative wealth. Speculatively, my results also suggest that high income inequality and large stock market changes can be detrimental to society through increased crime.

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Figure 1.1 Stockholder and Non-Stockholder Crime Propensity

This figure illustrates the hypothetical crime propensity (marginal utility) of stockholders and non-stockholders over the market return.

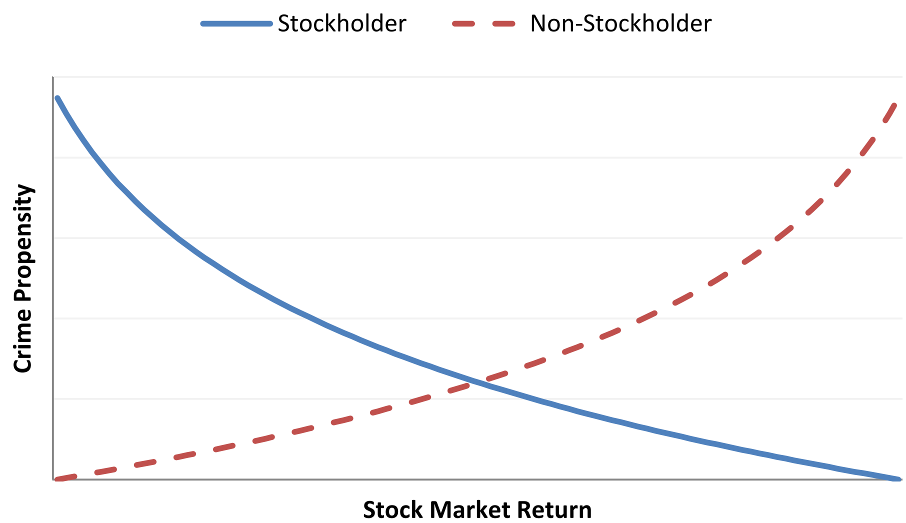

Figure 1.2 Hourly Crime Distribution

This figure illustrates the hourly distribution of crimes in the NIBRS database from 1/1991 – 12/2012. All crime incidents regardless of offense type are included.

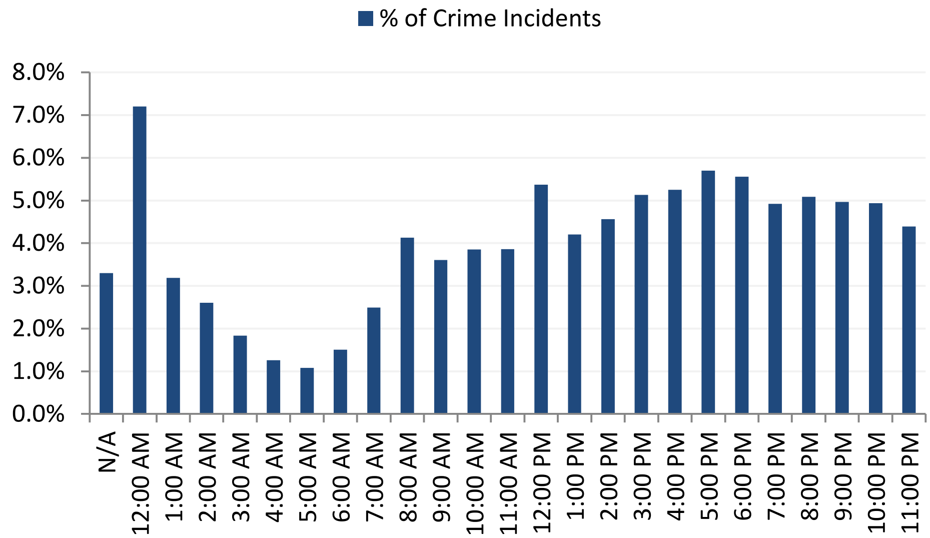

Figure 1.3 NIBRS Coverage

This figure illustrates the monthly coverage of the NIBRS database from 1/1991 – 12/2012. Agencies include all law enforcement agencies in the NIBRS database after the filters described in the text. Population only includes the population that the agencies cover and is measured in millions. Crimes include the number of all crime incidents regardless of offense type.

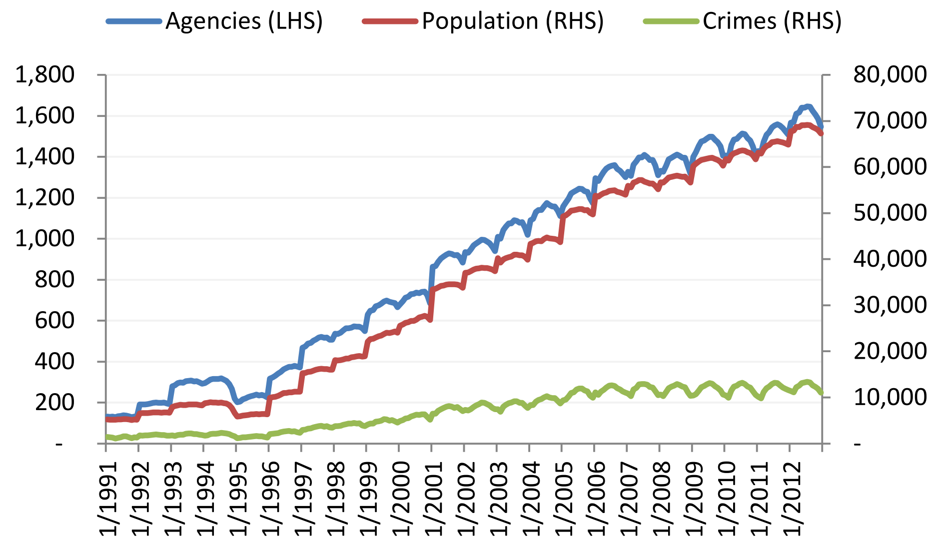

Figure 1.4 Crime Rate

This figure illustrates the aggregate US daily crime rate per 100 million people from 1/1991 – 12/2012 averaged over each month. The crime rate is calculated as the number of incidents across all agencies divided by the population covered by all agencies.

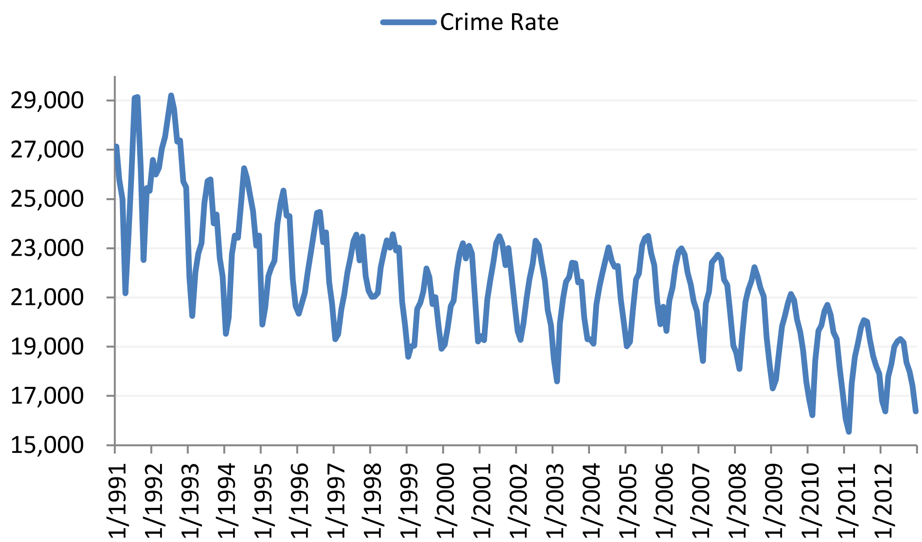

Figure 1.5 Stock Returns and All Assaults by Income

This figure illustrates the empirical relationship between market returns and assaults for high income and low income locations from 1991-2012 utilizing the coefficients in Panel D of Table 1.6. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Standardized market return is market capitalization weighted returns of all firms in CRSP, and divided by its trailing 252-day standard deviation. All assaults include aggravated assaults, simple assault, and intimidation. Each line is plotted on a separate axis.

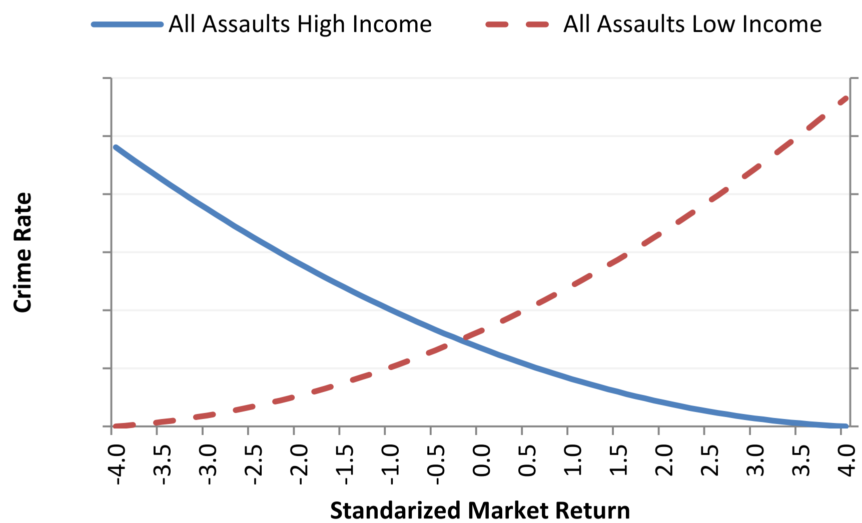

Table 1.1 NIBRS Coverage by State

Summary from 1991-2012. Start Date is the first date where at least one agency reports an incident within that state. Population only includes those covered by the agencies. Crime rate is per 100 million people per day.

State	Start Date	Average # of Agencies	Max # of Agencies	Average Population	Max Population	Average Crime Count	Average Crime Rate
AL	1/1991	14	70	545,940	2,434,391	139	18,615
AR	1/2001	47	96	1,154,888	2,266,027	303	28,966
AZ	7/2004	2	4	178,701	312,927	23	16,214
CO	1/1992	34	61	2,275,347	4,331,786	421	21,548
CT	1/1999	34	53	1,110,817	1,730,738	157	14,378
DE	1/2001	11	15	587,177	625,631	111	18,934
GA	1/2004	1	1	10,102	10,782	4	38,204
IA	1/1992	45	68	1,412,848	1,764,232	333	23,829
ID	1/1992	28	37	926,374	1,215,426	178	19,804
IL	1/1993	29	154	762,390	3,352,576	186	32,429
KS	1/2001	45	63	1,226,522	1,541,737	319	25,996
KY	1/1998	19	77	442,701	1,978,083	79	21,787
LA	1/2003	12	19	395,677	609,064	77	19,726
MA	1/1995	81	130	2,557,968	4,352,634	423	17,355
ME	8/2004	8	14	179,602	281,856	34	19,020
MI	1/1995	164	212	6,406,866	8,644,641	1,159	18,062
MO	1/2007	5	8	405,576	701,654	103	24,316
MS	1/2010	2	3	99,415	126,059	30	30,383
MT	1/2005	21	29	622,369	722,546	112	18,134
NE	1/1998	13	22	274,414	420,195	51	19,121
ND	1/1991	8	16	267,010	455,215	49	18,616
NH	1/2002	29	45	545,393	782,780	106	19,602
OH	1/1998	86	161	3,930,069	6,411,498	899	23,309
OK	1/2008	14	39	258,570	680,809	41	15,777
OR	12/2003	30	40	921,616	1,110,748	177	19,455
RI	1/2005	23	28	854,350	976,320	134	15,595
SC	1/1991	94	120	3,553,929	4,533,846	886	25,011
SD	1/2001	7	16	253,383	447,566	46	18,209
TN	1/1997	122	161	4,375,201	5,779,965	1,115	24,164
TX	1/1997	33	49	2,265,583	3,709,977	490	22,103
UT	1/1993	29	49	1,245,444	2,139,098	271	21,749
VA	1/1995	84	124	5,164,985	7,556,158	857	16,382
VT	1/1994	9	15	132,746	215,655	29	21,627
WA	1/2006	28	92	1,421,357	4,208,516	277	20,002
WI	1/2005	17	37	1,213,396	1,901,953	255	22,687
WV	6/1998	22	36	669,360	1,005,669	112	17,011

Table 1.2 Law Enforcement Agencies by Population

Law enforcement agencies in the NIBRS database with the largest population coverage as of 12/2012.

State	Agency	Population
VA	Fairfax County Police Department	1,072,723
OH	Columbus	797,384
TX	Fort Worth	770,101
MI	Detroit	707,096
TN	Memphis	657,436
CO	Denver	628,545
WA	Seattle	626,865
TN	Nashville	620,886
WI	Milwaukee	599,395
MO	Kansas City	464,073

Table 1.3 Summary Statistics by Offense Type

Daily US crime rates are calculated as the sum of offenses across all agencies divided by the population of all agencies and is per 100 million people. The average, median, and standard deviation of the US crime rate is calculated over the time series of the aggregate daily US crime rate. Daily agency crime rates are calculated as the daily sum of offenses for a specific agency divided by the agency population. The average, median, and standard deviation of the agency crime rate is calculated over the pooled daily agency crime rate. Agency percent is the percent of non-zero daily observations for the offense.

	US Med	US Avg	US Std. Dev	Agency Med	Agency Avg	Agency SD	Agency Pct
Violent Crime							
Homicide Offenses							
Murder/Non-negligent Manslaughter	12	13	11	0	14	333	0.7
Negligent Manslaughter	0	1	2	0	3	175	0.1
Justifiable Homicide	0	0	1	0	2	114	0.2
All Homicides	12	14	11	0	15	349	0.7
Assault Offenses							
Aggravated Assault	738	849	385	0	794	2,815	17.2
Simple Assault	2,676	2,749	518	0	3,138	5,753	44.8
Intimidation	751	699	234	0	1,049	3,440	19.8
All Assaults	4,211	4,298	787	2,444	4,938	7,607	56.8
Sex Offenses, Forcible							
Forcible Rape	95	101	40	0	114	962	3.8
Forcible Sodomy	18	20	14	0	29	503	1.0
Sexual Assault With An Object	10	11	9	0	21	401	0.7
Forcible Fondling	100	105	53	0	136	1,093	4.1
All Rape	226	237	90	0	278	1,548	8.1
Robbery	290	303	100	0	220	1,319	7.3
All Violent Crime	4,754	4,852	883	3,041	5,430	7,975	59.6
Property Crimes							
Larceny/Theft Offenses							
Pocket-picking	19	38	90	0	32	561	1.1
Purse-snatching	25	28	17	0	41	647	1.2
Shoplifting	1,096	1,151	290	0	1,367	4,033	24.1
Theft From Building	748	739	178	0	995	3,300	19.2
Theft From Coin-Operated Machine or Device	35	39	24	0	58	868	1.4
Theft From Motor Vehicle	1,665	1,678	312	0	1,625	4,458	28.1
Theft of Motor Vehicle Parts/Accessories	561	611	238	0	462	2,045	12.0
All Other Larceny	2,725	2,845	813	0	3,515	6,340	47.7
All Larceny/Theft	6,980	7,130	1,511	5,418	7,957	10,093	71.2
Burglary/Breaking and Entering	2,105	2,215	613	0	2,226	4,739	37.0
Motor Vehicle Theft	823	820	197	0	664	2,326	16.6
All Property Crime	9,899	10,164	2,166	8,031	10,835	11,855	80.9

Other Classified							
Fraud Offenses							
False Pretenses/Swindle/Confidence Game	263	267	131	0	378	2,202	9.3
Credit Card/Automatic Teller Machine Fraud	115	132	87	0	228	1,658	6.3
Impersonation	56	87	89	0	152	1,206	5.0
Welfare Fraud	0	2	5	0	12	394	0.2
Wire Fraud	6	8	8	0	25	489	0.9
All Fraud	444	496	264	0	726	2,974	16.5
Drug/Narcotic Offenses							
Drug/Narcotic Violations	1,049	1,039	348	0	1,475	4,241	26.4
Drug Equipment Violations	149	140	57	0	215	1,442	5.7
All Drugs	1,197	1,179	390	0	1,662	4,510	28.6
Sex Offenses, Non-forcible							
Incest	2	4	5	0	10	285	0.3
Statutory Rape	15	17	13	0	33	541	1.0
All Non-Forcible Sex	19	21	15	0	37	573	1.1
Gambling Offenses							
Betting/Wagering	0	2	4	0	5	239	0.2
Operating/Promoting/Assisting Gambling	0	2	6	0	6	253	0.2
Gambling Equipment Violations	0	1	4	0	7	276	0.2
Sports Tampering	0	0	0	0	3	123	0.1
All Gambling	2	5	9	0	9	327	0.3
Prostitution Offenses							
Prostitution	22	30	28	0	30	545	1.4
Assisting or Promoting Prostitution	5	8	13	0	16	507	0.6
All Prostitution	30	38	33	0	34	639	1.5
Other Offenses							
Kidnaping/Abduction	45	45	18	0	55	692	2.0
Arson	63	66	26	0	73	794	2.4
Extortion/Blackmail	2	3	4	0	7	236	0.3
Counterfeiting/Forgery	288	299	114	0	454	2,562	9.4
Embezzlement	65	67	37	0	114	1,077	3.3
Stolen Property Offenses	77	75	29	0	112	1,008	3.2
Destruction/Damage/Vandalism of Property	2,781	2,842	697	0	3,404	6,646	45.6
Pornography/Obscene Material	6	8	8	0	21	432	0.6
Bribery	0	0	2	0	4	179	0.1
Weapon Law Violations	137	143	52	0	167	1,294	4.9
All Incidents	20,201	20,302	3,420	17,835	22,976	19,011	100.0

Table 1.4 Law Enforcement Agencies by Median Income

Law enforcement agencies in the NIBRS database with the highest median income. Median income is calculated using the 2012 American Community Survey Public Use Microdata Sample from the US Census, and only includes income for full-time workers.

State	Agency	Median Income	Population
WA	Issaquah	99,930	31,341
VA	Falls Church	97,990	12,892
VA	Vienna	90,919	16,140
MA	Newton	87,888	86,710
MI	Birmingham	83,847	20,250
VA	Herndon	80,716	23,966
VA	Arlington County Police Department	79,990	218,385
VA	Loudoun	75,912	275,263
VA	Fairfax City	75,766	22,798
TX	Flower Mound	74,980	68,023

Table 1.5 Daily Return Statistics

State return statistics in percent that correspond to only time periods where crime data is available with start dates listed in Table 1.1. The state residual return is defined as the residual from a regression of state returns on non-state returns and represent the component of returns specific to that state.

Panel A: Daily Return Statistics by State

State	Avg # of Firms	Min # of Firms	Max # of Firms	Avg State Return	Std Dev of State Ret	Avg State Ret Residual	Std Dev of State Ret Residual
AL	29	18	40	0.02	2.14	0.00	1.09
AR	21	17	28	0.02	1.37	0.01	0.97
AZ	56	38	67	0.05	2.08	0.00	1.04
CO	120	81	183	0.04	1.60	0.00	1.02
CT	111	82	163	0.02	1.75	-0.01	1.01
DE	19	14	26	0.02	1.86	-0.01	0.98
GA	140	117	148	-0.01	1.22	0.02	1.10
IA	32	20	51	0.04	1.81	-0.01	1.05
ID	11	8	15	0.05	2.95	0.00	1.04
IL	203	156	298	0.03	1.25	0.01	1.01
KS	27	21	35	0.00	2.12	-0.01	0.99
KY	37	26	50	0.05	1.42	0.00	1.02
LA	30	26	34	0.04	1.47	-0.01	0.98
MA	281	187	388	0.04	1.57	0.00	1.02
ME	9	7	11	0.06	1.61	-0.01	1.05
MI	105	65	147	0.03	1.44	-0.01	1.01
MO	66	61	75	0.07	1.53	0.04	0.95
MS	14	13	14	0.00	1.77	0.02	0.99
MT	6	4	7	0.04	2.85	0.00	1.01
NE	17	14	25	0.03	1.42	0.00	1.04
ND	4	2	6	0.06	1.52	0.00	1.02
NH	15	9	24	0.03	1.97	0.00	1.03
OH	173	121	267	0.02	1.20	-0.02	1.02
OK	32	27	35	0.04	2.92	-0.01	1.10
OR	42	35	52	0.05	1.63	0.00	1.03
RI	14	13	15	0.04	1.67	0.00	1.05
SC	35	21	48	0.03	1.28	0.00	1.01
SD	8	6	9	0.00	1.79	-0.01	1.02
TN	74	58	103	0.03	1.43	-0.01	1.03
TX	454	339	650	0.04	1.45	0.00	1.04
UT	42	27	65	0.02	1.61	0.00	1.01
VA	152	112	205	0.04	1.28	0.00	1.01
VT	10	5	15	0.09	2.11	0.01	1.05
WA	84	67	98	0.02	1.78	-0.01	1.05
WI	59	53	65	0.02	1.82	-0.01	1.05
WV	10	7	17	0.04	1.88	0.01	1.04

Panel B: Daily Market and Pooled State Return Statistics

	Mean	Std Dev
Market Return	0.046	1.158
Market Return (Standardized)	0.055	1.029
State Return	0.035	1.756
State Residual Return	0.000	1.114
State Residual Return (Standardized)	-0.002	1.025
Non-State Return	0.031	1.332
Non-State Return (Standardized)	0.032	1.073

Table 1.6 Market Returns and Crime Rates by Income

Regression of daily crime rates on daily market returns by income from 1991-2012. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are market weighted returns of all firms in CRSP, and divided by its trailing 252-day standard deviation. The crime rate is for the incident indicated in the column header. Crime rates are measured as the number of incidents per 100 million people. Crime offenses are defined in Table 1.3. Controls are included in all specifications, but with coefficients only shown in Panel A. Moon fraction is the fraction of the moon illuminated, SAD is the estimated change in the proportion of individuals experiencing Seasonal Affective Disorder, temperature is in tenths of degrees Celsius, precipitation consists of rainfall and the liquid equivalent of any frozen precipitation in tenths of millimeters, snowfall is the amount of new snow that fell during the day in millimeters, snow depth is the total depth in millimeters of snow on the ground at the time of observation, and wind is the average wind speed in tenths of meters per second. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Panel A: All Incidents by income

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	35.56***	1.474	45.91***	65.57***
	(2.593)	(0.124)	(2.683)	(3.053)
Market Return Sq.	5.316	0.631	2.472	14.58*
	(1.002)	(0.137)	(0.370)	(1.800)
Moon Fraction	70.77*	32.24	30.93	152.6**
	(1.696)	(0.852)	(0.587)	(2.362)
SAD	-959.7**	-444.5	-1,339***	-1,019
	(-2.383)	(-1.394)	(-2.871)	(-1.634)
Temperature	13.11***	10.42***	15.04***	13.66***
	(39.28)	(32.62)	(34.77)	(25.65)
Precipitation	-2.282***	-1.505***	-2.535***	-2.341***
	(-5.942)	(-3.958)	(-4.849)	(-3.747)
Snowfall	-23.03***	-17.36***	-31.87***	-38.46***
	(-8.233)	(-7.289)	(-8.505)	(-6.832)
Snow Depth	-3.459***	-3.392***	-8.385***	-8.092***
	(-9.555)	(-10.41)	(-14.58)	(-9.778)
Wind	-17.56***	-14.55***	-21.02***	-19.81***
	(-15.92)	(-13.58)	(-14.05)	(-10.46)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel B: All Property Crime by Income

Incident	All Property Crime	All Property Crime	All Property Crime	All Property Crime
Income Level	ALL	HIGH	MED	LOW
Market Return	14.04*	4.071	20.57*	19.94
	(1.709)	(0.518)	(1.898)	(1.438)
Market Return Sq.	6.597**	2.582	14.19***	4.129
	(2.054)	(0.845)	(3.220)	(0.748)
Observations	3,728,566	1,313,862	1,216,699	1,195,425
R-squared	0.307	0.287	0.294	0.294
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel C: All Violent Crime by Income

Incident	All Violent Crime	All Violent Crime	All Violent Crime	All Violent Crime
Income Level	ALL	HIGH	MED	LOW
Market Return	0.183	-9.716**	-5.793	17.21**
	(0.0413)	(-2.065)	(-0.927)	(2.049)
Market Return Sq.	-0.298	1.699	-4.720*	2.206
	(-0.163)	(0.850)	(-1.848)	(0.569)
Observations	3,727,519	1,313,426	1,216,364	1,195,151
R-squared	0.260	0.234	0.260	0.228
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel D: All Assaults by Income

Incident	All Assaults	All Assaults	All Assaults	All Assaults
Income Level	ALL	HIGH	MED	LOW
Market Return	-1.103	-12.02***	-4.269	14.13*
	(-0.277)	(-2.701)	(-0.740)	(1.812)
Market Return Sq.	-0.617	1.316	-4.609*	1.476
	(-0.379)	(0.661)	(-1.926)	(0.402)
Observations	3,726,934	1,313,282	1,216,169	1,194,907
R-squared	0.247	0.223	0.246	0.217
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel E: All Fraud by Income

Incident	All Fraud	All Fraud	All Fraud	All Fraud
Income Level	ALL	HIGH	MED	LOW
Market Return	4.791**	1.861	6.547**	6.142*
	(2.457)	(0.894)	(2.062)	(1.827)
Market Return Sq.	1.440*	-0.369	0.121	4.838***
	(1.914)	(-0.475)	(0.104)	(3.528)
Observations	3,645,825	1,290,978	1,188,586	1,163,753
R-squared	0.054	0.057	0.052	0.055
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Table 1.7 Market Returns and Crime Rates with Lags

Regression of daily crime rates on market returns from 1991-2012. Returns lag indicates the timing of the market return relative to the crime rate at date *t*, where the date *t* crime rate includes non-trading days. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Returns Lag	*t - 3*	*t - 2*	*t - 1*	*t*
Market Return	8.163	19.17	8.510	35.56***
	(0.587)	(1.352)	(0.616)	(2.593)
Market Return Sq.	0.633	-1.878	5.199	5.316
	(0.114)	(-0.288)	(0.796)	(1.002)
Observations	3,921,805	3,905,421	3,814,634	3,728,775
R-squared	0.471	0.471	0.476	0.474
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Table 1.8 State Returns and Crime Rates by Income

Regression of daily crime rates on daily state residual returns and non-state returns by income from 1991-2012. The state residual return is defined as the residual from a regression of state returns on non-state returns and represent the component of returns specific to that state. State returns are market weighted returns of firms within the agency's state. Non-state returns are market weighted returns for firms outside of the agency's state. The state residual and non-state return are divided by their 252-day trailing standard deviation. The crime rate is for the incident indicated in the column header. Crime rates are measured as the number of incidents per 100 million people. Crime offenses are defined in Table 1.3. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Controls are defined in Table 1.6 and included in all specifications, but with coefficients only shown in Panel A. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Panel A: All Incidents by Income

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
State Residual Return	28.68***	21.28*	23.81	42.26**
	(2.655)	(1.875)	(1.544)	(2.270)
Non-State Return	35.06**	1.300	45.63***	64.44***
	(2.557)	(0.109)	(2.668)	(3.002)
State Residual Return Sq.	1.128	-4.763	-8.753	16.97**
	(0.220)	(-0.967)	(-1.245)	(2.105)
Non-State Return Sq.	5.518	1.177	3.225	13.92*
	(1.038)	(0.254)	(0.482)	(1.721)
Moon Fraction	70.55*	31.98	30.71	152.9**
	(1.690)	(0.845)	(0.583)	(2.367)
SAD	-964.1**	-448.5	-1,346***	-1,021
	(-2.393)	(-1.406)	(-2.884)	(-1.639)
Temperature	13.12***	10.42***	15.04***	13.66***
	(39.31)	(32.62)	(34.77)	(25.67)
Precipitation	-2.284***	-1.507***	-2.542***	-2.339***
	(-5.945)	(-3.961)	(-4.862)	(-3.743)
Snowfall	-23.03***	-17.36***	-31.85***	-38.37***
	(-8.218)	(-7.290)	(-8.462)	(-6.797)
Snow Depth	-3.455***	-3.388***	-8.374***	-8.081***
	(-9.550)	(-10.40)	(-14.56)	(-9.789)
Wind	-17.55***	-14.56***	-21.03***	-19.76***
	(-15.92)	(-13.60)	(-14.06)	(-10.43)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel B: All Property Crimes by Income

Incident	All Property Crime	All Property Crime	All Property Crime	All Property Crime
Income Level	ALL	HIGH	MED	LOW
State Residual Return	14.30**	8.961	15.78*	19.05
	(2.242)	(1.142)	(1.647)	(1.596)
Non-State Return	13.73*	3.973	20.08*	19.56
	(1.673)	(0.505)	(1.855)	(1.412)
State Residual Return Sq.	1.461	-1.412	-1.359	7.109
	(0.509)	(-0.412)	(-0.312)	(1.412)
Non-State Return Sq.	6.607**	2.719	14.33***	3.915
	(2.057)	(0.890)	(3.245)	(0.710)
Observations	3,728,566	1,313,862	1,216,699	1,195,425
R-squared	0.307	0.287	0.294	0.294
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel C: All Violent Crime by Income

Incident	All Violent Crime	All Violent Crime	All Violent Crime	All Violent Crime
Income Level	ALL	HIGH	MED	LOW
State Residual Return	6.123	2.744	4.396	11.66
	(1.499)	(0.593)	(0.704)	(1.437)
Non-State Return	0.0986	-9.787**	-5.785	16.98**
	(0.0222)	(-2.080)	(-0.926)	(2.020)
State Residual Return Sq.	1.718	1.079	-0.870	5.398
	(0.920)	(0.550)	(-0.324)	(1.405)
Non-State Return Sq.	-0.328	1.723	-4.616*	1.966
	(-0.180)	(0.863)	(-1.799)	(0.507)
Observations	3,727,519	1,313,426	1,216,364	1,195,151
R-squared	0.260	0.234	0.260	0.228
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel D: All Assaults by Income

Incident	All Assaults	All Assaults	All Assaults	All Assaults
Income Level	ALL	HIGH	MED	LOW
State Residual Return	4.534	2.460	3.156	8.209
	(1.183)	(0.565)	(0.539)	(1.059)
Non-State Return	-1.142	-12.08***	-4.221	13.99*
	(-0.286)	(-2.714)	(-0.731)	(1.792)
State Residual Return Sq.	1.045	0.836	-1.682	4.408
	(0.625)	(0.446)	(-0.686)	(1.240)
Non-State Return Sq.	-0.633	1.328	-4.472*	1.256
	(-0.389)	(0.667)	(-1.860)	(0.342)
Observations	3,726,934	1,313,282	1,216,169	1,194,907
R-squared	0.247	0.223	0.246	0.217
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel E: All Fraud by Income

Incident	All Fraud	All Fraud	All Fraud	All Fraud
Income Level	ALL	HIGH	MED	LOW
State Residual Return	0.237	-0.0703	-0.220	1.260
	(0.143)	(-0.0352)	(-0.0742)	(0.400)
Non-State Return	4.783**	1.860	6.611**	6.054*
	(2.452)	(0.893)	(2.085)	(1.802)
State Residual Return Sq.	0.0289	0.396	-2.007*	1.711
	(0.0416)	(0.455)	(-1.694)	(1.321)
Non-State Return Sq.	1.466*	-0.378	0.281	4.766***
	(1.939)	(-0.485)	(0.241)	(3.470)
Observations	3,645,825	1,290,978	1,188,586	1,163,753
R-squared	0.054	0.057	0.052	0.055
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Table 1.9 State Returns and Crime Rates with Daily Fixed Effects

Regression of daily crime rates on daily state residual returns and non-state returns from 1991-2012 including fixed effects for agency location and time. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. All other variables are as defined in Table 1.8. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
State Residual Return	36.18**	32.64**	22.86	47.56**
	(2.526)	(2.009)	(1.087)	(1.967)
Non-State Return	-27.11	10.06	-1,157	1,088
	(-0.0445)	(0.0154)	(-1.136)	(0.874)
State Residual Return Sq.	-3.292	-5.746	-14.10*	8.446
	(-0.633)	(-1.100)	(-1.853)	(0.921)
Non-State Return Sq.	-101.4	7.324	-120.1	-217.0
	(-0.581)	(0.0417)	(-0.366)	(-0.627)
Temperature	13.43***	11.68***	16.01***	12.90***
	(30.46)	(25.44)	(24.94)	(17.61)
Precipitation	-2.276***	-1.209**	-2.376***	-2.670***
	(-5.637)	(-2.457)	(-4.036)	(-4.222)
Snowfall	-20.98***	-15.39***	-31.31***	-36.05***
	(-6.973)	(-5.477)	(-7.378)	(-5.820)
Snow Depth	-2.161***	-2.309***	-7.194***	-6.788***
	(-5.537)	(-5.956)	(-11.65)	(-7.855)
Wind	-21.06***	-19.01***	-27.36***	-22.90***
	(-17.40)	(-14.26)	(-15.26)	(-10.68)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.478	0.457	0.464	0.456
Daily FE	YES	YES	YES	YES
Location FE	YES	YES	YES	YES

Table 1.10 Market Returns and Crime Rates with VIX

Regression of daily crime rates on daily market returns and changes in the VIX by income from 1991-2012. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	59.75***	5.425	84.95***	97.55***
	(2.702)	(0.282)	(3.090)	(2.765)
Market Return Sq.	4.442	0.656	1.059	13.25*
	(0.851)	(0.142)	(0.162)	(1.651)
ΔVIX	19.41	3.110	31.59**	25.73
	(1.468)	(0.278)	(1.979)	(1.189)
Observations	3,726,178	1,313,013	1,215,895	1,194,690
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Table 1.11 SUE and Crime Rates

Regression of daily crime rates on daily standardized unexpected earnings (SUE) by income from 1991-2012. At the firm level, SUE is defined as the difference between reported quarterly earnings and the median of all analyst earnings estimates made in the 90 days prior to the report date from IBES, scaled by the quarter end price. An aggregate market weighted SUE is calculated for all firms that report on a given day. To be included in the sample, at least ten firms must report on that date. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Panel A: Relationship with SUE only

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Aggregate SUE	4.670*	3.100*	-0.706	11.39***
	(1.653)	(1.868)	(-0.137)	(3.397)
Observations	2,543,096	896,378	830,756	814,269
R-squared	0.471	0.453	0.456	0.446
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Panel B: Relationship with market returns controlling for SUE

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	39.64***	13.87	41.86**	70.51***
	(2.580)	(1.015)	(2.135)	(2.879)
Market Return Sq.	2.365	-0.728	2.009	6.986
	(0.401)	(-0.143)	(0.263)	(0.736)
Aggregate SUE	4.135	2.891*	-1.283	10.48***
	(1.501)	(1.742)	(-0.253)	(3.214)
Observations	2,543,096	896,378	830,756	814,269
R-squared	0.471	0.453	0.456	0.446
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Table 1.12 State Return Falsification Test

Regression of daily crime rates on daily distant-state residual returns and non-distant-state returns by income from 1991-2012. The distant-state residual return is defined as the residual from a regression of distant-state returns on non-distant-state returns and represents the component of returns specific to the distant-state. Distant-state returns are market weighted returns of firms in states that are at least 500 miles away from the police agency's state. Non-distant-state returns are market weighted returns for firms outside of the distant-state. The distant-state residual and non-distant-state return are divided by their 252-day trailing standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Controls are defined in Table 1.6 and included in all specifications. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Distant-State Residual Return	8.041	-0.579	11.62	10.48
	(0.767)	(-0.0524)	(0.777)	(0.583)
Non-Distant-State Return	36.21***	1.698	45.75***	67.26***
	(2.643)	(0.142)	(2.676)	(3.133)
Distant-State Residual Return Sq.	-6.261	0.220	-8.730	-7.161
	(-1.156)	(0.0413)	(-1.153)	(-0.774)
Non-Distant-State Return Sq.	5.939	0.658	3.403	15.25*
	(1.110)	(0.141)	(0.506)	(1.868)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

CHAPTER 2

Does Crime Pay?

Asset Pricing with Revealed Utility of Heterogeneous Consumers

2.1 Abstract

I propose violent crime growth as a measure of revealed marginal utility growth of heterogeneous consumers in incomplete markets. Consumer heterogeneity is measured using the cross-sectional average and cross-sectional variance of crime growth exploiting a monthly panel of reported crime incidents from over 10,000 law enforcement agencies across the United States from 1975-2012. Consistent with heterogeneous consumer models such as Mankiw (1986), I find that the cross-sectional average and variance of violent crime growth can explain the cross-section of stock returns. Specifically, investors pay a premium for assets that have higher betas to the violent crime growth moments.

2.2 Introduction

In many asset pricing models, changes in the representative agent's marginal utility price all assets. However, these models rely on a number of assumptions and imperfect data. First, the existence of a representative agent implicitly assumes individual consumers have perfect insurance against idiosyncratic consumption risk so that they can equalize their marginal rates of substitution state by state. If consumers are unable to protect themselves against this risk, then measures of consumer heterogeneity matter for the estimation of the stochastic discount factor (SDF).[16] Second, measuring changes in marginal utility requires an assumed utility specification, but it remains unclear which specification of utility is appropriate.[17] Finally, utility is typically measured as some function of consumption, but it is well known that the key empirical input to testing consumption-based models, NIPA consumption expenditure, is poorly measured due to imputation, interpolation, and aggregation problems (Breeden, Gibbons, and Litzenberger, 1989; Savov, 2011).[18]

One potential solution that avoids an assumed specification of utility for the representative agent and poorly measured consumption is to use an estimate of marginal utility that directly reflects the psychological states of consumers. In this paper, I propose violent

[16] An exception includes when marginal utility is linear (utility is quadratic), where a representative consumer formulation can still exist without full insurance (Hansen, 1987).

[17] An incomplete list includes standard power utility (Hansen and Singleton, 1983), habit formation (Abel, 1990; Campbell and Cochrane, 1999), leisure (Dittmar, Palomino, and Wang, 2014) and prospect theory (Barberis, Huang, and Santos, 2001).

[18] Survey based household level consumption data also has its difficulties. Koijen, Van Nieuwerburgh, and Vestman (2013) compare high-quality tax registry-based consumption to survey based consumption for Swedish households and find large discrepancies. Attanasio, Battistin, and Leicester (2004) argue that the quality of Consumer Expenditure Survey (CEX) consumption relative to NIPA consumption has deteriorated over time, and express caution in using higher distributional moments of the CEX data. Meyer, Mok, and Sullivan (2015) report that many household surveys, including the CEX, have exhibited increased non-response rates, increased item imputation, and increased measurement error over time and suggest that respondents have become less cooperative due to being "over-surveyed", concerns about privacy, and time pressure.

crime growth as a new measure of revealed marginal utility growth for heterogeneous consumers in incomplete markets. High marginal utility states are assumed to be so painful that individual consumers lose control and behave in violent ways that involve law enforcement. By using a direct measure of marginal utility growth, I abstract away from what specification utility should take, and address a more general question in support of consumption-based asset pricing models: does the marginal utility growth of heterogeneous consumers matter for asset pricing?

This paper tests if stocks can be priced using the marginal utility (crime) growth of heterogeneous consumers in incomplete markets. The way I measure heterogeneity is by exploiting a second order Taylor expansion of my proxy for marginal utility growth and model the SDF as a function of both the cross-sectional average and cross-sectional variance of crime growth using a panel of crime data for almost every city and county in the US. Consistent with heterogeneous consumer models such as Mankiw (1986), I find that both the cross-sectional average and variance of violent crime growth can help explain the cross-section of stock returns. The significance of the cross-sectional variance of violent crime growth suggests that the representative agent framework may be too restrictive, and that measures of heterogeneity can be helpful for asset pricing. Both cross-sectional moments carry negative prices of risk when using both portfolios or individual stocks as test-assets in Fama and MacBeth (1973) regressions. I also show using time-series and cross-sectional tests that the results hold when using crime mimicking portfolios, which mitigates measurement error in using crime growth as a proxy for marginal utility growth and allows for asset pricing tests over a longer time period. Furthermore, the significance of the crime factors is verified using the generalized method of moments (GMM). In robustness tests I also show that the portfolio cross-sectional tests hold for crime growth in high-income locations for those individuals most likely to hold stocks, are not affected by weather or location specific time-invariant factors, and are robust to other proposed measures of heterogeneity and marginal utility. The results suggest that investors pay a premium for assets that have higher betas to the average and variance of violent crime growth. The negative prices of risk are expected because increases in the average and variance of violent crime growth are associated with bad states of the world, and assets that pay off in bad states provide insurance.

Interpreting violent crime as a measure of revealed utility has precedent. A similar assumption is made by Card and Dahl (2011) who posit that intimate partner violence (IPV) is a function of the utility of NFL game outcomes, and finds that local team losses are associated with higher rates of violence. Similarly, if poor stock market performance leads to increases in marginal utility (declines in utility) for investors, these individuals may act out in ways that lead to law enforcement involvement. The link between stock returns and utility is also made by Engelberg and Parsons (2014). They argue that hospital admissions are also a form of revealed utility, and show that declines in the stock market are associated with an increase in hospitalizations. Both findings suggest that when utility is low (marginal utility is high), these individuals may suffer from psychological or physiological distress. Accordingly, monthly changes in crime rates suggest a link with changes in marginal utility that can potentially price the cross section of stock returns.

Utility has alternatively been directly measured using Subjective Well Being (SWB) questions such as if the individual agrees with the statement, "Much of the time during the past week I was happy." It is well documented that answers to these questions can be sensitive to wording, framing, or question order among other factors (Bertrand and Mullainathan, 2001). Additionally, surveys are typically conducted at low frequencies and with a limited time dimension which hampers their usage in asset pricing. Crime data provides an alternative measure of utility with several advantages over surveys. First, crime can be considered a revealed response made by individuals. Revealed preferences have long been considered preferable in studies of consumer choice. Second, crime data is standardized across regions and time. This enhances the comparability of utility across individuals that could be biased if self-reported. Third, coverage of the crime data is extensive and encompasses over 99% of the US population in recent periods. Finally, the long time period and monthly frequency of the crime data provides us with a continuously updated pulse of individuals' utility.

One class of asset pricing models that have been proposed in explaining the cross-section of stock returns are heterogeneous consumer models with incomplete consumption insurance.[19] In these models, consumers are unable to self-insure against background risks (e.g., labor income shocks) and realized consumption growth rates can differ across individuals.[20] This is in contrast to representative agent models which implicitly assume that consumers are able to equalize their marginal rates of substitution state by state. Any heterogeneity of consumption growth suggests that asset prices depend not only on average

[19] An incomplete list includes Mankiw (1986), Telmer (1993), Heaton and Lucas (1996), Constantinides and Duffie (1996), Storesletten, Telmer, and Yaron (2007), Brav, Constantinides, and Geczy (2002), Cogley (2002), Jacobs and Wang (2004), and Constantinides and Ghosh (2014).

[20] A potential reason why consumers cannot perfectly insure against income shocks is due to private information (Telmer, 1993). The ensuing moral hazard problem results in the inability to write incentive compatible contracts based on idiosyncratic outcomes.

consumption growth, but also on the higher cross-sectional moments of individual consumers' consumption growth.

Each moment of consumption growth carries a price of risk that can differ in sign. Intuitively, assets that have higher betas to average consumption growth should be associated with higher expected returns because these assets payoff in good times (low marginal utility states), and have poor performance in bad times (high marginal utility states). Thus, investors set a positive price of risk on the beta for average consumption growth. Assets that have higher betas to the cross-sectional variance of consumption growth should be associated with lower expected returns because a higher cross-sectional variance indicates a larger probability of a decrease in consumption growth.[21] Since assets with larger betas to the cross-sectional variance of consumption growth payoff in bad times, these assets act as insurance. As such, investors set a negative price of risk on the beta for the variance of consumption growth. If increases in crime correspond with increases in marginal utility, then assets with higher betas to the cross-sectional average and variance of crime growth pay off in bad states and should be associated with lower returns, and thus negative prices of risk.

Heterogeneous consumer models with incomplete consumption insurance have had mixed success. In a calibrated economy in which consumers face uninsurable income risk, Telmer (1993) and Heaton and Lucas (1996) find that consumers are able to come close to complete risk sharing, and are unable to generate a large enough risk premia for most realistic parameterizations of the economy. Storesletten, Telmer, and Yaron (2007) are able to generate

[21] Although a higher cross-sectional variance also suggests a larger probability of a positive shock to consumption growth, the curvature of the utility function implies that the pain from any decrease in consumption will outweigh any elation from an equivalent increase in consumption.

a larger risk premia under the assumption that idiosyncratic shocks are persistent. Other studies have investigated stochastic discount factors (SDFs) that hold even when markets are incomplete, through the use of Taylor series expansions of the SDF that exploit higher cross-sectional consumption growth moments. A difficulty in estimating these models is that they require disaggregated household-level data. Unfortunately, the household-level data that is available to researchers typically has a short time dimension and a small cross-section, is infrequently measured, suffers from significant measurement error, and has been argued to exhibit deteriorating quality (Meyer, Mok, and Sullivan, 2015). At least partly due to these issues, there has been little consensus in the literature on the importance of heterogeneous consumers. Using a panel of individual consumption growth from the Consumer Expenditure Survey (CEX), Brav, Constantinides, and Geczy (2002) find that a non-linear SDF that depends on the cross-sectional average, variance, and skewness of consumption growth helps explain the value-weighted equity premium at low levels of risk aversion, but models that depend on just the cross-sectional average or the cross-sectional average and variance do not explain the equity premium. Using a similar setup, but on log consumption growth, Cogley (2002) finds that a non-linear SDF that depends on the cross sectional average, variance, and skewness cannot help explain the equity premium. Conversely using a similar subset of the CEX data, Jacobs and Wang (2004) find that an SDF that is linear in both the cross-sectional average and variance of consumption growth can explain the cross-section of stock and bond returns, but only if the presence of measurement error is addressed by calculating consumption growth on synthetic cohorts of consumers.

While the literature relating economics and crime is vast, the literature relating finance and crime is relatively unexplored. The finance literature has typically examined effects from corporate crimes such as financial misrepresentation on managerial turnover (Karpoff, Lee, and Martin, 2008), bribery on firm value (Zeume, 2014), and insider trading (Acharya and Johnson, 2010). The literature linking finance and non-corporate crimes such as violent or property crimes is particularly sparse. Garmaise and Moskowitz (2006) find evidence of spillover effects on crime from changes in credit conditions.

The economics and criminology literature suggests that crime is a plausible measure of marginal utility because crime increases in bad economic states. Exploiting a panel of annual state GDP growth, Arvanites and Defina (2006) find that property crime has a negative relationship with state GDP growth. Rosenfeld and Fornango (2007) and Rosenfeld (2009) find that property crime and homicide exhibit a negative relationship with changes in the regional components of the University of Michigan Consumer Sentiment Index. The literature generally supports a positive relationship between unemployment and crime (Freeman, 1999), while low legal wage opportunities have also been associated with increased crime (Gould, Weinberg, and Mustard, 2002). Fajnzylber, Ledeman, and Loayza (2002) find that violent crime increases with income inequality.

The psychology literature suggests that individuals that are depressed have an increased propensity of violent behavior (Oakley, Hynes, and Clark, 2009). Fazel, et al. (2015) match approximately 50,000 Swedish individuals with outpatient diagnoses of depression to 900,000 individuals in the general population and find that depressed individuals were three times as likely to commit a violent crime compared to the general population, and twice as likely compared to non-depressed siblings. Depression, anxiety, and chronic stress have been linked to low serotonin levels, while low serotonin levels have also been linked to increased violent behavior in mice, primates, and humans (Krakowski, 2003). Seo, Patrick, and Kennealy (2008) suggest that low serotonin levels can also reduce control over the dopamine system, which can compound impulsive and aggressive behavior towards the self and others. Depression has often been used as a proxy for utility in the economics literature (e.g., Luttmer, 2005), while neurotransmitters such as dopamine and serotonin have been linked to utility in the neuroeconomics literature (Bossaerts, 2009). This suggests a connection between an individual's utility and violent crime.

2.3 Economic Model of Crime

2.3.1 Crime as Marginal Utility

The key assumption is that violent crime is a behavioral response that reflects consumers' marginal utility. The notion that changes in marginal utility drive asset returns is standard in the literature, but has little empirical evidence with direct measures of utility. The assertion that crime is a behavioral response which reflects losses in utility is relatively novel in the finance literature, but has precedent. Card and Dahl (2011) posit that the gain-loss utility of NFL game outcomes affects the propensity of intimate partner violence. Huck (2016) finds that increases in the stock market are associated with decreases in violent crime in high income locations and increases in violent crime in low income locations, and attributes this to utility over relative wealth. This study builds on Huck (2016) on the presumption that if crime reflects high levels of marginal utility for stock holders, then changes in crime reflect changes in marginal utility which can price the cross-section of stock returns.

The channel by which violent behavior is typically modeled is through a visceral factor triggering a loss of control (Loewenstein, 2000). For example, in high marginal utility states an individual may experience increased visceral factors such as anger, anxiety, or hunger. These heightened visceral factors may trigger an individual to lose control and induce a fight. An alternative channel is the economic model of crime where an individual optimally chooses violent behavior based on the expected utility of that act (Becker, 1968). In this framework, the utility gained from the morbid pleasure of committing a violent act outweighs any costs of committing that act in high marginal utility states. Although the two models imply similar links between violent crime and marginal utility, the loss of control model is preferred as it does not rely on psychopathic behavior inherent in the economic model of crime. Modeling the link between violent crime and marginal utility explicitly, I posit that the crime rate, $z_{i,t}$, for city i in month t is a function of marginal utility, $u'(c_{i,t})$, with multiplicative error $\epsilon_{i,t} > 0$:

$$z_{i,t} = \phi \left(u'(c_{i,t})\right)^{1/\theta} \epsilon_{i,t}. \tag{2.1}$$

Because I am agnostic to the specification of marginal utility, $c_{i,t}$ can be thought of as any driver of marginal utility such as consumption, leisure, or wealth. Solving for marginal utility as a function of crime yields:

$$u'(c_{i,t}) = \left(\frac{1}{\phi} z_{i,t}\right)^{\theta} \epsilon_{i,t}^{-\theta}. \tag{2.2}$$

2.3.2 The Economy and Equilibrium

Following Mankiw (1986) and Brav, Constantinides, and Geczy (2002), I consider a set of households, $i = 1, \dots, I$, that participate in the capital markets. The households trade a set of securities, $n = 1, \dots, N$, with total return $R_{n,t}$ between dates $t-1$ and t. Each household i maximizes expected lifetime utility

$$E\left[\sum_{t=0}^{\infty} \delta^t u(c_{i,t})\right], \tag{2.3}$$

where δ is the subjective discount factor. In equilibrium, a set of $I \times N$ Euler equations are obtained between dates $t-1$ and t:

$$E\left[\delta \frac{u'(c_{i,t})}{u'(c_{i,t-1})} R_{n,t}\right] = 1. \tag{2.4}$$

Under the assumption that crime is revealed marginal utility as in (2.1), (2.2) can be substituted into (2.4) to yield the Euler equations in terms of crime:

$$E\left[\delta \left(\frac{z_{i,t}}{z_{i,t-1}}\right)^{\theta} \left(\frac{\epsilon_{i,t}}{\epsilon_{i,t-1}}\right)^{-\theta} R_{n,t}\right] = 1. \tag{2.5}$$

Letting $g_{i,t} = z_{i,t}/z_{i,t-1}$ and $\eta_{i,t} = \epsilon_{i,t}/\epsilon_{i,t-1}$, and using the definition for covariance, (2.5) can be expanded as:

$$E[\delta g_{i,t}^{\theta} R_{n,t}] E[\eta_{i,t}^{-\theta}] + cov(\delta g_{i,t}^{\theta} R_{n,t}, \eta_{i,t}^{-\theta}) = 1. \tag{2.6}$$

The covariance term can be further expanded using the asymptotic approximation for the covariance of products:[22]

$$E[\delta g_{i,t}^{\theta} R_{n,t}] E[\eta_{i,t}^{-\theta}] + E[\delta g_{i,t}^{\theta}] cov(R_{n,t}, \eta_{i,t}^{-\theta}) + \tag{2.7}$$

[22] Under multivariate normality, the definition used for the covariance of products in (2.7) is exact (Bohrnstedt and Goldberger, 1969).

$$E[R_{n,t}]cov(\delta g_{i,t}^{\theta}, \eta_{i,t}^{-\theta}) = 1.$$

Under the assumption that the error terms are independent of returns, and defining $E[\eta_{i,t}^{-\theta}]$ and $cov(\delta g_{i,t}^{\theta}, \eta_{i,t}^{-\theta})$ as the constants H and ρ respectively, (2.7) can be re-written as:

$$\mathrm{H}E[\delta g_{i,t}^{\theta} R_t\ ] + \rho E[R_{n,t}] = 1. \tag{2.8}$$

2.3.3 Stochastic Discount Factor

From the first-order condition of the consumer's maximization problem, the Euler equation holds for each household as does any weighted sum across households. I investigate the equal weighted sum of households' Euler equations, defining the SDF as:

$$M_t = \frac{1}{I}\sum_{i=1}^{I} \delta g_{i,t}^{\theta}. \tag{2.9}$$

Equation (2.9) can be expanded using a Taylor series up to quadratic terms around a constant ω to obtain the SDF:

$$M_t = \delta\omega^{\theta} + \delta\theta\omega^{\theta-1}(\bar{g}_t - \omega) + \frac{1}{2}\delta\theta(\theta-1)\omega^{\theta-2}[\bar{v}_t + (\bar{g}_t - \omega)^2], \tag{2.10}$$

where $\bar{g}_t = I^{-1}\sum_i g_{i,t}$ and $\bar{v}_t = I^{-1}\sum_i (g_{i,t} - \bar{g}_t)^2$. Thus, the SDF can be written in terms of the cross-sectional mean and variance of crime growth.

Next, solving (2.8) in terms of expected returns yields:

$$E[R_{n,t}] = \frac{1}{\mathrm{H}E[M_t] + \rho}\left(1 - \mathrm{H}cov(M_t, R_{n,t})\right). \tag{2.11}$$

Solving for $E[M_t]$ in terms of the risk free rate, and expressing (2.11) in terms of excess returns (R^e) gives the pricing equation:

$$E\left[R_{n,t}^{e}\right] = -\mathrm{H}R_{f}cov\left(M_{t}, R_{n,t}^{e}\right). \qquad (2.12)$$

Substituting (2.10) into (2.12) and simplifying yields the relationship:

$$E\left[R_{n,t}^{e}\right] = \pi_{g}cov\left(\bar{g}_{t}, R_{n,t}^{e}\right) + \pi_{v}cov\left(\bar{v}_{t}, R_{n,t}^{e}\right) + \pi_{g^{2}}cov\left(\bar{g}_{t}^{2}, R_{n,t}^{e}\right) \qquad (2.13)$$

where,

$$\pi_{g} = -\mathrm{H}R_{f}\delta\theta(2-\theta)\omega^{\theta-1}$$

$$\pi_{v} = -\frac{1}{2}\mathrm{H}R_{f}\delta\theta(\theta-1)\omega^{\theta-2}$$

$$\pi_{g^{2}} = -\frac{1}{2}\mathrm{H}R_{f}\delta\theta(\theta-1)\omega^{\theta-2}.$$

In practice, average crime growth $\bar{g}_{t}$ is highly correlated (96%) with the squared average crime growth $\bar{g}_{t}^{2}$ leading to problems in estimation and confounding the interpretation of the results. Therefore, the squared average crime growth term will be dropped in subsequent empirical tests. Appendix B.1 derives the bounds for the bias factor H. The derivation suggests that when accounting for error, the coefficients in (2.13) may be biased upwards by a factor of 1 to 1.58, with a plausible bias of 1.14. Although many of the subsequent empirical findings remain significant when accounting for this bias, it is worth noting that any proxy for an individual's true unobserved marginal utility will produce a similar upward bias.

The above derivation shows that the use of crime growth as a proxy for marginal utility growth can be used to support consumption based asset pricing models with heterogeneous consumers. This is in contrast to ad-hoc return based factor models such as Fama and French (1993). While return based factor models are extremely successful for relative pricing, they do not tell us where returns come from. For example, its hard to link the HML or SMB factors to marginal utility growth. At least with crime, there is a plausible relationship between crime growth and marginal utility growth.

2.4 Data

Monthly crime data is from the Uniform Crime Reports (UCR) which is under the jurisdiction of the Federal Bureau of Investigation (FBI).[23] The UCR is a voluntary system used by law enforcement agencies in the US for collecting and reporting data on crime. By 2012, there are over 18,000 law enforcement agencies active in the UCR program covering more than 99% of the US population. The dataset begins in January 1975 and ends in December 2012 and contains monthly counts of eight major Part I crime offenses that are reported to city and county police agencies, and are not necessarily associated with an arrest. The eight major offenses are homicide, manslaughter, aggravated assault, rape, robbery, burglary, larceny, and motor vehicle theft. In this study, I focus on an aggregate of the violent crimes of homicide, manslaughter, and aggravated assault because they are the most serious and best measured offenses in the UCR data and follow most closely with the loss of control argument.

To mitigate observation error, I only include crimes reported by city and county police agencies with twelve months of crime data and with populations greater than 2,000 individuals. I also remove outlier data with possible reporting errors. Specifically, following a similar methodology that Brav, Constantinides, and Geczy (2002) use for consumption growth, I remove crime growth $g_{i,t}$ and $g_{i,t+1}$ if $g_{i,t} < 0.5$ and $g_{i,t+1} > 2$, *or* $g_{i,t} > 2$ and $g_{i,t+1} < 0.5$.

[23] I utilize the dataset distributed by the Inter-university Consortium for Political and Social Research (ICPSR) available here: http://www.icpsr.umich.edu/icpsrweb/content/NACJD/guides/ucr.html

Additionally, I remove $g_{i,t}$ if $g_{i,t} > 5$ or $g_{i,t} = 0$. After all filters, roughly 10,000 law enforcement agencies remain. I use the monthly cross sectional average and variance of crime growth across all locations as the main factors to explain stock returns. Because both cross-sectional moments exhibit a strong monthly seasonal pattern, I run a regression of each series on twelve monthly dummies and extract the residual. Additionally, I difference the cross-sectional variance as it exhibits strong persistence. I denote the residual cross-sectional average and differenced residual cross-sectional variance as $\tilde{g}_t$ and $\tilde{v}_t$ respectively, and simply refer to them as the average and variance of crime growth in the subsequent text.

Figure 2.1 displays the time-series of the cross-sectional average and variance of crime growth, with associated summary statistics in Table 2.1. As expected, both moments are centered around zero, while the standard deviation of the average of crime growth (2.82) is slightly higher than that of the variance of crime growth (2.55).

2.5 Risk Premia

2.5.1 Test Portfolios

Many firm-specific characteristics have been proposed to guide portfolio formation of test-assets. Fama and French (1992) suggest that the cross-section of returns can be summarized by size and book-to market, but forming test-asset portfolios using only these two characteristics has come under criticism by Lewellen, Nagel, and Shanken (2010) due to the ease of fitting a model to its strong two-factor structure. To overcome this criticism I also investigate test-asset portfolios that are formed on a set of characteristics that Lewellen (2014) finds to be consistently significant in Fama and MacBeth (1973) regressions. These seven characteristics are book-to-market, market capitalization, past 12-month returns, asset growth, profitability, stock issuance, and total accruals. I utilize the 25 size and book-to-market and 10 momentum portfolios on Kenneth French's website,[24] and also form test-asset portfolios on the remaining characteristics by sorting all stocks by the characteristic, splitting the sample into decile portfolios, and market cap weighting the stocks within each portfolio.

2.5.2 Portfolio-Level Prices of Risk

I follow the standard approach to investigate whether risk exposures are related to average returns using Fama and MacBeth (1973) two-stage regressions. In the first stage I regress the time series of test-asset portfolio excess returns ($R^e_{n,t}$) on the cross-sectional average ($\tilde{g}_t$) and variance ($\tilde{v}_t$) of crime growth to estimate the betas:

$$R^e_{n,t} = \alpha_n + \beta_{n,g}\,\tilde{g}_t + \beta_{n,v}\,\tilde{v}_t + \xi_{n,t}. \tag{2.14}$$

In the second stage, I run cross sectional regressions on the estimated betas from the first stage to estimate a time series of the prices of risk ($\gamma_{k,t}$):

$$R^e_{n,t} = \gamma_{0,t} + \gamma_{g,t}\hat{\beta}_{n,g} + \gamma_{v,t}\hat{\beta}_{n,v} + u_{n,t}. \tag{2.15}$$

The price of risk associated with each beta is calculated as

$$\hat{\gamma}_k = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{k,t}, \tag{2.16}$$

with associated Fama and MacBeth (FM) standard error

[24] Thanks to Kenneth French for making this data available: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$s.e.(\hat{\gamma}_k) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\hat{\gamma}_{k,t} - \hat{\gamma}_k\right)^2. \quad (2.17)$$

An advantage of the FM standard errors are that they are simple to estimate, and do not require the estimation of large covariance matrices which makes it suitable for studying large cross sections of individual stocks. The FM standard errors are also robust to cross-correlation and heteroscedasticity, however, it does not account for the first stage estimation error and autocorrelation in the residuals. Therefore, in addition to the t-stats that use FM standard errors (t_{FM}), I also report t-stats that use generalized method of moments (GMM) standard errors (t_{GMM}) as advocated by Cochrane (2005). The GMM standard errors correct for first stage estimation error, cross-correlation, heteroscedasticity, and autocorrelation using 12 Newey-West lags. The GMM standard errors are typically larger than the FM standard errors resulting in lower GMM t-stats. For the portfolio level results, unless the inference of the two t-stats differs, I will refer only to the GMM t-stats in the text.

A good asset pricing model is generally considered to have statistically significant and stable prices of risk for $\hat{\gamma}_g$ and $\hat{\gamma}_v$, and small pricing errors on the test-assets. Small pricing errors are indicated by a high cross-sectional adjusted R^2, a small and insignificant price of risk on the zero-beta portfolio ($\hat{\gamma}_0$), a low mean absolute pricing error (MAPE), and a low Shanken T^2 statistic that tests if the pricing errors are jointly zero.[25]

[25] The $\bar{R}^2_{OLS}$ is defined as $1 - \frac{N-1}{N-K-1} var(\hat{u})/var(\bar{R}^e)$, where the vector of sample pricing errors is given by $\hat{u} = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_t$, and $\bar{R}^e$ is the vector of average excess returns. The T^2 test with the null that the pricing errors are jointly zero is calculated as $\hat{u}' cov(\hat{u})^{-1}\hat{u} \sim \chi^2_{N-K-1}$ with $cov(\hat{u}) = \frac{1}{T}(I_N - \beta(\beta'\beta)^{-1}\beta')\Omega_\xi(I_N - \beta(\beta'\beta)^{-1}\beta')\left(1 + \gamma'\Omega_f^{-1}\gamma\right)$, and Ω_ξ is the covariance matrix of the first stage residuals and Ω_f is the covariance of the factors. The MAPE is defined as $\frac{1}{N}\sum_{n=1}^{N}|\hat{u}_n|$.

Panel A of Table 2.2 presents the main results. The first three columns show the prices of risk estimated using the 25 size and book-to-market portfolios, while the last three columns show the prices of risk estimated using the 75 size and book-to-market, momentum, asset growth, profitability, stock issuance, and total accrual portfolios. Across all specifications, the prices of risk on both the cross-sectional average and variance of crime growth are negative and relatively stable. The prices of risk are expected to be negative, because assets that have higher betas to the average and variance of crime growth pay off in bad states of the world, and therefore act as insurance. Specifically, for the 25 size and book-to-market portfolios, the price of risk for the average of crime growth is -3.03 (t_{FM}=1.94, t_{GMM}=1.37), while the price of risk for the variance of crime growth is a significant -3.58 (t_{GMM}=2.99). The results are marginally weaker, but still significant when augmenting the 25 size and book-to-market test portfolios with 10 portfolios each of momentum, total accruals, asset growth, share issuance, and profitability (for a total of 75 test portfolios). Specifically, the price of risk for the average of crime growth declines marginally to a significant -2.97 (t_{GMM}=2.26), while the price of risk for the variance of crime growth declines to a significant -2.86 (t_{GMM}=3.23).

Comparing the pricing errors, the crime model performs reasonably well relative to the Fama and French (1993) three factor (FF3) model which includes the market (MKT), size (SMB), and value (HML) factors. The relatively strong performance of the crime model is noteworthy considering that it is not a return based factor model. Focusing on the results with only the 25 size and book-to-market portfolios, the crime model has a reasonably high adjusted R^2 of 0.46 and a low (but still significant) price of risk on the zero-beta portfolio of 0.69. The MAPE of the crime model is higher than the FF3 model but is a reasonable 0.133 vs 0.081 for the FF3 model.

The Shanken T^2 statistic for the crime model cannot reject the null that the pricing errors are zero, while the FF3 model strongly rejects that the pricing errors are jointly equal to zero. The seemingly good performance of the crime model according to the T^2 statistic is partly due to the larger covariance of the pricing errors. The performance of the models on the 75 test-asset portfolios is similar to that of the 25 size and book-to-market portfolios. Panel B of Table 2.2 reports the MAPE by each set of test assets. The crime model has a much higher MAPE than the FF3 model for the momentum (0.268 vs 0.175) and total accruals (0.177 vs 0.085) test assets, but performs relatively well for the asset growth (0.090 vs 0.097) and profitability (0.128 vs 0.111) test assets.

I also report the prices of risk for the crime factors when controlling for MKT, SMB, and HML. When including the FF3 factors, the prices of risk for the average of crime growth declines to -2.39 (t_{FM}=1.96, t_{GMM}=1.36) for the 25 size and book-to-market test-assets, while the price of risk for the variance of crime growth declines to a significant -2.33 (t_{GMM}=2.97). The prices of risk for the 75 test-asset portfolios also decline, but remain significant after controlling for the FF3 factors. The weaker prices of risk after controlling for the FF3 factors indicate that the Fama and French factors may proxy for the same underlying changes in marginal utility that the cross-sectional moments of crime growth capture. Furthermore, when including both the crime and FF3 factors, the pricing errors improve over both the stand-alone crime and FF3 model with a higher adjusted R^2, lower MAPE, but with a price of risk on the zero-beta portfolio that is similar to the FF3 model. The Shanken T^2 statistic does not reject the null of zero pricing errors for the 25 size and book-to-market portfolios, but rejects the null for the 75 test asset portfolios.

2.5.3 Firm-Level Prices of Risk

In the previous section, I showed that the price of risk on both the cross-sectional average and variance of crime growth are both negative when using various sets of test-asset portfolios. In this section, I utilize individual stocks to estimate prices of risk. The usage of firms as test assets avoids the criticism of easily fitting a model due to the strong factor structure in the test asset portfolios (Lewellen, Nagel, and Shanken, 2010). I follow the methodology of Fama and French (1992) to estimate betas for each firm. First, using all NYSE, NASDAQ, and AMEX stocks from CRSP with prices greater than $5, I estimate firm-level Dimson (1979) crime betas with one lag using a 60-month rolling window. Second, I sort firms into 10×10 portfolios first by the variance beta and then by the average beta. The sequential sorts are required over independent sorts to ensure diversified portfolios. Third, I estimate the post-ranking crime betas for all 100 portfolios over the entire time series and assign the post-ranking crime betas to the firms that belong to each portfolio. As in Fama and French (1992), the post-ranking portfolio betas are preferred over the imprecise individual betas when estimating prices of risk. Finally, using each firm's return and its assigned post-ranking beta, I calculate a time series of prices of risk following (2.15) and estimate the average price of risk and its standard error as in (2.16) and (2.17) respectively.

Table 2.3 shows that the price of risk is negative for both crime growth moments when using individual firms as test-assets. For example, column 1 shows that the price of risk for average crime growth is a not quite significant -0.87 (t_{FM}=1.61) while the price of risk for the variance of crime growth is a significant -1.21 (t_{FM}=3.01). As a comparison, column 2 shows that the average price of risk for two out of the three FF3 factors are insignificant, with only HML having a significantly positive price of risk of 0.66 (t_{FM}=2.23). When including the crime growth moments with the FF3 factors in column 3, the coefficients on the crime growth moments decline with only the variance of crime growth remaining significant. The fact that the negative price of risk generally holds with stock-level Fama and MacBeth regressions provides additional assurances that both moments of crime growth are priced.

2.5.4 Portfolio Sorts

An alternative procedure to show the relationship between crime and returns is to sort individual stocks by expected returns into portfolios and test for a significant spread between high and low expected return portfolios. Within each NYSE size quintile I sort each stock by its expected return and place them into quintiles. Sorting first by size ensures that a size effect is not biasing the results. Expected returns are estimated using rolling 60-month crime exposures for each stock applied to the prices of risk estimated in the previous section. The resulting quintile portfolios are equally weighted and rebalanced monthly.

Panel A of Table 2.4 shows that the realized crime returns increase monotonically with expected returns. For example, Q1 exhibits a monthly return of 1.03% while Q5 exhibits a return of 1.28% resulting in a long-short spread of 0.24% which is statistically different from zero (t=2.70). Figure 2.2 shows that the crime long-short portfolio performs well during recessions, and appears to be somewhat correlated with HML. Panel B of Table 2.4 confirms that the crime long-short portfolio exhibits positive correlation with HML (0.35), negative correlation with SMB (-0.17), and virtually no correlation with the excess market return (-0.02). The performance of the crime long-short portfolio also compares favorably to HML and SMB. The crime portfolio return is only bested by HML's average monthly return of 0.32%, but the crime portfolio's lower volatility gives it the highest monthly Sharpe ratio of 0.14. The strong performance of the crime long-short portfolios, and the monotonic relationship between expected and realized returns provides further evidence that crime exposure risk is priced.

2.5.5 Crime Beta Sorted Portfolios as Test-Assets

It was previously shown that the cross-sectional average and variance of crime growth can help price various anomaly portfolios and individual stocks as test-assets. In this section, I generate a new set of crime test-asset portfolios sorted by individual stock's exposure to the average and variance of crime growth, and examine whether the portfolios can be priced using the 2-factor crime and 3-factor Fama and French (FF3) models. The advantage of using the crime portfolios as test-assets is that it avoids the criticism of the strong two-factor structure in the size and book-to-market portfolios (Lewellen, Nagel, and Shanken, 2010). The crime test-asset portfolios are formed following a similar procedure used to estimate stock-level prices of risk. First, Dimson (1972) crime betas with one lag are estimated for each firm using a 60-month rolling window. Second, firms are sorted into 5×5 portfolios first by the variance beta and then by the average beta. The resulting 25 portfolios are equally weighted and rebalanced monthly. Table B.1 in Appendix B.3 shows that the returns are roughly decreasing in the average and variance of crime beta portfolios.

Table 2.5 shows that the prices of risk on both the cross-sectional average and variance of crime growth are both negative and are similar in magnitude to those using traditional test-asset portfolios. Specifically, the first column shows that the price of risk for the average of crime growth is a -2.24 (t_{FM}=1.85, t_{GMM}=1.30), while the price of risk on the variance of crime growth is a significant -3.05 (t_{GMM}=1.89). The second column shows that the FF3 factors have difficulty explaining the crime test-asset portfolios, with none of the factors significant at conventional levels. The final column shows that after controlling for the FF3 factors, the prices of risk on the crime factors are attenuated and generally insignificant. The performance of the crime model relative to the weak performance of the FF3 model indicates that the crime test-asset portfolios contain sources of risk which the FF3 model has difficulty pricing.

2.6 Crime Mimicking Portfolios

To conduct additional tests, the crime factors are projected onto the space of traded returns to form crime mimicking portfolios (CMPs) as in Breeden, Gibbons, and Litzenberger (1989). In testing the Consumption CAPM, Breeden et al. show that asset betas measured using consumption mimicking portfolios are proportional to the betas measured using true consumption. The use of mimicking portfolios has several advantages. First, mimicking portfolios can exploit a longer time series that are not constrained by the availability of the crime data. This avoids concerns that the results rely on the 1975-2012 time period. Second, since the crime mimicking portfolios are return-based factors, time-series alpha tests can be run without estimating cross-sectional prices of risk since the factor risk premium is equal to the sample mean of the factor return. Finally, mimicking portfolios can mitigate any measurement error in the time-series betas for crime growth as a proxy for marginal utility growth.

2.6.1 Construction of Crime Mimicking Portfolios

To construct the crime mimicking portfolios, the nontraded crime growth moments are projected onto the space of excess returns with the mimicking portfolio defined as the fitted value (excluding the constant). Specifically, a vector of weights (b_k) for each crime factor k is estimated using the following regressions:

$$f_{k,t} = a + b_k'[BL, BM, BH, SL, SM, SH]_t + \epsilon_{k,t}, \quad (2.18)$$

where $f_{k,t}$ is the cross sectional average of crime growth ($\tilde{g}_t$) or variance of crime growth ($\tilde{v}_t$) and $[BL, BM, BH, SL, SM, SH]$ are the excess returns of the six Fama and French benchmark portfolios sorted on size (Small and Big) and book-to-market (Low, Medium, and High). These portfolios are chosen to parsimoniously summarize the return space. The crime mimicking portfolio for crime factor k is given by

$$CMP_{k,t} = \hat{b}_k'[BL, BM, BH, SL, SM, SH]_t, \quad (2.19)$$

where, $\hat{b}_k$ are the fitted weights from (18) with $\hat{b}_g =$ [0.17,-0.07,-0.12,-0.14, 0.04, 0.11] indicating the fitted weights for the average of crime growth and $\hat{b}_v =$ [0.16, -0.17, -0.09, -0.15, 0.18, 0.03] for the variance of crime growth. The cross sectional average of crime growth and variance of crime growth mimicking portfolios have net short positions in small firms relative to big firms (-0.03 and -0.17 respectively), and net short positions in high book-to-market firms relative to low book-to-market firms (-0.04 and -0.07 respectively).

2.6.2 Portfolio-Level Prices of Risk using the Crime Mimicking Portfolios

In this section, the pricing performance of the crime mimicking portfolios is assessed using both cross-sectional and time-series tests over the 1975-2012 and 1952-2013 time periods. The cross-sectional tests follow the method described previously, but with the crime mimicking portfolios instead of the underlying crime factors. The time-series pricing errors are tested using the Gibbons, Ross, and Shanken (1989) *F*-statistic (GRS). The GRS statistic tests the null that the time-series alphas are jointly zero. The advantage of the time-series approach is that it avoids freely choosing the cross-sectional price of risk, since it imposes that the factor risk premium is equal to the sample mean of the factor return.

Table 2.6 illustrates the summary statistics for the crime mimicking portfolios over both sub-periods, while Figure 2.3 plots the cumulative returns over the full 1952-2013 period. Focusing on the full period results in Panel B of Table 2.6, the sample mean for both crime mimicking portfolios are negative. The average monthly return for the crime mimicking portfolio of the cross-sectional average of crime growth (CMP Avg) is -0.063% (t=4.95) while the average monthly return for the mimicking portfolio of the cross-sectional variance of crime growth (CMP Var) is -0.11% (t=6.99). The negative return is expected because the underlying crime factors (and mimicking portfolios) increase with marginal utility, and assets that pay off in high marginal utility states act as insurance and command negative risk premiums. The mimicking portfolios also exhibit the highest absolute Sharpe ratios, with a monthly Sharpe ratio of -0.18 for CMP Avg and -0.26 for CMP Var. Compared to the next largest Sharpe ratio of the market (0.13), the CMP Avg Sharpe ratio is 36% larger than the market in absolute terms, while the CMP Var Sharpe ratio is 92% larger, indicating that the crime mimicking portfolios are closer to the mean-variance frontier.

The cross-sectional and time-series pricing performance is presented in Table 2.7. Focusing on the full 1952-2013 period results in Panel C, as expected, the prices of risk on both crime moment mimicking portfolios are negative. For example, the price of risk using the 25 size and book-to-market test-asset portfolios is a significant -0.112 (t_{GMM}=4.22) on the CMP Avg portfolio and a significant -0.143 (t_{GMM}=5.17) on the CMP Var portfolio. These prices of risk are slightly more negative than the time-series average return. Comparing the crime mimicking portfolios to the Fama and French three factor model, the crime mimicking portfolios compare favorably. The crime mimicking portfolios have a low, but still significant pricing error on the zero beta portfolio of 0.59 (t_{GMM}=3.20), a high adjusted R^2 of 0.72, and a lower MAPE of 0.064 as compared to the FF3 models MAPE of 0.079. However, the Shanken T^2 statistic that tests the null that the cross-sectional pricing errors are jointly zero remain significant for both the crime and FF3 models, and the GRS *F*-statistic that tests the null that the time-series pricing errors (alphas) are jointly zero are also significant for both models. Combining the crime mimicking portfolios with the Fama and French three factors improves performance over either model alone (with the exception of a slightly larger, though less significant, zero-beta price of risk), while the crime mimicking portfolio prices of risk are slightly smaller but still highly significant. The results using the 75 test-asset portfolios are similar. Table B.2 in Appendix B.3 shows that the vast majority of the CMP time series betas are significant for the test-asset portfolios,[26] while Table B.3 to Table B.5 use the CMP factors to replicate many of the previous results that use the underlying crime factors in Table 2.3 to Table 2.5 show similar findings.

[26] Significance of the CMP betas is gauged using wild-bootstrapped standard errors with 10,000 replications that account for heteroscedasticity and estimation error in both the first and second stages. The multiplicative error term of the wild-bootstrap uses the asymmetric two-point distribution suggested by Mammen (1993). All time periods are sampled jointly to preserve the cross-correlation of the error terms.

2.7 GMM/SDF Estimates

The previous results showed that the crime factors can help explain returns using Fama and MacBeth regressions on portfolios and individual firms, that portfolio sorts on expected returns according to the crime model generate a significant spread, and that crime mimicking portfolios have significantly negative average returns in the time-series and significantly negative prices of risk in the cross-section. In this section, the relationship between crime and portfolio returns is confirmed using the generalized method of moments (GMM) stochastic discount factor (SDF) approach. While the cross-sectional regression approach produces asymptotically precise and identical estimates (after the appropriate transformation) as the GMM/SDF approach for linear models, they are often not identical in finite samples (Jagannathan and Wang, 2002). Details of the GMM estimation can be found in Appendix B.2. In all GMM tests, two alternative weighting matrices are considered: the optimal weighting matrix of the two-step procedure in Hansen (1982), and the inverse of the second moment matrix of returns as advocated by Hansen and Jagannathan (1997). The optimal weighting matrix produces the most precise parameter estimates, while the Hansen and Jagannathan (HJ) weighting matrix produces a misspecification measure that can be used to compare competing models.

The first column in Table 2.8 shows the crime model with the efficient weighting matrix. As expected, both cross-sectional moments of crime growth have significantly negative prices of risk. The coefficient on the cross-sectional average of crime growth is a significant -0.08 (*s.e.*=0.02), while the coefficient on the cross-sectional variance of crime growth is a significant -0.18 (*s.e.*=0.02). Multiplying the GMM coefficients by the variance of the cross-sectional average and variance of crime growth of 7.96 and 6.53 yields an estimate for the price of risk of -0.63 and -1.20 respectively. These coefficients compare favorably to the portfolio level prices of risk found in the Fama and MacBeth regression in column four of Table 2.2 of -2.97 and -2.86 respectively. The *p-value* of the TJ_T test of over-identifying restrictions for this model and in all linear specification discussed below is 0.000 which indicates that we can reject the null of zero pricing errors. The second column shows the crime model with the HJ weighting matrix. The coefficients remain negative, but are somewhat smaller and less significant. The coefficient on the cross-sectional average of crime growth becomes an insignificant -0.07 (*s.e.*=0.06), while the coefficient on the cross-sectional variance of crime growth is a significant -0.08 (*s.e.*=0.04).

Columns three and four show the linear GMM/SDF estimates for the Fama and French three factor model (FF3) using the efficient and HJ weighting matrices respectively. As expected the coefficients for the FF3 model are generally positive and significant. The minimum HJ distance in column four is 0.588 which is somewhat lower than the crime model's distance of 0.614. Finally, the last two columns show parameter estimates for the combined crime and FF3 model. The crime coefficients remain significantly negative when using the efficient weighting matrix, but decline and become insignificant with the HJ weighting matrix.

To gauge whether the combined crime and FF3 model improves upon the standalone crime and FF3 models, the Newey and West D-test is used to test the null that the pricing errors of the restricted standalone models are equal to the pricing errors of the unrestricted combined model with the efficient weighting matrix. For both the standalone crime and FF3 models, the null is rejected (p-value=0.000) which suggests that the combined model improves upon the pricing errors. In other words, neither set of factors is subsumed by the other.

2.8 Robustness

2.8.1 High Income Locations

Vissing-Jorgensen (2002) argues that the Euler equation holds only for households that possess a nonzero position in a financial asset. Using standard power utility over consumption, she finds significant estimates of the intertemporal elasticity of substitution (IES) for stock and bondholders, but finds insignificant IES estimates for non-asset holders. Previously, we saw that the price of risk on the crime moments were significant across all income locations. If the prices of risk remain significant across high income locations, we can be assured that crime growth in high income locations reflects changes in marginal utility for those most likely to hold stocks.[27] High income locations are defined as those cities and counties in the top third of household median income for each period. City and household median income is from the 1980, 1990, and 2000 decennial U.S. Census and the 2008-2012 U.S. Census' American Community Survey (ACS).[28] Crime data is matched to the nearest available census date. For example, crime data from 1975-1984 is matched to the 1980 census, while crime data from 2005-2012 is matched to the ACS.

[27] Using the National Incident Based Reporting System (NIBRS) daily crime dataset from 1991-2012, Huck (2015) states that the vast majority of assaults occur at home (61%) where the victim is related to or otherwise knows the offender (87% of home assaults). Therefore, we can be confident that the income groupings are meaningful for the offender.

[28] Census data is from the University of Minnesota Population Center's National Historical Geographic Information System (NHGIS): https://www.nhgis.org/.

Table 2.9 shows the cross-sectional pricing results for high income locations. The prices of risk remain negative and generally significant across all specifications. For example, the price of risk using the 25 size and book-to-market portfolios as test-assets is -4.64 (t_{FM}=2.36, t_{GMM}=1.37) for the cross-sectional average of crime growth and -4.07 (t_{GMM}=2.57) for the cross-sectional variance of crime growth. This is somewhat higher than the cross-sectional prices of risk across all income locations. The pricing errors for the crime specification compare reasonably well with those of the FF3 model. The crime model has a low pricing error on the zero-beta portfolio of 0.50 (t_{FM}=2.45, t_{GMM}=1.50), a reasonably high adjusted R^2 of 0.36, and a higher MAPE of 0.13 as compared to the FF3 model of 0.08. The T^2 test statistic remains insignificant for the crime model and significant for the FF3 model. The prices of risk for the crime moments also remain significant after controlling for the Fama and French factors with a price of risk of -3.51 (t_{GMM}=1.98) for the cross-sectional average of crime growth and -2.59 (t_{GMM}=1.92) for the cross-sectional variance of crime growth. The results are qualitatively similar on the 75 test-asset portfolios. The strong results for high-income locations suggest that the crime growth moments can proxy for the changes in marginal utility of those individuals who are most likely to hold stocks.

2.8.2 Controlling for Location Fixed-Effects and Weather

There is extensive literature that weather affects crime. For example, Jacob, Lefgren, and Moretti (2007) find that crime increases with temperature. There have also been a number of studies that link weather to market returns. For example, Cao and Wei (2005) find low temperatures are associated with higher returns internationally, while Saunders (1993) and

Hirshleifer and Shumway (2003) find that sunshine is associated with higher stock returns. To ensure that temperature is not driving the results, I orthogonalize the crime growth rate for each location using state-level heating and cooling degree day changes from NOAA.[29] Additionally, to ensure that unobserved location effects are not driving the results, I include police agency fixed effects. As previously, the cross-sectional average and variance of the orthogonal changes in crime rates are deseasonalized using monthly dummies, and the cross-sectional variance is differenced.

Table 2.10 shows the cross-sectional pricing results for the crime growth moments adjusted for weather and location fixed effects. The results are fairly consistent with the main results in Table 2.2. The prices of risk are generally significantly negative across all specifications, with the exception of the price of risk on the adjusted cross-sectional average of crime growth when controlling for the Fama and French factors using the 75 test-assets. The strong performance suggests that weather and time invariant location factors are not driving the results.

2.8.3 Common Idiosyncratic Volatility

Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2015) posit that the distribution of households' consumption growth inherits the same factor structure as firms' idiosyncratic risk in stock returns and cash flows because households cannot completely insulate their consumption from persistent shocks to their labor income. They construct an incomplete

[29] I utilize the weather data from the IHS database available on WRDS. Cooling degree days are defined as the sum over all days in the month of max(F-65,0), where F is the average population-weighted state temperature for that day in degrees Fahrenheit. Heating degree days are defined as the sum over all days in the month of max(65-F,0).

markets heterogeneous agent model where shocks to the common factor in idiosyncratic volatility (CIV) are priced. They argue that CIV carries a negative price of risk because an increase in idiosyncratic firm volatility raises the average household's marginal utility. Since assets that have higher betas to CIV pay off in bad times, they act as insurance and therefore command a negative price of risk.

To investigate whether the crime factors are priced in the presence of CIV shocks, I construct the CIV factor as in Herskovic et al. (2015). Each month, daily individual firm returns are regressed on the value-weighted market return for all CRSP firms with non-missing data that month. CIV is defined as the equal-weighted average of residual variance across firms, where residual variance is the variance of daily market model residuals within a month for each firm. CIV shocks are the factor of interest, and are monthly changes in CIV.

Table 2.11 shows the cross-sectional pricing results using the CIV shocks factor. The first column includes only the CIV factor, and shows that the price of risk on CIV is an insignificantly negative -0.07 (t_{GMM}=0.97) when using the 25 size and book-to-market portfolios as test-assets. The insignificant price of risk is surprising, given the results of Herskovic et al. (2015). However, their empirical results are over a longer time period and also includes the market factor. The second column shows that the crime factors remain significantly negative in the presence of CIV, with prices of risk that are similar to those in the base case. For example, the price of risk on the average of crime growth is -4.38 (t_{FM}=2.57, t_{GMM}=1.53), while that on the variance of crime growth is -2.97 (t_{GMM}=3.12). The third column shows a specification with the CIV and FF3 factors. Controlling for the FF3 factors, the price of risk on the CIV factor flips signs and becomes counterfactually positive and somewhat significant 0.12 (t_{FM}=1.84, t_{GMM}=1.61).

Finally, the fourth column shows a specification which includes the crime, CIV, and FF3 factors. The crime factors remain significantly negative, however, the price of risk on the CIV factor becomes insignificant. The remaining columns show the pricing results using the 75 test-asset portfolios and are qualitatively similar to the 25 test-asset portfolios. The strong performance of the crime factors suggest that crime captures changes in marginal utility that differ from those in CIV shocks.

2.8.4 Income Mimicking Portfolios

Next, I investigate whether the crime factors remain priced in the presence of factors that mimic the income growth distribution. Income growth is often used to proxy for consumption growth, and are often equivalent in theoretical models (e.g., Constantinides and Duffie, 1996). The highest quality source of cross-sectional income growth is from Guvenen, Ozkan, and Song (2014). Guvenen et al. report a number of cross-sectional moments of annual income growth using a 10% sample of males aged 24-60 from the Social Security Administration from 1979-2011. To match the monthly frequency and sample period of the crime data, I transform the income growth data using the mimicking portfolio technique. Specifically, I regress the median, variance, and skewness of annual income growth on annual returns of the six size and book-to-market portfolios. The coefficients on each of the annual size and book-to market portfolios are the weights used to construct the income mimicking portfolios (IMPs). The monthly IMP returns are thus the weights multiplied by the monthly size and book-to-market portfolio returns.

The expected signs for the cross-sectional moments of income growth (as a proxy for consumption growth) are positive for the average of income growth, negative for the variance of income growth, and positive for the skewness of income growth. Skewness commands a positive price of risk, because more positive income shocks (or less negative shocks) reflect good states, and assets that pay off in good states require higher expected returns. However, Table 2.12 shows that the prices of risk on the IMP factors diverge from expectations. Specifically, the first column shows that when using the 25 size and book-to-market portfolios as test assets, the price of risk on the median of income growth is an insignificantly positive 0.013 (t_{GMM}=1.27), on the variance of income growth is a counterfactually positive 0.001 (t_{GMM}=3.56), and on the skewness of income growth is a counterfactually negative -0.004 (t_{GMM}=2.40). The second column shows that the coefficients on the IMP factors are slightly lower in the presence of the FF3 factors. The third column shows that the crime factors remain similar to the base case after controlling for the IMP factors, with a price of risk of -3.54 (t_{FM}=2.51, t_{GMM}=1.86) on the average of crime growth and -1.86 (t_{FM}=2.20, t_{GMM}=1.63) on the variance of crime growth. The IMP factors remain similar to their base case. Finally, the fourth column shows a specification which includes both crime factors, the three IMP factors, and FF3 factors. The price of risk on the average of crime growth drops to an insignificant -1.09 (t_{GMM}=0.70), while that on the variance of crime growth remains a significant -1.65 (t_{GMM}=2.42). The remaining columns show the results with the 75 test asset portfolios and are qualitatively similar, with the exception of neither crime factor remaining significant when controlling for the three IMP and FF3 factors.

2.8.5 Initial Unemployment Claims

Schmidt (2015) proposes idiosyncratic tail risk as a key driver of asset prices and suggests initial unemployment claims as a high frequency observable proxy for the cross-sectional skewness of household income growth. Although he does not show the cross-sectional pricing implications of initial claims, he finds that the level of initial claims can help predict market returns at 3-month, 1-year, and 2-year horizons. To investigate whether the crime factors are priced in the presence of initial claims, I construct an initial claims index as in Schmidt (2015). The claims index is defined as the number of initial claims for unemployment insurance divided by the size of the workforce from the Bureau of Labor Statistics (BLS). The claims index is also differenced because it is highly persistent.

Table 2.13 shows the cross-sectional pricing results using the claims factor. The first column shows that initial claims by itself carries an insignificantly negative price of risk of -0.02 (t_{GMM}=0.60) when using the 25 size and book-to-market portfolios as test assets. A negative price of risk is expected because an increase in initial unemployment claims are associated with bad states. The second column shows that the crime factors remain significantly negative in the presence of the initial claims factor, with prices of risk that are similar to those in the base case. For example, the price of risk on the average of crime growth is -5.26 (t_{FM}=3.07, t_{GMM}=1.87), while that on the variance of crime growth is -3.53 (t_{GMM}=2.91). The third column shows a specification with initial claims and the FF3 factors. Controlling for the FF3 factors, the price of risk on initial claims flips signs and becomes insignificantly positive. Finally, the fourth column shows a specification which includes the crime, initial claims, and FF3 factors. The crime factors remain similar to the specification without the FF3 factors, however, the price of risk on the claims factor is insignificantly negative. The remaining columns show the pricing results using the 75 test-asset portfolios and are qualitatively similar to the 25 test-asset portfolios.

2.8.6 Other Macroeconomic Variables

As previously mentioned, the economics literature suggests that crime is a plausible measure of marginal utility because crime increases in bad economic states. For example, crime is negatively associated with state GDP growth (Arvanites and Defina, 2006), negatively associated with the Consumer Sentiment Index (Rosenfeld and Fornango, 2007; Rosenfeld, 2009), and positively associated with unemployment (Freeman, 1999). It is therefore helpful to understand whether the crime factors are driven out by these other measures of the economy. We previously saw that changes in unemployment claims do not price the cross-section of stock returns, and in Table 2.14 we see that changes in consumption and consumer sentiment also do not explain stock returns. For example, when using the 25 size and book-to-market portfolios as test assets, the price of risk on consumption growth is an insignificant 0.041 (t_{GMM}=0.379), while the price of risk on changes in consumer sentiment is an insignificant 0.003 (t_{GMM}=0.314). When the crime factors are combined with consumption, consumer sentiment, and unemployment claims, the crime factors remain significant, while the other economic factors remain generally insignificant. Similar results are found when using the 75 test asset portfolios. The significance of the crime factors in the presence of the economic factors suggest that the crime may be a better proxy of marginal utility than the other measures of the economy.

2.9 Conclusion

In this paper, I propose violent crime growth as a new measure of revealed marginal utility growth of heterogeneous consumers in incomplete markets. Heterogeneity is measured by exploiting a second order Taylor expansion of my proxy for marginal utility growth and modeling the SDF as a function of both the cross-sectional average and cross-sectional variance of crime growth using a panel of crime data for almost every city and county in the US. Consistent with heterogeneous consumer models such as Mankiw (1986), I find that the cross-sectional average and variance of violent crime growth can explain the cross-section of stock returns. Both cross-sectional moments carry negative prices of risk, which suggests that investors pay a premium for assets that have higher betas with the average and variance of violent crime growth. The negative price of risk is expected because increases in violent crime are associated with bad states of the world, and assets that pay off in bad states provide insurance. The results are supportive of consumption-based asset pricing models that assume changes in marginal utility price assets, but they also suggest that the assumption of a representative agent may be too strong and measures of heterogeneity should be considered.

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Figure 2.1 Average and Variance of Crime Growth

Monthly time series of the seasonally adjusted cross-sectional average of crime growth (top panel), and differenced seasonally adjusted cross-sectional variance of crime growth (bottom panel). Seasonal adjustment is performed by a regression of each cross-sectional moment on twelve monthly dummies and extracting the residual. Cross-sectional moments are calculated for a panel of crime growth for U.S. cities and counties as described in the text. Shaded areas in gray represent NBER recessions.

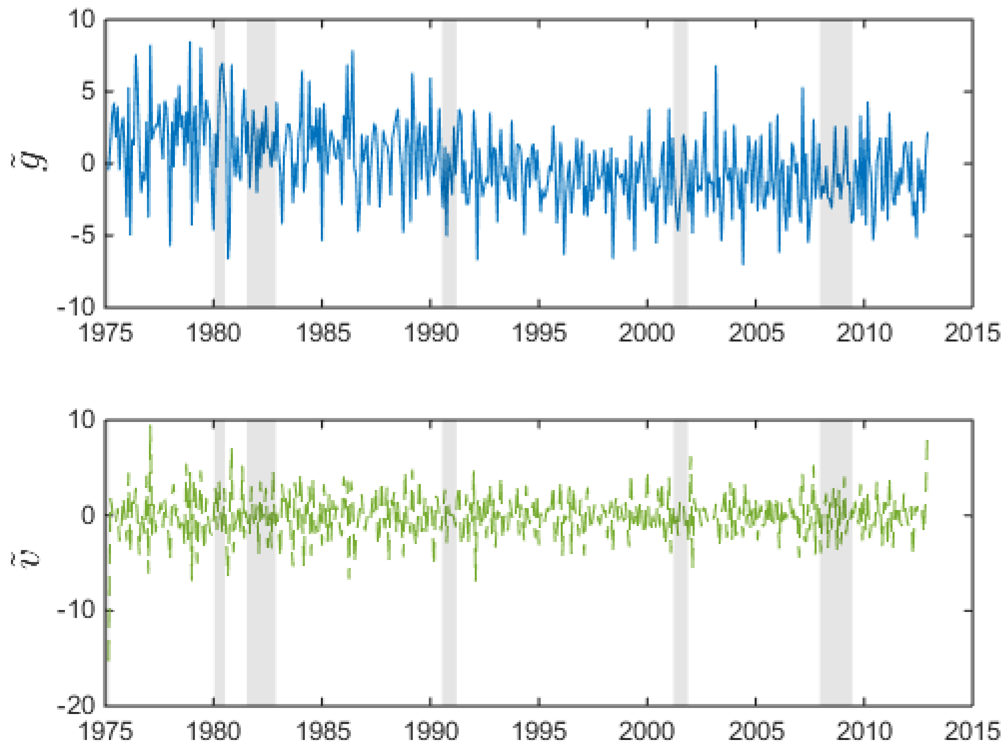

Figure 2.2 Long-Short Cumulative Returns

Crime long-short portfolios sorted by expected returns are generated using the following procedure. First, using all NYSE, NASDAQ, and AMEX stocks from CRSP with prices greater than $5, rolling 60-month crime exposures for each stock are estimated following (2.14). Second, expected returns are estimated using both the estimated crime betas and prices of risk for the firm-level regressions in the first column of Table 2.3. Third, within each NYSE size quintile each stock is sorted by its expected return and placed into quintiles, with the long side having the highest quintile of expected returns while the short side has the lowest quintile of expected returns. The resulting long and short portfolios are equal weighted and rebalanced monthly. For comparison, the long-short Fama and French (1993) HML (high minus low book to market) and SMB (small minus big) factors are also plotted. Cumulative returns represent the cumulative arithmetic sum of returns. Areas in gray represent NBER recessions.

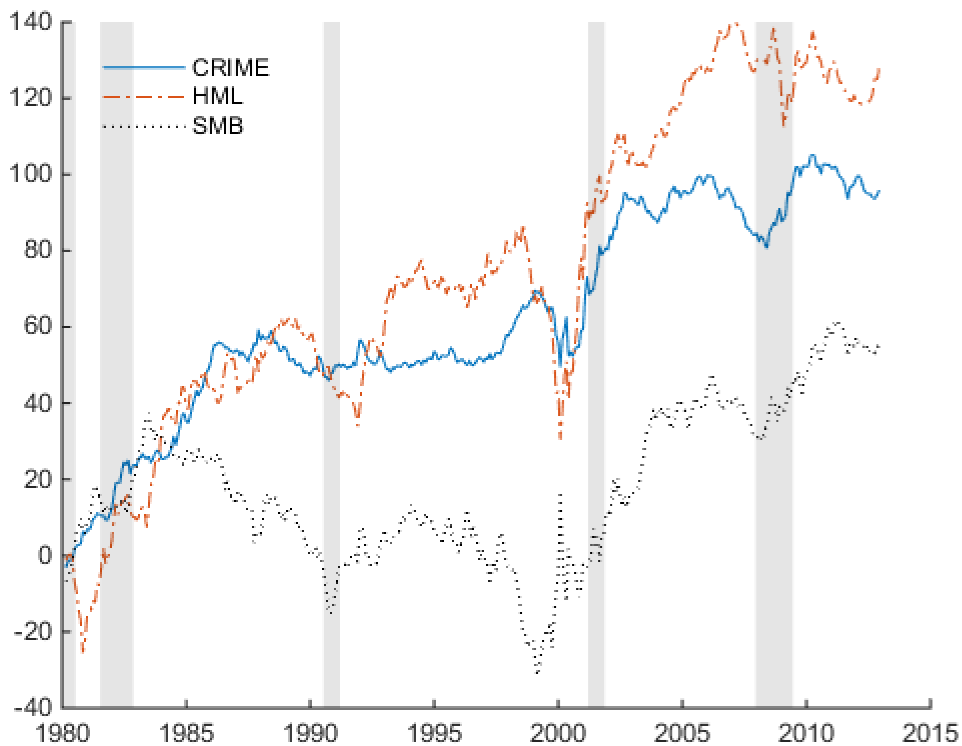

Figure 2.3 Crime Mimicking Portfolio Cumulative Returns

Cumulative returns for the cross-sectional average of crime growth mimicking portfolio (CMP Avg) and the cross-sectional variance of crime growth mimicking portfolio (CMP Var). The crime mimicking portfolios are constructed by regressing the nontraded crime growth moments ($\tilde{g}$ and $\tilde{v}$) onto a set of excess return benchmark portfolios with the mimicking portfolio defined as the fitted value (excluding the constant). The benchmark portfolios include the six Fama and French benchmark portfolios sorted on size and book-to-market. Cumulative returns cover July 1952 to December 2013, and represent the cumulative arithmetic sum of returns. Areas in gray represent NBER recessions.

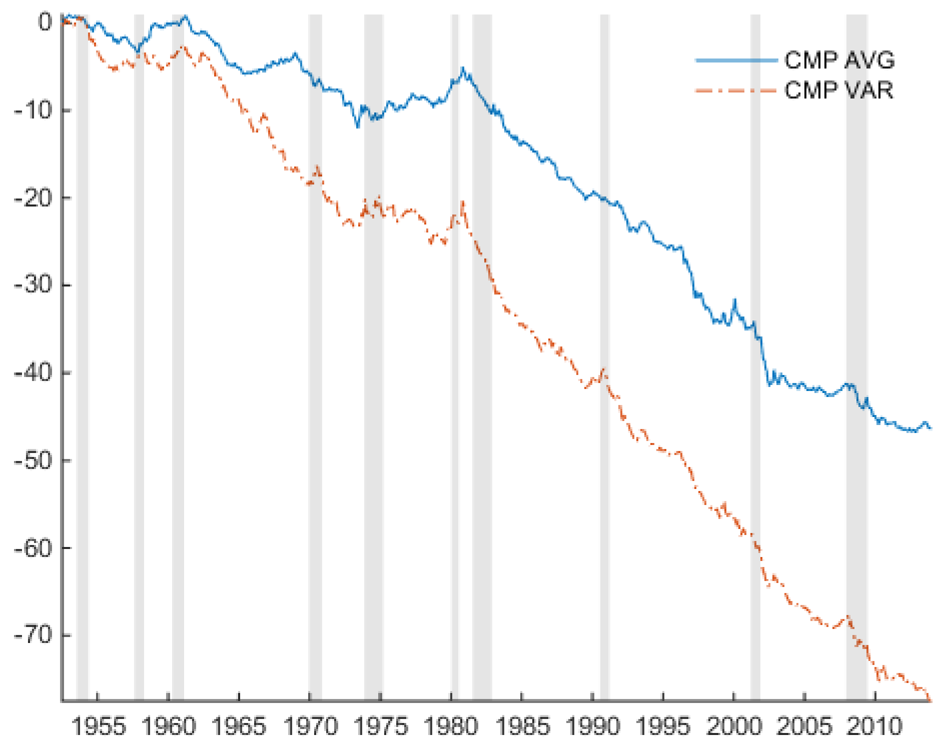

Table 2.1 Summary Statistics

Summary statistics of the seasonally adjusted cross-sectional average of crime growth ($\tilde{g}$), and differenced seasonally adjusted cross-sectional variance of crime growth ($\tilde{v}$). Seasonal adjustment is performed by a regression of each cross-sectional moment on twelve monthly dummies and extracting the residual. Cross-sectional moments are calculated for a panel of crime growth for U.S. cities and counties as described in the text. Also presented are summary statistics for the Fama and French (1993) three factors (MKT, HML, and SMB). The returns and crime factors are multiplied by 100 for all results. Data is monthly from March 1975 to December 2012.

	Avg	Std	Q1	Med	Q3
$\tilde{g}$	-0.018	2.820	-2.013	-0.096	1.751
$\tilde{v}$	-0.034	2.554	-1.560	-0.021	1.485
MKT	0.588	4.530	-1.960	1.030	3.600
HML	0.350	2.990	-1.200	0.335	1.780
SMB	0.271	3.063	-1.310	0.160	2.080

Table 2.2 Portfolio-Level Fama MacBeth Regressions Estimates

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure outlined in equations (2.14) through (2.17). Factors to explain test-asset returns include the cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios (SZ X BM), while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum (MO), total accruals (TA), asset growth (AG), share issuance (SI), and profitability (ROE). $\bar{R}^2_{OLS}$ denotes the OLS cross-sectional adjusted r-squared. MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

Panel A: Regression Estimates

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) ALL	(5) ALL	(6) ALL
$\hat{\gamma}_g$	-3.027		-2.386	-2.971		-1.089
	[1.941]		[1.963]	[2.799]		[2.340]
	{1.372}		{1.356}	{2.264}		{1.997}
$\hat{\gamma}_v$	-3.582		-2.330	-2.863		-1.344
	[4.867]		[3.684]	[4.456]		[2.868]
	{2.988}		{2.970}	{3.230}		{2.637}
$\hat{\gamma}_{MKT}$		-0.814	-0.863		-1.462	-1.392
		[2.214]	[2.267]		[3.925]	[3.671]
		{2.162}	{1.609}		{3.112}	{2.614}
$\hat{\gamma}_{SMB}$		0.194	0.247		0.225	0.253
		[1.322]	[1.697]		[1.528]	[1.737]
		{1.296}	{1.648}		{1.528}	{1.781}
$\hat{\gamma}_{HML}$		0.380	0.341		0.310	0.270
		[2.642]	[2.379]		[2.072]	[1.830]
		{2.127}	{1.893}		{1.628}	{1.491}
$\hat{\gamma}_0$	0.687	1.451	1.487	0.668	2.101	2.029
	[3.295]	[4.894]	[4.781]	[3.487]	[6.759]	[6.362]
	{2.113}	{4.042}	{3.116}	{2.250}	{4.736}	{3.954}
$\bar{R}^2_{OLS}$	0.459	0.620	0.790	0.257	0.595	0.622
MAPE	0.133	0.081	0.068	0.160	0.113	0.109
T^2	19.795	54.158	22.561	66.102	145.763	111.403
p-value	0.596	0.000	0.257	0.674	0.000	0.001

Panel B: Mean Absolute Pricing Errors (MAPE) by test assets

Asset	(1)	(2)	(3)	(4)	(5)	(6)
SZ X BM	0.133	0.081	0.068	0.154	0.100	0.083
MO				0.268	0.175	0.185
TA				0.177	0.085	0.110
AG				0.090	0.097	0.092
SI				0.150	0.131	0.120
ROE				0.128	0.111	0.101

Table 2.3 Firm-Level Fama MacBeth Regressions Estimates

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Betas for each firm are estimated following Dimson (1972) with one lag over a 60-month rolling window. Each month, firms are sequentially sorted first into 10 portfolios by the variance of crime growth beta and then into an additional 10 portfolios by the average of crime growth beta, for a total of 100 equal weighted portfolios. Full time series betas are estimated for all 100 portfolios, and assigned to the firms that belong to each portfolio. Prices of risk and standard errors are calculated as in equations (2.16) and (2.17) respectively. All NYSE, AMEX, and NASDAQ stocks in CRSP with prices greater than $5 are included. $\bar{R}^2_{FM}$ denotes the average cross-sectional adjusted r-squared, while $\bar{N}$ denotes the average cross-sectional number of test-assets across all *T* periods. In brackets are *t*-statistics that use Fama and MacBeth standard errors.

	(1)	(2)	(3)
$\hat{\gamma}_g$	-0.874		-0.359
	[1.612]		[1.214]
$\hat{\gamma}_v$	-1.210		-0.710
	[3.008]		[2.290]
$\hat{\gamma}_{MKT}$		-0.032	-0.042
		[0.077]	[0.102]
$\hat{\gamma}_{SMB}$		-0.011	-0.016
		[0.044]	[0.071]
$\hat{\gamma}_{HML}$		0.658	0.552
		[2.229]	[2.016]
$\hat{\gamma}_0$	0.812	0.629	0.685
	[3.721]	[2.056]	[2.217]
$\bar{R}^2_{FM}$	0.003	0.009	0.010
$\bar{N}$	2729	2729	2729
T	394	394	394

Table 2.4 Expected Return Portfolio Sorts

Portfolios sorted by expected returns are generated using the following procedure. First, using all NYSE, NASDAQ, and AMEX stocks from CRSP with prices greater than $5, rolling 60-month crime exposures for each stock are estimated following (2.14). Second, expected returns are estimated using both the estimated crime betas and prices of risk for the firm-level regressions in the first column of Table 2.3. Third, within each NYSE size quintile each stock is sorted by its expected return and placed into quintiles, with Q5 having the highest expected returns while Q1 has the lowest expected returns. The resulting quintile portfolios are equal weighted and rebalanced monthly. Panel A presents quintile returns for each portfolio, while Panel B presents returns and correlations of the Q5-Q1 long-short portfolio (CRIME) with the Fama and French (1993) factors. Returns are monthly from March 1980 to December 2012.

Panel A: Crime portfolio quintile returns

Quintile	Avg	*t*-stat
Q1 (Low)	1.033	3.67
Q2	1.192	5.23
Q3	1.239	5.55
Q4	1.261	5.43
Q5 (High)	1.275	4.56
Q5-Q1	0.243	2.70

Panel B: Return summary statistics and correlations

					Correlation			
	Avg	Std	Sharpe	*t*-stat	CRIME	MKT	HML	SMB
CRIME	0.243	1.783	0.136	2.705	1.000	-0.016	0.351	-0.169
MKT	0.574	4.592	0.125	2.481	-0.016	1.000	-0.344	0.238
HML	0.324	3.100	0.105	2.075	0.351	-0.344	1.000	-0.317
SMB	0.141	3.105	0.045	0.901	-0.169	0.238	-0.317	1.000

Table 2.5 Crime Beta Sorted Portfolios as Test Assets

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure outlined in equations (2.14) through (2.17). Factors to explain test-asset returns include the cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors (MKT, SMB, and HML). Test-assets include firms sorted by their crime betas. Betas for each firm are estimated following Dimson (1972) with one lag over a 60-month rolling window. Each month, firms are sequentially sorted first into 5 portfolios by the variance of crime growth beta and then into an additional 5 portfolios by the average of crime growth beta, for a total of 25 equal weighted portfolios. MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Returns are monthly from March 1980 to December 2012.

	(1)	(2)	(3)
$\hat{\gamma}_g$	-2.238		-0.886
	[1.851]		[1.428]
	{1.293}		{0.950}
$\hat{\gamma}_v$	-3.052		-1.868
	[2.645]		[1.996]
	{1.894}		{1.617}
$\hat{\gamma}_{MKT}$		0.004	0.36
		[0.006]	[0.544]
		{0.006}	{0.417}
$\hat{\gamma}_{SMB}$		-0.016	-0.273
		[0.041]	[0.600]
		{0.036}	{0.426}
$\hat{\gamma}_{HML}$		0.707	0.283
		[1.619]	[0.511]
		{1.498}	{0.388}
$\hat{\gamma}_0$	0.849	0.585	0.548
	[4.032]	[1.319]	[1.235]
	{2.350}	{1.436}	{0.944}
$\bar{R}^2_{OLS}$	0.325	0.454	0.531
MAPE	0.074	0.063	0.057
T^2	15.607	42.739	23.958
p-value	0.835	0.003	0.198

Table 2.6 Crime Mimicking Portfolio Summary Statistics

Monthly return summary statistics of the cross-sectional average of crime growth mimicking portfolio (CMP Avg), the cross-sectional variance of crime growth mimicking portfolio (CMP Var), and the Fama and French (1993) three factors (MKT, SMB, and HML). The crime mimicking portfolios are constructed by regressing the nontraded crime growth moments ($\tilde{g}$ and $\tilde{v}$) onto a set of excess return benchmark portfolios with the mimicking portfolio defined as the fitted value (excluding the constant). The benchmark portfolios include the six Fama and French benchmark portfolios sorted on size and book-to-market. Panel A covers March 1975 to December 2012, while Panel B covers July 1952 to December 2013.

Panel A: March 1975 to December 2012

					Correlation				
	Avg	Std	Sharpe	*t*-stat	CMP Avg	CMP Var	MKT	HML	SMB
CMP Avg	-0.079	0.368	-0.215	4.574	1.000	0.614	0.247	-0.290	0.298
CMP Var	-0.121	0.404	-0.300	6.382	0.614	1.000	-0.170	-0.128	-0.387
MKT	0.588	4.530	0.130	2.766	0.247	-0.170	1.000	-0.317	0.256
HML	0.350	2.990	0.117	2.494	-0.290	-0.128	-0.317	1.000	-0.272
SMB	0.271	3.063	0.088	1.885	0.298	-0.387	0.256	-0.272	1.000

Panel B: July 1952 to December 2013

					Correlation				
	Avg	Std	Sharpe	*t*-stat	CMP Avg	CMP Var	MKT	HML	SMB
CMP Avg	-0.063	0.346	-0.182	4.946	1.000	0.560	0.206	-0.198	0.311
CMP Var	-0.105	0.408	-0.257	6.991	0.560	1.000	-0.282	-0.093	-0.413
MKT	0.583	4.339	0.134	3.650	0.206	-0.282	1.000	-0.268	0.275
HML	0.354	2.713	0.130	3.545	-0.198	-0.093	-0.268	1.000	-0.211
SMB	0.199	2.908	0.068	1.859	0.311	-0.413	0.275	-0.211	1.000

Table 2.7 Crime Mimicking Portfolio Cross-Sectional and Time-Series Estimates

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure outlined in equations (2.14) through (2.17). Factors to explain test-asset returns include the cross-sectional average of crime growth mimicking portfolio (CMP Avg), the cross-sectional variance of crime growth mimicking portfolio (CMP Var), and the Fama and French (1993) three factors (MKT, SMB, and HML) described in Table 2.5. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum (MO), total accruals (TA), asset growth (AG), share issuance (SI), and profitability (ROE). $\bar{R}^2_{OLS}$ denotes the OLS cross-sectional adjusted r-squared. MAPE is the cross-sectional mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the cross-sectional pricing errors are jointly zero. The GRS (Gibbons, Ross, and Shanken, 1989) *F*-statistic and its associated *p*-value tests the null that the time-series pricing errors (alphas) are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Panel A covers March 1975 to December 2012, while Panel B covers July 1952 to December 2013.

Panel A: March 1975 to December 2012

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) ALL	(5) ALL	(6) ALL
$\hat{\gamma}_{CMP\ Avg}$	-0.108		-0.082	-0.150		-0.110
	[3.829]		[3.958]	[4.935]		[4.936]
	{2.936}		{3.590}	{3.983}		{4.309}
$\hat{\gamma}_{CMP\ Var}$	-0.140		-0.098	-0.188		-0.108
	[4.740]		[3.914]	[5.533]		[4.723]
	{3.653}		{3.941}	{4.301}		{4.217}
$\hat{\gamma}_{MKT}$		-0.814	-0.234		-1.462	-0.836
		[2.214]	[0.575]		[3.925]	[2.422]
		{2.162}	{0.693}		{3.112}	{2.061}
$\hat{\gamma}_{SMB}$		0.194	0.224		0.225	0.301
		[1.322]	[1.535]		[1.528]	[2.057]
		{1.296}	{1.485}		{1.528}	{1.995}
$\hat{\gamma}_{HML}$		0.380	0.310		0.310	0.263
		[2.642]	[2.170]		[2.072]	[1.764]
		{2.127}	{1.749}		{1.628}	{1.352}
$\hat{\gamma}_0$	0.660	1.451	0.903	0.582	2.101	1.480
	[2.972]	[4.894]	[2.679]	[2.845]	[6.759]	[5.385]
	{2.913}	{4.042}	{2.819}	{2.524}	{4.736}	{4.035}
$\bar{R}^2_{OLS}$	0.732	0.620	0.762	0.589	0.595	0.701
MAPE	0.071	0.081	0.066	0.117	0.113	0.096
T^2	52.774	54.158	45.015	132.524	145.763	131.151
p-value	0.000	0.000	0.001	0.000	0.000	0.000
GRS F	3.077	3.717	2.628	2.241	2.541	2.141
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: Mean absolute pricing errors (1975-2012)

Asset	(1)	(2)	(3)	(4)	(5)	(6)
SZ X BM	0.071	0.081	0.066	0.113	0.100	0.095
MO				0.186	0.175	0.151
TA				0.138	0.085	0.088
AG				0.080	0.097	0.067
SI				0.104	0.131	0.096
ROE				0.085	0.111	0.079

Panel C: July 1952 to December 2013

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) ALL	(5) ALL	(6) ALL
$\hat{\gamma}_{CMP\ Avg}$	-0.112		-0.079	-0.132		-0.092
	[5.333]		[4.900]	[6.274]		[5.503]
	{4.216}		{4.670}	{5.408}		{5.039}
$\hat{\gamma}_{CMP\ Var}$	-0.143		-0.098	-0.169		-0.084
	[6.109]		[4.557]	[6.705]		[4.123]
	{5.170}		{4.905}	{5.530}		{3.437}
$\hat{\gamma}_{MKT}$		-0.799	0.049		-1.503	-0.942
		[2.521]	[0.138]		[5.096]	[3.189]
		{2.447}	{0.151}		{4.035}	{2.660}
$\hat{\gamma}_{SMB}$		0.145	0.170		0.159	0.223
		[1.316]	[1.556]		[1.448]	[2.048]
		{1.184}	{1.383}		{1.322}	{1.803}
$\hat{\gamma}_{HML}$		0.372	0.323		0.231	0.227
		[3.620]	[3.159]		[2.160]	[2.126]
		{3.002}	{2.589}		{1.788}	{1.729}
$\hat{\gamma}_0$	0.590	1.405	0.592	0.474	2.140	1.580
	[3.492]	[5.142]	[1.918]	[2.953]	[8.514]	[6.298]
	{3.201}	{4.269}	{1.759}	{2.460}	{6.037}	{4.696}
$\bar{R}^2_{OLS}$	0.719	0.670	0.847	0.424	0.489	0.586
MAPE	0.064	0.079	0.052	0.122	0.115	0.100
T^2	39.941	45.700	29.011	164.379	178.273	159.675
p-value	0.011	0.001	0.066	0.000	0.000	0.000
GRS F	2.687	3.243	2.010	2.874	3.170	2.689
p-value	0.000	0.000	0.003	0.000	0.000	0.000

Panel D: Mean absolute pricing errors (1952-2013)

Asset	(1)	(2)	(3)	(4)	(5)	(6)
SZ X BM	0.064	0.079	0.052	0.113	0.097	0.083
MO				0.238	0.212	0.207
TA				0.134	0.091	0.092
AG				0.072	0.096	0.061
SI				0.117	0.144	0.119
ROE				0.071	0.078	0.066

Table 2.8 Linear GMM/SDF Estimates

Linear GMM estimates, where factors to explain test-asset returns include the cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors. Test-assets include the 25 size and book-to market portfolios, supplemented with 10 portfolios each sorted by the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). The weighting matrix used in the GMM estimation is indicated in the column header. S^{-1} signifies the optimal weighting matrix of Hansen (1982), while HJ signifies the inverse of the second moment matrix of returns as advocated by Hansen and Jagannthan (1997). TJ_T is the χ^2 test statistic of over-identifying restrictions and tests the null that the pricing errors are jointly zero. HJ *dist* is the Hansen and Jagannathan (1997) distance, which when using the HJ weighting matrix measures the least-square distance between the given candidate SDF and the nearest point to it in the set of all SDFs that price assets correctly. In parentheses are standard errors. Further details of the GMM procedure can be found in Appendix B.2. Data is monthly from March 1975 to December 2012.

	S^{-1}	HJ	S^{-1}	HJ	S^{-1}	HJ
$\hat{b}_g$	-0.079	-0.066			-0.154	-0.069
	(0.023)	(0.056)			(0.023)	(0.052)
$\hat{b}_v$	-0.184	-0.080			-0.147	-0.053
	(0.024)	(0.042)			(0.024)	(0.041)
$\hat{b}_{MKT}$			0.063	-0.019	0.062	-0.017
			(0.005)	(0.015)	(0.006)	(0.015)
$\hat{b}_{HML}$			0.111	0.054	0.096	0.050
			(0.008)	(0.020)	(0.009)	(0.020)
$\hat{b}_{SMB}$			0.059	0.061	0.025	0.059
			(0.006)	(0.016)	(0.007)	(0.016)
TJ_T	719.009	773.917	654.742	635.543	395.291	525.079
p-value	0.000	0.000	0.000	0.000	0.000	0.000
HJ dist	0.627	0.614	0.647	0.588	0.653	0.576
MAPE	0.636	0.670	0.648	0.933	0.480	0.910

Table 2.9 Hi Income Location Fama MacBeth Regressions Estimates

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include the cross-sectional average of crime growth for high income locations (gHi), the cross-sectional variance of crime growth for high income locations (vHi), and the Fama and French (1993) three factors (MKT, SMB, and HML). Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). $\bar{R}^2_{OLS}$ denotes the OLS cross-sectional adjusted r-squared. MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are t-statistics that use Fama and MacBeth standard errors, and in braces are t-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) ALL	(5) ALL	(6) ALL
$\hat{\gamma}_{gHi}$	-4.644		-3.505	-4.004		-2.118
	[2.361]		[3.094]	[4.540]		[3.710]
	{1.373}		{1.978}	{2.889}		{2.576}
$\hat{\gamma}_{vHi}$	-4.065		-2.592	-3.757		-2.186
	[4.173]		[2.909]	[3.795]		[2.806]
	{2.571}		{1.918}	{2.595}		{2.009}
$\hat{\gamma}_{MKT}$		-0.814	-0.641		-1.462	-1.201
		[2.214]	[1.594]		[3.925]	[3.440]
		{2.162}	{1.179}		{3.112}	{2.299}
$\hat{\gamma}_{SMB}$		0.194	0.265		0.225	0.266
		[1.322]	[1.823]		[1.528]	[1.819]
		{1.296}	{1.782}		{1.528}	{1.878}
$\hat{\gamma}_{HML}$		0.380	0.341		0.310	0.294
		[2.642]	[2.371]		[2.072]	[1.970]
		{2.127}	{1.931}		{1.628}	{1.606}
$\hat{\gamma}_0$	0.499	1.451	1.273	0.397	2.101	1.829
	[2.449]	[4.894]	[3.763]	[1.866]	[6.759]	[6.520]
	{1.497}	{4.042}	{2.581}	{1.239}	{4.736}	{3.637}
$\bar{R}^2_{OLS}$	0.355	0.620	0.792	0.261	0.595	0.661
MAPE	0.132	0.081	0.070	0.164	0.113	0.105
T^2	15.875	54.158	18.138	50.444	145.763	85.094
p-value	0.822	0.000	0.513	0.975	0.000	0.091

Table 2.10 Orthogonalized Fama MacBeth Regressions Estimates

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include the cross-sectional average of crime growth adjusted for temperature and location fixed effects ($gAdj$), the adjusted cross-sectional variance of crime growth ($vAdj$), and the Fama and French (1993) three factors (MKT, SMB, and HML). Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). $\bar{R}^2_{OLS}$ denotes the OLS cross-sectional adjusted r-squared. MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are t-statistics that use Fama and MacBeth standard errors, and in braces are t-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
	SZ X BM	SZ X BM	SZ X BM	ALL	ALL	ALL
$\hat{\gamma}_{gAdj}$	-3.927		-2.796	-2.634		-0.462
	[1.897]		[3.072]	[2.519]		[0.803]
	{1.266}		{2.046}	{1.767}		{0.500}
$\hat{\gamma}_{vAdj}$	-2.950		-1.915	-2.386		-1.290
	[3.812]		[3.163]	[3.750]		[2.741]
	{2.547}		{2.754}	{2.751}		{2.424}
$\hat{\gamma}_{MKT}$		-0.814	-0.888		-1.462	-1.456
		[2.214]	[2.388]		[3.925]	[3.883]
		{2.162}	{1.758}		{3.112}	{2.881}
$\hat{\gamma}_{SMB}$		0.194	0.249		0.225	0.255
		[1.322]	[1.708]		[1.528]	[1.748]
		{1.296}	{1.689}		{1.528}	{1.783}
$\hat{\gamma}_{HML}$		0.380	0.334		0.310	0.270
		[2.642]	[2.328]		[2.072]	[1.829]
		{2.127}	{1.839}		{1.628}	{1.485}
$\hat{\gamma}_0$	0.841	1.451	1.523	0.675	2.101	2.091
	[3.515]	[4.894]	[5.066]	[3.568]	[6.759]	[6.685]
	{2.214}	{4.042}	{3.412}	{2.403}	{4.736}	{4.389}
$\bar{R}^2_{OLS}$	0.487	0.620	0.822	0.178	0.595	0.620
MAPE	0.115	0.081	0.063	0.170	0.113	0.109
T^2	16.683	54.158	19.906	75.724	145.763	114.525
p-value	0.781	0.000	0.400	0.359	0.000	0.000

Table 2.11 Common Idiosyncratic Volatility Shocks

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include the common idiosyncratic volatility shocks, cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors (MKT, SMB, and HML). CIV is defined as the equal-weighted average of residual variance across firms, where residual variance is the variance of daily market model residuals within a month for each firm. CIV shocks are the factor of interest, and are monthly changes in CIV. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) SZ X BM	(5) ALL	(6) ALL	(7) ALL	(8) ALL
$\hat{\gamma}_g$		-4.377		-2.434		-3.447		-1.086
		[2.570]		[1.965]		[3.662]		[2.327]
		{1.531}		{1.374}		{2.727}		{1.967}
$\hat{\gamma}_v$		-2.966		-2.242		-2.511		-1.336
		[4.550]		[3.853]		[4.155]		[2.873]
		{3.119}		{3.022}		{3.181}		{2.629}
$\hat{\gamma}_{CIV}$	-0.069	-0.134	0.123	0.026	-0.026	-0.064	0.027	0.014
	[1.035]	[2.260]	[1.837]	[0.431]	[0.440]	[1.241]	[0.653]	[0.353]
	{0.968}	{1.159}	{1.613}	{0.340}	{0.415}	{0.670}	{0.554}	{0.271}
$\hat{\gamma}_{MKT}$			-0.593	-0.796			-1.453	-1.388
			[1.450]	[1.877]			[3.965]	[3.718]
			{1.331}	{1.335}			{3.175}	{2.649}
$\hat{\gamma}_{SMB}$			0.209	0.250			0.227	0.254
			[1.430]	[1.716]			[1.542]	[1.742]
			{1.432}	{1.683}			{1.557}	{1.799}
$\hat{\gamma}_{HML}$			0.391	0.343			0.311	0.271
			[2.705]	[2.391]			[2.081]	[1.838]
			{2.244}	{1.920}			{1.644}	{1.509}
$\hat{\gamma}_0$	0.580	0.462	1.243	1.424	0.591	0.572	2.093	2.026
	[2.419]	[1.973]	[3.671]	[4.016]	[2.819]	[2.719]	[6.871]	[6.468]
	{2.091}	{1.013}	{2.815}	{2.667}	{2.669}	{1.587}	{4.869}	{4.022}
$\bar{R}^2_{OLS}$	0.058	0.590	0.635	0.780	-0.004	0.274	0.590	0.617
MAPE	0.156	0.107	0.085	0.069	0.180	0.154	0.113	0.109
T^2	76.747	16.612	48.103	22.801	183.198	63.092	144.837	111.079
p-value	0.000	0.734	0.000	0.198	0.000	0.737	0.000	0.001

Table 2.12 Income Mimicking Portfolios

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include income mimicking portfolios (IMP) on the cross-sectional median, variance, and skewness of income growth, the cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors (MKT, SMB, and HML). Mimicking portfolios are constructed by regressing the annual income growth moments on annual returns of six size and book-to-market portfolios, and applying the fitted coefficients to monthly returns. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) SZ X BM	(5) ALL	(6) ALL	(7) ALL	(8) ALL
$\hat{\gamma}_g$			-3.544	-1.093			-1.000	-0.224
			[2.507]	[0.868]			[2.067]	[0.473]
			{1.863}	{0.698}			{1.802}	{0.364}
$\hat{\gamma}_v$			-1.855	-1.654			-0.985	-0.113
			[2.196]	[2.340]			[2.001]	[0.271]
			{1.630}	{2.418}			{1.741}	{0.257}
$\hat{\gamma}_{IMP\ Med}$	0.013	0.006	0.012	0.000	0.014	0.000	0.014	0.001
	[1.350]	[0.643]	[1.304]	[0.008]	[1.413]	[0.034]	[1.388]	[0.059]
	{1.268}	{0.693}	{1.086}	{0.008}	{1.233}	{0.033}	{1.300}	{0.057}
$\hat{\gamma}_{IMP\ Var}$	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.001
	[4.702]	[4.379]	[4.602]	[4.339]	[5.651]	[5.251]	[5.601]	[5.231]
	{3.594}	{3.626}	{3.160}	{3.451}	{3.889}	{4.840}	{4.495}	{4.797}
$\hat{\gamma}_{IMP\ Skew}$	-0.004	-0.003	-0.005	-0.005	-0.008	-0.007	-0.009	-0.007
	[2.428]	[1.639]	[2.832]	[2.458]	[3.766]	[3.535]	[4.046]	[3.677]
	{2.400}	{1.732}	{2.314}	{2.218}	{3.190}	{3.538}	{3.224}	{3.779}
$\hat{\gamma}_{MKT}$		-0.254		-0.636		-0.807		-0.793
		[0.627]		[1.587]		[2.312]		[2.324]
		{0.738}		{1.331}		{2.085}		{1.974}
$\hat{\gamma}_{SMB}$		0.242		0.250		0.305		0.305
		[1.674]		[1.725]		[2.093]		[2.092]
		{1.618}		{1.644}		{2.028}		{2.031}
$\hat{\gamma}_{HML}$		0.300		0.325		0.230		0.229
		[2.101]		[2.281]		[1.568]		[1.561]
		{1.713}		{1.822}		{1.217}		{1.207}
$\hat{\gamma}_0$	1.197	0.888	1.118	1.261	1.402	1.438	1.365	1.424
	[5.724]	[2.571]	[5.465]	[3.728]	[7.036]	[5.153]	[6.851]	[5.307]
	{5.271}	{2.655}	{4.119}	{2.873}	{5.566}	{4.011}	{4.805}	{3.898}
$\bar{R}^2_{OLS}$	0.577	0.767	0.623	0.770	0.561	0.703	0.562	0.694
MAPE	0.085	0.068	0.081	0.068	0.127	0.095	0.125	0.095
T^2	52.801	44.688	20.638	30.209	130.089	131.949	115.275	129.516
p-value	0.000	0.000	0.357	0.017	0.000	0.000	0.000	0.000

Table 2.13 Initial Unemployment Claims

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include initial unemployment claims (claims), cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors (MKT, SMB, and HML). Claims is the differenced series of the number of initial claims for unemployment insurance divided by the size of the workforce. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Data is monthly from March 1975 to December 2012.

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) SZ X BM	(5) ALL	(6) ALL	(7) ALL	(8) ALL
$\hat{\gamma}_g$		-5.256		-2.604		-3.143		-1.131
		[3.072]		[2.227]		[3.796]		[2.337]
		{1.865}		{1.569}		{2.556}		{1.829}
$\hat{\gamma}_v$		-3.532		-2.424		-2.851		-1.374
		[4.840]		[3.991]		[4.473]		[3.007]
		{2.911}		{3.154}		{3.378}		{2.727}
$\hat{\gamma}_{Claims}$	-0.020	-0.081	0.021	-0.016	0.013	-0.013	0.008	-0.006
	[0.591]	[2.876]	[0.985]	[0.867]	[0.479]	[0.552]	[0.485]	[0.392]
	{0.597}	{1.453}	{1.031}	{0.645}	{0.456}	{0.320}	{0.375}	{0.276}
$\hat{\gamma}_{MKT}$			-0.854	-0.831			-1.430	-1.410
			[2.375]	[2.243]			[4.008]	[3.874]
			{2.239}	{1.530}			{3.377}	{2.869}
$\hat{\gamma}_{SMB}$			0.204	0.245			0.227	0.252
			[1.395]	[1.682]			[1.546]	[1.730]
			{1.361}	{1.625}			{1.559}	{1.788}
$\hat{\gamma}_{HML}$			0.386	0.334			0.312	0.268
			[2.673]	[2.333]			[2.082]	[1.818]
			{2.144}	{1.863}			{1.646}	{1.510}
$\hat{\gamma}_0$	0.722	0.574	1.490	1.455	0.729	0.657	2.068	2.047
	[3.248]	[2.607]	[5.173]	[4.844]	[3.786]	[3.388]	[7.122]	[6.824]
	{2.970}	{1.083}	{4.085}	{3.089}	{4.152}	{2.019}	{5.152}	{4.393}
$\bar{R}^2_{OLS}$	-0.008	0.607	0.611	0.781	-0.002	0.248	0.590	0.617
MAPE	0.170	0.098	0.084	0.069	0.186	0.160	0.113	0.109
T^2	75.417	11.333	50.851	20.811	177.469	62.689	143.045	107.109
p-value	0.000	0.956	0.000	0.289	0.000	0.749	0.000	0.002

Table 2.14 Other Economic Variables

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include consumption growth (Cons), changes in the University of Michigan Consumer Sentiment Index (CSent), initial unemployment claims (claims), the cross-sectional average of crime growth ($\tilde{g}$), the cross-sectional variance of crime growth ($\tilde{v}$), and the Fama and French (1993) three factors (MKT, SMB, and HML). Cons is changes in real seasonally adjusted per capita non-durables and services consumption. Claims is the differenced series of the number of initial claims for unemployment insurance divided by the size of the workforce. Test-assets are indicated in the column header with SZ x BM indicating only 25 size and book-to market portfolios, while ALL also includes 10 portfolios for each of the following characteristics: 12-month price momentum, total accruals, asset growth, share issuance, and profitability (ROE). MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Crime, consumption, and unemployment claims data is monthly from March 1975 to December 2012. Monthly consumer sentiment data is from February 1978 to December 2012.

	(1) SZ X BM	(2) SZ X BM	(3) SZ X BM	(4) ALL	(5) ALL	(6) ALL
$\hat{\gamma}_g$			-4.783			-2.121
			[3.050]			[2.891]
			{2.019}			{1.873}
$\hat{\gamma}_v$			-3.071			-1.835
			[4.715]			[3.559]
			{2.677}			{3.013}
$\hat{\gamma}_{Cons}$	0.041		0.010	-0.020		0.063
	[0.370]		[0.133]	[0.214]		[0.925]
	{0.379}		{0.062}	{0.200}		{0.890}
$\hat{\gamma}_{CSent}$		0.003	0.030		-0.008	0.000
		[0.288]	[2.402]		[0.898]	[0.056]
		{0.314}	{1.247}		{0.854}	{0.034}
$\hat{\gamma}_{Claims}$			-0.028			0.006
			[1.265]			[0.417]
			{0.791}			{0.298}
$\hat{\gamma}_0$	0.732	0.699	0.407	0.711	0.840	0.718
	[2.922]	[2.517]	[1.494]	[3.383]	[3.800]	[3.167]
	{2.819}	{2.689}	{0.709}	{3.361}	{3.756}	{2.063}
$\bar{R}^2_{OLS}$	-0.030	-0.033	0.548	-0.011	0.036	0.192
MAPE	0.174	0.153	0.091	0.184	0.172	0.157
T^2	78.268	84.780	15.717	181.122	179.925	92.727
p-value	0.000	0.000	0.676	0.000	0.000	0.030

APPENDICIES

APPENDIX A

Taking a Beating on the Stock Market:

Crime and Stock Returns

Table A.1 Market Returns and Crime Rates without Quadratic Term

Regression of daily crime rates on daily market returns by income from 1991-2012. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	34.28**	1.320	45.30***	62.13***
	(2.561)	(0.113)	(2.682)	(2.946)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: Previously curvature of the utility function was accounted for by including a term for the squared market return. Although the quadratic term was insignificant in the overall relationship and for high and medium income locations, it was significantly positive for low income locations. The highly significant quadratic coefficient for low income locations is expected since these locations should have the highest marginal utility over relative wealth, and thus the curvature should be most pronounced for these individuals. Removing the quadratic term does not significantly alter the linear term, but underestimates the total relationship between stock market returns and crime rates for low income locations. In the quadratic specification a one standard deviation increase in the market is associated with a significant increase of 94.7 crimes per 100 million (46.7 bps), while here in the linear specification it is associated with an increase of 62.1 crimes (30.6 bps). This is a reduction of 34%.

Table A.2 Relationship between Extreme Market Returns and Crime Rates

Regression of daily crime rates on indicators for large positive and large negative market returns by income from 1991-2012. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Indicators are for market returns divided by their trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
1{Market Return > 1}	45.55	-19.44	54.75	118.0*
	(1.056)	(-0.509)	(1.014)	(1.748)
1{Market Return < -1}	-76.83*	-32.19	-78.83	-118.7*
	(-1.932)	(-0.875)	(-1.527)	(-1.886)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: A question that arises is whether the results are driven by large positive or large negative returns. To explore this, indicators are used for standardized returns that exceed one and those that are below negative one. The overall relationship between market returns and crime rates is larger for negative returns, with extreme negative return days associated with a significant decline of 77 crimes per 100 million individuals (-38 bps). Extreme positive return days associated with an insignificant increase of 46 crimes (22 bps). Although the overall relationship seems to be stronger for extreme negative returns, when breaking up the results by income either both coefficients are insignificant or both are significant which prohibits any conclusion that one extreme is driving the results. The relationship between returns and crime rates increases in absolute value as we go from high income locations to low income locations. Extreme positive returns are associated with an insignificant -19.4 crimes per 100 million individuals (9.6 bps) in high income locations, and increases to a significant 118 crimes (58.1 bps) in low income locations. Extreme negative returns are associated with an insignificant -32.2 crimes per 100 million (15.9 bps) individuals in high income locations, and decreases to a significant -118 crimes (-58.5 bps) in low income locations.

Table A.3 Market Returns and Crime Rates in Recessions

Regression of daily crime rates on daily market returns and recession indicator by income from 1991-2012. Recessions are defined by the NBER as occurring during the following dates: July 1, 1990 to March 31, 1991, March 1, 2001 to November 30, 2001, and December 1, 2007 to June 30, 2009. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	30.66**	2.422	37.28*	58.16**
	(1.983)	(0.177)	(1.960)	(2.380)
Market Return Sq.	5.147	0.220	4.328	12.87
	(0.828)	(0.0403)	(0.553)	(1.320)
Market × Recession	23.92	-4.534	44.79	34.31
	(0.720)	(-0.167)	(1.034)	(0.678)
Market Sq. × Recession	-0.916	0.873	-10.07	4.724
	(-0.0735)	(0.0857)	(-0.653)	(0.260)
Recession	151.1*	89.19	243.5**	143.1
	(1.763)	(1.184)	(2.263)	(1.104)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: Although crime rates are generally higher during recessions as defined by the NBER, the relationship between crime rates and market returns is not significantly different during recessions.

Table A.4 Market Returns and Crime Rates in Bear Markets

Regression of daily crime rates on daily market returns and bear markets indicator by income from 1991-2012. Bear markets are defined by Merrill Lynch as occurring when the S&P 500 drops by at least -20% without a +20% recovery and occur the following dates: March 24, 2000 to September 21, 2001 (-36.8%), January 4, 2002 to October 9, 2002 (-33.8%), October 9, 2007 to November 20, 2008 (-51.9%), and January 6, 2009 to March 9, 2009 (-27.6%). High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	26.82	-2.829	38.32*	51.44*
	(1.597)	(-0.192)	(1.849)	(1.944)
Market Return Sq.	2.203	-3.063	0.561	10.52
	(0.328)	(-0.528)	(0.0663)	(0.993)
Market × Bear	21.71	8.823	14.58	40.87
	(0.743)	(0.350)	(0.397)	(0.902)
Market Sq. × Bear	9.520	11.10	6.850	11.37
	(0.843)	(1.126)	(0.488)	(0.684)
Bear Market	-157.2**	-100.6*	-245.5***	-123.5
	(-2.455)	(-1.755)	(-3.046)	(-1.259)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.474	0.452	0.459	0.450
Controls	YES	YES	YES	YES
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: Although crime rates are generally lower during bear markets as defined by Merrill Lynch, the relationship between crime rates and market returns is not significantly different during bear markets.

Table A.5 Average Cumulative Market Returns and Crime Rates

Regression of daily crime rates on cumulative average daily market returns by income from 1991-2012. In Panel A, average cumulative market returns are from date *t – s* as indicated in the column header through date *t*, where lags are only performed on days the market is open. In Panel B, average market returns are from date *t – s* though *t – 1*. High income is defined as the top tercile of income for all agency locations, while low income is defined as the bottom tercile. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Additional control variables are defined in Table 1.6. Parentheses contain *t*-statistics with heteroskedasticity robust standard errors clustered by location and time. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Panel A: Average cumulative returns from *t – s* to *t*

Incident	All Incidents	All Incidents	All Incidents	All Incidents	All Incidents	All Incidents
t - s	*t*	*t - 1*	*t - 2*	*t - 3*	*t - 4*	*t - 5*
Avg Market Return$_{t-s,t}$	35.56***	39.73**	50.12**	40.94	6.796	6.904
	(2.596)	(1.985)	(1.989)	(1.339)	(0.194)	(0.181)
Avg Market Ret. Sq$_{t-s,t}$	5.316	7.361	20.26	16.16	5.397	-1.225
	(0.988)	(0.508)	(1.055)	(0.566)	(0.158)	(-0.0297)
Observations	3,728,775	3,728,775	3,728,775	3,728,775	3,728,775	3,728,775
R-squared	0.474	0.474	0.474	0.474	0.474	0.474
Controls	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES

Panel B: Contemporaneous and average cumulative returns from *t – s* to *t – 1*

Incident	All Incidents	All Incidents	All Incidents	All Incidents	All Incidents	All Incidents
t - s	*t*	*t - 1*	*t - 2*	*t - 3*	*t - 4*	*t - 5*
Market $Return_t$	35.56***	35.76***	36.24***	35.92***	35.18**	35.65**
	(2.596)	(2.594)	(2.632)	(2.599)	(2.541)	(2.551)
Market Return Sq_t	5.316	5.496	6.068	5.751	4.894	5.694
	(0.988)	(1.008)	(1.054)	(0.981)	(0.805)	(0.930)
Avg Market $Return_{t-s,t-1}$		5.488	13.89	6.648	-27.09	-25.47
		(0.405)	(0.697)	(0.252)	(-0.839)	(-0.717)
Avg Market Ret. $Sq_{t-s,t-1}$		0.587	0.343	-1.634	-14.96	-29.57
		(0.0847)	(0.0218)	(-0.0651)	(-0.419)	(-0.725)
Observations	3,728,775	3,728,775	3,728,775	3,728,775	3,728,775	3,728,775
R-squared	0.474	0.474	0.474	0.474	0.474	0.474
Controls	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES

Notes: It is interesting to see if average cumulative returns impact current utility, and thus crime rates. To examine this I measure returns from *t – s* to *t*, and also from *t – s* to *t - 1* while separately including date *t* returns. Here, lags are only performed on trading days (not calendar days). For example, in the second column in Panel A of Table A.5 labeled *t – 1*, a Monday crime rate on day *t* is associated with a cumulative return that includes that Monday and the previous Friday if the market is open on both days. First examining the relationship from *t* – s to *t* in Panel A, we see that the relationship between stock market returns and crime rates increases from a significant 46.2 crimes per 100 million individuals (22.8 bps) on day 0 to a significant 90.64 crimes (44.6 bps) for cumulative average returns from trading day *t* – 2 to trading day 0, however, the relationship declines steeply thereafter. This suggests a short memory for individuals. Panel B shows that the relationship is driven by the period *t* return and that previous cumulative returns are insignificant.

It is important to note that the overlapping returns used to calculate the cumulative average returns can create autocorrelation in the residuals. To account for this, the *t*-statistics utilize standard errors that are clustered by both location and time. The *t*-statistics for the first column are approximately equal to those reported in Table 1.6 (which only clusters on the time dimension), and indicates that the time dimension is the relevant dimension to cluster standard errors. Confirming this, when clustering by just location (unreported), the *t*-statistics are much larger.

Table A.6 Market Returns and Crime Rates with Log-Linear Specification

Regression of daily logged crime rates on market returns from 1991-2012. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Control variables are defined in Table 1.6. Heteroskedasticity robust *t*-statistics clustered by time in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	0.00106*	0.000183	0.00122*	0.00195***
	(1.874)	(0.299)	(1.791)	(2.665)
Market Return Sq.	0.000474**	0.000463*	0.000270	0.000731**
	(2.148)	(1.930)	(1.009)	(2.563)
Moon Fraction	0.00334**	0.00114	0.00323	0.00602***
	(1.963)	(0.591)	(1.546)	(2.748)
SAD	-0.0492***	-0.0403**	-0.0573***	-0.0475**
	(-2.932)	(-2.429)	(-2.958)	(-2.201)
Temperature	0.000607***	0.000591***	0.000666***	0.000536***
	(43.13)	(35.89)	(37.87)	(28.78)
Precipitation	-9.38e-05***	-8.93e-05***	-9.55e-05***	-8.87e-05***
	(-6.011)	(-4.246)	(-4.600)	(-4.258)
Snowfall	-0.00170***	-0.00148***	-0.00194***	-0.00220***
	(-11.35)	(-9.185)	(-12.70)	(-8.335)
Snow Depth	-0.000368***	-0.000307***	-0.000518***	-0.000530***
	(-22.60)	(-16.82)	(-20.60)	(-15.41)
Wind	-0.000878***	-0.000848***	-0.000992***	-0.000856***
	(-19.50)	(-15.51)	(-16.50)	(-13.25)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
R-squared	0.525	0.462	0.521	0.531
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: A common transformation for count data is the logarithmic transformation. This transformation is problematic if the data contains zeros, which is true with all individual crime offenses considered with the exception of when we examine all incidents. Table A.6 shows that the log specification produces the same increasing and convex relationship with significance levels that are similar to the linear specification. With a log specification, the coefficients can be interpreted as the percent increase in crime rates due to a unit increase in returns. As such, the first column shows that a one standard deviation in the market return corresponds with a 20.1 bps increase in crime rates. This is very similar to the original (non-logged) specification with an increase of 22.8 bps. Furthermore, the monotonic relationship across income groups between market returns and crime remains. For example, a one standard deviation increase in the market corresponds with a significant 34.1 bps increase in low income locations, and an 11.1 bps increase in high income locations.

Table A.7 Market Returns and Crime Rates with Poisson Specification

Poisson regression of daily crime rates on market returns from 1991-2012. Market returns are divided by its trailing 252-day standard deviation. Crime rates are measured as the number of incidents per 100 million people. All Incidents include all of the offenses listed in Table 1.3. Control variables are defined in Table 1.6. Heteroskedasticity robust *t*-statistics clustered by location in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively.

Incident	All Incidents	All Incidents	All Incidents	All Incidents
Income Level	ALL	HIGH	MED	LOW
Market Return	0.00154***	0.00102***	0.00169***	0.00185***
	(7.871)	(2.839)	(5.558)	(4.886)
Market Return Sq.	0.000514***	0.000486**	0.000356**	0.000704***
	(4.476)	(2.476)	(2.177)	(3.275)
Moon Fraction	0.00265***	0.00237*	0.00222*	0.00326***
	(3.739)	(1.794)	(1.811)	(2.827)
SAD	-0.0370***	-0.0204	-0.0525***	-0.0318***
	(-5.565)	(-1.638)	(-4.400)	(-3.582)
Temperature	0.000619***	0.000606***	0.000661***	0.000566***
	(45.94)	(30.55)	(32.24)	(20.65)
Precipitation	-8.56e-05***	-9.06e-05***	-8.19e-05***	-8.11e-05***
	(-11.42)	(-5.947)	(-6.690)	(-5.828)
Snowfall	-0.00217***	-0.00196***	-0.00228***	-0.00235***
	(-22.59)	(-14.40)	(-12.81)	(-10.37)
Snow Depth	-0.000444***	-0.000406***	-0.000482***	-0.000609***
	(-15.01)	(-14.87)	(-6.399)	(-11.37)
Wind	-0.000825***	-0.000838***	-0.000923***	-0.000703***
	(-17.38)	(-15.08)	(-12.85)	(-7.076)
Observations	3,728,775	1,313,926	1,216,759	1,195,510
Location FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Month of Year FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES

Notes: A specification that is typically applied to count data is the Poisson regression model. The advantage of using a Poisson model is that it explicitly models the non-negativity and discrete nature of count data. The standard criticism of Poisson regressions is that it assumes a Poisson distribution where the variance is equal to the mean, a condition that is typically violated. This restriction usually manifests itself by predicting less zero counts than observed in the sample and grossly deflated standard errors which can be mitigated using a robust variance estimator. Although most of the individual crime incidents suffer from a high incidence of zeros and over-dispersion, this is not a significant issue when examining all incidents combined. For example, Table 1.3 illustrates that for all incidents there are no zeros and the pooled mean crime rate of 22,976 is reasonably close to the standard deviation of 19,011.

Table A.7 shows that the Poisson specification produces the same increasing and convex relationship with significance levels that are much higher than the linear specification. For computational convenience, standard errors are clustered by location instead of time in this specification, however, this does not affect the coefficients. With a Poisson specification, the coefficients can be interpreted as the change in log crime counts, while the exponential of the coefficients (i.,e., $exp(\beta)$) are interpreted as incidence-rate ratios (IRRs). The IRRs minus one ($exp(\beta) - 1$) are interpreted as the percent change in the crime count. Since the coefficients are particularly small, $exp(\beta) - 1$ is approximately equal to β, so we can simply interpret the stated coefficients as the percent change in crimes. For example, a one standard deviation increase in the market return corresponds with a 25.7 bps increase in crime rates. This is very similar to the original (non-logged) linear specification with an increase of 22.8 bps and the log specification of 20.1 bps. Furthermore, the roughly monotonic relationship across income groups between market returns and crime remains. For example, a one standard deviation increase in the market corresponds with a significant 32.7 bps increase in low income locations, and a 19.9 bps increase in high income locations. The similar results provide assurances that the linear specification is reasonable, and may in fact be conservative.

APPENDIX B

Does Crime Pay?

Asset Pricing with Revealed Utility of Heterogeneous Consumers

B.1 Error in the Relationship of Crime as Marginal Utility

I derive the lower and upper bounds for the bias factor H. Assuming the error term, $\epsilon_{i,t}$, in (2.1) is identically distributed and greater than 0, then the lower bound to H can be estimated by:

$$1 = E\left[\left(\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}\right)\left(\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}\right)^{-1}\right] \leq$$
$$E\left[\left(\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}\right)\right]E\left[\left(\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}\right)^{-1}\right] = \left\{E\left[\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}\right]\right\}^{2}, \tag{B.1}$$

where the inequality follows from an application of Jensen's inequality and the definition of covariance, and the second equality follows from the fact that $\epsilon_{i,t}^{-\theta}\epsilon_{i,t-1}^{\theta}$ and its inverse are symmetrically distributed. Therefore, the coefficients are biased upwards by the factor $\mathrm{H} \geq 1$.

An upper bound to H can be derived under the additional assumption that the error term, $\epsilon_{i,t}$, is i.i.d. lognormal with mean μ and variance σ^2, and noting that $\mathrm{H} = E\left[\eta_{i,t}^{-\theta}\right] = \exp(\theta^2\sigma^2)$. Therefore, bounds for σ^2 and θ^2 will be sufficient to bound H. An upper bound to σ^2 is provided by exploiting log changes in (2.1),

$$\ln(g_{it}) = \frac{1}{\theta}\ln\left(\frac{u'\left(c_{i,t}\right)}{u'\left(c_{i,t-1}\right)}\right) + \ln\left(\eta_{i,t}\right), \tag{B.2}$$

and using the definition of the R^2 from the OLS regression given in (A2):

$$var(\ln(\eta_{i,t})) = var(\ln(g_{i,t}))(1 - R^2). \quad \text{(B.3)}$$

Finally, the upper bound of σ^2 is given using the property that the R^2 is bounded between 0 and 1:

$$\sigma^2 \leq \frac{1}{2} var(\ln(g_{i,t})). \quad \text{(B.4)}$$

Next, an upper bound for θ can be derived under the assumption that increases in marginal utility are associated with increases in crime, and that the cross-sectional average and variance of crime growth are associated with bad states of the world and thus command negative prices of risk. Using the definition of the coefficients derived in (13), this suggests that θ must take on a value between one and two. Given that the pooled variance of log crime growth in the data is 0.23, the upper bound for H can be derived as:

$$\mathrm{H} = \exp(\theta^2\sigma^2) = \exp\left(\frac{1}{2} \times 0.23(1 - R^2)\theta^2\right) \leq 1.12^{\theta^2} \leq 1.58. \quad \text{(B.5)}$$

The above results suggest that the prices of risk may be biased by a factor of 1 to 1.58. A more plausible estimate of the bias can be derived if θ takes on its mid-point value of 1.5, resulting in a bias of 1.29. If it is further assumed that the regression of log crime growth on marginal utility growth has an R^2 of 0.5, the bias declines to 1.14. It is worth noting that although using crime as revealed marginal utility may lead to an upward bias of the pricing coefficients, any proxy for an individual's true unobserved marginal utility will produce a similar upward bias.

B.2 Linear GMM Estimation

B.2.1 Euler Equation and SDF

The Euler equation is

$$E\left[M_t R_{n,t}^e\right] = 0. \tag{B.6}$$

The linear SDF is defined as

$$M_t = 1 - b' f_t \tag{B.7}$$

where f is a $K \times 1$ vector of factors, and b is a $K \times 1$ vector of parameters.

B.2.2 GMM Estimation

B.2.2.1 Moment Conditions

The GMM objective function is

$$\min_{\{b\}} g_T' W g_T, \tag{B.8}$$

with

$$g_T = \begin{bmatrix} E_T\left[u_{1,t}\right] \\ \vdots \\ E_T\left[u_{N,t}\right] \end{bmatrix}, \tag{B.9}$$

$N \times N$ weighting matrix W, $E_T[x_t] = T^{-1} \sum_{t=1}^{T} x_t$, and the pricing errors for excess returns is

$$u_{n,t} = M_t R_{n,t}^e. \tag{B.10}$$

B.2.2.2 Weighting Matrix

Two alternative weighting matrices are considered. The first is the optimal weighting matrix of the two step procedure in Hansen and Singleton (1982), which sets the weighting matrix equal to the inverse of the long run covariance matrix of the pricing errors ($W = S^{-1}$). The long run covariance matrix is estimated using the pricing errors from the first stage that sets the weighting matrix to the identity matrix, and is estimated following the methodology of Newey and West (1987) with 12 lags

$$S = \sum_{j=-k}^{k} \left(\frac{k - |j|}{k} \right) \frac{1}{T} \sum_{t=1}^{T} (u_t - E_T[u_t])(u_t - E_T[u_t])'. \tag{B.11}$$

The second weighting matrix uses the inverse of the second moment matrix of returns, $W = E_T[R_t' R_t]^{-1}$, as advocated by Hansen and Jagannathan (1997).

B.2.2.3 GMM Standard Errors

Standard errors are the square root of the diagonal elements of

$$\frac{1}{T}(d'Wd)^{-1} d'WSWd(d'Wd)^{-1}, \tag{B.12}$$

where under the optimal weighting matrix it simplifies to

$$\frac{1}{T} d' S^{-1} d, \tag{B.13}$$

where

$$d = \frac{\partial g_T}{\partial b'} = \begin{bmatrix} \frac{\partial g_T(R^e_{1,t})}{\partial b'} \\ \vdots \\ \frac{\partial g_T(R^e_{N,t})}{\partial b'} \end{bmatrix}. \tag{B.14}$$

and

$$\frac{\partial g_T(R^e_{n,t})}{\partial b'} = -E_T[R^e_{n,t} f_t{}']. \tag{B.15}$$

B.2.2.4 Test of over-identifying restrictions

The test of over-identifying restrictions tests the null that the pricing errors are zero. Using the optimal weighting matrix, the test is

$$TJ_T = Tg_T{}'S^{-1}g_T \sim \chi^2_{N-K} \tag{B.16}$$

where K is the number of parameters estimated. With a non-optimal weighting matrix the test is

$$TJ_T = Tg_T{}'((I - d(d'Wd)^{-1}d'W)S(I - W(d'Wd)^{-1}d'))^{+}\, g_T \sim \chi^2_{N-K}. \tag{B.17}$$

B.2.2.5 Hansen-Jagannathan statistic

Following Hansen and Jagannathan (1997), the HJ statistic is estimated with weighting matrix $W = E_T[R_t' R_t]^{-1}$ as

$$HJ = \sqrt{g_T' W g_T}. \tag{B.18}$$

B.2.2.6 Newey-West D-test

The Newey and West (1987) χ^2 difference test (D-test) compares the TJ_T statistic of a restricted model to its unrestricted counterpart and is defined as

$$\Delta TJ_T = Tg'_{T,R}S_{UR}^{-1}g_{T,R} - Tg'_{T,UR}S_{UR}^{-1}g_{T,UR} \sim \chi_L^2 \qquad \text{(B.19)}$$

where, $g_{T,R}$ and $g_{T,UR}$ indicate the average pricing errors for the restricted and unrestricted models respectively, S_{UR} indicates the spectral density matrix for the unrestricted model, and L indicates the number of restrictions. It is important to note that using the same unrestricted spectral density matrix for both TJ_T statistics ensures that the ΔTJ_T statistic is positive.

B.3 Additional Tables

Table B.1 Crime Beta Sorted Portfolios

Portfolios of firms sorted by their cross-sectional average of crime growth beta (AVG) and cross-sectional variance of crime growth beta (VAR). Betas for each firm are estimated following Dimson (1972) with one lag over a 60-month rolling window. Each month, firms are sequentially sorted first into 5 portfolios by the variance of crime growth beta and then into an additional 5 portfolios by the average of crime growth beta, for a total of 25 equal weighted portfolios. Panel A displays average returns, while Panel B displays *t*-statistics. Returns are monthly from March 1980 to December 2012.

Panel A: Excess Returns

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR5-1
AVG1	1.29	1.24	1.25	1.39	1.01	-0.28
AVG2	1.31	1.36	1.27	1.20	1.26	-0.05
AVG3	1.26	1.27	1.18	1.29	1.05	-0.20
AVG4	1.20	1.36	1.19	1.23	1.07	-0.13
AVG5	1.01	1.16	1.23	1.14	0.79	-0.22
AVG5-1	-0.27	-0.08	-0.01	-0.25	-0.21	

Panel B: *t*-Statistics

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR5-1
AVG1	4.39	4.81	5.10	5.20	3.13	2.01
AVG2	4.98	6.05	5.92	5.50	4.36	0.39
AVG3	4.92	5.70	5.64	6.04	4.07	1.66
AVG4	4.30	6.05	5.44	5.51	3.93	1.11
AVG5	2.88	4.39	4.63	4.22	2.46	1.64
AVG5-1	1.53	0.67	0.11	2.01	1.61	

Table B.2 Time-Series Betas and Expected Excess Returns

Time-series betas and expected excess returns for test-asset and Fama and French 48 industry portfolios. Factors to explain returns include the cross-sectional average of crime growth, the cross-sectional variance of crime growth, and their respective mimicking portfolios (CMP Avg and CMP Var). Expected returns are calculated using the betas indicated below, and the prices of risk from column 4 of Table 2.2 for the crime factors and column 4 of Panel A of Table 2.6 for the CMP factors. Test-assets are indicated in the first column. Portfolios are sorted by CMP expected returns. Heteroskedasticity consistent standard errors are used to calculated t-statistics for the crime factors, while wild-bootstrapped standard errors with 10,000 replications are used for the CMP factors which account for estimation error in both the first and second stages. Data covers March 1975 to December 2012.

Panel A: Size and book to market portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
S2B1	0.58	7.15	0.22	1.77	-0.15	1.06	0.46	17.87	4.00	-12.89	2.98	0.32
S5B3	0.57	4.52	0.05	0.64	0.01	0.05	0.50	3.70	3.36	-1.65	1.55	0.34
S1B1	0.27	7.92	0.23	1.58	-0.15	0.90	0.40	20.31	3.98	-15.00	3.04	0.36
S3B1	0.64	6.61	0.19	1.70	-0.20	1.48	0.66	15.17	3.94	-11.36	3.06	0.44
S4B1	0.74	5.98	0.15	1.50	-0.19	1.62	0.76	12.14	3.88	-9.33	3.10	0.51
S5B4	0.61	4.44	0.04	0.48	-0.04	0.47	0.68	4.56	3.50	-3.33	2.66	0.53
S5B2	0.68	4.59	0.06	0.70	-0.03	0.37	0.60	4.12	3.38	-3.03	2.60	0.53
S5B5	0.71	5.10	0.08	0.94	-0.04	0.40	0.55	7.26	3.73	-5.55	2.98	0.54
S1B2	0.94	6.72	0.20	1.52	-0.17	1.24	0.59	16.91	3.85	-13.93	3.31	0.66
S4B2	0.75	5.19	0.08	0.92	-0.12	1.12	0.79	7.93	3.62	-6.88	3.30	0.69
S2B2	0.85	5.83	0.18	1.82	-0.23	1.95	0.79	13.41	3.79	-11.49	3.40	0.73
S3B2	0.91	5.44	0.14	1.59	-0.17	1.56	0.75	10.37	3.66	-9.30	3.47	0.78
S4B4	0.85	4.78	0.07	0.94	-0.13	1.39	0.81	6.99	3.49	-6.63	3.49	0.78
S4B3	0.79	5.17	0.10	1.23	-0.14	1.40	0.77	7.07	3.42	-6.81	3.49	0.80
S4B5	0.89	5.33	0.09	1.06	-0.16	1.55	0.85	7.77	3.45	-7.48	3.52	0.82
S5B1	0.51	4.75	0.07	0.87	-0.09	1.02	0.73	5.15	3.13	-5.42	3.52	0.83
S3B4	0.94	4.91	0.06	0.81	-0.09	0.93	0.74	7.75	3.38	-7.81	3.63	0.89
S3B3	0.90	4.95	0.10	1.26	-0.17	1.81	0.87	8.36	3.45	-8.37	3.67	0.90
S1B3	0.99	5.74	0.18	1.71	-0.17	1.37	0.62	13.13	3.61	-12.43	3.63	0.95
S2B3	1.02	5.25	0.11	1.31	-0.16	1.50	0.80	10.79	3.51	-10.64	3.69	0.96
S2B4	1.05	5.18	0.11	1.30	-0.16	1.55	0.79	9.56	3.36	-10.13	3.81	1.05
S1B4	1.12	5.39	0.12	1.32	-0.17	1.45	0.77	11.35	3.44	-11.69	3.79	1.08
S3B5	1.16	5.39	0.07	0.80	-0.15	1.43	0.90	8.38	3.17	-9.48	3.87	1.11
S1B5	1.22	5.88	0.14	1.43	-0.19	1.45	0.78	11.75	3.35	-12.58	3.85	1.18
S2B5	1.04	5.97	0.15	1.48	-0.23	1.92	0.89	11.07	3.31	-12.10	3.87	1.20

Panel B: 12-month price momentum portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
MO1	-0.12	8.26	0.22	1.67	-0.24	1.52	0.70	13.52	3.86	-9.80	2.90	0.40
MO2	0.44	6.24	0.09	0.98	-0.07	0.60	0.59	8.66	3.67	-6.89	3.05	0.58
MO4	0.62	4.71	0.04	0.57	-0.07	0.83	0.75	5.69	3.53	-4.75	3.09	0.62
MO8	0.79	4.51	0.08	1.08	-0.04	0.39	0.52	5.30	3.48	-4.52	3.13	0.64
MO6	0.56	4.49	0.10	1.32	-0.05	0.50	0.50	4.98	3.42	-4.33	3.15	0.65
MO10	1.12	6.40	0.15	1.29	-0.14	1.11	0.64	11.36	3.73	-9.47	3.26	0.66
MO3	0.56	5.30	0.07	0.84	-0.11	1.14	0.78	6.62	3.51	-5.76	3.22	0.67
MO5	0.49	4.45	0.05	0.70	-0.08	0.88	0.73	5.46	3.44	-4.89	3.26	0.68
MO9	0.81	4.96	0.14	1.58	-0.10	0.92	0.55	5.83	3.45	-5.26	3.29	0.70
MO7	0.65	4.43	0.05	0.66	-0.03	0.33	0.60	4.39	3.18	-4.26	3.29	0.72

Panel C: Total accruals portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
TA2	0.70	5.23	0.14	1.61	-0.04	0.41	0.38	8.44	3.83	-6.21	2.93	0.48
TA10	0.38	6.45	0.15	1.43	-0.16	1.15	0.67	11.20	3.84	-8.48	3.02	0.50
TA3	0.60	4.86	0.05	0.57	-0.05	0.52	0.67	6.59	3.69	-4.88	2.84	0.51
TA1	0.61	6.26	0.18	1.73	-0.06	0.53	0.32	9.97	3.74	-7.87	3.09	0.57
TA4	0.67	4.41	0.06	0.76	-0.07	0.79	0.70	5.93	3.65	-4.72	3.03	0.58
TA6	0.68	4.42	0.03	0.46	-0.04	0.51	0.69	5.76	3.47	-5.14	3.27	0.69
TA8	0.52	5.06	0.11	1.33	-0.11	1.06	0.64	6.95	3.55	-6.12	3.30	0.69
TA5	0.67	4.20	0.08	1.09	-0.12	1.45	0.79	5.27	3.41	-4.95	3.40	0.72
TA9	0.52	5.73	0.12	1.29	-0.14	1.15	0.71	9.30	3.61	-8.30	3.39	0.75
TA7	0.48	4.67	0.06	0.82	-0.12	1.27	0.81	5.75	3.22	-6.00	3.59	0.85

Panel D: Asset growth portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
AG10	0.24	6.75	0.26	2.37	-0.17	1.20	0.38	12.68	3.99	-8.38	2.72	0.25
AG9	0.47	5.73	0.12	1.27	-0.09	0.81	0.57	9.76	3.78	-7.63	3.08	0.55
AG4	0.71	4.04	0.04	0.62	-0.03	0.39	0.63	5.13	3.59	-4.12	3.01	0.59
AG6	0.64	4.41	0.06	0.85	-0.11	1.22	0.79	5.14	3.49	-4.40	3.13	0.64
AG7	0.59	4.67	0.08	1.01	-0.10	1.02	0.71	6.43	3.58	-5.47	3.20	0.64
AG2	0.92	5.06	0.02	0.26	-0.05	0.49	0.75	7.89	3.58	-6.98	3.33	0.71
AG8	0.61	5.37	0.05	0.57	-0.06	0.57	0.69	8.08	3.54	-7.20	3.33	0.72
AG5	0.67	4.33	0.04	0.62	-0.07	0.81	0.73	5.24	3.36	-4.96	3.37	0.73
AG1	0.88	5.97	0.09	0.89	-0.16	1.28	0.88	11.24	3.69	-9.82	3.39	0.74
AG3	0.75	4.64	0.08	1.05	-0.11	1.15	0.73	6.01	3.41	-5.69	3.42	0.75

Panel E: Share issuance portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
SI10	0.18	5.47	0.15	1.68	-0.12	1.10	0.57	9.00	3.87	-6.44	2.88	0.44
SI9	0.39	5.24	0.12	1.37	-0.09	0.87	0.59	8.48	3.82	-6.40	3.00	0.51
SI8	0.51	5.21	0.09	1.09	-0.05	0.54	0.56	8.50	3.75	-6.66	3.07	0.56
SI7	0.59	5.24	0.11	1.30	-0.07	0.72	0.55	8.50	3.75	-6.74	3.10	0.57
SI4	0.77	4.47	0.03	0.41	-0.04	0.40	0.68	5.33	3.45	-4.65	3.18	0.66
SI3	0.64	4.29	0.04	0.54	-0.07	0.76	0.74	4.96	3.41	-4.41	3.20	0.67
SI6	0.68	5.22	0.07	0.80	-0.11	1.14	0.79	8.00	3.61	-6.96	3.30	0.69
SI2	0.74	4.38	0.11	1.42	-0.07	0.73	0.53	4.67	3.26	-4.47	3.33	0.72
SI5	0.68	4.90	0.08	0.96	-0.10	1.05	0.73	6.72	3.42	-6.41	3.46	0.78
SI1	1.09	4.59	0.07	0.91	-0.13	1.36	0.82	5.92	3.35	-5.81	3.50	0.79

Panel F: Profitability (ROE) portfolios

Test Asset	Ret Avg	Ret SD	β_g	t	β_v	t	$E[R]$	$\beta_{CMP\ Avg}$	t	$\beta_{CMP\ Var}$	t	$E[R_{CMP}]$
ROE1	-0.09	8.80	0.16	1.08	-0.06	0.32	0.36	19.98	3.96	-14.15	2.90	0.25
ROE2	0.37	7.62	0.13	1.06	-0.07	0.49	0.49	15.95	3.92	-11.59	2.95	0.37
ROE3	0.39	5.94	0.21	2.17	-0.16	1.39	0.53	11.16	3.90	-8.29	3.02	0.47
ROE6	0.66	4.64	0.09	1.16	-0.10	1.04	0.69	7.22	3.80	-5.41	2.95	0.52
ROE5	0.51	4.50	0.08	1.12	-0.04	0.43	0.53	7.64	3.81	-5.80	3.00	0.53
ROE7	0.52	4.70	0.07	0.92	-0.05	0.56	0.60	6.95	3.72	-5.36	2.99	0.55
ROE4	0.48	5.13	0.09	1.13	-0.13	1.29	0.78	8.69	3.78	-6.80	3.08	0.56
ROE8	0.58	4.71	0.06	0.77	-0.03	0.31	0.57	6.08	3.55	-5.17	3.16	0.64
ROE9	0.70	4.55	0.11	1.43	-0.11	1.17	0.65	5.72	3.48	-5.14	3.30	0.69
ROE10	0.65	4.57	0.04	0.54	-0.07	0.71	0.73	5.17	3.29	-4.93	3.33	0.73

Table B.3 Firm-Level Estimates Using Crime Mimicking Portfolios (CMPs)

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. CMP betas for each firm are estimated following Dimson (1972) with one lag over a 60-month rolling window. Each month, firms are sequentially sorted first into 10 portfolios by the variance of crime growth mimicking portfolio (CMP Var) beta and then into an additional 10 portfolios by the average of crime growth mimicking portfolio (CMP Avg) beta, for a total of 100 equal weighted portfolios. Full time series betas are estimated for all 100 portfolios, and assigned to the firms that belong to each portfolio. Prices of risk and standard errors are calculated as in equations (2.16) and (2.17) respectively. All NYSE, AMEX, and NASDAQ stocks in CRSP with prices greater than \$5 are included. $\bar{R}^2_{FM}$ denotes the average cross-sectional adjusted r-squared, while $\bar{N}$ denotes the average cross-sectional number of test-assets across all *T* periods. In brackets are *t*-statistics that use Fama and MacBeth standard errors.

Panel A: March 1980 to December 2012

	(1)	(2)	(3)
$\hat{\gamma}_{CMP\ Avg}$	-0.073		-0.083
	[2.147]		[2.325]
$\hat{\gamma}_{CMP\ Var}$	-0.098		-0.092
	[2.393]		[2.077]
$\hat{\gamma}_{MKT}$		0.107	0.270
		[0.249]	[0.618]
$\hat{\gamma}_{SMB}$		0.201	0.065
		[0.729]	[0.252]
$\hat{\gamma}_{HML}$		0.567	0.093
		[2.062]	[0.398]
$\hat{\gamma}_0$	0.652	0.404	0.487
	[3.478]	[1.549]	[1.874]
$\bar{R}^2_{FM}$	0.027	0.027	0.030
$\bar{N}$	2729	2729	2729
T	394	394	394

Panel B: July 1957 to December 2013

	(1)	(2)	(3)
$\hat{\gamma}_{CMP\ Avg}$	-0.059		0.001
	[2.135]		[0.023]
$\hat{\gamma}_{CMP\ Var}$	-0.085		-0.050
	[2.687]		[1.588]
$\hat{\gamma}_{MKT}$		0.496	0.388
		[1.317]	[1.025]
$\hat{\gamma}_{SMB}$		0.042	-0.019
		[0.205]	[0.096]
$\hat{\gamma}_{HML}$		0.541	0.431
		[2.604]	[2.441]
$\hat{\gamma}_0$	0.595	0.133	0.309
	[4.386]	[0.546]	[1.225]
$\bar{R}^2_{FM}$	0.032	0.032	0.034
$\bar{N}$	2204	2204	2204
T	678	678	678

Table B.4 Expected Return Portfolio Sorts using Crime Mimicking Portfolios (CMPs)

Portfolios sorted by expected returns are generated using the following procedure. First, using all NYSE, NASDAQ, and AMEX stocks from CRSP with prices greater than $5, rolling 60-month crime mimicking portfolio exposures for each stock are estimated following (2.14). Second, expected returns are estimated using both the estimated crime betas and prices of risk for the firm-level regressions in the first column of Table B.3. Third, within each NYSE size quintile each stock is sorted by its expected return and placed into quintiles, with Q5 having the highest expected returns while Q1 has the lowest expected returns. The resulting quintile portfolios are equal weighted and rebalanced monthly.

Panel A: March 1980 to December 2012

Quintile	Avg	*t*-stat
Q1 (Low)	1.029	3.59
Q2	1.190	5.23
Q3	1.270	5.72
Q4	1.240	5.24
Q5 (High)	1.271	4.55
Q5-Q1	0.242	2.07

Panel B: July 1957 to December 2013

Quintile	Avg	*t*-stat
Q1 (Low)	1.066	5.23
Q2	1.198	6.75
Q3	1.223	6.78
Q4	1.272	6.58
Q5 (High)	1.226	5.45
Q5-Q1	0.160	1.84

Table B.5 CMP Beta Sorted Portfolios as Test Assets

Cross-sectional regression estimates of monthly risk premia following the Fama and MacBeth (1973) procedure. Factors to explain test-asset returns include the cross-sectional average of crime growth mimicking portfolio (CMP Avg), the cross-sectional variance of crime growth mimicking portfolio (CMP Var), and the Fama and French (1993) three factors (MKT, SMB, and HML). Test-assets include firms sorted by their crime betas. Betas for each firm are estimated following Dimson (1972) with one lag over a 60-month rolling window. Each month, firms are sequentially sorted first into 5 portfolios by the variance of crime growth beta and then into an additional 5 portfolios by the average of crime growth beta, for a total of 25 equal weighted portfolios. MAPE is the mean absolute pricing errors. The T^2 statistic and its associated *p*-value tests the null that the pricing errors are jointly zero. In brackets are *t*-statistics that use Fama and MacBeth standard errors, and in braces are *t*-statistics that use GMM standard errors with a Newey-West spectral density matrix with 12 lags. Returns are monthly and over the period indicated in the panel title.

Panel A: March 1980 to December 2012

	(1)	(2)	(3)
$\hat{\gamma}_{CMP\ Avg}$	-0.076		-0.123
	[2.167]		[2.799]
	{1.715}		{2.175}
$\hat{\gamma}_{CMP\ Var}$	-0.103		-0.102
	[2.406]		[2.027]
	{1.960}		{1.593}
$\hat{\gamma}_{MKT}$		0.050	0.264
		[0.095]	[0.516]
		{0.080}	{0.440}
$\hat{\gamma}_{SMB}$		0.270	0.041
		[0.808]	[0.136]
		{0.732}	{0.123}
$\hat{\gamma}_{HML}$		0.635	-0.181
		[2.061]	[0.617]
		{1.451}	{0.533}
$\hat{\gamma}_0$	0.645	0.398	0.585
	[3.482]	[1.251]	[1.856]
	{2.902}	{0.917}	{1.442}
$\bar{R}^2_{OLS}$	0.641	0.420	0.629
MAPE	0.055	0.075	0.050
T^2	20.398	24.415	18.015
p-value	0.558	0.273	0.521
GRS F	1.597	1.519	1.364
p-value	0.036	0.055	0.116

Panel B: July 1957 to December 2013

	(1)	(2)	(3)
$\hat{\gamma}_{CMP\ Avg}$	-0.064		-0.005
	[2.240]		[0.128]
	{1.847}		{0.111}
$\hat{\gamma}_{CMP\ Var}$	-0.093		-0.054
	[2.797]		[1.543]
	{2.380}		{1.341}
$\hat{\gamma}_{MKT}$		0.524	0.500
		[1.110]	[1.064]
		{0.759}	{0.767}
$\hat{\gamma}_{SMB}$		0.042	-0.056
		[0.171]	[0.233]
		{0.137}	{0.180}
$\hat{\gamma}_{HML}$		0.576	0.420
		[2.600]	[2.080]
		{1.743}	{1.630}
$\hat{\gamma}_0$	0.582	0.094	0.229
	[4.318]	[0.305]	[0.700]
	{3.467}	{0.189}	{0.483}
$\bar{R}^2_{OLS}$	0.532	0.575	0.572
MAPE	0.056	0.055	0.053
T^2	29.266	29.037	27.107
p-value	0.137	0.113	0.102
GRS F	1.861	1.565	1.417
p-value	0.007	0.040	0.087