Perceptions of Crime and the Gender Commuting Gap

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Abstract. On average, women are less willing than men to commute long distances to find higher paying jobs. It's well established that this commute-time discrepancy contributes to the gender wage gap. Less well understood are its causes. In this paper, I study whether perceived crime risk may drive gender disparities in commuting time. I combine the Census Bureau's American Community Survey with the FBI's Uniform Crime Reporting data from 2005 to 2018, to test the effect of perceived crime risk on gender disparities in commute time and public transportation use. Preliminary results suggest that perceptions of crime matter in modest but significant ways: increases in the rates of reported violent crimes are associated with decreased commuting times and public transit use for both genders, while increases in the rates of reported rapes have differentially stronger associations with women's commuting behavior. To better identify a causal effect, I'll outline a potential diff-in-diff strategy I could use in a next stage of this project. Finally, I present a simple dynamic belief-updating model that shows how higher perceived risk of rape leads to shorter commutes, which in turn leads to overweighting news signals that sensationalize crime. I show how this dynamic can lead to persistent gender gaps in public transit behavior.

Introduction

The commuting time gap is a persistent issue in most industrialized countries. In the United States, from 1999 to 2014, men's commute times were on average more than 47% longer than those of women (OECD, 2014). Even though the gap has been steadily decreasing in recent years (Le Barbanchon, Rathelot and Roulet, 2020), it remains relatively large. In the United States in 2010, men on average still had 15% longer commute times than women (OECD, 2014).

The impact of gender commute time differences on the gender wage gap has been well studied in previous literature (Le Barbanchon, Rathelot and Roulet, 2020; Troncoso, de Grange and Rodriguez, 2021; Crane, 2007; Farre, Jofre-Monseny and Torrecillas, 2020). Women's aversion to long commutes negatively impacts the quality of their job market matches, thereby contributing to the gender wage gap. Although the effects of the gender commute time discrepancy are well studied, little research exists on its causes. Previous literature has focused primarily on the higher burden of family responsibilities on women. However, this higher burden has only been shown to exacerbate the problem, and does not fully account for the gender differences in commute times (Farre, Jofre-Monseny and Torrecillas, 2020). Understanding the underlying causal mechanism behind the discrepancy is key to determining how to close the gender wage gap.

Significant literature also exists on the effect of crime on men and women commuters, with a heavy focus on differences in the perception of danger. Empirical findings suggest women are more concerned with safety on public transit than men, and perceive more danger while using public transport than men do (Ouali et al., 2020; Yavuz and Welch, 2010; Fan, Guthrie and Levinson, 2016). There does not exist any previous research on the effect of urban crime on the gender commute time gap. This paper contributes to the existing literature by connecting the dots and exploring a novel link between the gender commute time gap and the gender gap in the perception of safety. This question is relevant as it would show how perceptions of crime can disparately limit women's economic and spatial mobility.

Using census data from the American Community Survey (ACS), as well as crime data from the FBI's Uniform Crime Reporting (UCR) program from 2005 to 2018, I will test the following four null hypotheses with a focus on the rape rate.

- H1. Perceived crime risk does not affect commuting time.
- H2. Perceived crime risk does not affect the gender disparity in commuting time.
- H3. Perceived crime risk does not affect the use of public transportation.
- H4. Perceived crime risk does not affect the gender disparity in the use of public transportation.

The preliminary results suggest that all violent crime rates are negatively associated with commuting for men and women, and that the rape rate increases with the gender commuting time gap and gender disparity in use of public transit. The results further suggest that moving from a city with a low rape rate to a city with a high rape rate is associated with a 0.546-minute increase in the gender commuting time gap.

The current empirical strategy does not support causal claims. I outline two potential next steps for identifying a causal relationship: a difference-in-differences (DiD) approach and an IV approach.

First, I would implement an event-study–based DiD design that uses crime-perception shocks. I could scrape local newspapers to identify periods of unusually high crime reporting within cities. Using high-frequency commuting data such as the veraset smartphone mobility data, I would then construct a synthetic DiD analysis to test whether commute times in shocked cities reduced more than those in comparable cities in the weeks following the shock. As a second stage, I would compare the responses by gender, either using a triple difference estimator or a Wald test.

I could also use the FBI's Uniform Crime Reporting Program annual counts of law enforcement employees by agency. The number of officers would work as an IV, because they only affect the dependent variable commute time through their impact on crime. Although the crime rate in a given period may affect the number of police officers in the next period, it cannot significantly affect the number of officers in the same period. This is because it takes time to adjust the number of government employees (Figure 1). Therefore, there is no reverse causality between the number of officers and the crime rate in a given period.

$$\begin{tikzcd}
\text{number of officers}_t \arrow[r] & \text{crime rate}_t \arrow[r] \arrow[d, leftrightarrow] \arrow[rr, bend left] & \text{number of officers}_{t+1} \arrow[r] & \text{crime rate}_{t+1} \arrow[d, leftrightarrow] \\
& \text{commute time}_t & & \text{commute time}_{t+1}
\end{tikzcd}$$

FIGURE 1. Causal diagram of law enforcement, crime, and commute times across periods t and $t+1$.

The paper is divided into six sections. Section 1 presents a comprehensive review of the literature on gender, commuting, crime, and belief updating. Section 2 describes the data and variables used in the empirical analysis. Section 3 describes the model, hypotheses, and testing methodology. Section 4 discusses the empirical results and limitations. Section 5 presents a stylized toy model of how departures from Bayesian belief updating can lead to a self-reinforcing gender commuting gap. Section 6 concludes the paper.

1. Literature Review

1.1. Gender and Commuting. Workers' commuting decisions are constrained by the labor market, social roles, and transportation infrastructure (Hanson, 2010). From a job-matching model perspective, the time a worker is willing to commute increases the number of potential firms the worker can match with. Commuting is also crucial to a healthy social life, and the lack of ability to commute freely can lead to social isolation. Thus, understanding the gender gap in commuting behavior is important to better understand the mechanisms of gender inequality.

The gender commuting gap has a sizable negative effect on women's wages. Le Barbanchon, Rathelot and Roulet (2020) use a matched data set of French unemployment and employment registers to connect gender differences in workers' willingness to commute to the gender wage gap. Considering a worker firm matching model, a worker can only be matched to a firm they are willing to commute to. Men's willingness to commute longer increases the number of potential firms they can be matched with. This results in better matches leading men to have higher incomes. Le Barbanchon, Rathelot and Roulet (2020) also find that gender differences in commute times have decreased over time, alongside gender gaps in annual earnings. Troncoso, de Grange and Rodriguez (2021) build on Le Barbanchon, Rathelot and Roulet (2020) by analyzing the gender wage gap in the city of Santiago, Chile. They find that commute time accounted for 10% to 47% of the logarithmic wage gap explained by worker characteristics. Estimating the labor supply elasticity of commuting time from a sample of men and women in U.S. cities using microdata from the Census, Farre, Jofre-Monseny and Torrecillas (2020) find that travel times observed in the U.S. have contributed to the persistence of gender disparities in labor market outcomes.

Although the gender commuting gap is well studied, research looking into the underlying mechanism that leads to the discrepancy is relatively novel. Most studies point towards women's greater family responsibilities than men (Crane, 2007). These responsibilities may include but are not limited to taking care of the children, buying groceries, and cooking. Taylor, Ralph and Smart (2015) use data from the American Time Use Survey (ATUS) to calculate the female-to-male ratio of household-serving trips in a household. They find that even in households where women had higher incomes and were better educated or worked more hours than their male partners, they still made more child-serving and grocery trips than their male partners. Hu (2021) use the 2017 U.S. National Household Travel Survey to analyze how the effects of the household structure differ across racial and ethnic groups. The results suggest that the effect is large for Hispanic people, small for Black people, and moderate for White and Asian people.

1.2. Gender and Fear of Crime. I use crime data to understand the behavioral differences between men and women in commuting. It is important to note that actual crime does not necessarily reflect the perception of crime. People generally believe crime is worse than it is. Although actual property crimes and violent crimes have steadily decreased in recent years, survey respondents consistently and overwhelmingly believe that U.S. crime has increased from the previous year (Koerth and Thomson-DeVeaux, 2020). The perception of crime also differs strongly across demographics such as race, age, income, and sex (Loukaitou-Sideris, 2014). It is well-known from previous literature that women are more concerned about crime than men (Clemente and Kleiman, 1977; Ferraro, 1996). As a result, women can disproportionally suffer from social exclusion and fewer opportunities than their male counterparts (Loukaitou-Sideris, 2014). Snedker (2015) find that women interpret signals of crime, such as disorder and incivilities, differently than men, whose fear of crime is more abstract.

Early researchers have claimed that the gender gap in fear of crime is unreasonable, pointing to the fact that even though men are more likely to experience violent crime, women are more likely to fear crime (Clemente and Kleiman, 1977; Moeller, 1989). More recently, researchers have argued that the discrepancy can be better explained by the type of crime and gender norms in society. Reid and Konrad (2004) find that men had a greater fear of crimes for which they were more likely to be victimized than women had of those same crimes. Although men are more likely to be the victims of violent crime, women are far more likely to be the victims of sexual assault and rape. The police reports of such crimes are likely lower since they are severely under-reported. Women may be less frequent victims of violent crime because they take greater precautions, or because they are less likely to instigate aggression. Another reason women may report a greater fear of crime on survey responses is that society and popular culture have framed women as weak and victimized and men as strong and fearless (Reid and Konrad, 2004). Sutton and Farrall (2005) use survey data to find empirical evidence that men's but not women's reported fear of crime levels are inversely proportional to their lie score, which measures whether their answers are candid or rather socially desirable.

1.3. Crime and Commuting. Researchers have also looked into the effect of crime or perceived crime on public transportation. Ouali et al. (2020) find empirical evidence of a gender gap in the perception of safety. They find that women are 10% more likely to feel unsafe in metros than men and 6% for buses. Similarly, Yavuz and Welch (2010) find that experience with safety-related problems affects women significantly more than men. At the same time, Fan, Guthrie and Levinson (2016) find that women waiting in perceived dangerous places for more than ten minutes for public transport reported waiting times much longer than they were and more prolonged than those reported by men. Vilalta (2011) use 2007 Survey on Victimization and Institutional Efficacy conducted in the Mexico City and find that those who have been previously victimized experience higher levels of fear. Considering that many sexual assault and rape cases go unreported, previous exposure to sexual assault may explain some differences in perception of crime. Spicer and Song (2017) use cognitive maps to show that the perception of crime increased due to transit growth at a large transit hub in Canada. They also find that women were more concerned with improving safety in public transpiration. Given that men and women have different views on what aspect of public transit needs to be improved, Yavuz and Welch (2010) suggest a need for gender-specific policies to make women feel safe in public transportation.

1.4. Belief Updating. A large body of literature shows that individuals do not update their beliefs in a fully Bayesian manner, especially in environments where signals are correlated. Local news is well known for sensationalizing crime. A single crime incident might be reported in multiple news outlets. Agents that neglect the correlation among signals can become overconfident in the form of overprecise beliefs (Levy and Razin, 2017; Eyster and Rabin, 2010). Enke and Zimmermann (2017) experimentally show that prolific users were unable to account for correlated signals even when they were informed of the signal structure.

If people pay more attention when a crime is reported or they themselves are the victims of crime, they may neglect times in which no crime occurs. Consequently, they develop upward-biased beliefs about the risk of crime. Models of channeled attention show that people may ignore or discard information they mistakenly deem irrelevant, preventing them from learning about their mistaken theories (Gagnon-Bartsch, Rabin and Schwartzstein, 2018; Hanna, Mullainathan and Schwartzstein, 2014). If a commuter is more likely to update based on news about rapes than their long and uneventful commutes, they will hold inflated beliefs about the risks of commuting.

Additionally, once a person believes a hypothesis to be more likely than another, they may interpret neutral signals as additional evidence of their hypothesis. Rabin and Schrag (1999) show that a confirmatory biased agent may in the long run become fully convinced of the wrong state. In the context of commuting, someone who already believes public transit is dangerous may interpret ambiguous experiences, such as dirty buses or a commuter shouting, as confirming their fears. This further strengthens their beliefs.

These mechanisms have implications for gender disparity in the perception of crime. If women hold higher priors about the risk of commuting, they may choose shorter commutes or avoid using public transit. As a result, they are exposed to fewer unbiased experiential signals about the safety of public transportation. Fudenberg and Levine (1993) formalize this idea in their model of self-confirming equilibrium: if agents' choices limit the information they receive, incorrect beliefs can persist indefinitely, because they are not contradicted by the off-path evidence.

Incorporating the existing literature on belief updating, I present a stylized dynamic toy model in section 5. The model demonstrates how higher perceived rape risk leads women to choose shorter commutes, which reduces the number of unbiased experiential signals they receive and increases the relative weights of correlated crime news. I show how this self-reinforcing dynamic can lead to persistent gender gaps in perceived risk and commuting time.

2. Data and Data Cleaning

The data on commuting time, transportation method, and the control variables are collected from the Census Bureau's American Community Survey (ACS) 1-year Public Use Microdata Sample (PUMS). The ACS is a U.S. national household and individual-level yearly survey of social, economic, housing, and demographic data. The 1-year PUMS data is an anonymized subset of the ACS representing 1% of the population. The data on crime is collected using the FBI's Uniform Crime Reporting (UCR) Program. The FBI's UCR program includes a public dataset with yearly observations on crime by police departments. Yearly observations from both data sets are included from 2005 to 2018. The time range is restricted due to the lack of variables for specific years in the ACS, such as commute time and mode of transportation. I also used gasoline prices by state and year from the U.S. Energy Information Administration

(EIA) as an explanatory variable in understanding commuters' choices on whether or not to commute by car.

The UCR data contains monthly offenses known to law enforcement at the police department level. To get estimates for yearly crime rates, I summed up yearly offenses known by month and divided them by the population served by that police department. I then multiplied the per-person crime rates by 100,000 to get the crime rate per 100,000 population.

Each observation in my analysis is an individual commuter in a particular year. To measure the effect of neighborhood crime on commuting behavior, I combined the Census Data with the FBI data. To match each commuter to their neighborhood crime rate, I used the census *city* variable to match police departments to cities whose names are part of the department name. After merging the data sets and removing observations for which commuting behavior was not reported, I was left with data on 2,357,757 commuters from 2005 to 2018.

The final working data set is a micro data set of commuters and control variables from 2005 to 2018 with neighborhood and year-specific crime rates for 172 U.S. cities. The city with the largest number of observations is NYC, followed by L.A. and Chicago, with 393,506, 224,269, and 128,403 observations, respectively.

Table 1 shows a summary of city crime rates per 100,000 people. For this analysis, I will focus on the rape rate. I will also include results for murder, assault, robbery, and violent crime[1] in the appendix.

TABLE 1. Summary Statistics of Crime Rates

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**IQR**
Violent crime	2,357,757	1730.528	1097.959	0	6495.396	1426.519
Murder	2,357,757	9.733952	8.713962	0	64.762	8.80312
Assault	2,357,757	1408.621	990.0942	0	5920.954	1376.515
Robbery	2,357,757	5971.694	7026.817	0	24722	198.0424
Rape[a]	2,357,757	32.54788	26.01033	0	257.4814	32.13867

All crime variables are yearly crime rates per 100,000 population, constructed from the FBI's UCR Program (2005-2018).
[a] The rape rate reflects the *forcible rape* definition (pre-2013 UCR).

It is important to note that a lot of violent crime, especially rape, happens at home from domestic violence. Thus, comparing crime rates across cities might not accurately measure the

[1]Violent crime is the sum of the other four crime rates.

relative danger in the use of cities' public transportation networks. According to the National Crime Victimization Survey, from 2005-2010, only 39.2% of violent crime was committed by strangers. Specifically, only 24% of rape/sexual assaults, 51.7% of robberies, and 42.3% of aggravated assaults were committed by strangers from 2005-2010. However, people are more likely to be exposed to aggregate statistics through news reports on crime and are unlikely to be familiar with violent crime rates specific to public transit. For this reason, city level crime rates are a good proxy for people's *perception* of crime in public transit.

Table 2. Summary of Commute Time to Work by Sex

Sex	**Mean (minutes)**	**Std. Dev.**	**Frequency**
Female	27.98775	23.364859	1,210,871
Male	26.51914	22.404815	1,146,886
Total	27.27337	22.914646	2,357,757

Commute time data is collected from the ACS PUMS dataset (2005-2018).

Table 2 presents a summary of commuting behavior by sex. Most of the respondents in the sample commute by car, with approximately 1,700,000 out of the total 2,357,757 commuters choosing to commute by auto, truck, or van. Commuters who did not commute by car only accounted for roughly 660,000, with approximately 200,000 using subways and 170,000 commuting by bus. Noticeably, this sample's gender commute time gap is relatively small, with average commutes of 28.0 and 26.5 minutes for men and women, respectively. Commuting time differences also appear more profound in commuters who drive by car or motorcycle than those who use public transportation.

3. Method

The dependent variables to test the hypotheses will be travel time to work (*trantime*) and means of transportation to work (*tranwork*) from the ACS's PUMS. The independent variables for the analysis will be crime rate statistics from the FBI's UCR. Thanks to the exhaustive nature of the ACS, there are many control variables available at both the personal and household level.

To test hypothesis H1, I will use a household clustered time-fixed effects model. This will be of the form:

$$\text{trantime}_{i,h,c,t} = \beta_0 + \beta_1 \text{crimerate}_{c,t} + \beta_2 \text{pcontrols}_{i,h,c,t} + \beta_2 \text{hcontrols}_{h,c,t} + \gamma_t + \epsilon_{i,h,c,t}, \tag{1}$$

where $\text{trantime}_{i,h,c,t}$ represents the travel time to work of a single commuter i in household h living in city c in year t, $\text{pcontrols}_{i,h,c,t}$ and $\text{hcontrols}_{h,c,t}$ represent person-specific and household-specific control variables respectively, γ_t represents the time-fixed effects and $\epsilon_{i,h,c,t}$ is the error term.

It seems reasonable to assume that crime rates only affect the commuting time of those who walk, bicycle or use public transportation, since commuting by car limits public exposure. To account for this, I will measure the effect of crime only on commuters who do not commute by car. However, crime might affect a commuter's decision to commute by car. Therefore, I use a Heckman Correction model to correct for the bias inflicted by using a non-randomly collected sample. Gasoline prices by state and year and population density are used as variables that only affect the decision on whether to commute by car or not and not how long one commutes in non-car commuting methods.

Similarly, to test hypothesis H2, I will use two household time-fixed effects models of the form given in Equations 1. The first model will only use male commuters, while the second will only use female commuters as observations. As in H1, I will also measure the effect of crime on non-car commuters using a Heckman Correction model. I then test for the difference between $\beta_{1female}$ and β_{1male}. I will use a Wald test of the form

$$\text{Test H2}: \quad \beta_{1female} - \beta_{1male} = 0. \tag{2}$$

To find the increase in gender commuting disparity from moving from a low-crime city to a high-crime city, $\delta_{crimerate}$, I use the following calculation

$$\delta_{crimerate} = (\text{75th percentile crime rate - 25th percentile crime rate})(\beta_{1male} - \beta_{1female}). \tag{3}$$

Lastly, to test hypotheses H3 and H4, I will repeat the methodology used to test H1 and H2 but replace the dependent variable for travel time to work (*trantime*) with a dummy variable for not commuting in a car, motorcycle or taxi (*notcardum*) constructed from the variable *tranwork*.

This will be a probit model of the form

(4)

$$P(\text{notcardum}_{i,h,c,t} = 1|\mathbf{x}_{i,h,c,t}) = \Phi(\beta_0 + \beta_1\text{crimerate}_{c,t} + \beta_2\text{pcontrols}_{i,h,c,t} + \beta_2\text{hcontrols}_{h,c,t} + \gamma_t),$$

where $\mathbf{x}_{i,h,c,t}$ is the vector of regressors, and Φ is the cumulative distribution function of the standard normal distribution. To test H4, I will use a Wald test on the male and female coefficient of crime rate, as seen in Equation 2.

4. Results

This section presents empirical tests of hypotheses H1-H4. Throughout the focus will be on the rape rate. Other crime categories (murder, assault, robbery and violent crime) are treated as robustness checks with tables in the Appendix.

4.1. Testing H1: Does perceived crime risk affect commuting time? Table 3 reports estimates of equation 1 with the rape rate as the main explanatory variable. Across all specifications, the rape rate is negatively and significantly associated with the average commute time. On average, a one-unit increase in the rape rate (per 100,000 population), ceteris paribus, is associated with a reduction in commute time of 0.150 minutes. Other crime categories also yield negative coefficients, but with smaller magnitudes and less robustness across specifications.

To estimate the relative effect on commuting time, I multiply each crime rate coefficient by the mean crime rate (Table 1). The calculations demonstrate that the rape rate and assault rate have the largest relative effect on commuting time.

4.2. Testing H2: Does perceived crime risk affect the gender disparity in commuting time? To test H2, I estimate equation 1 separately for female and male commuters. Table 3 shows that the association of rape rate with commute time is negative and highly significant for both genders, but larger for women. The results suggest that on average, a one-unit increase in the rape rate, ceteris paribus, reduces female commute time by 0.157 minutes and male commute time by 0.140 minutes (0.166 and 0.147 minutes without control variables).

A Wald test of coefficient equality rejects H2 for the rape rate at the 0.1% significance level for both the regressions with and without control variables. Thus, an increase in the rape rate is associated with a wider gender commuting gap. Using the interquartile range for each crime rate calculated in Table 1, the increase in gender commuting disparity of moving from a low-crime city to a high-crime city is 0.946.

Of all violent crime rates, the rape rate has the strongest correlation with the commute time gap when moving from a low-crime city to a high-crime city. Specifically, the results suggest that moving from a city with a low rape rate (25th percentile) to a city with a high rape rate (75th percentile), ceteris paribus, is associated with a 0.546-minute increase in gender commuting time disparity. Given that the average overall gender commuting disparity in the sample is 1.469 minutes, the results suggest that the rape rate accounts for a significant part of the gender commuting disparity.

Table 3. Heckman selection model regression results for rape rate

	(1) all	(2) female	(3) male	(4) all control	(5) female control	(6) male control
Outcome: Commute Time						
rape-rate	-0.157***	-0.166***	-0.147***	-0.150***	-0.157***	-0.140***
	(0.00196)	(0.00250)	(0.00254)	(0.00187)	(0.00244)	(0.00249)
athrho	-0.200***	-0.206***	-0.197***	-0.179***	-0.189***	-0.169***
lnsigma	3.371***	3.367***	3.375***	3.336***	3.330***	3.342***
Controls included	No	No	No	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
race dummies	No	No	No	Yes	Yes	Yes
Test H2		5.08e-08			0.000000833	
Observations	2357421	1146745	1210676	2357421	1146745	1210676

Standard errors in parentheses. Estimates obtained using a Heckman selection model to correct for bias from non-random selection into non car commuting methods. The selection equation includes state-by-year gasoline prices and population density as exclusion restrictions. Controls include: age, marital status, education, education missing, number of children, and household income. Test H2 = Prob > chi2: [female]rape-rate = [male]rape-rate. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4.3. Testing H3: Does perceived crime risk affect the use of public transport?

The probit estimate of equation 4, shown in Table 4, indicates that the rape rate is negatively associated with the likelihood of using public transportation. The finding is robust after adding controls.

The estimates for robbery and assault rate with control have positive coefficients. One possible reason is that the regression likely suffers from reverse causality. Cities that support the necessary infrastructure for public transportation inadvertently enable more robberies. Public transportation networks result in crowds of people standing near each other, creating an ideal place for robberies. Thus, the positive coefficient might suggest that the use of public transportation causes an increase in the robbery rate. Another possible reason is that the robbery coefficient picks up on neighborhood poverty since the model lacks community income-level controls. The same is true for the assault rate. Given these limitations, the coefficients for robbery and assault will likely suffer from an upward bias. Reverse causality is less likely to affect the coefficients on the murder rate and rape rate given that these are generally more severe crimes and, thus, less likely to happen due to increased opportunity for committing a crime. Overall, the results suggest H3 can be rejected for the rape rate.

4.4. Testing H4: Does perceived crime risk affect affect the gender disparity in public transport? To test H4, I estimate equation 4 separately for male and female commuters. Table 4 shows that higher rape rates are associated with lower use of public transportation for both genders. The Wald test rejects H4 for rape rate at the 0.1% significance level for both the regressions with and without control variables. Other crime categories provide mixed results. Assault and violent crime also show significant gender disparities, but the results are not robust for murder and robbery.

Table 4. Probit regression results for rape rate

	(1) all	(2) female	(3) male	(4) all control	(5) female control	(6) male control
Outcome: Not car dummy						
rape-rate	-0.0129***	-0.0138***	-0.0121***	-0.00277***	-0.00298***	-0.00252***
	(0.0000547)	(0.0000556)	(0.0000556)	(0.0000512)	(0.0000616)	(0.0000618)
controls included	No	No	No	Yes	Yes	Yes
year dummies	Yes	Yes	Yes	Yes	Yes	Yes
race dummies	No	No	No	Yes	Yes	Yes
Test H2		1.51e-73			0.000000692	
Observations	2357421	1146745	1210676	2357421	1146745	1210676

Standard errors in parentheses

Controls include: age, marital status, education, education missing, number of children, household income, gasoline price, and density.

Test H2 = Prob > chi2: [female]fraperate = [male]fraperate.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.5. Limitations. The study's main limitations are that the crime rates are recorded at the city level. Crime rates can differ significantly within city neighborhoods. The study could be improved by matching commuters to the crime rates within their city neighborhoods. The scope of the study is also restricted to U.S. cities where people primarily commute to work by car. If the study were done in Europe, where public transportation is generally more accessible and common, the results might be more significant. The study was further limited by the number of cities that could be matched to police departments and the number of ACS respondents for whom commuting information was available. As a result, the analysis is restricted to 2,357,75 observations of which approximately 1,700,000 commute by auto, truck, or van.

In the meantime, less than half of violent crimes and even fewer rapes happen in public transit, perpetrated by strangers, but instead occur in people's homes. Therefore, variations in crime may not accurately reflect the true variation in the danger of public transportation. However, since overall crime rates and news drive people's perceptions of commuting risk, the effect of this inaccuracy on the analysis is likely small.

Another potential issue is that shorter commutes can affect peoples perception of crime as they update their beliefs. People generally hold exaggerated beliefs about the levels of crime in their cities. These incorrect priors are reinforced by news that sensationalizes crime. The shorter a person commutes, the less they may realize that commuting is safer than they thought it would be. In the next section, I illustrate this concept with a short stylized toy model.

5. Toy Model

I present a stylized dynamic toy model that illustrates how differences in perceived rape risk result in gender commuting time gaps, which reinforce the gender differences in perceived risk. Even with learning about the true risk of rape when commuting, consuming news that sensationalizes crime results in a self-reinforcing cycle that sustains the gender commuting gap. An agent of gender $g \in \{m, f\}$ chooses how long to commute $T_{g,t}$ in period $t \in \{0, 1, 2, \dots\}$ by maximizing their utility. Commuting yields utility $U_{g,t}(T_{g,t}) = w(T_{g,t}) - T_{g,t} - \lambda T_{g,t}\mu_{g,t}$, where $w(T) = \sqrt{T}$ captures increasing but concave job-matching benefits, $T_{g,t}$ is a commuting-time cost, and $\lambda\mu_{g,t}T_{g,t}$ is the disutility from the agent's perceived expected amount of crime incidents. Here, $\lambda > 0$ measures the agent's sensitivity to crime, and $\mu_{g,t}$ is agent's subjective belief in period t about the probability of being victimized while commuting.

The true probability of a crime incident per minute of commuting is a very small $\theta^{true} \in (0, 1)$. Agents do not observe θ^{true}, treat it as an unknown parameter, and have beliefs $\theta|\mathcal{F}_t \sim \text{Beta}(A_{g,t}, B_{g,t})$, where $\mathcal{F}_t$ is the information set at time t.[2] They then use the posterior mean $\mu_{g,t} = \frac{A_{g,t}}{A_{g,t}+B_{g,t}}$ as their expected belief about the crime risk. To capture that women are

[2]For simplicity, I do not assume that θ^{true} is higher for women than for men even though the data suggests otherwise. Assuming a higher true crime rate for women would however only increase the gender commuting gap in my toy model.

more likely to be victims of rape and that people overestimate the risk of crime, I assume $\mu_{f,0} > \mu_{m,0} \geq \theta^{true}$.

Each period, given beliefs $\mu_{g,t}$, the agent solves $\max_T U_{g,t}(T)$. The first-order condition, $1/(2\sqrt{T}) = 1 + \lambda\mu_{g,t}$, yields the unique interior optimum[3]

$$T^*_{g,t} = \frac{1}{4(1+\lambda\mu_{g,t})^2}. \tag{5}$$

Since $T^*_{g,t}$ is strictly decreasing in $\mu_{g,t}$, the female agent—who begins with a higher perceived rape risk—initially chooses a shorter commute.

After choosing $T^*_{g,t}$, the agent gets signals about θ^{true} from two sources. First, agents observe $n_{g,t} = kT_{g,t}$ experience signals from commuting $T^*_{g,t}$ minutes. Experience signals are drawn from $s^{exp}_{g,t} \sim \text{Binomial}(n_{g,t}, \theta^{true})$. Each period the agent also gets news from observing m news items, each reporting a crime with probability R so that $s^{news}_t \sim \text{Binomial}(m, R)$. To capture how media sensationalism of crime, we assume $R > \theta^{true}$.

At the end of each period, agents update their beliefs with the experience and news signals they received that period. Their Beta-posterior is given by beliefs updated according to Beta-Binomial conjugacy. The posterior parameters update to $A_{g,t+1} = A_{g,t} + s^{exp}_{g,t} + s^{news}_t$ and $B_{g,t+1} = B_{g,t} + (n_{g,t} - s^{exp}_{g,t}) + (m - s^{news}_t)$. The posterior mean becomes

$$\mu_{g,t+1} = \frac{A_{g,t+1}}{A_{g,t+1} + B_{g,t+1}} = \frac{A_{g,t} + s^{exp}_{g,t} + s^{news}_t}{A_{g,t} + B_{g,t} + n_{g,t} + m}. \tag{6}$$

To see the mechanism more clearly, consider the expected posterior mean. Since $\mathbb{E}[s^{exp}_{g,t}] = n_{g,t}\theta^{true}$ and $\mathbb{E}[s^{news}_t] = mR$,

$$\mathbb{E}[\mu_{g,t+1}] = \frac{A_{g,t} + n_{g,t}\theta^{true} + mR}{A_{g,t} + B_{g,t} + n_{g,t} + m}. \tag{7}$$

Because $n_{g,t} = kT_{g,t}$, $\frac{A_{g,0}}{A_{g,0}+B_{g,0}} > \theta$ and $R > \theta^{true}$, $T_{g,t}$ will initially be decreasing in $\mu_{g,t+1}$. As a result of choosing shorter commutes, woman will be exposed to fewer unbiased signals and in expectation have higher posterior means about the rape risk.

This stylized model highlights how gender differences in perceived rape risk can generate persistent gender commuting gaps even when the true risk θ^{true} is very small. Although the long run analysis of this toy model is outside the scope of this writing sample, Figure 2 simulates T^* and μ by gender and shows how the discrepancies persist across many periods.

[3]Assuming that agents need some positive income to survive we can assume an interior solution.

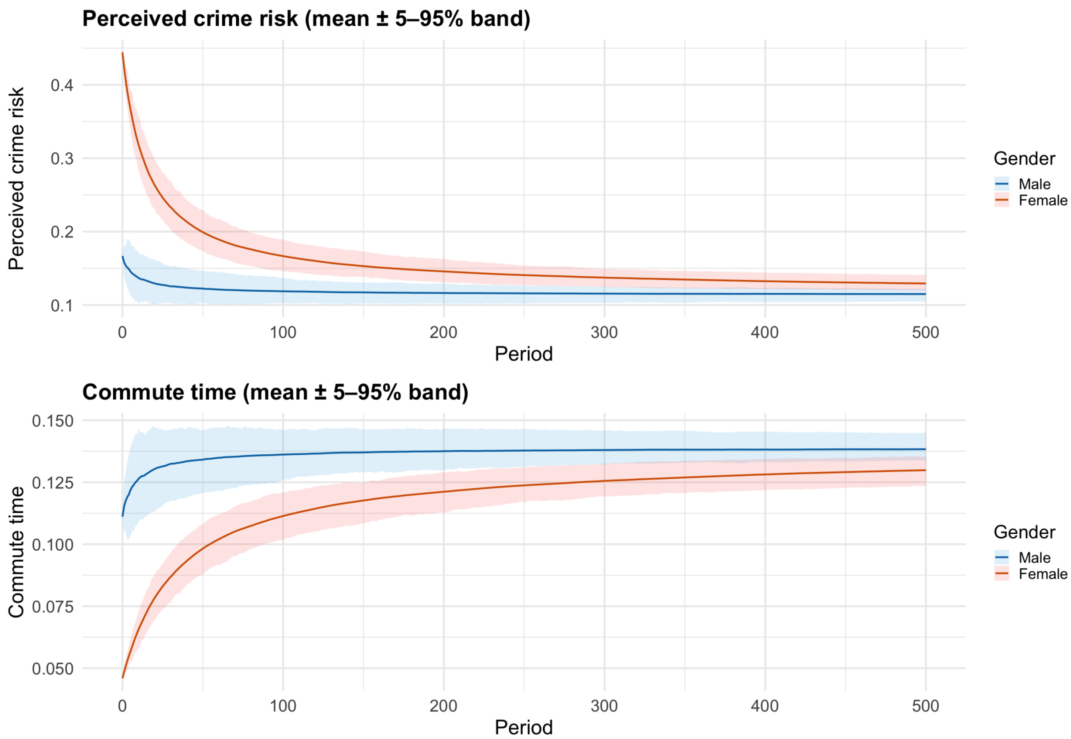

FIGURE 2. Monte Carlo Simulation: Posterior Beliefs and Commuting Time Over Periods

6. Conclusion

This paper examines a novel mechanism behind the persistent gender gap in commuting behavior: people's perception of crime risk in public transportation, with a particular focus on rape. While previous studies emphasized women's higher responsibility in the household, the empirical results suggest that perception of the risk of crime when commuting (proxied by aggregate city crime rates) explains a significant variation in women's shorter commutes and lower use of public transportation.

Using a merged microdata set of 2.4 million commuters from the ACS and city-level crime rates from the FBI's UCR program from 2005 to 2018, I find significant evidence to reject H1 through H4 for the rape rate. First, higher rape rates are associated with shorter commutes for both men and women. Second, the effect is significantly stronger for women, suggesting a positive relationship between rape and the gender commuting gap. Specifically, I find that moving from a city with a low rape rate to a city with a high rape rate is associated with a 0.546-minute increase in the gender commuting time gap. Given that the average commuting disparity of the sample is only 1.47 minutes, the results suggest that the rape rate accounts for a significant portion of the gender commuting disparity.

The study is limited by the lack of a micro-level dataset that captures commuters' heterogeneous perceptions of crime, true crime levels on their commutes to work and commuting time. The study also lacks a test for a causal relationship. I outline a potential instrumental-variable approach based on police staffing that could address concerns about reverse causality or omitted-variable bias in future research.

The stylized model shows how non-Bayesian updating can exacerbate the issue. Gender differences in perceived crime can result in self-reinforcing cycles. If, due to higher priors about commuting risk, women choose to shorten their commutes or refuse public transit, they will consequently receive fewer unbiased signals about commuting risk. As a result, women may place a higher weight on news that sensationalize crime compared to men. This self-fulfilling process reinforces the gender commuting gap in perceptions of commuting risk and time.

Both the empirical result and theoretical insights point to a main conclusion: perceptions of crime, composed of both true crime rates and inflated beliefs, represent a barrier to women's economic and spatial mobility. Policy makers should therefore focus on improving perceptions of safety in public transit, both by addressing actual crime and by enhancing public awareness of transit safety. By connecting the dots between perceptions of crime and commuting decisions, this paper provides a foundation for future research on a novel mechanism explaining the gender commuting gap.

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