Research on the Relationship Between Unemployment Rate and Cybercrime

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Abstract. While previous literatures on unemployment have primarily focused on its effects on traditional forms of crime, the relationship between unemployment and cybercrime remains underexplores. This paper addresses this gap by investigating how state-level unemployment rates influence the incidence of cybercrime complaints across the United States, using panel data spanning from 2004 to 2019. Drawing the data from the Internet Crime Complaint Center (IC3), the analysis employs both Ordinary Least Squares (OLS) and Fixed Effects (FE) regression models to estimates this relationship. Recognizing the role of technological infrastructure in facilitating or deterring cybercrime, the paper further examines the interaction between unemployment rates and broadband coverage. Results suggest that higher unemployment rates are positively associated with increased cybercrime complaints, especially in areas with widespread internet access, indicating a compounding effect. The findings have policy implications for cybersecurity enforcement and labor market interventions, especially during periods of economic downturn.

Keywords: Cybercrime, Internet Fraud, Unemployment rates, Internet accessibility.

1. Introduction

This paper investigates the determinants of cybercrime victimization using state-level data. The focus on victimization rather than perpetrators is dictated by the nature of the data, which consists of self-reported incidents from victims. An Ordinary Least Squares (OLS) analysis finds a positive association between unemployment rates and cybercrime complaint rates. To address potential bias from unobserved factors, a fixed effects (FE) model incorporating state-fixed and year-fixed effects is estimated. The FE results indicate that unemployment rates are not statistically significant, while broadband coverage positively correlates with cybercrime complaint rates. Additionally, the paper examine the interaction between unemployment rates and broadband coverage to assess their combined effect on cybercrime complaints. However, the results do not show a statistically significant relationship. Limitations of this paper include potential endogeneity, reverse causality, and measurement errors inherent in self-reported IC3 data.

Unlike traditional crimes such as murder, assault, or burglary, cybercrime refers to criminal activities conducted over the internet, encompassing offenses such as identity theft, auction fraud, and credit card fraud. Between 2015 and 2019, the Internet Crime Complaint Center (IC3) received 1,707,618 cybercrime complaints, with total reported losses amounting to $10.2 billion. The FBI highlights that cybercriminals continuously exploit cybersecurity vulnerabilities, making it increasingly difficult for individuals and businesses to protect themselves from online fraud. Economic pressure caused by unemployment may contribute to cybercrime, both by increasing individuals' susceptibility to online fraud and by incentivizing criminal behavior. While substantial research has explored the relationship between unemployment and traditional crime, the link between unemployment and cybercrime remains underexplored. This paper aims to address this gap.

Ewuzie [1] examined youth unemployment and cybercrime in Nigeria, finding that entrenched youth unemployment significantly contributed to the rise of cybercrime. This finding aligns with my hypothesis that unemployment increases vulnerability to both committing and falling victim to cybercrime. Similarly, Hameed [2] found that unemployment and financial stress were key drivers of cyber fraud, identity theft, and online harassment. Chen [3] suggests that higher education attainment can also facilitate cybercrime, as individuals with technical expertise can easily manipulate cyber activities. The study reinforces that economic pressure, such as joblessness or income disparities, leads to increased cybercriminal activity from both perpetrators and victims. Vasilyeva [4] further supports the idea that economic vulnerability plays a crucial role in cybercrime exposure, with one in ten EU residents reportedly falling victim to financial cybercrime in 2020. The paper also identifies that married women with two or more children, individuals aged 55–74, and rural residents are more likely to be targeted by cybercriminals. In terms of gender dynamics, Lazarus et al [5] highlight that romance fraud and other psychosocial cybercrimes disproportionately affect women, while financial cyber fraud shows no substantial gender differences. Finally, Mohsin [6] explores how the rise of digital communication technologies has created opportunities for interpersonal cybercrimes such as cyberstalking, harassment, and online abuse. The paper emphasizes how easy internet access and online anonymity facilitate harmful behavior without immediate punishment, reinforcing my argument that unemployment-related vulnerability is magnified in a digital environment.

2. Analysis of unemployment rate and cybercrime complaint rate

2.1. OLS

Ordinary Least Squares (OLS) is a fundamental econometric method used to estimate the relationship between independent and dependent variables in a linear regression framework. The OLS estimator minimizes the sum of squared residuals to obtain the best linear unbiased estimates (BLUE) under the assumptions of the classical linear regression model, including linearity, independence, homoscedasticity, and no perfect multicollinearity [7].

In the context of this paper, OLS is employed to examine the association between unemployment rates and cybercrime complaint rates. By estimating a linear relationship, OLS provides an initial understanding of how changes in unemployment influence cybercrime. However, OLS estimates may be biased due to omitted variable bias, reverse causality, or unobserved heterogeneity [8]. To address these potential issues, a fixed effects (FE) model is implemented as an alternative approach.

2.2. Fixed Effects Model

The Fixed Effects (FE) model is a panel data estimation technique that accounts for time-invariant unobserved heterogeneity by allowing each cross-sectional unit to have its own intercept. This approach controls for unobserved characteristics specific to each state that may influence cybercrime complaint rates but remain constant over time [9]. The FE model is particularly useful in addressing omitted variable bias, as it eliminates the impact of time-invariant confounding factors by differencing out state-specific fixed characteristics.

In this paper, the FE model includes both state-fixed effects and year-fixed effects to control for state-level heterogeneity and time-specific shocks that may influence cybercrime trends. By doing so, the FE model provides more robust estimates of the relationship between unemployment, broadband coverage, and cybercrime complaint rates [10]. However, while the FE model mitigates endogeneity concerns related to omitted variables, it does not fully address potential reverse causality or measurement errors in self-reported cybercrime data.

2.3. Interaction Term

An interaction term in regression analysis captures the combined effect of two independent variables on the dependent variable. It assesses whether the effect of one variable on the outcome depends on the level of another variable [11]. Interaction terms are particularly useful when analyzing complex relationships where two factors may jointly influence the dependent variable in ways that cannot be explained by their individual effects alone.

In this paper, the interaction term between the unemployment rate and broadband coverage rate is included to examine whether the effect of unemployment on cybercrime complaints varies depending on internet accessibility. The rationale behind this interaction is that higher broadband coverage may amplify the impact of unemployment on cybercrime by increasing individuals' exposure to online activities, both as potential victims and as perpetrators. The coefficient of the interaction term provides insight into whether broadband access strengthens or weakens the relationship between unemployment and cybercrime complaints.

3. Empirical strategy

This paper estimates the effect of the unemployment rate on cybercrime complaints by analyzing the relationship between state-level unemployment rates, broadband coverage rate, and their interaction. estimate the following regression equation by OLS and Fixed Effect model:

$$\ln(y_{st}) = \alpha + \beta_1 \text{unemployme ntrate}_{st} + \beta_2 \text{broadbandcoverage}_{st} + \beta_3(\text{unemployme ntrate}_{st} \cdot B\text{roadband}_{st}) + \lambda_t + \delta_s + \in_{st} \quad (1)$$

Where s indexes individual states and t indexes year. The primary interests are the unemployment and broadband coverage rates and their interaction terms. Expect the sign of β_1 and β_2 to be positive. Higher unemployment is likely to increase susceptibility to cybercrime victimization, and more broadband access may increase the likelihood of individua exposure to cybercrime. Finally, β_3 is the interaction term, which expected to reflect whether the effect of unemployment on cybercrime is amplified in states with higher broadband coverage.

The dependent variable is the natural logarithm of the total number of cybercrime complaints per state year. In some specifications, the dependent variable is also a particular online crime type in Table 1, such as identity theft and romance fraud. The log transformation is used because the original data exhibits significant right skewness, as shown in Figure 1. By logging the dependent variable, the regression captures percentage changes in cybercrime complaints, which is more interpretable and addresses the issue of heteroskedasticity.

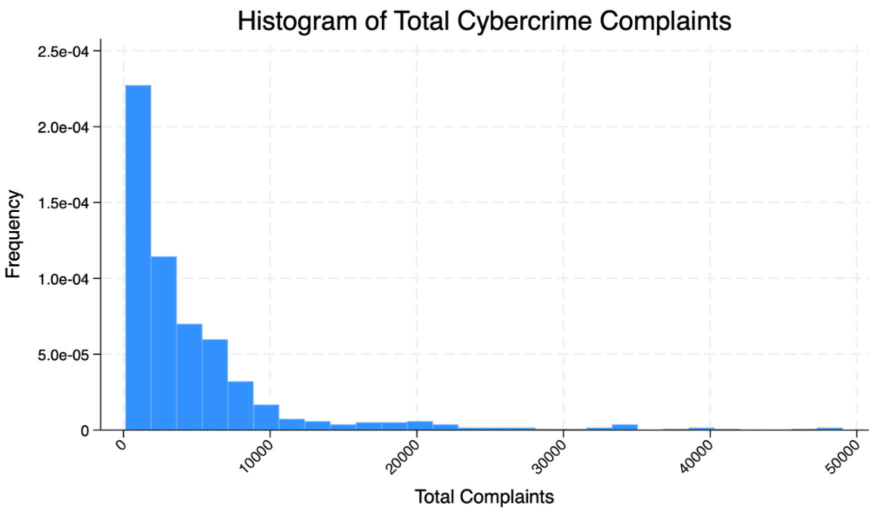

Figure 1. Distribution of total number of cybercrime complaints by state from 2004 to 2019

Recognizing the potential endogeneity of state-level and year-level characteristics, where unobserved factors may simultaneously influence cybercrime complaints and the predictors. I address the limitation by estimating a fixed-effect (FE) model. The FE model incorporates state fixed effects, δ_s, which account for differences across states, such as demographic or policy variations, that remain constant over time. Year fixed effects, λ_t, to control for time-specific factors, such as technological advancements or national economic shocks, that could influence cybercrime rates in all states. Under the FE model, I predict that all three coefficients in the equation are positive but might be smaller than the OLS model. The error term, ϵ_{st}, captures unobservable factors that may influence cybercrime rates.

4. Result

Table 1 shows the OLS and FE estimation results with the cybercrime complaint rate per state population as the dependent variable. The first three columns use the OLS specification, and the last three columns add state- and year-fixed effects. I add three variables in each equation in turn: unemployment rate, broadband coverage rate, and the interaction term of unemployment and broadband coverage rate. All the estimations include the control variables: age groups, poverty rate, house ownership rate and median annual household income.

Table 1. Estimated effects of unemployment and internet characteristics on the cybercrime complaints rate

Dep. Var ln(complaints rate)	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate (%)	0.1726**	0.1874***	0.2533***	0.0160*	0.0049	0.0010
	(0.0173)	(0.0190)	(0.0410)	(0.0084)	(0.0081)	(0.0111)
Broadband coverage Rate (%)		-0.1518	0.7730		0.2272**	0.1572
		(0.2935)	(0.6136)		(0.1009)	(0.1412)
Unemployment Rate × Broadband Rate			-0.0014			0.0001
			(0.0009)			(0.0002)
Adjusted R-square	0.4861	0.5634	0.5652	0.9763	0.9881	0.9881
N	694	479	479	694	479	479
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Standard errors are clustered at state-level and reported in parentheses.
The dependent variable is the log transformation of complaint per 100,000.
Control variables include Median Household Income, Percent Poverty Status, Homeownership Rate, and Age groups.
Cols (1)-(3) are estimated with OLS, Cols (4)-(6) are estimated using FE model.

In the OLS model (columns 3), the unemployment rate has a significant positive effect on the cybercrime complaint rate at a 1% significance level, indicating that the overall cybercrime complaints rate increased by 25.33% per state per year as a 1% increase in the unemployment rate. The positive correlation coefficient supports the hypothesis that rising unemployment is driving cybercrime. However, in the OLS model, the coefficient for broadband coverage rate is positive but not significant, suggesting that internet characteristic may not have a larger effect on the cybercrime complaints rate.

In the FE model (column 6), the effect of the unemployment rate is positively correlated with the complaints rate but not statistically significant. The coefficient of the interaction term changes from negative (column 3) to positive (column 6), but the effect of this coefficient is still weak and insignificant. The significant positive impact of the unemployment rate on cybercrime complaints in the OLS model becomes insignificant in the fixed effects model. The shift shows that results in the OLS model largely depend on the differences between states (in-state economic level, internet availability, or law enforcement intensity) and temporal trends (macroeconomic cycles, the spread of internet use). When state- and year-fixed effects are included, the unobservable, time-invariant characteristics within states and time trends are effectively controlled in the FE model. The result in column 6 reveals that the direct impact of the unemployment rate on the cybercrime complaint rate is not significant in the FE model, and the fixed effects also weaken the interaction effect.

Overall, through OLS and FE estimation, the effect of the unemployment rate is positively correlated with the cybercrime complaints rate, which result is consistent with my hypothesis. Unemployed individuals may spend more time applying for jobs or leisure time online, increasing the likelihood of victimization in cybercrime activities. Another explanation for the increased unemployment rate with higher cybercrime complaints rate is that, in high unemployment periods, there are fewer opportunities to find a job and have a legitimate income, pushing some individuals toward cybercriminal activities to alleviate financial pressure. However, the interaction term of the unemployment rate and broadband coverage rate is not statistically significant in the FE models, which is contrary to my initial assumption. The possible explanation is the independent influence of either the unemployment rate or the broadband coverage rate being more substantial than their interaction effect.

The results are consistent with existing literature. Waldrop emphasizes that economic pressure can drive individuals to engage in cybercrime activities. Pratt et al. point out that an increase in an individual's daily online activities significantly increases their exposure to cybercriminals and makes them more likely to become targets of cyber fraud. Their conclusion is consistent with my hypothesis that unemployed people may spend more time on leisure or job-seeking online activities, increasing their exposure to cybercrime risks. The unemployed may also use cybercrime to obtain substitute income during their unemployment period. Therefore, the higher the unemployment rate, the higher the rate of cybercrime complaints.

Table 2. Estimated effects of unemployment and broadband coverage rate on six types of cybercrime

	(1) In(advance)	(2) In(auction)	(3) In(non-delivery)	(4) In(credit)	(5) In(id theft)	(6) In(romance)
Unemployment Rate (%)	-0.0026	-0.0112	0.0019	0.0632***	0.0618**	-0.0883**
	(0.0285)	(0.0262)	(0.0151)	(0.0240)	(0.0306)	(0.0430)
Broadband coverage Rate (%)	0.4158	1.0465***	0.7123**	0.0171	-0.4121	-0.4972
	(0.3735)	(0.3582)	(0.2968)	(0.3178)	(0.4515)	(0.3505)
Unemployment Rate × Broadband Rate	0.0005	-0.0005	-0.0001	0.0006	0.0008*	0.0014***
	(0.0004)	(0.0004)	(0.0001)	(0,0004)	(0.0004)	(0.0005)
Adjusted R-square	0.9477	0.9762	0.9812	0.9607	0.9537	0.9720
N	379	235	327	381	376	288
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors are clustered at state-level and reported in parentheses.

The dependent variable is the log transformation of advance fraud, auction fraud, non-delivery, credit fraud, identity theft and romance fraud. Control variables include Median Household Income, Percent Poverty Status, Homeownership Rate, and Age groups.

In addition, I examine the complaint rates for different types of cybercrimes in Table 2. The coefficients of the interaction terms are very small, consistent with the results in Table 1. The impact of broadband coverage on different types of cybercrime shows significant variation. Notably, the coefficients for unemployment are negative across all cybercrime types in this paper, except for non-delivery fraud.

5. Conclusion

This paper extends previous research by exploring the relationship between the unemployment rate and cybercrime, with a focus on total and multiple sub-categories of cybercrime types at the state-level. The regression results align with prior studies regarding a positive association between the unemployment rate and the total cybercrime complaint rate. However, this positive relationship does not hold consistently across the subcategories of cybercrime. Additionally, broadband coverage rate also positively correlated with the total cybercrime complaint rate, consistent with previous findings linking economic distress and technological accessibility to higher crime rates. However, this study faces several limitations. Results from the fixed-effects model indicate the positive relationship becomes insignificant after controlling for the state- and year-fixed effects. Furthermore, Inconsistent identification strategies and under-reporting issues from the database limit the ability to draw definitive conclusions. Future research should further investigate this relationship using more comprehensive data and robust methodologies to address these limitations.

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