The Cyclicality of Fraud*

Devesh Raval† Ted Rosenbaum‡

Abstract

We examine the cyclicality of fraud by examining how consumer complaints – our measure of fraud – respond to local shocks to employment. Pooling across several unique databases, fraud is acyclical. However, investment scams and fraud involving money transfers are procyclical, as are high dollar losses. Complaints about credit and debt related issues are countercyclical, as are identity theft and telemarketing complaints, complaints from older adults, and complaints with low dollar losses. The supply side of fraud appears procyclical using our primary database, but ranges from countercyclical for one money transfer dataset to strongly procyclical for CFPB complaints.

*The views in this article are those of the authors and do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. We thank Emma Fletcher, Patti Poss, Jessica Rich, Seth Sacher, and Paul Witt for their comments on this paper, as well as Donna Gregory, Doug McKenney, and Paul Witt for providing data on consumer complaints and Miriam Larson-Koester for discussing this paper. In addition, we thank Rayut Weiser-Rosenbaum for inspiring this paper.

†Federal Trade Commission, draval@ftc.gov

‡Federal Trade Commission, trosenbaum@ftc.gov

1 Introduction

Fraud has become an increasingly prevalent problem for society. Consumers reported $12.5 billion in losses to fraud to the Consumer Sentinel Network in 2024,[1] with millions of consumers reporting fraud and hundreds of thousands victimized in individual scams.[2]

Policymakers have been increasingly concerned with how such fraud varies with economic conditions. During the COVID-19 pandemic, federal relief efforts – such as unemployment claims and emergency small business loans – were stymied by fraudulent actors stealing some of the stimulus payments.[3] Consumer complaints to the government on identity theft spiked during that period – as shown in Figure 1. As Jessica Rich, former head of the Bureau of Consumer Protection (BCP) at the Federal Trade Commission (FTC), told Congress in 2021:[4]

> In "normal" times, fraud is a serious and widespread problem, ranging from telemarketing and get-rich-quick scams, to pyramid schemes and income frauds, to phishing and identity theft. In times of crisis, fraud can be relentless. Con artists seize the opportunity to prey on distressed consumers, offering bogus health cures, defective emergency supplies, non-existent financial aid, and many other scams – often posing as a government agency or official. This happened with Hurricane Katrina and the Great Recession, and it is happening again now with the COVID-19 pandemic.

Policymakers can adjust enforcement priorities in response to shifts in the business cycle. The COVID-19 pandemic offers a clear example. Under the American Rescue Plan Act of 2021, Congress allocated $30.4 million to the Federal Trade Commission (FTC) for expanded consumer protection efforts, including $24 million to hire additional full-time staff.[5] Separately, the COVID-19 Consumer Protection Act granted the FTC new civil penalty authority to combat pandemic-related scams.[6] If certain types of fraud fluctuate systematically with economic conditions, targeted enforcement

[1] See https://public.tableau.com/app/profile/federal.trade.commission/viz/ConsumerSentinel/Infographic.

[2] For example, the FTC refunded 821,000 consumers in the AMG Services case (see https://public.tableau.com/app/profile/federal.trade.commission/viz/Refunds_15797958402020/RefundsbyCase), and Raval (2020b) reports almost 2 million victims in the Ideal Financial case.

[3] See, for example, https://www.justice.gov/criminal/criminal-fraud/cares-act-fraud.

[4] See the following statement: https://docs.house.gov/meetings/IF/IF17/20210204/111139/HHRG-117-IF17-Wstate-RichJ-20210204.pdf. In addition, the following speech by former BCP Director Sam Levine details the FTC's efforts to combat COVID related scams: https://www.ftc.gov/system/files/documents/public_statements/1600629/p210100stoppingcovid19fraudpricegougingtestimony.pdf.

[5] See https://www.congress.gov/bill/117th-congress/house-bill/1319/text/.

[6] See https://www.commerce.senate.gov/2020/12/cantwell-schakowsky-legislation-cracking-down-on-covid-19-scams-passes-senate-and-house.

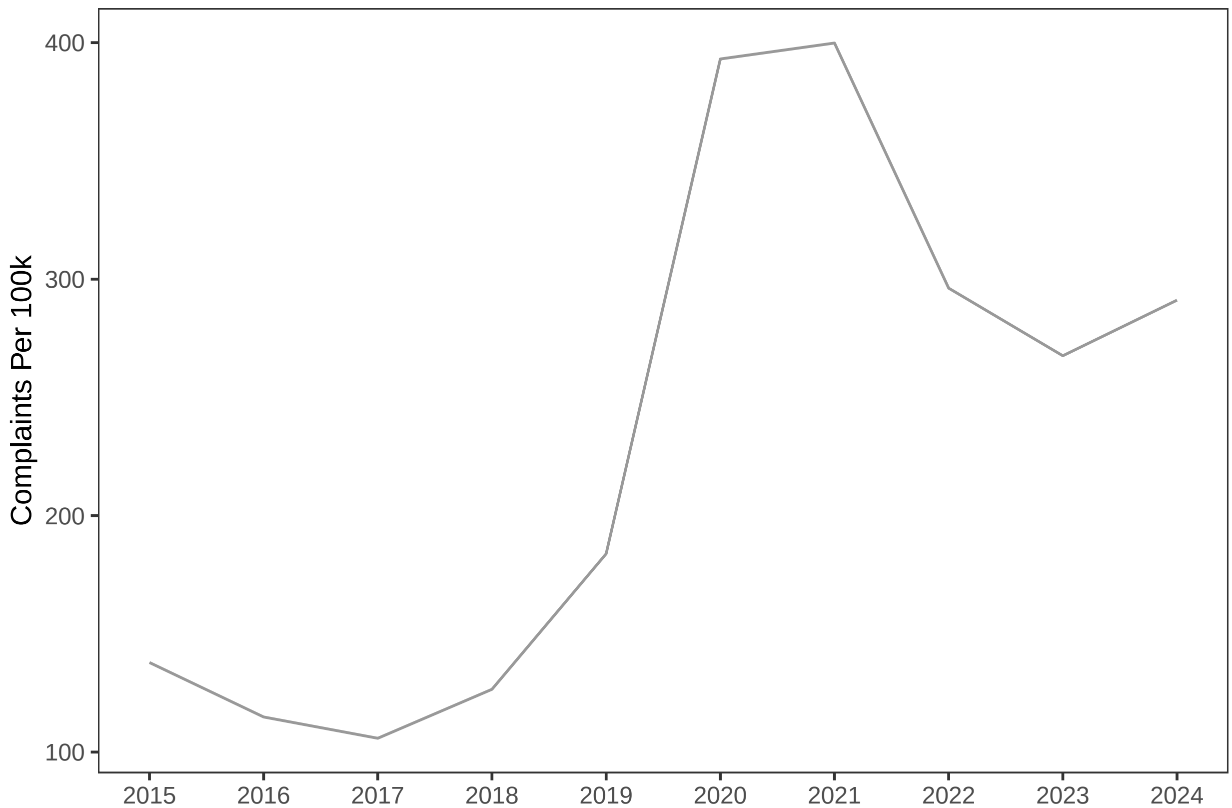


Figure 1: Identity Theft Complaints Over Time

could help address these shifts more effectively.

Despite this policy interest, little empirical evidence exists on how fraud varies over the business cycle. This article fills that gap by analyzing how consumer complaints about fraud and other deceptive business practices respond to changes in local economic conditions by using state- and MSA-level employment as proxies for the business cycle.

A major advantage of our approach is that we have access to several different databases on consumer complaints, and so can examine rich heterogeneity in how fraud complaints respond to economic conditions. Our primary database is fraud and other complaints from the Consumer Sentinel Network, which aggregates complaints from federal agencies such as the FTC and Consumer Financial Protection Bureau (CFPB), non-governmental sources such as the Better Business Bureaus (BBB), state and local enforcers, and private firms such as major money transfer firms. We examine all complaints on fraud and other issues to Consumer Sentinel, as well as complaints disaggregated to the FTC, BBB, CFPB, and money transfer firms. From the FTC, we also have data on complaints to the Identity Theft and Do Not Call databases. Beyond Consumer Sentinel, we have data from the complaint databases of the FBI's Identity Crime Complaint Center, the Federal Communications Commission (FCC), and an anonymous major money transfer company.

Our empirical approach is to regress the number of consumer complaints at the state-year level or MSA-year level on local employment after controlling for local population, local area fixed effects, and year fixed effects. We first pool across all of our datasets to estimate an overall elasticity between consumer complaints and employment. We find that fraud is acyclical in these aggregate regressions, with point estimates between -0.51 and 0.23, and can reject elasticities greater than 1 in absolute value. Using datasets that collect complaints on a broad range of issues, such as the FTC and BBB, we continue to find that fraud is approximately acyclical.

However, certain types of scams do vary with the business cycle. Complaints to money transfer firms in both databases across different time periods are procyclical, as are complaints about investment scams. These procylical effects are consistent with investments and remittances increasing during expansions. Complaints to the CFPB, as well as complaints about credit bureaus, banks, and debt collection, are countercyclical, as are complaints about telemarketing and identity theft. We would expect credit to tighten during recessions, which would explain more complaints involving credit bureaus and debt collectors. In addition, many of the complaints about identity theft concern fraudsters stealing money from "automatic stabilizers" such as unemployment insurance and government stimulus programs.

With the Consumer Sentinel database, we can also examine how business cycle effects vary by the age and amount of money lost by consumers. Complaints related to high dollar losses are procyclical, which may reflect the procyclicality of investment scams, whereas complaints with low dollar losses are countercyclical. We find that complaints by young adults and prime age adults are approximately acyclical; complaints by older adults are countercylical.

Local economic conditions can also influence the opportunity cost of engaging in fraudulent activity. To examine the supply side of fraud, we use the location of the firm named in each Consumer Sentinel complaint. For money transfer complaints, we rely on the more precise receiving location of the transfer. Supply-side estimates indicate that money transfer complaints are generally countercyclical or acyclical, while complaints in the broader Sentinel database—as well as those to the BBB and CFPB—are procyclical, and FTC complaints are acyclical. These patterns likely reflect whether a fraud type complements legitimate business activity, and so tends to increase in expansions, or substitutes for it, and so tends to increase in downturns.

Our work is related to the literature examining consumer complaints about fraud. So far, this literature has focused on profiling the types of consumers affected by different frauds and scams (Anderson (2019), Deliema et al. (2020), DeLiema et al. (2020), Raval (2021)). Researchers have also shown that consumers' willingness to complain about fraud varies with demographic factors (Anderson (2021), DeLiema and Witt (2021), Raval (2020a), Raval (2020b)) as well as with market structure (Gans et al. (2021)). Finally, complaints about fraud exhibit "gravity" like trade flows, with fewer complaints about firms in countries located farther away from consumers (Grosz and Raval (2022)).

In addition, following Becker (1968)'s seminal work on the economics of crime, several papers have examined how crime varies with the business cycle. Researchers have used business cycle fluctuations at the national level for the US (Cook and Zarkin (1985), Bushway et al. (2013)) and Italy (Detotto and Otranto (2012)), at the US state level (Raphael and Winter-Ebmer (2001)) and at the US city level (Garrett and Ott (2008)). This research generally finds that property crime, such as burglary or robbery, is countercyclical whereas violent crimes are acyclical. Detotto and Otranto (2012) examines fraud using national-level business cycle fluctuations in Italy and finds that fraud is countercyclical.

2 Data

2.1 Consumer Complaints

When consumers are defrauded, they can report their experience by filing complaints with several organizations, including government agencies and non-profits. These complaints are the primary source of data on fraud available to law enforcers, who use complaints to identify problems in the marketplace, warn consumers about potential threats, and provide evidence in court. Our main source of information on fraud in this paper is such complaints reported to several different sources.

The largest single database of complaints on fraud and other deceptive business practices is the non-public Consumer Sentinel Network, a consortium run by the Federal Trade Commission (FTC). Consumer Sentinel includes complaints from federal government agencies such as the FTC and Consumer Financial Protection Bureau (CFPB); private sector organizations such as the Better Business Bureaus (BBB); state and local government agencies such as state attorneys general and police departments; and private companies such as Western Union and MoneyGram.[7]

We use data on fraud and other complaints from Consumer Sentinel in the aggregate and disaggregated by specific contributors. We both analyze all complaints to the database ("AllSentinel") to obtain a broad picture of fraud, as well as data from the BBB, CFPB, and FTC separately, which are the three largest contributors to Consumer Sentinel (Raval (2020a)). The CFPB complaints primarily concern financial products and firms such as banks, credit reporting agencies, and debt collectors, whereas the BBB and FTC complaints cover a much wider range of fraudulent and deceptive business practices. We also separately analyze complaints to money transfer agencies such as Western Union and MoneyGram ("MT1"), which cover fraud where payment occurred through a money transfer.

Consumer Sentinel complaints include information on the incident that the consumer is complaining about, including a narrative text field, the company involved, the topic of the complaint, and identifying information on the complaining consumer such as their name and address. Many data contributors also provide information on the dollar losses of the consumer. We use complaint level data from Consumer Sentinel from 2014 to 2023 to examine heterogeneity in business cycle effects across age groups, amounts of money lost, and types of fraud that consumers self-report.

[7] See https://www.ftc.gov/enforcement/consumer-sentinel-network/reports for the Consumer Sentinel Data Book, which contains further detail on the Consumer Sentinel and statistics on the complaints included in it.

We also examine several additional datasets on consumer complaints which focus on specific types of fraud. First, the FTC separately collects complaints about identity theft ("IDT") and violations of the Do Not Call Act from telemarketing and other spam calls ("DNC"). Second, the FBI collects complaints about online fraud through the Internet Crime Complaint Center ("IC3"). Third, the Federal Communications Commission collects complaints related to telecom issues ("FCC"). Finally, we also have data from a major money transfer company from 2004 to 2014 ("MT2"). We discuss the details of each of these datasets in the Data Appendix.

Table 1 summarizes the aggregated complaint datasets we use in our analysis. We have two sources of local variation: state and metro area or MSA. Except for the AllSentinel and IDT datasets, which only have metropolitan statistical areas, our definition of "MSA" includes both metropolitan and micropolitan areas.[8] We have between 7 to 20 years of data for each dataset at the MSA level, and between 8 and 23 years at the state level.[9] The per capita number of complaints varies substantially across datasets; at the metro level, we observe an average complaint rate from 11.6 complaints per 100,000 residents to money transfer agencies to 789.4 complaints per 100,000 residents to the Do Not Call complaint database. A large standard deviation implies that complaint rates vary substantially across geographies as well.

2.2 Local Economic Activity

To measure local economic activity, we use data on state and MSA wage and salary employment from the Bureau of Economic Analysis ("BEA") (U.S. Bureau of Economic Analysis (2023c), U.S. Bureau of Economic Analysis (2023a), U.S. Bureau of Economic Analysis (2023b), U.S. Bureau of Economic Analysis (2024)).[10] For all of our analyses, we control for changes in population using the BEA's annual estimates.

3 Identification and Estimation

The main identifying assumption in our model is that selection into complaining does not vary with business cycle shocks. In that case, our estimates of how complaint rates vary with business cycle shocks should identify how fraud varies with the business cycle.

[8]We use the "MSA" abbreviation for metropolitan and micropolitan statistical areas combined for compactness of notation, even though that differs from the Census's official usage.

[9]For some datasets (e.g., "IDT"), we only have aggregated data on complaints at the state level for earlier years.

[10]The MSA area series was discontinued by the BEA and so the last year for which we have those data is 2022, which is why 2022 is the last year for the MSA data in Table 1.

Table 1: Summary Statistics

	MSA				State		
			Complaints/100k			Complaints/100k	
	Years	Geo	Mean	Std. Dev	Years	Mean	Std. Dev
Consumer Sentinel							
AllSentinel	2008-2022	397	489.5	230.2	2008-2024	618.4	319.1
BBB	2012-2022	927	151.0	82.0	2012-2023	186.4	85.9
CFPB	2012-2022	927	61.3	85.0	2012-2023	102.9	99.7
FTC	2012-2022	927	198.3	108.8	2012-2023	235.8	108.2
MT1	2012-2022	927	11.6	10.7	2012-2023	11.3	7.6
Other							
DNC	2017-2022	867	789.5	503.5	2009-2024	1087.5	556.0
FCC	2016-2022	912	81.5	105.1	2015-2024	90.9	30.5
ICCC	2001-2020	868	59.3	114.7	2001-2023	83.7	56.3
IDT	2006-2022	398	122.9	121.0	2002-2024	124.3	146.8
MT2	2004-2014	912	12.4	10.5	2004-2014	12.9	6.0

To estimate the effect of business cycles on fraud, we estimate a Poisson regression, where we model the conditional expectation of complaints as:

$$E[C_{jdt}|d, j, t, E_{jt}] = \exp(\beta_E \log(E_{jt}) + \beta_P \log(P_{jt}) + \gamma_{dj} + \rho_{dt} + \delta_j \times t), \tag{1}$$

where j indexes the local area, d the dataset, and t the year. Our dependent variable C_{jdt} is the number of complaints for a given local area, dataset, and year. Our main independent variable is local employment E_{jt}, and so our main parameter of interest is β_E, the elasticity of complaints with respect to employment. In addition, since complaints will increase with total population size, we control for local population P_{jt}. We estimate equation (1) pooled across all fraud datasets and separately across datasets.[11]

In all of our specifications, we allow for the average number of complaints to differ for each dataset within each geography and for each dataset within each year by controlling for two main sets of fixed effects – γ_{dj}, a dataset cross metro area fixed effect, and ρ_{dt}, a dataset cross year fixed effect. In robustness specifications, we allow local areas to have separate time trends by including $\delta_j \times t$ terms in the estimation.[12]

[11]We include the data derived from the "AllSentinel" dataset and the four individual subcomponents to Consumer Sentinel as separate observations in these regressions.

[12]We implement the analysis using the ppmlhdfe package in Stata (Correia et al. (2020)).

4 Results

4.1 Main Effects

We find evidence that consumer complaints are acyclical in the aggregate. In Table 2, we report estimates of equation (1) using complaints from all of our datasets. In our MSA estimates, we find a 10% increase in employment leads to a -1.56% decrease in complaints without MSA level trends and a 1.88% increase in complaints with MSA level trends. In our state estimates, we find a 10% increase in employment leads to a -5.06% decrease in complaints without MSA level trends and a 2.29% increase in complaints with MSA level trends. Only the state-level estimate without trends is statistically significantly different from zero, and we can reject elasticities above one in absolute value across all specifications. We can thus reject that fraud is strongly pro or countercyclical.

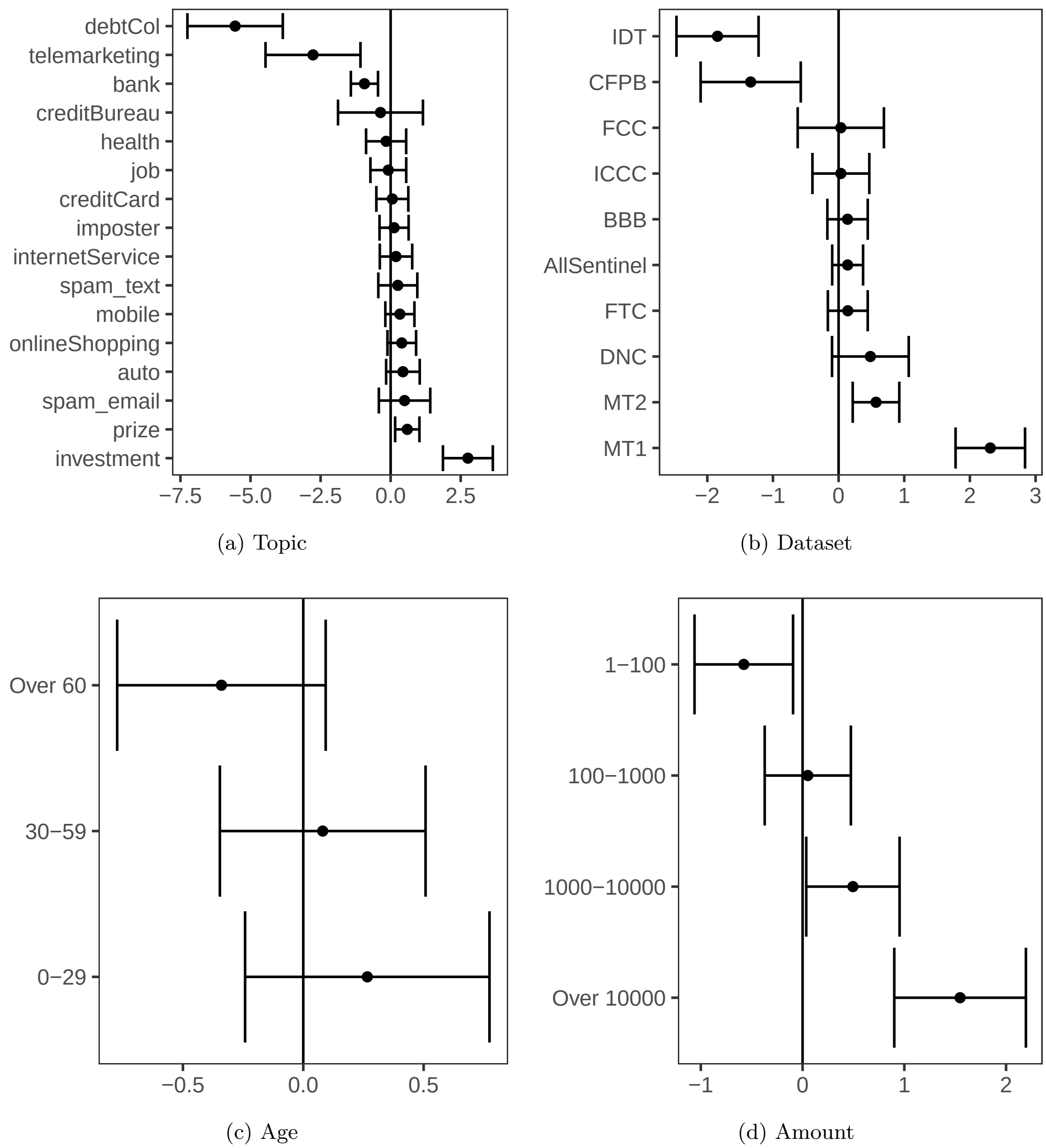
Aggregate acyclicality may conceal large differences in cyclicality across different types of fraud. We explore this heterogeneity by examining differences in business cycle effects across fraud types, the age of the victim, and the dollar amount involved. In all of these analyses, we present results in the text using MSA–level data, which we view as a better reflection of local labor market conditions, with corresponding state-level estimates in the appendix.

4.2 Type of Fraud

We first examine how business cycle effects vary by the types of fraud that consumers are exposed to. We examine the type of fraud in two ways. First, we use information on the category and product codes reported in individual Sentinel complaints to create sixteen topics, which range from

Table 2: The Effect of Employment Shocks on Consumer Complaints: Pooled Mean Estimates Across Datasets

	MSA		State	
	(1)	(2)	(3)	(4)
Employment	−0.156	0.188	−0.506	0.229
	(0.080)	(0.100)	(0.180)	(0.290)
Population	1.071		1.234	
	(0.120)		(0.260)	
Local Area X Trend FE	-	X	-	X
N	91624	91624	6885	6885



(a) Topic

(b) Dataset

(c) Age

(d) Amount

Figure 2: The Effect of Employment Shocks on Consumer Complaints: Heterogeneity by Category, Dataset, Age, and Amount

Impostor Scams and Online Shopping to Debt Collection and Spam Texts. We estimate equation (1) separately for complaints on each topic. Third, we estimate equation (1) for each dataset separately, as some complaint sources specialize in specific types of fraud.

We report these results in Figure 2, panels (a) and (b).[13] Fraud is acyclical for most of the topics and datasets that we examine; we cannot reject an elasticity of zero between complaints and employment for six out of ten datasets and ten out of seventeen topics. The overall Sentinel database had an elasticity of 0.14, close to zero, while datasets that contain complaints on a wide range of topics, such as the FTC and IC3 complaint databases, also have elasticities quite close to zero at 0.14 and 0.03.

However, certain types of complaints do vary substantially with the business cycle. First, complaints involving investments ("investments" topic, elasticity of 2.76) and money transfer ("MT1" and "MT2" datasets, elasticities of 2.31 and 0.57) are procyclical. Money transfers and investments both rely on people having income to remit or invest. Since individuals, on average, have more income when the local economy is performing well, we would expect more investment fraud, as well as fraud using money transfers, during good economic times.

On the other hand, complaints involving debt are countercyclical, including complaints to the CFPB on consumer finance issues (elasticity of -1.34) and topics related to debt collection (elasticity of -5.55), banks (elasticity of -0.93), and credit bureaus (elasticity of -0.36). Economists have documented a "credit cycle" with declines in credit during recessions (Bernanke and Gertler (1989), Kiyotaki and Moore (1997)), so consumers might be more likely to be harassed by debt collectors or have their credit lowered during recessions.

In addition, identity theft complaints ("IDT", elasticity of -1.84) are also strongly countercylical. This countercylicality is likely due to the utilization of government assistance programs (e.g., Unemployment Insurance), as well as government stimulus payments, being countercyclical. Thus, the payoff from identity theft to fraudulently receive such payments should be higher during recessions.

Finally, we find conflicting results on the cyclicality of telemarketing. Complaints to Consumer Sentinel about telemarketing are strongly countercyclical with an elasticity of -2.77, although complaints on Do Not Call violations are not with an elasticity of 0.48.

[13]The full estimation tables are in Appendix Table A.1 and Table A.2, with state level results also depicted in Appendix Figure A.1.

4.3 Victim Age

A major concern of policymakers has been scams targeted to seniors; for example, Congress passed the "Stop Senior Scams Act" in 2022, and the FTC regularly publishes reports detailing its enforcement and consumer education efforts to combat scams related to older adults (Federal Trade Commission (2024)). FTC research has shown that older adults are more likely to report specific types of fraud, such as tech support and prize/sweepstakes scams, than younger adults, and less likely to report other topics such as online shopping.[14] In addition, the literature on business cycles has found larger business cycle effects for the young, and those near retirement, compared to prime age workers (Gomme et al. (2005), Jaimovich and Siu (2009)). We thus examine the heterogeneity of our estimates by the age group self-reported in Consumer Sentinel complaints.

Using information on the age of the victim from the Consumer Sentinel dataset, we estimate fraud complaint elasticities for three age groups – consumers under 30, age 30-59, and 60 and over – which are displayed in panel (c) of Figure 2.[15] While fraud complaints for those under 60 are acyclical, fraud for those over 60 is countercyclical with an elasticity of -0.34.

4.4 Loss from Fraud

Finally, we examine how the cyclicality of fraud complaints varies by the amount of money that consumers lose. The vast majority of reported fraud losses are for consumers losing more than \$10,000 (Federal Trade Commission (2024)), whereas most fraud reports concern much smaller losses. Using information on the value of the fraud from the Consumer Sentinel dataset, we estimate fraud complaint elasticities by value of fraud, shown in panel (d) of Figure 2.[16] While complaints for frauds over \$10,000 are procyclical on average, complaints for frauds of under \$100 are countercyclical on average, and fraud of values in between are acyclical. The procyclicality of high dollar fraud may reflect the procyclicality of investment scams found above, as many of the high dollar loss reports concern investment scams.

[14] See https://www.ftc.gov/news-events/data-visualizations/data-spotlight/2022/12/who-experiences-scams-story-all-ages.

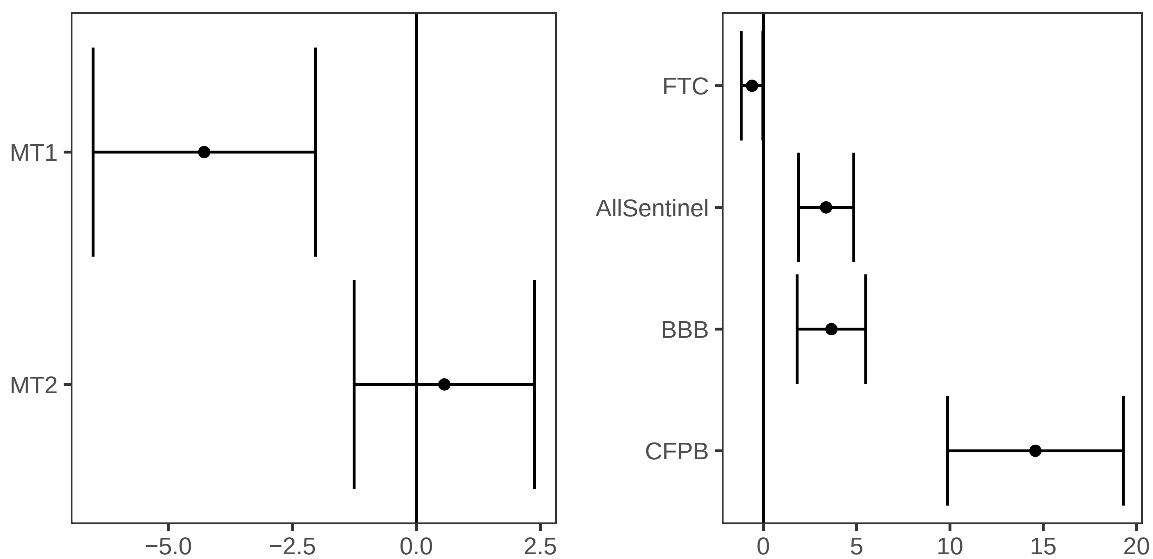
[15] The full estimation tables are in Appendix Table A.3, with state level results depicted in Appendix Figure A.2.

[16] The full estimation tables are in Appendix Table A.4 and state level results are in Appendix Figure A.2.

4.5 Supply Side of Fraud

Our analysis thus far has focused on the "demand side" of fraud. Economic conditions can also have an effect on the supply side of fraud by changing the opportunity cost of engaging in fraudulent or criminal behavior. We analyze this supply side by running a regression similar to (1), except that we analyze the complaints, population, and employment at the location of the company that is the subject of the complaint.[17]

We implement this analysis for money transfer complaints from the MT1 and MT2 datasets and for complaints to the overall Sentinel database as well as its three largest contributors. For the Sentinel database and its contributors, we use the location of the company provided by consumers to identify the location of individuals committing fraud. For the money transfer complaints, we use the precise location where the money is transferred which we consider a more accurate proxy for the location of fraud suppliers.



(a) Money Transfer

(b) Other

Figure 3: The Effect of Employment Shocks on Consumer Complaints: Supply Side Estimates

In Figure 3, we show results for money transfer complaints in the left panel and complaints to the other databases in the right panel.[18] For money transfer complaints to MT1, we see some evidence

[17]We remove all complaints to credit bureaus from these analyses, as all such complaints are to the three main credit bureaus and are unlikely to be due to business cycle changes where the credit bureaus are located. This restriction primarily affects the CFPB database.

[18]The full regression tables are in Appendix Table A.5 and state level regressions graphs are in Appendix Figure A.3.

of countercyclicality with a fraud elasticity of -4.3. However, for MT2, the elasticity is approximately centered around zero.

All complaints to the Sentinel database are procyclical, with an elasticity of 3.4. Examining the three main contributors, we find a positive elasticity of 3.6 for the BBB and of 14.6 for the CFPB. The estimate for the CFPB in particular is quite large. In contrast, the elasticity for the FTC is slightly negative and close to zero (-0.6).

We interpret these patterns as reflecting whether fraudulent activities complement legitimate business activity or substitute for it during economic downturns. Fraud that is complementary to legitimate business activity appears procyclical: for example, non–money transfer complaints may arise when expanding firms cut corners, generating more disputes and fraudulent conduct alongside growth in legitimate transactions. In contrast, fraud that substitutes for legitimate business activity appears countercyclical: money transfer complaints may increase when declining employment induces greater participation in illicit activities.

5 Discussion and Conclusion

In this article, we have assessed the cyclicality of fraud by estimating how consumer complaints respond to local employment shocks. In the aggregate, complaint volumes are acyclical. Disaggregating by category, however, reveals substantial heterogeneity: investment scams and money transfer complaints are procyclical, while credit- and debt-related complaints, identity theft, and telemarketing complaints are countercyclical. On the supply side, certain types of fraud are complementary with expansions in legitimate business activity and others are substitutes. Understanding these patterns may help policymakers target their efforts against fraud in response to economic fluctuations.

A key limitation of our analysis is that filing a complaint is voluntary, and most victims do not report fraud (Anderson (2021); Raval (2020b)). Thus, interpreting changes in complaint volumes as changes in fraud incidence assumes that selection into complaining is stable over the business cycle. If complaint propensities rise in recessions because redress is more valuable or the time cost of complaining is lower, selection into complaining would induce a countercyclical bias to our estimates.[19] In addition, our reliance on local business cycle variation will miss some of the

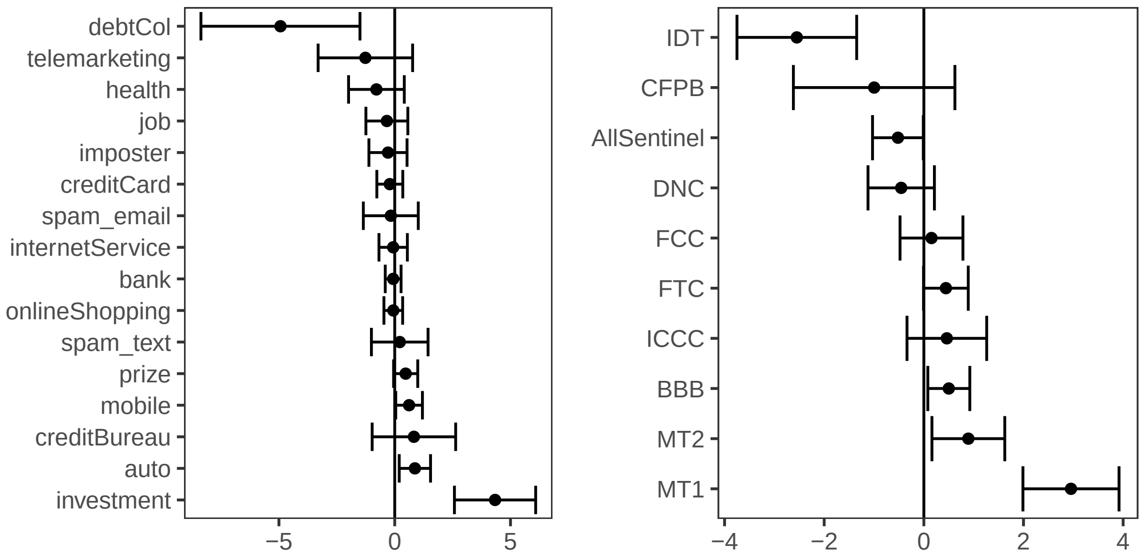
[19]Consumers might report fraud for several reasons, including altruistic motives such as warning others about what happened to them or providing evidence for law enforcement actions, as well as to obtain monetary redress from the

nationwide effects of macroeconomic conditions on fraud victimization.

company that defrauded them (Grosz and Raval (2024)). Grosz and Raval (2024) find that improvements to the FTC's website, which both make it easier to file complaints and emphasize the prosocial benefits of complaining, substantially increase complaint rates.

A Supplemental Appendix

A.1 Appendix Tables and Figures



(a) Topic (b) Dataset

Figure A.1: The Effect of Employment Shocks on Consumer Complaints: Estimates by Type of Fraud (State Level Estimates)

Table A.1: The Effect of Employment Shocks on Consumer Complaints: Estimates by Topic

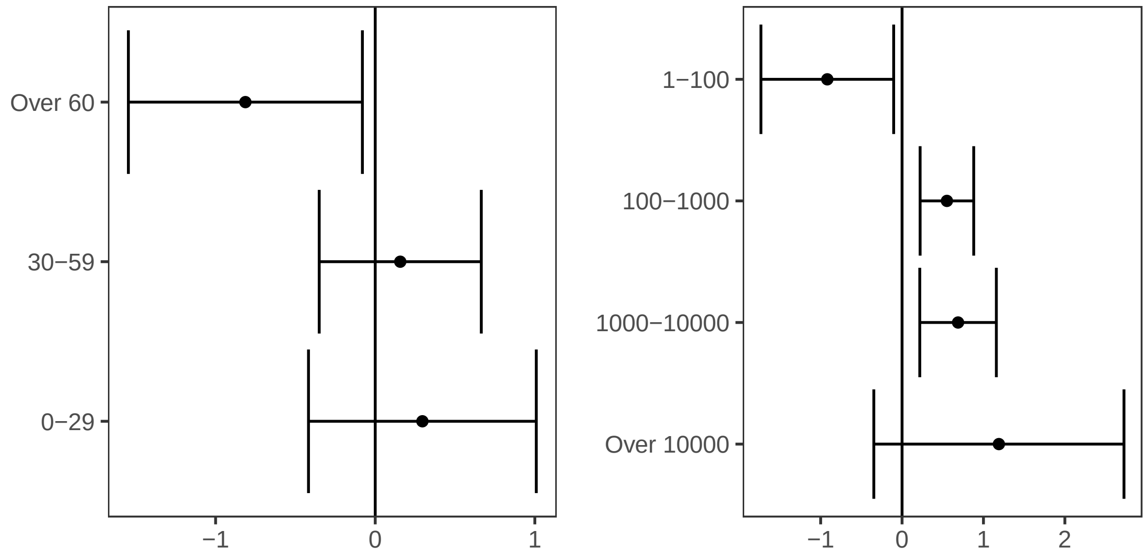
Data Set	Metro	State
auto	0.44	0.87
	(0.31)	(0.34)
bank	-0.93	-0.07
	(0.25)	(0.17)
creditBureau	-0.36	0.83
	(0.77)	(0.92)
creditCard	0.06	-0.21
	(0.29)	(0.29)
debtCol	-5.55	-4.93
	(0.87)	(1.75)
health	-0.16	-0.79
	(0.36)	(0.61)
imposter	0.12	-0.29
	(0.26)	(0.42)
internetService	0.19	-0.07
	(0.3)	(0.31)
investment	2.76	4.33
	(0.45)	(0.9)
job	-0.08	-0.34
	(0.33)	(0.46)
mobile	0.33	0.62
	(0.26)	(0.29)
onlineShopping	0.4	-0.06
	(0.26)	(0.21)
prize	0.59	0.47
	(0.22)	(0.27)
spam-email	0.5	-0.17
	(0.47)	(0.6)
spam-text	0.26	0.22
	(0.36)	(0.62)
telemarketing	-2.77	-1.27
	(0.86)	(1.04)

Table A.2: The Effect of Employment Shocks on Consumer Complaints: Estimates by Dataset

Data Set	Metro	State
AllSentinel	0.14	-0.52
	(0.12)	(0.26)
BBB	0.14	0.5
	(0.16)	(0.22)
CFPB	-1.34	-1
	(0.39)	(0.83)
DNC	0.48	-0.45
	(0.3)	(0.34)
FCC	0.03	0.15
	(0.34)	(0.32)
FTC	0.14	0.44
	(0.16)	(0.23)
ICCC	0.03	0.46
	(0.22)	(0.41)
IDT	-1.84	-2.55
	(0.32)	(0.61)
MT1	2.31	2.95
	(0.27)	(0.49)
MT2	0.57	0.89
	(0.18)	(0.37)

Table A.3: Log Employment Coefficient Results by Age (Metro Results)

Data Set	Metro	State
0-29	0.27	0.3
	(0.26)	(0.36)
30-59	0.08	0.16
	(0.22)	(0.26)
60Over	-0.34	-0.81
	(0.22)	(0.37)



(a) Age (b) Amount

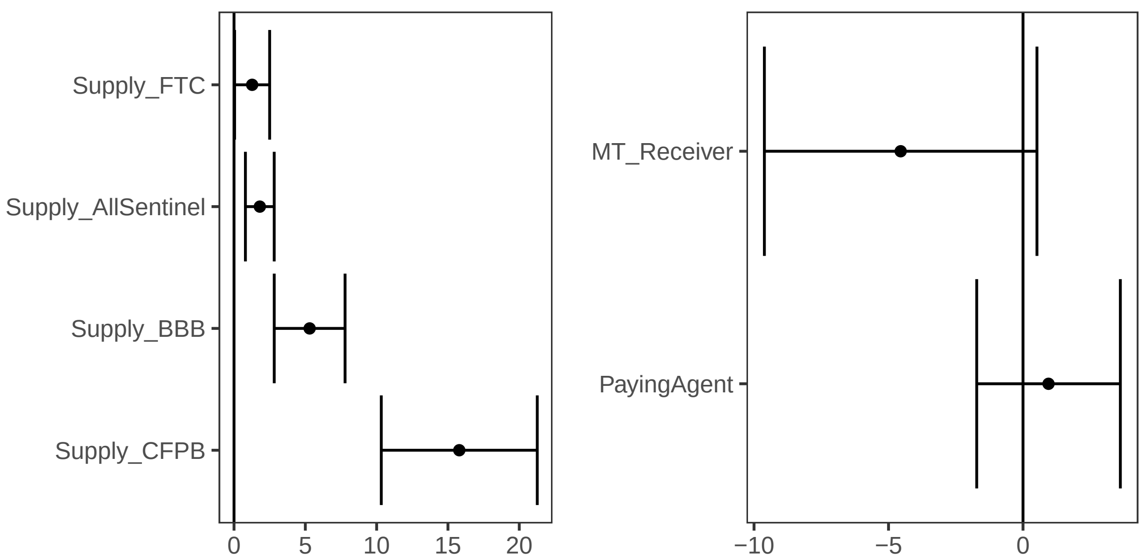
Figure A.2: The Effect of Employment Shocks on Consumer Complaints: Estimates by Victim Age and Loss Amount (State Level)

Table A.4: The Effect of Employment Shocks on Consumer Complaints: Estimates by Loss Amount

Data Set	Metro	State
1-100	-0.58	-0.92
	(0.25)	(0.42)
100-1000	0.05	0.55
	(0.22)	(0.17)
1000-10000	0.49	0.69
	(0.23)	(0.24)
Over 10000	1.55	1.19
	(0.33)	(0.78)

Table A.5: The Effect of Employment Shocks on Consumer Complaints: Supply Side Estimates

Data Set	Metro	State
Supply-AllSentinel	3.36	1.81
	(0.76)	(0.52)
Supply-BBB	3.65	5.3
	(0.94)	(1.27)
Supply-CFPB	14.58	15.79
	(2.4)	(2.79)
Supply-FTC	-0.61	1.27
	(0.3)	(0.63)
Supply-MT-Company	-0.61	0.35
	(0.88)	(2.34)
Supply-MT-Receiver	-4.28	-4.55
	(1.14)	(2.58)
Supply-Payee	-1.25	0.06
	(0.93)	(1.26)
Supply-PayingAgent	0.56	0.95
	(0.93)	(1.36)



(a) Money Transfer (b) Other

Figure A.3: The Effect of Employment Shocks on Consumer Complaints: Supply Side Estimates (State Level)

A.2 Data Appendix

A.2.1 Consumer Complaint Databases

A.2.1.1 Consumer Sentinel We use several different data sources for data from the Consumer Sentinel Network. First, publicly available databooks provide the number of complaints by state and metropolitan statistical area every year for both the Consumer Sentinel database, encompassing both "Fraud" or "Other" complaints, as well as Identity Theft complaints. We use these databooks to construct the "Consumer Sentinel" and "Identity Theft" sources.

These databooks are available at https://www.ftc.gov/enforcement/consumer-sentinel-network/reports from 2006 onwards, with raw data available at https://www.ftc.gov/policy-notices/open-government/data-sets#csn%5D= from 2009 onwards. Prior to 2008, the FTC only reported statistics on Fraud complaints and not Other complaints, so these years are excluded from our analysis.[20] Our data series for state level data for Identity Theft complaints goes back to 2002, as we obtained older databooks on the number of identity theft complaints by state from the Wayback Machine. These databooks are available upon request.

In addition, we have access to more micro-level data on complaints – data on individual complaints since 2014 and complaints aggregated to the zip code and source organization (e.g., CFPB or FTC Mobile Complaints) for 2012 and 2013. We use this data to construct sources by disaggregating the Consumer Sentinel into the "FTC", "BBB", "CFPB", and "MT1", aggregate of all money transfer sources, datasets.[21]

For 2012 and 2013, we aggregate zip code level complaints to the State level based upon the state recorded in the data for that zip code. For MSA level complaints, we use crosswalks from zip code to CBSA developed by HUD available at https://www.huduser.gov/portal/datasets/usps_crosswalk.html and aggregate complaints based on the ratio of residences for a given zip code in a given CBSA (res_ratio). For 2014 onwards, the database on individual complaints records the state and MSA of each complaint. We use this information to aggregate complaints to the state-year or

[20] The Consumer Sentinel Network broadly classifies all complaints as "Fraud" or "Other", in part based on their broader complaint categorization. Other complaints include complaints related to automobiles ("Auto Related"), debt collection, banks and lenders, and credit reporting, among other sources. See Raval (2020a) for more details.

[21] We have access to all complaints to the CFPB, not just the publicly reported complaints available at https://www.consumerfinance.gov/data-research/consumer-complaints/ (for example, the CFPB does not publicly report complaints about depository institutions with less than $10 billion in assets). See https://files.consumerfinance.gov/f/documents/201503_cfpb_disclosure-of-consumer-complaint-narrative-data.pdf for details on the publication criteria for the CFPB public data.

MSA-year level. We then match the state and MSA names to equivalent FIPS codes.

Finally, we also use the micro-level data on complaints from Consumer Sentinel from 2014 onwards to construct the number of complaints by category. We define a set of categories based upon the categories and subcategories reported in Consumer Sentinel, which have changed slightly over time.[22] We define the following set of categories:

1. *Auto*: Category is Auto Related
2. *Bank*: Category is Banks and Lenders
3. *BusOpp*: Category is Business and Job Opportunities
4. *Credit Bureau*: Category is "Credit Bureaus, Information Furnishers and Report Users"
5. *Credit Card*: Category is "Credit Cards and Loss Protection" (current category) or "Credit Cards"
6. *Debt Collection*: Category is "Debt Collection"
7. *Health Care*: Category is "Health Care"
8. *Imposter*: Category is "Imposter Scams"
9. *Internet Service*: Category is "Internet Services"
10. *Investment*: Category is "Investment Related"
11. *Online Shopping*: Category is "Online Shopping and Negative Reviews" (current category) or "Internet Auction" or "Shop-at-Home and Catalog Sales" (old categories)
12. *Prize*: Category is "Prizes, Sweepstakes and Lotteries"
13. *Spam Email*: Subcategory is "Unsolicited Email"
14. *Spam Text*: Subcategory is "Unsolicited Email" (current category) or "Mobile: Text Messages" (old category)
15. *Telemarketing*: Subcategory is "Unwanted Telemarketing Calls" (current category) or "Telemarketing Practices" (old category)
16. *Telephone*: Category is "Telephone and Mobile Services", excluding subcategory "Mobile: Text Messages" (old category)

We then aggregate to the state-year or MSA-year level using the State or MSA fields for each complaint.

[22]The current categories and subcategories are available at https://www.ftc.gov/system/files/attachments/data-sets/category_definitions.pdf and https://www.ftc.gov/system/files/ftc_gov/pdf/CSNPSCFullDescriptions.pdf.

A.2.1.2 Do Not Call The FTC also operates the Do Not Call complaint database. We use the publicly available databooks on Do Not Call complaints to construct the "Do Not Call" source. These databooks are available at https://www.ftc.gov/enforcement/consumer-sentinel-network/reports, with raw data available at https://www.ftc.gov/policy-notices/open-government/data-sets#csn. These databooks report the number of complaints to the Do Not Call list for each state.

From 2017 onwards, the FTC reports the county that complaining consumers live in if they report their address. Across years, 53% to 63% of consumers have county information. To aggregate to MSA, we use a county to CBSA crosswalk from https://towardsdatascience.com/the-ultimate-state-county-fips-tool-1e4c54dc9dff.

A.2.1.3 FCC The Federal Communications Commission (FCC) provides data on consumer complaints to the FTC on its website, available at https://opendata.fcc.gov/Consumer/CGB-Consumer-Complaints-Data/3xyp-aqkj/about_data. We aggregate individual level complaints to the State level based upon the state recorded in the data. For MSA level complaints, we use the zip code of the consumer recorded in the data and crosswalks from zip code to CBSA developed by HUD available at https://www.huduser.gov/portal/datasets/usps_crosswalk.html and aggregate complaints based on the ratio of residences for a given zip code in a given CBSA (res_ratio).

A.2.1.4 Internet Crime Complaint Center Our main data source on complaints to the FBI's Internet Crime Complaint Center is a database of all individual complaints to the database from 2001 to 2020. We use the state recorded in the data (as well as city or county information if the state field is blank) to identify states and aggregate to the state level. We use the county recorded in the data to match to CBSAs. If county is missing, we use the city and state recorded and match to counties based upon a crosswalk available at https://simplemaps.com/data/us-cities. Of individuals with a recorded state, 93.2% have county information based on the above procedure. We then use the county of the consumer and crosswalks from county to CBSA available at https://towardsdatascience.com/the-ultimate-state-county-fips-tool-1e4c54dc9dff to aggregate to the CBSA level.

A.2.1.5 Money Transfer Firm Finally, we have data from a major money transfer firm's internal complaint database from 2004 to 2014 ("MT2"). We aggregate to the state level using the state reported in the consumer's address. For MSA level complaints, we use the zip code of the consumer recorded in the data and crosswalks from zip code to CBSA developed by HUD available at https://www.huduser.gov/portal/datasets/usps_crosswalk.html and aggregate complaints based on the ratio of residences for a given zip code in a given CBSA (res_ratio).

References

Anderson, K. B. (2019). Mass-market consumer fraud in the united states: A 2017 update. *Federal Trade Commission. Washington, DC*.

Anderson, K. B. (2021). To whom do victims of mass-market consumer fraud complain? *Available at SSRN 3852323*.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of political economy*, 76(2):169–217.

Bernanke, B. and Gertler, M. (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review*, pages 14–31.

Bushway, S., Cook, P. J., and Phillips, M. (2013). The net effect of the business cycle on crime and violence. *Economics and youth violence: Crime, disadvantage and community*, pages 23–52.

Cook, P. J. and Zarkin, G. A. (1985). Crime and the business cycle. *The Journal of Legal Studies*, 14(1):115–128.

Correia, S., Guimarães, P., and Zylkin, T. (2020). Fast poisson estimation with high-dimensional fixed effects. *The Stata Journal: Promoting communications on statistics and Stata*, 20(1):95–115.

DeLiema, M., Deevy, M., Lusardi, A., and Mitchell, O. S. (2020). Financial fraud among older americans: Evidence and implications. *The Journals of Gerontology: Series B*, 75(4):861–868.

Deliema, M., Shadel, D., and Pak, K. (2020). Profiling victims of investment fraud: Mindsets and risky behaviors. *Journal of Consumer Research*, 46(5):904–914.

DeLiema, M. and Witt, P. (2021). Mixed methods analysis of consumer fraud reports of the social security administration impostor scam.

Detotto, C. and Otranto, E. (2012). Cycles in crime and economy: leading, lagging and coincident behaviors. *Journal of Quantitative Criminology*, 28:295–317.

Federal Trade Commission (2024). Protecting older consumers 2023–2024: A report of the federal trade commission. Technical report.

Gans, J. S., Goldfarb, A., and Lederman, M. (2021). Exit, tweets, and loyalty. *American Economic Journal: Microeconomics*, 13(2):68–112.

Garrett, T. A. and Ott, L. S. (2008). City business cycles and crime. *FRB of St. Louis Working Paper No.*

Gomme, P., Rogerson, R., Rupert, P., and Wright, R. (2005). The business cycle and the life cycle. *NBER Macroeconomics Annual 2004*, (19):415.

Grosz, M. and Raval, D. (2022). Fraud across borders. *Available at SSRN 4197797*.

Grosz, M. and Raval, D. (2024). Amplifying consumers' voice: The federal trade commission's report fraud website redesign. *Marketing Science*.

Jaimovich, N. and Siu, H. E. (2009). The young, the old, and the restless: Demographics and business cycle volatility. *American Economic Review*, 99(3):804–826.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of political economy*, 105(2):211–248.

Raphael, S. and Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *The journal of law and economics*, 44(1):259–283.

Raval, D. (2020a). Which communities complain to policymakers? evidence from consumer sentinel. *Economic Inquiry*, 58:1628–1642.

Raval, D. (2020b). Whose voice do we hear in the marketplace? evidence from consumer complaining behavior. *Marketing Science*, 39(1):168–187.

Raval, D. (2021). Who is victimized by fraud? evidence from consumer protection cases. *Journal of Consumer Policy*, 44:43–72.

U.S. Bureau of Economic Analysis (2023a). Personal income summary: Personal income, population, per capita personal income (cainc1). Accessed via BEA Regional Data on 7-21-2024.

U.S. Bureau of Economic Analysis (2023b). State quarterly personal income summary (sainc1). Accessed via BEA State Personal Income Data on 7-21-2024.

U.S. Bureau of Economic Analysis (2023c). Total full-time and part-time employment by industry (caemp25n). Accessed via BEA Regional Data on 7-21-2024.

U.S. Bureau of Economic Analysis (2024). State quarterly employment by industry (saemp25n). Accessed via BEA State Employment Data on 8/19/2025.