Real Estate Shocks and Financial Advisor Misconduct

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Abstract

We test whether household wealth shocks affect professional misconduct by financial advisors. Using a panel of advisors' home addresses, we exploit within-advisor variation and show that advisors increase misconduct following declines in their homes' values. Using cumulative house price returns, we find similar results in specifications that limit the comparison to advisors living in the same ZIP code during the same year. We find evidence that the increase in misconduct is due, in part, to willful actions by advisors, such as unauthorized or excessive trading. We also show that advisors' housing returns explain misconduct committed against out-of-state customers, breaking the link between customer and advisor housing shocks. Further, the results are stronger for advisors with lower career risk from committing misconduct.

Keywords: Financial advisors, Financial misconduct, Fraud, Real estate, Bankruptcy

JEL: G2, G20, G28, K2, K22, R31

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Do household level financial shocks cause employees to commit financial misconduct? The relation between financial well-being and deviant behavior has been noted as far back as Aristotle who called poverty the "parent" of crime. In the context of financial misconduct, Cressey (1971) interviewed individuals convicted of white collar crimes and found that financial pressure nearly always preceded misconduct. Interpreting the observed relation between financial pressure and misconduct is challenging, however, because financial pressure is often the result of the individual's own choices. For example, Cressey (1971) found that financial pressure was primarily due to gambling, alcoholism, drug use, and extravagant spending. Thus, it is unclear if negative financial shocks cause misconduct or if they are both symptoms of the same underlying personality traits or preferences.

Theory also does not provide definitive guidance, because the effect of wealth shocks on misconduct is ambiguous without strong assumptions about utility. On the one hand, financial misconduct is a risky activity; it could create illicit gains, but could result in penalties and negative career consequences.[1] Under decreasing absolute risk aversion, negative wealth shocks increase sensitivity to risk, implying less willingness to engage in misconduct. On the other hand, Block and Heineke (1975) show that, if individuals have ethical preferences, the relation between wealth and misconduct is considerably more complicated, and the effect of a wealth shock depends upon whether ethical behavior is a normal or an inferior good. Their model further shows that understanding the relation between wealth and misconduct is critical for evaluating policy responses.

Ultimately, whether financial pressure causes misconduct is an empirical question that can only be tested with exogenous wealth shocks. In this paper, we use plausibly exogenous shocks to financial advisors' wealth based on housing price shocks. We use a series of fixed effect strategies to exploit within advisor, within ZIP code, and within firm-year variation in housing price shocks to identify whether household wealth shocks affect the propensity of

[1] Prior studies showing negative career consequences for financial misconduct include Egan, Matvos, and Seru (2018a) for financial advisors, Karpoff, Lee, and Martin (2008) for corporate executives, and Fich and Shivdasani (2007) for corporate directors.

financial advisors to engage in misconduct.

We examine the financial advisory industry for several reasons. First, advisors have large effects on household financial well-being. Hung, Clancy, Dominitz, Talley, Berribi, and Suvankulov (2008) show that the majority of investors consult an advisor for financial decisions, and Foerster, Linnainmaa, Melzer, and Previtero (2017) show advisors strongly influence household portfolio choice. Second, advisors are primarily compensated through commissions, which creates conflicts of interest and incentives for misconduct (see Inderst and Ottaviani, 2012). Empirical studies such as Dimmock, Gerken, and Graham (2018) and Egan et al. (2018a) show that misconduct is common (e.g., churning, unauthorized trading, misrepresentation, and unsuitability). Third, the data for this industry allow us to link misconduct to specific individuals within a firm.

Our data come from detailed mandatory disclosure filings made by financial advisors, which identify financial misconduct committed by specific advisors as well as their employment histories (see Dimmock, Gerken, and Graham, 2018; Egan, Matvos, and Seru, 2018a,b). In addition, these mandated filings also include the advisors' home addresses and the dates of residency. We combine the advisor addresses with ZIP code level house price indexes created by Zillow and impute a purchase price and time-series of house price returns for each advisor in the sample.[2]

We use house price returns as exogenous shocks to financial advisors' personal wealth. For our purposes, we require a shock that is both unanticipated and economically meaningful. Cheng, Raina, and Xiong (2014) analyze whether midlevel managers working in securitized finance believed there was a housing bubble in 2004–2006 by examining the managers' personal home transactions; they find no evidence that these individuals anticipated the housing crisis. A large literature shows that housing price fluctuations have large, economically meaningful

[2]In robustness tests, we show that the imputed house price returns are a highly significant predictor of actual bankruptcies filed by financial advisors. We also have a subsample of advisors for whom we have residence-specific Zillow valuation estimates. We find that the average time series correlation between the residence-specific price changes and the ZIP code price changes is 0.803.

effects on consumption (see Campbell and Cocco, 2007; Carroll, Otsuka, and Slacalek, 2011; Mian, Rao, and Sufi, 2013; DeFusco, 2018). Gan (2010) shows that housing shocks affect consumption even for households that do not refinance or otherwise change their borrowing, and argues this is consistent with changes in precautionary savings due to real estate wealth effects. Thus, real estate shocks appear to be both unexpected and economically meaningful.

Following other studies on risk taking by professionals around the housing crisis (Bernstein, McQuade, and Townsend, 2018; Pool, Stoffman, Yonker, and Zhang, 2018), we estimate differences-in-differences models, in which we regress changes in an advisor's misconduct on his housing price shock during the financial crisis. These specifications include firm fixed effects, which control for potential confounding variation among employees within a firm (e.g., if within-firm incentives to commit misconduct change during the financial crisis). The results show that advisors who suffer larger housing price declines during the financial crisis subsequently increase their commission of misconduct. Misconduct increases by 41% for advisors whose homes suffer a price decline of 10% or greater during the crisis.

We then extend the differences-in-differences results to fixed effect panel regressions using cumulative housing returns since purchase. In these tests, the unit of observation is advisor-year, which allows us to use housing price declines that occurred at any point during the 1999–2013 sample period. These specifications include advisor, firm-year, and ZIP code fixed effects. The advisor fixed effects remove the advisor's overall propensity to commit misconduct, as well as individual characteristics such as gender, education, and religious background. The firm-year fixed effects remove variation from the employing firms' tolerance of misconduct or its business model (even if these effects are time-varying). The firm-year fixed effects also remove any time-series changes that affect all advisors, such as the overall economy. The ZIP code fixed effects remove the characteristics of the area, such as demographics, local culture, state-level regulation, etc. The panel regression results are consistent with the differences-in-differences test: advisors who suffer negative house price shocks are significantly more likely to commit misconduct. Additional results show that the relation between cumulative housing returns and misconduct is non-linear and that misconduct is significantly more sensitive to large losses on housing.

In the next set of tests we exploit our ability to observe each advisor's *cumulative* house price return since purchase. Even advisors living in the same ZIP code at the same time can have very different cumulative returns on their residence. For example, consider two advisors living in the same ZIP code in 2008 but who purchased their homes at different times. Although prices declined in 2008, an advisor who purchased home in 1986 would likely have a positive cumulative return, while an advisor who purchased a home in 2006 would likely have a negative cumulative return. This variation in cumulative returns across advisors in the same ZIP code during the same year allows us to include ZIP-year fixed effects to remove any local time-varying confounding variation, such as shocks to the home prices of the local customer base. In an additional test, we go further and include branch-ZIP-year fixed effects. In this specification, the fixed effects limit the comparison to be between advisors who live in the same ZIP code during the same year, and who also work at the same branch of the same firm. Even with these more stringent fixed effects, we continue to find that large negative cumulative returns are associated with higher misconduct.

In our next tests, we use two alternative dependent variables based on misconduct reported by non-local parties. This alleviates concerns about the commonality of home price shock suffered by the advisor and the shock suffered by local customers. First, we limit the dependent variable to include only instances of misconduct for which the advisor and the customer live in different states. Second, we define misconduct as either a finalized regulatory sanction or a termination of the advisor by his employer (and exclude all advisor-year observations that include a customer-driven complaint to ensure this alternative dependent variable is distinct from the primary dependent variable). For both of the alternative dependent variables, we continue to find a significant negative relation between cumulative returns and misconduct.

We next examine cross-sectional variation in the risk that an advisor is terminated for misconduct. Egan, Matvos, and Seru (2018a,b) show there is large variation in the likelihood an advisor is terminated after committing misconduct — some firms are more tolerant of misconduct and women are punished more severely than men. All else equal, higher career risk implies a lower expected return to committing misconduct, reducing the incentive to commit misconduct. Consistent with this intuition, we find that the relation between cumulative housing returns and misconduct is stronger for advisors who are less likely to be terminated following the detection of misconduct.

We next explore the mechanisms through which housing losses affect professional misconduct. The relation could be caused by *active* misconduct, in which advisors deliberately exploit clients for financial gain. Alternatively, the relation could be caused by *passive* misconduct, in which advisors harm clients through inattention when they are distracted due to financial distress. To test these competing mechanisms, we categorize misconduct as active (misrepresentation, churning, unauthorized trading, etc.) or passive (negligence or omission of key facts). We find evidence of passive misconduct, but more importantly we find highly significant evidence of *active* misconduct; following housing losses, advisors deliberately exploit their clients.

In additional tests, we show that the results are robust to alternative definitions of misconduct. We also validate our key independent variable by showing that our measure of housing price changes accurately predicts actual bankruptcy filings and underwater home sales by financial advisors.

Our paper is related to the recent literature on misconduct by financial advisors. Dimmock, Gerken, and Graham (2018) show evidence of peer effects in misconduct; financial advisors are more likely to commit misconduct if they are exposed to co-workers with a history of misconduct. Egan, Matvos, and Seru (2018a) study how misconduct affects the labor market for financial advisors and find that certain firms specialize in misconduct while others strive to maintain clean reputations. Egan, Matvos, and Seru (2018b) study gender differences in the punishment for misconduct and find that following misconduct female advisors are more likely to be terminated and less likely to find new positions. Charoenwong, Kwan, and

Umar (2017) show that variation in regulatory oversight affects the propensity of advisors to engage in misconduct. Clifford and Gerken (2017) show that the assignment of property rights to client relationships reduces misconduct by advisors. Qureshi and Sokobin (2015) show that an advisor's record of past misconduct and regulatory actions is correlated with future misconduct. In our paper, we show that willingness to engage in misconduct is a pliable characteristic of the individual advisor; advisors are more likely to commit misconduct when they are under personal financial pressure. Understanding such causes of financial misconduct is important for designing and implementing monitoring and regulatory systems.

Our paper is also related to several recent studies that show how personal financial issues affect professional behavior. Pool, Stoffman, Yonker, and Zhang (2018) show that mutual fund managers who suffer negative shocks to their home's value subsequently reduce portfolio risk and tracking error. Bernstein, McQuade, and Townsend (2018) show that workerswho suffered larger losses on their house values during the financial crisis subsequently undertook less risky and less innovative projects. Maturana and Nickerson (2017) show that when teachers declare bankruptcy, their students' scores on standardized tests fall. Our paper also studies the effect of household financial losses on professional behavior, but we study misconduct rather than portfolio risk or productivity.

We also document another important externality of housing price shocks. Aside from the direct wealth effects of housing price declines, several papers document less obvious adverse consequences. Campbell, Giglio, and Pathak (2011) show that foreclosures have spillover effects that reduce the value of neighboring houses. Mian, Rao, and Sufi (2013) highlight the decline in consumption following the housing crisis. We show another externality — investors suffer increased active misconduct and passive mismanagement as a result of their financial advisors' real estate price shocks.

1. Data and Sample Construction

Our financial advisor data come from a panel of mandatory disclosures made in Form U4 filings. All registered representatives[3] in the U.S. are required to file and update these forms following any material changes. FINRA assigns each advisor a unique individual permanent identifier that allows us to track advisors even if they switch employers. We obtain this panel through a combination of Freedom of Information Act (FOIA) requests filed with state regulators by the authors, third-party data obtained from a vendor (Meridian IQ), and the FINRA BrokerCheck Website.[4] See Dimmock, Gerken, and Graham (2018) and Egan, Matvos, and Seru (2018a,b) for detailed explanations of the data and industry.

The financial advisor data include residential addresses over the period 1999–2013, as well as all misconduct disclosures made during the 1999–2017 period. The sample includes 428,108 advisors with complete residential histories. We combine the advisor data with ZIP code level housing price data from Zillow. However, because Zillow does not provide the necessary data for all ZIP codes,[5] our final sample contains 329,418 advisors.

1.1. Financial Advisor Data

The Form U4 data includes each advisor's employment history, licenses, qualifications, and any mandated disclosures. Advisors are required to disclose certain information about customer complaints, regulatory actions, civil and criminal legal cases, terminations, and bankruptcies. Table 1 summarizes this disclosure information. Columns (1) and (2) report the number of advisor-years with the disclosure and the percentage, respectively. Column (3) reports the percent of advisors who make a disclosure at any time during the sample period.

Following Dimmock, Gerken, and Graham (2018), our primary measure of misconduct

[3] "Registered representative" is the term FINRA uses for these individuals. Following the recent academic literature, in this paper we use the term financial advisor. These individuals are also commonly referred to as brokers or financial planners.

[4] The BrokerCheck website allows investors to access a subset of the data reported in the Form U4 filings. BrokerCheck does not report the advisors' home addresses. See `https://brokercheck.finra.org/`.

[5] Since the Zillow data is also limited to the United States we are unable to include foreign addresses.

is based on validated customer complaints. Customer complaints are formal complaints, in which a customer demands compensation for damages caused by an advisor's misconduct. Although some customer complaints allege negligence, most complaints allege improper behavior taken to increase the advisor's compensation. Financial advisors are compensated primarily based on the amount of revenue they generate for their firm (see Hung, Clancy, Dominitz, Talley, Berribi, and Suvankulov, 2008), which creates strong incentives for advisors to generate trading commissions or to sell products with high distribution fees. Theoretical models show that these incentives encourage misconduct[6] and empirical tests find support for the models' predictions.[7]

After a customer files a complaint, it can be resolved through arbitration, settlement, or withdrawal. Following Dimmock, Gerken, and Graham (2018), we create the variable *Misconduct* based on customer disputes for which either the arbitration panel rules in the customer's favor or the dispute is settled for at least a certain minimum cash payment to the customer.[8] Thus, this variable includes only customer complaints that are validated either through an arbitration decision or a sizable monetary payment (i.e., we do not include customer complaints that are withdrawn or still unresolved as of the end of our sample). Table 1 shows that 0.63% of advisor-years and 4.7% of advisors in our final sample report at least one *Misconduct* event.

Table 1 also summarizes additional disclosures that are used in several robustness tests. *Out-of-state Misconduct* is a subcategory of the main *Misconduct* variable, which includes only cases in which the customer and advisor live in different states. *Regulatory* reports finalized regulatory sanctions from entities such as the SEC, FINRA, or state regulators. *Employment Separation After Allegations* reports whether the advisor has ever been terminated or permitted

[6] See Inderst and Ottaviani (2009, 2012) and Stoughton, Wu, and Zechner (2011).

[7] See Hackethal, Inderst, and Meyer (2011), Mullainathan, Noeth, and Schoar (2012), and Hoechle, Ruenzi, Schaub, and Schmid (2018).

[8] Financial advisors must report settlements of $10,000 or more before May 19, 2009 and settlements of $15,000 or more afterwards. Settlements smaller than these thresholds need not be disclosed, as they are potentially "nuisance" settlements and do not represent valid complaints.

to resign following allegations of misconduct.[9]

In robustness tests, we follow Egan, Matvos, and Seru (2018a) and combine *Misconduct* with *Regulatory*, *Employment Separation After Allegations*, and certain civil law and criminal disclosures,[10] to create the variable *EMS Misconduct*. The summary statistics show that 6.1% of advisors in our final sample report at least one event under the broader Egan, Matvos, and Seru (2018a) definition.

Panel A of Table 2 reports additional summary statistics related to advisor misconduct. For advisors with a settled or awarded customer complaint, the average (median) alleged damages is $659,666 ($19,000) and the average (median) settlement amount is $239,485 ($15,754). For advisors with regulatory sanctions, the average (median) penalty is $13,125 ($5,000). Note that for approximately 40% of the cases we are unable to observe settlement, award, or penalty amounts.

In addition to the misconduct information, Table 2 summarizes additional information from the Form U4 filings. The median advisor has 10 years of industry experience, and in all regressions we control for the logarithm of this variable. Table 1 shows that 1.55% of advisors report a bankruptcy and 0.53% of advisors report a compromise with creditors in relation to selling a home for less than the outstanding mortgage amount (i.e., underwater sale). We use these variables as checks of the validity of our primary measure of financial distress.

[9] *Employment Separation After Allegations* occurs if the advisor is discharged, voluntarily resigns, or is permitted to resign after allegations accusing the advisor of: "(1) violating investment-related statutes, regulations, rules, or industry standards of conduct; (2) fraud or wrongful taking of property; or (3) failure to supervise in connection with investment-related statutes, regulations, rules, or industry standards of conduct." For more details see `https://www.finra.org/sites/default/files/AppSupportDoc/p015111.pdf`.

[10] The civil law disclosures report court issued injunctions regarding investment-related activity, findings of a violation of any investment-related statute or regulation, and actions brought by a state or foreign financial regulatory authority that are dismissed by a court pursuant to a settlement agreement. The criminal disclosures report any felony convictions or charges, as well as certain misdemeanors such as bribery, perjury, fraud, or wrongful taking of property even if these occur outside of their financial advisory role.

1.2. Financial Advisor's Homes and Real Estate Price Shocks

The Form U4 disclosures include residence histories, which report the advisors' home addresses and ZIP codes.[11] Each advisor must report the address and dates of occupation for each residency throughout the sample period. E.g., an advisor who has resided in the same house since July of 1960 would report a move-in date of July 1960 even though the sample period does not begin until 1999. We do not observe whether the advisor rents or owns the home. However, robustness tests reported in Internet Appendix 1 that use proxies for ownership likelihoods suggest it is unlikely that renting materially affects our results.[12]

We filed FOIA requests with all state regulators, however, numerous states did not supply home addresses. As a result, we have home addresses only for advisors who register in the District of Columbia, Florida, Georgia, Hawaii, Indiana, Iowa, New Jersey, Oregon, Rhode Island, Tennessee, Texas, Washington, or West Virginia. Because advisors must register with each state in which they plan to do business, and many advisors register in all states, we have home addresses of advisors in all 50 states (e.g., we have home addresses for 69,167 advisors who live in New York and are registered in at least one state that provided data). Thus, although our collection of home addresses is not comprehensive, it covers all major real estate markets. Importantly, the selection mechanism is the state regulator's interpretation of The Privacy Act of 1974 as it relates to our FOIA request. It is not obvious that this selection mechanism would be systematically related to the correlation between local housing shocks and misconduct by financial advisors, and thus we do not see reasonable concerns related to selection bias.

We match the advisor residences to the Zillow ZIP code house price indexes. The combined

[11] Section 11 of the Uniform Application for Securities Industry Registration (Form U4) asks advisors to "provide their residential addresses for the past five (5) years. Leave no gaps greater than three (3) months between addresses. Begin by entering your current residential address. Enter 'Present' as the end date for your current address. Post Office boxes are not acceptable. Report changes as they occur."

[12] If measurement error from incorrectly assigning housing returns to renters is pure measurement error, it will result in attenuation bias our results will understate the true effect. If, however, renting is disproportionately associated with areas that had the largest price declines and is also positively correlated with increased misconduct following price declines, this could bias upwards our results (although it is not obvious why this pattern of associations would occur).

advisor-residence-Zillow price dataset spans 13,679 ZIP codes, which collectively contain 74.7% of the U.S. population. Using the Zillow ZIP code indexes, we impute a purchase price and annual price changes for each advisor-residence combination.[13] This approach is similar to that in Bernstein, McQuade, and Townsend (2018), who also impute individual house price shocks using ZIP code level price indexes.[14] In Internet Appendix 2, we also use the House Price Index produced by the Federal Housing Finance Agency[15] as an alternative measure of real estate prices and find similar results. For advisors who report multiple residences at the same time (e.g., vacation homes), we use the purchase-price-weighted average return for all residences. In Internet Appendix 3 we show our results are robust to using only the highest value residence.

Panel A of Table 2 shows that the average house in the sample has an imputed purchase price of $320,539 and a current price of $373,679. On average, the advisors have lived in their current house for 5.8 years. Panel B reports the distribution of annual house price changes. The median annual price change is $3,700, which is 1.72% of the beginning of year value. As the percentiles show, there is considerable variation and many advisor-year observations experience negative returns.

We use the imputed purchase price and imputed annual returns to calculate the cumulative price change for each advisor-year. Importantly, this varies across advisors even within a fixed ZIP code depending upon when the advisors purchased their house. For example, suppose Advisor A purchased a home in 2000 at an imputed price of $200,000. House prices then doubled by 2007, when Advisor B purchased a house at an imputed price of $400,000. The next year, house prices declined by 25% to $300,000. The cumulative return for Advisor A is +50%, but the cumulative return for Advisor B is -25%. Panel B of Table 2 shows that

[13] Pool, Stoffman, Yonker, and Zhang (2018) use house level imputed values from Zillow, instead of ZIP code level imputation. This is feasible in their study as they have fewer than 1,000 individuals. This approach is not feasible for us given our large sample size.

[14] Bernstein, McQuade, and Townsend (2018) use the indexes developed by Bogin, Doerner, and Larson (2016), but report that robustness results using the Zillow indexes are similar.

[15] See `https://www.fhfa.gov/DataTools/Downloads/pages/house-price-index.aspx`.

the median cumulative return is 9.72%, but the variation is large and many advisor-year observations have negative cumulative returns. In our baseline specification, we focus on cumulative returns for several reasons. First, it is natural to evaluate the current price relative to the purchase price, due to the salience of the purchase price. Second, mortgages are a function of purchase prices and so cumulative returns are important determinants of whether an advisor is underwater on his house. Third, because of variation in the timing of purchases, cumulative returns vary across advisors within a ZIP code in any given year, which allows for the inclusion of more stringent fixed effects in some tests.

To summarize the time-series and regional variation in real estate prices during our sample period, Figure 1 shows the percentage of financial advisors who experience an annual price decline of at least 10% during our sample period. The figure plots results for the entire U.S. as well as for a few select states. There is a clear time-series pattern. Negative real estate price shocks are concentrated around the housing market crash of 2007–2009, although there is some variation across states in the timing of the crash. For example, the peak of the housing market crash occurred earlier in Nevada than in Illinois. There is also considerable cross-sectional variation: in 2008 real estate price shocks of 10% or worse affected more than 96% of advisors in Nevada but fewer than 6% of advisors in Texas. The figure also shows that price declines are not limited to the financial crisis period; many advisors experience substantial price declines in 2010 and 2011. Indeed, 70,537 advisors experience a 10% annual housing price decline outside of the 2007–2009 period.

There is also large cross-sectional variation within states and even within metropolitan statistical areas (MSA), as documented by Bogin, Doerner, and Larson (2016) and Edlund, Machado, and Sviatschi (2016). For example, Figure 2 displays ZIP-code level declines in housing prices for the Atlanta metropolitan area in 2008: the hardest hit ZIP codes lost as much as 27%, while other (often nearby) ZIP codes had negligible losses.

1.3. Real Estate Shocks and Misconduct by Financial Advisors

Figures 3 and 4 present simple visual summaries of the unconditional relation between real estate shocks and misconduct by financial advisors. In Figure 3, we categorize the advisor-year observations into ventiles based on the advisor's annual house price change, with the average return within each ventile shown along the x-axis. We then plot the average misconduct rate for each ventile. The dashed line shows the unconditional average for the entire sample and the gray shaded area shows the 95% confidence interval (with standard errors clustered by individual and by ZIP code). The annual return switches from negative to positive in the seventh ventile; the misconduct rate increases as returns decline in the negative return region and is largely flat in the positive return region except for a small but insignificant increase for the highest return ventiles.

In Figure 4, we plot the average misconduct rate in event time for the sample of advisors who experience an annual real estate price shock of -10% or worse.[16] The average misconduct rate is flat in the years before the shock, rises sharply in the year of the shock, remains high for the next two years, and then reverts in the subsequent year. Thus, the simple visual evidence in both figures is consistent with a relation between real estate shocks and misconduct. Of course, this simple visual evidence should be interpreted cautiously, as the figures do not control for potential confounding factors, such as year effects, advisor characteristics, or regional differences — issues we address in the next section.

2. Identification Strategy

Identifying whether wealth shocks cause financial advisors to commit misconduct is complicated because of various unobservable factors that affect both housing prices and misconduct. For example, Miami has one of the highest rates of financial misconduct and also suffered large price declines during the financial crisis. This does not necessarily indicate a causal relation between housing prices and misconduct; possibly, the type of individual who

[16]If an advisor experiences multiple shocks of -10% or worse we include only the first shock for the figure.

commits misconduct also prefers to live in a metropolitan area such as Miami. To remove the potential effect of such unobservable variation, we use two identification strategies. First, we use ZIP-code level housing return shocks and estimate a differences-in-differences model. Second, in our primary specification we use individual-specific housing return shocks based on cumulative housing returns since purchase and multiple fixed effects to remove confounding variation.

2.1. Differences-in-Differences

Following the identification strategy used by Bernstein, McQuade, and Townsend (2018) and Pool, Stoffman, Yonker, and Zhang (2018), we examine cross-sectional variation around the 2008 financial crisis. Although the crisis affected all advisors in our sample, as Figures 1 and 2 show, there was significant cross-sectional variation in its effect on local real estate prices. To exploit this variation, we estimate the following differences-in-differences specification:

$$\Delta Misconduct_i = \beta \cdot \textit{Crisis Price Change}_z + \gamma \cdot \textit{log(Experience)}_i + \delta_f + \delta_{lr} + \epsilon_i \,, \tag{1}$$

where i indicates a financial advisor, z indicates a ZIP code, f indicates a financial advisory firm, and lr indicates the decile of the advisor's length of residency in their current home. The dependent variable, $\Delta Misconduct_i$, measures the change in the number of misconduct events committed by advisor i over the three year post-crisis period (2008–2010)[17] compared to the three year pre-period, (2005–2007).[18] $\textit{log(Experience)}_i$ is the natural logarithm of the number of years that the advisor has worked in the industry.

In this specification, time-invariant effects are differenced away at the advisor level. Advisors in ZIP codes unaffected by the housing price collapse provide a control for any

[17] To avoid survival bias, we include advisors who exit the industry during this three year period. The results are robust if we instead exclude these advisors in the sample.

[18] Our results are robust in Internet Appendix 4 to using the time periods of Pool, Stoffman, Yonker, and Zhang (2018), who defined the pre-period as 2005–2006 and the post-period as 2009–2010. The results are also robust to using the time periods of Bernstein, McQuade, and Townsend (2018), who defined the pre-period as 2005–2007 and the post-period as 2008–2012. The results are also robust if we treat 2008 as a gap year and define the post-period as 2009–2011.

time varying change in the level of misconduct (e.g., a general increase in misconduct or the detection of misconduct around the financial crisis). The firm-level fixed effects control for any firm-specific changes in misconduct (e.g., perhaps firms in areas more severely affected by the crisis changed in response to the crisis). The length-of-residency decile fixed effects control for any effects related to how long an advisor has lived in his house.

2.2. Cumulative House Price Changes

Our second identification strategy is a panel approach using cumulative housing returns.[19] As described earlier, we construct the *Cumulative Return* for each advisor-year, using the change in the advisor's house price since purchase, and estimate the following specification:

$$Misconduct_{i,t} = \beta \cdot \textit{Cumulative Return}_{i,t} + \gamma \cdot \textit{log(Exp.)}_{i,t} + \delta_i + \delta_z + \delta_{f,t} + \delta_{lr} + \epsilon_{i,t}\,, \quad (2)$$

where $\textit{Misconduct}_{i,t}$ is an indicator variable equal to one if the advisor reports a validated customer complaint during the current year.[20] $\textit{Cumulative Return}_{i,t}$ is the cumulative price change since purchase for advisor i, which varies across advisors in the same ZIP code at a given point in time. In addition to $\textit{log(Exp.)}_i$, we rely on advisor, ZIP code, firm-year, and length of residence decile fixed effects to remove potential sources of confounding variation.

First, the financial advisor fixed effect, δ_i, removes all time-invariant characteristics of the advisor, including his overall propensity to commit misconduct, and also reduces the effect of advisor characteristics that are largely fixed throughout the sample, such as education and religious background. This fixed effect also removes the time-invariant part of the advisor's business activities, such as customer characteristics, the types of products sold, etc. The advisor fixed effect also captures any time-invariant real estate preferences.

Second, the ZIP code fixed effect, δ_z, removes the time-invariant characteristics of the area

[19]In Internet Appendix 5, we employ panel regressions with *annual* housing price returns. The results are similar, in that we find a negative relation between housing price returns and misconduct.

[20]Robustness tests reported in Internet Appendix 6 show the results are robust to using an indicator variable for misconduct occurring in the subsequent year or during a three-year window.

in which the advisor lives. This is important as Parsons, Sulaeman, and Titman (2018) show there are large differences in misconduct rates across cities. This fixed effect also removes stable demographic and economic characteristics of the neighborhood.

Third, the firm-year fixed effect, $\delta_{f,t}$, removes the time-invariant characteristics of the firm that employs the advisor, as well as time-varying firm characteristics such as changes in the firm's product offerings or monitoring procedures. Removing firm effects is important as Egan, Matvos, and Seru (2018a) show that certain firms specialize in committing misconduct. The firm-year fixed effects also subsume year-effects, removing the common time-series variation in housing returns and misconduct (e.g., it would remove any common time-series relation between asset prices and complaint rates).

Fourth, the length-of-residency fixed effects, δ_{lr}, remove variation across advisors based on how long they have lived in their current residence. The length-of-residency is potentially important for several reasons. The loan-to-value ratio typically decreases with length of residency, and differences in leverage ratios may affect financial advisors' actions. Further, longer residency may be associated with deeper community ties, increasing the reputational cost of engaging in misconduct.

3. Main Results

3.1. Changes in Misconduct and House Price Shocks during the Financial Crisis

Table 3 reports results from differences-in-differences specifications, in which there is one observation per advisor. The dependent variable is the change in misconduct, defined as the number of instances of misconduct during the three-year period[21] 2008–2010 less the number during 2005–2007. The key independent variables are based on the advisor's housing price shock during the financial crisis (the house return in 2008). In column (1), the independent

[21] Figure 3 shows that misconduct rates are higher for a three-year period following a real estate price shock. Accordingly, and following the existing literature on financial advisor misconduct around shocks (e.g., Dimmock, Gerken, and Graham, 2018; Charoenwong, Kwan, and Umar, 2017), we use a three-year window for misconduct.

variable is *Crisis Price Change* which is the percentage price change of the advisor's house. In columns (2), (3), and (4) the independent variables are indicators equal to one if the return on the advisor's house was less than -5%, -10%, or -15%, respectively. All columns include a control for the logarithm of years of industry experience. All specifications include firm fixed effects to absorb any variation common to an advisory firm such as its product offerings, internal monitoring procedures, etc., as well as length of residence fixed effects to absorb any variation related to how long an advisor has lived in his house. The standard errors are clustered by ZIP code.

The results in all four columns show a significant relation between house price shocks and changes in misconduct; misconduct increases for advisors who suffer the largest house price declines during the financial crisis. The economic magnitudes implied by the results are large relative to the baseline misconduct rate. For example, the coefficient estimate in column (3) implies that an advisor with a 10% price drop on his house is 0.61 percentage pointsmore likely to commit misconduct in the next three years (a 41% increase relative to the baseline).

3.2. Misconduct and Cumulative House Price Changes

Table 4 reports results from panel regressions in which the unit of observation is advisor-year. The dependent variable is an indicator variable equal to one if the advisor commits misconduct in the current year. The key independent variable is *Cumulative Return*, which is the cumulative percentage return on the advisor's house since purchase. In column (1), we do not include advisor fixed effects, and instead control for the advisor characteristics: age, gender, previous misconduct, and licensing (Series 6, 7, 24, 65, and 66). In columns (2) and (3), we include advisor fixed-effects. All specifications include controls for the logarithm of years of industry experience and firm-year, length of residence, and ZIP fixed effects. In column (3), we test whether the effect of returns on misconduct is non-linear. In this specification, we add an interaction term, $Cumulative\ Return \times I_{Extreme}$, where $I_{Extreme}$ indicates a cumulative return worse than -20%. The standard errors are clustered by advisor and ZIP code.

Column (1) of Table 4 reports the simplest of the three specifications. We report this specification, which does not include individual fixed effects, because it is easier to interpret and to show the results are not dependent upon the inclusion of these fixed effects. The negative coefficient shows that advisors with worse cumulative returns on their house are significantly more likely to commit misconduct. The inclusion of firm-year fixed effects means that the specification limits the comparison to advisors who work for the same firm during the same year — even within this limited comparison group, advisors with worse returns commit more misconduct. The specification also includes ZIP and length of residency fixed effects, meaning that the findings for *Cumulative Return* are relative to other advisors living in the same area and advisors with similar lengths of residency.

The specification reported in Column (2), which we use as our benchmark specification for the remainder of the paper, includes individual fixed effects. In this specification, the advisor is effectively benchmarked against their own behavior throughout the sample. The results show that, even relative to his average misconduct behavior throughout the sample, an advisor is more likely to commit misconduct when his *Cumulative Return* is low. The results imply that a one standard deviation decrease in cumulative returns (35.8 percentage points change) results in an 7.5 basis point increase in the likelihood of misconduct, which is a 12% increase relative to the baseline misconduct rate.

The specification reported in column (3) includes an interaction term, $(Cumulative\ Return - (-20\%))\ \times I_{Extreme}$, where $I_{Extreme}$ indicates a cumulative return worse than -20%. We include this specification with a cutoff of -20% for two reasons. First, as Kau, Keenan, and Kim (1994) show, the probability of financial distress increases non-linearly with the size of the cumulative loss and with the probability increasing sharply well below a cumulative return of 0% (i.e., for small losses down payments provide some protection). Second, most homeowners likely have only an imprecise estimate of their home's value based on their neighbors' home sales, local news stories, observing new construction, etc. But it is unlikely the homeowner knows precisely when their return switches from slightly positive to slightly negative. By using a large negative cumulative return, we focus on individuals who almost surely know they have suffered large losses. The results in column (3) show the relation between cumulative housing returns and misconduct is non-linear. The increase in misconduct is much greater for large negative returns, indicating that misconduct is significantly more sensitive to large losses on housing.

3.3. A Placebo Test

As a robustness test, we employ a bootstrap-placebo procedure. For each repetition of this procedure, we randomly match each ZIP code with another ZIP code from a different state. We then assign each advisor-year the cumulative housing return from the matched ZIP code-year based on the advisor's year of purchase. The match between ZIP codes is fixed for all years within a single repetition of the bootstrap procedure. For example, suppose that in 2006 an advisor named Bob lived in a house in ZIP code 48823 that he purchased in 2000. Further suppose that, for this repetition of the bootstrap, ZIP code 48823 was randomly assigned returns from ZIP code 78722. Then, in 2006 Bob would be assigned the six-year cumulative housing return from ZIP code 78722. If Bob continued living in the same house, then in 2007 he would be assigned the seven-year cumulative housing return from ZIP code 78722. Other advisors in ZIP code 48823 would also be assigned returns from ZIP code 78722, but their cumulative housing returns would vary depending on their year of purchase. Using these pseudo-cumulative housing returns, we estimate the specification reported in column (2) of Table 4. We repeat this procedure 10,000 times.

This procedure assigns random cumulative returns for each advisor-year observation, but crucially, preserves all other time-series and cross-sectional relations in the panel. The time-series relations are preserved because the advisor's pseudo cumulative return is drawn from the same randomly assigned ZIP code for each year. The cross-sectional relations between advisors in a single ZIP code are preserved because they are all assigned returns from the same randomly assigned ZIP code. Further, any effects caused purely by the length of residency are preserved. For example, suppose that advisors with greater length of residency generally: (1) have higher cumulative returns and (2) are less likely to increase misconduct following house price shocks because of deeper community ties. This relation would be preserved in the placebo test because the pseudo cumulative return is a function of length of residency.

Figure 5 plots a histogram of the coefficient estimates on the *Pseudo-Cumulative Return* variable. The actual coefficient estimate of -0.2082 lies over six standard deviations below the mean of the bootstrapped coefficients (-0.010), and none of the 10,000 placebo estimates are below the actual coefficient estimate. Thus, the placebo results suggest that it is the *actual* loss suffered by the advisor that drives the relation between housing returns and misconduct.

4. Addressing Concerns about Commonality in Customer and Advisor Shocks

As is most studies of fraud and misconduct, we observe *detected* misconduct not *actual* misconduct. This creates the possibility of bias if variation in the detection rate is correlated with the independent variable of interest. In our study, a possible concern is that a customer's propensity to file a complaint against her advisor varies with the customers' real estate returns. That is, if a customer is under financial pressure due to losses on her home, she may become more likely to file a formal complaint against her advisor. In this section, we present a number of tests that address this concern.

4.1. ZIP-Year Fixed Effects

Column (1) of Table 5 is similar to the baseline specification, but includes ZIP-year fixed effects instead of ZIP fixed effects. These fixed effects exploit the fact that cumulative housing returns vary across advisors in the same ZIP code during the same year, based on when the advisors purchased their homes combined with the price path of housing in that ZIP code. The ZIP-year fixed effects remove variation that is common to all advisors in the same ZIP code during the year, such as local housing price shocks during the year, the economic and demographic characteristics of the local customer base, and any other local commonalities including the propensity of local customers to file complaints. In this specification, the variation in the dependent variable is limited to the time-series increase in misconduct by an advisor *relative* to the time-series increase of other advisors who live in the same ZIP code in that year. The variation in the key independent variable is limited to the cross-sectional variation across advisors living in the same ZIP code at that point in time.

This specification is quite conservative and likely removes much of the variation of interest, but it eliminates potential confounding effects. For example, suppose that dishonest advisors prefer to live in exciting metropolitan areas that have volatile real estate prices. These advisors commit misconduct regardless of local housing returns. Further suppose that customers are more likely to detect misconduct following a market downturn because of price declines, greater vigilance, or other reasons. Such a combination of events could create a spurious relation between housing returns and misconduct, however, it would be removed by the inclusion of the ZIP-year fixed effects.

The results in column (1) show that the relation between misconduct and cumulative housing returns remains negative and significant even after including the ZIP-year fixed effects. Even with these fixed effects, we find that advisors with worse cumulative returns are significantly more likely to commit misconduct. Further, the magnitude of the coefficient is similar to that in the baseline specification.

4.2. Branch-Year and Branch-ZIP-Year Fixed Effects

Column (2) of Table 5 includes branch-year fixed effects, which subsume the firm-year fixed effects in the baseline specification. This specification removes any variation common to advisors who work at the same branch[22] of the same firm during the year, including local housing price shocks, the economic circumstances of the firm's local customer base, local monitoring and oversight, and the firm's product offerings. Even with these more stringent fixed effects, the results show a significant relation between housing returns and misconduct.

Column (3) of Table 5 includes branch-year-ZIP fixed effects, which subsume both the

[22] This definition of branch follows from Egan, Matvos, and Seru (2018b), but differs from that of Dimmock, Gerken, and Graham (2018) who use business address information that is not provided by all states.

firm-year and zip-year fixed effects. This specification effectively limits the comparison to be between advisors who work for the same branch of the same firm and live in the same ZIP code during the year. These are very restrictive fixed effects that remove many sources of potentially confounding variation. The cost of including these fixed effects, however, is that we likely remove variation of interest and that we must drop more than half the observations due to insufficient variation within the fixed effect unit. The results show that, once again, there is a significant negative relation between *Cumulative Return* and misconduct. Advisors with worse cumulative returns on their home are significantly more likely to commit misconduct even relative to their local co-workers.

4.3. Out-of-State Customers

The previous fixed effect specifications include ZIP-year and branch-ZIP-year fixed effects. These fixed effects remove all variation common to advisors living in the same ZIP code during the same year — such as shared variation in the advisors' customer base. It is possible, however, that even after removing ZIP-year variation, there remains a positive correlation between the real estate shocks of advisors and their customers. For example, suppose that because of demographic similarity advisors who recently purchased a house are disproportionately likely to match with customers who also recently purchased a house, resulting in similar cumulative real estate returns *even within ZIP-year*. In this section, we address the issue of advisor-customer commonality by using an alternative dependent variable.

Although many customer-advisor matches are between geographically proximate individuals, this is not always the case. In the data, we can observe the state of residence for customers who file complaints[23] and find that 15.4% of customer complaints are out-of-state customer complaints.[24] In the results reported in column (4) of Table 5, we limit the dependent variable

[23]Unfortunately, we do not observe the state of residence for customers who do not file complaints.

[24]As multiple customers can file a complaint in a year, 27.3% of advisor-years with *Misconduct* include at least one out-of-state complaint.

to include only customer complaints filed by out-of-state customers.

The results show that the relation between the advisor's *Cumulative Return* and misconduct remains significant even with this restricted dependent variable. This test breaks the link between the local real estate price shock suffered by the advisor and the shock suffered by the (geographically distant) customer, suggesting that it is not the customers' real estate losses that drive our results.

4.4. Regulatory Actions and Employment Terminations

In this section, we present another test to address the potential concern that, even after the inclusion of the fixed effects, an advisor's *Cumulative Return* is correlated with his customer's housing returns, or more generally, correlated with time-variation in his customer's propensity to file complaints. Specifically, in column (5) of Table 5 the dependent variable is set equal to one if the advisor discloses a regulatory action or is terminated by his employer. For this test, we exclude all advisor-year observations that include a customer complaint so to ensure the regulatory actions and terminations are not responses to customer complaints (e.g., if a firm terminated an advisor because of a customer complaint).

Government regulation of financial advisors is conducted by state governments. We include state-year fixed effects to remove the state regulator's overall propensity to take actions in a given year.[25] We also continue to include firm-year fixed effects to remove each firm's propensity to terminate its employees during a given year. These fixed effects remove the most obvious sources of confounding variation — as there is no obvious reason to expect that a state regulator or firm would systematically take harsher actions against advisors with worse cumulative housing returns.

The results in column (5) show that, even when misconduct is limited to exclude customer complaints, advisors with worse *Cumulative Return* are significantly more likely to commit misconduct. Overall, the results in Table 5 support the argument that wealth shocks affect

[25]FINRA is responsible for some regulation at the national level, but national level effects will be subsumed by the state-year fixed effects.

the propensity of financial advisors to commit misconduct.

5. Cross-Sectional Variation in Termination Risk

In this section, we test how cross-sectional variation in termination risk affects the relation between real estate shocks and misconduct. Prior studies show that there is large variation in the likelihood that an advisor is terminated after committing misconduct (e.g., Egan, Matvos, and Seru, 2018a,b). Higher termination risk implies a lower expected return to committing misconduct. Thus, all else held equal, we expect advisors with higher termination risk will be less likely to increase misconduct following a real estate shock.

Egan, Matvos, and Seru (2018a) show large across-firm variation in tolerance for misconduct. We measure each advisor's termination risk based on the fraction of the other advisors working at the firm who have a history of prior misconduct. If this fraction is above the sample average, we set the indicator variable *High Firm-Year* equal to one.[26] The results, reported in column (1) of Table 6, show that the coefficient on the interaction term $Cumulative\ Return \times High\ Misconduct\ Firm\text{-}Year$ is significant and negative. Even after controlling for firm-year fixed effects, the effect of a real estate shock on misconduct is greater when the career risk associated with committing misconduct is smaller.

The specification in column (2) of Table 6 is conceptually similar to that in column (1), but here we consider tolerance for misconduct at a finer geographic level. In this test, we classify firms at the branch-year level. That is, we create an indicator variable *High Branch-Year*, which is set to one if an above average proportion of the advisor's fellow employees *who work at the same branch* have a history of past misconduct. This variable allows for the possibility that a firm's tolerance for misconduct in a given year could vary across branches due to the

[26]We do not include the advisor's own history of misconduct when constructing this variable because of biases that occur in fixed effect regressions in which an independent variable is a function of lagged values of the dependent variable. See Nickell (1981) for further discussion. Because the advisor's own history of misconduct is not included in this variable, its direct effect is not fully subsumed by the firm-year fixed effect, and so it is included in the regression. However, due to its high correlation with the firm-year fixed effects, the coefficient on the direct effect is unreliable due to multicollinearity. However, the issue of multicollinearity does not affect the coefficient on the interaction term, which is the coefficient of interest.

local manager, state regulators, or other reasons. The coefficient on the interaction term is significant and negative; advisors are more likely to commit misconduct following a real estate shock when they work for a branch with a high tolerance for misconduct.

Column (3) of Table 6 considers individual-level career risk from committing misconduct, rather than firm or branch level career risk as in the previous columns. Egan, Matvos, and Seru (2018b) show that, relative to men, women are more likely to be terminated for misconduct and less likely to find new employment following termination. Accordingly, women face relatively more severe career risk for committing misconduct. As in Egan, Matvos, and Seru (2018b), 25% of advisors in our sample are female. The coefficient on the interaction term $Cumulative\,Return \times Female$ is significant and positive. Indeed, for females the net effect of *Cumulative Return* is not significant. Overall, the results in this section show that the relation between real estate shocks and misconduct is stronger when there is less career risk from committing misconduct.

6. Active versus Passive Misconduct

Throughout the paper, we have interpreted misconduct as an *active* choice. That is, that advisors deliberately exploit their clients for financial gain. If advisors derive utility from ethical behavior,[27] and ethical behavior is a normal good, then advisors' "consumption" of ethical behavior will decrease when wealth decreases. Alternatively, as advisors approach the bankruptcy boundary the financial penalties associated with detected misconduct may no longer provide a deterrent (for further discussion see Block and Lind, 1975).

In this section, we consider an alternative possibility — that real estate shocks result in "passive" misconduct through inattention or negligence. Passive misconduct could increase following real estate shocks if the advisor becomes distracted and less effective at work due to financial pressure (e.g., Maturana and Nickerson, 2017, show that students' standardized test

[27] Deriving utility from ethical behavior implies an advisor may forgo at least some opportunities to commit misconduct even when the misconduct has a positive *financial* net present value. For formal modeling of ethical preferences, see Block and Heineke (1975) and Morrison and Thanassoulis (2017).

scores suffer when their teacher undergoes financial distress). Note that active and passive misconduct are not mutually exclusive, and both could occur even for the same individual.

We separate misconduct into active and passive categories by parsing the text fields in the advisors' disclosure statements and classifying misconduct based on key words. *Active Misconduct* includes misrepresentation, unauthorized trading, fee or commission related misconduct, churning, and fraud. These are acts of commission (intentional actions) that will enrich the advisor if undetected. *Passive Misconduct* includes negligence and omission of key facts. These include acts of omission, and are more consistent with carelessness or inattention instead of enrichment. There are some categories of misconduct, such as unsuitability and violations of fiduciary duty, that we do not classify. Of advisor-years with misconduct events, 53.6% are classified as active, 17.0% as passive, and the remainder cannot be unambiguously classified.

In column (1) of Table 7 the dependent variable includes only *Active Misconduct*. The coefficient on *Cumulative Return* is significant and negative. The result shows that, following a decline in the value of their home, advisors are more likely to commit active misconduct — taking deliberate actions to exploit customers for financial gain. The results in column (2) show there is also evidence of passive misconduct.

7. Robustness Tests

7.1. Alternative Types of Misconduct

Robustness specifications discussed in this subsection are identical to the baseline specification, but with alternative definitions of misconduct. In column (3) of Table 7 the dependent variable is an indicator variable equal to one if the advisor committed misconduct involving mutual funds. Mutual funds are a relatively straightforward category of financial products, and are typically regulated and distributed at the national level. In contrast, other financial products may vary across states due to regulator differences (e.g., annuities and some insurance products) or may be distributed primarily in a limited geographic area (e.g., local micro-cap stocks). Limiting the dependent variable to include only mutual funds reduces the possibility that some type of assortative matching of local products to local customers could confound our analysis. Consistent with the baseline specification, column (3) finds a significant negative coefficient on *Cumulative Return*.

In column (4) of Table 7 the dependent variable is set equal to one if there is an incident of misconduct in which the damages exceed $100,000. A potential concern with the results is that the advisors' actions are unrelated to their own real estate returns but that customers become more likely to file complaints following negative real estate shocks (given the fixed effects, this concern would also require within-ZIP-year commonality in real estate returns between advisors and customers). This possibility is most plausible for borderline cases with relatively small dollar damages as it is unlikely that customers would tolerate severe misconduct regardless of real estate wealth. The results show that, even with this restrictive definition of misconduct, there is a significant negative relation between the advisor's cumulative real estate returns and large cases of misconduct.

In column (5) of Table 7, we define misconduct following Egan, Matvos, and Seru (2018a) who use a broader measure of misconduct that, in addition to customer complaints, also includes regulatory actions, terminations by an employing firm, and criminal and civil disclosures. The results are similar to those in the baseline specification. Overall, the results in Table 7 show that advisors who suffer declines in the value of their home are more likely to commit misconduct of all types.

7.2. Imputed Housing Returns and Advisor Financial Distress

Throughout the paper we use imputed house price returns to measure wealth shocks to financial advisors. As a validation test of this measure, we test whether imputed house price returns predict actual financial distress. FINRA requires financial advisors to disclose any bankruptcy filing or other "compromise with creditors" in which "a creditor agrees to accept less than the full amount owed"[28] for a 10 year period (because advisors no longer need to disclose these events after 10 years, for these tests the sample period begins in 2008). We use these disclosures to create two measures of financial distress.

In column (1) of Table 8, the dependent variable is an indicator equal to one if the advisor files for bankruptcy in the next year. Aside from this change to the dependent variable, the specification is identical to the baseline specification. The results show that advisors with worse cumulative housing returns are significantly more likely to declare bankruptcy. Further, the implied economic magnitudes of the estimates are large relative to the baseline rate of bankruptcy; the coefficient estimate implies that a one standard deviation decline in *Cumulative Return* is associated with an 0.11 percentage point increase in the probability of bankruptcy (a 36.4% increase relative to the baseline rate of bankruptcy).

In column (2) of Table 8, the dependent variable is an indicator equal to one if the advisor discloses a "compromise with creditors" related to an underwater sale (a house sale in which the proceeds are less than the debts secured by the property and the advisor does not pay the lender the difference) in the next year. This provides a very direct measure of financial distress related to housing returns. The results show that advisors with worse cumulative house returns are significantly more likely to disclose underwater home sales. Further, the implied magnitudes are large; the coefficient estimate implies that a one standard deviation decline in *Cumulative Return* is associated with a 0.14 percentage point increase in underwater sales (a 130.4% increase relative to the baseline rate). Overall, the results in Table 8 provide evidence that our imputed measure of housing price returns captures meaningful wealth shocks for financial advisors.

[28]See `www.finracompliance.com/wp-content/uploads/2015/04/Finra-U4-U5-QnA.pdf` for a more detailed definition of the reporting requirements.

8. Conclusion

This paper studies whether household level financial shocks affect the propensity of employees to engage in financial misconduct. We measure household financial shocks using housing price declines, and measure misconduct using validated customer complaints disclosed by financial advisors in mandatory regulatory filings. The results show that a financial advisor who suffers a large price decline on his house becomes significantly more likely to commit misconduct — and many of these misconduct events are clearly willful actions on the part of the advisor. This increase is relative to the advisor's own historical rate of misconduct and relative to the advisor's co-workers who had smaller housing price declines.

Our results provide useful information for firms designing compliance and monitoring systems and for regulators allocating limited auditing resources. Our findings show that the willingness to commit misconduct is a pliable characteristic of the individual advisor; advisors are more likely to commit misconduct when they are under financial pressure. We also document an externality of real estate price fluctuations — when advisors suffer negative financial shocks they are more likely to financially exploit their clients.

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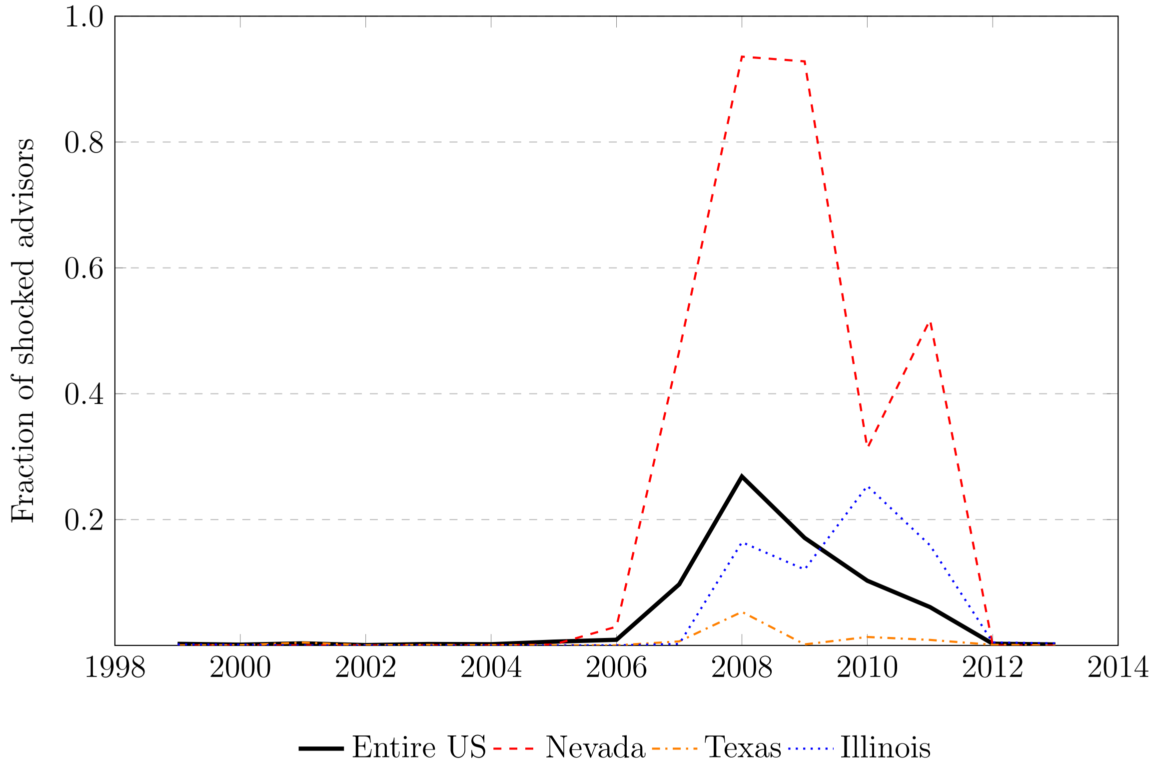

Figure 1: Real Estate Price Shocks by Year

This figure plots the fraction of financial advisors whose residence experiences a year-over-year decline in price of at least 10%, as measured by the Zillow ZIP code level house price index, over our sample period. We plot this measure separately for the entire U.S. (black) and select states.

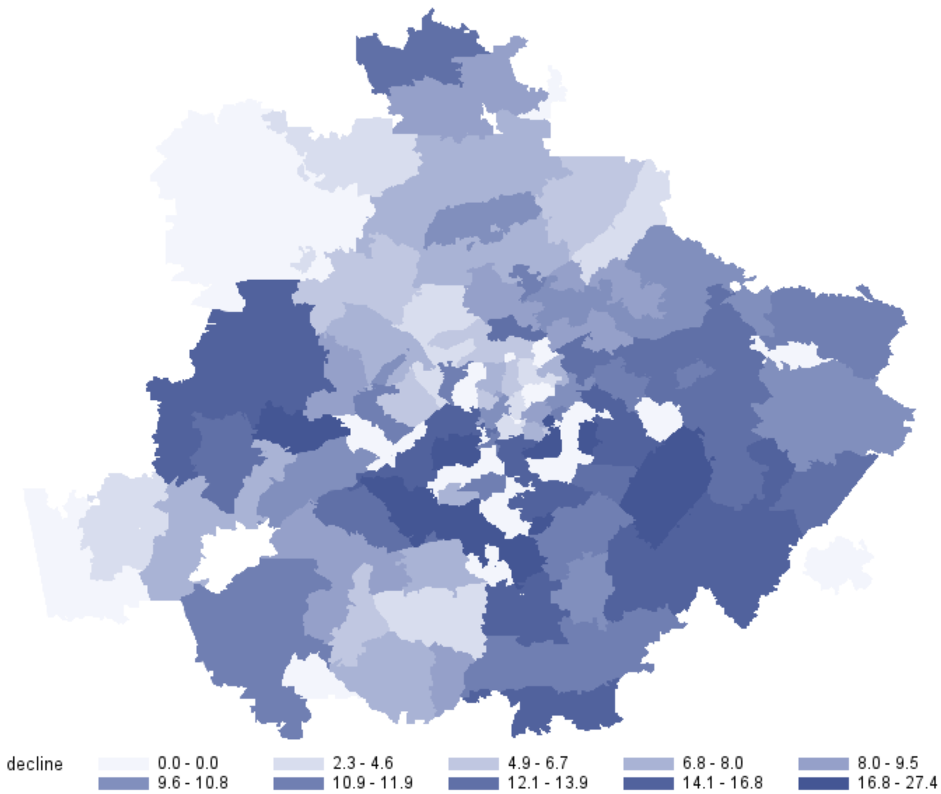

Figure 2: Crisis Price Changes in Metro Atlanta
This figure displays price declines by ZIP code in the Atlanta, GA metropolitan statistical area for 2008. ZIP codes are color coded by level of 2008 loss where darker shades indicate more severe losses. (Note, 0.0-0.0 indicates Zillow ZIP code level house price data is unavailable.)

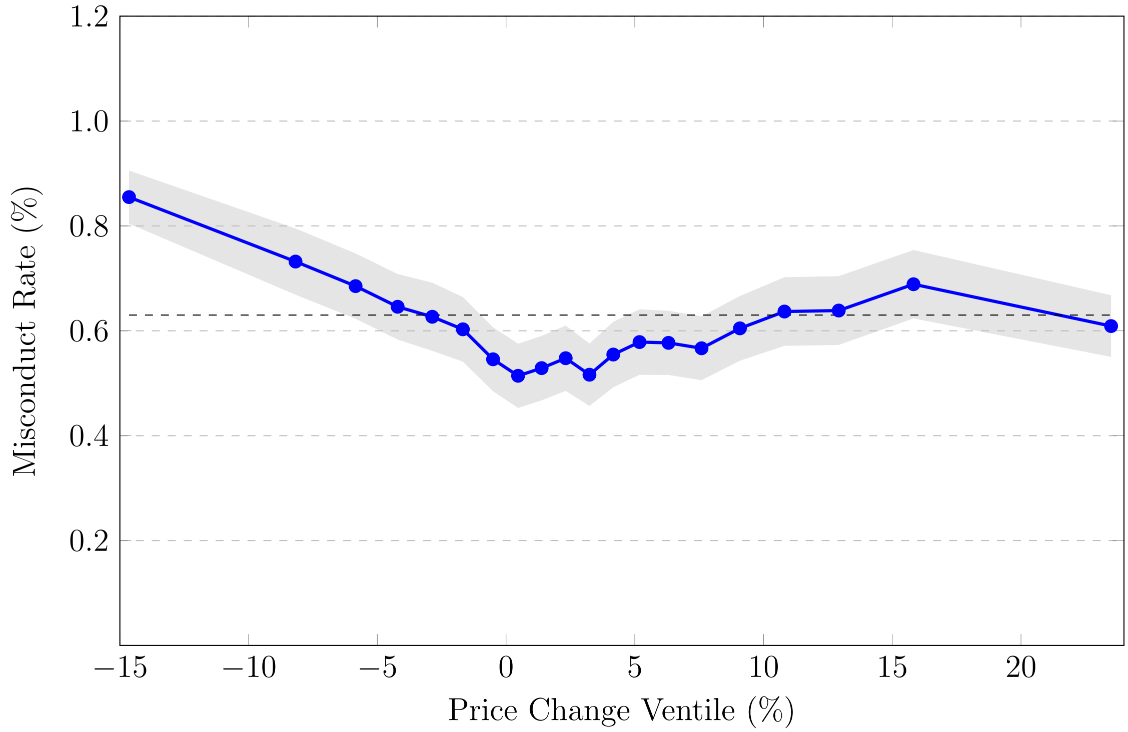

Figure 3: Misconduct by Ventile of Annual House Price Changes
This figure plots the misconduct rate of advisors by ventile of annual housing price changes, as measured by the Zillow ZIP code level house price index. The grey shaded area around the plot is the 95% confidence interval. The dashed line marks the unconditional average of misconduct (0.63%). Misconduct is measured as in Dimmock, Gerken, and Graham (2018) and includes customer disputes that are either settled or awarded in favor of the customer.

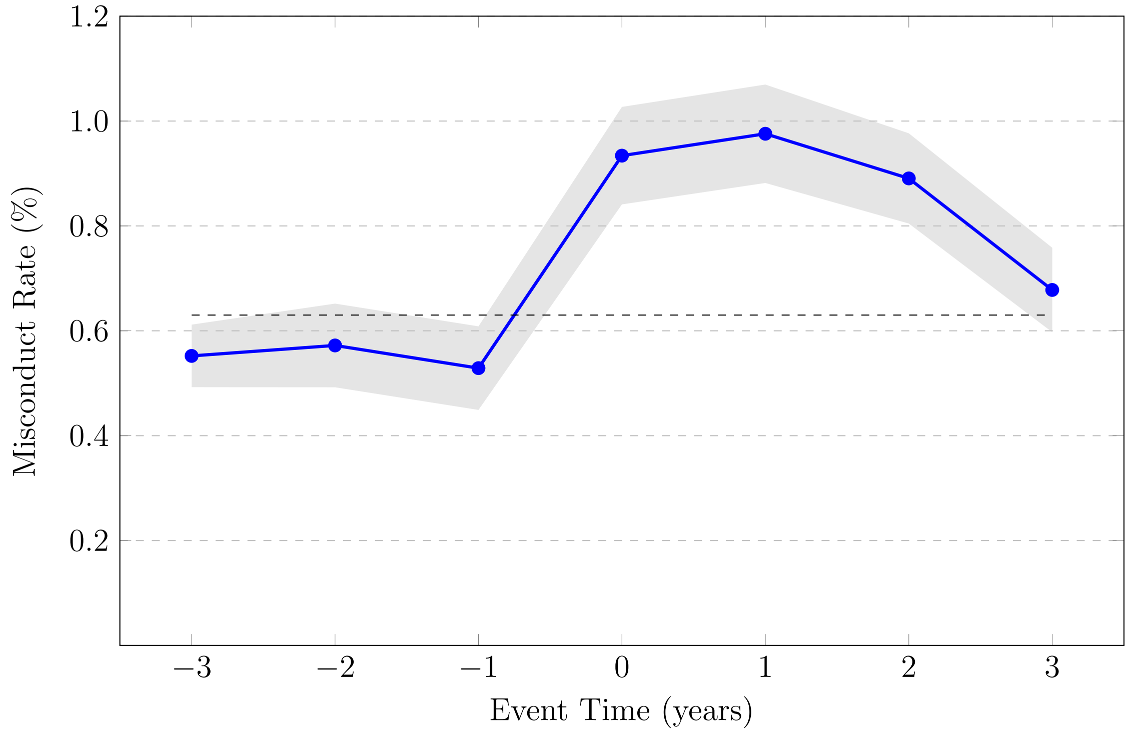

Figure 4: Misconduct Timing around Real Estate Shocks
This figure plots the average misconduct rate in event time, where the event is a 10% or worse decline in an advisor's house price, as measured by the Zillow ZIP code level house price index. Three years before and three years after the event are included. The grey shaded area around the plot is the 95% confidence interval. The dashed line marks the unconditional average of misconduct (0.63%). Misconduct is measured as in Dimmock, Gerken, and Graham (2018) and includes customer disputes that are either settled or awarded in favor of the customer.

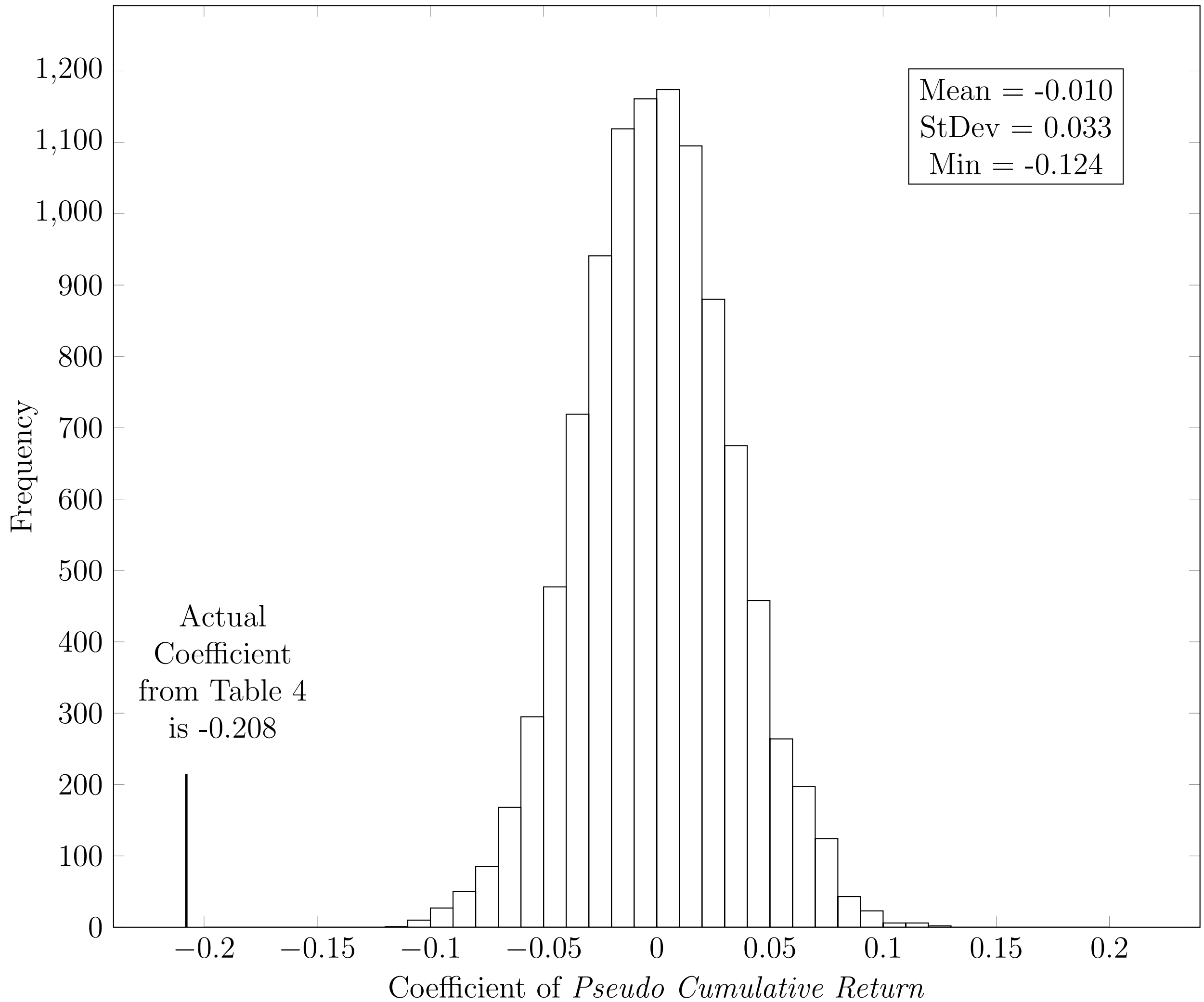

Figure 5: Coefficient of *Cumulative Return* in placebo samples.
The figure shows a histogram of *Pseudo Cumulative Return* coefficients from 10,000 iterations of the model in Table 4, column (2). For each iteration, each ZIP code is randomly assigned the returns of another out-of-state ZIP code (creating new counterfactual values for *Cumulative Return*. The model is re-estimated using the counterfactual *Cumulative Return* values. All other advisor characteristics remain the same.

Table 1:
Advisors and Disclosures
This table summarizes misconduct disclosures that financial advisors are required to make. The first column reports the number of advisor-years with the associated misconduct measure. The second and third columns report the percent of offending advisor-years and advisors, respectively. *Misconduct* is defined using customer disputes as in Dimmock, Gerken, and Graham (2018) and is comprised of customer disputes that either receive an award in arbitration or are settled for at least a certain dollar value ($10,000 or $15,000 depending upon the time period). *Out-of-state Misconduct* is defined using customer disputes only from out-of-state customers. *Regulatory* is a disclosure of finalized regulatory sanctions from entities such as the SEC, FINRA, or state regulators. *Employment Separation* reports whether the advisor has ever been terminated or permitted to resign following allegations of misconduct. *EMS Misconduct* is defined using a broader set of disclosures as in Egan, Matvos, and Seru (2018a) and includes *Misconduct*, *Regulatory*, and *Employment Separation*, as well as certain civil law and criminal disclosures. *Bankruptcy* are disclosures of bankruptcies by financial advisors. *Underwater Sale* are disclosures that pertain specifically to an underwater sale of a property. *Bankruptcy* and *Underwater Sale* are only available for the years 2008 through 2017.

	Observations	% of Advisor-Years	% of Advisors
Misconduct	14,691	0.63%	4.66%
Out-of-state Misconduct	4,016	0.16%	1.28%
Regulatory	2,535	0.10%	0.80%
Employment Separation	3,420	0.12%	1.09%
EMS Misconduct	19,232	0.85%	6.11%
Bankruptcy	4,773	0.31%	1.55%
Underwater Sale	1,643	0.11%	0.53%

Table 2:
Summary Statistics
This table provides summary statistics on variables at the advisor-year level. Panel A reports statistics regarding advisor residency, experience, and misconduct. Panel B summarizes the distribution of house price changes.

Panel A: Advisor-Year variables	1%	25%	Median	Mean	75%	99%	N
Alleged Damages from Customer Disputes ($)	0	5,000	19,000	659,666	100,000	3,500,000	36,554
Settle Amount for Customer Disputes ($)	0	2,870	15,754	239,485	59,347	3,100,000	13,444
Regulatory Damages ($)	100	1,000	5,000	13,125	10,000	200,000	899
Industry Experience (years)	1	5	10	11.82	17	37	2,860,572
Firm Tenure (years)	0	2	4	5.89	8	27	2,860,572
House Purchase Price ($)	65,800	153,100	229,700	320,539	376,300	1,502,300	2,723,779
Zillow ZIP Price ($)	73,800	176,000	268,900	373,679	445,700	1,714,400	2,860,572
Years at Residence	1	3	5	5.82	8	22	2,860,572
Number of Residences	1	1	1	1.65	2	5	2,860,572
Panel B: Distribution of House Price Changes	1%	5%	10%	Median	90%	95%	99%
Annual Dollar Change	-91,300	-42,600	-26,000	3,700	49,000	76,400	164,100
Annual Percent Change	-18.13	-10.66	-7.61	1.72	13.68	17.77	26.75
Cumulative Dollar Change	-212,200	-97,900	-54,000	23,500	198,900	303,800	618,800
Cumulative Percent Change	-37.90	-20.92	-13.10	9.72	64.09	92.06	150.00

Table 3:
Housing Price Shocks and Misconduct — Crisis Difference in Difference
This table reports OLS estimates of differences-in-differences regressions around the 2008 financial crisis. The dependent variable is the difference in the number of advisor misconduct incidences between the post-event period and the pre-event period. The pre-event period is a three-year window from 2005 to 2007. The post-event period is a three-year window from 2008 to 2010. The unit of observation is the advisor. *Crisis Price Change* is the 2008 house price return in the advisor's ZIP code. *Crisis Price Drop (X%)* is an indicator variable equal to 1 if the percentage change in house prices in the advisor's ZIP code decreases more than X%. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. All specifications include firm fixed effects and length at residency decile fixed effects. Standard errors are clustered by ZIP code. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔMisconduct			
	(1)	(2)	(3)	(4)
Crisis Price Change	-0.0509***			
	(0.0121)			
Crisis Price Drop (5%)		0.0055***		
		(0.0013)		
Crisis Price Drop (10%)			0.0061***	
			(0.0015)	
Crisis Price Drop (15%)				0.0067***
				(0.0020)
log(Industry Experience)	0.0050***	0.0050***	0.0050***	0.0050***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Firm FE	Yes	Yes	Yes	Yes
Length at Residency FE	Yes	Yes	Yes	Yes
R-squared	0.025	0.025	0.025	0.025
Observations	248,432	248,432	248,432	248,432

Table 4:
Cumulative House Price Return and Misconduct
This table provides estimates from regressions of misconduct on an advisor's cumulative house price return since purchase. The unit of observation is the advisor-year. The dependent variable is an indicator variable for advisor misconduct (multiplied by 100). *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. In column (3), the specification also includes an interaction term, $Cumulative\,Return \times I_{Extreme}$, where $I_{Extreme}$ indicates a cumulative return worse than -20%. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. Specification (1) includes advisor control variables and firm×year, ZIP code, and length at residency decile fixed effects. The latter specifications replace the advisor controls with advisor fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		Misconduct	
	(1)	(2)	(3)
Cumulative Return	-0.0847***	-0.2082***	-0.1951***
	(0.0205)	(0.0303)	(0.0310)
Cumulative Return × $I_{Extreme}$			-0.4664*
			(0.2777)
log(Industry Experience)	0.2382***	0.4914***	0.4916***
	(0.0079)	(0.0219)	(0.0219)
Advisor Controls	Yes	No	No
Advisor FE	No	Yes	Yes
Length at Residency FE	Yes	Yes	Yes
Firm×Year FE	Yes	Yes	Yes
ZIP FE	Yes	Yes	Yes
R-squared	0.032	0.146	0.146
Observations	2,882,302	2,860,572	2,860,572

Table 5:
Addressing Concerns about Commonality in Customer and Advisor Shocks
This table provides estimates from regressions of measures of misconduct on an advisor's cumulative house price return since purchase. The unit of observation is the advisor-year. In columns (1)-(3), the dependent variable is an indicator variable for advisor misconduct in a year. In column (4), the dependent variable equals one if advisor misconduct is reported by clients who live in a different state than the advisor. In column (5), the dependent variable equals one if a regulator or firm reported incidences of misconduct. In column (5), we exclude sample observations if a client also reports an incident of misconduct in the same year. In each column, we multiply the dependent variable by 100. *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. In all columns, the specifications include advisor, firm×year, length at residency decile, and ZIP code fixed effects. In column (1), the specification also includes ZIP×year fixed effects. In column (2), the specification also includes branch×year fixed effects. In column (3), the specification also includes branch×year×ZIP fixed effects. In column (5), the specification also includes state×year fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Misconduct			Out-of-State	Reg/Firm
	(1)	(2)	(3)	(4)	(5)
Cumulative Return	-0.1574***	-0.1268***	-0.1707**	-0.0463***	-0.0441**
	(0.0374)	(0.0385)	(0.0796)	(0.0149)	(0.0181)
log(Industry Experience)	0.5016***	0.5125***	0.4651***	0.1064***	0.0643***
	(0.0229)	(0.0283)	(0.0509)	(0.0100)	(0.0134)
Advisor FE	Yes	Yes	Yes	Yes	Yes
Length at Residency FE	Yes	Yes	Yes	Yes	Yes
Firm×Year FE	Yes	Subsumed	Subsumed	Yes	Yes
ZIP FE	Subsumed	Yes	Subsumed	Yes	Yes
ZIP×Year FE	Yes	No	Subsumed	No	No
Branch×Year FE	No	Yes	Subsumed	No	No
State×Year FE	Subsumed	No	Subsumed	No	Yes
Branch×Year×ZIP FE	No	No	Yes	No	No
R-squared	0.188	0.241	0.491	0.140	0.179
Observations	2,833,467	2,312,551	1,076,138	2,860,572	2,842,344

Table 6:
Cross-Sectional Variation in Termination Risk
This table provides estimates from regressions of misconduct on an advisor's cumulative house price return since purchase, interacted with indicator variables. The unit of observation is the advisor-year. The dependent variable is an indicator variable for advisor misconduct (multiplied by 100). *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. *High Firm-Year* is an indicator variable set to one if the firm-year has an above average misconduct rate (excluding the advisor's own misconduct). *High Branch-Year* is an indicator variable set to one if the branch-year has an above average misconduct rate (excluding the advisor's own misconduct). *Branch* is defined as a firm-county. *Female* is an indicator variable for gender. All specifications include advisor, firm×year, length at residency decile, and ZIP code fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		Misconduct	
	(1)	(2)	(3)
Cumulative Return	-0.1606***	-0.1397***	-0.2839***
	(0.0306)	(0.0309)	(0.0355)
High Firm-Year	5.0681***		
	(0.4191)		
Cumulative Return×High Firm-Year	-0.0899*		
	(0.0464)		
High Branch-Year		0.0706***	
		(0.0237)	
Cumulative Return×High Branch-Year		-0.1429***	
		(0.0442)	
Cumulative Return×Female			0.3020***
			(0.0423)
log(Industry Experience)	0.4898***	0.4901***	0.4922***
	(0.0219)	(0.0219)	(0.0220)
Advisor FE	Yes	Yes	Yes
Length at Residency FE	Yes	Yes	Yes
Firm×Year FE	Yes	Yes	Yes
ZIP FE	Yes	Yes	Yes
R-squared	0.146	0.146	0.146
Observations	2,860,572	2,860,572	2,843,273

Table 7:
Alternative Measures of Misconduct
This table provides results from regressions with alternative measures of misconduct as the dependent variables. *Active* and *Passive* are misconduct measures separated out by type. We define *Active* misconduct as Misrepresentation, Unauthorized Activity, Fee/Commission Related, Churning/Excessive Trading, and Fraud. We define *Passive* misconduct as Negligence and Omission of Key Facts. *Mutual Fund* is an indicator variable if the advisor had misconduct related to mutual funds. In column (4), the dependent variable is a misconduct indicator in which the damages exceed $100,000. *EMS* is the misconduct measure from Egan, Matvos, and Seru (2018a). In each column, we multiply the dependent variable by 100. The unit of observation is the advisor-year. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. All specifications include advisor, firm×year, length at residency decile, and ZIP code fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Active (1)	Passive (2)	Mutual Fund (3)	≥$100k (4)	EMS (5)
Cumulative Return	-0.0771***	-0.0491***	-0.0767***	-0.0795***	-0.2584***
	(0.0218)	(0.0126)	(0.0230)	(0.0179)	(0.0345)
log(Industry Experience)	0.2300***	0.0725***	0.4694***	0.1724***	0.5469***
	(0.0155)	(0.0085)	(0.0169)	(0.0127)	(0.0261)
Advisor FE	Yes	Yes	Yes	Yes	Yes
Length at Residency FE	Yes	Yes	Yes	Yes	Yes
Firm×Year FE	Yes	Yes	Yes	Yes	Yes
ZIP FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.140	0.131	0.126	0.135	0.163
Observations	2,860,572	2,860,572	2,860,572	2,860,572	2,860,572

Table 8:
Predicting Financial Stress

This table tests whether our cumulative return measure reliably predicts negative financial outcomes for advisors. The unit of observation is the advisor-year. In the first column we report estimates from regressions of a bankruptcy or other compromises with creditors on an advisor's cumulative house price change since purchase. In the second column we report estimates from regressions of underwater home sales on an advisor's cumulative house price change since purchase. The *Bankruptcy* and *Underwater Sale* dependent variables are indicator variables for any financial disclosures related to bankruptcies or underwater sales, respectively. In both columns, the dependent variable is multipled by 100 and only available starting in 2008. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. All specifications include advisor, firm×year, length at residency decile, and ZIP code fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Bankruptcy (1)	Underwater Sale (2)
Cumulative Return	-0.3120***	-0.3962***
	(0.0703)	(0.0536)
log(Industry Experience)	-0.1137**	0.0939***
	(0.0515)	(0.0300)
Advisor FE	Yes	Yes
Length at Residency FE	Yes	Yes
Firm×Year FE	Yes	Yes
ZIP FE	Yes	Yes
R-squared	0.263	0.274
Observations	1,272,337	1,272,337

Internet Appendix Table 1:
Home Ownership

This table reports estimates from regressions of misconduct on an advisor's cumulative house price change since purchase for subsamples of our dataset. The unit of observation is the advisor-year. The dependent variable is an indicator variable for advisor misconduct in the current year (multiplied by 100). *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. In the first column we exclude ZIP codes with low levels of home ownership (<50%) as reported in the American Community Survey. In the second column we exclude multi-dwelling unit (MDU) addresses (e.g., apartment buildings). log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. All specifications include advisor, firm×year, length at residency decile, and ZIP code fixed effects. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Misconduct	
	(1)	(2)
Cumulative Return	-0.2054***	-0.2076***
	(0.0364)	(0.0332)
log(Industry Experience)	0.5174***	0.5007***
	(0.0249)	(0.0240)
Advisor FE	Yes	Yes
Length at Residency FE	Yes	Yes
Firm×Year FE	Yes	Yes
ZIP FE	Yes	Yes
Exclude Low Ownership ZIPs	Yes	No
Exclude MDUs	No	Yes
R-squared	0.151	0.151
Observations	2,342,187	2,522,052

Internet Appendix Table 2:
Federal Housing Price Index

This table reports estimates from regressions of misconduct on an advisor's cumulative house price return since purchase. The unit of observation is the advisor-year. Specification (1) reports OLS estimates of differences-in-differences regressions around the 2008 financial crisis. The dependent variable is the difference in the number of advisor misconduct incidences between the post-event period and the pre-event period. The pre-event period is a three-year window from 2005 to 2007. The post-event period is a three-year window from 2008 to 2010. The dependent variable for specifications (2) and (3) is an indicator variable for advisor misconduct (multiplied by 100). *Crisis Price Change* is the 2008 house price return in the advisor's ZIP code. *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. Both measures of house price returns use the House Price Index produced by the Federal Housing Finance Agency instead of Zillow estimates. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. The presence of control variables and fixed effects is indicated at the bottom of the table. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔMisconduct (1)	Misconduct (2)	Misconduct (3)
Crisis Price Change	-4.9129***		
	(1.0609)		
Cumulative Return		-0.0427***	-0.0706***
		(0.0118)	(0.0210)
log(Industry Experience)	0.4635***	0.2473***	0.4952***
	(0.1119)	(0.0067)	(0.0181)
Advisor Controls	No	Yes	No
Advisor FE	Yes	No	Yes
Firm FE	Yes	Subsumed	Subsumed
Firm×Year FE	No	Yes	Yes
Length at Residency FE	Yes	Yes	Yes
ZIP FE	No	Yes	Yes
R^2	0.025	0.029	0.131
Observations	252,183	3,737,534	3,716,283

Internet Appendix Table 3:
Highest Value Residence

This table reports estimates from regressions of misconduct on an advisor's cumulative house price return since purchase. The unit of observation is the advisor-year. This table also limits the sample, using only the highest value residence when an advisor owns more than one property in a year. The dependent variable is an indicator variable for advisor misconduct (multiplied by 100). *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. The presence of control variables and fixed effects is indicated at the bottom of the table. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Misconduct	
	(1)	(2)
Cumulative Return	-0.0779***	-0.1816***
	(0.0219)	(0.0304)
log(Industry Experience)	0.2416***	0.5061***
	(0.0080)	(0.0228)
Advisor Controls	Yes	No
Advisor FE	No	Yes
Length at Residency FE	Yes	Yes
Firm×Year FE	Yes	Yes
ZIP FE	Yes	Yes
R^2	0.033	0.149
Observations	2,730,735	2,709,002

Internet Appendix Table 4:
Alternate Differences in Differences Specifications

This table reports OLS estimates of differences-in-differences regressions around the financial crisis. The dependent variable is the difference in the number of advisor misconduct incidences between the post-event period and the pre-event period. In specification (1) we follow Pool, Stoffman, Yonker, and Zhang (2018), who define the pre-period as 2005–2006 and the post-period as 2009–2010. In specification (2) we follow Bernstein, McQuade, and Townsend (2018), who define the pre-period as 2005–2007 and the post-period as 2008–2012. The last specification is similar to our main specification in Table 3, except that we introduce a gap year: the pre-event period is a three-year window from 2005 to 2007, and the post-event period is a three-year window from 2009 to 2011. The unit of observation is the advisor. *Crisis Price Change* is the 2008 house price return in the advisor's ZIP code. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. All specifications include firm fixed effects and length at residency decile fixed effects. Standard errors are clustered by ZIP code. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ΔMisconduct		
	PSYZ	BMT	Gap Year
	(1)	(2)	(3)
Crisis Price Change	-2.8925***	-6.7787***	-3.6606***
	(1.0338)	(1.4731)	(1.1965)
log(Industry Experience)	0.2154**	1.1904***	0.3469***
	(0.0877)	(0.1373)	(0.1061)
Firm FE	Yes	Yes	Yes
Length at Residency FE	Yes	Yes	Yes
R^2	0.022	0.030	0.027
Observations	248,432	247,514	248,432

Internet Appendix Table 5:
Annual Returns

This table reports estimates from regressions of misconduct on an advisor's annual house price return. The unit of observation is the advisor-year. The dependent variable is an indicator variable for advisor misconduct (multiplied by 100). *Annual Return* is the annual price change divided by the house price at the beginning of the year. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. The presence of control variables and fixed effects is indicated at the bottom of the table. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Misconduct	
	(1)	(2)
Annual Return	-0.1937**	-0.2364***
	(0.0775)	(0.0804)
log(Industry Experience)	0.2369***	0.4809***
	(0.0067)	(0.0183)
Advisor Controls	Yes	No
Advisor FE	No	Yes
Length at Residency FE	Yes	Yes
Firm×Year FE	Yes	Yes
ZIP FE	Yes	Yes
R^2	0.029	0.132
Observations	3,910,975	3,890,805

Internet Appendix Table 6:
One-Year Ahead & Three-Year Misconduct

This table reports estimates from regressions of misconduct on an advisor's cumulative house price return since purchase. The unit of observation is the advisor-year. In specifications (1) and (2), the dependent variable is an indicator variable for advisor misconduct (multiplied by 100) in the subsequent year. In specifications (3) and (4), the dependent variable is an indicator variable for advisor misconduct (multiplied by 100) in the three year window from t=0 to t=2. *Cumulative Return* is the aggregated cumulative price change divided by the purchase price. log(*Industry Experience*) is the logarithm of the number of years an advisor has worked in the industry. The presence of control variables and fixed effects is indicated at the bottom of the table. Standard errors, clustered by advisor and ZIP code, are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Misconduct_1		$\text{Misconduct}_{0\text{–}2}$	
	(1)	(2)	(3)	(4)
Cumulative Return	-0.0516**	-0.1451***	-0.1454***	-0.3605***
	(0.0207)	(0.0306)	(0.0508)	(0.0691)
log(Industry Experience)	0.2006***	0.4569***	0.5668***	1.2585***
	(0.0082)	(0.0224)	(0.0209)	(0.0519)
Advisor Controls	Yes	No	Yes	No
Advisor FE	No	Yes	No	Yes
Length at Residency FE	Yes	Yes	Yes	Yes
Firm×Year FE	Yes	Yes	Yes	Yes
ZIP FE	Yes	Yes	Yes	Yes
R^2	0.031	0.149	0.054	0.326
Observations	2,882,302	2,860,572	2,882,302	2,860,572