Predictive Signals: Do Mental Health-Related Google Searches Reflect Eviction Trends in Real Estate?

Eren Cifci[1], Scott Glasgow[2], Anthony Ramos[3]

Working Paper

Abstract

Google search history offers valuable insights into various aspects of an individual's personal, financial, emotional, and private life. As a result, research utilizing Google search data has garnered significant attention across multiple disciplines. With expanding access to this data, the volume of impactful studies leveraging such information continues to grow. However, in the field of real estate, research incorporating Google search data remains relatively underdeveloped. To address this gap, this study examines the relationship between mental health-related Google search activity and local real estate market dynamics, specifically eviction rates. By integrating insights from behavioral economics, housing studies, and mental health research, we contribute to the emerging literature on the intersection of psychological well-being and housing stability. Our findings indicate an association between stress-related Google search activity and local eviction and mortgage default rates. These results suggest that increased engagement with mental health resources, as reflected in search behavior, may play a role in mitigating eviction risks.

[1] College of Business, Austin Peay State University, Clarksville, TN, USA. E-mail: cifcie@apsu.edu
[2] FinMango, Cleveland/Akron, OH, USA. E-mail: scott@finmango.org
[3] FinMango, Cleveland/Akron, OH, USA. E-mail: tony@finmango.org

Introduction

Google search history could provide valuable insights into an individual's personal, financial, emotional, and private life. Consequently, research utilizing Google search data has gained significant attention across various disciplines. As access to Google search data expands, the volume of impactful studies based on this information continues to grow. However, in the field of real estate, this research remains relatively underdeveloped. To fill this gap, we connect mental health related Google search data with the local real estate market.

Housing is a fundamental determinant of well-being, influencing physical, behavioral, and mental health (Rahman & Steeb, 2024). Individuals invest substantial financial, temporal, and psychological resources in their homes (Evans, Wells, & Moch, 2003). Financial hardship can contribute to mental health challenges (Frankham, Richardson, & Maguire, 2020), and housing instability, particularly the threat of eviction, has been shown to deteriorate mental health outcomes (Vásquez-Vera et al., 2017; Acharya, Bhatta, & Dhakal, 2022). Given the strong connection between housing and well-being, further research integrating real estate and behavioral health perspectives—potentially through Google search data—could provide valuable insights into these complex relationships.

While much of the existing literature using Google search data has focused on normalized trend indicators, such as those provided by the standard Google Trends interface (which reports values on a 0–100 relative popularity scale), these metrics do not capture the actual frequency or probability of specific search terms. In contrast, this study leverages the Google Trends API to access conditional probability data based on a uniformly distributed random sample of web searches since 2004. This methodological approach provides a significant advantage by allowing us to analyze actual search probabilities rather than relying on scaled or relative indices.

This study contributes to the growing body of literature at the intersection of mental health and housing by investigating the relationship between stress-related Google search activity and eviction rates in local real estate markets. The motivation for this research stems from the premise

that tenants facing financial distress or the threat of eviction may also experience mental health challenges, leading them to seek information or support through online searches.

Our findings reveal that stress-related search activity is positively associated with local eviction rates. Specifically, increases in such search volume are linked to higher eviction rates in the subsequent month, as well as at three- and twelve-month horizons. These results suggest that heightened mental health-related search activity may serve as an early warning signal of future housing instability, both in the short and long term. Similarly, we find that stress-related search activity is a leading indicator of rising mortgage default rates, particularly over a two- to three-month horizon.

Taken together, the evidence implies that improved access to mental health resources and increased awareness may help mitigate both eviction and mortgage default risks. This study offers valuable insights for policymakers, real estate investors, and community stakeholders by highlighting the importance of integrating mental health considerations into broader housing stability strategies.

Literature

Several existing studies have utilized Google search data as indicators of various economic and demographic trends. These studies typically rely on publicly available Google Trends data or relative Google Trends data, as illustrated in Table 1.

Table 1: Differentiating Our Google API Data

Paper Title	Author	Differentiation
Use of Google Trends to Predict the Real Estate Market: Evidence from the United Kingdom	Grzegorz Michal Bulczak (2021)	**Query Indexes**: They collected data on the popularity of specific search terms related to real estate between 2004-2014. • The indexes range from 0-100, with 100 representing maximum popularity *They used the basic public Google Trends interface (with its 0-100 relative popularity scale), and our research utilizes the Google Trends API to access conditional probability data derived from Google's uniformly distributed random sample of web searches*

		since 2004. This provides a key advantage: we obtain actual probability values rather than normalized indexes.
Does Google Trends Show the Strength of Social Interest as a Predictor of Housing Price Dynamics?	Mirosław Bełej (2022)	They used Relative Search Volume (RSV) index on a scale from 0-100 (popularity) *Our Google Health Trends API data provides actual conditional probability values derived from a uniformly distributed random sample since 2004, while Bełej's study used the standard Google Trends interface with its 0-100 relative search volume index. Our approach yields more statistically robust measurements with precise probability values, whereas Bełej relied on normalized popularity indexes that show relative interest but lack the mathematical precision of probability-based measurements.*
The Future of Prediction How Google Searches Foreshadow Housing Prices and Sales	Lynn Wu and Erik Brynjolfsson (2015)	They used Relative Search Volume (RSV) index on a scale from 0-100. *Wu and Brynjolfsson's study uses relative Google Trends data, which provides relative search volume indexes on a scale of 0-100 based on query share (calculated as search volume for a query in a given location divided by total queries in that region). They examined pre-defined search categories like "real estate agencies" and "real estate listings" from 2004-2011 to predict housing market indicators, finding that search behavior could predict home sales and prices months in advance. Their approach differs from our Google Trends API data, which provides actual conditional probability values derived from a uniformly distributed random sample of Google searches since 2004. Our methodology yields more statistically robust measurements with precise probability values that enable more sophisticated analysis compared to the normalized popularity indexes used in previous research.*
Financial Market Prediction using Google Trends	Farrukh Ahmed, Dr. Raheela Asif, Dr. Saman Hinam, Muhammad Muzammil (2017)	They used Relative Search Volume (RSV) index on a scale from 0-100. *Our Google Health Trends API methodology differs fundamentally from Ahmed et al.'s approach in how search data is accessed and represented. While their study collected standard Google Trends relative search volumes (0-100 scale) for specific events and then transformed these from weekly/monthly to daily formats using DateTime libraries, our research leverages the Google Trends API to access the underlying conditional probability values derived*

		from a uniformly distributed random sample of searches since 2004.
Google search volumes and the financial markets during the COVID-19 outbreak	Michele Costola a , Matteo Iacopini b , Carlo R.M.A. Santagiustina (2021)	They used Relative Search Volume (RSV) index on a scale from 0-100. *Our Google Trends data differs fundamentally from that used by Costola et al. (2021) through its probabilistic foundation. While they relied on Google's standard normalized indexes (scaled from 0-100 relative to peak search volume), our data utilizes a conditional probability metric ($v = P(\text{Search Term} \mid t^d \cap d) * 10^7$) that provides a statistically sound measure of search behavior. This probabilistic approach allows for direct comparison across different terms and time periods, unlike their normalized data which makes such comparisons impossible. Additionally, our dataset incorporates both raw search strings and higher-order concept terms from Google's knowledge graph (terms with "--Topic" suffix), providing multi-level analysis capabilities. Figure 1 in their paper illustrates their data normalization process, showing how Google applies arbitrary scaling that distorts the relationship between search volumes, whereas our approach preserves these relationships through proper probabilistic measurement, potentially enabling more robust statistical analysis and forecasting.*
Collective Attention and Stock Prices: Evidence from Google Trends Data on Standard and Poor's 100	Raphael H. Heiberger (2015)	*Used relative search volumes normalized by Google (scale 0-100)* ***Calculation method**: Calculated relative changes in search volumes as:* • $\Delta n_i(t,\Delta t) = n_i(t) - N_i(t-1,\Delta t)$ • *Where $N_i(t-1,\Delta t)$ = average of previous 3 weeks' volumes*
The COVID-19 pandemic and residential mobility intentions in the United States: Evidence from GoogleTrends data	Lei Lei | Xialu Liu (2022)	Lei and Liu use Google Trends' normalized data (scaled from 0-100), where 100 corresponds to the month with highest search volume for a term. Our approach is a more precise probabilistic measure rather than a relative scale.
Employing Google Trends and Deep Learning in Forecasting Financial Market Turbulence	Anastasios Petropoulos, Vasileios Siakoulis, Evangelos Stavroulakis, Panagiotis Lazaris,	Petropoulos et al. use Google Trends indices "on a scale from 0 to 100, representing the monthly relative search volume" (p.353)

	and Nikolaos Vlachogiannakis (2022)	
Quantifying Trading Behavior in Financial Markets Using Google Trends	Tobias Preis, Helen Susannah Moat & H. Eugene Stanley (2022)	Unlike Preis et al. (2013) who calculate relative search volume changes ($\Delta n(t,\Delta t) = n(t) - N(t-1,\Delta t)$) using Google Trends' normalized 0-100 scale to predict stock market movements, our approach applies a direct conditional probability framework ($v = P(\text{Search Term} \mid t_d \cap d) \times 10^7$) from the Google Trends API to analyze real estate markets.
The link between cryptocurrencies and Google Trends attention	Nektarios Aslanidis, Aurelio F. Bariviera, Óscar G. López (2022)	Unlike Aslanidis et al. (2022) who used Google Trends data normalized on a 0-100 scale to construct a specialized cryptocurrency attention index by averaging multiple keywords (which they later rescaled to [0,1] for analysis), our approach applies a formal conditional probability framework.
ARMAX-MODELLING WITH GOOGLE TRENDS DATA FOR PREDICTION OF CHANGES IN VOLUME IN CRYPTOCURRENCIES	WILLEM BERNER, CASPAR LENNER (2025)	On page 11, section 4.1, they state: "For fetching data from Google-Trends, which does not provide an API, the data had to be retrieved in a less efficient manner. This was done by manually downloading the trends-data into a CSV-file which then could be accessed from the Python code." They also mention using a normalization technique to extend their data range beyond Google Trends' 6-month daily data limitation by retrieving two 6-month periods with a 7-day overlap, then using the median scaling factor of the overlapping points to combine them into a longer time series.
Exploring infodemiology: unraveling the intricate relationships among stress, headaches, migraines, and suicide through Google Trends analysis	Rapuru Rushendra, Vellapandian Chitra (2025)	This paper collected normalized data (0-100) from the Google Trends website interface, which they further adjusted by dividing values by total regional searches.
Assessing Global Interest in Financial Inclusion Information	Peterson K. Ozili (2025)	Used normalized data (0-100) from the Google Trends interface and then made a manual adjustment by total regional searches.
Time Series Interpolation (TSI): Leveraging Google Trends and LSTM	Azizallah Farhadi, Sara Ramazani (2024)	The research by Farhadi and Ramazani uses normalized Google Trends data on a 0-100 scale, obtained through the gtrendsR package. Their data represents a standardized "Search Ratio" formula ($SRig = (Sig / \sum Sig) \times 100$) where 100 indicates maximum popularity of a term in the given region and time period.

What drives the real estate market? Could behavioral indicators be useful in house pricing models?	Evangelos Vasileiou, Elroi Hadad, Georgios Melekos (2024)	Our approach differs from Vasileiou et al.'s by using a precise conditional probability formula(v=P(SearchTerm|td∩d)∗107v = P(Search Term | t_d \cap d) * 10^7 v=P(SearchTerm|td ∩d)∗107) rather than their simple 0-100 normalized indices. They also use the pytrend library. Our API data has the following benefits versus the pytrend library wrapper: • Mathematical rigor: Your conditional probability formula provides a statistically sound measure versus their normalized scale • Data quality: Direct API access gives you unfiltered data compared to Pytrends' wrapper • Precision: Your approach likely captures search behavior with greater mathematical precision • Interpretability: Your results have a clearer probabilistic interpretation rather than relative scores • Customization: Direct API access allows for more sophisticated query construction and data manipulation
Development and Validation of a Real-Time Happiness Index Using Google Trends	Talita Greyling, Stephanié Rossouw (2024)	The paper states on page 8: "Google Trends ™ is an open data service provided by Google Inc... It offers access to a single metric: the Relative Search Volume (RSV), a standardised measure reflecting search activity relative to the chosen time frame and geographic region. The RSV values range from 0 to 100, enabling comparisons of search volume trends across different queries, time periods, and locations." However, the authors do additional processing on this data - they standardize all search volumes to have a mean of zero and standard deviation of one, focusing on changes in volume within each search term rather than absolute comparisons between terms.
Statistical methods for inflation forecasting in Morocco: Insights fromGoogle trends data	Mariem Bikourne, Sokaina El khamlichi,, Adil Ez-Zetouni, Khadija Akdim (2024)	They extract Relative Search Volume (RSV) data ranging from 0-100 for inflation-related keywords in three languages
The measurement errors of google trends data	Kerry Liu (2024)	Our research improves upon standard Google Trends methodologies by utilizing direct API access and

		applying a robust conditional probability formula (v = P(Search Term | td ∩ d) * 10^7) rather than relying on the problematic 0-100 normalized scale that Liu (2024) critiqued. While most studies use this normalized data—which Liu demonstrated can show search results for terms before they existed or insufficient results for widely discussed topics—our approach provides mathematical rigor through true conditional probabilities. This methodological advancement is particularly valuable for real estate applications where search behaviors tend to follow more consistent patterns, making our data less susceptible to the measurement errors identified after Google's January 2022 update that compromised many existing studies using the standard normalized approach.
Using Google Trends Data to Study High-Frequency Search Terms: Evidence for a Reliability-Frequency Continuum	Tobias Gummer and Anne-Sophie Oehrlein (2024)	The Gummer and Oehrlein (2024) study uses Google Trends (GT) data that is normalized on a scale from 0 to 100, where 100 represents the maximum search volume within the specified time period. These relative search volumes (RSVs) don't represent absolute search counts but rather normalized values where the peak is set to 100 and all other points are relative to this maximum
Predicting macroeconomic indicators from online activity data: A review	Eduardo André Costaa and Maria Eduarda Silva (2024)	The paper uses Google Trends data normalized on a scale from 0 to 100 (the Google Index or GI), where 100 represents maximum search popularity within a specified time period.

However, this form of data may have limitations for our research, as mental health issues may not be readily observable through general search trends. Given the nature of our study, a more in-depth analysis of mental health-related search behavior is warranted to uncover localized patterns.

To address this, our research employs the Google Health Trends API, which provides access to conditional probability data derived from a uniformly distributed random sample of Google web searches dating back to 2004. This approach offers a key methodological advantage: instead of relying on normalized popularity indexes, we obtain actual probability values. As a result, our analysis yields more statistically robust measurements and enables more nuanced and sophisticated interpretations than those possible with the standard normalized data used in prior studies.

Data

Our analysis utilizes monthly county-level data spanning from January 2020 to December 2023. We collect Google search data at the designated market area (DMA) level using Google Health Trends' Interest over Time metric (IPA). Our Google Trends API data provides actual conditional probability values derived from a uniformly distributed random sample since 2004, while Bełej's study used the standard Google Trends interface with its 0-100 relative search volume index. Our approach yields more statistically robust measurements with precise probability values, whereas Bełej relied on normalized popularity indexes that show relative interest but lack the mathematical precision of probability-based measurements.

We derived our search terms through a comprehensive review of the existing literature. As summarized in Table 2, several prior studies were analyzed to identify relevant keywords and thematic indicators associated with mental health issues.

Our analysis includes 26 mental health-related search terms, encompassing a wide range of conditions and emotional states. These terms include: *Addiction, ADHD, Anorexia, Antidepressants, Anxiety, Attention Deficit-Hyperactivity Disorder, Bipolar, Breakdown, Breakup, Bulimia, Burnout, Depression, Divorce, Insomnia, Mania, Mental Breakdown, Mental Crisis, Mental Health, Obsessive Compulsive Disorder, OCD, Panic, Sad, Schizophrenia, Stress, Suicide,* and *Worried.*

Table 2: Mental Health Words from Google Sears History

Paper Title	Authors	Relevant Keywords/Details
Tracking Population-level Anxiety using search engine data	Barnabas James Gilbert, Chunling Lu, Elad Yom-Tov (2023)	"Having kids", "pregnancy", "anxious about, "worried about", "my health", "my reputation."
Cloud Behavioral Medicine lead the web data revolution?	J. Ayers, B. Althouse, Mark Dredze (2014)	Paper with several citations in web data r
Internet Searches for Acute Anxiety during the early staged of the COVID-19 pandemic	John W Ayers, Eric C Leas, Derek C Johnson, Adam Poliak, Benjamin M Althouse, Mark Dredze, Alicia L Nobles (2020)	Anxiety attack symptoms, panic attack, panic attack symptoms
Using Google searches on the internet to monitor suicidal behavior	John F Gunn, David Lester (2013)	Suicide, teen suicide, depression, unemployment, divorce

Google Searches and Suicide Rates in Spain 2004 - 2013	Alberto Jimenez, Miguel-Angel Santed-Germán, Victoria Ramos (2020)	Antidepressants, alcohol abstinence, relationship breakup, "Depression AND help", anxiety disorder, etc
Impact of Covid-19 on mental health: real-time surveillance of Google Search Trends	Hoerger, Michael; Alonzi, Sarah; Perry, Laura M.; Voss, Hallie M.; Easwar, Sanjana; Gerhart, James I. (2020)	
Seasonality in Seeking Mental Health Information on Google	JW Ayers, BM Althouse, JP Allem, JN Rosenquist, DE Ford (2013)	adhd (attention deficit-hyperactivity disorder); anxiety; bipolar; depression; anorexia or bulimia (eating disorders); OCD (obsessive compulsive disorder); schizophrenia; and suicide
Associations of lockdown stringency and duration with Google searches for mental health terms during the COVID-19 pandemic: A nine-country study	Pedro A. de la Rosa, Richard G. Cowden, Renato de Filippis, Stefan Jerotic, Mahsa Nahidi, Dorottya Ori, Laura Orsolini, Sachin Nagendrappa, Mariana Pinto da Costa, Ramdas Ransing, Fahimeh Saeed, Sheikh Shoib, Serkan Turan, Irfan Ullah, Ramyadarshni Vadivel, Rodrigo Ramalho (2022)	Anxiety," "Depression," "Suicide," "Mental Health
Google Trends reveals increases in internet searches for insomnia during the 2019 coronavirus disease (COVID-19) global pandemic	Kirsi-Marja Zitting, Heidi M. Lammers-van der Holst, Robin K. Yuan, Wei Wang, Stuart F. Quan, Jeanne F. Duffy (2021)	insomnia
Putative impact of the COVID-19 pandemic on anxiety, depression, insomnia and stress	Giuseppe Lippi, Brandon M. Henry, Fabian Sanchis-Gomar (2020)	anxiety," "depression," "insomnia," and "stress.
COVID-19 blues: Lockdowns and mental health-related google searches in Latin America	Adan Silverio-Murillo, Lauren Hoehn-Velasco, Abel Rodriguez Tirado, Jose Roberto Balmori de la Miyar (2021)	insomnia, stress, anxiety, and sadness, depression, or suicide-related searches
The Quality of Mental Health Information Commonly Searched For on the Internet	John M. Grohol, Joseph Slimowicz, and Rebecca Granda (2014)	depression, anxiety, ADHD, bipolar, schizophrenia, dysthymia, phobia, social anxiety, post-traumatic stress disorder (PTSD), panic, and generalized anxiety disorder

Based on these references, we developed the final set of search terms employed in our analysis, as presented in Table 3.

Table 3: The List of Mental Health Words from Google Sears History

Mental Health Words from Google Sears History	
Addiction	Insomnia
Adhd	Mania
Anorexia	Mental Breakdown
Antidepressants	Mental Crisis
Anxiety	Mental Health
Attention Deficit-Hyperactivity Disorder	Obsessive Compulsive Disorder
Bipolar	Ocd
Breaddown	Panic
Breakup	Sad
Bulimia	Schizophrenia
Burnout	Stress
Depression	Suicide
Divorce	Worried

After collecting monthly Google search data, we merge it with the corresponding county-level data. Eviction data is obtained from the Legal Services Corporation Civil Court Data Initiative,[4] covering counties across 27 states in the continental United States from January 2016 until December, 2022. These states include Alaska, Arizona, Arkansas, Connecticut, Delaware, Florida, Georgia, Indiana, Kansas, Kentucky, Maine, Minnesota, Mississippi, Missouri, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Vermont, and Virginia. Additionally, our analysis will incorporate relevant economic control variables in the future steps of the study to account for broader market conditions and ensure robustness in our findings.

Table 4: **summary statistics**

	N	Min	Mean	Median	SD	Max
Eviction fillings	30986	0	134.818	0	1008.888	21093
Mortgage def rate	28512	.1	2.392	2.3	1.246	11.3
Google stress search	9573	0	.002	.002	.001	.006

[4] *Legal Services Corporation Civil Court data initiative*. (2024). Retrieved from: https://civilcourtdata.lsc.gov/data/eviction

Empirical Analysis

We estimate the model shown in Equation 1 using time and market fixed effect:

$$Ln(NumberofEvictions)_{it} = B_0 + B_1 L.ln(GoogleSearchProbavility)_{it} + B_2 X_{it} + \mathrm{r}_t + \sigma_i + \varepsilon_{it} \quad \textbf{(1)}$$

$Ln(NumberofEvictions)$ is the dependent variable measured as the natural log of the number of evictions in a given market, $ln(GoogleSearchProbavility)$is the sum of the probability measure of each stress word in a given market, X is a vector of control variables, tau, and sigma stand for time and city fixed effects respectively, and i and t are for the city and year.

We estimate a fixed effects model with robust standard errors to account for unobserved heterogeneity across local markets. The results are presented in Table 5. The findings indicate that the probability of Google stress-related searches is positively associated with eviction rates across all model specifications, with statistically significant effects observed at 1-month, 3-month, and 12-month horizons. Specifically, in the one-month model, a 1 percentage point increase in the probability of stress-related searches in a given market is associated with a 4.17% increase in the eviction rate. This effect is statistically significant at the 5% level.

Table 5

	(1) ln(NumEvic)	(2) ln(NumEvic)	(3) ln(NumEvict)	(4) ln(NumEvic)	(5) ln(NumEvic)
L.ln(StressSearches)	0.0409**				
	(0.0171)				
L2. ln(StressSearches)		0.0242			
		(0.0149)			
L3. ln(StressSearches)			0.0334*		
			(0.0183)		
L6. ln(StressSearches)				0.0086	
				(0.0156)	
L12. ln(StressSearches)					0.0266**
					(0.0121)
_cons	3.7997***	3.6919***	3.7513***	3.5872***	3.6941***
	(0.1048)	(0.0915)	(0.1123)	(0.0956)	(0.0741)
Observations	7848	7768	7683	7388	6834
Adj R^2	0.0011	0.0003	0.0007	-0.0001	0.0004
Market Fixed Effect	YES	YES	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Mortgage Default Rate

We use 30–89 day late payments as an indicator of mortgage default. Findings are reported in

Table 6. To account for unobserved heterogeneity across local housing markets, we estimate a fixed effects model with robust standard errors. The results indicate that the probability of Google stress-related searches is positively associated with mortgage default rates across all model specifications, with statistically significant effects emerging at the 2-month and 3-month horizons. For instance, in Model 2 (the 2-month specification), a 1 percentage point increase in the probability of stress-related searches within a given market is associated with a 4.17% increase in the mortgage default rate. This effect is statistically significant at the 10% level.

Table 6

	(1) ln(MtgDef)	(2) ln(MtgDef	(3) ln(MtgDef	(4) ln(MtgDef	(5) ln(MtgDef
L.ln(StressSearches)	0.0115				
	(0.0102)				
L2. ln(StressSearches)		0.0208*			
		(0.0108)			
L3. ln(StressSearches)			0.0257**		
			(0.0107)		
L6. ln(StressSearches)				0.0165	
				(0.0105)	
L12. ln(StressSearches)					0.0140
					(0.0091)
_cons	0.4553***	0.5069***	0.5337***	0.4682***	0.4286***
	(0.0625)	(0.0661)	(0.0654)	(0.0641)	(0.0559)
Observations	7025	7025	7025	7025	7025
Adj R^2	0.0002	0.0008	0.0014	0.0005	0.0003
Market Fixed Effect	YES	YES	YES	YES	YES

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Conclusion

This study provides novel insights into the intersection of mental health and housing instability by examining how stress-related Google search activity correlates with future eviction and mortgage default rates across local real estate markets. By leveraging actual probability data from the Google Trends API, rather than relying on relative popularity indices, we offer a more precise and informative measure of public stress-related search behavior. Our findings indicate that increases in such online search activity are predictive of elevated eviction rates and mortgage defaults, particularly within short- to medium-term horizons. These results underscore the potential of digital search data as a real-time signal for emerging housing distress. Importantly, the study highlights the need for policies that incorporate mental health support as part of broader efforts to promote housing stability. By identifying early warning indicators of financial and housing

vulnerability, our work contributes to a growing evidence base that can inform more proactive and integrated responses from policymakers, housing professionals, and mental health practitioners alike.

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